Gravity in International Trade:

Econometric Challenges and Environmental Extensions

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For my parents.

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Introduction

Why do some country pairs trade more than others? Which trade policies are successful in fostering bilateral exchange? What determines whether two countries start to trade with each other at all? And how do international trade linkages influence the effectiveness of efforts against the inherently global problem of climate change? This dissertation aims to contribute to our understanding of these questions, drawing on what is known as the gravity model of international trade. I will present (i) econometric advances that allow a closer link between model and empirics than previously possible, (ii) theoretical extensions that explicitly incorporate environmental concerns into quantitative trade models, and (iii) specific applications of the proposed methods and extensions, investigating for instance whether sharing a common currency leads countries to trade more with each other or by how much the effectiveness of the Paris Agreement in reducing global greenhouse gas emissions is harmed by the United States' (US) withdrawal.

The general idea of gravity in international trade is simple: the closer and larger two countries are, the more they will trade with each other. Or put formally:

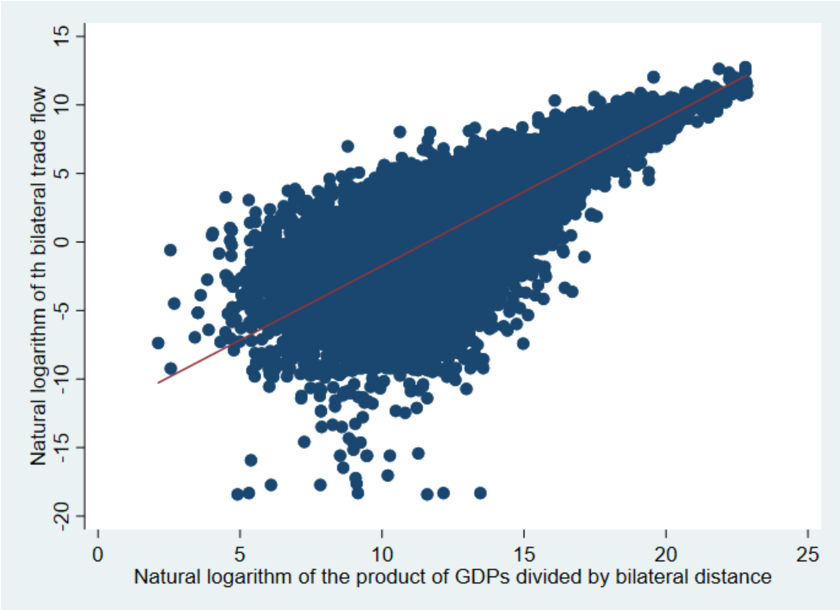
$$X_{ij} = A\frac{Y_i^{\beta_1} Y_j^{\beta_2}}{dist_{ij}^{\beta_3}}, \tag{1}$$

where X_{ij} denotes trade flows from country i to j, A is a "gravitational constant", Y denotes a country's economic size (typically captured by its gross domestic product, GDP), $dist$ represents the physical distance, and $\beta_k > 0$ ($k \in \{1, 2, 3\}$) are the corresponding elasticities.

Tinbergen (1962) was the first to estimate a trade gravity equation.[1] Today, gravity is *the* standard approach to estimate the determinants of bilateral trade flows and an important tool for (trade) policy evaluation. The success story of the gravity model can be credited to two main factors: its impressive empirical performance and its solid

[1] The very first gravity application in economics was a migration study conducted already in the 19th century by Ravenstein (1885, 1889).

Figure 1: The Gravity of Bilateral Trade Flows



theoretical foundation.

Leaving the role of economic theory aside for a moment, the empirical persuasiveness of gravity is illustrated in Figure 1. It displays the positive bilateral trade flows between 166 ex- and importing countries in 2006 against a very simple ad-hoc measure of the country pairs' "gravitational force", namely the product of their gross domestic products divided by the bilateral distance.[2] The pattern is clear: the higher the gravitational force between two countries, the larger the trade flow between them.

A first straightforward approach to improve upon this fit and gain further insights into the drivers of bilateral trade flows is to actually estimate coefficients for GDPs and distance rather than simply imposing unit elasticities (as has been done for Figure 1). Note that in order to do so, one has to make an econometric choice, namely which estimator to use. While it was long common practice to take the logarithm of equation (1) and estimate the resulting linear expression with ordinary least squares (OLS), Santos Silva and Tenreyro (2006) show that the resulting estimates are biased and suggest a nonlinear Poisson pseudo-maximum likelihood (PPML) estimator instead.

A second way to better capture the pattern of bilateral trade flows is to generalize the notion of distance and include other aspects beyond being physically apart that may also influence trade costs between two countries, e.g. whether these countries share a common language, have a colonial history, or whether they are joint members of a regional trade agreement. In doing so, one can infer the effect of these additional vari-

[2]Variables on both axes are in logarithms. The data is taken from Head, Mayer, and Ries (2010).

ables on bilateral trade by learning from the *deviations* from the systematic relationship illustrated in Figure 1.

Third, panel data can be used to gauge the different drivers of bilateral trade flows more precisely. As pointed out by Baier and Bergstrand (2007), they are particularly attractive if the effect of trade *policies* is estimated which are likely to be endogenous. For instance, two countries may decide to sign a trade agreement precisely because they face high trade barriers and finally want to make use of their full trade potential. Observing trade flows over multiple periods allows the inclusion of country pair fixed effects and therefore to control for all observable and unobservable time-invariant bilateral characteristics.

Up to this point, economic theory was absent from all considerations. Equation (1) is not derived from any theoretical trade model, but rather based on its intuitive appeal only. However, the ad-hoc nature of gravity specifications along the lines of (1) has important limitations. These limitations become evident when considering a thought experiment by Krugman (1995): Imagine two small European countries — say Belgium and the Netherlands — being taken out of the heart of Europe and put on Mars. Their bilateral distance does not change, but still we would expect them to trade more with each other than before as they become remote vis-à-vis the rest of the world and therefore do not have other trading partners anymore. The thought experiment illustrates that the simple gravity structure given in equation (1) lacks an important component — remoteness. However, while exemplifying *that* remoteness matters, it is not informative about *how* it can be captured when using gravity to estimate trade determinants. It is here that the embedding of gravity into trade theory becomes crucial for the first time.

In two seminal papers, Eaton and Kortum (2002) and Anderson and van Wincoop (2003) derive theory-consistent gravity equations in a Ricardian and an Armington (1969)-type framework of international trade, respectively. These equivalent gravity equations capture the notion that bilateral trade flows indeed depend on *relative* bilateral trade costs rather than on the absolute level. Bergstrand, Egger, and Larch (2013) and Chaney (2008) show that the same gravity equation also holds in a Krugman (1980)-type model with homogeneous firms and a Melitz (2003)-type heterogeneous firm model with a Pareto productivity distribution. Feenstra (2004) argues that the "multilateral resistance terms" (Anderson and van Wincoop, 2003), which formalize the ex- and importers' overall remoteness discussed intuitively above, can be econometrically taken into account with two sets of fixed effects, namely exporter and importer fixed effects. Following the same logic in a panel data environment (see e.g. Baldwin and Taglioni, 2007), economic theory asks for the inclusion of exporter-time and importer-time fixed effects. Fally (2015) shows that if the gravity equation is estimated using the PPML estimator, the estimated fixed effects can be directly translated into the theoretical multilateral resistance terms.

A theory-consistent estimation procedure for gravity equations that takes into account the nonlinear structure and uses panel data to tackle the potential endogeneity of trade policy hence demands a PPML estimator with three sets of high-dimensional fixed effects. However, for large samples, computational issues associated with these exporter-time, importer- time, and country pair fixed effects currently recommended in the gravity literature[3] have limited the choice of estimator, leaving an important methodological gap. To address this gap, in the first chapter of this dissertation, which is joint work with Mario Larch, Yoto Yotov, and Tom Zylkin, we introduce an iterative PPML estimation procedure that facilitates the inclusion of these fixed effects for large data sets and also allows for correlated errors across countries and time. We apply this procedure to analyze the effect of a common currency on bilateral trade in a comprehensive sample with more than 200 countries trading over 65 years. In our analysis, we build on the contribution by Glick and Rose (2016) who — based on OLS estimation of a log-linearized gravity equation — find that sharing a currency generally fosters bilateral trade flows and that the Euro has been especially successful compared to other currency unions, increasing its members' bilateral trade by 50%. It turns out that our innovations flip the conclusions of their otherwise rigorously specified linear model. Most importantly, our estimates for both the overall currency union effect and the Euro effect specifically are economically small and statistically insignificant.

One of the often cited advantages of the PPML estimator is that zero trade flows can be included in the estimation, because the gravity equation is estimated in its original multiplicative form rather than after linearizing it by taking the logarithm. Country pairs not trading with each other at all are an important feature of international trade data. For example, in order to plot Figure 1, more than a quarter of the observations had to be omitted because zero trade flows cannot be depicted on the logarithmic scale used. However, in spite of the prominent role of zeros in the data, the previously mentioned trade theories that give rise to a structural gravity estimation with PPML and the according sets of fixed effects do not actually predict any zero trade flows (only in the theoretical case of infinitely high trade costs). For example, the consumers "love of variety" that motivates international trade in the Armington (1969)-type model ensures

[3] See Yotov, Piermartini, Monteiro, and Larch (2016) for a compilation of best practice recommendations in gravity estimation.

that consumers in any country want to consume at least a small amount of products from all other countries and the Pareto productivity distribution typically assumed in Melitz (2003)-type heterogeneous firm models ensures that there is always a firm productive enough to overcome the fixed costs of exporting and serve any foreign market. One important strand of extensions of gravity models therefore deals with the explicit incorporation of zero trade flows into gravity theory. Prominently, Helpman, Melitz, and Rubinstein (2008) and Eaton, Kortum, and Sotelo (2013) consider versions of Melitz (2003)'s heterogeneous firm model of international trade and introduce zero trade flows by considering a truncated productivity distribution and a finite set rather than a continuum of firms, respectively. Just as at the intensive margin, economic theory shows that there are unobservable exporter(-time) and importer(-time) characteristics that can be controlled for using fixed effects in the estimation. Similarly, endogeneity concerns with respect to trade policy again suggest the inclusion of bilateral fixed effects. However, in a binary choice setting, these fixed effects pose an additional econometric challenge, namely an incidental parameter problem. This problem — first identified by Neyman and Scott (1948) — describes the phenomenon that for most nonlinear estimators, the inclusion of fixed effects (i.e. of a set of nuisance parameters the number of which increases with sample size) leads to asymptotically biased estimates. Furthermore, the literature on the firm-level exporting decision (see e.g. Das, Roberts, and Tybout, 2007) stresses the role of market entry costs which introduce a dynamic feature to the consideration as today's cost (and therefore probability) of serving a market depends on yesterday's activity in the respective market. Econometrically speaking, this potentially induces true state dependence at the aggregate extensive margin of trade, too, asking for the inclusion of the lagged dependent variable in the empirical specification. In such a dynamic model, the incidental parameter bias is potentially amplified.

In the second chapter of this thesis, which is joint work with Amrei Stammann and Julian Hinz, we document that the aggregate extensive margin of bilateral trade exhibits a high level of persistence that cannot be explained by geography or trade policy. We combine the heterogeneous firm model of international trade with bounded productivity by Helpman, Melitz, and Rubinstein (2008), with features from the firm dynamics literature (see e.g. Alessandria and Choi, 2007; Das, Roberts, and Tybout, 2007), to derive expressions for an exporting country's participation in a specific destination market in a given period. The model framework asks for a dynamic binary choice estimator with two or three sets of high-dimensional fixed effects. To mitigate the incidental parameter problem associated with nonlinear fixed effects models, we characterize and implement suitable bias corrections. Extensive Monte Carlo simulations confirm the desirable statistical properties of the bias-corrected estimators. Empirically, taking two sources of persistence — true state dependence and unobserved heterogeneity — into account using a dynamic specification, along with appropriate fixed effects and bias corrections, changes the estimated effects considerably: out of the most commonly studied potential extensive margin determinants (joint WTO membership, common regional trade agreement, and shared currency), only sharing a common currency retains a significant effect on whether two countries trade with each other at all in our preferred estimation. The empirical applications of the first two chapters hence jointly imply that a common currency makes two countries more likely to trade with each other, but does not affect the extent of their bilateral trade flows.

As outlined up to this point, the first half of this dissertation deals with the theory-consistent estimation of the determinants of the in- and extensive margins of bilateral trade using gravity models and econometric challenges associated with it. However, gravity's success story is not limited to the estimation of trade determinants. Rather, the theoretical foundations for the gravity equation by Eaton and Kortum (2002) and Anderson and van Wincoop (2003) additionally paved the way for a second important area of application: general equilibrium (GE) policy analyses. Having embedded the trade determinants into a sound economic theory, it is possible to solve for the trade and welfare effects of a policy change. First of all, one can investigate changes in trade costs: Eaton and Kortum (2002) consider for instance a scenario in which all trade costs are infinitely high, such that all countries move to autarky. Anderson and van Wincoop (2003) simulate the absence of an international border between Canadian provinces and US states. But while gravity *estimation* is all about the determinants of bilateral trade costs, GE analysis based on gravity is not restricted to trade cost changes. For example, a second application by Eaton and Kortum (2002) is the international spreading of gains from new technology in one country via trade and hence looks at the multilateral implications of a unilateral shock. The second half of this thesis is related to the role of gravity as quantitative trade theory, i.e. as a tool for policy analyses. Specifically, it presents gravity model extensions that incorporate environmental aspects and therefore allow a theory-founded quantitative GE analysis of the interplay of climate policy and international trade.

An international perspective on climate policy is essential because any climate policy that is not implemented on a global scale runs the risk of facing so-called "carbon leakage" (Felder and Rutherford, 1993). This refers to the phenomenon that part of the emission reduction achieved by a country or region undertaking a mitigation effort is offset by *increases* in emissions by other countries. One important channel for carbon leakage is the shift of emission-intensive industries from countries undertaking climate policies (e.g. pricing carbon emissions) to other countries that gain comparative advantage in such industries by not internalizing the costs associated with the occurring emissions. Clearly, a gravity model that incorporates a sectoral structure and emissions from production is a viable candidate for the analysis of these GE trade effects, complementing the widespread use of large-scale computable general equilibrium (CGE) models in the trade and environment literature (see e.g. Böhringer, Balistreri, and Rutherford, 2012, for an overview of CGE models in this field). One trade policy that may potentially mitigate carbon leakage is the introduction of so-called carbon tariffs, the idea of which is to compensate carbon price differentials between trading partners by levying import duties that depend both on the given differential and the amount of carbon emissions embodied in the good that is traded.

In the third chapter, which is joint work with Mario Larch, we contribute to the discussion regarding the potential of carbon tariffs to restore competitiveness, avoid carbon leakage, and reduce global carbon emissions. To analyze the effects of carbon tariffs on trade, welfare, and carbon emissions, we develop a multi-sector, multi-factor structural gravity model that allows an analytical and quantitative decomposition of the emission changes into scale, composition, and technique effects following Grossman and Krueger (1993) and Copeland and Taylor (1994). Our analysis shows that carbon tariffs are able to reduce world emissions, mainly via altering the production composition within and across countries, hence reducing carbon leakage. This reduction comes at the cost of lower world trade flows and lower welfare, especially for developing countries. Applying our framework to investigate the effects of the emission reduction pledges made by the Annex I countries in the Copenhagen Accord, we find that combining national emission targets with carbon tariffs would increase the Accord's effectiveness by lowering the leakage rate from 13.4% to 4.1%.

The second main channel of carbon leakage acts via the international energy market. For instance, if the European Union decides to extend the Emission Trading Scheme to more sectors and/or to lower the available number of certificates in the covered sectors, this will lower the European demand for fossil fuels. This negative demand shock will, however, drive down prices for fossil fuels on the world market and therefore create an incentive for all other countries to use more fossil fuels, again offsetting part of the mitigation effort, similarly to the production shift channel discussed above.

The threat of carbon leakage makes evident the advantage of global cooperation in the fight against climate change. If all countries have binding emission reduction targets, there is no place emission-intensive production can shift to in order to avoid carbon taxation and there are no countries that use falling fossil fuel prices to shift towards more carbon intensive production. For this reason, the supposedly global coverage of the Paris Agreement might have been the accord's major strength. However, the US have already announced that they are going to withdraw from the agreement and a number of signing countries have so far failed to ratify, eliminating the intially truly global character of the treaty.

In the fourth chapter, which is again joint work with Mario Larch, we investigate the implications of unilateral withdrawals from the Paris Agreement. Countries that drop out of the Paris Agreement harm the effectiveness of the international initiative to lower greenhouse gas emissions in two ways. First, by canceling their own reduction commitments, they fall back on a business as usual emission path, directly reducing the extent of the global emission reduction. Second, carbon leakage may occur in response to the climate policy of Paris member countries, actually increasing the withdrawing country's emissions above the level it would have experienced in the complete absence of the Paris Agreement. This leakage in turn occurs via the two channels discussed above: emission-intensive production is shifted from the committed to non-committed countries and the climate policies of Paris members lower their fossil fuel demand, driving down energy prices and hence leading to more energy-intensive production in non-committed countries. We extend the multi-sector structural gravity model with emissions from production developed in the third chapter by a constant elasticity of fossil fuel supply function (as suggested in the CGE context by Boeters and Bollen, 2012) that allows us to capture the energy-market leakage channel without relying on a fixed resource in the production process. The resulting model remains tractable enough to still allow the decomposition of emission changes into scale, composition, and technique effects. We use the extended framework to simulate the consequences of unilateral withdrawals from the Paris Agreement. We find that a US withdrawal would have the strongest effect, eliminating a third of the world emission reduction, while a potential Chinese withdrawal would imply the highest leakage rate (12.1%). We find leakage to be primarily driven by technique effects that are induced via the energy-market leakage channel. Both the overall magnitude of the reduction losses and the relative importance of the different leakage channels have significant policy implications.

To summarize, this thesis aims to contribute to the understanding of the drivers and effects of international trade flows in two distinct ways. First, it offers solutions to econometric challenges that arise in the estimation of trade cost determinants both at the extensive and the intensive margin, i.e. both in determining which country pairs are likely to trade with each other at all and in identifying factors that lead country pairs to trade more or less with each other. Second, it incorporates environmental aspects into quantitative trade theory models in order to foster the understanding of the role of international economic exchange in shaping the success or failure of international greenhouse gas mitigation efforts. Both strands of the thesis rely on a common theoretical ground: the gravity model of international trade.

1

Currency Unions and Trade: A PPML Re-assessment with High-dimensional Fixed Effects[1]

1.1 Introduction and Motivation

> *To us, a plausible methodology to estimate the currency union effect on trade involves panel estimation with dyadic fixed effects. We [. . .] await computational advances to be able to estimate the Poisson analogues. (Glick and Rose, 2016, p. 86)*

Writing at the beginning of a transformative period in the empirical study of international trade, Rose (2000) reported the stunning finding that sharing a common currency more than triples trade between countries. While this estimate was regarded as puzzlingly high at the time, it succeeded in stimulating a vibrant and ongoing empirical literature

[1]This chapter is joint work with Mario Larch, Yoto Yotov, and Tom Zylkin. It has been published under the same title in the *Oxford Bulletin of Economics and Statistics*, 2019, 81(3), 487–510. Thomas Zylkin is grateful for research support from the NUS Strategic Research Grant (WBS: R-109-000-183-646) awarded to the Global Production Networks Centre (GPN@NUS) for the project titled "Global Production Networks, Global Value Chains, and East Asian Development". We thank Andy Rose, João Santos Silva, three referees, the handling editor James Fenske, as well as participants at the European Trade Study Group 2017 in Florence and the workshop "International Economics" 2018 in Göttingen. *Note*: The procedure presented in this chapter is implemented in Stata and freely available via ssc (to install, type "`ssc install ppml_panel_sg, replace`") or at https://econpapers.repec.org/software/bocbocode/S458249.htm (accessed on August 16th, 2019).

investigating the trade-creating effects of currency unions (CUs), having garnered over 3,100 citations since its original publication in google scholar and 356 citations in Web of Science Core Collection. This literature has notably included frequent re-examinations of the original evidence by Rose himself—such as Glick and Rose (2002, 2016)—as well as fervent interest in whether the European Monetary Union (EMU) in particular, as the largest CU to date, might have had similarly remarkable effects.[2]

Parallel to this literature, the past two decades have seen the development and wide adoption of many new econometric best practices for consistently identifying the determinants of international trade. These have most notably included the use of Poisson Pseudo-Maximum Likelihood (PPML) estimation to address issues related to heteroscedasticity and zeroes (Santos Silva and Tenreyro, 2006), time-varying exporter and importer fixed effects to account for changes in the "multilateral resistance" constraints implied by theory (Anderson and van Wincoop, 2003; Feenstra, 2004; Baldwin and Taglioni, 2007), and time-invariant pair fixed effects to absorb unobservable barriers to trade (such as bilateral history) and to address the endogeneity of trade policy variables due to time-invariant unobserved bilateral heterogeneity (Baier and Bergstrand, 2007).[3] Aiding these developments, empirical researchers working in trade have also benefited from a new-found consensus on the theoretical underpinnings of the gravity equation (Arkolakis, Costinot, and Rodríguez-Clare, 2012) as well as recent computational advances that permit swift estimation of linear models with a large number of fixed effects (Carneiro, Guimarães, and Portugal, 2012; Correia, 2016a).

Reassuringly, as these new methods have filtered into the literature on currency unions, they have led to more reasonable and reliable estimates. In their latest instalment,

[2]Along with Glick and Rose (2002, 2016), some of Rose's other work in this area includes Rose (2001), Rose (2002), and Rose (2017). Contributions by Persson (2001), Nitsch (2002), Levy-Yeyati (2003), Barro and Tenreyro (2007), de Sousa (2012), and Campbell (2013) are examples of reactions to Rose's initial finding. Finally, Micco, Stein, and Ordonez (2003), Baldwin and Taglioni (2007), Bun and Klaassen (2007), Berger and Nitsch (2008), Santos Silva and Tenreyro (2010a), Eicher and Henn (2011), Olivero and Yotov (2012), Herwartz and Weber (2013), and Mika and Zymek (2018) specifically investigate the effect of the EMU. Santos Silva and Tenreyro (2010a) and Rose (2017) survey each of these literatures.

[3]Of course, endogeneity of common currencies may also arise from time-varying bilateral effects. Our investigation does not tackle these sources of selection into currency unions.

which emphasizes the use of time-varying exporter and importer fixed effects as well as time-invariant pair fixed effects, Glick and Rose (2016) find—under their most rigorous specification—that CUs generally increase trade by 40%, that CU entry and exit have symmetric effects on trade, and that the EMU—which could not be included in earlier studies—has promoted trade more than other CUs.[4]

Doing their due diligence, Glick and Rose (2016) also experiment with PPML estimation with two-way (exporter-time and importer-time) fixed effects.[5] However, as captured in the opening quote, they are unable to obtain estimates for one particularly important and desirable specification: the case of a PPML model with a *full* set of fixed effects (i.e., with pair fixed effects also added to the exporter-time and importer-time fixed effects from the two-way model).[6]

In this paper, we pick up where Glick and Rose (2016) leave off. The main technical challenge we overcome is Glick and Rose (2016)'s preference for as large a sample as possible, covering trade between more than 200 countries over 65 years and therefore necessitating the use of more than 50,000 fixed effects. In order to clearly demonstrate the importance of our methods, we employ the same dataset as Glick and Rose (2016) and we rely on the same theory-consistent gravity model with added pair fixed effects, reflecting the latest developments in the gravity literature noted above. Thus, the differences in our results are driven exclusively by the following two innovations. First (and most importantly), we present an iterative PPML algorithm that specifically

[4]Glick (2017) demonstrates that these results are robust to controlling for EU membership and further shows that there is heterogeneity in the trade effects between new and old EMU members.

[5]Glick and Rose (2016) include these results in an earlier working paper available online (Glick and Rose, 2015). They still estimate a generally positive "additional effect" for the EMU versus other CUs, but find the overall CU effect disappears over time, echoing an earlier finding by de Sousa (2012).

[6]Even before Glick and Rose (2016), computational challenges with PPML have been quietly simmering for some time. For example, Bratti, De Benedictis, and Santoni (2014) study the impact of immigrants on trade and note that "[t]he use of [...] the Pseudo Poisson Maximum Likelihood (PPML) estimator [...] clashes with the use of a large set of fixed effects that hamper convergence." Henn and McDonald (2014) find PPML "impracticable [because] convergence of PPML is usually not achieved with fixed effects of a dimensionality as high as ours." And in their services trade handbook, Sauve and Roy (2016) explain that "[u]nfortunately, PPML estimation with several high-dimensional fixed effects led to non-convergence [...] even with the application of different work-around strategies suggested in the recent literature." Dutt, Santacreu, and Traca (2014), Kareem (2014), and Magerman, Studnicka, and Van Hove (2016) share similar frustrations.

addresses the computational burden of the three different types of high-dimensional fixed effects ("HDFEs") that need to be computed to obtain consistent point estimates of Glick and Rose (2016)'s preferred specification.[7] Second, with these consistent point estimates in hand, we take advice from Cameron, Gelbach, and Miller (2011) and Egger and Tarlea (2015) and base our inferences on standard errors that are clustered on all possible dimensions of the panel—here, exporter, importer, and time—and similarly show how such "multi-way" clustering techniques may be adapted to the HDFE PPML context.[8]

These two methodological changes—changing the underlying estimator and method of clustering—lead to dramatic reversals in what we would otherwise consider the current benchmark estimates from the literature. Unlike the vast majority of studies, we do not find that the average effect of CUs on trade is statistically significant. This is for two main reasons. First, multi-way clustering generally leads to more conservative inferences of all estimates. Using standard, "robust" error corrections, for example, the overall CU effect is positive and measured with high precision. Second, the implications of switching from OLS to PPML are especially pronounced for our estimates of the EMU effect, which disappears with the PPML estimator. However, for all CUs *other than the EMU,* we find (as much of the literature had until more recently) the effect of sharing a currency has been very large and highly significant, increasing trade by more than 100%.

We are not the first to document either a small EMU effect (c.f., Micco, Stein, and Ordonez, 2003; Baldwin and Taglioni, 2007), or, indeed, an insignificant EMU effect (c.f., Santos Silva and Tenreyro, 2010a; Olivero and Yotov, 2012). However, other methodological differences aside, these studies have mainly relied on relatively small samples.[9]

[7]The algorithm we present draws on an earlier method devised by Guimarães and Portugal (2010) for PPML with two-way HDFEs. It was originally programmed by Zylkin (2017) and is available in Stata via ssc (to install, type "`ssc install ppml_panel_sg, replace`") or at https://econpapers.repec.org/software/bocbocode/S458249.htm (accessed on August 16th, 2019).

[8]While the current focus is on currency unions and trade, the methods we describe are equally well-suited to a wide variety of other applications that call for the estimation of a gravity model.

[9]A notable exception is Mika and Zymek (2018), who also show that the EMU effect vanishes using PPML with many countries. In their paper, the computational issues surrounding PPML are addressed

As Glick and Rose (2016) and Rose (2017) rightly point out, using a sample with many countries and years is in principle always the most sensible approach. However, in practice, it is also this preference that contributes to the large difference in estimates. As Santos Silva and Tenreyro (2006) highlight, OLS estimation of the log-linearised gravity model will in general be inconsistent in the presence of heteroscedasticity. We investigate the degree of heteroscedasticity in Glick and Rose (2016)'s data by plotting estimation residuals against expected trade values for different benchmark subsamples split by development status, regions, and size. This analysis reveals that trade flows involving the many smaller, poorer countries needed for a comprehensive sample are noticeably more heteroscedastic than trade flows involving other countries. The inclusion of these countries in Glick and Rose (2016)'s data (and in other similarly large data sets) should therefore be expected to exacerbate the difference between PPML and OLS estimates, a pattern we can confirm by comparing coefficient estimates for different subsamples. We also use the example of the EMU effect to demonstrate that the addition of very small countries that contribute only a tiny portion of world trade can have a noticeable impact on OLS estimates of a currency union even if they are not part of the currency union, whereas PPML estimates will tend to discount the addition of such countries.[10]

We now turn to describing our HDFE PPML estimation procedure. The following sections then add our estimates and conclusions.

by "artificially balancing" bilateral trade (such that the usual "exporter-time" and "importer-time" FEs become only "country-time" FEs) and by only using more recent years. Glick and Rose (2016) question whether these adjustments lead to truly comparable results. Our findings, however, support those of Mika and Zymek.

[10]Indeed, Glick and Rose (2016)'s own sensitivity analysis—replicated in Table A.2 of Appendix A.7—makes it plain that linear estimates of the EMU effect do depend non-trivially on which non-EMU reference countries are included in the sample. Another recent follow-up study by Campbell and Chentsov (2017) adds further emphasis on this point.

1.2 PPML with High-Dimensional Fixed Effects

Following the latest developments in the gravity literature, we now describe and implement a PPML estimation procedure that can be used to obtain estimates for a large number of exporter-time, importer-time, and exporter-importer ("pair") fixed effects. We also discuss how to resolve the subsequent technical challenge of how to obtain multi-way clustered PPML standard errors in the presence of these fixed effects.

1.2.1 Estimation Procedure

Let X_{ijt} denote trade flows from exporter i to importer j at time t. $\mathbf{w}_{ijt}$ is a vector containing our covariates of interest, including currency unions and other controls. With exporter-time (λ_{it}), importer-time (ψ_{jt}), and exporter-importer ("pair") fixed effects (μ_{ij}), the estimating equation is

$$X_{ijt} = \exp\left(\lambda_{it} + \psi_{jt} + \mu_{ij} + \mathbf{b}'\mathbf{w}_{ijt}\right) + \nu_{ijt}, \tag{1.1}$$

where ν_{ijt} denotes the remainder error term. This specification is in line with the best practices for panel gravity estimation recommended by Yotov, Piermartini, Monteiro, and Larch (2016) and has appeared in a number of recent empirical studies on the effects of trade agreements, albeit only with smaller samples.[11] Our goal is to obtain PPML estimates for coefficient vector $\mathbf{b}$ for large samples in the presence of these three high-dimensional fixed effects. To fix ideas, we first write an expression for the corresponding estimate of $\mathbf{b}$, denoted by $\widehat{\mathbf{b}}$, in the form of a generalized PPML first-order condition:

$$\widehat{\mathbf{b}}: \quad \sum_i \sum_j \sum_t \left[X_{ijt} - \exp\left(\widehat{\lambda}_{it} + \widehat{\psi}_{jt} + \widehat{\mu}_{ij} + \widehat{\mathbf{b}}'\mathbf{w}_{ijt}\right)\right] \mathbf{w}_{ijt} = \mathbf{0}. \tag{1.2a}$$

[11] See, for example, Dai, Yotov, and Zylkin (2014), Bergstrand, Larch, and Yotov (2015), Anderson, Vesselovsky, and Yotov (2016), Anderson and Yotov (2016), and Heid and Larch (2016) who investigate samples with 13 to 41 regions or countries. Some of these papers facilitate estimation of this specification by further making the simplifying assumption that the pair fixed effect μ_{ij} applies symmetrically in both directions. Thanks to the algorithm introduced in this paper, these compromises are no longer necessary.

Noting that the PPML first-order condition for a group fixed effect equates the sum of the dependent variable with the sum of the conditional mean for that group, the remaining first-order conditions associated with (1.1) may be written as [resume]

$$\widehat{\lambda}_{it}: \quad Y_{it} - e^{\widehat{\lambda}_{it}} \sum_j \exp\left(\widehat{\psi}_{jt} + \widehat{\mu}_{ij} + \widehat{\mathbf{b}}'\mathbf{w}_{ijt}\right) = 0, \tag{1.3a}$$

$$\widehat{\psi}_{jt}: \quad X_{jt} - e^{\widehat{\psi}_{jt}} \sum_i \exp\left(\widehat{\lambda}_{it} + \widehat{\mu}_{ij} + \widehat{\mathbf{b}}'\mathbf{w}_{ijt}\right) = 0, \tag{1.3b}$$

$$\widehat{\mu}_{ij}: \quad \sum_t X_{ijt} - e^{\widehat{\mu}_{ij}} \sum_t \exp\left(\widehat{\lambda}_{it} + \widehat{\psi}_{jt} + \widehat{\mathbf{b}}'\mathbf{w}_{ijt}\right) = 0, \tag{1.3c}$$

where $Y_{it} \equiv \sum_j X_{ijt}$ and $X_{jt} \equiv \sum_i X_{ijt}$ respectively denote the sums of all flows associated with each exporter i and importer j at time t.[12]

Along with (1.2a), these equations could be used to solve the complete system in terms of $\widehat{\mathbf{b}}$, $e^{\widehat{\lambda}_{it}}$, $e^{\widehat{\psi}_{jt}}$, and $e^{\widehat{\mu}_{ij}}$ by extending the "zig-zag" algorithm demonstrated in Guimarães and Portugal (2010) for the case of two-way HDFEs.[13] However, to follow more closely the actual methods used, and to emphasize the tight connection linking estimation with theory, it is useful instead to re-write our system of equations in the form of a "structural gravity" model *à la* Anderson and van Wincoop (2003). To do so, first define

$$\Psi_{it} \equiv \frac{Y_{it}/\sqrt{X_{Wt}}}{e^{\widehat{\lambda}_{it}}}, \qquad \Phi_{jt} \equiv \frac{X_{jt}/\sqrt{X_{Wt}}}{e^{\widehat{\psi}_{jt}}}, \qquad D_{ij} \equiv e^{\widehat{\mu}_{ij}}, \tag{1.4}$$

where $X_{Wt} \equiv \sum_i \sum_j X_{ijt}$ denotes total world trade at time t, to be used as a scaling factor.[14] We make these substitutions because, after plugging these definitions into (1.1), we arrive at a new version of our estimating equation that closely resembles the famous

[12]Most empirical applications, including the present one, tend not to include "self-trade" (i.e., "X_{ii}") in the estimation. Thus, in our case, Y_{it} is i's total exports and X_{jt} is j's total imports. However, Yotov, Piermartini, Monteiro, and Larch (2016) describe several applications in which including X_{ii} might be appealing. The algorithm allows for either possibility without loss of generality. Furthermore, either approach is compatible with structural gravity (c.f., eq. (17) in French, 2016).

[13]The PPML Hessian is negative definite (Gourieroux, Monfort, and Trognon, 1984). Thus, so long as a solution for $\widehat{b}$ exists—a finer point we discuss further in Appendix A.4—it is guaranteed to be unique. However, the fixed effects in (1.3a)-(1.3c) are only determined up to $2N + T$ normalizations, where N and T respectively denote the numbers of countries and time periods.

[14]The utility of this scaling factor is that, as in the analogous system used in Anderson and van Wincoop (2003), imposing $D_{ij} = \Phi_{jt} = \Psi_{it} = 1$ (with $\widehat{\mathbf{b}} = 0$) equates to a world where trade frictions do not affect choice of trade partner. We thus may use $D_{ij} = \Phi_{jt} = \Psi_{it} = 1$ as natural initial guesses for the fixed effects when first solving for $\widehat{\mathbf{b}}$.

"structural gravity" equation of Anderson and van Wincoop (2003):

$$X_{ijt} = \left(\frac{Y_{it}X_{jt}}{X_{Wt}}\right)\left(\frac{D_{ij}e^{\widehat{\mathbf{b}}'\mathbf{w}_{ijt}}}{\Psi_{it}\Phi_{jt}}\right) + \nu_{ijt}.$$

And, furthermore, we may also now re-write our system of first-order conditions as follows:

$$\mathbf{0} = \sum_i \sum_j \sum_t \left[X_{ijt} - \left(\frac{Y_{it}X_{jt}}{X_{Wt}}\right)\left(\frac{D_{ij}e^{\widehat{\mathbf{b}}'\mathbf{w}_{ijt}}}{\Psi_{it}\Phi_{jt}}\right)\right]\mathbf{w}_{ijt}, \tag{1.5a}$$

$$\Psi_{it} = \sum_j \frac{X_{jt}/X_{Wt}}{\Phi_{jt}} D_{ij}e^{\widehat{\mathbf{b}}'\mathbf{w}_{ijt}}, \tag{1.5b}$$

$$\Phi_{jt} = \sum_i \frac{Y_{it}/X_{Wt}}{\Psi_{it}} D_{ij}e^{\widehat{\mathbf{b}}'\mathbf{w}_{ijt}}, \tag{1.5c}$$

$$D_{ij} = \frac{\sum_t X_{ijt}}{\sum_t \left(\frac{Y_{it}X_{jt}}{X_{Wt}}\right)\left(\frac{e^{\widehat{\mathbf{b}}'\mathbf{w}_{ijt}}}{\Psi_{it}\Phi_{jt}}\right)}. \tag{1.5d}$$

In (1.5b) and (1.5c), Ψ_{it} and Φ_{jt} are analogues of the "multilateral resistances" from structural gravity. As in Anderson and van Wincoop (2003) (and the vast subsequent literature following Anderson and van Wincoop, 2003), they capture the general equilibrium effects of trade with third countries. The form of these constraints is well-known and Fally (2015) has previously shown they naturally derive from the FOC's of PPML with two-way fixed effects. The new term we add, however, is D_{ij} in (1.5d), the "pair" fixed effect recommended by Baier and Bergstrand (2007). As with our other fixed effects, we may obtain this last term by equating sums: in this case, pair-wise sums of actual and fitted trade flows over time, as in (1.5d).

With this system in place, the steps to follow are exactly as outlined in (1.5a)-(1.5d). That is: (i) given initial guesses for $\{D_{ij}, \Psi_{it}, \Phi_{jt}\}$, compute a solution for $\widehat{\mathbf{b}}$ using (1.5a); (ii)-(iii) Update Ψ_{it} and Φ_{jt} using (1.5b) and (1.5c); (iv) update D_{ij} using (1.5d); and (v) return to step (i) with new values for $\{D_{ij}, \Psi_{it}, \Phi_{jt}\}$, iterating until convergence.[15]

[15]One way to obtain $\widehat{\mathbf{b}}$ in step (i) would be to solve for it directly via a nonlinear solver. However, an even more efficient approach is to modify the procedure so that $\widehat{\mathbf{b}}$ can be solved for using iteratively re-weighted least squares (IRLS), inspired by Guimarães (2016) and further discussed in Appendix A.1. Appendix A also covers other important details such as how to compute clustered standard errors and how to implement the pre-estimation "existence check" recommended by Santos Silva and Tenreyro (2010a)

1.2.2 Standard Errors

Of course, computing the point estimates themselves is just one part of the overall high dimensionality problem we must overcome in obtaining inferences. Estimating standard errors also poses a significant technical challenge in this context. Even though in principle we may readily construct from our iterative procedure the complete Hessian matrix associated with our estimation, the usual method of inverting the Hessian to obtain the estimated Poisson variance matrix is likely to be impractical, because of the number and variety of the included fixed effects. Fortunately, recent advances in the related literature offer better alternatives. For the slightly simpler case of a PPML model with two-way HDFEs, Figueiredo, Guimarães, and Woodward (2015) show how the high dimensionality associated with this latter problem may be efficiently discarded by recognizing the variance-covariance matrix of a Poisson regression is proportional to that of an appropriately weighted linear regression, such that the Frish-Waugh-Lovell theorem may then be applied. This same strategy also extends naturally to the case of three-way HDFEs, as we show in Appendix A.3.

More generally, however, our emphasis on standard errors stems from our desire to incorporate assumptions about error correlation (or "clustering") patterns that are most reasonable for our data and model. Again, we draw on recent innovations. In particular, Egger and Tarlea (2015) convincingly argue that standard errors for a panel-data gravity model should allow for simultaneous correlations across all three main dimensions of the panel—exporter, importer, and time—by implementing the "multi-way" clustering methodology first introduced in Cameron, Gelbach, and Miller (2011). Adopting the logic of Egger and Tarlea (2015), it is reasonable to believe there are auto-correlations across time within countries having to do with inertia in trade, as, e.g., bilateral trade responds sluggishly in the short-run to long-run changes in local prices. A similar logic applies to possible cross-sectional dependence within time periods, as general equilibrium price linkages across countries may not fully reflect an idiosyncratic shock

in the high-dimensional fixed effects context.

to trade at time t.

For added motivation, we also note that clustering simultaneously on i, j, and t actually allows for correlation in the error term within all six possible cluster dimensions $\{i, j, t, it, jt, ij\}$. It thus explicitly nests the typical practice of assuming errors are solely clustered across time within each country-pair ij. For this reason, we will expect multi-way clustering to lead to more conservative inferences, just as in Egger and Tarlea (2015). The details for implementing multi-way clustering in our setting largely follow Cameron, Gelbach, and Miller (2011), requiring only some slight modification to account for the high dimensionality mentioned above. Again, for brevity, we leave these specifics to Appendix A.3.

In sum, our methods allow us to rapidly obtain estimates and flexibly clustered standard errors for our key parameters of interest, even for data structures that would ordinarily be too large for direct estimation to be feasible. Applying three-way FEs to Glick and Rose (2016)'s data, for example, will require us to account for more than 50,000 fixed effects.[16] Thus, their data will serve as an interesting test, which we now turn to.

1.3 Re-assessing the Effects of Currency Unions

Following Glick and Rose (2016)'s notation, we define CU_{ijt}—a dummy variable equal to 1 if i and j share a common currency in year t—as our main regressor of interest. Thus, we may re-produce Glick and Rose's preferred specification with three-way fixed effects either in its original OLS form,

$$\ln X_{ijt} = \lambda_{it} + \psi_{jt} + \mu_{ij} + \boldsymbol{\beta}'\mathbf{z}_{ijt} + \gamma CU_{ijt} + \epsilon_{ijt}, \tag{1.6}$$

[16] Table A.1 of Appendix A.6 summarizes computation times for different sample sizes (both in terms of countries and years considered) for the `ppml`-command of Santos Silva and Tenreyro (2011) and the HDFE `ppml_panel_sg`-command of Zylkin (2017). The gains in terms of whether and how fast convergence is achieved will obviously vary with the specific soft- and hardware used to implement the procedure. The main takeaway from Table A.1 is that there are substantial speed and feasibility gains using our suggested estimation procedure for high-dimensional fixed effects models compared with previously available methods.

or in the form of our own preferred alternative, using PPML:

$$X_{ijt} = \exp\left(\lambda_{it} + \psi_{jt} + \mu_{ij} + \boldsymbol{\beta}'\mathbf{z}_{ijt} + \gamma CU_{ijt}\right) + \nu_{ijt}, \tag{1.7}$$

where, in either case, $\mathbf{z}_{ijt}$ denotes a set of non-CU controls (namely dummies indicating the presence of regional trade agreements and current colonial relationships[17]) and the final terms (ϵ_{ijt} and ν_{ijt}) denote residual errors.

To motivate our preference for PPML, we note, as Santos Silva and Tenreyro (2006) have, that imposing the OLS moment condition $E[\ln X_{ijt} - \widehat{\ln X}_{ijt}|\cdot] = 0$ does not also imply that $E[X_{ijt} - \widehat{X}_{ijt}|\cdot] = 0$. As a consequence, OLS estimates of γ will only be consistent when the OLS error term ϵ_{ijt} is homoscedastic, whereas PPML is consistent under much more general circumstances. Since trade data are generally taken to be heteroscedastic—a supposition we will later confirm—OLS is likely to be biased and inconsistent, with the bias increasing in the degree of heteroscedasticity.[18] For some further motivation, we also note that, unlike with PPML, OLS first-order conditions for the exporter-time and importer-time fixed effects λ_{it} and ψ_{jt} do not re-produce the adding-up constraints (1.5b) and (1.5c) typically implied by theory; instead, they equate sums of log trade flows with sums of fitted log flows.

1.3.1 Main Results

Columns (1) to (3) of Table 1.1 reproduce the right panel of Table 5 from Glick and Rose (2016). Columns (4) to (6) estimate the same specifications but with PPML. Additionally,

[17]Note this last variable is mainly identified by former colonies gaining independence during the period. It is debatable whether the trade effect of a country's independence is appropriately captured by this dummy. We therefore re-ran our main specifications after dropping all colonies from the sample (reducing the number of observations by 70%). Our results are both qualitatively identical and quantitatively similar.

[18]Santos Silva and Tenreyro (2006, 2011) provide an extensive discussion of this point as well as a comparison study of PPML versus a range of other nonlinear estimators. While PPML implicitly assumes that the variance of ν_{ijt} is proportional to the conditional mean, this assumption only affects the efficiency of the estimator and PPML turns out to generally perform adequately even when this assumption is not met. Fernández-Val and Weidner (2016) and Jochmans (2017) have documented favourable small-sample properties for PPML with two-way FEs. We note that similar investigations for the case of three-way FEs would be valuable additions to the literature.

Table 1.1: Linear Specification vs. PPML

	Linear Specifications			PPML		
	All CUs	Disagg. EMU	Disagg. CUs	All CUs	Disagg. EMU	Disagg. CUs
	(1)	(2)	(3)	(4)	(5)	(6)
All CUs	0.343			0.130		
	(0.018)***			(0.010)***		
	{0.080}***			{0.081}		
EMU		0.429	0.432		0.030	0.027
		(0.021)***	(0.021)***		(0.010)***	(0.010)***
		{0.149}***	{0.149}***		{0.092}	{0.091}
All Non-EMU CUs		0.298			0.700	
		(0.025)***			(0.025)***	
		{0.097}***			{0.172}***	
CFA Franc Zone			0.583			0.137
			(0.100)***			(0.108)
			{0.186}***			{0.307}
East Caribbean CU			-1.637			-1.014
			(0.106)***			(0.081)***
			{0.334}***			{0.319}***
Aussie $			0.389			0.168
			(0.196)**			(0.121)
			{0.248}			{0.282}
British £			0.554			1.004
			(0.034)***			(0.034)***
			{0.101}***			{0.234}***
French Franc			0.874			2.096
			(0.083)***			(0.062)***
			{0.269}***			{0.302}***
Indian Rupee			0.522			0.082
			(0.115)***			(0.149)
			{0.110}***			{0.308}
US $			-0.051			0.014
			(0.063)			(0.022)
			{0.229}			{0.066}
Other CUs			-0.104			0.788
			(0.058)*			(0.052)***
			{0.247}			{0.247}***
RTAs	0.395	0.392	0.389	0.167	0.169	0.168
	(0.009)***	(0.010)***	(0.010)***	(0.009)***	(0.009)***	(0.009)***
	{0.062}***	{0.061}***	{0.061}***	{0.076}**	{0.075}**	{0.076}**
CurCol	0.262	0.275	0.248	0.733	0.545	0.303
	(0.032)***	(0.032)***	(0.033)***	(0.059)***	(0.050)***	(0.042)***
	{0.155}*	{0.159}*	{0.170}	{0.288}**	{0.251}**	{0.150}**
N	877,736	877,736	877,736	877,736	877,736	877,736
# of clusters						
exporters	212	212	212	212	212	212
importers	212	212	212	212	212	212
years	66	66	66	66	66	66
(Pseudo-)R^2	0.855	0.855	0.855	0.987	0.987	0.987
Park-Test (p-value)	-	-	-	<0.001	<0.001	<0.001

Notes: Columns (1) to (3) of this table reproduce the right panel of Table 5 from Glick and Rose (2016). Columns (4) to (6) estimate the same specifications but with PPML. 877,736 observations for more than 200 countries for the years 1948 to 2013. All columns include (roughly) 11,000 exporter-time, 11,000 importer-time, and 32,000 pair FEs. Robust standard errors in parentheses. Standard errors clustered by exporter, importer, and year in curly brackets. * $p < 0.10$, ** $p < .05$, *** $p < .01$. See text for further details.

we report for each coefficient two types of standard errors: in parentheses we report Huber-White heteroscedasticity-robust standard errors (Huber, 1967; White, 1982) as in Glick and Rose (2016); in curly brackets we report multi-way clustered standard errors clustered by exporter, importer, and year, as advocated by Egger and Tarlea (2015).[19]

For all PPML specifications, as suggested by Santos Silva and Tenreyro (2006) and Manning and Mullahy (2001), we perform a Park (1966)-type test for the hypothesis that the multiplicative gravity model can be consistently estimated in the log-linearised form. We obtain a p-value less than 0.001 in all cases, implying that the adequacy of estimating the constant-elasticity model in log-linear form is strongly rejected. As a goodness of fit measure, we also calculate the squared correlation coefficients between observed and predicted dependent variable values (which coincides with the R^2 in the linear case). The R^2 values we obtain are 0.855 for the linear model and 0.987 for PPML, in line with the typical good fit of gravity models.[20]

Our main observations from the estimates themselves are as follows. First, note that the main effect for CUs is substantially smaller than in Glick and Rose (2016) (compare, for example, columns (1) and (4).) If multi-way clustered standard errors are used, it also becomes statistically insignificant.

Second, our PPML estimates for the EMU effect in columns (5) and (6) are even less favourable. The estimated EMU coefficients—0.030 and 0.027, respectively—are an order of magnitude smaller than the corresponding linear model estimates shown in columns (2) and (3). Furthermore, when clustered standard errors are used, the EMU loses significance.[21]

[19]Note that we drop singleton groups (i.e. fixed effects groups with only a single observation) in order to avoid artificially low standard errors due to an overstated number of clusters (see Correia, 2015). This is achieved with the `dropsingletons`-option in the `ppml_panel_sg`-command.

[20]Note that the higher values for PPML are not only driven by its better fit, but also by considering the correlation of the levels of (fitted and observed) trade flows rather than of their logs as in the OLS case.

[21]Olivero and Yotov (2012) find the Euro effect is only significant when one accounts for slow, dynamic adjustments over time. On the other hand, Berger and Nitsch (2008) argue the Euro effect is biased upward by not accounting for long-term trends in European trade. For this reason, it is worth mentioning that our results are robust to using pair time-trends, lagged CU and EMU terms, and/or wider time intervals.

Third, for all other currency unions *except the EMU*, PPML leads to significant positive effects and the magnitude is nearly tripled versus Glick and Rose (2016), suggesting a trade-promoting effect of $e^{.700} - 1 = 101.3\%$ (versus $e^{.298} - 1 = 34.7\%$). The strong positive result for the "net EMU effect" from Glick and Rose (2016) thus completely reverses, suggesting the EMU has been a major disappointment in this regard. The negative net EMU effect we observe could be for several reasons. For example, the EMU countries are mainly developed countries that already had comparably strong and stable individual currencies and were already well-integrated economically. It may be that the types of transaction costs that currency unions alleviate may be more pronounced for countries that are less integrated with one another and/or have weaker currencies to start with. Or, as de Sousa (2012) has argued, it could also be that the importance of a common currency for trade has generally fallen over time due to increased globalization, with the surprising lack of an EMU effect being part of a broader trend.[22] However, it is worth noting that estimates of the effect of non-EMU currency unions are potentially less reliable, because a substantial part of the identifying variation is due to currency union dissolutions that coincided with political events such as warfare, communist takeovers, or colonial independence (Campbell, 2013).

Finally, other individual CU estimates, shown in column (6), are also affected, to varying degrees. In particular, we see the large PPML estimate for non-EMU CUs is driven by the British $\pounds$, the French Franc, and "other CUs".[23] The finding of very large heterogeneity in the trade effects across different currency unions is in line with previous findings by Eicher and Henn (2011) and Glick and Rose (2016). However, an additional note of caution is in order (aside from the potential confounding with geopolitical events) for the estimated effects of individual non-EMU currency unions: they tend to be identified based on very little variation in the data. For example, the effects of the French Franc, the East Caribbean Dollar, and the Australian Dollar are estimated based on the variation

[22] We investigate how the non-EMU effect changes over time in Section 1.3.3 and find further evidence that the currency union effect has generally fallen over time.

[23] Note we treat missing observations in the Glick and Rose (2016) data set as missing for both our linear and PPML specifications. As PPML allows zero trade flows, we also run specifications (4)-(6) treating all missing observations as zero trade flows, presented as robustness check later on.

in bilateral trade flows between only six, four, and three countries, respectively.

In sum, our PPML estimates of the trade-promoting effects of currency unions in Table 1.1 (and of the EMU and other individual currency unions in particular) are very different than their OLS counterparts. Given the large magnitude of these differences, it is only natural to wonder: Why do the two estimators give us such strikingly different results here? And is there anything about this particular setting—with an unusually large sample of countries—that would lead these estimates to offer such diverging conclusions? We address these questions next.

1.3.2 Comparing OLS and PPML Estimates for Different Samples

Because the data set from Glick and Rose (2016) we work with is notably very large, there is likely but one main reason behind the difference in the OLS and PPML estimates we obtain. As our Park test results have confirmed, OLS is an inconsistent estimator in this context because it suffers from a heteroscedasticity-induced bias that does not disappear in large samples, whereas PPML can be shown to be consistent.[24]

Thus, to investigate why the difference in estimates is as large as it is, we need to be able to say something about the pattern of heteroscedestacity and why it might induce an especially large bias for this particular sample. Recall that OLS estimates are consistent in the special case where the OLS error term (ϵ_{ijt}) is homoscedastic.[25] A useful way of visualizing how far off the data is from satisfying this assumption is to use what Tukey

[24]Another reason sometimes cited in the literature for why PPML and OLS estimates differ is that the implied moment conditions of OLS estimation make the regressors orthogonal to the difference between the observed and fitted logged trade flows (i.e., $\ln X_{ijt} - \ln \widehat{X}_{ijt}$), whereas the moment conditions used by PPML establish orthogonality to the deviations in levels (i.e., $X_{ijt} - \widehat{X}_{ijt}$). For this reason, Eaton, Kortum, and Sotelo (2013) and Head and Mayer (2013, 2014) conclude that PPML will assign more importance to larger trade flows relative to OLS. However, these implied weighting differences should affect only the efficiency of each estimator in small samples; for large samples, the consistency properties of the two estimators should explain most of the difference in an otherwise correctly specified model.

[25]This special case of a homoscedastic error term from the log-transformed model corresponds to the situation described in Santos Silva and Tenreyro (2006) where the conditional variance from the multiplicative model is proportional to the square of the conditional mean. Both estimators should be consistent when this assumption is satisfied; thus, we would expect them to give similar results in this context.

(1977) calls a "wandering schematic" diagram. To create this diagram—demonstrated in Figure 1.1—we first group all residuals from the estimation into 20 equal-sized bins, with each bin collecting observations with similar predicted trade values. We then sort these bins from smallest to largest predicted value and construct modified box plots summarizing the distribution of the error term within each bin. As the top left panel of Figure 1.1 shows—in a visual confirmation of our earlier Park test results—the residuals from our main OLS specification (i.e., from column 2 in Table 1.1) are clearly not homoscedastic. In particular, both the boxes for each bin (reflecting the first and third quartiles of the distribution) and their associated whiskers (reflecting the adjacent values) grow steadily smaller from left to right as we consider observations with a higher expected trade value, implying that the variance of these residuals is inversely related to the conditional mean across the entire sample.[26] Note that this does not imply that the differences between observed and fitted trade flows get smaller for larger trade flows. It rather implies a decrease in the percentage difference.

To say something about the "degree" of heteroscedasticity using this type of analysis, it is first necessary to offer some concrete benchmarks for comparison. Glick and Rose (2016)'s robustness analysis offers us some standard ways of restricting the sample that are convenient for this purpose. Drawing on Glick and Rose (2016)'s Table 8, the alternative country subsamples we use are: "industrialized countries plus present/future EU" (countries with an IFS code below 200 plus all current EU countries); "upper income" (countries whose GDP per capita exceeds the World Bank "upper income" threshold of \$12,736); "rich and big" (countries with a GDP per capita of at least \$10,000 and/or a GDP exceeding \$10 billion), and one sample each for OECD members and for current and future EU members. Figure 1.2 presents comparisons of OLS and PPML estimates for these various subsamples, along with 90% and 95% multi-way clustered confidence bounds. From these comparisons, it is easy to see that OLS estimates of the EMU effect are only positive and significant for the full sample; otherwise, the OLS estimate is

[26]The adjacent values of a distribution, which occur at a distance 1.5 times the inter-quartile range past the nearest edge of the "box", are a standard concept used in data analysis to determine where the tails of the distribution lie.

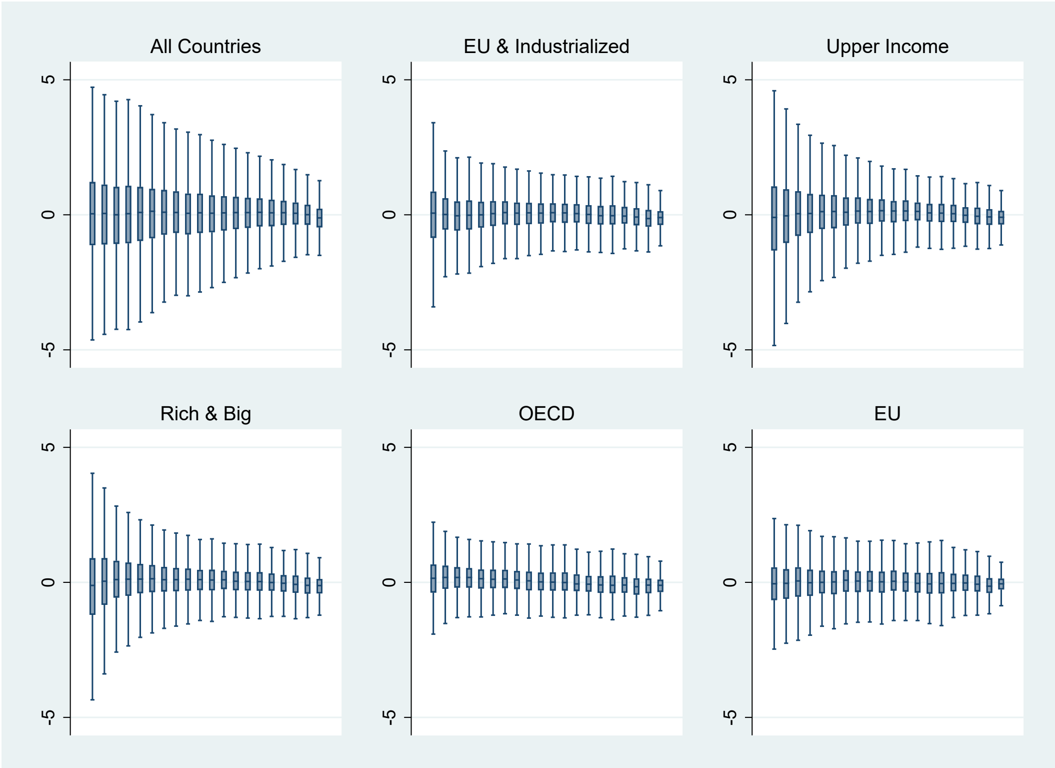


Figure 1.1: Visualizing Heteroscedesticity in the Data: OLS Residuals vs. Predicted Log Trade Flows, Binned by Size.

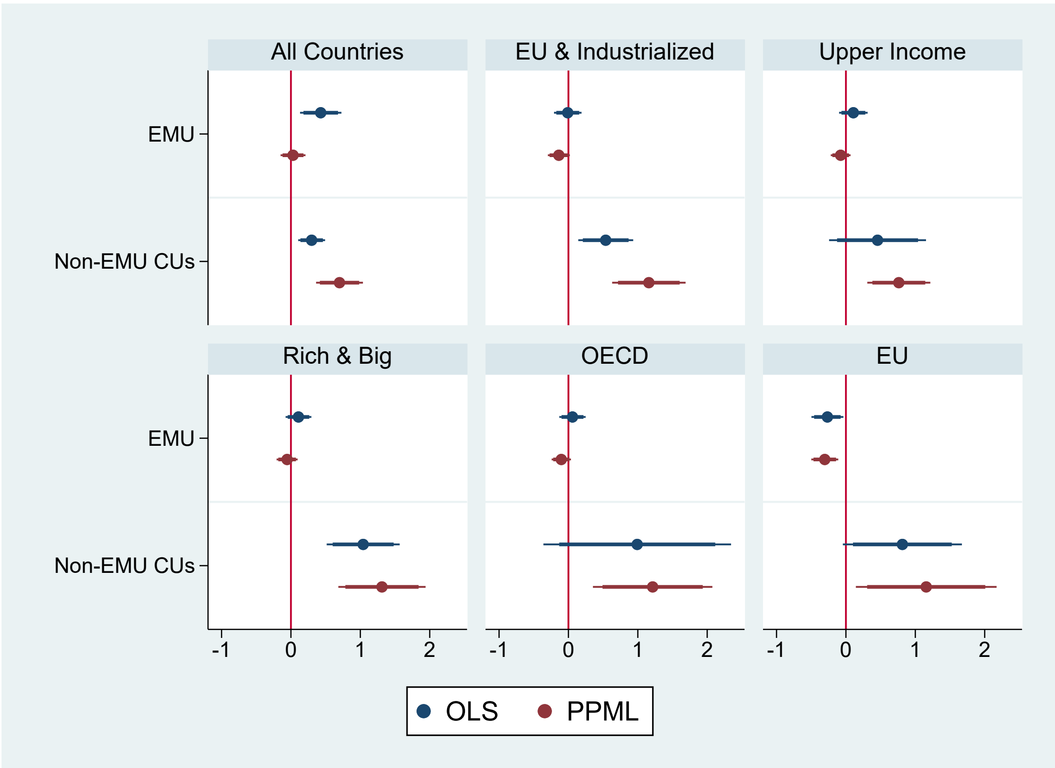


Figure 1.2: Comparing OLS and PPML Results Across Different Country Samples (with 90% and 95% Multi-way Clustered Confidence Bounds).

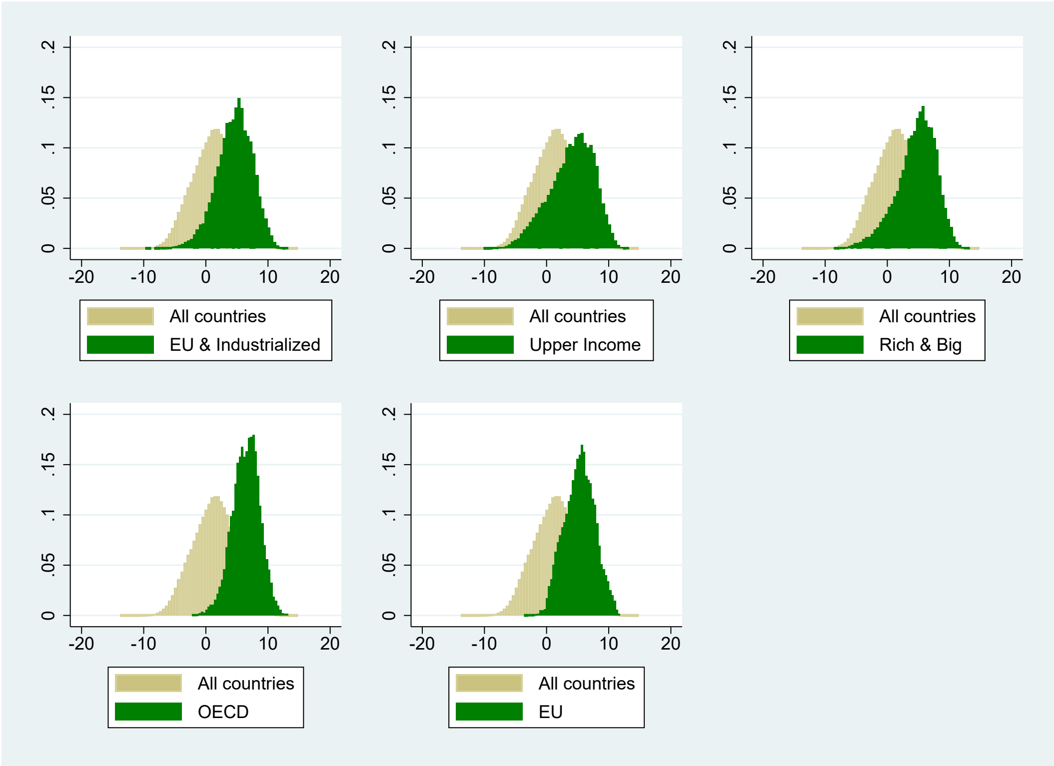


Figure 1.3: Density Plots of Expected Log Trade Values, by Subsample.

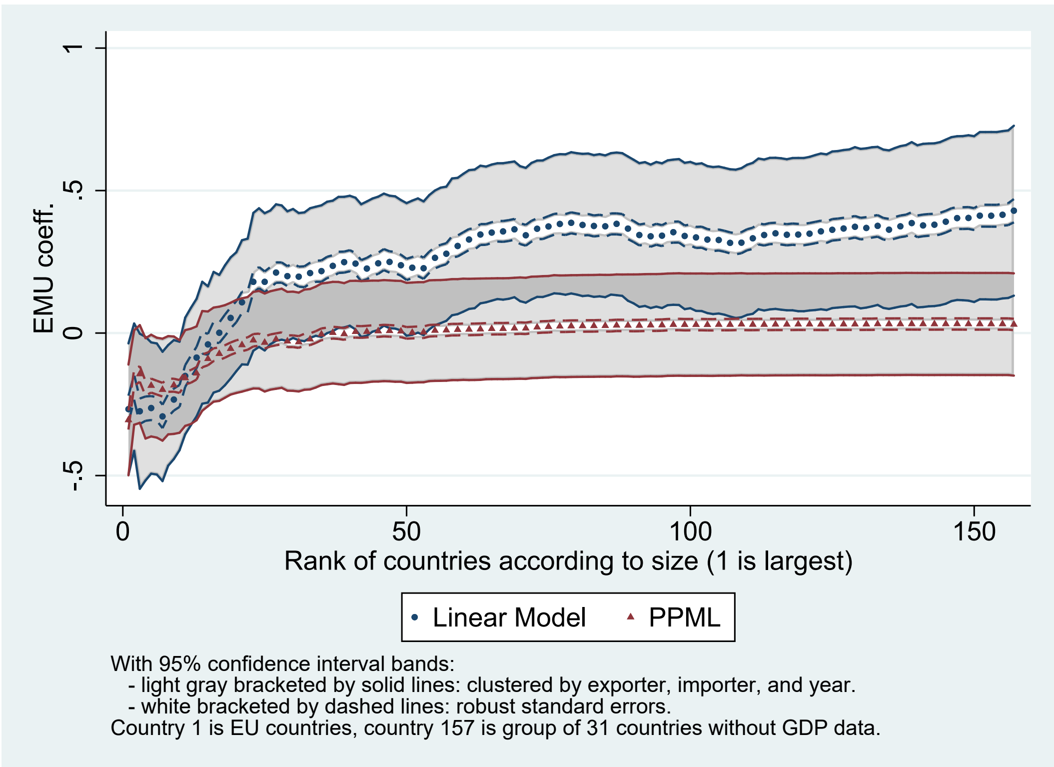


Figure 1.4: The Effect of Varying the Reference Group of non-EMU Countries on EMU Coefficient Estimates

generally much closer to the PPML estimate and is near-zero and statistically insignificant for all subsamples except the "present/future EU" subsample, where it is negative and significant. For non-EMU CUs, we generally observe the PPML estimate is somewhat larger than the corresponding OLS estimate across each of these subsamples, consistent with our results for the full sample. It is also apparent that OLS estimates of both CU variables are generally more sensitive to varying which countries are used, whereas PPML estimates are relatively more stable across different subsamples.

The remaining panels of Figure 1.1 then show how the heteroscedasticity in the data changes when we restrict the sample to any of these benchmark country groupings. As we observed earlier for the full sample, all the different subsamples feature observations with smaller predicted values exhibiting higher variance than other observations. However, unlike with the full sample, the heteroscedasticity in these subsamples is mainly limited to the observations with smaller expected values versus the rest of the sample. With the exception of the full sample, the righthand-sides of each of these panels are at least close to homoscedastic. As Figure 1.3 suggests, this is likely because the full sample includes disproportionately more observations with smaller expected trade values, which generally seem to exhibit more variance and more heteroscedasticity than other observations. We can therefore plausibly conclude that moving to a comprehensive sample from any of these benchmark subsamples fundamentally alters the pattern of heteroscedasticity and amplifies the bias affecting the OLS estimates.

Continuing further with our analysis of these subsamples, another result from Figure 1.2 that draws our curiosity is the close correspondence between the OLS and PPML estimates of the EMU effect across all the samples we consider except for the full sample. The similarity between estimates for the sample of current/future EU members is particularly interesting to us because this sample already includes all the EMU members; the only difference with the larger sample is that the larger sample also adds many non-EU countries to the "reference group" of trade partners against which within-EMU trade is compared in order to identify the EMU effect. Or, more precisely, the addition of more reference group countries mainly affects the estimation via the exporter-time and importer-time fixed effects λ_{it} and ψ_{jt}. Since trade with a smaller trade partner contributes more to the sum of a country's total log trade flows (the key moment used to identify these fixed effects in OLS) than to its total trade in levels (the key moment used in PPML), it's conceivable that at least some of the divergence in estimates reflects the relatively higher importance that OLS places on the many smaller non-EMU countries present in the full sample.

To explore in more detail how differences between linear and PPML estimates evolve with the composition of the reference group, Figure 1.4 plots estimates from both the linear model and PPML starting with the EU as a whole and then adding one country at a time ranked by 2013 GDP. These estimates reveal that adding more and more (smaller) countries leads to a continually rising OLS estimate—even for the addition of the world's tiniest economies—while the PPML estimates stabilize after the inclusion of around 40 additional countries. Based on the preceding discussion, this divergence is by no means surprising: as we add smaller and smaller countries to the sample, we are tending to make the data more heteroscedastic, thereby amplifying the bias in the OLS estimate. However, we also note that the PPML and OLS estimates shown in Figure 1.4 are usually influenced in the same direction whenever the next-largest country is added to the sample. As such, the PPML and OLS estimates shown in the figure both seem to agree that trade has fallen between EMU members relative to their trade with the rest of the EU as well as with the six largest non-EU economies (the US, China, Japan, Brazil, and India), which together constitute more than two-thirds of world non-EMU GDP. Intra-EMU trade appears to have risen, however, relative to trade with smaller partners, starting with the seventh largest non-EMU economy (Canada). To interpret our earlier results in light of these patterns, the positive and significant overall OLS estimate of the EMU effect we observe appears to be heavily influenced by the apparent decline in trade between the EMU and the many smaller non-EMU countries in the sample relative to intra-EMU trade. Since PPML naturally discounts the addition of smaller reference group countries, and since this pattern is nowhere to be found for the EMU's most important outside partners, this feature of the data could help explain some of the difference between the PPML and OLS estimates of the EMU effect.[27]

1.3.3 Other Robustness

To add some final experiments, we consider here the possible role played by zero trade flows (which cannot be included in log-linear models) as well as some possible omitted temporal factors such as lags, trends and anticipation effects. We also examine how the effect of currency unions has changed over time.

Missing and Zero Trade Flows. As noted earlier, in order to obtain the main estimation results, we treated missing observations in the Glick and Rose (2016) data set as missing for both our linear and PPML specifications. Omitting zero trade flows could potentially lead to a sample selection problem biasing our results. If a currency union induces country-pairs to start trading (versus not at all), estimates based on positive trade flows only may lead to a downward bias of the estimated effect of currency unions on trade. While OLS cannot handle zero trade flows without further adjustments, such as adding a small, arbitrary number (see e.g. Linnemann, 1966) or applying the inverse hyperbolic sine transformation (see e.g. Kristjánsdóttir, 2012), they can be directly included into the PPML estimation. In Table 1.2, we therefore show the results of re-estimating specifications (4)-(6), now treating all missing observations as zero trade flows. The results indicate that including zero trade flows hardly affects the estimates. Most importantly, estimating the gravity equation in its multiplicative form still erases the EMU effect. The one small change from our earlier results is that the general CU effect now remains marginally significant even when clustering at the exporter, importer, and year dimension.

[27]To investigate this intuition, we ran our OLS main specification (column (2) of Table 1.1) with the product of GDPs as weights. Indeed, the results from the weighted OLS regression are more similar to the PPML estimates than the unweighted ones. Most importantly, the estimated EMU coefficient is 0.335 (compared to 0.429 and 0.030 for unweighted OLS and PPML, respectively) and the estimated currency union effect for all other CUs is 0.450 (compared to 0.298 and 0.700 for unweighted OLS and PPML, respectively).

Table 1.2: PPML with Missings as Zero Trade Flows

	All CUs (1)	Disagg. EMU (2)	Disagg. CUs (3)
All CUs	0.153 (0.010)*** {0.083}*		
EMU		0.0521 (0.010)*** {0.095}	0.0489 (0.010)*** {0.095}
All Non-EMU CUs		0.728 (0.026)*** {0.180}***	
CFA Franc Zone			-0.126 (0.100) {0.354}
East Caribbean CU			-0.877 (0.083)*** {0.296}***
Aussie $			0.384 (0.119)*** {0.226}*
British £			1.060 (0.035)*** {0.239}***
French Franc			2.096 (0.063)*** {0.308}***
Indian Rupee			0.170 (0.147) {0.304}
US $			0.0183 (0.022) {0.051}
Other CUs			0.766 (0.053)*** {0.250}***
RTAs	0.159 (0.009)*** {0.077}**	0.160 (0.009)*** {0.077}**	0.159 (0.009)*** {0.076}**
CurCol	0.827 (0.064)*** {0.291}***	0.630 (0.055)*** {0.257}**	0.387 (0.047)*** {0.156}**
N	1,610,165	1,610,165	1,610,165
# of clusters			
exporters	213	213	213
importers	213	213	213
years	66	66	66
Pseudo-R^2	0.986	0.987	0.987
Park-Test (p-value)	<0.001	<0.001	<0.001

Notes: This table reproduces the results from Table 1.1 after treating all missing observations in the sample as zeroes. Robust standard errors in parentheses. Standard errors clustered by exporter, importer, and year in curly brackets. * $p < 0.10$, ** $p < .05$, *** $p < .01$. See text for further details.

Time Periods. Our main specifications rest on the strong assumption that the influence of the currency unions on trade has not changed over the last seventy years. But some recent evidence provided by de Sousa (2012) suggests this may not be a good assumption. In addition, since the EMU does not begin until relatively late in the sample, it is worth investigating whether our estimates change if we use a more recent time series that is more centred on the EMU specifically.

We thus use Table 1.3 to investigate how the effects of currency unions change over time, both for our full country sample as well as for the benchmark subsamples considered in Glick and Rose (2016)'s Table 8 and in our own Figure 1.2. The estimates using all years from 1948-2013 for all subsamples are given in the first column; estimates presented in subsequent columns then experiment with how CU effects vary when the sample period begins in either 1985 or 1995 and/or ends in 2005.[28] Consistent with our earlier Figure 1.2, we find that no single subsample leads to a positive significant effect for the Euro and that the large and positive non-EMU CU effect is robust for all samples with a large time span. For samples beginning in 1985 or 1995, however, the non-EMU effect is always statistically insignificant when multi-way clustered standard errors are used. This latter set of findings lends support to de Sousa (2012)'s earlier observation that the trade-promoting effect of currency unions seems to have weakened significantly over the course of the 20th century. As discussed in de Sousa (2012), one plausible reason for the decreasing effect of currency unions may be increased international economic integration, both in terms of trade and financial globalization. However, we also note that subsamples without observations prior to 1985 include only very few observations of country-pairs leaving or joining non-EMU currency unions. Thus, we find no significant effects (or even cannot identify the effects) for some subsamples.

Quadrennial Data. Because trade flows may require some time to adjust to changes in trade costs, Cheng and Wall (2005) have suggested using intervals of several years rather

[28]The corresponding OLS results, which largely replicate Glick and Rose (2016)'s Table 8, are provided in Table A.2 in Appendix A.7.

Table 1.3: PPML Estimation of Different Subsamples

	1948-2013	1985-2013	1995-2013	1948-2005	1985-2005	1995-2005
				All countries		
EMU	0.030 (0.010)*** {0.092}	0.006 (0.010) {0.058}	0.010 (0.013) {0.038}	-0.055 (0.013)*** {0.082}	-0.063 (0.010)*** {0.050}	-0.052 (0.011)*** {0.034}
All Non-EMU CUs	0.700 (0.025)*** {0.172}***	0.084 (0.027)*** {0.073}	0.052 (0.031)* {0.087}	0.685 (0.025)*** {0.156}***	-0.002 (0.030) {0.056}	0.009 (0.035) {0.072}
				Industrial countries plus present/future EU		
EMU	-0.138 (0.012)*** {0.081}*	-0.055 (0.011)*** {0.055}	-0.009 (0.014) {0.037}	-0.200 (0.017)*** {0.080}**	-0.122 (0.012)*** {0.046}***	-0.075 (0.012)*** {0.034}**
All Non-EMU CUs	1.159 (0.043)*** {0.270}***	-0.188 (0.147) {0.366}	0.007 (0.268) {0.160}	1.066 (0.041)*** {0.232}***	-0.050 (0.145) {0.282}	0.018 (0.172) {0.095}
				Upper income (GDP p/c $\geq$ \$ 12,736)		
EMU	-0.076 (0.012)*** {0.073}	-0.027 (0.011)** {0.052}	-0.002 (0.015) {0.037}	-0.134 (0.015)*** {0.066}**	-0.089 (0.012)*** {0.043}**	-0.063 (0.013)*** {0.032}**
All Non-EMU CUs	0.762 (0.130)*** {0.232}***			0.743 (0.107)*** {0.194}***		
				Rich Big (GDP$\geq$\$ 10bn, GDP p/c$\geq$\$ 10k)		
EMU	-0.055 (0.012)*** {0.077}	-0.025 (0.011)** {0.053}	-0.004 (0.015) {0.038}	-0.108 (0.015)*** {0.073}	-0.088 (0.012)*** {0.043}**	-0.073 (0.013)*** {0.032}**
All Non-EMU CUs	1.312 (0.059)*** {0.321}***			1.223 (0.055)*** {0.256}***		
				OECD		
EMU	-0.103 (0.012)*** {0.071}	-0.047 (0.012)*** {0.054}	-0.027 (0.016)* {0.040}	-0.140 (0.016)*** {0.067}**	-0.092 (0.013)*** {0.042}**	-0.069 (0.013)*** {0.032}**
All Non-EMU CUs	1.214 (0.062)*** {0.439}***			1.171 (0.370)*** {0.365}***		
				Present/future EU		
EMU	-0.305 (0.017)*** {0.099}***	-0.068 (0.014)*** {0.055}	0.021 (0.017) {0.041}	-0.448 (0.026)*** {0.124}***	-0.192 (0.018)*** {0.084}**	-0.060 (0.017)*** {0.063}
All Non-EMU CUs	1.157 (0.054)*** {0.517}**			1.131 (0.052)*** {0.469}**		

Notes: This table reports robustness estimates of the findings of Specification (5) with respect to country sample and period of investigation, as in Table 8 of Glick and Rose (2016). RTAs and CurCol are included in the regressions, but their coefficient estimates are not shown for brevity. Robust standard errors in parentheses. Standard errors clustered by exporter, importer, and year in curly brackets. * $p < 0.10$, ** $p < .05$, *** $p < .01$. See text for further details.

Table 1.4: PPML with Time Trends, Leads, and Lags

	Intervals (1)	Trends (2)	Lags (3)	Leads (4)
EMU	0.022	-0.058	-0.056	0.020
	(0.020)	(0.023)**	(0.025)**	(0.028)
	{0.091}	{0.072}	{0.070}	{0.048}
All Non-EMU CUs	0.701	0.387	0.181	0.556
	(0.050)***	(0.050)***	(0.071)**	(0.067)***
	{0.176}***	{0.133}***	{0.080}**	{0.164}***
RTAs	0.178	0.125	0.077	0.216
	(0.018)***	(0.013)***	(0.018)***	(0.020)***
	{0.086}**	{0.052}**	{0.060}	{0.083}***
CurCol	0.619	0.347	-0.026	0.605
	(0.117)***	(0.096)***	(0.108)	(0.148)***
	{0.300}**	{0.285}	{0.134}	{0.279}**
EMU_{t-4}			0.083	
			(0.026)***	
			{0.035}**	
All Non-EMU CUs_{t-4}			0.488	
			(0.062)***	
			{0.140}***	
RTAs_{t-4}			0.146	
			(0.017)***	
			{0.063}**	
CurCol_{t-4}			0.674	
			(0.118)***	
			{0.232}***	
EMU_{t+4}				-0.031
				(0.026)
				{0.074}
All Non-EMU CUs_{t+4}				0.219
				(0.076)***
				{0.126}*
RTAs_{t+4}				0.019
				(0.021)
				{0.060}
CurCol_{t+4}				-0.040
				(0.144)
				{0.173}
N	221,170	221,170	217,462	196,559
# of Clusters				
Exporters	212	212	212	211
Importers	212	212	212	211
Years	17	17	16	16
Pseudo-R^2	0.987	0.995	0.987	0.986
Park-Test (p-value)	<0.001	<0.001	<0.001	<0.001

Notes: Column (1) of this table reproduces the results of column (5) of Table 1.1 but using the data in four year intervals. In addition, we add bilateral linear time trend in column (2) and lags and leads in columns (3) and (4), respectively. Robust standard errors in parentheses. Standard errors clustered by exporter, importer, and year in curly brackets. * $p < 0.10$, ** $p < .05$, *** $p < .01$. See text for further details.

than yearly data. Following this advice has become general practice in the regional trade agreements literature (see for example Baier and Bergstrand, 2007; Bergstrand, Larch, and Yotov, 2015) and a similar argument conceivably applies to currency unions as well. We therefore re-estimate our main specification based on 4-year intervals instead of using consecutive years. As can be seen from column (1) of Table 1.4, this hardly affects our point estimates and standard errors, even though we only use about a quarter of the data.[29]

Time Trends. The inclusion of bilateral fixed effects only captures bilateral time-invariant heterogeneity. One step towards capturing bilateral unobservables in a more flexible way is to interact the pair fixed effects with the linear variable year in order to account for pair-specific trends, as suggested in the EMU context by Bun and Klaassen (2007) and for the estimation of regional trade agreement effects by Bergstrand, Larch, and Yotov (2015). The estimates from column (2) of Table 1.4 demonstrate that the EMU effect continues to be insignificant when these bilateral linear time trends are added, while the effect of all other CUs is about halved.[30] A possible explanation is that when not controlling for bilateral linear time trends, part of the CU effect captures common changes in bilateral unobserved heterogeneity among CU members. The addition of this time trend also requires a further extension to our PPML estimation procedure, which we provide in Appendix A.5.

Lags. As discussed above, our failure to find a significant EMU effect could plausibly be because trade adjusts slowly to the introduction of a common currency rather than all at once. On top of using 4-year intervals, an additional way to explicitly capture sluggish adjustments and phasing-in effects of trade policies is to follow Baier and Bergstrand (2007)'s suggestion of adding lagged explanatory variables. After adding lags of all variables, the contemporaneous EMU effect is still insignificant (see column (3) of Table 1.4.) However, the lagged value is now small, positive, and statistically significant. The

[29]The OLS results for all specifications of Table 1.4 are presented in Table A.3 in Appendix A.7.

[30]These results and all subsequent results in Table 1.4 continue to use every four years (as in column 1). Our results are similar if we use every year.

combined EMU (defined as the sum of the contemporaneous effect and the lagged effect) is 0.027, which is again not statistically different from zero ($std.err. = 0.093$). For all other CUs, both the contemporaneous and lagged value are positive, and statistically significant. Their joint size of 0.668 (with $std.err. = 0.188$) is not statistically significantly different from the value from column (1).

Leads. Lastly, in column (4) of Table 1.4, we estimate specifications including the leads of all variables. A possible interpretation of this experiment is as a placebo test, as we should not see any effect of CUs that are not already in place. Indeed, for the EMU, the lead effect is close to zero and statistically insignificant. For the other CUs the lead is marginally significant, but substantially smaller than the contemporaneous coefficient. The significance of the lead variable could hint at an endogeneity problem or capture anticipation effects or the impact of any other unobserved drivers of trade. Hence, while our analysis demonstrates the effectiveness and empirical relevance of our methods, we again note that estimates of the effects of the non-EMU CUs—both here and in the literature more generally—should be interpreted with at least some caution.

1.4 Conclusions

We make three main contributions. First, we offer practical methods to overcome important challenges with the estimation of structural gravity models with high-dimensional fixed effects and clustered standard errors using PPML. Second, these innovations lead to very different conclusions about the effects of currency unions on trade, especially with regards to whether the Euro has had a statistically significant effect on trade. Third, we identify a cautionary example where OLS and PPML gravity estimates differ to an especially dramatic degree. We relate this difference to the underlying heteroscedasticity, which renders OLS inconsistent and which increases in the number of small countries included in our sample. Notably, the increasing divergence between estimates for larger samples with more small countries indicates that the computational issues we resolve in this paper would otherwise limit a researcher's choice of estimator precisely when this choice seems to matter most.

2

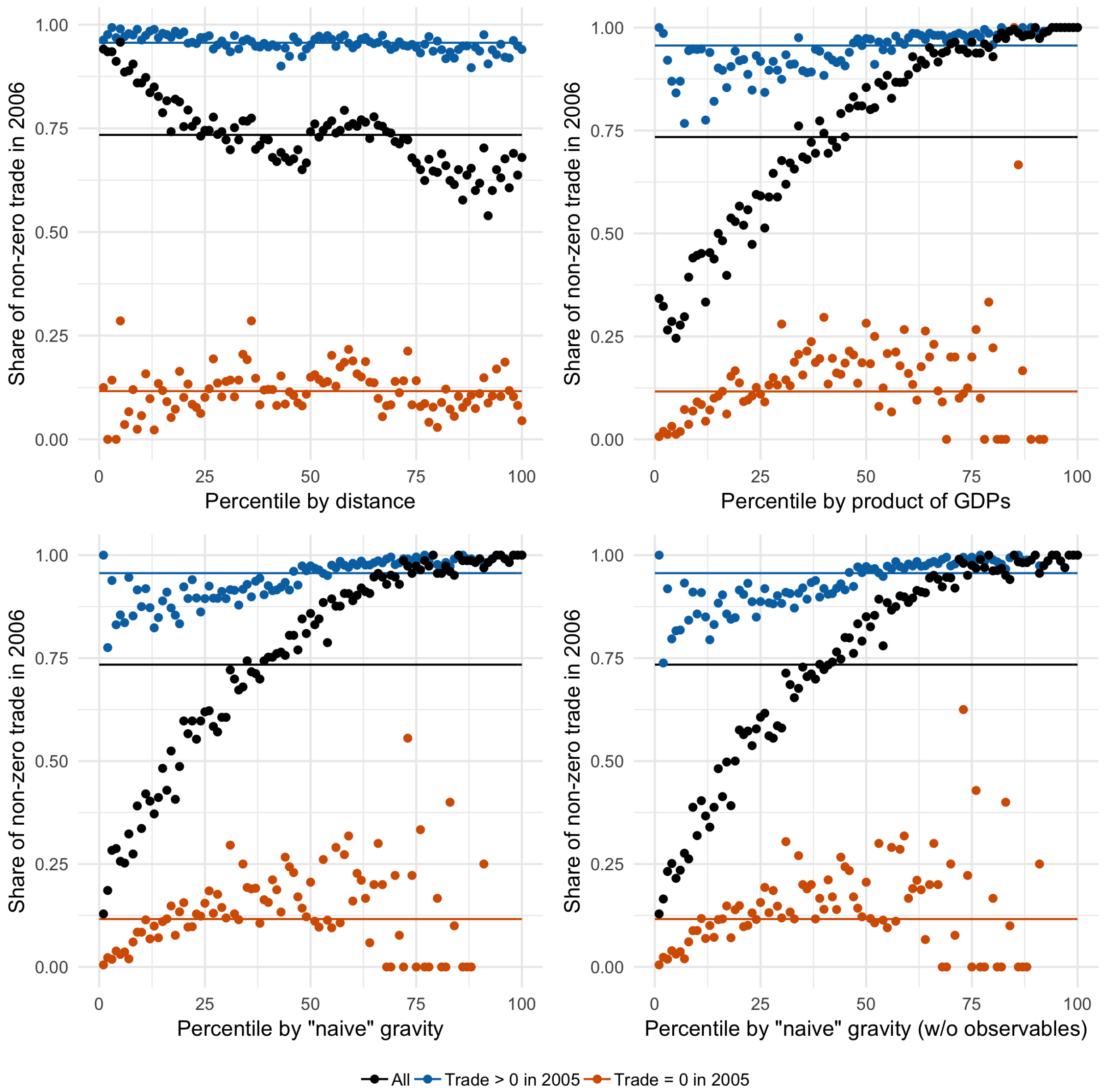
Persistent Zeros: The Extensive Margin of Trade[1]

2.1 Introduction

What induces country pairs to trade? In 2006, still more than one quarter of potential bilateral trade relations reported zero trade flows. Figure 2.1 breaks down the share of nonzero trade flows in 2006 along the percentiles of four different ad-hoc indicators of "trade potential": bilateral distance; product of GDPs; "naive" gravity, i.e. the product of GDPs divided by their bilateral distance; and the latter when excluding country pairs in FTAs, with common currencies or common colonial history. The x-axis indicates the potential trade volume, i.e. the joint economic size and/or proximity of any two countries. All four plots paint a common picture: the black dots, covering all country pairs, show a strong general relationship between trade potential and actual nonzero trade. The blue and red dots split the country pairs according to whether the two did or did not engage in trade in the previous year. The clearly separated pattern for the

[1]This chapter is joint work with Julian Hinz and Amrei Stammann. We thank Tanmay Belavadi, Daniel Czarnowske, Miriam Frey, Mario Larch, and Yuta Watabe for helpful comments. *Note*: An R implementation of the estimators developed in this chapter will be provided on CRAN and is currently available from the authors upon request.

Figure 2.1: Determinants of the Extensive Margin of Trade — Gravity and Persistence.



two groups highlights a remarkable persistence of trade relations, even after controlling for differences in trade potential in terms of distance, size, and bilateral trade policy. More than 75 percent of those country pairs in the lowest percentile of trade potential trade again in 2006, provided they already did so in 2005. On the other hand, even comparably large and close pairs are likely not to trade in 2006 if they did not trade in 2005 either.[2,3]

[2]Note that throughout the paper, "country pair" refers to a *directed* pair of countries, i.e. Germany-France and France-Germany are two distinct country pairs.

[3]The years 2005–2006 are the last available in our data set. A very similar pattern emerges for other points in time (see Figure B.1 in Appendix B.1 where the same graph is reproduced for the years 1990–1991). If longer time intervals are considered, a similar picture remains, but the relationship

In this paper we examine the determinants of the extensive margin of international trade, explicitly taking its persistence into account. We combine a heterogeneous firms model of international trade with bounded productivity with features from the firm dynamics literature to derive expressions for an exporting country's participation in a specific destination market in a given period. These expressions depend on partly unobserved (i) exporter-time, (ii) destination-time, and (iii) exporter-destination specific components, as well as on (iv) whether the exporter has already served the market in the previous period, and on (v) exporter-destination-time specific gravity-type trade cost determinants. We estimate the model making use of recent advances in the estimation of binary choice estimators with high-dimensional fixed effects to address (i)-(iii). The inclusion of fixed effects in a binary choice setting induces an incidental parameter problem, potentially aggravated by the dynamics introduced by (iv). To mitigate this bias, we characterize and implement new analytical and jackknife bias corrections for coefficients and estimates of average partial effects in our specifications with two- and three-way fixed effects. Extensive simulation experiments demonstrate the desirable statistical properties of our proposed bias-corrected, two- and three-way fixed effect logit and probit estimators. The empirical results provide evidence that both unobserved bilateral factors and true state dependence due to entry dynamics contribute strongly to the high persistence. Taking this persistence into account changes the coefficients considerably: out of the most commonly studied potential determinants (joint WTO membership, common regional trade agreement, and shared currency), only sharing a common currency has a significant effect on whether two countries trade with each other at all.

Our paper builds on recent insights from three flourishing strands of literature. First, our paper is related to the literature on the extensive margin of international trade. A number of theoretical frameworks have sought to propose mechanisms behind the decisions of firms to export, and their aggregate implications of zero or nonzero trade flows at the country pair level. Analogous to the intensive margin counterpart, these

becomes considerably weaker (see Figure B.2 in Appendix B.1 for the years 1997–2006).

theories have established *gravity*-like determinants, such as two countries' bilateral distance, a free trade agreement, a common currency and joint membership of the WTO. Egger and Larch (2011) and Egger, Larch, Staub, and Winkelmann (2011) append an extensive margin to an Anderson and van Wincoop (2003)-type model by assuming export participation to be determined by (homogeneous) firms weighing operating profits and bilateral fixed costs of exporting. This results in a two-part model in which, given a country's participation in exporting to any given destination, trade flows follow structural gravity. Helpman, Melitz, and Rubinstein (2008) build a model of international trade with heterogeneous firms. Here, the volume of trade between two countries can change either because incumbent firms expand their operations, or because of new competitors entering into a market. Eaton, Kortum, and Sotelo (2013) move away from the arguably simplifying notion of a continuum of firms and develop a model of a finite set of heterogeneous firms. Here no firm may export to a given market because of their individual efficiency draws. Our model proposed in this paper directly builds on Helpman, Melitz, and Rubinstein (2008) and extends it by features from the literature on firm dynamics.

In this firm-level literature, Das, Roberts, and Tybout (2007) develop a dynamic discrete-choice model in which current export participation depends on previous exporting, and hence sunk costs, and observable characteristics of profits from exporting. Alessandria and Choi (2007) extend this line of research and develop a general equilibrium framework that takes sunk costs and "period-by-period" fixed costs into account, showing that, contrary to previous partial equilibrium evidence, aggregate effects are negligible for the US. More recent works have looked at *new* exporter dynamics (Ruhl and Willis, 2017), emphasizing that sunk costs may be relatively smaller and continuation costs relatively larger than previously assumed. Bernard, Bøler, Massari, Reyes, and Taglioni (2017) stand somewhat in contrast to this finding, showing that first and second year growth rates may suffer from a bias because of different entry dates throughout the year. Berman, Rebeyrol, and Vicard (2019) note the important role of "demand learning" and firms' updating of their future demand and market participation. In a similar vein, Piveteau (2019) develops a model in which new firms accumulate consumers — or fail to do so — determining entry and exit. While these newer models feature rich firm-level predictions, they require tailor-made econometric models for their estimation. Our model abstracts from the specific role of *new* firms and has the advantage of yielding an econometric specification and demanding an estimator that remains general and flexible to be applied in other contexts.

Second, our paper builds on advances in the literature on the gravity equation and the *intensive* margin of international trade. With the advent of what has now been coined *structural* gravity (Head and Mayer, 2014), the gravity framework has gained rich microfoundations. Anderson and van Wincoop (2003) and Eaton and Kortum (2002) each formulate an underlying structure for exporting and importing countries that in estimations can easily be captured by appropriate two-way country(-time) fixed effects, as first noted by Feenstra (2004) and Redding and Venables (2004). Although not theoretically motivated, since Baier and Bergstrand (2007) it has furthermore become standard to include country pair fixed effects to tackle unobservable bilateral characteristics. Estimating the model introduced in this paper similarly calls for *at least* two sets of fixed effects, specific to exporters and importers in a given year. Additionally, and following Baier and Bergstrand (2007), there is no reason to believe that bilateral unobservables should not be a problem in the context of the extensive margin. Our preferred estimation of the model thus includes the "full set" of fixed effects that has become standard in the estimation of gravity models of the intensive margin of trade: exporter-year, importer-year and bilateral fixed effects that leave only bilateral-time-specific variation for the estimation of parameters of interest.

Third, the paper builds on and contributes to the literature on the econometrics of generalized linear models (GLMs) with fixed effects. Recent advances in this literature have made it possible to go beyond ordinary linear models in the context of high-dimensional fixed effects by providing fast and feasible algorithms (see Guimarães and

Portugal (2010), Stammann (2018), and Hinz, Hudlet, and Wanner (2019)).[4] As known since Neyman and Scott (1948), the inclusion of fixed effects potentially introduces an incidental parameter problem, leading to biased estimates. In the last few years, there have been a number of advances to correct this bias, and a variety of approaches have been proposed (see Fernández-Val and Weidner (2018) for a recent overview). Fernández-Val and Weidner (2016) develop analytical and jackknife bias corrections for nonlinear maximum likelihood estimators in static and dynamic models with individual and time effects for structural parameters and average partial effects. In Fernández-Val and Weidner (2018) they generalize their previous findings and show that the order of the bias induced by fixed effects in a wide family of models translates into a simple heuristic p/n, with n being the sample size and p the number of estimated parameters. Recently, Czarnowske and Stammann (2019) show how analytical bias corrections can be efficiently implemented in a high-dimensional fixed effects setting using the methods described by Stammann (2018).

Our paper is complementary to computational and econometric contributions on the estimation of the intensive margin of trade. Larch, Wanner, Yotov, and Zylkin (2019) present a feasible procedure to estimate pseudo-poisson (PPML) models with three high-dimensional fixed effects. Correia, Guimarães, and Zylkin (2019) generalize this estimation procedure to arbitrary sets of fixed effects. Weidner and Zylkin (2018) investigate the incidental parameter problem in three-way fixed effects PPML models under fixed T asymptotics and suggest an appropriate jackknife bias correction. We contribute to this literature by characterizing and implementing analytical and jackknife bias corrections for our specific two- and three-way fixed effects in the context of binary choice models. This helps us mitigate the bias induced by estimating our theory-consistent model, requiring exporter-time (it), importer-time (jt), and in our preferred

[4]Stammann, Heiß, and McFadden (2016) have shown in the context of binary choice models with individual fixed effects that a weighted version of the Frisch-Waugh-Lovell theorem (Frisch and Waugh (1933), Lovell (1963)) can be incorporated in a standard Newton-Raphson optimization procedure. This result paved the way to derive a computationally efficient algorithm for all GLMs with high-dimensional multi-way fixed effects (see Stammann (2018)). More recently, Hinz, Hudlet, and Wanner (2019) offer a different way to partial out fixed effects using a modification of the Gauss-Seidel algorithm proposed by Guimarães and Portugal (2010).

specification bilateral fixed effects (ij).

The remainder of the paper is structured as follows. In Section 2.2 we build a dynamic model of the extensive margin of international trade. The model yields aggregate predictions that can be structurally estimated using a probit model with high-dimensional fixed effects. In Section 2.3 we describe the estimator and bias correction procedure. We show its performance in Monte Carlo simulations in Section 2.4, before finally estimating the theoretical model in Section 2.5. Section 2.6 concludes.

2.2 An Empirical Model of the Extensive Margin of Trade

As a theoretical foundation for our econometric specification, we consider a stylized dynamic Melitz (2003)-type heterogeneous firms model of international trade. Following Helpman, Melitz, and Rubinstein (2008, henceforth HMR) we assume a bounded productivity distribution, like a truncated Pareto in HMR's case. We deviate from HMR by explicitly stating a time dimension and, unlike in the standard Melitz setting, separate fixed exporting costs into costs of entering a new market and costs of selling in a given market (as in Alessandria and Choi, 2007; Das, Roberts, and Tybout, 2007).

There are N countries, indexed by i and j, each of which consumes and produces a continuum of products. The representative consumer in j receives utility according to a CES utility function:

$$u_{jt} = \left(\int_{\omega \in \Omega_{jt}} (\xi_{ijt})^{\frac{1}{\sigma}} q_{jt}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}} \quad \text{with} \quad \sigma > 1. \tag{2.1}$$

where $q_{jt}(\omega)$ is j's consumption of product ω in period t, Ω_{jt} is the set of products available in j, σ is the elasticity of substitution across products, and ξ_{ijt} is a log-normally distributed idiosyncratic demand shock (with $\mu_\xi = 0$ and $\sigma_\xi = 1$) for goods from country i in country j and period t (similar to Eaton, Kortum, and Kramarz, 2011). Demand in country j for good ω depends on this demand shock, j's overall expenditure E_{jt}, and the good price $p_{jt}(\omega)$ relative to the overall price level as captured by the price index P_{jt}:

$$q_{jt}(\omega) = \frac{p_{jt}(\omega)^{-\sigma}}{P_{jt}^{1-\sigma}} \xi_{ijt} E_{jt},$$
$$\text{with} \qquad P_{jt} = \left(\int_{\omega \in \Omega_{jt}} \xi_{ijt} p_{jt}(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}} .$$

Each country has a fixed continuum of potentially active firms that have different productivities drawn from the distribution $G_{it}(\varphi)$, where $\varphi \in (0, \varphi^*_{it}]$. The productivity distribution evolves over time and firms' ranks within the productivity distribution can also change from period to period, though firms that in the last period did not export to a market already served by a domestic competitor are assumed not to directly jump to being the country's most productive firm in the next period.[5] Each period, a firm can decide to pay a fixed cost f^{prod}_{it} and start production of a differentiated variety using labour l as its only input, such that $l_t(\omega) = f^{prod}_{it} + q_t(\omega)/\varphi_t(\omega)$. A firm's marginal cost of providing one unit of its good to market j consists of iceberg trade costs τ_{ijt} and labour costs $w_{it}/\varphi_t(\omega)$. Firms compete with each other in monopolistic competition and charge a constant markup over marginal costs. Therefore, the price of a good ω produced in i and sold in j is:

$$p_{ijt}(\omega) = \frac{\sigma}{\sigma - 1} \frac{\tau_{ijt} w_{it}}{\varphi_t(\omega)}.$$

A firm's *operating* profits in market j are hence given by:

$$\tilde{\pi}_{ijt}(\omega) = \frac{1}{\sigma} \left(\frac{\sigma}{\sigma - 1} \frac{\tau_{ijt} w_{it}}{\varphi_t(\omega)} \right)^{1-\sigma} P_{jt}^{\sigma-1} \xi_{ijt} E_{jt}.$$

If a firm wants to export to a market j in period t, it has to pay a fixed exporting cost f^{exp}_{ijt}. The exporting fixed cost is higher by a market entry cost factor $f^{entry} \geq 1$ if the firm has not been active in the respective market in the previous period. For tractability, the entry cost factor is assumed to be constant across countries and time. Capturing the

[5]Note that we could in principle also allow for new firm entry into the pool of potential producers without changing our final expression for the extensive margin as long as the new entrants cannot become the country's most productive firm right away.

export decision by a binary variable $y_{ijt}(\omega)$, i.e. equal to one if the firm decides to serve market j in period t, we can formalize a firm's *realized* profits in market j as follows:

$$\pi_{ijt}(\omega) = y_{ijt}(\omega)\left\{\tilde{\pi}_{ijt}(\omega) - f_{ijt}^{exp}(f^{entry})^{[1-y_{ij(t-1)}(\omega)]}\right\}.$$

In the absence of entry costs, a firm would simply compare its operating profits to the fixed exporting cost and decide to serve a market if the former are greater than the latter. With market entry costs, a firm might be willing to incur a loss in the current period if expected future profits from that same market outweigh the initial loss. Firms discount future profits at a rate δ per period. To keep things tractable and allow us to derive a theory-consistent estimation expression below, we assume that firms expect their future operating profits from, and fixed costs of serving, a given market to be equal to today's values, i.e. $\mathbb{E}_t[\tilde{\pi}_{ij(t+s)}] = \tilde{\pi}_{ijt}$ and $\mathbb{E}_t[f_{ij(t+s)}^{exp}] = f_{ijt}^{exp}$ $\forall s \in \mathbb{N}$.[6] The current value of today's and all future operating profits from market j is then given by $\sum_{s=0}^{\infty}(1-\delta)^s\tilde{\pi}_{ijt} = \frac{\tilde{\pi}_{ijt}}{\delta}$. A firm will decide to serve a destination market if these discounted expected profits exceed the sum of today's and discounted future fixed costs of entry and exporting, given by

$$f_{ijt}^{exp}(f^{entry})^{(1-y_{ij(t-1)}(\omega))} + \sum_{s=1}^{\infty}(1-\delta)^s f_{ijt}^{exp} = \frac{f_{ijt}^{exp}}{\delta}\Big(1+\delta(f^{entry}-1)\Big)^{(1-y_{ij(t-1)}(\omega))}.$$

Given this model setup, the question whether a country exports to another country *at all* can be considered by looking at the most productive firm (with φ_t^*) only. Denoting that firm's product by ω^*, we can capture the aggregate extensive margin by the binary variable y_{ijt} as follows:

$$y_{ijt} = y_{ijt}(\omega^*) = \begin{cases} 1 & \text{if} \quad \dfrac{\left(\frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{\tau_{ijt}w_{it}}{\varphi_{it}^*}\right)^{1-\sigma}P_{jt}^{\sigma-1}\xi_{ijt}E_{jt}\right)}{f_{ijt}^{exp}(1+\delta(f^{entry}-1))^{(1-y_{ij(t-1)})}} \geq 1, \\ 0 & \text{else.} \end{cases} \tag{2.2}$$

Country i is hence more likely to export to country j in period t if (i) bilateral variable

[6] Note that our final expression for the extensive margin also holds if firms instead expect their operating profits from serving an export market to grow at a constant rate $\bar{g} < \delta$.

trade costs are lower; (ii) wages in i, and hence production costs, are lower; (iii) the productivity of the most productive firm is higher, again reducing production costs; (iv) competitive pressure, inversely captured by the price index, in j is lower, corresponding to the idea of inward multilateral resistance coined by Anderson and van Wincoop (2003) in the intensive margin context; (v) the market in j is larger; (vi) bilateral fixed costs of exporting are smaller; or (vii) i's most productive firm already served market j in the previous period and therefore does not have to pay the market entry cost. Note that (i) to (iv) all act via higher operating profits and depend on the elasticity of substitution between goods. The higher this elasticity, the stronger the reaction of profits to changes in any of these factors. At the same time, a higher elasticity reduces the mark-up firms can charge and hence makes it generally harder to earn enough profits to mitigate the fixed costs of exporting. Further note that the importance of the entry costs depends on the discount factor. Intuitively, if agents are more patient, the one-time entry costs matter less compared to the repeatedly earned profits.

In order to turn equation (2.2) into the empirical expression that we will bring to the data, we take the natural logarithm and group all exporter-time and importer-time specific components and capture them with corresponding sets of fixed effects. Further, we need to specify the fixed and variable trade costs. In keeping with the existing literature, we model them as a linear combination of different observable bilateral variables, such as geographical distance, whether i and j are both WTO members, or whether i and j share a common currency. In our most general specification, we additionally include country pair fixed effects. Following Baier and Bergstrand (2007), this is common practice in the estimation of the determinants of the intensive margin of trade in order to avoid endogeneity due to unobserved heterogeneity. Further, these bilateral fixed effects may capture (part of) the strong persistence documented above.[7]

[7]If the trade costs further include any exporter(-time) or importer(-time) specific components, these are captured by the aforementioned corresponding sets of fixed effects.

We then arrive at the following econometric model:

$$y_{ijt} = \begin{cases} 1 & \text{if} \quad \kappa + \lambda_{it} + \psi_{jt} + \beta_y y_{ij(t-1)} + \mathbf{x}'_{ijt}\boldsymbol{\beta}_x + \mu_{ij} \geq \zeta_{ijt}, \\ 0 & \text{else}, \end{cases} \tag{2.3}$$

where $\kappa = -\sigma \log(\sigma) - (1-\sigma)\log(\sigma-1) - \log(1+\delta(f^{entry}-1))$, $\lambda_{it} = (1-\sigma)(\log(w_{it}) - \log(\varphi^*_{it}))$, $\psi_{jt} = (\sigma-1)\log(P_{jt}) + \log(E_{jt})$, $\beta_y = \log(1+\delta(f^{entry}-1))$, $\mathbf{x}'_{ijt}\boldsymbol{\beta}_x + \mu_{ij} = (1-\sigma)\log(\tau_{ijt}) - \log(f^{exp}_{ijt})$, and $\zeta_{ijt} = -\log(\xi_{ijt}) \sim \mathcal{N}(0,1)$. The error term distribution implies that a probit estimator is the appropriate choice to estimate our model. Alternatively, we could deviate from Eaton, Kortum, and Kramarz (2011) and assume a log-logistic distribution for the idiosyncratic demand shocks, which would lead to a logit specification.

Our theoretical framework implies a flexible empirical specification that can reconcile the extensive margin estimation with the stylized fact presented in Section 2.1. Note that we chose to make a number of simplifying assumptions in order to achieve the clear theory-consistent interpretation of specification (2.3). An alternative interpretation of equation (2.3) as a reduced-from representation of a more elaborate and realistic model (similar e.g. to how Roberts and Tybout, 1997, motivate their empirical consideration) is equally justifiable. At the same time, while our model is written along the lines of Helpman, Melitz, and Rubinstein (2008), which remains the benchmark for the empirical assessment of the (aggregate) extensive margin of trade, it is not decisive for our empirical specification that zero trade flows result from a truncated productivity distribution instead of a discrete number of firms (as in Eaton, Kortum, and Sotelo, 2013) or from fixed exporting costs in a Krugman (1980)-type homogeneous firms setting (as in Egger and Larch, 2011; Egger, Larch, Staub, and Winkelmann, 2011).

2.3 Binary Response Estimators with High-Dimensional Fixed Effects

Having set up the empirical framework, we now turn to the estimation procedure. As equation (2.3) demands two- or three-way fixed effects to capture unobservable characteristics, we describe how to implement suitable binary choice estimators. In a first step, we review a recent procedure for estimating probit and logit models with high-dimensional fixed effects. In a second step, we characterize appropriate bias correction techniques to address the induced incidental parameter problem.

2.3.1 Feasible Estimation

In this subsection, we sketch how to estimate structural parameters, average partial effects (APEs), and the corresponding standard errors in a binary response setting in the presence of high-dimensional fixed effects. Let $\mathbf{Z} = [\mathbf{D}, \mathbf{X}]$, where $\mathbf{D}$ is the dummy matrix corresponding to the fixed effects and $\mathbf{X}$ is a matrix of further regressors. Note that $\mathbf{X}$ may also include predetermined variables. Further, let $\boldsymbol{\alpha}$ denote the vector of fixed effects, $\boldsymbol{\beta}$ the vector of structural parameters, and $\boldsymbol{\theta} = [\boldsymbol{\alpha}', \boldsymbol{\beta}']'$. The log-likelihood contribution of the ijt-th observation is

$$\ell_{ijt}(\boldsymbol{\beta}, \boldsymbol{\alpha}_{ijt}) = y_{ijt} \log(F_{ijt}) + (1 - y_{ijt}) \log(1 - F_{ijt}),$$

where $\boldsymbol{\alpha}_{ijt} = [\lambda_{it}, \psi_{jt}]'$ in the case of two-way fixed effects and $\boldsymbol{\alpha}_{ijt} = [\lambda_{it}, \psi_{jt}, \mu_{ij}]'$ in the case of three-way fixed effects.[8] Further, F_{ijt} is either the logistic or the standard normal cumulative distribution function. See Table 2.1 for the relevant expressions and derivatives.

[8]Note that we use for brevity notation for balanced data.

Table 2.1: Expressions and Derivatives for Logit and Probit Models

	Logit	Probit
F_{ijt}	$(1+\exp(-\eta_{ijt}))^{-1}$	$\Phi(\eta_{ijt})$
$\partial_{\eta} F_{ijt}$	$F_{ijt}(1-F_{ijt})$	$\phi(\eta_{ijt})$
$\partial_{\eta^2} F_{ijt}$	$\partial_{\eta} F_{ijt}(1-2F_{ijt})$	$-\eta_{ijt}\phi(\eta_{ijt})$
ν_{ijt}	$(y_{ijt}-F_{ijt})/\partial_{\eta} F_{ijt}$	$(y_{ijt}-F_{ijt})/\partial_{\eta} F_{ijt}$
H_{ijt}	1	$\partial_{\eta} F_{ijt}/(F_{ijt}(1-F_{ijt}))$
ω_{ijt}	$\partial_{\eta} F_{ijt}$	$H_{ijt}\partial_{\eta} F_{ijt}$
$\partial_{\eta} \ell_{ijt}$	$y_{ijt}-F_{ijt}$	$H_{ijt}(y_{ijt}-F_{ijt})$

Note: $\eta_{ijt} = \mathbf{x}'_{ijt}\boldsymbol{\beta}+\lambda_{it}+\psi_{jt}$ or $\eta_{ijt} = \mathbf{x}'_{ijt}\boldsymbol{\beta}+\lambda_{it}+\psi_{jt}+\mu_{ij}$ is the linear predictor.

The standard approach to estimate binary choice models is to maximize the following log-likelihood function:

$$\mathcal{L}(\boldsymbol{\beta}, \boldsymbol{\alpha}) = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} \ell_{ijt}(\boldsymbol{\beta}, \boldsymbol{\alpha}_{ijt})$$

using Newton's method. The update in the r-th iteration is

$$\boldsymbol{\theta}^{r} - \boldsymbol{\theta}^{r-1} = (\mathbf{Z}'\widehat{\boldsymbol{\Omega}}\mathbf{Z})^{-1}\mathbf{Z}'\widehat{\boldsymbol{\Omega}}\hat{\boldsymbol{\nu}} \ , \tag{2.4}$$

where $(\mathbf{Z}'\widehat{\boldsymbol{\Omega}}\mathbf{Z})^{-1}$ and $\mathbf{Z}'\widehat{\boldsymbol{\Omega}}\hat{\boldsymbol{\nu}}$ denote the Hessian and gradient of the log-likelihood, respectively, and $\widehat{\boldsymbol{\Omega}}$ is a diagonal weighting matrix with $\text{diag}(\widehat{\boldsymbol{\Omega}}) = \hat{\boldsymbol{\omega}}$.

The brute-force computation of equation (2.4) quickly becomes computationally demanding, if not impossible.[9] Thus Stammann (2018) suggests a straightforward strategy called pseudo-demeaning, which mimics the well-known within transformation for linear regression models. The approach allows us to update the structural parameters without having to explicitly update the incidental parameters, which leads to the following

[9]In a balanced data set ($I = J = N$) with two-way fixed effects the routine requires to estimate $\approx 2NT$ fixed effects associated with a $2NT \times 2NT$ Hessian. In the case of three-way fixed effects, the number of parameters to be estimated is even $\approx N(N-1) \times 2NT$. In a trade panel data set with 200 countries and 50 years, the number of fixed effects in the latter case amounts to 59800 parameters.

concentrated version of equation (2.4)

$$\boldsymbol{\beta}^{r} - \boldsymbol{\beta}^{r-1} = \left((\widehat{\mathbb{M}}\mathbf{X})'\widehat{\boldsymbol{\Omega}}(\widehat{\mathbb{M}}\mathbf{X})\right)^{-1}(\widehat{\mathbb{M}}\mathbf{X})'\widehat{\boldsymbol{\Omega}}(\widehat{\mathbb{M}}\hat{\boldsymbol{\nu}}) \, , \tag{2.5}$$

where $\widehat{\mathbb{M}}\hat{\boldsymbol{\nu}}$ is the concentrated gradient, $\widehat{\mathbb{M}}\mathbf{X}$ is the concentrated Hessian, and $\widehat{\mathbb{M}} = \mathbf{I}_{IJT} - \widehat{\mathbb{P}} = \mathbf{I}_{IJT} - \mathbf{D}(\mathbf{D}'\widehat{\boldsymbol{\Omega}}\mathbf{D})^{-1}\mathbf{D}'\widehat{\boldsymbol{\Omega}}$ is known as the residual projection that partials out the fixed effects. After convergence of the optimization routine, the standard errors associated with the structural parameters can be computed from the inverse of the concentrated Hessian.

Since the computation of $\widehat{\mathbb{M}}$ itself is problematic even in moderately large data sets, Stammann (2018) proposes to calculate $\widehat{\mathbb{M}}\hat{\boldsymbol{\nu}}$ and $\widehat{\mathbb{M}}\mathbf{X}$ using the method of alternating projections (MAP), which only requires repeatedly performing group-specific one-way weighted within transformations. This approach is feasible, since these within transformations translate into simple scalar transformations (see Stammann, Heiß, and McFadden, 2016).[10] Note that all expressions containing $\widehat{\mathbb{M}}$ or $\widehat{\mathbb{P}}$ can be calculated efficiently based on the MAP.

Next, we address the estimation of APEs. An estimator for the APEs is

$$\hat{\delta}_k = \frac{1}{IJT}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T}\widehat{\Delta}_{ijt}^{k} \, ,$$

where the partial effect of the k-th regressor $\widehat{\Delta}_{ijt}^{k}$ is either $\widehat{\Delta}_{ijt}^{k} = \partial\widehat{F}_{ijt}/\partial x_{ijtk}$ in the case of a continuous regressor or $\hat{\Delta}_{ijt}^{k} = \widehat{F}_{ijt}|_{x_{ijtk=1}} - \widehat{F}_{ijt}|_{x_{ijtk=0}}$ in the case of a binary regressors. Another question that arises in the context of APEs is how to calculate appropriate standard errors, even in the case of high-dimensional fixed effects. A possible candidate is the delta method, but in its standard form it requires the entire covariance matrix, which we do not obtain using the pseudo-demeaning approach. However, as outlined in Fernández-Val and Weidner (2016) and Czarnowske and Stammann (2019) in the

[10]For further details, we refer the reader to Appendix B.2.1, where we sketch the MAP for our application of two-way and three-way models, and provide the entire optimization routine corresponding to equation (2.5).

context of individual and time fixed effects, it is possible to use a concentrated version of the delta method. In the following we present the feasible covariance estimators for our two-way and three-way error structure.[11] An appropriate covariance estimator for the APEs of the two-way fixed effects model is

$$\widehat{\mathbf{V}}^{\delta} = \frac{1}{I^2 J^2 T^2} \left(\underbrace{\left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \widehat{\overline{\mathbf{\Delta}}}_{ijt} \right) \left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \widehat{\overline{\mathbf{\Delta}}}_{ijt} \right)'}_{v_1} + \underbrace{\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \widehat{\mathbf{\Gamma}}_{ijt} \widehat{\mathbf{\Gamma}}'_{ijt}}_{v_2} \right) , \tag{2.6}$$

and of the three-way error component model

$$\begin{aligned} \widehat{\mathbf{V}}^{\delta} = \frac{1}{I^2 J^2 T^2} & \left(\underbrace{\left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \widehat{\overline{\mathbf{\Delta}}}_{ijt} \right) \left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \widehat{\overline{\mathbf{\Delta}}}_{ijt} \right)'}_{v_1} + \underbrace{\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \widehat{\mathbf{\Gamma}}_{ijt} \widehat{\mathbf{\Gamma}}'_{ijt}}_{v_2} \right. \\ & \left. + \underbrace{2 \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{s>t}^{T} \widehat{\overline{\mathbf{\Delta}}}_{ijt} \widehat{\mathbf{\Gamma}}'_{ijs}}_{v_3} \right) , \end{aligned} \tag{2.7}$$

where in both cases $\widehat{\overline{\mathbf{\Delta}}}_{ijt} = \widehat{\mathbf{\Delta}}_{ijt} - \hat{\boldsymbol{\delta}}$, $\widehat{\mathbf{\Delta}}_{ijt} = [\widehat{\Delta}^1_{ijt}, \ldots, \widehat{\Delta}^m_{ijt}]'$, $\hat{\boldsymbol{\delta}} = [\hat{\delta}_1, \ldots, \hat{\delta}_m]'$, and

$$\widehat{\mathbf{\Gamma}}_{ijt} = \left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \partial_{\beta} \widehat{\mathbf{\Delta}}_{ijt} - \left(\widehat{\mathbb{P}} \mathbf{X} \right)_{ijt} \partial_{\eta} \widehat{\mathbf{\Delta}}_{ijt} \right)' \widehat{\mathbf{W}}^{-1} \left(\widehat{\mathbb{M}} \mathbf{X} \right)_{ijt} \hat{\omega}_{ijt} \hat{\boldsymbol{\nu}}_{ijt} - \left(\widehat{\mathbb{P}} \widehat{\mathbf{\Psi}} \right)_{ijt} \partial_{\eta} \hat{\ell}_{ijt} \,,$$

with $\widehat{\mathbf{\Psi}}_{ijt} = \partial_{\eta} \widehat{\mathbf{\Delta}}_{ijt} / \hat{\omega}_{ijt}$, and $\partial_{\eta} \hat{\ell}_{ijt}$ defined in Table 2.1. To clarify notation, $\partial_{\iota} g(\cdot)$ denotes the first order partial derivative of an arbitrary function $g(\cdot)$ with respect to some parameter ι. Note, that the term v_2 refers to the concentrated delta method. The terms v_1 and v_3 are in the spirit of Fernández-Val and Weidner (2016) to improve the finite sample properties. These are, on the one hand, the variation induced by estimating sample instead of population means (v_1). On the other hand, if we are concerned about the strict exogeneity assumption (as we are in the case of dynamic three-way error structure models), the covariance between the estimation of sample means and

[11] The corresponding asymptotic distribution of the estimators is provided in Appendix B.2.3.

parameters is another factor that should be incorporated (v_3). These computationally efficient covariance estimators can be readily applied not only to uncorrected APE estimators, but also to the bias-corrected APE estimators, which we will introduce below.

2.3.2 Incidental Parameter Bias Correction

As in many nonlinear estimators, standard fixed effects versions of the logit and probit models suffer from the well-known incidental parameter problem first identified by Neyman and Scott (1948). The problem stems from the necessity to estimate many nuisance parameters, which contaminate the estimator of the structural parameters and average partial effects. It can be further amplified by the inclusion of a lagged dependent variable. Note that this induces an incidental parameter problem even in the linear three-way fixed effects setting (see Nickell, 1981) — and hence in our case also affects a linear probability model specification. Fernández-Val and Weidner (2018) derive the order of the bias induced by incidental parameters to be given by $bias \sim p/n$, where p and n are the numbers of parameters and observations, respectively. The literature suggests different types of bias corrections to reduce this incidental parameter bias. Jackknife corrections, like the leave-one-out jackknife proposed by Hahn and Newey (2004), or the split-panel jackknife (SPJ) introduced by Dhaene and Jochmans (2015), are the simplest approaches to obtain a bias correction, at the expense of being computationally costly. In contrast to analytical corrections, their application only requires knowledge of the order of the bias to form appropriate subpanels that are used to reestimate the model and to form an estimator of the bias terms. For analytical bias correction (ABC), it is necessary to derive the asymptotic distribution of the maximum likelihood estimator (MLE), in order to obtain an explicit expression of the asymptotic bias. This is then used to form a suitable estimator for the bias terms. Fernández-Val and Weidner (2016) propose analytical and split-panel jackknife bias corrections for structural parameters and APEs in the context of nonlinear models with individual and time fixed effects. In the following two subsections, we adapt and extend the bias corrections of Fernández-Val and Weidner (2016) to our two-way and three-way error component.[12]

Two-way fixed effects

The two-way fixed effects case with exporter-time and importer-time fixed effects is closely related to the two-way fixed effects models with a classical panel structure and individual and time fixed effects or with a pseudo-panel ij-structure and exporter and importer fixed effects as discussed by Fernández-Val and Weidner (2016) and Cruz-Gonzalez, Fernández-Val, and Weidner (2017), respectively. It is straightforward to see that in our case the overall bias consists of two components that are due to the inclusion of importer-time and exporter-time fixed effects, respectively, and takes the form $B_1/I + B_2/J$.[13]

The form of the bias suggests to separately split the panel by I and J, leading to the following split-panel corrected estimator for the structural parameters:

$$\begin{aligned} \widehat{\boldsymbol{\beta}}^{sp} &= 3\widehat{\boldsymbol{\beta}}_{I,J,T} - \widehat{\boldsymbol{\beta}}_{I/2,J,T} - \widehat{\boldsymbol{\beta}}_{I,J/2,T}, \quad \text{with} \qquad (2.8) \\ \widehat{\boldsymbol{\beta}}_{I/2,J,T} &= \frac{1}{2}\left[\widehat{\boldsymbol{\beta}}_{\{i:i\leq\lceil I/2\rceil\},J,T} + \widehat{\boldsymbol{\beta}}_{\{i:i\geq\lfloor I/2+1\rfloor\},J,T}\right], \\ \widehat{\boldsymbol{\beta}}_{I,J/2,T} &= \frac{1}{2}\left[\widehat{\boldsymbol{\beta}}_{I,\{j:j\leq\lceil J/2\rceil,T\}} + \widehat{\boldsymbol{\beta}}_{I,\{j:j\geq\lfloor J/2+1\rfloor,T\}}\right], \end{aligned}$$

where $\lfloor\cdot\rfloor$ and $\lceil\cdot\rceil$ denote the floor and ceiling functions. To clarify the notation, the subscript $\{i : i \leq \lceil I/2\rceil\}, J, T$ denotes that the estimator is based on a subsample, which contains all importers and time periods, but only the first half of all exporters.

In order to form the appropriate analytical bias correction, we need to specify the asymptotic distribution of the MLE, which we show in Appendix B.2.3. The analytical bias-corrected estimator $\tilde{\boldsymbol{\beta}}^a$ is formed from estimators of the leading bias terms that are

[12]We do not elaborate on the leave-one-out jackknife bias correction because the large number of fixed effects in our panel structure makes it unnecessarily computationally demanding.

[13]See Appendix B.2.3. We also report the appropriate Neyman and Scott (1948) variance example in Appendix B.2.2 as an illustration.

subtracted from the MLE of the full sample $\widehat{\boldsymbol{\beta}}_{I,J,T}$. More precisely:

$$\tilde{\boldsymbol{\beta}}^{a} = \hat{\boldsymbol{\beta}}_{I,J,T} - \frac{\widehat{\mathbf{B}}_1^{\beta}}{I} - \frac{\widehat{\mathbf{B}}_2^{\beta}}{J}, \quad \text{with} \quad \widehat{\mathbf{B}}_1^{\beta} = \widehat{\mathbf{W}}^{-1}\widehat{\mathbf{B}}_1, \widehat{\mathbf{B}}_2^{\beta} = \widehat{\mathbf{W}}^{-1}\widehat{\mathbf{B}}_2, \quad \text{and}$$

$$\widehat{\mathbf{B}}_1 = -\frac{1}{2JT}\sum_{j=1}^{J}\sum_{t=1}^{T}\frac{\sum_{i=1}^{I}\widehat{H}_{ijt}\partial_{\eta^2}\widehat{F}_{ijt}\left(\widehat{\mathbb{M}}\mathbf{X}\right)_{ijt}}{\sum_{i=1}^{I}\hat{\omega}_{ijt}},$$

$$\widehat{\mathbf{B}}_2 = -\frac{1}{2IT}\sum_{i=1}^{I}\sum_{t=1}^{T}\frac{\sum_{j=1}^{J}\widehat{H}_{ijt}\partial_{\eta^2}\widehat{F}_{ijt}\left(\widehat{\mathbb{M}}\mathbf{X}\right)_{ijt}}{\sum_{j=1}^{J}\hat{\omega}_{ijt}},$$

$$\widehat{\mathbf{W}} = \frac{1}{IJT}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T}\hat{\omega}_{ijt}\left(\widehat{\mathbb{M}}\mathbf{X}\right)_{ijt}\left(\widehat{\mathbb{M}}\mathbf{X}\right)_{ijt}^{\prime},$$

where $\partial_{\iota^2}g(\cdot)$ denotes the second order partial derivative of an arbitrary function $g(\cdot)$ with respect to some parameter ι. The explicit expressions of H_{ijt} and $\partial_{\eta^2}F_{ijt}$ are reported in Table 2.1.

The split-panel jackknife estimator works similarly with APEs as with structural parameters. We simply replace in formula (2.8) the estimators for the structural parameters with estimators for the APEs. The following analytically bias-corrected estimator for the APEs is formed based on the asymptotic distribution presented in Appendix B.2.3:

$$\tilde{\boldsymbol{\delta}}^{a} = \tilde{\boldsymbol{\delta}} - \frac{\widehat{\mathbf{B}}_1^{\delta}}{I} - \frac{\widehat{\mathbf{B}}_2^{\delta}}{J}, \quad \text{with}$$

$$\widehat{\mathbf{B}}_1^{\delta} = \frac{1}{2JT}\sum_{j=1}^{J}\sum_{t=1}^{T}\frac{\sum_{i=1}^{I}-\widehat{H}_{ijt}\partial_{\eta^2}\widehat{F}_{ijt}\left(\widehat{\mathbb{P}}\widehat{\boldsymbol{\Psi}}\right)_{ijt}+\partial_{\eta^2}\widehat{\boldsymbol{\Delta}}_{ijt}}{\sum_{i=1}^{I}\hat{\omega}_{ijt}},$$

$$\widehat{\mathbf{B}}_2^{\delta} = \frac{1}{2IT}\sum_{i=1}^{I}\sum_{t=1}^{T}\frac{\sum_{j=1}^{J}-\widehat{H}_{ijt}\partial_{\eta^2}\widehat{F}_{ijt}\left(\widehat{\mathbb{P}}\widehat{\boldsymbol{\Psi}}\right)_{ijt}+\partial_{\eta^2}\widehat{\boldsymbol{\Delta}}_{ijt}}{\sum_{j=1}^{J}\hat{\omega}_{ijt}}.$$

$\tilde{\boldsymbol{\delta}}$ are the APEs evaluated at bias-corrected structural parameters and the corresponding estimates of the fixed effects. Note that the latter can be obtained by reestimating the model using an offset algorithm as in Czarnowske and Stammann (2019). The covariance can be estimated according to equation (2.6).

Three-way fixed effects

Having adapted the two-way fixed effects bias correction of Fernández-Val and Weidner

(2016) to the ijt-panel setting, we now move on to the more difficult case of extending the consideration to three-way fixed effects. Fernández-Val and Weidner (2018) conjecture, based on their previously discussed formula, $bias \sim p/n$, that the bias is of order $(IT + JT + IJ)/(IJT)$ and of the form $B_1/I + B_2/J + B_3/T$. Intuitively, the inclusion of dyadic fixed effects induces another bias of order $1/T$ because there are only T informative observations per additionally included parameter. We support their conjecture by providing the appropriate Neyman and Scott (1948) variance example in Appendix B.2.2 and propose novel analytical and jackknife bias corrections for three-way fixed effects models.

For the split-panel jackknife bias correction, this bias structure implies that we add an additional splitting dimension, leading to the following estimator for the structural parameters:

$$\begin{aligned} \widehat{\boldsymbol{\beta}}^{sp} &= 4\widehat{\boldsymbol{\beta}}_{I,J,T} - \widehat{\boldsymbol{\beta}}_{I/2,J,T} - \widehat{\boldsymbol{\beta}}_{I,J/2,T} - \widehat{\boldsymbol{\beta}}_{I,J,T/2}, \quad \text{with} \\ \widehat{\boldsymbol{\beta}}_{I/2,J,T} &= \frac{1}{2}\Big[\widehat{\boldsymbol{\beta}}_{\{i:i\leq\lfloor I/2\rfloor,J,T\}} + \widehat{\boldsymbol{\beta}}_{\{i:i\geq\lceil I/2+1\rceil,J,T\}}\Big], \\ \widehat{\boldsymbol{\beta}}_{I,J/2,T} &= \frac{1}{2}\Big[\widehat{\boldsymbol{\beta}}_{\{I,j:j\leq\lfloor J/2\rfloor,T\}} + \widehat{\boldsymbol{\beta}}_{\{I,j:j\geq\lceil J/2+1\rceil,T\}}\Big], \\ \widehat{\boldsymbol{\beta}}_{I,J,T/2} &= \frac{1}{2}\Big[\widehat{\boldsymbol{\beta}}_{\{I,J,t:t\leq\lfloor T/2\rfloor\}} + \widehat{\boldsymbol{\beta}}_{\{I,J,t:t\geq\lceil T/2+1\rceil\}}\Big]. \end{aligned} \tag{2.9}$$

Combining insights from the classical panel structure in Fernández-Val and Weidner (2016), the pseudo-panel setting in Cruz-Gonzalez, Fernández-Val, and Weidner (2017), and the three-way fixed effects conjecture by Fernández-Val and Weidner (2018), we formulate a conjecture for the asymptotic MLE distribution in the three-way setting (which we present in Appendix B.2.3) and propose to extend the analytical two-way bias correction by a third part $\widehat{\mathbf{B}}_3$, such that

$$\tilde{\boldsymbol{\beta}}^a = \hat{\boldsymbol{\beta}}_{I,J,T} - \frac{\widehat{\mathbf{B}}_1^\beta}{I} - \frac{\widehat{\mathbf{B}}_2^\beta}{J} - \frac{\widehat{\mathbf{B}}_3^\beta}{T}, \quad \text{with} \quad \widehat{\mathbf{B}}_3^\beta = \widehat{\mathbf{W}}^{-1}\widehat{\mathbf{B}}_3$$

$$\widehat{\mathbf{B}}_3 = -\frac{1}{2IJ}\sum_{i=1}^{I}\sum_{j=1}^{J}\left(\sum_{t=1}^{T}\hat{\omega}_{ijt}\right)^{-1}\left(\sum_{t=1}^{T}\widehat{H}_{ijt}\partial_{\eta^2}\widehat{F}_{ijt}\left(\widehat{\mathbb{M}}\mathbf{X}\right)_{ijt}\right.$$
$$\left. +2\sum_{l=1}^{L}(T/(T-L))\sum_{t=l+1}^{T}\partial_{\eta}\hat{\ell}_{ijt-l}\hat{\omega}_{ijt}\left(\widehat{\mathbb{M}}\mathbf{X}\right)_{ijt}\right).$$

L is a bandwidth parameter and is used for the estimation of spectral densities (Hahn and Kuersteiner, 2007). In a model where all regressors are exogenous, L is set to zero, such that the second part of $\widehat{\mathbf{B}}_3$ vanishes and all three estimators of the bias terms are symmetric. Otherwise, for instance in the dynamic model, Fernández-Val and Weidner (2016) suggest conducting a sensitivity analysis with $L \in \{1, 2, 3, 4\}$.

Again, for the APEs the split-panel jackknife estimator is formed by replacing the estimators for the structural parameters with estimators for the APEs in formula (2.9). The analytically bias-corrected estimator, based on our conjecture for the asymptotic distribution provided in Appendix B.2.3, is given by

$$\tilde{\boldsymbol{\delta}}^a = \tilde{\boldsymbol{\delta}} - \frac{\widehat{\mathbf{B}}_1^\delta}{I} - \frac{\widehat{\mathbf{B}}_2^\delta}{J} - \frac{\widehat{\mathbf{B}}_3^\delta}{T}, \quad \text{with}$$

$$\widehat{\mathbf{B}}_3^\delta = \frac{1}{2IJ}\sum_{i=1}^{I}\sum_{j=1}^{J}\left(\sum_{t=1}^{T}\hat{\omega}_{ijt}\right)^{-1}\left(\sum_{t=1}^{T}-\widehat{H}_{ijt}\partial_{\eta^2}\widehat{F}_{ijt}\left(\widehat{\mathbb{P}}\widehat{\boldsymbol{\Psi}}\right)_{ijt} + \partial_{\eta^2}\widehat{\boldsymbol{\Delta}}_{ijt}\right.$$
$$\left. +2\sum_{l=1}^{L}\left(T/\left(T-l\right)\right)\sum_{t=l+1}^{T}\partial_{\eta}\hat{\ell}_{ijt-l}\hat{\omega}_{ijt}\left(\widehat{\mathbb{M}}\widehat{\boldsymbol{\Psi}}\right)_{ijt}\right).$$

The last part of the numerator is again dropped if all regressors are assumed to be strictly exogenous. As previously mentioned, standard errors can still be obtained from equation (2.7).

2.4 Monte Carlo Simulations

In this section, we conduct extensive simulation experiments to investigate the properties of different estimators for both the structural parameters and the APEs. The estimators we study are MLE, ABC, SPJ and a (bias-corrected) ordinary least squares fixed effects estimator (LPM).[14] Our main focus are the biases and inference accuracies. To this end, we compute the relative bias and standard deviation (SD) in percent, the ratio between standard error and standard deviation (SE/SD), the relative root mean square error (RMSE) in percent, and the coverage probabilities (CPs) at a nominal level of 95 percent.

For the simulation experiments we adapt the design for a dynamic probit model of Fernández-Val and Weidner (2016) to our ijt-panel structure for the two cases with two- and three-way fixed effects.[15]

2.4.1 Two-way Fixed Effects

The simulations in this section correspond to a theory-consistent estimation of the extensive margin outlined in Section 2.2, taking into account unobserved, time-varying, exporter- and importer-specific terms as well as dynamics, but not allowing for bilateral unobserved heterogeneity. Specifically, we generate data according to

$$y_{ijt} = \mathbf{1}[\beta_y y_{ijt-1} + \beta_x x_{ijt} + \lambda_{it} + \psi_{jt} \geq \epsilon_{ijt}] \; ,$$
$$y_{ij0} = \mathbf{1}[\beta_x x_{ij0} + \lambda_{i0} + \psi_{j0} \geq \epsilon_{ij0}] \; ,$$

where $i = 1, \ldots, N$, $j = 1, \ldots, N$, $t = 1, \ldots, T$, $\lambda_{it} \sim \text{iid.}\, \mathcal{N}(0, 1/16)$, $\psi_{jt} \sim \text{iid.}\, \mathcal{N}(0, 1/16)$, and $\epsilon_{ijt} \sim \text{iid.}\, \mathcal{N}(0, 1)$.[16] Further, $x_{ijt} = 0.5 x_{ijt-1} + \lambda_{it} + \psi_{jt} + \nu_{ijt}$, where $\nu_{ijt} \sim \text{iid.}\, \mathcal{N}(0, 0.5)$, $x_{ij0} \sim \text{iid.}\, \mathcal{N}(0, 1)$. To get an impression of how the different statis-

[14]Details on LPM and our suggested bias correction in this context are given in Appendix B.2.4.
[15]Further simulation experiments including static panel models are presented in Appendix B.4.
[16]Since $\{\lambda_{it}\}_{IT}$ and $\{\psi_{jt}\}_{JT}$ are independent sequences, and λ_{it} and ψ_{jt} are independent for all it, jt, we follow Fernández-Val and Weidner (2016) and incorporate this information in the covariance estimator for the APEs. The explicit expression is provided in the Appendix B.2.3.

tics evolve with changing panel dimensions, we consider all possible combinations of $N \in \{50, 100, 150\}$ and $T \in \{10, 20, 30, 40, 50\}$. For each of these combinations we generate $1,000$ samples.

Tables B.4 – B.9 in Appendix B.3.1 report the extensive simulation results for the exogenous and predetermined regressors, respectively. The left panels contain the results of the structural parameters and the right panels the results of the APEs. In the following, we focus on the biases and coverage probabilities for $N \in \{50, 150\}$, which we visualize in Figures 2.2 and 2.3 for better comprehensibility.

First of all, we start by analyzing the properties of the different estimators for the structural parameters. MLE exhibits persistent biases that do not fade with increasing T but with increasing N. This result is as expected, since MLE is fixed T consistent as shown in Appendix B.2.3. Further, its CPs are too low and decreasing in T. The bias-corrected estimators clearly perform better than MLE. First, they reduce the bias considerably. ABC shows basically no bias for any considered sample size. SPJ performs slightly worse. Second, the bias corrections also dramatically improve the coverage probabilities. Whereas the CPs of ABC are close to the nominal value in all cases, the CPs of SPJ are somewhat too low for the exogenous regressor in the case of $N = 50$.

Next, we turn to the estimators of the APEs, where we now also consider LPM. It turns out that MLE, as well as the two bias-corrected estimators, are essentially unbiased. This is particularly noteworthy for MLE, since it exhibits a non-negligible bias for the structural parameters. Remarkably, LPM displays persistent biases that — differently to the nonlinear estimators — do not vanish with larger N. The bias is very small for the exogenous regressor but for the predetermined regressor it ranges between 5 and 6 percent.[17] These persistent biases also explain that LPM delivers too small CPs that decrease in T. Contrary, the CPs of the three nonlinear estimators are close to the nominal value in most cases.

[17] We found that the predicted probabilities of LPM exceed the boundaries of the unit interval considerably. This, in turn, affects the APEs for binary regressors, since they are based on differences of predicted probabilities.

Figure 2.2: Dynamic: Two-way Fixed Effects — Predetermined Regressor

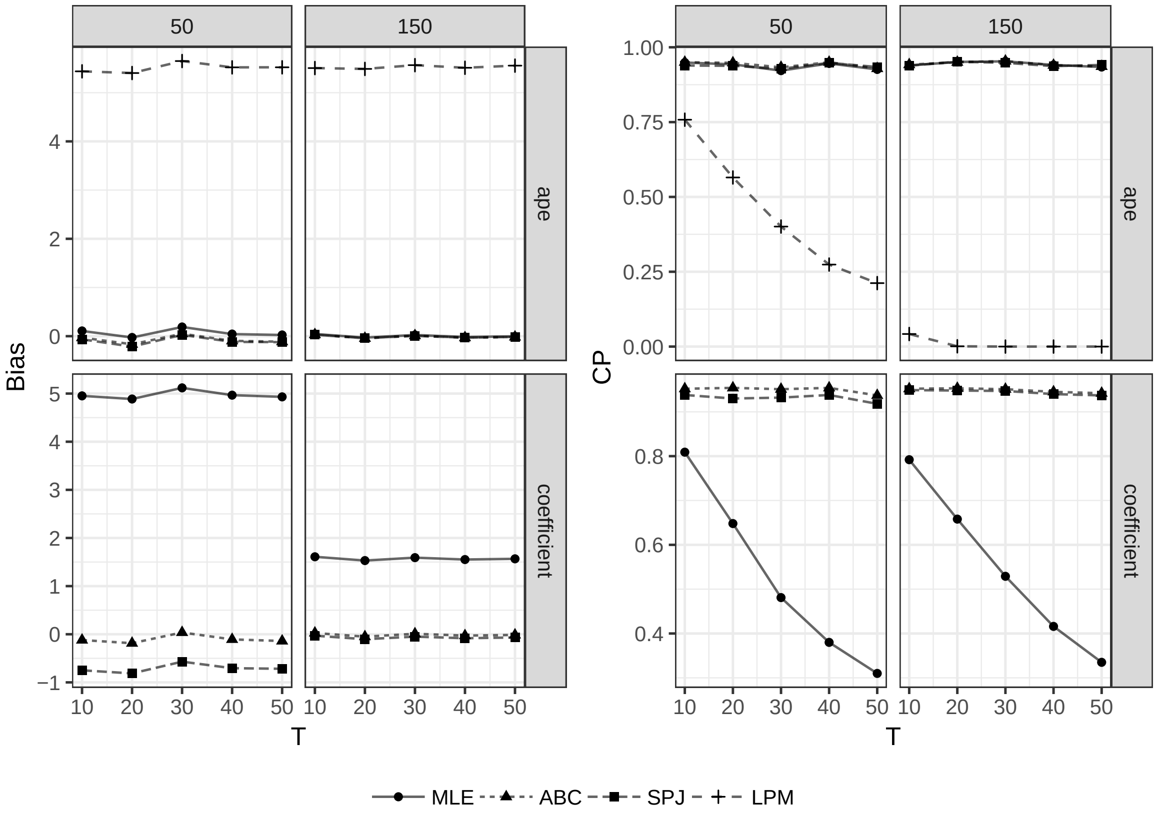
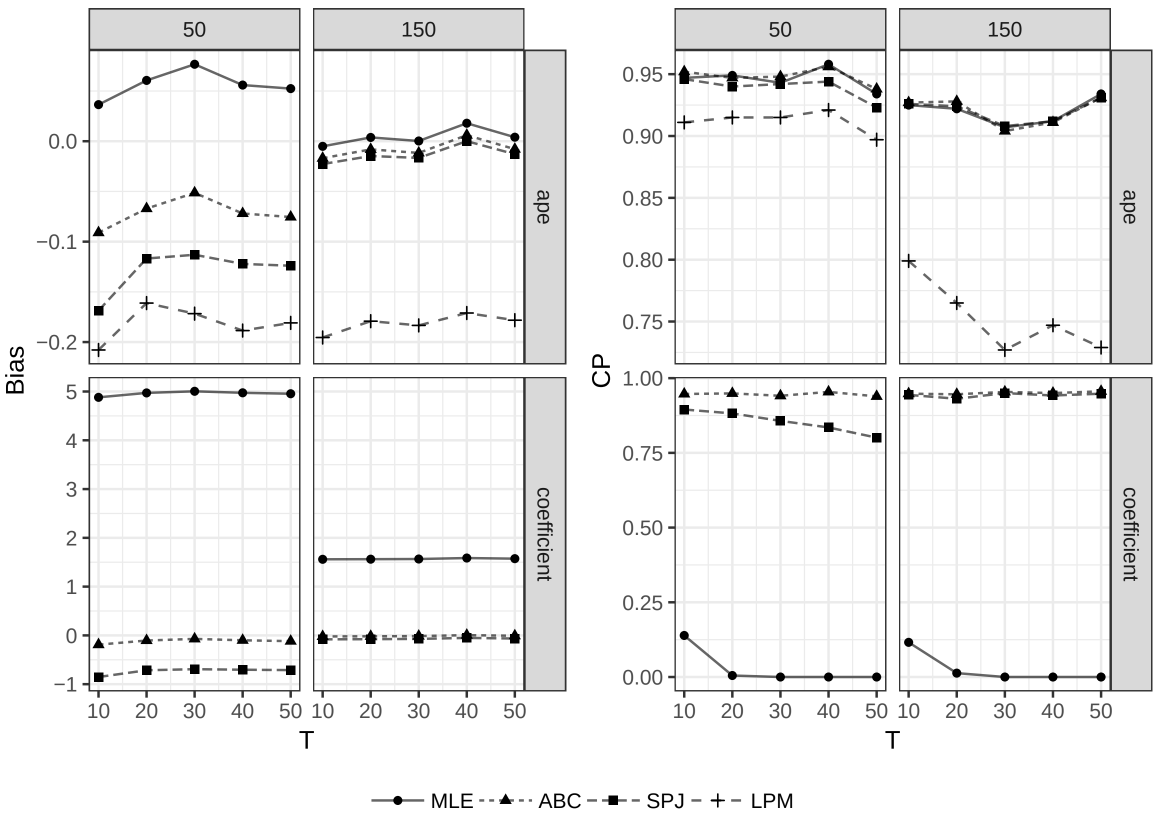


Figure 2.3: Dynamic: Two-way Fixed Effects – Exogenous Regressor



All in all, our two-way fixed effects simulation results demonstrate that the bias-corrected estimators work extremely well in this context — for both structural parameters and APEs and both bias and coverage probabilities. Between the two, the analytical correction slightly outperforms the split-panel jackknife correction. If the interest lies only in APEs, the MLE estimator works well, too, but for the structural parameters it shows bias and essentially useless coverage probabilities. LPM performs clearly worse than the probit estimators and should — given the availability of the nonlinear alternatives — only be used with great caution.

2.4.2 Three-way Fixed Effects

The simulations in this section correspond to our preferred empirical specification for the extensive margin of international trade, in which we not only take into account the theoretically motivated it- and jt-fixed effects, but additionally allow for bilateral unobserved heterogeneity. In this three-way error structure environment, we generate data according to

$$y_{ijt} = \mathbf{1}[\beta_y y_{ijt-1} + \beta_x x_{ijt} + \lambda_{it} + \psi_{jt} + \mu_{ij} \geq \epsilon_{ijt}] \ ,$$
$$y_{ij0} = \mathbf{1}[\beta_x x_{ij0} + \lambda_{i0} + \psi_{j0} + \mu_{ij} \geq \epsilon_{ij0}] \ ,$$

where $i = 1, \ldots, N$, $j = 1, \ldots, N$, $t = 1, \ldots, T$, $\beta_y = 0.5$, $\beta_x = 1$, $\lambda_{it} \sim \text{iid.}\, \mathcal{N}(0, 1/24)$, $\psi_{jt} \sim \text{iid.}\, \mathcal{N}(0, 1/24)$, $\mu_{ij} \sim \text{iid.}\, \mathcal{N}(0, 1/24)$, and $\epsilon_{ijt} \sim \text{iid.}\, \mathcal{N}(0, 1)$.[18] The exogenous regressor is modeled as an AR-1 process, $x_{ijt} = 0.5 x_{ijt-1} + \lambda_{it} + \psi_{jt} + \mu_{ij} + \nu_{ijt}$, where $\nu_{ijt} \sim \text{iid.}\, \mathcal{N}(0, 0.5)$ and $x_{ij0} \sim \text{iid.}\, \mathcal{N}(0, 1)$. Again, we consider different sample sizes, specifically $N \in \{50, 100, 150\}$ and $T \in \{10, 20, 30, 40, 50\}$ and generate $1,000$ data sets for each.

Tables B.13 – B.12 in Appendix B.3.2 summarize the extensive simulation results for both

[18] We again follow Fernández-Val and Weidner (2016) and incorporate the information that $\{\lambda_{it}\}_{IT}$, $\{\psi_{jt}\}_{JT}$, and $\{\mu_{ij}\}_{IJ}$ are independent sequences, and λ_{it}, ψ_{jt}, and μ_{ij} are independent for all it, jt, ij in the covariance estimator for the APEs. The explicit expression is provided in Appendix B.2.3.

regressors. For ABC and LPM we report two different choices of the bandwidth parameter, $L = 1$ and $L = 2$. Here, we again focus on the biases and coverage probabilities for $N \in \{50, 150\}$ which are shown in Figures 2.4 and 2.5.

We start by considering the different estimators for the structural parameters. For both kinds of regressors, MLE exhibits a severe bias that decreases with increasing T. However, even with $T = 50$, the estimator shows a distortion of 11 percent in the case of the predetermined regressor and 5 percent in the case of the exogenous regressor. We also find that the inference is not valid, since the CPs are zero or close to zero. The bias corrections bring a substantial improvement. First, they reduce the bias considerably. For example, the MLE estimator of the predetermined regressor shows a distortion of 63 percent for $T = 10$ and $N = 150$. ABC reduces the bias to 8 percent and SPJ to 20 percent. In the case of the exogenous regressor, MLE exhibits a bias of 23 percent, whereas ABC has a bias of 1 percent and SPJ of 7 percent. Irrespective of the type of the regressor, both bias-corrected estimators also converge quickly to the true parameter value with growing T. Second, the bias corrections improve the CPs. For the exogenous regressor the CPs of ABC are close to the desired level of 95 percent for all T, whereas SPJ remains far away from 95 percent even at $T = 50$. In the case of the predetermined regressor, the CPs of both corrections approach the nominal level when T rises. This happens faster for ABC.

We again proceed with the APEs, where we also consider LPM as an alternative estimator. Overall, we obtain similar findings as for the structural parameters. MLE is distorted over all settings, but the bias decreases as T increases. The distortion is especially severe in the case of the predetermined regressor. Even at $T = 50$, MLE suffers a bias of 15 percent. The bias corrections bring a substantial reduction in this case. Whereas ABC shows only a small distortion of 1 percent in the case of the exogenous regressor at $T = 10$, SPJ is even more heavily distorted than MLE. However, with increasing T, both SPJ and ABC quickly converge to the true APE. Furthermore, unlike ABC, SPJ needs a sufficiently large number of time periods to get its CPs close to 95 percent. For the predetermined

Figure 2.4: Dynamic: Three-way Fixed Effects — Predetermined Regressor

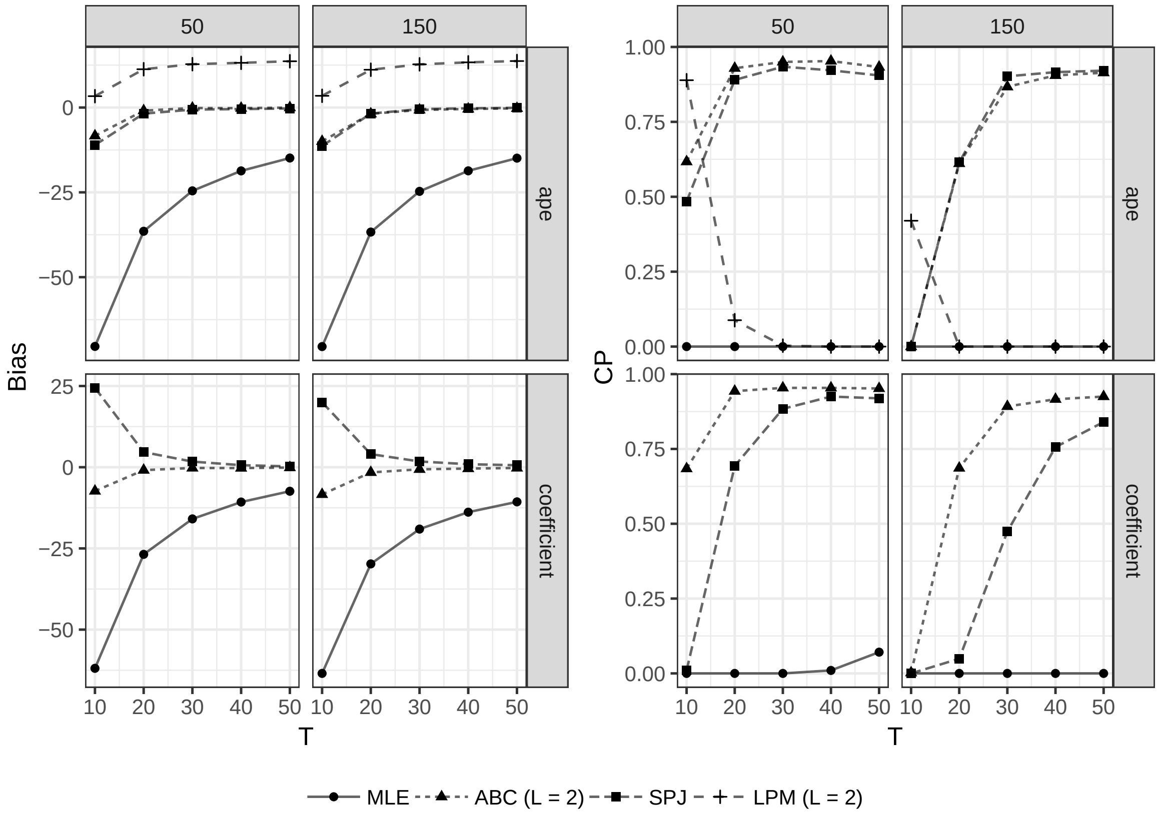
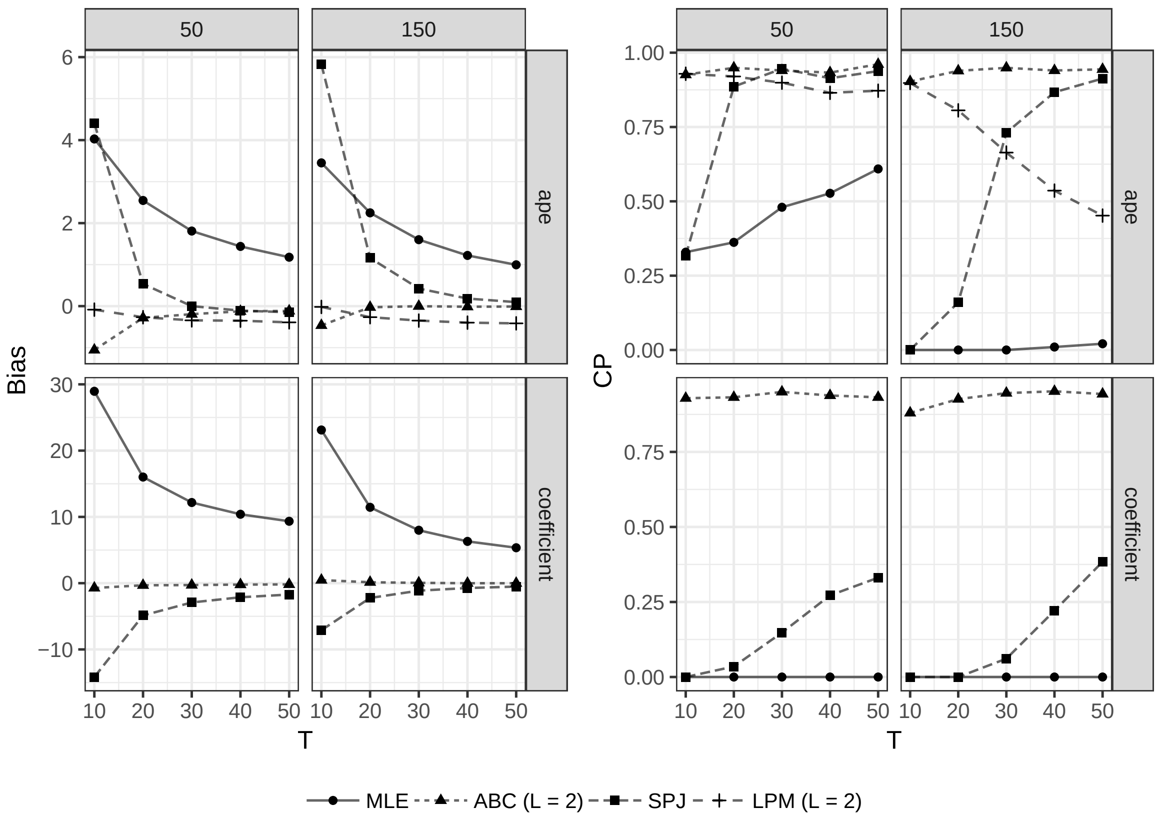


Figure 2.5: Dynamic: Three-way Fixed Effects – Exogenous Regressor



regressor, these convergence processes last longer for both bias corrections. Looking at LPM in the case of the exogenous regressors, it produces almost unbiased estimates irrespective of T, but its CPs fall dramatically with increasing T. Moreover, in the case of the predetermined regressor, we observe an increase in the bias up to 14 percent with increasing T.[19] These results illustrate the superiority of ABC and SPJ over LPM.

Overall, our three-way fixed effects simulation results confirm the conjecture of Fernández-Val and Weidner (2018) about the general form and lend support to our conjecture for the specific structure of the bias terms in the three-way fixed effects specification. First, we find that the bias corrections indeed substantially mitigate the bias. Second, as already found in other studies, analytical bias corrections clearly outperform split-panel jackknife bias corrections (see among others Fernández-Val and Weidner (2016), and Czarnowske and Stammann (2019)). For samples with shorter time horizons, ABC is often less distorted and its dispersion is generally lower. This is also reflected by better CPs. Further, our three-way fixed effects simulation results suggest that estimates based on MLE or LPM should be treated with great caution. Generally, in the three-way fixed effects setting, a sufficiently large number of time periods appears to be crucial to obtain reliable results, even for the bias-corrected estimators.

2.5 Determinants of the Extensive Margin of Trade

Having described the estimation and bias correction procedures, we now turn to the estimation of the determinants of the extensive margin of international trade outlined in Section 2.2.

[19] A similar behaviour of LPM has been observed by Czarnowske and Stammann (2019) in the context of a dynamic probit model with individual and time fixed effects. To ensure that the bias correction presented in Appendix B.2.4 in our three-way fixed effects specification is implemented correctly we have tested it in a data generation process for classical linear models, i.e. without binary dependent variables, and found that it works as intended. The undesirable behavior in our simulation design for the probit model is driven by the fact that, because of the autoregressive process of $\mathbf{x}$, the predicted probabilities of LPM exceed the boundaries of the unit interval more and more frequently as T increases. This is particularly reflected in the APEs for binary regressors, since they are based on differences of predicted probabilities.

Recall equation (2.3) that relates the incidence of nonzero aggregate trade flows to exporter-time and importer-time specific characteristics, as well as trade in the previous period, next to fixed and variable trade costs:

$$y_{ijt} = \begin{cases} 1 & \text{if} \quad \kappa + \lambda_{it} + \psi_{jt} + \beta_y y_{ij(t-1)} + \mathbf{x}'_{ijt}\boldsymbol{\beta}_x \geq \zeta_{ijt}, \\ 0 & \text{else}\,. \end{cases}$$

This yields the following probit model:

$$\Pr(y_{ijt} = 1|\mathbf{x}_{ijt}, y_{ij(t-1)}, \lambda_{it}, \psi_{jt}) = F\left(\mathbf{x}'_{ijt}\boldsymbol{\beta}_x + \beta_y y_{ij(t-1)} + \lambda_{it} + \psi_{jt}\right)\,, \tag{2.10}$$

in case we assume to capture bilateral variables and fixed trade costs entirely with observables, or:

$$y_{ijt} = \begin{cases} 1 & \text{if} \quad \kappa + \lambda_{it} + \psi_{jt} + \beta_y y_{ij(t-1)} + \mathbf{x}'_{ijt}\boldsymbol{\beta}_x + \mu_{ij} \geq \zeta_{ijt}, \\ 0 & \text{else} \end{cases}$$

and:

$$\Pr(y_{ijt} = 1|\mathbf{x}_{ijt}, y_{ij(t-1)}, \lambda_{it}, \psi_{jt}, \mu_{ij}) = F\left(\mathbf{x}'_{ijt}\boldsymbol{\beta}_x + \beta_y y_{ij(t-1)} + \lambda_{it} + \psi_{jt} + \mu_{ij}\right)\,, \tag{2.11}$$

in case we include a time-invariant bilateral fixed effect to capture unobservable country pair characteristics. $y_{ij(t-1)}$ is the lagged dependent variable, $\mathbf{x}$ is a vector of observable bilateral variables, β_y and β_x are the corresponding parameters. We largely follow Helpman, Melitz, and Rubinstein (2008) and the wider literature on the determinants of the *intensive* margin of trade (compare Head and Mayer, 2014) in the choice of these variables: distance, a common land border, the same origin of the legal system, common language, previous colonial ties, a joint currency, an existing free trade agreement, or joint membership in the WTO. In terms of data, we turn to the comprehensive gravity dataset provided alongside Head, Mayer, and Ries (2010), which encompasses information on trade flows and these variables of interest from 1948 – 2006.

Table 2.2: Probit Estimation: Coefficients

	Dependent variable: y_{ijt}				
	(1)	(2)	(3)	(4)	(5)
Lagged DV	-	-	1.664***	-	1.140***
	[-]	[-]	[1.719]	[-]	[1.057]
	(-)	(-)	(0.004)	(-)	(0.005)
log(Distance)	-	-0.800***	-0.528***	-	-
	[-0.656***]	[-0.821]	[-0.546]	[-]	[-]
	(0.003)	(0.003)	(0.004)	(-)	(-)
Land border	-	0.207***	0.118***	-	-
	[0.260***]	[0.214]	[0.124]	[-]	[-]
	(0.014)	(0.016)	(0.018)	(-)	(-)
Legal	-	0.137***	0.089***	-	-
	[0.090***]	[0.141]	[0.093]	[-]	[-]
	(0.004)	(0.004)	(0.005)	(-)	(-)
Language	-	0.426***	0.280***	-	-
	[0.380***]	[0.436]	[0.289]	[-]	[-]
	(0.005)	(0.006)	(0.007)	(-)	(-)
Colonial ties	-	0.657***	0.487***	-	-
	[0.190***]	[0.702]	[0.542]	[-]	[-]
	(0.02)	(0.031)	(0.036)	(-)	(-)
Currency union	-	0.631***	0.424***	0.303***	0.214***
	[0.381***]	[0.649]	[0.443]	[0.335]	[0.255]
	(0.012)	(0.015)	(0.017)	(0.032)	(0.034)
FTA	-	0.543***	0.359***	0.073*	0.038
	[0.508***]	[0.552]	[0.364]	[0.072]	[0.033]
	(0.017)	(0.019)	(0.021)	(0.038)	(0.04)
WTO	-	0.152***	0.101***	0.052***	0.039**
	[0.286***]	[0.154]	[0.104]	[0.058]	[0.048]
	(0.005)	(0.008)	(0.009)	(0.016)	(0.017)
Fixed effects	i, j, t	it, jt	it, jt	it, jt, ij	it, jt, ij
Sample size	1204671	1204671	1171794	1204671	1171794
- perf. class.	12298	147760	141537	370617	374067
Deviance	8.891×10^5	7.019×10^5	5.183×10^5	4.76×10^5	4.189×10^5

Notes: Uncorrected coefficients in square brackets. Standard errors in parenthesis.

We report the bias-corrected coefficients in Table 2.2 and the corresponding average partial effects in Table 2.3.[20] For each uncorrected and (analytically) bias-corrected coefficients and average partial effects we also report the uncorrected one in square brackets, as well as the standard error in parenthesis below. In column (1) we first

[20]While the error term distribution assumed in Section 2.2 suggests a probit estimator, we also estimate equations 2.10 and 2.11 with a logit estimator and show the corresponding results in Tables B.22 and B.23 in Appendix B.5. The coefficients and average partial effects are similar to those estimated with the probit model.

Table 2.3: Probit Estimation: Average Partial Effects

	Dependent variable: y_{ijt}				
	(1)	(2)	(3)	(4)	(5)
Lagged DV	-	-	0.346***	-	0.179***
	[-]	[-]	[0.344]	[-]	[0.138]
	(-)	(-)	(0.003)	(-)	(0.052)
log(Distance)	-	-0.135***	-0.066***	-	-
	[-0.136***]	[-0.135]	[-0.066]	[-]	[-]
	(0.005)	(0.005)	(0.001)	(-)	(-)
Land border	-	0.035***	0.015***	-	-
	[0.054***]	[0.035]	[0.015]	[-]	[-]
	(0.004)	(0.004)	(0.003)	(-)	(-)
Legal	-	0.023***	0.011***	-	-
	[0.019***]	[0.023]	[0.011]	[-]	[-]
	(0.001)	(0.001)	(0.001)	(-)	(-)
Language	-	0.071***	0.035***	-	-
	[0.078***]	[0.071]	[0.035]	[-]	[-]
	(0.003)	(0.001)	(0.001)	(-)	(-)
Colonial ties	-	0.107***	0.061***	-	-
	[0.039***]	[0.111]	[0.066]	[-]	[-]
	(0.004)	(0.007)	(0.005)	(-)	(-)
Currency union	-	0.103***	0.053***	0.038***	0.024***
	[0.078***]	[0.103]	[0.054]	[0.037]	[0.025]
	(0.004)	(0.003)	(0.002)	(0.005)	(0.009)
FTA	-	0.090***	0.045***	0.009	0.004
	[0.103***]	[0.088]	[0.044]	[0.008]	[0.003]
	(0.005)	(0.004)	(0.003)	(0.007)	(0.006)
WTO	-	0.026***	0.013***	0.006**	0.004
	[0.061***]	[0.026]	[0.013]	[0.006]	[0.005]
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)
Fixed effects	i, j, t	it, jt	it, jt	it, jt, ij	it, jt, ij
Sample size	1204671	1204671	1171794	1204671	1171794
- perf. class.	12298	147760	141537	370617	374067
Deviance	8.891×10^5	7.019×10^5	5.183×10^5	4.76×10^5	4.189×10^5

Notes: Uncorrected average partial effects in square brackets. Standard errors in parenthesis.

mimic the specification estimated by Helpman, Melitz, and Rubinstein (2008).[21] Their specification includes exporter, importer and time fixed effects.[22] All coefficients have

[21]Helpman, Melitz, and Rubinstein (2008) use a dataset that ranges from 1970 to 1997. They also include dummy variables for whether both countries are landlocked or islands, or follow the same religion. Hence our coefficients deviate somewhat from theirs, while remaining qualitatively similar.

[22]Note that following Fernández-Val and Weidner (2018) the incidental bias problem is small enough to ignore in this setting with i, j and t fixed effects, since the order of the bias is $1/IT + 1/JT + 1/IJ$, which in our case becomes negligible small since I, J and T are large.

the expected sign, i.e. a negative impact of distance on the probability to trade, while all other variables are estimated to have a positive impact. Note the strong and highly significant impact of a common currency, free trade agreement or joint membership of the WTO. Ceteris paribus, each is estimated to increase the probability of nonzero flows by between 6 and 10 percentage points. Column (2) introduces a stricter set of fixed effects, namely at the exporter-time and importer-time level. Most coefficients and average partial effects are similar to those in column (1). This changes in column (3), which keeps the same fixed effects, but adds a lagged dependent variable. Assuming no unobservable bilateral heterogeneity, as in equation (2.10), this specification correctly estimates the model set up in Section 2.2. The first thing to note is the highly significant coefficient for the lagged dependent variable, which reflects the strong impact of previous nonzero trade flows on current ones. Ceteris paribus, the average partial effect shows a 34 percentage points higher probability of nonzero trade, given the two countries were also engaged in trade in the previous year. The second observation is that essentially all coefficients are remarkably smaller than those in column (2), and average partial effects are reduced by about 50 percent across the board. This result underlines the need to explicitly take persistence into account. Note, however, that the APEs of the two specifications are not directly comparable, because the static model forces immediate effects and long-run dynamic adjustments into a single estimate.

Column (4) then takes one step back and one forward. While not including the lagged dependent variable in the estimation, it introduces a bilateral fixed effect that controls for bilateral unobserved heterogeneity. This follows the important insight by Baier and Bergstrand (2007), who show that controlling for unobserved bilateral heterogeneity produces a considerably different estimated impact of free trade agreements, among other variables, on the intensive margin of trade. While now an identification of many of the variables of interest is no longer possible anymore because of their time invariance, this specification reveals a much reduced estimated impact of the time-varying variables. The impact of a common currency on the probability of exporting is reduced to 3.8 percentage points, while those of a common free trade agreement and

WTO are decreased to less than 1 percentage point. This result highlights the importance of controlling for unobserved country pair heterogeneity and possible endogeneity. Finally, in column (5) we present our preferred specification, estimating equation (2.11). The estimation now includes the "full set" of fixed effects, i.e. exporter-time, importer-time and bilateral fixed effect, in addition to the lagged dependent variable.[23] Again, the coefficient on the latter is highly significant, entailing an average partial effect of about 18 percentage points. Importantly, the only remaining statistically significant average partial effect is estimated for a common currency at 2.4 percentage points. The impact of a free trade agreement or joint membership of the WTO are statistically insignificant.

Contrasting the results from column (5) to those of column (1), which currently constitutes the de-facto standard of estimating the determinants of the extensive margin of trade, underlines the importance of (i) appropriate exporter-time and importer-time fixed effects that capture all country-time specific variation; (ii) country pair fixed effects that capture all unobserved bilateral heterogeneity and address endogeneity concerns, analogous to Baier and Bergstrand (2007) on the intensive margin; (iii) dynamics, in that country pairs that have previously traded are significantly more likely to do so than otherwise comparable country pairs. This corroborates the stylized facts from Section 2.1, which showed country pairs that had previously engaged in trade to be likely to do so again in the next year. Failing to observe any of these three insights produces widely different estimates.

Another important insight is that the magnitude of the incidental parameter problem — at least in this specific setting — is not as severe as one might have feared. The most significant impact is observed on the coefficient for the lagged dependent variable, which in Table 2.2 column (5) differs by about 10 percent, and even almost 24 percent in the respective average partial effect reported in Table 2.3 column (5). However, this does not carry through to other variables, in particular for average partial effects. As shown in simulations in Section 2.4, this may not come as a big surprise. In this application we

[23] Note that in the analytical bias correction we set the bandwidth parameter to $L = 2$. We report results for $L \in \{0, 1, 2, 3, 4\}$ in Tables B.24 to B.29 in Appendix B.5. The results remain robust with $L = 1 - 4$.

Table 2.4: Probit vs. OLS Estimation: Average Partial Effects with Three-way Fixed Effects

	Dependent variable: y_{ijt}				
	(1)	(2)	(3)	(4)	(5)
lagged DV	-	-	0.444***	0.474***	0.179***
	(-)	(-)	(0.001)	(0.001)	(0.052)
Currency Union	0.009***	0.038***	0.008***	0.008**	0.024***
	(0.003)	(0.005)	(0.003)	(0.003)	(0.009)
FTA	-0.121***	0.009	-0.065***	-0.062***	0.004
	(0.003)	(0.007)	(0.002)	(0.002)	(0.006)
WTO	0.017***	0.006**	0.008***	0.008***	0.004
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Estimator	OLS	Probit	OLS	OLS	Probit
bias corrected	-	true	false	true	true
Sample size	1204671	1204671	1171794	1171794	1171794

Notes: All columns include Origin × Year, Destination × Year and Origin × Destination fixed effects. Standard errors in parenthesis.

consider a panel that covers 57 years, meaning the relatively large T inhibits a strong bias (e.g. compare Figure 2.5). As shown in the simulations, the bias is more severe in settings with fewer time periods and should be handled appropriately.

To show the superiority of using suitable binary choice estimators with high-dimensional fixed effects we also contrast the results to estimating equations (2.10) and (2.11) with a linear probability model. Table 2.4 shows that OLS with the same set of three-way fixed effects produces estimates that are far off the probit ones.[24] Columns (1) and (2) compare estimates without, columns (3) to (5) those with a lagged dependent variable.[25] Figure B.3 underlines this impression: the LPM produces up to 28 percent of fitted probabilities < 0 or > 1. This result highlights that binary choice estimators with high-dimensional fixed effects cannot easily be mimicked by an OLS estimator.

[24] As for the probit estimates, we also report the bias-corrected LPM estimates with different bandwidth parameters in Table B.29. All in all, the results remain robust with $L = 1 - 4$. We also report estimates for two-way fixed effects in Table B.28 in Appendix B.5.

[25] In column (3) we ignore and in column (4) we apply the appropriate bias correction for the LPM with endogenous regressor, as detailed in Appendix B.2.4.

2.6 Conclusions

In this paper we reexamine the determinants of the extensive margin of international trade. We set up a model that exhibits a dynamic component and allows for time-invariant unobserved bilateral trade cost factors, generating persistence — a feature in the data that has so far been given little attention. We estimate the model using a probit estimator with high-dimensional fixed effects. As fixed effects create an incidental parameter problem in binary choice settings, we characterize and implement bias corrections for estimations with appropriate two- and three-way fixed effects. Finally, we show that our estimates of the determinants of the extensive margin of trade differ significantly from previous ones. This highlights the importance of true state dependence and unobserved heterogeneity and therefore strongly supports the use of our bias-corrected dynamic fixed effects estimator.

The extensive margin of trade obviously extends beyond the aggregate level, warranting further research at lower levels of aggregation, in particular in the context of firms. While our model's prediction and its empirical specification rely on some abstractions, it provides a very tractable and flexible framework that can be estimated with recently established estimation procedures, when combined with the bias correction technique we introduce.

3

Carbon Tariffs: An Analysis of the Trade, Welfare, and Emission Effects[1]

3.1 Introduction

The struggle against anthropogenic climate change is one of the most urgent tasks of humankind in the 21st century. A large strand of economic literature has evolved around the question of how to reduce global greenhouse gas (GHG) emissions in an efficient way. It is obvious that a first-best solution would involve the participation of all countries, including developing nations (see for example Branstetter and Pizer, 2014). But the past United Nations climate conferences have shown the difficulties associated with agreeing on an effective and binding global agreement. Instead, national and regional initiatives have prevailed. The lack of global coordination has raised questions concerning the

[1]This chapter is joint work with Mario Larch. It has been published under the same title in the *Journal of International Economics*, 2017, 109, 195–213. Funding from the DFG under project 592405 is gratefully acknowledged. We thank Rahel Aichele, Gabriel Felbermayr, Carol McAusland, Sergey Nigai, Alejandro Riaño, João Santos Silva, Yoto Yotov, two anonymous referees, the handling editor Giovanni Maggi and the participants at the European Trade Study Group 2013, the Goettinger Workshop "Internationale Wirtschaftsbeziehungen" 2014, the GEP Postgraduate Conference 2014, the Congress of the European Economic Association 2014, the Conference of the European Association of Environmental and Resource Economists 2015, the FIW Research Conference "International Economics" 2015, and the EAERE FEEM VIU European Summer School 2017, as well as the seminar participants at the University of Bayreuth for their helpful comments. All remaining errors are our own.

relationship of national (or regional) climate policies and international trade. Unilateral emission reductions can for example be partly offset by resulting increases in other countries, i.e. emissions can be shifted via international trade, a phenomenon known as carbon leakage (see Felder and Rutherford, 1993).

One possible measure against carbon leakage is the introduction of carbon tariffs. With carbon tariffs, countries that have a stricter climate policy would impose an import tariff on goods from countries with a laxer regulation (or lower carbon prices), based on the amount of carbon emissions embodied in the good. Carbon tariffs are very prominently discussed in the environmental policy debate. For example, the House of Representatives in the USA released the American Clean Energy and Security Act (H.R.2454) in 2009 that enables the introduction of carbon tariffs from 2020 onwards in some carbon intensive sectors. In Europe, French politicians have repeatedly called for carbon tariffs by the European Union, most prominently the former President Nicolas Sarkozy in 2009.[2] Claims for carbon tariffs also received prominent academic support. Nobel laureate Paul Krugman (2009a,b) argues for carbon tariffs in his New York Times column by highlighting the fact that trade policy may indeed be a good tool in the case of non-economic objectives such as carbon emissions that do not respect national borders. This policy measure is the object of investigation of this work.

As carbon tariffs have a strong international perspective, we analyze the effects in a trade model typically used to evaluate trade policies. We therefore use as a starting point an empirically very successful structural empirical trade model, which explains trade flows by country sizes, distances and multilateral resistance terms, where the latter capture the embedding of a country into the world economy. These models are known as structural gravity models (see for example Eaton and Kortum, 2002, and Anderson and van Wincoop, 2003, as well as the survey by Head and Mayer, 2014). We want to investigate the effects of carbon tariffs on trade, welfare, and emissions and therefore have to adopt existing structural trade models to incorporate important aspects related

[2] See http://discours.vie-publique.fr/notices/097002465.html (accessed on September 13th, 2017).

to carbon emissions. First, we add a production structure that uses energy as an input. Second, we allow for emissions as a side output of production related to the amount of energy employed. Third, we allow for multiple sectors to distinguish between varying sectoral emission intensities. Fourth, we introduce revenue-generating carbon tariffs. With the resulting structural model it is possible to evaluate ex ante the effects of the introduction of carbon tariffs. Importantly, our model structure allows a decomposition of the emission effects into scale, composition, and technique effects as first proposed by Grossman and Krueger (1993) and formalized by Copeland and Taylor (1994). The decomposition helps to understand the cross-country differences of the effects as well as the effects on the world as a whole.

There are already some studies quantifying the carbon emission effects of carbon tariffs based on Computational General Equilibrium (CGE) models (for a discussion, see Section 3.2). However, to the best of our knowledge, we are the first to consider carbon tariffs and empirically implement the decomposition as in Copeland and Taylor (2003) based on a structural multi-sector, multi-country gravity framework. Costinot and Rodríguez-Clare (2014) see the following main advantages of structural gravity models: i) they are better micro-founded than other quantitative work, like many CGE models, ii) they provide a close link between the theory and the data by estimating the parameters from the same model and data as are used for the counterfactual analysis, and iii) they are still small enough to understand the driving mechanisms and do not hide important mechanisms behind a very large number of equations. What we see as the major strength of our framework is related to the third point raised by Costinot and Rodríguez-Clare (2014): it allows the analytical and quantitative decomposition of emission changes into scale, composition, and technique effects.

We use our estimable structural model to conduct different counterfactual analyses. First, we find that the introduction of pure carbon tariffs, which equalize energy tax differentials across countries, reduces trade flows and welfare for most countries, most strongly for developing countries. Concerning carbon emissions, we indeed see a partial shift of carbon emissions from low carbon tax countries to high carbon tax countries. Hence, carbon tariffs reduce carbon leakage. Our analysis further reveals that world carbon emissions would decrease by 0.50 percent if carbon tariffs were introduced. The bootstrapped 95% confidence interval of [-0.58, -0.44] for this counterfactual calculation shows that the decrease is statistically significant. About one third of this reduction can be attributed to a decrease in world production (-0.17 percent with bootstrapped 95% confidence interval [-0.19, -0.16]), while the other two thirds result from changes in the composition of production across countries (-0.33 percent with bootstrapped 95% confidence interval [-0.40, -0.28]).

Second, we investigate the effects of the pledges made by the Annex I countries in the Copenhagen Accord. We first consider the emission targets only and then compare the findings to a scenario in which the targets are combined with carbon tariffs. If the committed emission targets are fully met, we predict a world carbon emission decrease of 8.4 percent (with bootstrapped 95% confidence interval [-8.6, -8.1]). The costs of the world carbon emission reduction is reflected in a quite substantial decrease of welfare in the committing countries, ranging up to -4.7 percent. The non-committing countries see an increase in welfare due to reduced global carbon emissions and increased competitiveness in pollution-intensive sectors. If countries introduce carbon tariffs as an accompanying policy, world carbon emissions decrease by 9.3 percent (with bootstrapped 95% confidence interval [-9.3, -9.2]). This larger reduction stems from a lower leakage rate (i.e. a lower percentage part of domestic emission reductions that is offset by foreign increases) of 4.1 percent (with bootstrapped 95% confidence interval of [3.3, 4.9]) rather than 13.4 percent (with bootstrapped 95% confidence interval of [11.5, 15.8]) in the scenario without carbon tariffs. This additional reduction undoes a large part of the welfare gains for the non-committing countries.

The rest of this work proceeds as follows: Section 3.2 introduces carbon leakage and the concept of carbon tariffs in some more detail, also giving a short overview of other work in the area. In Section 3.3, we develop a structural gravity model in the vein of Anderson and van Wincoop (2003), incorporating a sectoral structure, a multi-factor production function, and non-resource consuming, revenue-generating tariffs. We also introduce the decomposition of the emission effects in this framework. Further, we present a model extension incorporating a production structure for energy. In Section 3.4, we describe the estimation of the gravity equation and explain how the remaining model parameters are obtained. Section 3.5 presents the data sources and some descriptive statistics. In Section 3.6, first, we provide a short discussion of the model validation before proceeding to discuss the results obtained for the counterfactuals. Section 3.7 concludes.

3.2 Carbon Leakage and Carbon Tariffs

The relationship between carbon policy and international trade has been of major interest in the last years. One phenomenon that has been discussed in this context is carbon leakage. Carbon leakage arises if stricter climate policy and a resulting reduction of emissions in one country (or region, such as e.g. the European Union) leads to an increase of carbon emissions elsewhere. This can mainly occur due to two reasons (see Felder and Rutherford, 1993). First, a higher carbon price (via a carbon tax, tradable certificates or simply stricter regulation) makes goods from the country implementing the policy relatively more expensive. This can lead to a shift of carbon emission-intensive production to countries with laxer regulation or lower carbon prices and hence increase emissions in these countries. Secondly, a higher carbon price can lead to a lower demand for energy in the countries imposing the regulation. This could lead to falling world market prices for energy and hence lead to a more emission-intensive production in other countries. This mechanism is called energy-market leakage (see for example McAusland and Najjar, 2015). We will focus on the former type of carbon leakage in the base model. The model extension in Section 3.3.5 will additionally incorporate energy-market leakage effects.

Several empirical studies have investigated the extent of carbon leakage. For example, Aichele and Felbermayr (2012, 2015) conduct ex post analyses of the Kyoto Protocol's ability to reduce world carbon emissions. They find strong evidence that the Kyoto Protocol led to carbon leakage. In fact, the reductions in the committing countries may have been completely offset (or possibly even overcompensated) by increases in other countries. On the other hand, Chan, Li, and Zhang (2013) investigate the effects of the European Union emission trading scheme and find little evidence for carbon leakage.

A second approach in the literature is the use of computable general equilibrium (CGE) models (see Burniaux and Oliveira Martins, 2012, for a good overview). Estimated leakage rates in these models range between two and 20 percent in most cases, but can also go up as high as 100 percent (see for example Babiker, 2005).

Another approach that, just as CGE models, allows ex ante investigations of policy scenarios in an international trade context is the use of structural gravity models. Aichele (2013) explicitly investigates carbon leakage in a one-sector Anderson and van Wincoop (2003)-type framework which she augments with a multi-factor production structure. She investigates several counterfactual scenarios, finding for example a leakage rate of 10 percent for an increase of the EU emission allowance price by 15 US-$. Besides Aichele (2013), Egger and Nigai (2012, 2015) use structural gravity models in a similar context. In both cases, these authors employ an Eaton and Kortum (2002)-type framework. Egger and Nigai (2012) analyze the implications of the Copenhagen Accord. Based on the pledges countries made in the Accord, required carbon prices are calculated and used in different counterfactual scenarios. Their quantification shows that welfare losses from stricter climate policies are substantially reduced for individual countries if implemented in an internationally cooperative way. Egger and Nigai (2015) include an energy sector in their model and compare different policy measures meant to reduce a country's energy demand. Shapiro (2016) introduces CO_2 emissions from both production and shipping into a structural gravity model and investigates the effects of carbon taxes on transportation. He finds that such carbon taxes lead to an increase in global welfare and lower world emissions, but reduce real income in poor, non-participating countries. Shapiro and Walker (2015) develop a Melitz (2003)-type structural model with endogenous pollution abatement. They use their framework to identify the main drivers of past pollution reductions in U.S. manufacturing, finding environmental regulation to be the most important factor.

Even though its extent remains a matter of scientific debate, carbon leakage is likely to at least reduce the effectiveness of unilateral climate policies. One measure that could be taken in order to reduce carbon leakage is the introduction of carbon tariffs. Leaving the question of legal and practical feasibility aside[3], questions arise of how these tariffs would influence trade flows, welfare, and carbon emissions.

Theoretically, the potential of tariffs to internalize international externalities is for example discussed by Markusen (1975). Hoel (1996) specifically investigates the theoretical properties of tariffs in the carbon emission context demonstrating their ability to mitigate leakage. Hémous (2016) extends the theoretical consideration of carbon tariffs to a dynamic framework featuring directed technical change. He shows that a combination of clean research subsidies and trade taxes is the optimal unilateral policy to ensure environmentally sustainable growth. He also calibrates his two-sector, two-country model and provides simulation evidence.

Besides these primarily theoretical contributions, carbon tariffs are mainly investigated within the framework of CGE models. For example, Elliott, Foster, Kortum, Munson, Pérez Cervantes, and Weisbach (2010) find that accompanying a higher carbon tax in some countries with full border tax adjustment (i.e. a combination of import tariffs and export subsidies) eliminates carbon leakage but has no noteworthy effect on world carbon emissions. Elliott, Foster, Kortum, Khun Jush, Munson, and Weisbach (2013) investigate a similar scenario without export subsidies and find that carbon tariffs reduce world carbon emissions. Böhringer, Carbone, and Rutherford (2018) also find that

[3]For short treatments of the legal issues in the WTO context and practical implementation issues, see Branstetter and Pizer (2014, pp. 26–27 and pp. 34–35, respectively).

carbon tariffs shift emissions back from developing to developed countries, i.e. reduce carbon leakage, but without reducing world emissions. They argue that the main effect of introducing carbon tariffs is to shift the welfare costs of climate policy to developing countries. Babiker and Rutherford (2005) compare different accompanying measures for the Kyoto Coalition countries' abatement policies. They also find that carbon tariffs partly push the abatement costs to non-coalition countries, minimizing the coalition's welfare costs, and therefore are more attractive than alternative measures such as voluntary export restraints. Böhringer, Müller, and Schneider (2015) focus on the competitiveness effects of carbon tariffs on energy-intensive and trade-exposed industries. They show that these industries are not necessarily made better off in the countries imposing carbon tariffs. The effect rather depends on the specific industry structure as carbon tariffs would e.g. also make these industries' imported intermediate goods more expensive.

In the gravity framework, one of the policy measures investigated by Egger and Nigai (2015) are import tariffs. They investigate tariffs as a mean to reduce domestic emissions by imposing a tariff on imported energy inputs, but do not consider carbon tariffs that are specifically based on the products' carbon contents. Hence, to the best of our knowledge, carbon tariffs have not yet been analyzed within a structural gravity model. Besides closely linking theory and data, this has the additional advantage of allowing a decomposition of the emission changes induced by carbon tariffs into scale, composition, and technique effects.

3.3 A Multi-Sector, Multi-Factor Gravity Model with Tariffs

3.3.1 Trade Flows

In this section, we develop a gravity model in the vein of Anderson and van Wincoop (2003). Their model aggregates over all sectors. As the aim of this work is to investigate the effects of a policy measure that will influence sectors differently according to their carbon intensities, this level of aggregation is inappropriate in the given context. We therefore allow for a sectoral structure including multiple tradable sectors and one non-tradable sector in the model, following Anderson and Yotov (2010), Caliendo and Parro (2015) and most closely the approach of Egger, Larch, and Staub (2012), who introduce a sectoral structure into a Krugman (1980)-type gravity model.[4]

Let us assume there is one non-tradable sector S and a set $\mathcal{L}$ containing L tradable goods sectors (l) in each of N countries. Following Armington (1969), goods within each tradable sector are differentiated by country of origin and each country produces one variety per sector. The utility of the representative consumer from consumption in a specific tradable sector is given by a constant elasticity of substitution (CES) utility function:

$$U_l^j = \left[\sum_{i=1}^{N} (\beta_l^i)^{\frac{1-\sigma_l}{\sigma_l}} (q_l^{ij})^{\frac{\sigma_l - 1}{\sigma_l}} \right]^{\frac{\sigma_l}{\sigma_l - 1}}, \tag{3.1}$$

where β_l^i is a positive, country- and sector-specific distribution parameter (which can for example be interpreted as representing quality differences), q_l^{ij} is the amount of goods from country i in tradable sector l that the representative consumer in country

[4]Following this literature, we stick to a static framework. This implies an interpretation of our results as a long-run steady-state comparison. More recent developments, as the ones by Eaton, Kortum, Neiman, and Romalis (2016) and Anderson, Larch, and Yotov (2015), extend the gravity framework to allow for dynamic channels. Adding for example capital accumulation would lead to additional adjustments of countries, which would potentially magnify the trade, welfare and emission effects. In a dynamic framework, one would also want to consider endogenous technological change, e.g. along the lines of Hémous (2016). We view the extension to allow for a dynamic channel as an important area for future research.

j buys, and σ_l is the elasticity of substitution in sector l. CES utility functions have the desirable property of accounting for a "love of variety" of the consumers, i.e. for a given consumption level, a higher utility level is achieved if more different varieties are consumed. In addition, we assume a homogenous non-tradable goods sector S with utility U_S^j given by the quantity consumed in country j, q_S^j.

The total utility of the representative consumer is given by a Cobb-Douglas function over the consumption in the different sectors combined with multiplicative damages from CO_2 pollution following Shapiro and Walker (2015):

$$U^j = \left(U_S^j\right)^{\gamma_S^j} \left[\prod_{l \in \mathcal{L}} (U_l^j)^{\gamma_l^j}\right] \left[\frac{1}{1 + \left(\frac{1}{\mu^j} \sum_{i=1}^N E^i\right)^2}\right], \tag{3.2}$$

where $\gamma_S^j + \sum_{l \in \mathcal{L}} \gamma_l^j = 1$, and the second bracket captures disutility from carbon emissions.[5] The country-specific parameter μ^j translates pollution into social costs, and E^i are CO_2 emissions in country i. As in Shapiro and Walker (2015), it is assumed that pollution is a pure externality and the representative consumer therefore ignores the last term from equation (3.2) in making expenditure choices.

The representative consumer in each country earns income from energy E with energy price e, and from unskilled and skilled labor, capital, land, and natural resources, which are summarized in the set $\mathcal{F}$. Total income of the representative consumer in country j is therefore given by:

$$Y^j = e^j E_S^j + \sum_{l \in \mathcal{L}} e^j E_l^j + \sum_{f \in \mathcal{F}} v_f^j V_{Sf}^j + \sum_{l \in \mathcal{L}} \sum_{f \in \mathcal{F}} v_f^j V_{lf}^j + \sum_{l \in \mathcal{L}} \sum_{i=1}^N (\tau_l^{ij} - 1) X_l^{ij}, \tag{3.3}$$

where E_S^j and E_l^j are the amounts of energy used in country j in the non-tradable

[5]This disutility term captures all damages from CO_2 pollution, such as reduced agricultural output, lower labor productivity, polar bear extinction, or mortality increases (see Dell, Jones, and Olken, 2014, for an overview of the manifold effects of climate change on economic, social, and environmental outcomes). An alternative approach, taken in integrated assessment modeling, allows climate change to directly affect the production function (see Metcalf and Stock, 2017, for a recent survey). As in our framework technology as well as capital stocks are exogenous, including these additional channels is beyond the scope of this paper.

sector S and tradable sectors l, respectively, e^j is the energy price in country j, V^j_{Sf} and V^j_{lf} are the sectoral usages of factor $f \in \mathcal{F}$ with corresponding factor prices of factor f in country j denoted by v^j_f in the non-tradable sector S and the tradable sectors l, respectively. The last term are tariff revenues distributed to the consumers of country j, where τ^{ij}_l is one plus the ad valorem tariff rate and X^{ij}_l is the value of exports from country i to country j in sector l. The representative consumer in j hence maximizes U^j subject to $Y^j = p^j_S q^j_S + \sum_{l\in\mathcal{L}} \sum_{i=1}^N p^{ij}_l q^{ij}_l$, where Y^j is given by (3.3), p^j_S is the price for the non-tradable good in country j, q^j_S denotes the quantity of the non-tradable goods consumed, p^{ij}_l is the price in country j for goods from sector l from country i, and q^{ij}_l is the quantity of goods from sector l from country i consumed in country j.[6]

Denoting total expenditure of country j by $\mathfrak{X}^j$, expenditure in tradable sector l in country j can be written as $\mathfrak{X}^j_l = \gamma^j_l \mathfrak{X}^j = \sum_{i=1}^N p^{ij}_l q^{ij}_l$, and expenditure in the non-tradable sector S is given by $\mathfrak{X}^j_S = \gamma^j_S \mathfrak{X}^j = p^j_S q^j_S$. The balanced trade assumption then implies $Y^j = \mathfrak{X}^j = \mathfrak{X}^j_S + \sum_{l\in\mathcal{L}} \mathfrak{X}^j_l$.

In the non-tradable sector, demand in country j is given by $q^j_S = \mathfrak{X}^j_S / p^j_S$. Demand in country j for goods from tradable sector l from country i is given by:

$$q^{ij}_l = \left(\frac{\beta^i_l p^{ij}_l}{P^j_l}\right)^{-\sigma_l} \left(\frac{\beta^i_l \mathfrak{X}^j_l}{P^j_l}\right), \tag{3.4}$$

where P^j_l is the sectoral price index, given by

$$P^j_l = \left[\sum_{i=1}^N (\beta^i_l p^{ij}_l)^{1-\sigma_l}\right]^{\frac{1}{1-\sigma_l}}. \tag{3.5}$$

Assuming (sector-specific) iceberg transport costs ($T^{ij}_l \geq 1$), the price consumers in j pay for imports from i can be restated as $p^{ij}_l = T^{ij}_l \tau^{ij}_l p^i_l$, where p^i_l is the factory-gate price of products from country i in sector l. We assume frictionless intra-national trade flows ($T^{ii}_l = 1$) and trade costs are, in contrast to tariffs, additionally assumed to be symmetric,

[6] We assume multilaterally balanced trade at the country level. This implies that total expenditure equals total income in each country.

i.e. $T_l^{ij} = T_l^{ji}$. The value of exports from i to j can then be expressed as

$$X_l^{ij} = p_l^i q_l^{ij} T_l^{ij} = \left(\tau_l^{ij}\right)^{-\sigma_l} \left(\frac{\beta_l^i p_l^i T_l^{ij}}{P_l^j}\right)^{1-\sigma_l} \mathfrak{X}_l^j. \tag{3.6}$$

Goods market clearing ensures that the sectoral production of a country is equal to the world-wide demand for its good $Y_l^i = \sum_{j=1}^N X_l^{ij}$. Replacing X_l^{ij} by the expression given in equation (3.6), rearranging to solve for $(\beta_l^i p_l^i)^{1-\sigma_l}$, replacing $(\beta_l^i p_l^i)^{1-\sigma_l}$ in equation (3.6) by the resulting expression, defining $Y^W \equiv \sum_{j=1}^N Y^j$, $\theta^j \equiv Y^j/Y^W$, $\theta_l^i \equiv Y_l^i/Y^W$, and using $\mathfrak{X}_l^j = \gamma_l^j \mathfrak{X}^j = \gamma_l^j Y^j$ gives an expression that strongly resembles the well-known expression obtained by Anderson and van Wincoop (2003) and Anderson and Yotov (2010), accounting for tariffs and the sectoral structure:

$$X_l^{ij} = \frac{\gamma_l^j Y^j Y_l^i}{Y^W} \left(\frac{T_l^{ij}}{\Pi_l^i P_l^j}\right)^{1-\sigma_l} \left(\tau_l^{ij}\right)^{-\sigma_l}, \tag{3.7}$$

with

$$\Pi_l^i = \left[\sum_{j=1}^N \left(\frac{T_l^{ij}}{P_l^j}\right)^{1-\sigma_l} \left(\tau_l^{ij}\right)^{-\sigma_l} \gamma_l^j \theta^j\right]^{\frac{1}{1-\sigma_l}} \tag{3.8}$$

and

$$P_l^j = \left[\sum_{i=1}^N \left(\frac{T_l^{ij} \tau_l^{ij}}{\Pi_l^i}\right)^{1-\sigma_l} \theta_l^i\right]^{\frac{1}{1-\sigma_l}}. \tag{3.9}$$

Π_l^i and P_l^j represent so-called outward and inward multilateral resistance terms, respectively, indicating that bilateral trade flows depend on *relative* trade costs. The multilateral resistance terms were introduced by Anderson and van Wincoop (2003) and capture any third-country effects resulting from changes between two countries, such as trade diversion effects due to the relative trade cost changes. Any theory-consistent gravity estimation takes into account these terms and doing so is a key feature of structural gravity (see Head and Mayer, 2014, for a good survey on gravity estimation).

A country's total income is given by the sum of its sectoral production values and its tariff revenues:

$$Y^j = Y_S^j + \sum_{l \in \mathcal{L}} Y_l^j + \sum_{l \in \mathcal{L}} \sum_{i=1}^N (\tau_l^{ij} - 1) X_l^{ij}. \tag{3.10}$$

3.3.2 Introducing a Multiple-Factor Production Function

The Anderson and van Wincoop (2003) framework relies on the assumption of an endowment economy. Without a production structure as in an endowment economy, there is no convincing way to include for example energy as an input factor or emissions as a side output into the model. As such features are of great interest in the carbon leakage context, we follow an approach as in Aichele (2013) and Caliendo and Parro (2015) to incorporate a production function that allows for multiple input factors. As the use of energy is highly correlated with the emission of CO_2 (see for example Egger and Nigai, 2015), we include energy into the production function and treat the emissions as a proportional side output. Sectoral production in country i is modeled by the following Cobb-Douglas production functions:

$$q_l^i = A_l^i (E_l^i)^{\alpha_{lE}^i} \prod_{f \in \mathcal{F}} (V_{lf}^i)^{\alpha_{lf}^i}, \tag{3.11}$$

$$q_S^i = A_S^i (E_S^i)^{\alpha_{SE}^i} \prod_{f \in \mathcal{F}} (V_{Sf}^i)^{\alpha_{Sf}^i}, \tag{3.12}$$

where A_l^i is a sector- and country-specific productivity parameter, α_{lE}^i is the country- and sector-specific cost share of energy, and α_{lf}^i are the cost shares of the F other factors (unskilled and skilled labor, capital, land, and natural resources), and accordingly for the non-tradable sector S. We assume constant returns to scale, implying that $\alpha_{lE}^i + \sum_{f \in \mathcal{F}} \alpha_{lf}^i = 1$ and $\alpha_{SE}^i + \sum_{f \in \mathcal{F}} \alpha_{Sf}^i = 1$.

All factors are assumed to be perfectly mobile between sectors but internationally immobile. For all factors except energy, factor endowments are given and constant for all countries and factor prices adjust endogenously. Energy is treated differently: for countries without binding emission targets, we take energy prices as given and there is an endogenous, completely elastic, supply of energy at the given price.[7] For

[7] An energy price that is held constant may in fact be quite plausible given the important role of the oil market and OPEC's role as a dominant producer therein. OPEC may have incentives to adjust the amount of oil in order to keep the oil price stable. This role of OPEC and its influence on energy-market leakage is analyzed in detail by Böhringer, Rosendahl, and Schneider (2013).

countries with binding emission targets as e.g. in our Copenhagen scenarios, the amount of energy used is exogenously given by these targets and national energy prices adjust endogenously in such a way that the factor market clearing condition holds.[8]

With this production structure, one can derive expressions for the equilibrium amount or price of energy and all other factor rewards, which we use in deriving counterfactual expressions.[9]

3.3.3 Counterfactuals

An important feature of structural gravity models is that they allow ex ante evaluations of policies by counterfactual analyses. For the model derived in Sections 3.3.1 and 3.3.2, this means that for example the effects of climate policy (associated with a change in e^i/P^i), of trade policy (such as the reduction of trade costs via regional trade agreements) or of the introduction of carbon tariffs (a combined climate and trade policy instrument, so to say) on trade flows, welfare and carbon emissions can be investigated. In this section, we will show how to solve the model for counterfactual sectoral production values, income, and prices from which expressions for the counterfactual values of the other variables of interest can be obtained.

Let the additional subscripts b and c denote the benchmark and the counterfactual cases, respectively. Let us start by rewriting the market clearing condition for each tradable sector $Y_l^i = \sum_{j=1}^N X_l^{ij}$ for the benchmark case, defining scaled equilibrium prices $\psi_{l,b}^i \equiv (\beta_l^i p_{l,b}^i)^{1-\sigma_l}$,[10] inserting the price index (3.5), and using equation (3.6) as well as $\mathfrak{X}_{l,b}^j = \gamma_l^j Y_b^j$:

$$Y_{l,b}^i = \psi_{l,b}^i \sum_{j=1}^N \frac{(T_{l,b}^{ij})^{1-\sigma_l}(\tau_{l,b}^{ij})^{-\sigma_l}}{\sum_{k=1}^N \psi_{l,b}^k (T_{l,b}^{kj}\tau_{l,b}^{kj})^{1-\sigma_l}} \gamma_l^j Y_b^j. \tag{3.13}$$

[8]Note that this model structure rules out energy-market leakage effects. In order to be able to capture such effects, we develop a model extension incorporating a more elaborate energy market model in Section 3.3.5.

[9]For further details on these derivations, see Appendix C.1.2.

[10]Prices are scaled by the positive, country- and sector-specific distribution parameter β_l^i and transformed with the elasticity of substitution because this highlights that there is no need to identify β_l^i and the transformation eases notation.

Given data for the sectoral values of production in country i in the benchmark scenario, $Y^i_{l,b}$, and for the total value of production in country i in the benchmark scenario, Y^i_b, and values for γ^j_l, σ_l, $T^{ij}_{l,b}$ and $\tau^{ij}_{l,b}$, the LN equations represented by (3.13) can be solved for the LN values of the scaled equilibrium prices in the benchmark scenario, $\psi^i_{l,b}$.[11]

The most fundamental counterfactual variable is the sectoral value of production, $Y^i_{l,c}$. Restating expression (3.13) for the counterfactual case therefore is a good starting point:

$$Y^i_{l,c} = \psi^i_{l,c} \sum_{j=1}^{N} \frac{(T^{ij}_{l,c})^{1-\sigma_l} (\tau^{ij}_{l,c})^{-\sigma_l}}{\sum_{k=1}^{N} \psi^k_{l,c} (T^{kj}_{l,c} \tau^{kj}_{l,c})^{1-\sigma_l}} \gamma^j_l Y^j_c. \tag{3.14}$$

As there are L tradable sectors, this leads to a system of LN equations. Whereas we only had to solve for the scaled equilibrium prices in the benchmark, we also have to account for sectoral and overall production value changes in the counterfactual. Hence, there are $(2L+1)N$ unknowns ($Y^i_{l,c}$, $\psi^i_{l,c}$ and Y^i_c), and we need additional equations to solve for these variables. We use the factor-market clearing conditions as well as our production structure to obtain the additional equations.

Note that spending for the non-tradable sector, $\mathfrak{X}^i_{S,c}$, is equal to production, i.e. $\mathfrak{X}^i_{S,c} = Y^i_{S,c}$, and can be expressed as a constant share γ^i_S of Y^i_c. Using this in combination with our expression for total nominal income (equation (3.10)), the price index (equation (3.5)), and the expression for the value of exports (equation (3.6)), the following additional expression can be obtained for a country's counterfactual total income:

$$Y^i_c = \gamma^i_S Y^i_c + \sum_{l \in \mathcal{L}} \left(Y^i_{l,c} + \sum_{j=1}^{N} (\tau^{ji}_{l,c} - 1) \frac{\psi^j_{l,c} (T^{ji}_{l,c})^{1-\sigma_l} (\tau^{ji}_{l,c})^{-\sigma_l}}{\sum_{k=1}^{N} \psi^k_{l,c} (T^{ki}_{l,c} \tau^{ki}_{l,c})^{1-\sigma_l}} \gamma^i_l Y^i_c \right). \tag{3.15}$$

This adds N equations to the system. Using the production structure of our model given by equation (3.11), we can find an expression for the counterfactual change in sectoral equilibrium prices for each tradable sector, which adds another LN equations with the

[11]Note that the system of equations is only defined up to a normalization for each sector (see e.g. Anderson and Yotov, 2016). We put sectoral scaled equilibrium prices in Albania to one. The choice of normalization does not affect any of our reported results.

N further unknowns e_c^i (see Appendix C.1.3 for details of the derivation):

$$\left(\frac{\psi_{l,c}^i}{\psi_{l,b}^i}\right)^{\frac{1}{\sigma_l-1}} = \left(\frac{e_b^i}{e_c^i}\right)^{\alpha_{lE}^i} \prod_{f\in\mathcal{F}} \left(\frac{\alpha_{Sf}^i\gamma_S^i Y_b^i + \sum_{m\in\mathcal{L}}\alpha_{mf}^i Y_{m,b}^i}{\alpha_{Sf}^i\gamma_S^i Y_c^i + \sum_{m\in\mathcal{L}}\alpha_{mf}^i Y_{m,c}^i}\right)^{\alpha_{lf}^i}. \tag{3.16}$$

An additional equation can be derived using factor market clearing for energy. As noted above, we distinguish two cases. For countries without binding emission reduction targets, we keep real energy prices between the baseline and any counterfactual scenario constant, i.e. $e_c^i/P_c^i = e_b^i/P_b^i$, hence ensuring that our calculated changes are independent of the choice of the numéraire. In this case, counterfactual nominal energy prices can be solved by:

$$e_c^i = e_b^i\frac{P_c^i}{P_b^i} = e_b^i\prod_{l\in\mathcal{L}}\left(\frac{P_{l,c}^i}{P_{l,b}^i}\right)^{\gamma_l^i}\left(\frac{p_{S,c}^i}{p_{S,b}^i}\right)^{\gamma_S^i}, \tag{3.17}$$

with $P_{l,c}^i = [\sum_{j=1}^N (T_{l,c}^{ji}\tau_{l,c}^{ji})^{1-\sigma_l}\psi_{l,c}^j]^{1/(1-\sigma_l)}$ and $p_{S,c}^i/p_{S,b}^i = (e_c^i/e_b^i)^{\alpha_{SE}^i}\prod_{f\in\mathcal{F}}[(\alpha_{Sf}^i Y_{S,c}^i + \sum_{l\in\mathcal{L}}\alpha_{lf}^i Y_{l,c}^i)/(\alpha_{Sf}^i Y_{S,b}^i + \sum_{l\in\mathcal{L}}\alpha_{lf}^i Y_{l,b}^i)]^{\alpha_{Sf}^i}$.[12]

For countries with binding emission reduction targets, real energy prices are endogenous and are calculated as follows:

$$e_c^i = \frac{\alpha_{SE}^i\gamma_S^i Y_c^i + \sum_{l\in\mathcal{L}}\alpha_{lE}^i Y_{l,c}^i}{E_c^i}, \tag{3.18}$$

with the amount of counterfactual emissions E_c^i now exogenously given.

Equations (3.14) to (3.17) (for countries with endogenous emissions) or (3.14) to (3.16) and (3.18) (for countries with binding emission targets) represent systems of $(2L+2)N$ equations in $(2L+2)N$ unknowns. There are data or exogenously set values for Y_b^i, $Y_{l,b}^i$, σ_l, γ_l^i, γ_S^i, α_{lf}^i, α_{lE}^i, α_{Sf}^i, and e_b^i or E_b^i, estimates or exogenously set values for $T_{l,c}^{ij}$ and $\tau_{l,c}^{ij}$, and values for $\psi_{l,b}^i$ can be obtained by solving (3.13). Hence, the system is solvable for N values of Y_c^i and e_c^i, as well as LN values of $Y_{l,c}^i$ and $\psi_{l,c}^i$, each.[13]

[12] See Appendix C.1.3 for a detailed derivation.

[13] Note that in our counterfactual scenario for carbon tariffs, we do not change the estimated trade costs, i.e. $T_{l,b}^{ij} = T_{l,c}^{ij}$. We nonetheless stick to the general notation above to show that counterfactual analyses involving exogenous changes in this variable could just as well be conducted in the given framework.

The aim of counterfactual analyses in this modeling framework is to evaluate policy scenarios (such as the introduction of carbon tariffs) in terms of their impact on trade flows, welfare, and carbon emissions. Given the solved values for counterfactual nominal sectoral production values, nominal total income, scaled equilibrium prices, and nominal energy prices, these impacts can be calculated.[14]

3.3.4 Decomposing the Emission Effects

Since the contributions by Grossman and Krueger (1993) and Copeland and Taylor (1994), decompositions of emissions changes into scale, composition, and techniques effects have become an import part of the toolbox in the trade and environment literature.[15] In this section, we show how such a quantifiable decomposition can be derived in our model framework.

We start off with an expression for total emissions from production in multiple tradable and one non-tradable sectors: $E^i = \left(\alpha^i_{SE} Y^i_S + \sum_{l\in\mathcal{L}} \alpha^i_{lE} Y^i_l\right)/e^i$. Defining total nominal income without tariff revenues $\tilde{Y}^i \equiv Y^i_S + \sum_{l\in\mathcal{L}} Y^i_l$, sectoral production shares $\kappa^i_S = Y^i_S/\tilde{Y}_i$ and $\kappa^i_l = Y^i_l/\tilde{Y}_i$, and a country's production-share-weighted average energy cost share $\bar{\alpha}^i_E \equiv \alpha^i_{SE}\kappa^i_S + \sum_{l\in\mathcal{L}} \alpha^i_{lE}\kappa^i_l$, we can rewrite total emissions in terms of this energy cost term (capturing sectoral composition), the real value of production and the real energy price as:

$$E^i = \bar{\alpha}^i_E \frac{\tilde{Y}^i}{P^i}\left(\frac{e^i}{P^i}\right)^{-1}. \tag{3.19}$$

Following Copeland and Taylor (1994, 2003), taking the total differential yields the following decomposition:

$$dE^i = \underbrace{\frac{\partial E^i}{\partial(\tilde{Y}^i/P^i)} d(\tilde{Y}^i/P^i)}_{\text{scale effect}} + \underbrace{\frac{\partial E^i}{\partial \bar{\alpha}^i_E} d\bar{\alpha}^i_E}_{\text{composition effect}} + \underbrace{\frac{\partial E^i}{\partial(e^i/P^i)} d(e^i/P^i)}_{\text{technique effect}}. \tag{3.20}$$

[14]See Appendix C.1.4 for the derivations.

[15]See Cherniwchan, Copeland, and Taylor (2017) for a recent survey as well as an extension to a firm-level decomposition.

Scale effect. The effect of a ceteris paribus increase of a country's production on its emissions is positive and directly proportional to the rise in production:

$$\frac{\partial E^i}{\partial(\tilde{Y}^i/P^i)} = \frac{\bar{\alpha}_E^i}{e^i/P^i} > 0 \text{ and } \frac{\partial E^i}{\partial(\tilde{Y}^i/P^i)}\frac{(\tilde{Y}^i/P^i)}{E^i} = 1. \tag{3.21}$$

Composition effect. The effect of an increase of the average energy cost share on emissions is always positive and directly proportional to the increase in the energy share:

$$\frac{\partial E^i}{\partial \bar{\alpha}_E^i} = \frac{\tilde{Y}^i}{e^i} > 0 \text{ and } \frac{\partial E^i}{\partial \bar{\alpha}_E^i}\frac{\bar{\alpha}_E^i}{E^i} = 1. \tag{3.22}$$

Technique effect. The effect of an increase of the real energy price on emissions is always negative and inversely proportional to the increase in the real energy price:

$$\frac{\partial E^i}{\partial(e^i/P^i)} = -\frac{\bar{\alpha}_E^i\tilde{Y}^i/P^i}{(e^i/P^i)^2} < 0 \text{ and } \frac{\partial E^i}{\partial(e^i/P^i)}\frac{(e^i/P^i)}{E^i} = -1. \tag{3.23}$$

Note that capturing the sectoral composition via the average energy cost share in our framework is equivalent to considering changes in the dirty production share if there are only two sectors as in Copeland and Taylor (2003). We demonstrate this equivalence in Appendix C.1.5.

Further note that in our base model, the real energy price is constant and we do not change it in our counterfactual scenario for countries without an emission target. Hence, there is no technique effect for those countries in our baseline results. This changes in the extended model considered in Section 3.3.5.

To obtain an index of the relative importance of the three channels, we in some cases also report the shares of the absolute values of the three effects in the overall emission change, i.e. scale share $= |\text{scale effect}|/(|\text{scale effect}| + |\text{composition effect}| + |\text{technique effect}|)$, and accordingly for the composition and technique shares.

We also report world scale, composition, and technique effects which are obtained by summing each of the three components of equation (3.20) over all countries.

So far, we have introduced a decomposition of the emission effects that relies on total differentials and is therefore a linear approximation around the baseline values. While this will work well for small changes, the approximation error may be substantial for large counterfactual scenarios (such as our Copenhagen Accord scenarios).

Given the multiplicative structure of the expression for emissions in equation (3.19), we therefore additionally propose an alternative log-change decomposition similar to Copeland and Taylor (2003) and Cherniwchan, Copeland, and Taylor (2017). Denoting changes from the baseline to the counterfactual by hats ($\hat{x} \equiv x_c/x_b$), we can write:

$$\hat{E}^i = \frac{\hat{\tilde{\alpha}}^i_E \widehat{\tilde{Y}^i/P^i}}{\widehat{e^i/P^i}}. \tag{3.24}$$

We next take the log and divide by the log emission change:

$$1 = \underbrace{\frac{\ln\left(\widehat{\tilde{Y}^i/P^i}\right)}{\ln \hat{E}^i}}_{\text{log scale effect}} \underbrace{+\frac{\ln \hat{\tilde{\alpha}}^i_E}{\ln \hat{E}^i}}_{\text{log composition effect}} \underbrace{-\frac{\ln\left(\widehat{e^i/P^i}\right)}{\ln \hat{E}^i}}_{\text{log technique effect}}. \tag{3.25}$$

The corresponding world effect can be calculated as:

$$1 = \frac{\sum_i \ln \hat{\tilde{\alpha}}^i_E}{\sum_i \ln \hat{E}^i} + \frac{\sum_i \ln\left(\widehat{\tilde{Y}^i/P^i}\right)}{\sum_i \ln \hat{E}^i} - \frac{\sum_i \ln\left(\widehat{e^i/P^i}\right)}{\sum_i \ln \hat{E}^i}. \tag{3.26}$$

As for the approximate decomposition, we again also calculate the shares of the absolute values of the three effects, i.e. $\text{log scale share} = |\text{log scale effect}| / (|\text{log scale effect}| + |\text{log composition effect}| + |\text{log technique effect}|)$, and accordingly for the composition and technique shares.[16]

In our results, we make use of both decompositions. While the approximate decompositions based on the total differentials are easier to interpret than the log-change decomposition, the latter are exact even for large changes.

[16]As the shares based on the approximative total differential decomposition and the log shares are almost perfectly correlated in cases where the approximation works well, we are confident that the log-decomposition shares are also informative about the relative importance of the different effects in cases when our approximation is off.

3.3.5 Extension: Incorporating Energy Production

The model developed above did not allow for energy-market leakage effects. But the introduction of carbon tariffs influences energy demand around the world. Therefore, it would be a desirable feature of the model if the national energy prices were not exogenous but would also be influenced by the price of internationally tradable energy resources, such as oil.

We therefore extend the model by specifying a production function of the following form: $E^i = E^i_S + \sum_{l \in \mathcal{L}} E^i_l = A^i_E (R^i)^{\xi^i_R} \prod_{f \in \mathcal{F}} (V^i_{Ef})^{\xi^i_f}$, where R is a freely internationally tradable input resource as in Egger and Nigai (2015) and the E subscript denotes the energy sector which is neither part of the $l \in \mathcal{L}$ tradable sectors nor of the non-tradable sector S. Further, we assume $\xi^i_R + \sum_{f \in \mathcal{F}} \xi^i_f = 1$, which implies constant returns to scale in the production of energy. The international character of the resource factor implies that factor income associated with production in a certain country no longer incurs only in that country. We take this fact into account when defining total national income. For further details on the model extension, please refer to Appendix C.1.6.[17]

3.4 Estimation Method

3.4.1 Gravity Estimation

Trade costs T^{ij}_l are not observable and therefore have to be approximated. The standard procedure is to approximate them as an exponential function of K observable variables $\mathbf{z}^{ij} = (z^{ij}_1, z^{ij}_2, \ldots, z^{ij}_K)'$: $T^{ij}_l = \exp((\mathbf{z}^{ij}_l)'\mathbf{b}_l)$, where $\mathbf{b}_l$ is a $(K \times 1)$ parameter vector. Adding a stochastic expression to equation (3.7) and pooling all exporter- or importer-

[17] In fact, climate policies may also influence the extraction path of fossil fuels which would additionally influence the amount of carbon leakage. As the incorporation of this effect would require a dynamic model structure, we leave this extension of our empirical framework for future research. For a theoretical treatment in a general equilibrium framework, see Eichner and Pethig (2011).

specific components, the following stochastic expression for the value of exports is obtained:

$$X_l^{ij} = \frac{1}{Y^W} \exp((\mathbf{z}_l^{ij})'\boldsymbol{\beta}_l)(\tau_l^{ij})^{-\sigma_l} n_l^i m_l^j u_l^{ij}, \tag{3.27}$$

where $n_l^i \equiv Y_l^i \left(\Pi_l^i\right)^{\sigma_l - 1}$, $m_l^j \equiv \gamma_l^j Y^j \left(P_l^j\right)^{\sigma_l - 1}$, $\boldsymbol{\beta}_l = \mathbf{b}_l(1 - \sigma_l)$, and u_l^{ij} is a random error which is mean independent of all right-hand side variables with conditional expectation equal to one. As carbon tariffs are not yet implemented in any country, tariffs are zero in the benchmark case, in which T_l^{ij} is estimated (i.e. $\tau_l^{ij} = 1$).

Equation (3.27) represents a multiplicative constant-elasticity model. As has been pointed out by Santos Silva and Tenreyro (2006), OLS estimation of a log-linearized version of this gravity equation is generally inconsistent due to heteroskedasticity and zero trade flows. They suggest to consistently estimate (3.27) in its multiplicative form using the Poisson Pseudo-Maximum-Likelihood (PPML) estimator. Santos Silva and Tenreyro (2006, 2011) further demonstrate that the PPML estimator is generally well behaved in the context of constant elasticity models by conducting Monte Carlo simulations. Additionally, Fally (2015) highlights that using PPML with exporter and importer fixed effects ensures that the equilibrium constraints imposed by our model are satisfied. We therefore follow this by now standard approach and will base the empirical investigation on sector-wise PPML estimation of (3.27). As it is common practice, we will also estimate the model with OLS and use the resulting estimates as a robustness check.

Estimation of equation (3.27) with PPML yields (alongside the fixed effects) the parameter vector estimate $\hat{\boldsymbol{\beta}}_l$ with corresponding variance-covariance matrix $\hat{\boldsymbol{\Omega}}_l$.[18] Based on this, the estimated trade costs can be obtained as

$$\hat{T}_l^{ij} = \exp\left(\frac{1}{1 - \sigma_l}\left(\left(\mathbf{z}_l^{ij}\right)' \hat{\boldsymbol{\beta}}_l\right)\right). \tag{3.28}$$

[18]The regression results are given in Table C.4 in Appendix C.3.1.

3.4.2 Determination of Remaining Model Parameters

We will now show how the carbon tariffs for the first counterfactual scenarios are calculated. Let λ^i denote the implicit carbon tax in country i (calculated as i's producers' energy tax expenses over i's carbon emissions). Then, carbon tariffs $\tau^{ij}_{l,c}$ that equalize carbon tax differentials between countries can be obtained as follows:

$$\tau^{ij}_{l,c} = \begin{cases} 1 + \frac{E^j_l}{Y^j_l}(\lambda^j - \lambda^i) & \text{if } \lambda^j > \lambda^i, \\ 1 & \text{if } \lambda^j \leq \lambda^i, \end{cases} \tag{3.29}$$

where E^j_l/Y^j_l is the carbon intensity of production in sector l in the importing country. Of course, it is also possible to use the carbon intensities of the exporting country instead. This would be a production-based rather than a product-based calculation of the carbon tariff rates. In our main counterfactual carbon tariff scenario, we will follow equation (3.29) and hence work with product-based carbon tariffs, because they can possibly be regarded as being comparable to VAT border tax adjustments which are legitimate under WTO law (see Metcalf and Weisbach, 2009, p. 546 f.). However, to investigate the differences between product- and production-based carbon tariffs, we also consider the latter. Note that we treat tariffs as exogenous. Hence, we do not model the strategic policy interaction of countries, neither in terms of tariffs (as done when calculating Nash tariffs, see e.g. Bagwell and Staiger, 2002), nor in terms of other policies, such as carbon taxes (see e.g. Böhringer, Carbone, and Rutherford, 2016).

The expenditure share for sector l in country i, γ^i_l is calculated from the data as $\gamma^i_l = \mathfrak{X}^i_l/\mathfrak{X}^i$. For the sectoral elasticity of substitution, we use estimates provided in our main data source (see Section 3.5).

As was mentioned in Section 3.3, we treat energy and emissions as if there was a perfectly linear relationship. This allows us to infer the energy price of country i as $e^i = EC^i/E^i$, where EC^i are total energy costs in country i and E^i are total emissions in country i.[19] Treating energy and emissions as perfectly correlated further makes it

[19]Note that the energy price is given per unit of carbon emissions, rather than per a typical energy unit

possible to calculate the sectoral energy cost shares in country i as $\alpha^i_{lE} = EC^i_l / TC^i_l$, where TC^i_l are the total costs in the corresponding sector. The remaining factor cost shares can be calculated as $\alpha^i_{lf} = (1 - \alpha^i_{lE}) VC^i_{lf} / \sum_{g \in \mathcal{F}} VC^i_{lg}$, where VC^i_{lf} are the costs for factor f in sector l in country i. The factor cost shares in the non-tradable sector can be obtained accordingly.

For the model extension, we have to calculate additional parameters. First, a country's resource endowment share is obtained by dividing a country's resource costs RC^i by the world expenditure for natural resources, i.e. $\omega^i = RC^i / \sum_j RC^j$. Second, the resource cost share in energy production is calculated as $\xi^i_R = RC^i / TC^i_E$, where TC^i_E denote the total costs in energy production. Accordingly, the other factor cost shares are given by $\xi^i_f = VC^i_{Ef} / TC^i_E$.

3.5 Data

3.5.1 Data Sources

For most of the data in this work, we use the Global Trade Analysis Project (GTAP) 8 database (see Narayanan, Aguiar, and McDougall, 2012). This database comprises data for 128 regions covering all countries in the world.[20] The data are given for 57 sectors, which we aggregate to one non-tradable and 14 tradable sectors.[21] All further data taken from the GTAP 8 database were then aggregated to this sectoral structure. These are the bilateral trade flows used for the estimation of the gravity equation, sectoral production and expenditure values[22], sectoral total costs, energy expenses (and the tax

such as kilowatt-hour. This is unproblematic due to the linear relationship of energy and emissions.

[20]Most of these regions are identical with countries, but some countries are pooled together as one region. For a list of the regions please refer to Appendix C.2.1.

[21]For a list of the industries and their grouping to the 15 sectors see Appendix C.2.2.

[22]For an explanation of the calculation of the sectoral expenditures from the GTAP raw data, see Appendix C.2.3.

part thereof)[23], other factor costs, and national carbon emissions.[24] The GTAP 8 data base uses 2007 as its most recent reference year. We therefore construct the whole data set as a cross-section for this year.

Bilateral data on regional trade agreement (RTA) memberships are taken from Mario Larch's Regional Trade Agreements Database from Egger and Larch (2008).[25] All geographic variables for the estimation of the gravity equation stem from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) data set constructed by Head, Mayer, and Ries (2010).

For the calibration of the social cost of carbon to our welfare function, we follow Shapiro and Walker (2015) and use two additional data sources. For the overall costs per ton of CO_2, we linearly extrapolate the estimates provided by the Interagency Working Group on the Social Cost of Carbon (2013) for the years 2010 (32 US-$) and 2015 (37 US-$) to the year 2007 to obtain a social cost of carbon of 29 US-$ per ton of CO_2. The relative distribution of these costs across different world regions is obtained using estimates from Nordhaus and Boyer (2000).[26] Additionally, we use national real income data from the Penn World Tables 9.0.[27]

For the model extension, we additionally use data on the resource cost share in energy production and the resource revenues across countries from the GTAP 8 database. For this flow variable to be a valid measure, both the law of one price and a common

[23]For expenditure on the factor energy in our model, we use data on intermediate input expenditure for the following GTAP energy industries: "coal", "oil", "gas", "petroleum, coal products", "electricity", and "gas manufacture, distribution".

[24]As our framework does not distinguish between emissions from the production and the consumption of a good, we add those values up.

[25]The RTA data can be downloaded from Mario Larch's website at http://www.ewf.uni-bayreuth.de/en/research/index.html (accessed on September 13th, 2017).

[26]Note that Nordhaus and Boyer (2000) obtain climate change damage estimates for a scenario in which the world heats up by 2.5 degrees. We therefore only rely on the *relative* costs of climate change across regions from this source (i.e. the share of the world costs that a specific region has to bear), combining them with a recent estimate of the social costs of carbon in our calibration of the welfare function. See Appendix C.1.1 for details.

[27]The data is available for download at http://www.rug.nl/research/ggdc/data/pwt/pwt-9.0 (accessed on September 13th, 2017). Specifically, we use expenditure-side real GDP at current PPPs (in mil. 2011US$) converted to 2007 values using the price level of real consumption of households and government, at current PPPs in order to be comparable with the rest of our data.

extraction rate across countries need to hold. In a robustness check, we therefore base the calculation of the national resource shares on stock data on fossil fuel endowments from the U.S. Energy Information Administration (EIA) instead.[28]

In our analyzes of the Copenhagen Accord, we make use of the country-specific emission reduction pledges specified in Appendix I of the Copenhagen Accord.[29] Some countries give a range in which their reduction is targeted to be. In these cases, we use the center of the respective intervals for our calculations. As the national reduction targets are given for different base years, we convert the corresponding pledges to our model base year 2007 using national emission time series provided in the World Development Indicators. For some countries, this procedure leads to a negative emission reduction target because they already strongly lowered their emissions before 2007. For these countries, we assume that they commit to not increasing their emissions.

To investigate the sensitivity of our results with respect to the implicit carbon taxes (λ^i), we use an additional data source rather than only relying on our own calculations based on energy taxation data from GTAP. Specifically, we employ effective carbon prices provided by the OECD (2016, pp. 146f.).[30]

3.5.2 Descriptive Statistics

In this subsection, we briefly describe the most important summary statistics of the data involved. Tables 3.1 to 3.3 show descriptive statistics for all model parameters and variables in the baseline.[31] Table 3.1 depicts the country-level variables and parameters.

[28]The data are available to download at http://www.eia.gov/cfapps/ipdbproject (accessed on September 13th, 2017). Specifically, for each country we multiply total recoverable coal reserves, proved reserves of dry natural gas, and proved reserves of crude oil by their respective energy contents, sum them up to obtain a country's overall fossil fuel reserves in BTU and divide this sum by the global sum of these reserves to obtain national fossil fuel endowment shares.

[29]The respective documents specifying the national targets are available at http://unfccc.int/meetings/copenhagen_dec_2009/items/5264.php (accessed on September 13th, 2017).

[30]Details on and descriptive statistics of the implicit carbon taxes are given in Appendix C.2.5.

[31]Descriptive statistics of the gravity variables used for the trade cost estimation are given in Table C.1 in Appendix C.2.4.

The total value of production in one country is 839 billion US-$ on average, ranging

Table 3.1: Model Variables and Parameters, Country-Level

	Mean	S.D.	Min.	Max.
Production (Y, in billion US-$)	839	2,617	3	25,167
Emissions (E, in mT of CO_2)	207	698	0	5,583
Energy price (e, inUS-$/t CO_2)	327	166	81	1,148
Carbon tax (λ, in US-$/t CO_2)	26	32	-13	138
Resource share (GTAP, ω)	0.0078	0.018	0	0.100
Resource share (EIA, ω)	0.0078	0.024	0	0.168
Resource cost share (ξ_R)	0.137	0.137	0	0.473

Notes: All values in this table are either taken directly or calculated from the GTAP 8 data. The parameters in the separated bottom part of the table are only relevant for the extended model.

from three billion up to 25 trillion. This production is associated with an average 207 million tons of carbon emissions, varying between almost none and close to 5.6 billion tons. Energy prices also show huge variation, from 81 US-$ per ton of CO_2 up to 1,148 US-$/ton of CO_2. The tax component of this price (i.e. the implicit carbon tax) is even negative in a few cases, implying that some countries subsidize the use of energy. Implicit carbon taxes therefore range from -13 to 138 US-$ per ton of CO_2. The summaries for the two additionally required model parameters for the model extension are also shown. National shares of the tradable energy resource (from GTAP data) vary from zero to 10 percent. The alternative calculation of national resource shares using data from the EIA gives a very similar pattern, with a correlation coefficient between the two measures of 0.84. The resource cost share in energy production ranges from zero to 47.3 percent with an average value of 13.7 percent.

Table 3.2 shows the sectoral production and emission values as well as the sectoral energy cost and expenditure shares. Both production and expenditure shares indicate that the non-tradable sector is the largest one (accounting for almost one quarter on average). The mineral sector accounts for the largest part of the emissions and is also characterized by the highest energy cost share (51 percent on average).

Table 3.3 shows the sectoral carbon tariffs (based on either the importing or the exporting country's carbon intensities), trade costs, and elasticities of substitution. It is evident

Table 3.2: Model Variables and Parameters, Sector-Level (I)

	Production (Y) (billion US-$)	Emissions (E) (mT of CO_2)	Energy cost share (α)	Expenditure share (γ)
Non-tradables	218,448	32.97	0.07	0.24
	(804,791)	(113.75)	(0.06)	(0.07)
Agriculture	25,498	4.62	0.04	0.08
	(67,654)	(15.61)	(0.04)	(0.06)
Apparel	8,381	0.40	0.02	0.01
	(27,683)	(1.87)	(0.03)	(0.01)
Chemical	37,829	18.46	0.21	0.04
	(112,164)	(63.71)	(0.24)	(0.02)
Equipment	31,296	1.01	0.03	0.03
	(102,585)	(4.29)	(0.10)	(0.02)
Food	38,695	3.07	0.02	0.07
	(94,316)	(9.91)	(0.03)	(0.04)
Machinery	61,382	2.84	0.05	0.06
	(203,526)	(11.89)	(0.11)	(0.03)
Metal	35,953	12.61	0.12	0.04
	(109,750)	(62.98)	(0.12)	(0.02)
Mineral	32,605	73.55	0.51	0.05
	(86,679)	(258.70)	(0.23)	(0.02)
Mining	22,397	3.94	0.09	0.03
	(49,379)	(15.81)	(0.14)	(0.04)
Other	7,750	0.53	0.12	0.01
	(22,407)	(1.22)	(0.22)	(0.01)
Paper	14,678	2.59	0.09	0.01
	(47,936)	(9.14)	(0.16)	(0.01)
Service	288,220	48.79	0.09	0.29
	(976,964)	(159.90)	(0.06)	(0.08)
Textile	8,515	1.27	0.03	0.01
	(32,248)	(7.98)	(0.03)	(0.01)
Wood	7,419	0.54	0.04	0.01
	(28,600)	(2.33)	(0.10)	(0.00)

Notes: Values without parentheses give the means of the variables and parameters, while values in parentheses are the respective standard deviations. All values in this table are either taken directly or calculated from the GTAP 8 data.

Table 3.3: Model Variables and Parameters, Sector-Level (II)

	Carbon Tariffs (τ) (product-based)	Carbon Tariffs (τ) (production-based)	Trade Costs ($t^{1-\sigma}$)	Elasticity of Substitution (σ)
Agriculture	0.002	0.002	0.011	4.76
	(0.004)	(0.008)	(0.032)	
Apparel	0.001	0.002	0.023	7.64
	(0.001)	(0.007)	(0.041)	
Chemical	0.007	0.016	0.029	6.60
	(0.020)	(0.052)	(0.049)	
Equipment	0.001	0.003	0.042	6.26
	(0.004)	(0.032)	(0.063)	
Food	0.001	0.002	0.015	5.01
	(0.001)	(0.009)	(0.038)	
Machinery	0.001	0.005	0.048	8.36
	(0.005)	(0.033)	(0.058)	
Metal	0.004	0.009	0.023	7.28
	(0.008)	(0.026)	(0.047)	
Mineral	0.019	0.034	0.011	4.51
	(0.032)	(0.072)	(0.033)	
Mining	0.004	0.005	0.008	11.88
	(0.011)	(0.017)	(0.027)	
Other	0.003	0.011	0.040	7.50
	(0.011)	(0.049)	(0.047)	
Paper	0.003	0.009	0.016	5.90
	(0.006)	(0.041)	(0.041)	
Service	0.003	0.006	0.166	3.80
	(0.006)	(0.016)	(0.077)	
Textile	0.001	0.002	0.017	7.50
	(0.003)	(0.007)	(0.038)	
Wood	0.001	0.003	0.018	6.80
	(0.003)	(0.018)	(0.046)	

Notes: Values without brackets give the means of the variables and parameters, while values in brackets are the respective standard deviations. The values of t are obtained by estimating the gravity equation. The values of the carbon tariffs (τ) refer to the scenarios in which carbon tariffs are given exogenously in such a way as to equalize carbon tax differentials between countries (see equation (3.29)).

that carbon tariffs are low on average (partly due to the fact that for each country-pair, only one country will impose a tariff) and tend to be considerably higher in the production-based case than in the product-based case. This implies that countries with low carbon taxes have higher emission intensities on average. The mineral sector has the highest tariffs, with an average rate of 1.9 percent if the calculation is based on the importer's carbon intensity and 3.4 percent if the exporter's emission intensity is used. Estimated international trade costs vary strongly across sectors, with services being most easily traded internationally. Sectoral elasticities of substitution lie between 3.8 for the service sector and 11.9 for the mining sector.

Table 3.4 gives a list of the committing countries of the Copenhagen Accord (not considering the voluntary additional pledges made by other countries in Appendix II of the Accord) along with their respective reduction targets.[32]

Table 3.4: National Pledges Made in the Copenhagen Accord (Appendix I)

Australia	23.0%	Austria	37.9%	Belarus	0.0%	Belgium	22.9%
Bulgaria	0.0%	Canada	16.7%	Croatia	48.4%	Cyprus	57.4%
Czech Rep.	15.7%	Denmark	10.1%	Estonia	8.5%	Finland	39.3%
France	24.9%	Germany	10.7%	Greece	43.3%	Hungary	6.8%
Ireland	47.6%	Italy	32.3%	Japan	34.4%	Kazakhs.	0.0%
Latvia	0.0%	Lithuania	0.0%	Luxemb.	31.9%	Malta	40.0%
Netherl.	30.7%	New Zeal.	40.2%	Norway	54.8%	Poland	12.1%
Portugal	48.0%	R. o. EFTA	25.0%	Romania	0.0%	Russia	0.1%
Slovakia	9.9%	Slovenia	42.4%	Spain	54.2%	Sweden	18.9%
Switzerl.	15.9%	Ukraine	0.0%	UK	21.1%	USA	17.0%

3.6 Results

3.6.1 Model Validation

Before we proceed with our counterfactual analysis, we discuss how our model fits the data and the world economy's response to shocks. In any structural gravity model,

[32] A similar table for the pledges made in Appendix II of the Copenhagen Accord that we will additionally discuss briefly is given in Appendix C.2.6.

output values are fitted perfectly. This also holds in our framework, even at the sectoral level. Due to our focus on carbon tariffs and their implications specifically for emissions, we construct our model in such a way that national emission data are also perfectly replicated in our baseline equilibrium. As sectoral emissions are obtained based on sectoral energy expenditure, they are not perfectly replicated. However, our model-predicted sectoral emission data are highly correlated with the observed sectoral emission data (with an average sectoral correlation coefficient of 0.96).

We follow a large strand of the structural gravity literature and obtain model consistent trade flows based on estimated trade costs (see Head and Mayer, 2014, for an overview). The generally good fit of gravity models, even at the sectoral level, is confirmed in our estimations as indicated by the high Pseudo-R^2 reported in Table C.4 in Appendix C.3.1.

While our framework relies on a workhorse model to evaluate the effects of trade policies for trade flows and welfare, it is far less common to use a structural gravity framework to evaluate environmental policies. We therefore use our framework to evaluate the same scenario which is compared by Böhringer, Balistreri, and Rutherford (2012) for a number of computable general equilibrium models. Specifically, the scenario consists of all countries of Annex I of the Kyoto Protocol[33] (including the United States of America and excluding the Russian Federation) jointly lowering their emissions by 20 percent while all other countries have no emission target and therefore endogenously adjust their emissions. The necessary national policies are implemented once with and once without carbon tariffs. The resulting leakage rates from our model are 3.6 percent (with a bootstrapped 95% confidence interval of [2.8, 4.3]) and 12.5 percent (with a bootstrapped 95% confidence interval of [10.7, 14.8]), and hence lie well within the range of leakage rates in the CGE models surveyed by Böhringer, Balistreri, and Rutherford (2012) of 2 to 12 percent and 5 to 19 percent, respectively.[34]

[33] See http://unfccc.int/parties_and_observers/parties/annex_i/items/2774.php (accessed on September 13th, 2017).

[34] In fact, the leakage rates for the tariff scenario in Böhringer, Balistreri, and Rutherford (2012) are obtained with full carbon border tax adjustment (i.e. a combination of import tariffs and export subsidies). However, Böhringer, Balistreri, and Rutherford (2012) mention on page S104 that considering full carbon border tax adjustment or only border tariffs, as we do, has very similar impacts in the models they survey.

3.6.2 Counterfactual Scenarios

As was stated above, structural gravity models allow the investigation of counterfactual scenarios, taking into account general equilibrium effects. The model developed in Section 3.3 can be used to conduct scenarios for exogenous changes in trade costs, energy/carbon prices or carbon tariffs. We first analyze the latter case. Afterwards, we consider the effects of the Copenhagen Accord.

To obtain information about the precision of our counterfactual results, we bootstrap 500 times from our parameter estimates reported in columns (1) to (14) of Table C.4 in Appendix C.3.1 along with the corresponding variance-covariance matrix obtained in the estimation, i.e. we draw 500 sets of vectors from the sector-specific K-dimensional multivariate normal distributions $\mathcal{N}_K(\hat{\boldsymbol{\beta}}_l, \hat{\boldsymbol{\Omega}}_l)$. We then solve the model in the benchmark case and the counterfactual for each of the 500 bootstraps. We report the obtained standard errors in parentheses below the corresponding point estimates in tables C.6 to C.15 in Appendix C.3.2. All confidence intervals reported for counterfactual values are also obtained using this bootstrapping procedure.

Pure Carbon Tariffs: Base Model

In our first counterfactual scenario, we introduce carbon tariffs that equalize the differences in the levels of the implicit carbon taxes and are obtained as described in Section 3.4.2.[35] Then the model is solved for the scaled equilibrium prices, sectoral productions, total national incomes, and nominal energy prices (using the scaled equilibrium price in the agricultural sector in Albania as the numéraire[36]) and the percentage changes in normalized trade flows (X_l^{ij}/Y^i), welfare, and carbon emissions are calculated. In this section, we will (mostly graphically) present the results for the latter three variables. Additionally, in Appendix C.3.2, the exact numerical results are given as well as numerical

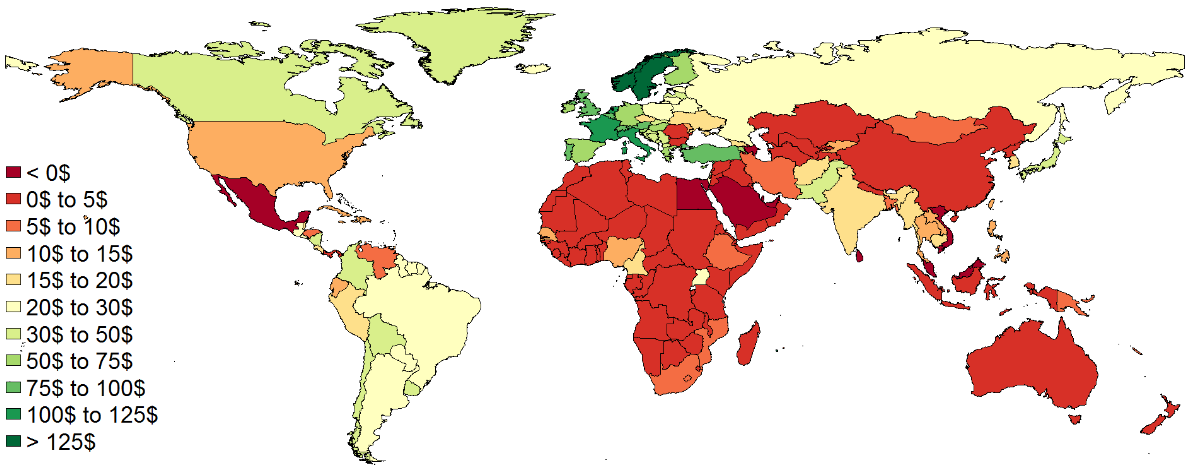
[35]Denoting our first scenarios as "pure" carbon tariff scenarios refers to the fact that the only counterfactual policy change in these cases is the introduction of carbon tariffs. This is in contrast to other scenarios, where we additionally introduce national emission targets.

[36]As already stated above, none of our reported results depend on the choice of numéraire.

and graphical representations of the percentage change in real income.

The way in which the carbon tariffs are calculated implies that for each country-pair the country with the higher implicit carbon tax imposes a tariff on imported goods from the other country. In order to give an overview which countries are imposing tariffs in most cases and which countries more often have to pay them, Figure 3.1 presents the national implicit carbon taxes in all 128 countries.[37] The larger the difference

Figure 3.1: Implicit Carbon Taxes



Notes: This figure shows national implicit carbon taxes (λ^i) around the world. The values range between -13 US-$ in Malaysia and 138 US-$ in Norway and Sweden. Red represents low carbon taxes, while green represents high values of λ^i. Values below zero are due to implicit carbon subsidies in a few Arabic and Asian countries.

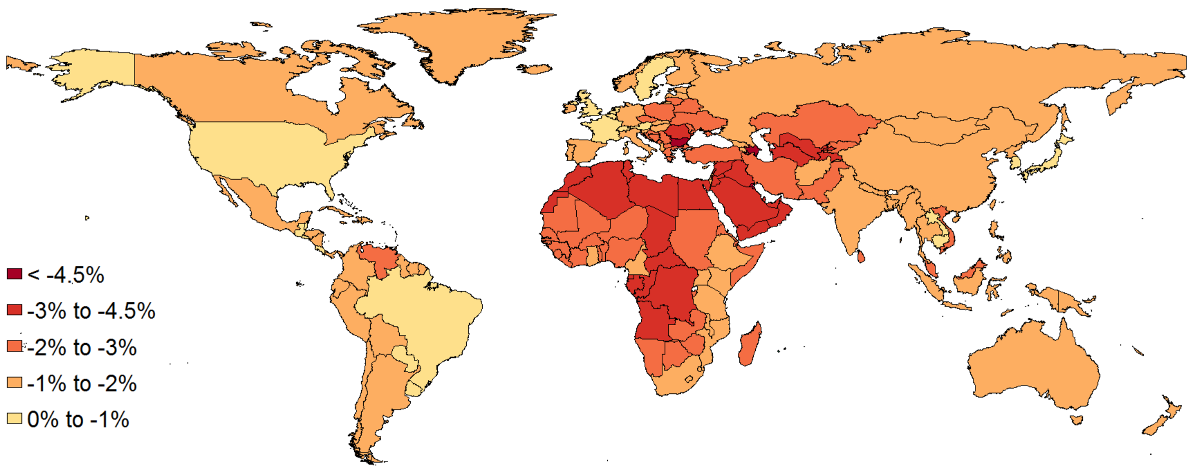
between two countries' carbon taxes, the higher is the carbon tariff imposed by the high-price country. Additionally, the percentage carbon tariff is higher in sectors with a higher carbon intensity. The implicit national carbon taxes (λ^i) vary between -13 US-$ in Malaysia (i.e. an implicit carbon subsidy) and 138 US-$ in Norway and Sweden. Generally, carbon taxes tend to be very high in European countries and very low for large parts of Africa, Asia and Oceania. It follows that European countries most often impose tariffs, while African, Asian, and Oceanic countries in many cases have to pay tariffs. Further, many North and South American countries have to pay tariffs when exporting to Europe and impose tariffs in most other cases.

Figures 3.2 to 3.4 show the most important results of the counterfactual introduction of

[37]For the exact values of the carbon prices, see Table C.6 in Appendix C.3.2.

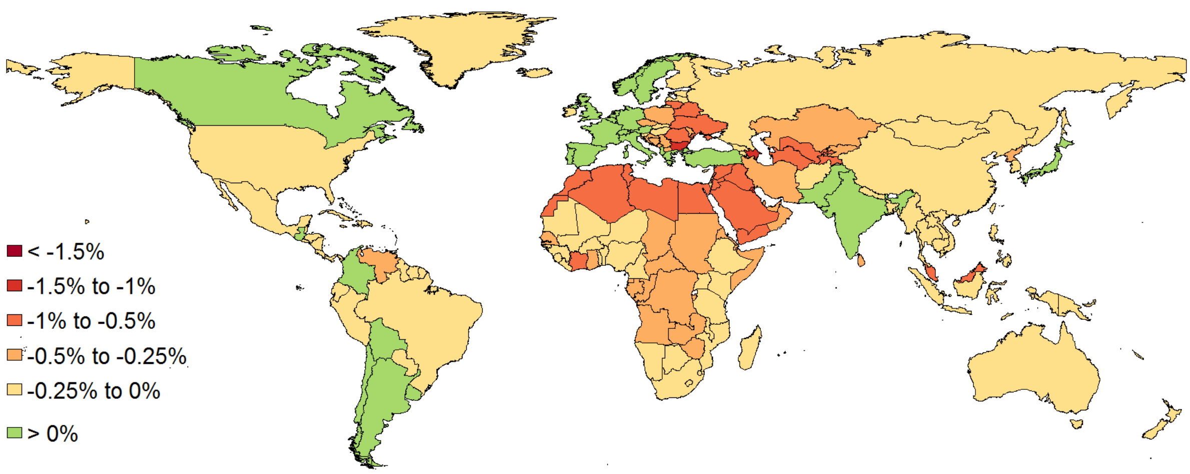
carbon tariffs. As carbon tariffs are a (climate-policy related) trade-policy instrument,

Figure 3.2: Percentage Changes in Normalized Trade Flows



Notes: This figure shows the percentage changes in trade flows due to the counterfactual introduction of carbon tariffs. Darker shades of reds represent stronger reductions in a country's international trade flows. The values range between -5.9 percent for Azerbaijan and -0.66 percent for Sweden. The corresponding change in world trade flows is a 1.9 percent decrease.

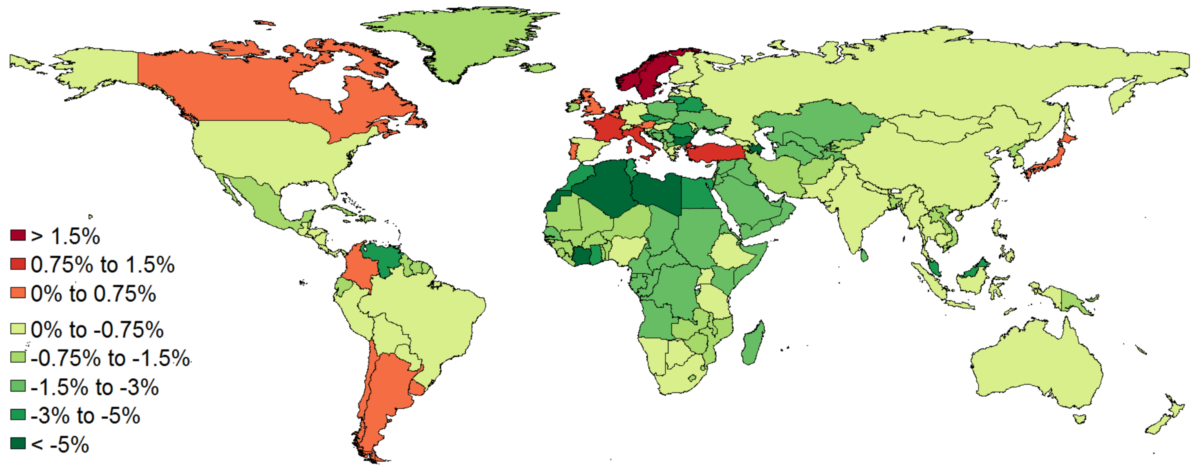
Figure 3.3: Percentage Changes in Welfare



Notes: This figure shows the percentage changes in welfare due to the counterfactual introduction of carbon tariffs. Green represents an increase in a country's welfare, while red represents a reduction. The values range between -1.5 percent for Bahrain and 0.30 percent for Norway.

a plausible starting point for the evaluation of its effects is to look at the changes in trade flows. The changes in normalized international trade flows are given in Figure 3.2. It is apparent that trade flows are reduced for all countries, but there are considerable differences in the effects for different countries. The reductions vary between 5.9 percent for Azerbaijan and 0.66 percent for Sweden. Comparing the figure with the representation of the carbon taxes given by Figure 3.1, one can state a distinct

Figure 3.4: Percentage Changes in Carbon Emissions



Notes: This figure shows the percentage changes in carbon emissions due to the counterfactual introduction of carbon tariffs. Red represents an increase in a country's emission level, while green represents a reduction. The values range between -7.0 percent for Bulgaria and 2.1 percent for Norway. The corresponding change in world carbon emissions is a 0.50 percent decrease.

relation between a country's carbon tax and the trade effects of carbon tariffs: those countries with low carbon taxes (which hence have to pay most and highest carbon tariffs) undergo the strongest negative effects in the counterfactual scenario. While most European countries (except a few Eastern European ones with low carbon taxes) experience only a mild decrease in their trade flows and most American countries face moderate effects, many African and Asian countries with very low carbon taxes are subject to a comparatively strong reduction of their trade flows. Overall, aggregate world trade flows decrease by 1.9 percent.

Figure 3.3 shows the percentage changes in welfare. First of all, welfare effects are negative for the majority of countries (79 percent), the largest being a -1.5 percent effect for Bahrain. While there are also countries with positive effects, these welfare gains are comparatively small (the largest being a 0.30 percent increase for Norway). Overall, the relative picture of the different effects for different countries given by Figure 3.3 is strongly linked to the respective image obtained for the trade flows: those countries which experience strong reductions in trade flows also tend to experience strong welfare losses. As most of these countries are developing countries in Africa and Asia, the counterfactual scenario would mostly decrease the welfare of already relatively poor countries.

Besides welfare changes, we also calculate the percentage changes in real income (i.e. welfare effects net of the environmental effects).[38] For the pure carbon tariff scenario, the welfare and real income effects are almost identical. This is due to the comparably small overall reduction of emissions. This close similarity breaks if the world emission reduction is stronger and/or the social costs of carbon used to calibrate our utility parameter μ^j are substantially larger. We will consider a case with higher social costs of carbon as a sensitivity check in one of our Copenhagen Accord scenarios.

Figure 3.4 shows the percentage changes of carbon emissions around the world. The introduction of carbon tariffs leads to significant changes in national carbon emissions. ”Clean“ industrialized countries with comparatively high carbon taxes tend to experience an increase or only a slight reduction in their carbon emissions. In contrast, most of the ”dirtier“ developing countries (especially in Africa and parts of Asia) strongly reduce their emissions after the tariff introduction. The changes range between -7.0 percent for Bulgaria and 2.1 percent for Norway. The corresponding change in world carbon emissions is a 0.50 percent decrease, with a bootstrapped 95% confidence interval of [-0.58, -0.44].

Comparing Figure 3.4 to Figure 3.1, one can see that emissions are shifted from countries with low carbon taxes to countries with high carbon taxes. If we see carbon tax differences as a cause for carbon leakage, carbon tariffs are able to reduce this effect.

The pattern in Figure 3.4 is mainly driven by the composition effect. On average, it accounts for 67 percent of the change in national carbon emissions. It ranges from -5.6 percent for Bulgaria to 2.4 percent for Norway and is negative for 80 percent of the countries (see Table C.6 in Appendix C.3.2 for further details). The scale effect is negative for all countries, less strong (between -1.6 percent for Bahrain and -0.02 percent for Japan) and positively correlated with the composition effect. The latter implies that countries that experience lower emissions due to a shift of production towards cleaner sectors at the same time also reduce their overall production more

[38]The corresponding Figure C.1 is given in Appendix C.3.2.

strongly, which further lowers their emissions.[39]

The relative importance of the scale and composition effect is similar on the aggregate level. 34 percent of the world emission reduction are due to the world scale effect (-0.17 percent with bootstrapped 95% confidence interval [-0.19, -0.16]) and 66 percent are due to the world composition effect (-0.33 percent with bootstrapped 95% confidence interval [-0.40, -0.28]).

Naturally, the numerical results of our counterfactual scenario depend on the specific level of tariffs implemented. As we have shown in equation (3.29), the level of carbon tariffs depends on the national implicit carbon taxes as well as on the carbon intensities. As we have already mentioned, we will investigate the sensitivity of our results with respect to using importer's or exporter's carbon intensities by distinguishing between product- and production-based tariffs. Additionally, we employ alternative data from the OECD (2016) for implicit carbon taxes. With these, we run the same counterfactual analysis as discussed above. Overall, the qualitative results are identical and the quantitative results are very similar but effects tend to be somewhat smaller using OECD data. This is due to the generally lower level of carbon taxes reported by the OECD. For example, the world carbon emissions go down by only 0.38 percent (with a bootstrapped 95% confidence interval of [-0.44, -0.34]) as compared to the 0.50 percent using GTAP data. Again, two thirds of this reduction are explained by composition.[40]

So far, we considered product-based carbon tariffs. Production-based carbon tariffs lead to overall stronger effects on carbon emissions. The largest reductions occur for Bulgaria with -13.6 percent, whereas Norway experiences a 3.2 percent increase in emissions. World carbon emissions are reduced by 1.4 percent, with a bootstrapped 95% confidence interval of [-1.6, -1.3]. The overall larger effects are driven by two

[39]Note that our emission decomposition also relates to the national welfare effects. While the real income part is by definition almost entirely driven by the scale effect (not perfectly due to tariff income), emission changes and hence the emission part of welfare changes is mainly driven by the composition effect, as just described.

[40]Detailed results for this scenario (as for all counterfactual scenarios considered in this section) can be found in Appendix C.3.2.

factors: First, the average level of production-based tariffs is higher than the average level of product-based tariffs. Secondly, production-based tariffs target more specifically emission-intensive industries in the country of production. These two effects are also reflected in our decomposition: First, both the scale and composition effects become stronger compared to the product-based scenario. Secondly, the relative importance of the composition effect increases. National scale effects now vary between -4.1 percent and -0.04 percent, while the composition effects range from -10.9 percent to 3.8 percent. Again, 82 percent of countries have a negative composition effect. The average share of the country-level changes explained by the composition effect increases to 72 percent. At the aggregate level, 71 percent of the world emission reduction are due to the world composition effect (-1.0 percent with bootstrapped 95% confidence interval [-1.2, -0.9]), magnifying the importance of the composition effect as compared to the product-based scenario.

To sum up, the decomposition of the emission helps to understand "both common and divergent effects on the economy" (Copeland and Taylor, 2003, p. 46) of different types of policies, like the production- and product-based carbon tariffs investigated here.

Pure Carbon Tariffs: Extended Model

We conduct the same counterfactual experiment as described in the first part of this section in the extended framework. Again, world carbon emissions decrease. The effect is less strong: -0.25 percent (with bootstrapped 95% confidence interval [-0.30, -0.21]) compared to -0.50 percent in the base model. This result is driven by the technique effect which is no longer zero in the extended model. The overall lower energy demand drives down the international energy resource price. This makes a more energy-intensive production worthwhile, leading to higher world emissions due to a positive world technique effect of 0.18 percent (with bootstrapped 95% confidence interval [0.17, 0.20]). This partly counterbalances the negative world scale and composition effects of -0.11 percent (with bootstrapped 95% confidence interval [-0.12, -0.11]) and -0.31

percent (with bootstrapped 95% confidence interval [-0.37, -0.26]), respectively, reducing the decrease in world carbon emissions compared to the scenario with purely country-specific energy prices. Using our alternative measure for the national resource shares, we obtain almost identical results for all variables of interest (see Table C.10 in Appendix C.3.2 for details).

When considering production-based instead of product-based carbon tariffs, we again see stronger effects on carbon emissions. World carbon emissions are reduced by 0.76 percent, with a bootstrapped 95% confidence interval of [-0.88, -0.67]. As before, this stronger reduction is due to the larger average level and the more pinpoint character of the production-based tariffs. The world emission reduction of 0.76 percent decomposes into a positive world technique effect of 0.44 percent (with bootstrapped 95% confidence interval [0.40, 0.48]), a negative world scale effect of -0.24 percent (with bootstrapped 95% confidence interval [-0.26, -0.23]), and an also negative world composition effect of -0.96 percent (with bootstrapped 95% confidence interval [-1.09, -0.84]). As in the base model, the composition effect again gains in importance, explaining 58 percent of the overall world emission change compared to 51 percent for the product-based tariffs.

Figure 3.5: Comparison of Decompositions

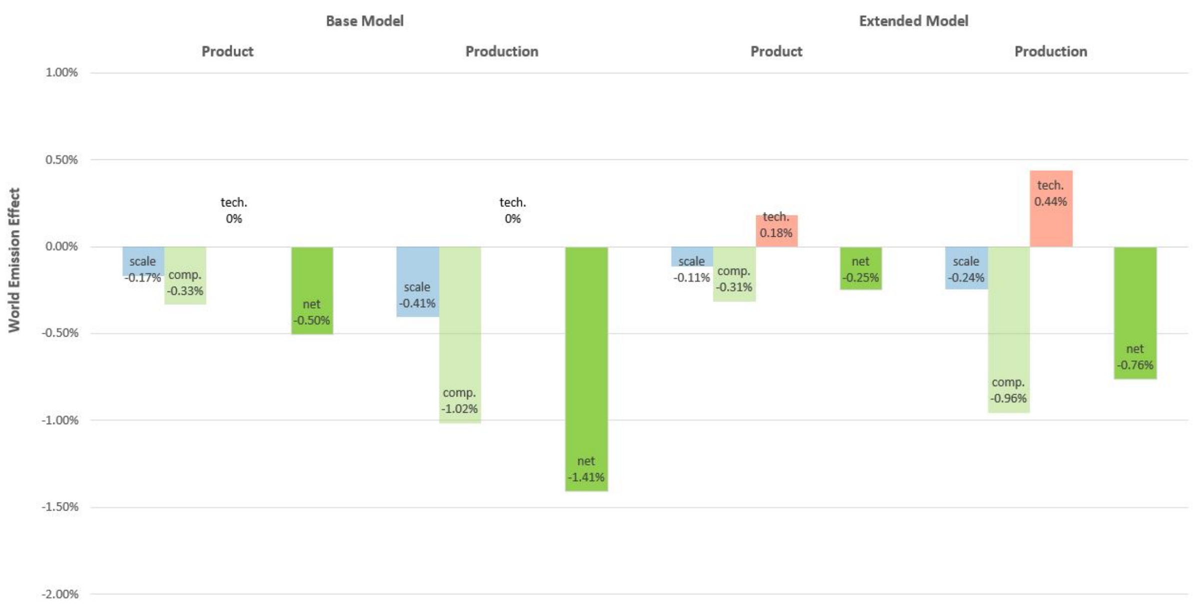


Figure 3.5 compares the decompositions of the world emission effects of our baseline and

extended model for both product- and production-based carbon tariffs. Several features discussed above are evident: First, composition is more important than scale in all scenarios. Second, compositional effects become more influential with production-based tariffs. Third, our model extension introduces a counteracting technique effect that lowers the overall effectiveness of carbon tariffs as an emission reduction policy.

At first sight, our large composition effects seem to be at odds with Levinson (2009) and Shapiro and Walker (2015), who decompose the change in U.S. manufacturing pollution over the last decades. They both find a small composition effect and rather identify pollution intensities/technology (related to our technique effect) as the most important driver of pollution reductions. While Levinson (2009) and Shapiro and Walker (2015) undertake an ex post decomposition of actual U.S. manufacturing emissions, we analyze the ex ante effects of counterfactual carbon tariffs. As these have never been implemented, a decomposition of the actual, historically realized, emission changes can not be informative about the decomposition of carbon tariff emission effects. As carbon tariffs specifically target the composition of production, the comparably stronger composition effect in our decomposition compared to Levinson (2009) and Shapiro and Walker (2015) is in fact plausible and does not contradict the findings based on historical emission developments. Policy-wise, this finding suggests that if a government wants to achieve compositional changes, carbon tariffs may be a suitable instrument. As carbon tariffs tend to shift dirty production to countries with a more ambitious climate policy, an additional advantage might arise in a model with directed technical change as in Hémous (2016): the scope of any unilateral climate policy, such as green R&D subsidies, to reduce CO_2 emissions becomes larger due to the higher average emission intensity in countries undertaking the policies. This may also induce more positive welfare effects of carbon tariffs.

Copenhagen Accord

At the fifteenth session of The Conference of the Parties (COP), the international community took note of the Copenhagen Accord in an attempt to come up with a follow-up agreement for the Kyoto Protocol.[41] In the Accord, one subset of countries (the Annex I countries of the Kyoto Protocol) were requested to formulate binding national emission targets in an appendix (Appendix I) to the Accord. Different than in the Kyoto Protocol, a second subset of (mainly developing and emerging) countries specified voluntary emission reduction targets, specified in Appendix II of the Accord.

Our framework is well suited to study the trade, welfare, and emission effects of a scenario in which all countries with emission targets fulfill these targets while other countries do not take climate policy actions of their own. In our main analysis, we focus on the pledges made by the Annex I countries in Appendix I, because the commitments made in Appendix II – different than the Appendix I pledges – are not "[...] measured, reported and verified in accordance with existing and any further guidelines adopted by the Conference of the Parties"[42]. We will shortly discuss how the results change if these Appendix II pledges are also considered to be binding at the end of this subsection.[43]

As is well understood and discussed in Section 3.2, the Copenhagen Accord will – just as any type of sub-global climate policy – potentially suffer from substantial carbon leakage. Therefore, we will additionally report the percentage leakage rate (LR) of the

[41]For details and the text of the Copenhagen Accord, see http://unfccc.int/meetings/ copenhagen_dec_2009/items/5262.php (accessed on September 13th, 2017).

[42]See p. 6 in the legal text of the Accord available at http://unfccc.int/resource/docs/2009/cop15/eng/11a01.pdf (accessed on September 13th, 2017).

[43]On November 4th, 2016, the more recent Paris Agreement entered into force (see http://unfccc.int/paris_agreement/items/9485.php). In this agreement, all parties agreed to individually provide Intended Nationally Determined Contributions (INDCs) (see http://unfccc.int/focus/indc_portal/items/8766.php, accessed on September 13th, 2017). We focus on the Copenhagen Accord rather than on the Paris Agreement mainly for two reasons: first, as all countries are required to formulate national emission targets in the Paris Agreement, carbon leakage would not be a problem in this context (at least assuming that all countries ratify the Agreement and actually fulfill their targets). This would eliminate one important effect of carbon tariffs, that we are interested in and want to investigate in our counterfactual analysis. (Of course, carbon tariffs would still influence trade patterns and the distribution of the welfare effects associated with the implementation of the Paris Agreement as national emission targets will differ in their stringency. Further, carbon leakage will again arise if some countries do not adhere to their commitments. We are therefore convinced that a better understanding of the effects of carbon tariffs keeps its policy relevance even in the light of the Paris Agreement.) Secondly, existing literature on the Copenhagen Accord allows us to compare our results for scenarios without carbon tariffs to previous findings.

implementation of the Copenhagen Accord, calculated as follows:

$$LR = \left[\frac{\left(\sum_{i \notin cop} E_b^i + \sum_{i \in cop} \bar{E}_c^i - \sum_i E_b^i \right) - \left(\sum_i E_c^i - \sum_i E_b^i \right)}{\sum_{i \notin cop} E_b^i + \sum_{i \in cop} \bar{E}_c^i - \sum_i E_b^i} \right] \times 100$$

$$= \frac{\sum_{i \notin cop} E_b^i + \sum_{i \in cop} \bar{E}_c^i - \sum_i E_c^i}{\sum_{i \notin cop} E_b^i + \sum_{i \in cop} \bar{E}_c^i - \sum_i E_b^i} \times 100, \qquad (3.30)$$

where $\bar{E}_c^i$ are the emission levels to which the Copenhagen Accord countries, which constitute the set cop, committed. Note that $\left(\sum_{i \notin cop} E_b^i + \sum_{i \in cop} \bar{E}_c^i - \sum_i E_b^i \right)$ is the amount of emissions that would result without carbon leakage, i.e. if non-committing countries would have constant emissions, and $\left(\sum_i E_c^i - \sum_i E_b^i \right)$ are the actually realized emissions. Hence, the leakage rate gives the share of the emission reduction that is lost due to leakage.

Figure 3.6 shows the percentage changes in carbon emissions in our Copenhagen scenario. For all countries that committed to a specific emission reduction (the Annex I countries listed in Appendix I), we plot this target, which is equal to the actual emission reduction in our counterfactual. Some countries only commit to holding their emissions constant, whereas others commit to large emission reductions, like Cyprus with a reduction target of 57.4 percent.

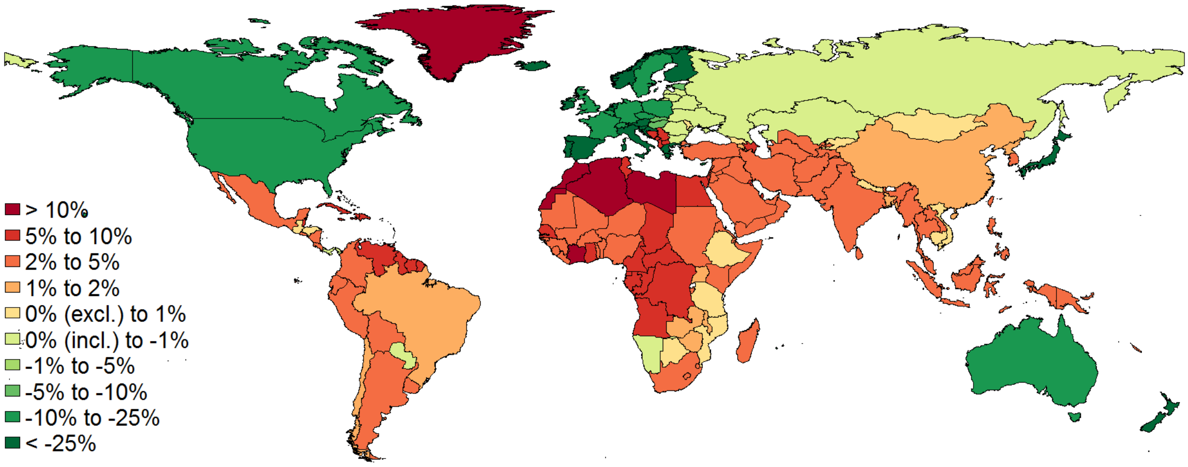
Further, we see quite strong endogenous emission increases for many non-committing countries, specifically in Latin America, Africa and parts of Asia ranging up to 12.6 percent. This leads to a substantial leakage rate of 13.4 percent (with bootstrapped 95% confidence interval of [11.5, 15.8]) and an overall carbon emission reduction of 8.4 percent (with bootstrapped 95% confidence interval of [-8.6, -8.1]). Egger and Nigai (2012) obtain a reduction of world carbon emissions of 17 percent in a multi-sector Ricardian-model of trade. This larger reduction is partly explained by the near absence of carbon leakage in their model of 33 OECD countries and a Rest of the World, their consideration of not only Appendix I but also Appendix II countries (such as Brazil, China, and India), and partly due to the different model structure and calibration. Note that Egger and Nigai (2012) do not investigate carbon tariffs in their framework, which we will do below.

For the non-committing countries, our total differential decomposition remains a very good approximation. It turns out that the emission changes are overwhelmingly due to the composition effect which accounts for 88.7 percent on average. The remaining part is explained by the scale effect, as we do not consider the energy market leakage channel and keep real energy prices for these countries constant. For the countries with emission targets, our decomposition leads to partly substantial approximation errors due to very ambitious emission goals. In the following, we therefore use the exact log-decomposition. Two things are noteworthy: First, for the committing countries we have a substantial technique effect amounting to 77.7 percent of the national changes on average.[44] The reason is that introducing an exogenous emission target leads to a large endogenous adjustment of the real energy price. Second, also for the committing countries we find a larger average national share for composition (18.8 percent) than for scale (3.5 percent). The absolute world emission effect decomposes into 83.4 percent technique effect, 14.3 percent composition effect, and 2.3 percent scale effect. The corresponding world log technique, composition, and scale effects are 1.17, -0.20, and 0.03, respectively. Hence, the composition effect works in the opposite direction of the technique and scale effects and actually increases world emissions due to carbon leakage. The increase in the importance of the technique effect at the world level is explained by the fact that country-level technique effects are all negative and hence sum up, while national composition and scale effects partially cancel each other.

In Figure 3.7, we plot the welfare effects of our Copenhagen scenario. It basically gives the inverse picture of Figure 3.6. Hence, the committing countries bear the costs of the global emission reduction due to the higher energy price, whereas non-committing countries gain twofold: first, there is the direct welfare increase due to the decrease of

[44]For the countries with an emission target of no change, we use our total differential decomposition for the calculation of the shares, as the log of zero is not defined and the approximation works well due to the fact that emissions do not change.

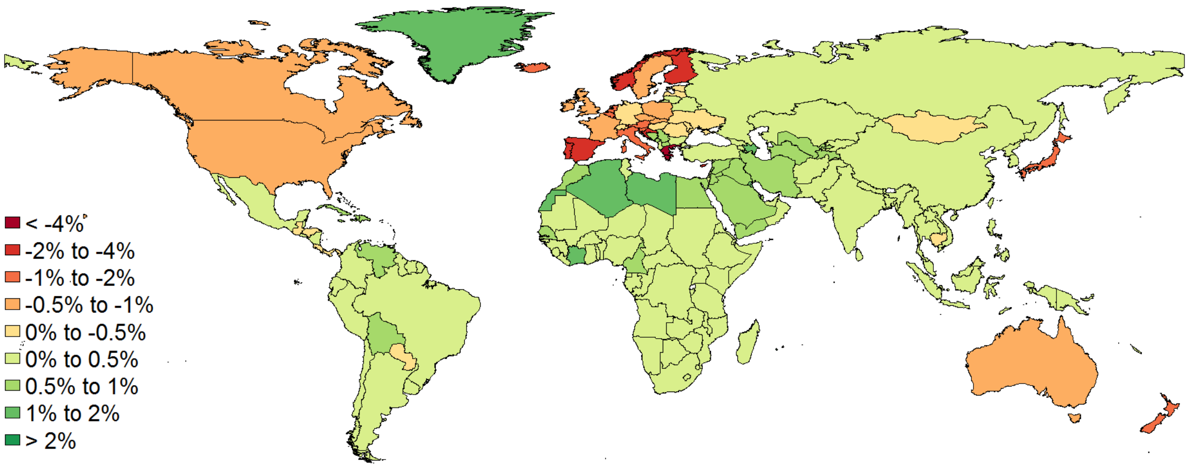
Figure 3.6: Percentage Changes in Carbon Emissions (Copenhagen Scenario)



Notes: This figure shows the percentage changes in carbon emissions due to the counterfactual implementation of the Copenhagen Accord. Red represents an increase in a country's emission level, while green represents a reduction. The values range between -57.4 percent for Cyprus and 12.6 percent for Rest of North Africa. The corresponding change in world carbon emissions is a 8.4 percent decrease.

emissions. Second, those countries gain comparative advantage in the emission-intensive industries, and can now serve the committing countries' markets with those products. The welfare effects range from -4.7 percent for Greece to 2.2 percent for Bahrain.

Figure 3.7: Percentage Changes in Welfare (Copenhagen Scenario)

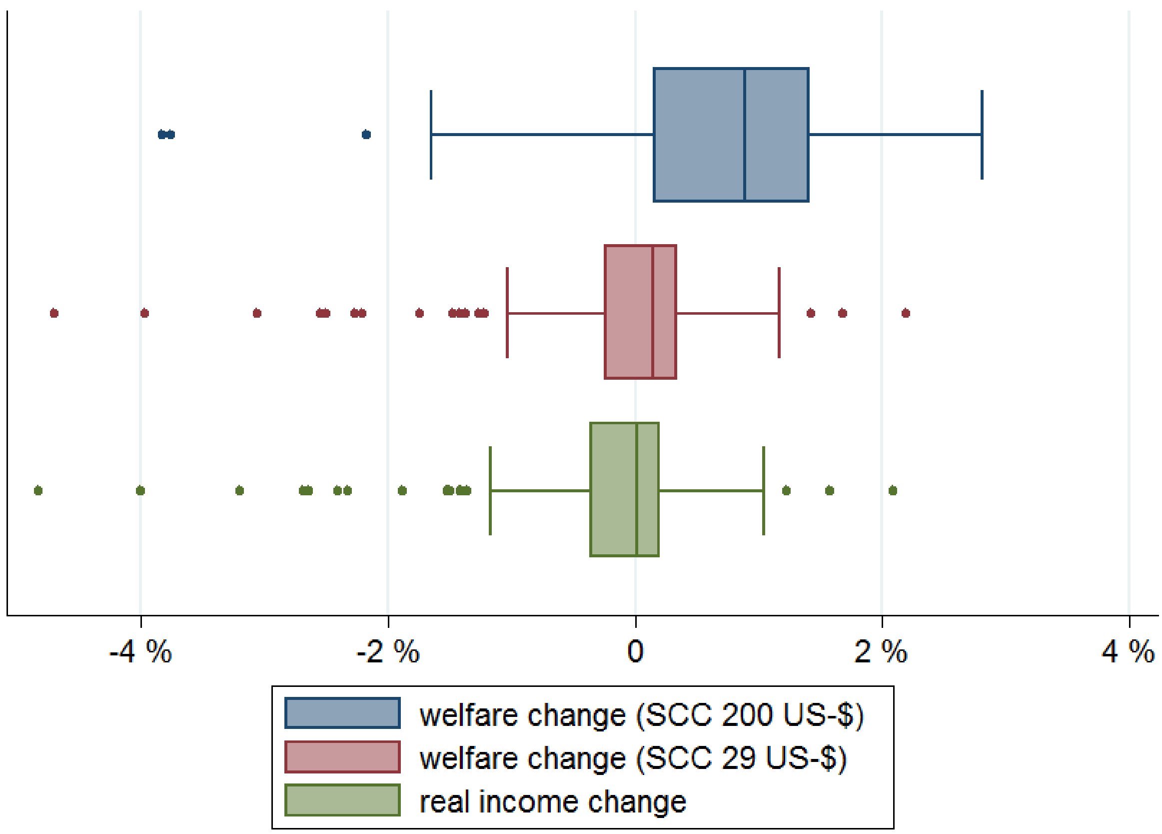


Notes: This figure shows the percentage changes in welfare due to the counterfactual implementation of the Copenhagen Accord. Green represents an increase in a country's welfare, while red represents a reduction. The values range between -4.7 percent for Greece and 2.2 percent for Bahrain.

Comparing the welfare effects with the real income effects, we see that the difference of these two measures is non-negative for all countries. On average, the percentage change in welfare is 0.12 percentage points higher than the percentage change in real income. While this seems small, looking for example at the largest absolute difference of

0.25 percentage points for India implies more than a doubling of the gains experienced by India (turning the 0.20 percent gain in real income into a 0.45 percent increase in welfare). This noticeable difference between the two measures not seen in the pure tariff scenario is due to the considerably stronger world emission reduction in the Copenhagen scenario. The extend to which welfare and real income differ depends strongly on the social cost of carbon assumed in the calibration of our welfare function. In addition to our base calibration of the social costs of carbon of 29 US-$ per metric ton of CO_2, we follow Shapiro and Walker (2015) and use a more extreme value of 200 US-$ as a sensitivity check. Note that changing the social costs of carbon does only affect our welfare results. The welfare effects then range between -3.8 percent for Greece and 2.8 percent for Bahrain. The difference between welfare and real income increases to 0.89 percentage points on average. The real income as well as welfare effects for social costs of carbon of either 29 US-$ or 200 US-$ are illustrated in Figure 3.8.

Figure 3.8: Comparison of Real Income and Welfare Effects (Copenhagen Scenario)



Other studies of the effects of the Copenhagen Accord also consider real income changes.

Our finding that committing countries bear income losses for the reduction of world emissions is consistent with previous findings in the literature (see e.g. Saveyn, Van Regemorter, and Ciscar, 2011; Egger and Nigai, 2012; Ciscar, Saveyn, Soria, Szabo, Van Regemorter, and Van Ierland, 2013). While Saveyn, Van Regemorter, and Ciscar (2011) and Ciscar, Saveyn, Soria, Szabo, Van Regemorter, and Van Ierland (2013) find more moderate real income losses than we obtain (ranging up to -1.9 percent and -3.0 percent, respectively), Egger and Nigai (2012) obtain stronger real income losses (ranging up to -15.7 percent).

As discussed above, the Copenhagen scenario leads to a substantial leakage rate of 13.4 percent. One of the main reasons to consider carbon tariffs is exactly their ability to mitigate leakage. We therefore additionally consider to accompany the emission targets with the introduction of carbon tariffs. While the tariffs considered in the first two parts of this section were meant to compensate for differences in the *level* of carbon taxation, we will now introduce carbon tariffs that equalize the *increase* in committing countries' real energy price vis-à-vis non-committing countries as carbon tariffs are now an accompanying measure to the national commitments. We implement this by the following formula for the carbon tariffs $\tau_{l,c}^{ij}$:

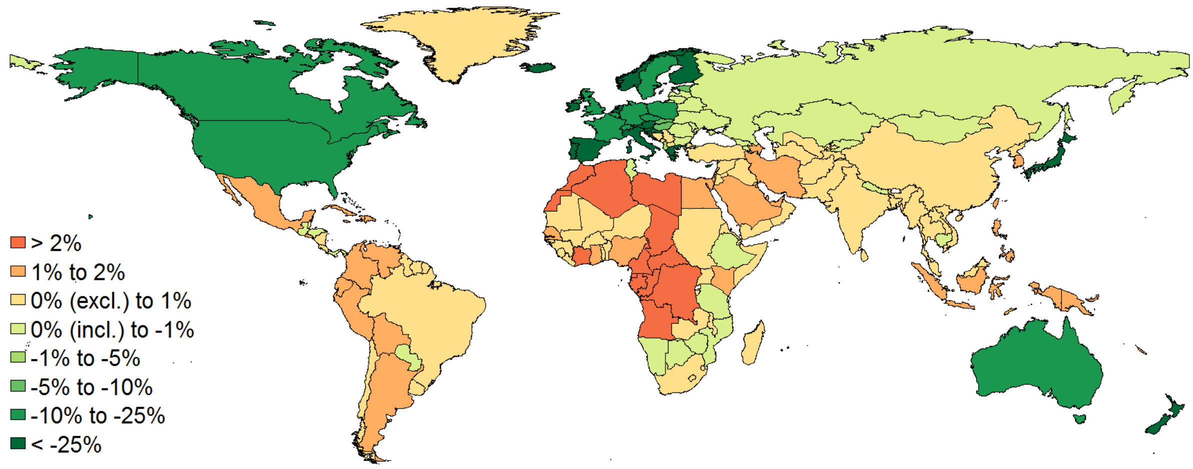
$$\tau_{l,c}^{ij} = \begin{cases} 1 + \frac{E_{l,c}^{j}}{Y_{l,c}^{j}/P_{c}^{j}} \left(\frac{e_{c}^{j}}{P_{c}^{j}} - \frac{e_{b}^{j}}{P_{b}^{j}} \right) & \text{if } i \notin cop \wedge j \in cop, \\ 1 & \text{if } i \in cop \vee j \notin cop, \end{cases} \tag{3.31}$$

which we jointly endogenously solve with our other model equations.[45]

Figure 3.9 plots the percentage changes in carbon emissions of the Copenhagen scenario with tariffs. As before, for the committing countries we plot the committed targets corresponding to the actual emission reductions. For the non-committing countries, we see that the adjustment is substantially mitigated if the emission targets are accompanied by carbon tariffs, ranging now only up to a 2.4 percent increase in emissions.

[45]Note that we now calculate the emission intensity using the real production value as we compensate for changes in the real energy price, different from equation (3.29) where we compensated for nominal carbon tax differentials.

Figure 3.9: Percentage Changes in Carbon Emissions (Copenhagen Scenario with Tariffs)

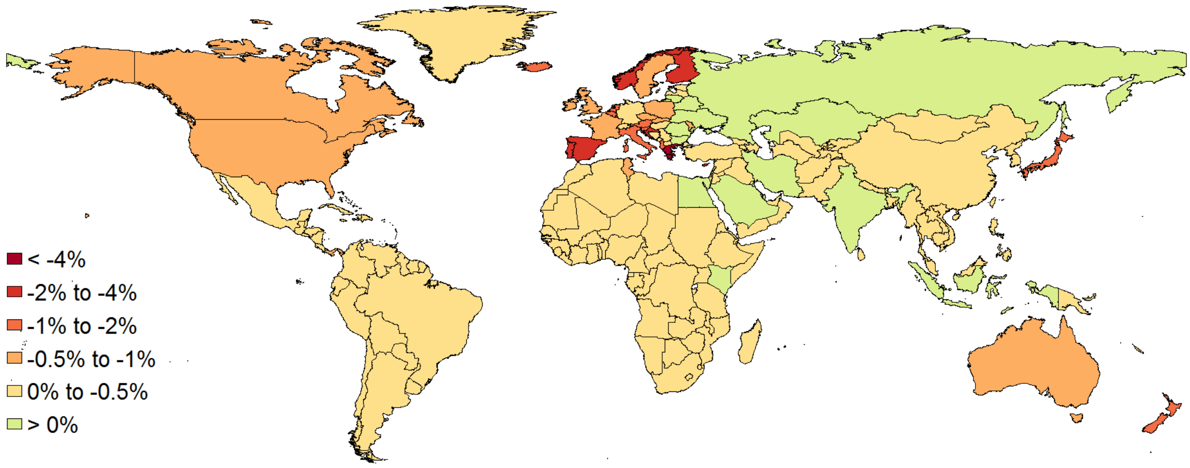


Notes: This figure shows the percentage changes in carbon emissions due to the counterfactual implementation of the Copenhagen Accord with carbon tariffs. Red represents an increase in a country's emission level, while green represents a reduction. The values range between -57.4 percent for Cyprus and 2.4 percent for Cote d'Ivoire. The corresponding change in world carbon emissions is a 9.3 percent decrease.

Carbon tariffs hence strongly reduce carbon leakage from 13.4 percent to 4.1 percent (with bootstrapped 95% confidence interval of [3.3, 4.9]). This leads to a stronger world carbon emission reduction of 9.3 percent (with bootstrapped 95% confidence interval of [-9.3, -9.2]) compared to 8.4 percent in the scenario without carbon tariffs. To understand the driving forces of this increase, one needs to consider the altered composition effect in the non-committing countries. As discussed above, the changes in composition lead to an average increase in emissions in these countries by 3.4 percent in the Copenhagen scenario without tariffs. Carbon tariffs reduce this increase to 1.0 percent on average. Due to this reduction, the composition effects of committing and non-committing countries cancel each other out almost exactly, leading to a decomposition of the absolute world emission effects into 94.8 percent technique, 4.0 percent scale, and only 1.2 percent composition.

In terms of welfare, we find that the additional introduction of carbon tariffs destroys most of the welfare gains of the non-committing countries (see Figure 3.10). While the non-committing countries initially profit from the commitments due to reduced carbon emissions and increased comparative advantage in dirty goods production, the carbon tariffs load the burden of the additional world carbon emission reduction on the non-committing countries due to the tariff expenses and the (partial) reversion of the comparative advantage effect. Welfare effects for the committing countries remain very similar, tending to be a little less negative due to tariff revenues, re-gained comparative advantages, and the additional world carbon emission reduction.

Figure 3.10: Percentage Changes in Welfare (Copenhagen Scenario with Tariffs)



Notes: This figure shows the percentage changes in welfare due to the counterfactual implementation of the Copenhagen Accord with carbon tariffs. Green represents an increase in a country's welfare, while red represents a reduction. The values range between -4.6 percent for Greece and 0.40 percent for Belarus.

As previously stated, we take our policy (i.e., the targets and the decision whether to use carbon tariffs or not) as exogenous and therefore do not allow countries to change any of their policies in reaction to carbon tariff changes. Böhringer, Carbone, and Rutherford (2016) investigate strategic reactions to the threat of carbon tariffs by a climate coalition (similar to the set of committed countries in the Copenhagen Accord). They consider three policy options for the non-committed countries, namely no reaction, tariff retaliation, and cooperation (i.e., the introduction of own reduction targets). Their main finding is that China and Russia would choose the cooperative solution. Applied to our framework, allowing for endogenous policy reactions may hence even increase the effectiveness of carbon tariffs by incentivizing pollution-intensive countries to take climate policy actions of their own. However, Böhringer, Carbone, and Rutherford (2016) do not allow high-pollution countries to lower their carbon taxes in reaction to carbon tariffs. In principle, countries could use this channel to restore international competitiveness of energy-intensive industries (unless carbon tariffs are defined to react to any carbon tax changes), re-intensifying carbon leakage effects.

The results presented so far for the Copenhagen scenarios only considered the pledges made in Appendix I of the Accord. We also conducted the same counterfactual experiments additionally taking into account the voluntary emission targets of further countries according to Appendix II of the Accord (see Table C.3 in Appendix C.2.6 for the specific countries and their pledges).

Assuming that the partly very ambitious goals of both Appendix I and Appendix II of the Copenhagen Accord are actually met, world emissions go down by 19.0 percent (with bootstrapped 95% confidence interval [-19.2, -18.9]) in a scenario without carbon tariffs. This magnification of the reduction is explained by two factors: first, additional main polluters such as China, Brazil, and India now also reduce their emissions keeping up with their voluntary targets. Second, the overall larger number of committing countries reduces the scope for carbon leakage. This is confirmed by the new leakage rate that we find in this scenario of 6.0 percent (with bootstrapped 95% confidence interval [5.3, 6.9]). Comparing the leakage rates we obtain in our two Copenhagen scenarios without carbon tariffs with the results of Peterson, Schleich, and Duscha (2011) who also investigate a number of Copenhagen Accord scenarios with differently strict pledges, our 6.0 and 13.4 percent leakage rates are similar to their obtained range of 4.3 to 13.1 percent.

Again, carbon tariffs can substantially reduce the leakage rate. If all committing countries in the larger scenario accompany their national climate policies with the introduction of carbon tariffs, the leakage rate goes down to 1.4 percent (with bootstrapped 95% confidence interval [1.0, 1.8]), leading to an even stronger reduction of global emissions amounting to 20.0 percent (with bootstrapped 95% confidence interval [-20.1, -19.9]). Note that also taking into account the pledges of the Appendix II, our overall world emission reductions are now much closer to the predictions of Egger and Nigai (2012).

Table 3.5 summarizes the world emission effects and their decomposition for all counterfactual scenarios considered in this section.

Table 3.5: World Emission Effects Across Scenarios

Pure Carbon Tariff Scenarios					
	ΔWE	WPSE	WPCE	WPTE	
Base model, product-based	-0.50	-0.17	-0.33	0	
	(0.04)	(0.01)	(0.03)		
Base model, product-based (OECD data)	-0.38	-0.13	-0.26	0	
	(0.03)	(0.01)	(0.02)		
Base model, production-based	-1.41	-0.41	-1.02	0	
	(0.08)	(0.02)	(0.07)		
Extended model, product-based	-0.25	-0.11	-0.31	0.18	
	(0.02)	(0.00)	(0.03)	(0.01)	
Extended model, product-based (EIA data)	-0.24	-0.11	-0.31	0.18	
	(0.02)	(0.00)	(0.03)	(0.01)	
Extended model, production-based	-0.76	-0.24	-0.96	0.44	
	(0.05)	(0.01)	(0.07)	(0.02)	
Copenhagen Accord Scenarios					
	ΔWE	WLSE	WLCE	WLTE	LR
Appendix I, no tariffs	-8.37	0.03	-0.20	1.17	13.40
	(0.11)	(0.00)	(0.01)	(0.02)	(1.15)
Appendix I, with tariffs	-9.27	0.07	0.00	0.93	4.14
	(0.04)	(0.00)	(0.00)	(0.00)	(0.43)
Appendix I and II, no tariffs	-19.05	0.03	-0.31	1.28	6.01
	(0.08)	(0.00)	(0.02)	(0.03)	(0.41)
Appendix I and II, with tariffs	-19.98	0.08	-0.02	0.95	1.41
	(0.05)	(0.02)	(0.02)	(0.02)	(0.23)

Notes: ΔWE denotes the percentage changes in world carbon emissions, WPSE the world percentage scale effects, WPCE the world percentage composition effects, WPTE the world percentage technique effects, WLSE the world log scale effects, WLCE the world log composition effects, WLTE the world log technique effects, and LR the leakage rates. Note that $WPSE + WPCE + WPTE = \Delta WE$ (up to the approximation and rounding errors), while $WLSE + WLCE + WLTE = 1$ (up to rounding errors). The numbers in parentheses below the reported values give the corresponding bootstrapped standard errors.

3.7 Conclusions

The effectiveness of unilateral or at least sub-global climate policies is undermined by carbon leakage. One policy measure that may tackle this problem and that is widely discussed in this context is the introduction of carbon tariffs.

Using a multi-sector, multi-factor Anderson and van Wincoop (2003)-type structural gravity model, we first counterfactually introduce carbon tariffs to investigate their trade, welfare, and emission effects. We find that trade decreases, welfare is reduced in most countries (and most strongly in the developing world), carbon emissions are partly shifted from countries with low carbon taxes to countries with high carbon taxes (i.e. carbon leakage is reduced), and world carbon emissions decrease by 0.50 percent, driven primarily by composition effects. Hence, based on our model, we find that carbon tariffs have some desirable effects: a reduction of carbon leakage and a decrease of world emission. But these effects have welfare costs which are mainly borne by developing countries. Qualitatively similar but stronger effects are obtained when considering production-based instead of product-based carbon tariffs. Allowing for energy market leakage reduces the effectiveness of carbon tariffs due to a counteracting technique effect.

We additional apply our framework to analyze the effects of one of the latest attempts to obtain binding emission reduction commitments at an international level, namely the Copenhagen Accord. We find that the effectiveness of such a sub-global climate agreement is hampered by carbon leakage. Specifically, 13.4 percent of the potential emission reduction are lost. Accompanying the emission targets with carbon tariffs towards non-committing countries significantly reduces the leakage rate to 4.1 percent. The 8.4 percent reduction of world emissions (mainly driven by the technique effect) in the scenario without tariffs is payed for with high welfare losses in committing countries, while non-committing countries tend to strongly gain in this case. The welfare costs of the further reduction of an additional 0.9 percentage points in the scenario with tariffs, however, is mainly borne by the non-committing countries.

There are several issues in the given model framework which ask for further research. For example, there are no dynamic effects, technology is fixed (in the sense that the parameters of the production function do not change), climate change impacts on countries' productivities are not directly taken into account, and policies are exogenous. Nevertheless, this paper contributes to the literature by providing a framework with a sectoral structure in which counterfactual analyses of exogenous changes in trade costs, national emission targets, and carbon tariffs can be conducted and the resulting emission changes can be decomposed into scale, composition, and technique effects.

4

The Consequences of Unilateral Withdrawals from the Paris Agreement[1]

4.1 Introduction

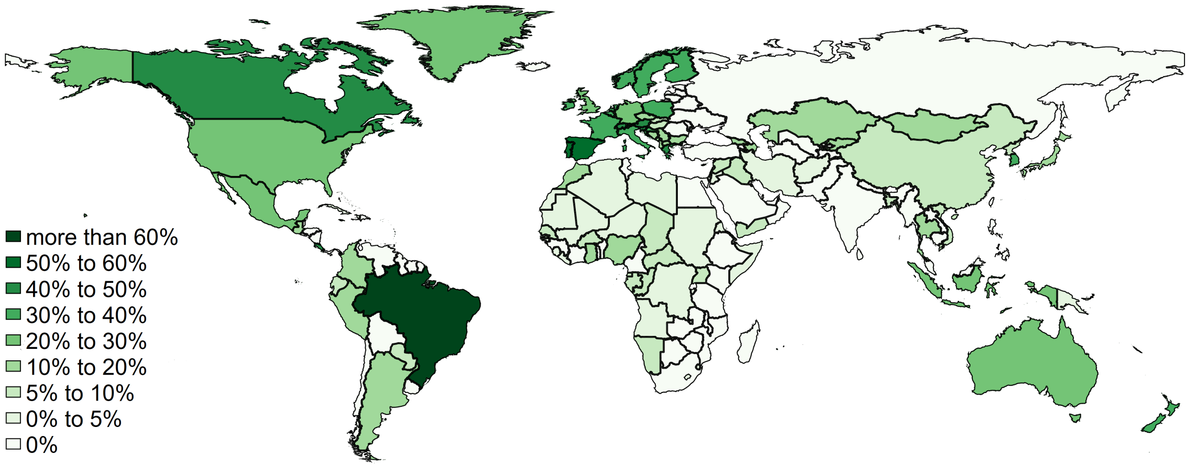
> *The coming into force of [the] Paris Agreement has ushered in a new dawn for global cooperation on climate change.*
> (UN Secretary General Ban Ki-Moon, November 15th, 2016)
>
> *[I]n order to fulfill my solemn duty to protect America and its citizens, the United States will withdraw from the Paris Climate Accord.*
> (US President Donald Trump, June 1st, 2017)

In December 2015, the parties to the United Nations Framework Convention on Climate Change (UNFCCC) reached a joint agreement to combat climate change. With its 195 signing countries, the Paris Agreement constitutes a truly global consensus to take

[1]This chapter is joint work with Mario Larch. We thank participants at the TRISTAN workshop 2018 in Bayreuth, ETSG 2018 in Warsaw, FIW Research Conference "International Economics" 2018 in Vienna, Midwest International Economics Group Meeting 2019 in Bloomington, as well as at research seminars in Innsbruck, Nottingham, St. Catharines (Brock University), Penn State, Philadelphia (Drexel University), and Paris (CEPII).

appropriate measures to keep global warming well below two degrees Celsius. One centerpiece of the agreement are the Nationally Determined Contributions (NDCs) in which every country specifies an individual greenhouse gas (GHG) emission reduction target. Figure 4.1 shows the different national reduction targets, standardized to reductions compared to a business as usual (BAU) scenario in 2030, to make the targets comparable.

Figure 4.1: Emission Reduction Targets in the Paris Agreement

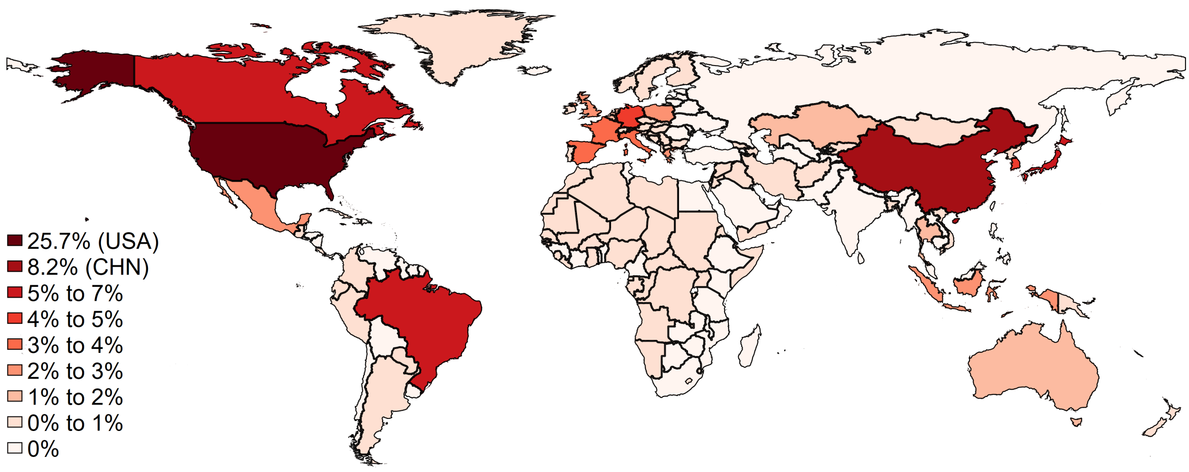


Notes: This figure shows the emission reduction targets specified in the individual countries' NDCs (or, where no NDCs are available, the Intended NDCs). To make the targets comparable, all are given as reductions below the business as usual emission path in 2030. National targets aggregate to a 14.7% global reduction compared to a BAU emission path. For details on the targets and their standardization, see Section 4.3.

The large heterogeneity in ambition of the targets becomes evident at first sight. While some Asian and African countries merely commit to not *increase* their emissions beyond the BAU path and some have very mild targets (like the 5.0% of China), large parts of Europe and the Americas formulate strong targets that in some cases lower their emission by more than half. What is more crucial though and most likely explains at least part of the enthusiasm expressed for example in the first opening quote by the former UN Secretary General Ban Ki-Moon, is the fact that *every country* has a target. The subglobal coverage of the Paris Agreement's most prominent predecessor, the Kyoto Protocol, has severely harmed its effectiveness due to leakage effects (see e.g. Aichele and Felbermayr, 2012, 2015). Carbon leakage refers to the phenomenon that climate policies undertaken in some countries can actually lead to *increased* emissions in other places where no such policies are undertaken due to (i) production shifts of emission-intensive goods towards the un- (or less) regulated countries and (ii) falling fossil fuel prices on the world market that incentivize a more fossil fuel-intensive production (see e.g. Felder and Rutherford, 1993). The underlying free-riding problem of international climate policy is analyzed by Nordhaus (2015).

As the second opening quote by US President Donald Trump clearly shows, the hope of actually achieving the world emission reduction that would result from adding up all national targets appears overly optimistic. The United States have announced their withdrawal, other signing countries of the agreement (such as e.g. Iran, Russia, and Turkey) have not yet moved on to ratification. Countries that decide not to commit to their emission targets harm the effectiveness of the Paris Agreement in two ways. First and most obviously, the sum of the national targets is lowered if some countries drop their target. Second and potentially just as importantly, withdrawals can induce carbon leakage that lowers the actually achieved world reduction below the remaining sum of national targets. The first effect can easily be calculated by combining the national targets shown in Figure 4.1 with data on the national emission levels and is shown in Figure 4.2 and (for the five countries with the strongest effects) in Table 4.1.

Figure 4.2: World Reduction Lost by Withdrawn Commitments (Direct Effect Only)



Notes: This figure shows for every country in turn, which share of the world emission reduction due to the Paris Agreement would be lost if the respective country withdraws from the agreement and its target specified in the NDC is hence no longer part of the global reduction. Endogenous adjustments of withdrawing country to other countries' climate policies with potentially resulting emission *increases* in the withdrawing country beyond the BAU path are not taken into account at this point.

Table 4.1: Top Five Direct Reduction Losses

Withdrawing country	USA	CHN	BRA	CAN	JPN
World reduction lost (direct effect)	25.7%	8.2%	5.8%	5.5%	5.1%

China (7241 Mt CO_2)[2] and the United States (5108 Mt CO_2) are by far the largest emitters. Unsurprisingly, their withdrawals would directly lower the world emission reduction comparatively strongly. Even though the US comes second in terms of emissions, its combination of large emissions with a rather ambitious NDC reduction target (21%) makes the direct effect of a US withdrawal the by far strongest of all countries: more than a quarter of the global reduction would be lost due to the absence of the US target. China (8.2% world reduction loss) comes in second, while Brazil (5.8%) has the third strongest effect. These two countries' strong effects come about in very different ways: very large emissions and a mild target in one case (China) and much lower emissions (about 5% of the Chinese level) and a very ambitious target (65%) in the other case (Brazil). Besides these three countries, a group of European countries, as well as a few more large developed countries (Canada, Japan, and South Korea) combine high emission levels and strong targets to notable direct reduction losses in case of withdrawal of three to five percent. All African and most Asian countries have either sufficiently low emissions or very small targets (or both), so that the loss of their target would not alter the achieved world reduction conceivably.

Two prominent examples illustrate the limitations of considering only the direct effect of removing a withdrawing country's target particularly well: India and Russia. Both these countries have targets that imply only a commitment to *not increase* emissions above the BAU path. Obviously, removing such a "zero target" does not change the sum of targets and hence, these countries' withdrawals are depicted with a zero effect in Figure 4.2. But indeed, an Indian or Russian decision to withdraw from the Paris Agreement and to not take any climate policy measures may induce carbon leakage and therefore harm the achieved global emission reduction indirectly. Such leakage effects will not

[2]The emission data used here refer to the year 2011 and capture only carbon and no other GHG emissions. For details, see Section 4.3.

only introduce effects for countries with zero targets, but it will also amplify the effects of all other countries' withdrawals.

Different from the direct effects, leakage effects (and hence the total effects) of unilateral withdrawals cannot be simply calculated, but have to be solved using a multi-country general equilibrium framework. The most common approach to investigate the global effects of different trade and climate policies is the use of computable general equilibrium (CGE) models (see e.g. Böhringer, Balistreri, and Rutherford, 2012, for an overview of various prominent CGE models). A recent strand of literature (Egger and Nigai, 2015; Larch and Wanner, 2017; Larch, Löning, and Wanner, 2018; Shapiro, 2016; Shapiro and Walker, 2018) incorporates environmental components into structural gravity models as an alternative approach.[3] Gravity models are the workhorse models in the empirical international trade literature. Just as CGE models, they can be used to conduct ex ante analyzes of different policy scenarios. Compared to typical CGE models, they tend to sacrifice some detail in the model structure in favor of higher analytical tractability and direct estimation of key model parameters.

Given gravity's great success in predicting trade flows (see e.g. Head and Mayer, 2014; Costinot and Rodríguez-Clare, 2014, for surveys on gravity models and their performance), it is likely to capture well leakage that occurs via production shifts and international trade. In fact, the main model of Larch and Wanner (2017), as well as the models by Shapiro (2016) and Shapiro and Walker (2018) exclusively focus on this leakage channel. In this paper, we extend the model of Larch and Wanner (2017) by considering fossil fuel resources that are internationally traded and supplied according to a constant elasticity of fossil fuel supply function as proposed in the CGE context by Boeters and Bollen (2012). The resulting extended gravity model will capture leakage effects via international trade and via the international fossil fuel market and hence allow a quantification of the total emission reduction losses associated with unilateral withdrawals from the Paris Agreement. At the same time, the model structure remains

[3]Pothen and Hübler (2018) develop a hybrid model, combining an Eaton and Kortum (2002)-type gravity trade structure with a CGE model production structure.

tractable enough to allow an analytical and quantitative decomposition of the national emission changes into scale, composition, and technique effects as is often done in the theoretical and empirical literature on trade and the environment (see e.g. Grossman and Krueger, 1993; Copeland and Taylor, 1994, 2003). Such a decomposition can generate important insights on the channels via which international climate policies are effective.

Our analysis of the effects of unilateral withdrawals complements other studies that investigate the Paris Agreement and its implications. For example, Rogelj, den Elzen, Höhne, Fransen, Fekete, Winkler, Schaeffer, Sha, Riahi, and Meinshausen (2016) analyze whether the individual national targets are sufficient to jointly achieve the two (or even 1.5) degree Celsius target. Aldy and Pizer (2016), Aldy, Pizer, and Akimoto (2017), and Iyer, Calvin, Clarke, Edmonds, Hultman, Hartin, McJeon, Aldy, and Pizer (2018) aim to make the different NDCs comparable in their implied required mitigation efforts of the different countries. Rose, Wei, Miller, Vandyck, and Flachsland (2018) investigate one particular way for actually achieving the reduction pledges in an efficient way, namely by linking different emissions trading schemes. Nong and Siriwardana (2018) analyze the consequences of a US withdrawal on the US economy, finding besides others a significant drop in energy prices. Böhringer and Rutherford (2017) and Winchester (2018) show that the introduction of carbon tariffs is not a credible threat towards the US in order to try to keep them in the agreement. Kemp (2017) considers measures that can be taken in order to reduce the harm done to the effectiveness of the agreement due to a US withdrawal, e.g. by incorporating cooperation with US states. We contribute to the literature by quantifying the harm done by countries withdrawing from the Paris Agreement taking into account both direct effects and emission shifts (leakage) resulting from general equilibrium adjustments of supply and demand of goods and fossil fuels.

The rest of this paper proceeds as follows. Section 4.2 develops our extended structural gravity model, shows how counterfactual analyzes can be performed in this framework, and derives the emission change decomposition. In Section 4.3, the data sources and descriptive statistics are presented, as well as the gravity estimation procedure. We discuss the results of simulating the unilateral withdrawal for every country in Section 4.4. In Section 4.5, we derive a model extension with multiple fossil fuels of varying carbon intensities, demonstrate how this extension leads to a fourth, substitution, effect on emissions, and rerun the simulations using the extended model. Section 4.6 concludes.

4.2 Model

In this section, we develop an extended structural gravity model including a non-tradable and multiple tradable sectors, a multi-factor production function including an energy input, energy production including an internationally tradable fossil fuel resource, a constant elasticity of fossil fuel supply (CEFS) function following Boeters and Bollen (2012), as well as emissions associated to the fossil fuel usage. The model builds on the framework by Larch and Wanner (2017), but importantly deviates by (i) modeling the energy-market leakage channel using a CEFS function[4], (ii) linking emissions directly to fossil fuel use rather than to general energy use, and (iii) explicitly including a carbon tax which countries can use to achieve emission reduction targets.

Demand

Consumers in country $j \in \mathcal{N}$ (where $\mathcal{N}$ denotes the set of all countries in the world) obtain utility according to the following utility function:

$$U^j = (U_S^j)^{\gamma_S^j} \left[\prod_{l \in \mathcal{L}} (U_l^j)^{\gamma_l^j} \right] \left[\frac{1}{1 + \left(\frac{1}{\mu^j} \sum_{i \in \mathcal{N}} R^i \right)^2} \right], \tag{4.1}$$

[4]The base model of Larch and Wanner (2017) only features the trade leakage channel, while the small model extension presented in their work relies on an energy resource in fixed supply.

with

$$U_l^j = \left[\sum_{i \in \mathcal{N}} (\beta_l^i)^{\frac{1-\sigma_l}{\sigma_l}} (q_l^{ij})^{\frac{\sigma_l - 1}{\sigma_l}} \right]^{\frac{\sigma_l}{\sigma_l - 1}}, \tag{4.2}$$

where subscript S denotes the non-tradable sector, $l \in \mathcal{L}$ is one of the tradable sectors (with $\mathcal{L}$ being the set of all tradable sectors), γ_l^j represents the expenditure share of sector l in country j, μ^j is a parameter that captures j's disutility from global carbon emissions, R^i is country i's fossil fuel use which is proportional to its emissions, β_l^i represents the utility parameter for tradable goods, q_l^{ij} is the amount of good l from country i consumed in country j, and σ_l stands for the sectoral elasticity of substitution. Equations (4.1) and (4.2) hence combine linear utility from non-tradable good consumption and CES utility from tradable goods consumption in an upper-tier Cobb-Douglas utility function (implying constant sectoral expenditure shares), as well as disutility from global emissions in the functional form chosen by Shapiro (2016) in order to ensure almost constant social costs of carbon around the baseline emission level.

Carbon emissions are treated as a pure externality (and are therefore not taken into account in the consumption decisions). Demand for non-tradable goods is then simply given by the corresponding expenditure $\mathfrak{X}_S^j$ divided by the non-tradable good price $\left(q_S^j = \mathfrak{X}_S^j / p_S^j\right)$. Demand for tradable goods l from i in j follows from CES utility as:

$$q_l^{ij} = \left(\frac{\beta_l^i p_l^{ij}}{P_l^j} \right)^{-\sigma_l} \left(\frac{\beta_l^i \mathfrak{X}_l^j}{P_l^j} \right), \tag{4.3}$$

where p_l^{ij} is the price including trade costs from i to j and P_l^j is the sectoral price index in j, given by:

$$P_l^j = \left[\sum_{i \in \mathcal{N}} (\beta_l^i p_l^{ij})^{1-\sigma_l} \right]^{\frac{1}{1-\sigma_l}}. \tag{4.4}$$

Supply

Each country produces a non-tradable good S, as well as a differentiated variety of each of $l \in \mathcal{L}$ tradable goods according to the following Cobb-Douglas production functions:

$$q_S^i = A_S^i (E_S^i)^{\alpha_{SE}^i} \prod_{f \in \mathcal{F}} (V_{Sf}^i)^{\alpha_{Sf}^i}, \tag{4.5}$$

$$q_l^i = A_l^i (E_l^i)^{\alpha_{lE}^i} \prod_{f \in \mathcal{F}} (V_{lf}^i)^{\alpha_{lf}^i}, \tag{4.6}$$

where A_S^i and A_l^i are sector- and country-specific productivity parameters, α_{SE}^i, α_{lE}^i, α_{Sf}^i, and α_{lf}^i denote production cost shares, and V_{Sf}^i and V_{lf}^i the usages of a production factor $f \in \mathcal{F}$. Countries are endowed with a fixed factor supply V_f^i and factors are mobile across sectors, but internationally immobile. E_S^i and E_l^i denote the energy inputs in producing non-tradable and tradable goods, respectively. Different from the other production factors, countries are not endowed with a fixed energy supply, but the energy inputs have to be produced themselves according to the following Cobb-Douglas production function:

$$E^i = A_E^i (R^i)^{\xi_R^i} \prod_{f \in \mathcal{F}} (V_{Ef}^i)^{\xi_f^i}, \tag{4.7}$$

where ξ_R^i and ξ_f^i denote the input cost shares and R^i is the usage of a freely internationally tradable fossil fuel resource. National factor markets are assumed to clear, i.e. $V_f^i = V_{Sf}^i + \sum_{l \in \mathcal{L}} V_{lf}^i + V_{Ef}^i$, determining the factor prices v_f^i. Countries can charge a national carbon tax λ^i on the use of fossil fuels in order to fulfill specific emission reduction targets and the fossil fuel price r is determined on the world market by global market clearing:

$$r = \frac{1}{R^W} \sum_{i \in \mathcal{N}} \left(\frac{1}{1 + \lambda^i} \right) \xi_R^i \left(\alpha_{SE}^i Y_S^i + \sum_{l \in \mathcal{L}} \alpha_{lE}^i Y_l^i \right), \tag{4.8}$$

where $Y_S^i = q_S^i p_S^i$ and $Y_l^i = q_l^i p_l^i$ are the sectoral values of production. Following Boeters and Bollen (2012), a change in the fossil fuel price is translated into a change in the global supply of the fossil fuel with a constant elasticity of fossil fuel supply function:

$$\widehat{R^W} = (\widehat{r})^{\eta}\,, \tag{4.9}$$

where η denotes the supply elasticity and the hat notation (introduced into the structural gravity literature by Dekle, Eaton, and Kortum, 2007, 2008) indicates the change of the respective variables, i.e. $\widehat{R^W} = \frac{R^{W\prime}}{R^W}$ and $\widehat{r} = \frac{r'}{r}$, where the prime indicates a counterfactual value in response to a policy shock and values without a prime correspond to the baseline equilibrium. The total fossil fuel supply R^W stems from the different countries according to their varying fossil fuel endowment shares ω^i (with $\sum_{i \in \mathcal{N}} \omega^i = 1$).

A change in the fossil fuel world market price further leads to an adjusted national energy price:

$$\widehat{e}^i = \left(\widehat{(1+\lambda^i)}\widehat{r}\right)^{\xi_R^i} \prod_{f \in \mathcal{F}} \left[\frac{(\alpha_{Sf}^i + \xi_f^i \alpha_{SE}^i) Y_S^{i\prime} + \sum_{l \in \mathcal{L}} (\alpha_{lf}^i + \xi_f^i \alpha_{lE}^i) Y_l^{i\prime}}{(\alpha_{Sf}^i + \xi_f^i \alpha_{SE}^i) Y_S^i + \sum_{l \in \mathcal{L}} (\alpha_{lf}^i + \xi_f^i \alpha_{lE}^i) Y_l^i}\right]^{\xi_f^i}. \tag{4.10}$$

Note that the adjustment of the energy price in response to a policy shock further depends on the endogenously adjusted, counterfactual production values. Subsection 4.2.1 will lay out the full system of equations that can—for a given counterfactual policy shock—be solved for the values of a sufficient set of endogenous variables from which all variables of interest can then be obtained.

Income

Countries generate income from (i) the expenditure on their national production factors, (ii) their share of the global supply of the fossil fuel, and (iii) the carbon tax charged on its fossil fuel use:

$$Y^i = \sum_{f\in\mathcal{F}} \left[(\alpha^i_{Sf} + \xi^i_f \alpha^i_{SE}) Y^i_S + \sum_{l\in\mathcal{L}} (\alpha^i_{lf} + \xi^i_f \alpha^i_{lE}) Y^i_l \right] + \omega^i \sum_{j\in\mathcal{N}} \left(\frac{1}{1+\lambda^j} \right) \xi^j_R \left(\alpha^j_{SE} Y^j_S + \sum_{l\in\mathcal{L}} \alpha^j_{lE} Y^j_l \right) + \left(\frac{\lambda^i}{1+\lambda^i} \right) \xi^i_R \left(\alpha^i_{SE} Y^i_S + \sum_{l\in\mathcal{L}} \alpha^i_{lE} Y^i_l \right). \tag{4.11}$$

Trade Flows

Introducing iceberg trade costs T^{ij}_l (with $T^{ij}_l = T^{ji}_l \geq 1$ and $T^{ii}_l = 1$) and defining sectoral scaled equilibrium prices as $\psi^i_l \equiv (\beta^i_l p^i_l)^{1-\sigma_l}$, the exports of country i to country j in sector l can be obtained from the bilateral demand given in Equation (4.3) as:

$$X^{ij}_l = \left(\frac{\psi^i_l T^{ij}_l}{P^j_l} \right)^{1-\sigma_l} \mathfrak{X}^j_l. \tag{4.12}$$

This gravity equation links bilateral trade flows to bilateral trade costs, the importer's market size and overall openness (captured by the price index which is equivalent to Anderson and van Wincoop (2003)'s inward multilateral resistance), as well as the overall exporting capability of country j (summarized by ψ^i_l which implicitly captures the exporter's size in terms of production and its outward multilateral resistance).

Assuming balanced trade and market clearing, as well as using the sectoral price index given by Equation (4.4), from Equation (4.12) we can obtain an expression which links the sectoral production to the international trade cost matrix:

$$Y^i_l = \psi^i_l \sum_{j=1}^{N} \frac{(T^{ij}_l)^{1-\sigma_l}}{\sum_{k=1}^{N} \psi^k_l (T^{kj}_l)^{1-\sigma_l}} \gamma^j_l Y^j. \tag{4.13}$$

4.2.1 Comparative Statics

Equation (4.8) for the world market price of fossil fuels, Equation (4.9) depicting the constant elasticity of fossil fuel supply function, Equation (4.10) that captures the response in energy prices, Equation (4.11) which describes total national income, and Equation (4.13) linking sectoral production values and scaled equilibrium prices to the trade cost matrix (or the counterfactual equilibrium counterparts of these equations) describe a system of equations that can almost be solved for a given policy shock. Cost minimization in production allows to derive the second last necessary equation which captures the change in factory-gate prices (or equivalently in scaled equilibrium prices):

$$\left(\widehat{\psi}_l^i\right)^{\frac{1}{\sigma_l - 1}} = \left(\widehat{e}^i\right)^{\alpha^i_{lE}} \prod_{f \in \mathcal{F}} \left(\frac{(\alpha^i_{Sf} + \xi^i_f \alpha^i_{SE}) Y^i_S + \sum_{m \in \mathcal{L}} (\alpha^i_{mf} + \xi^i_f \alpha^i_{mE}) Y^i_m}{(\alpha^i_{Sf} + \xi^i_f \alpha^i_{SE}) Y^{i\prime}_S + \sum_{m \in \mathcal{L}} (\alpha^i_{mf} + \xi^i_f \alpha^i_{mE}) Y^{i\prime}_m} \right)^{\alpha^i_{lf}} . \tag{4.14}$$

The last equation needed to solve the model for the counterfactual equilibrium stems from the specific policy scenario under investigation. We will run different scenarios in all of which all countries around the world will fulfill the emission reduction targets specified in their NDCs, except for one country that decides to withdraw from the agreement. We can link this scenario to the choice of the carbon tax λ^i in the model. Denoting the set of committed (or cooperating) countries by cop, the country that is not part of the agreement chooses a zero carbon tax, while all other countries choose their carbon tax exactly at the required level to ensure that their realized emissions are equal to their targeted emission level (denoted by $\overline{R^{i\prime}}$):

$$\lambda^i = \begin{cases} 0 \quad \text{if } i \notin cop, \\ \frac{\xi^i_R \left(\alpha^i_{SE} Y^{i\prime}_S + \sum_{l \in \mathcal{L}} \alpha^i_{lE} Y^{i\prime}_l\right)}{\overline{R^{i\prime}} r^\prime} - 1 \quad \text{if } i \in cop. \end{cases} \tag{4.15}$$

4.2.2 Decomposition of Emission Changes

As emissions are proportional to a country's fossil fuel use, emissions in country i can be written as:

$$R^i = \frac{\xi_R^i \left(\alpha_{SE}^i Y_S^i + \sum_{l \in \mathcal{L}} \alpha_{lE}^i Y_l^i\right)}{(1+\lambda^i)r} = \xi_R^i \bar{\alpha}_E^i \frac{\tilde{Y}^i}{P^i} \left(\frac{r^i}{P^i}\right)^{-1}, \tag{4.16}$$

where $\tilde{Y}^i \equiv Y_S^i + \sum_{l \in \mathcal{L}} Y_l^i$ denotes total production, $\bar{\alpha}_E^i \equiv \alpha_{SE}^i \frac{Y_S^i}{\tilde{Y}^i} + \sum_{l \in \mathcal{L}} \alpha_{lE}^i \frac{Y_l^i}{\tilde{Y}^i}$ is the production-share-weighted average energy cost share, and $r^i \equiv (1+\lambda^i)r$ is the national price for fossil fuels (including the carbon tax). Intuitively, the level of emissions in a country depends on (i) how much is spend for energy inputs in production, (ii) which share of the energy input expenditure is paid for fossil fuel inputs in energy production, and (iii) how expensive fossil fuels are (both in terms of the world market price and the national carbon tax).

Following Grossman and Krueger (1993) and Copeland and Taylor (1994) (as well as Larch and Wanner, 2017, in a structural gravity context), the change in emissions can then be decomposed into three parts:

$$dR^i = \underbrace{\frac{\partial R^i}{\partial(\tilde{Y}^i/P^i)} d(\tilde{Y}^i/P^i)}_{\text{scale effect}} + \underbrace{\frac{\partial R^i}{\partial \bar{\alpha}_E^i} d\bar{\alpha}_E^i}_{\text{composition effect}} + \underbrace{\frac{\partial R^i}{\partial(r^i/P^i)} d(r^i/P^i)}_{\text{technique effect}}.$$

Scale Effect. A country's fossil fuel use (and hence emissions) increases proportionally with the size of the economy (measured as the real value of production):

$$\frac{\partial R^i}{\partial(\tilde{Y}^i/P^i)} = \frac{\xi_R^i \bar{\alpha}_E^i}{(1+\lambda^i)r/P^i} > 0 \quad \text{and} \quad \frac{\partial R^i}{\partial(\tilde{Y}^i/P^i)} \frac{(\tilde{Y}^i/P^i)}{R^i} = 1.$$

Composition Effect. An increase in the average energy intensity of production in a country (measured by the weighted average energy cost share) proportionately increases the country's carbon emissions:

$$\frac{\partial R^i}{\partial \bar{\alpha}_E^i} = \frac{\xi_R^i \tilde{Y}^i}{(1+\lambda^i)r} > 0 \quad \text{and} \quad \frac{\partial R^i}{\partial \bar{\alpha}_E^i}\frac{\bar{\alpha}_E^i}{R^i} = 1.$$

Technique Effect. An increase in the fossil fuel resource price—either due to a higher world market price or due to a higher national carbon tax—proportionately *lowers* a country's carbon emissions:

$$\frac{\partial R^i}{\partial (r^i/P^i)} = -\frac{\xi_R^i \bar{\alpha}_E^i \tilde{Y}^i/P^i}{(r/P^i)^2} < 0 \quad \text{and} \quad \frac{\partial R^i}{\partial (r^i/P^i)}\frac{r^i/P^i}{R^i} = -1.$$

4.3 Data and Estimation

4.3.1 Data Sources

Our main data source is the Global Trade Analysis Project (GTAP) 9 database (Aguiar, Narayanan, and McDougall, 2016). From GTAP, we take the data on carbon emissions, sectoral production, trade flows, factor expenditures, and expenditure for and income from fossil fuels.[5] GTAP also provides estimates for the sectoral elasticities of substitution of which we make use. Unfortunately, no estimate is available for the fossil fuel supply elasticity. For our main model, we therefore choose the simple average of the values reported by Boeters and Bollen (2012) for the three different specific fossil fuels oil, gas, and coal, namely $\eta = 2$.[6]

The GTAP 9 data is given for the base year 2011. We hence construct our whole data set for this year. It captures 139 countries (some of which are in fact aggregates of

[5] See Appendix D.2 for details on the parametrization of the model.

[6] In our model extension presented in Section 4.5 we can directly use Boeters and Bollen (2012)'s values, specifically $\eta_{oil} = \eta_{gas} = 1$, $\eta_{coal} = 4$.

several countries) covering the whole world. We aggregate the sectoral structure to one non-tradable and 14 tradable sectors.[7]

For the gravity estimation of bilateral trade costs, we rely on a set of standard gravity variables from the CEPII dataset by Head, Mayer, and Ries (2010), namely bilateral distance ($DIST$), an indicator variable for whether two countries share a common border ($BRDR$), and a second indicator variable for a common official language ($LANG$). We complement these variables by an indicator variable for joint regional trade agreement (RTA) membership taken from Mario Larch's RTA database (Egger and Larch, 2008).

The (I)NDCs of the signatory states of the Paris Agreement are collected and made available online at the United Nations NDC Registry and summarized by the World Resources Institute.[8] In order to translate the different emission targets into 2030 BAU reduction targets, we additionally use GDP and carbon emission projections by the US Energy Information Administration's (EIA) International Energy Outlook 2016.

The gravity and emission target data are aggregated to the regional structure of the GTAP data base.

4.3.2 Standardization of Reduction Targets

The reduction targets depicted in Figure 4.1 are percentage reductions of carbon emissions below the 2030 business as usual emission level.[9] They hence relate to the counterfactual emission level enforced in the counterfactual scenarios by $target^i = 1 - \overline{R^{i\prime}}/R^i$. Note that while we calculate the reduction targets for the 2030 time frame, we will refrain from projecting all model variables and parameters to 2030 and therefore im-

[7] The 14 tradable sectors are agriculture, apparel, chemical, equipment, food, machinery, metal, mineral, mining, other, paper, service, textile, and wood. See Larch and Wanner (2017) for the concordance to the 57 original GTAP sectors.

[8] See https://www4.unfccc.int/sites/NDCStaging/Pages/All.aspx (accessed on August 16th, 2019) and https://cait.wri.org/indc/ (accessed on August 16th, 2019).

[9] Note that strictly speaking the targets refer to CO_2 equivalents of all greenhouse gas emissions. Due to better data availability, we use carbon emission paths for the projections to 2030.

plement all scenarios as changes from the 2011 baseline equilibrium (implying that R^i refers to national emissions in 2011).

Different countries' (I)NDCs are specified in different ways, e.g. in terms of emission levels or intensities and compared to varying base years or to a BAU projection. In the simplest case, a country specifies a reduction target relative to BAU ($target = target^{NDC}_{BAU}$, suppressing the country superscript for ease of notation).

Some countries specify a specific targeted reduction of the *level* of emissions in 2030 compared to a reference (ref) year ($target^{NDC}_{level}$), as was e.g. the case for all targets in the Kyoto Protocol, which translates into our business as usual target as follows:

$$target = 1 - \left(1 - target^{NDC}_{level}\right) \frac{CO_{2,ref}}{CO^{proj}_{2,2030}}, \tag{4.17}$$

where $CO^{proj}_{2,2030}$ are projected BAU emissions in 2030.

The final type of target is an emission intensity target. In this case, a country specifies the reduction of emissions per (value) unit of GDP it aims to achieve compared to a reference year intensity ($target^{NDC}_{int}$). This corresponds to a 2030 BAU target as follows:[10]

$$target = 1 - (1 - target^{NDC}_{int}) \frac{CO_{2,ref}/GDP_{ref}}{CO^{proj}_{2,2030}/GDP^{proj}_{2030}}. \tag{4.18}$$

Whenever countries reported a range for their targeted reduction, we chose the center of this range. We did not take into account additional, higher reduction promises that are conditional on other parties' behavior (e.g. financial support).[11] Neither did we incorporate any other components of the NDCs beyond the greenhouse gas reduction commitments (such as additionally targeted renewable energy shares). In a few cases the combination of NDCs and GDP and emission projections imply a target that represents an increase over the BAU emission path. For these Paris member countries, we assume

[10]Israel reported an intensity target per capita rather than per unit of GDP. In this case, simply substitute the GDP values by observed and projected population sizes.

[11]In some cases, countries did not specify which part of the target is conditional. We treated these commitments as entirely conditional.

in the counterfactual scenarios that they commit to not emit more CO_2 than in the BAU case (i.e. $target = 0$). For both level and intensity targets, some countries deviated from the 2030 target year and reported for instance targets for 2025. We treated these targets as if they were specified for 2030. Finally, some countries reported only certain mitigation actions rather than reduction targets or targets for specific sectors only. We treated these countries as committing to the BAU scenario (i.e. $target = 0$). Table D.2 in Appendix D.2 reports the targets that result from this procedure and which are used in our counterfactual analyses.

4.3.3 Selected Descriptive Statistics

Given the critical role of initial emission levels for the importance of the different national reduction targets (and, as will turn out, for the leakage potential), Figure 4.3 displays the national levels of carbon emissions. China and the US stand out as the strongest emitters, followed by other large developed or emerging economies, such as India, Russia, Japan, Germany, and Canada.

Figure 4.3: National Carbon Emissions in 2011

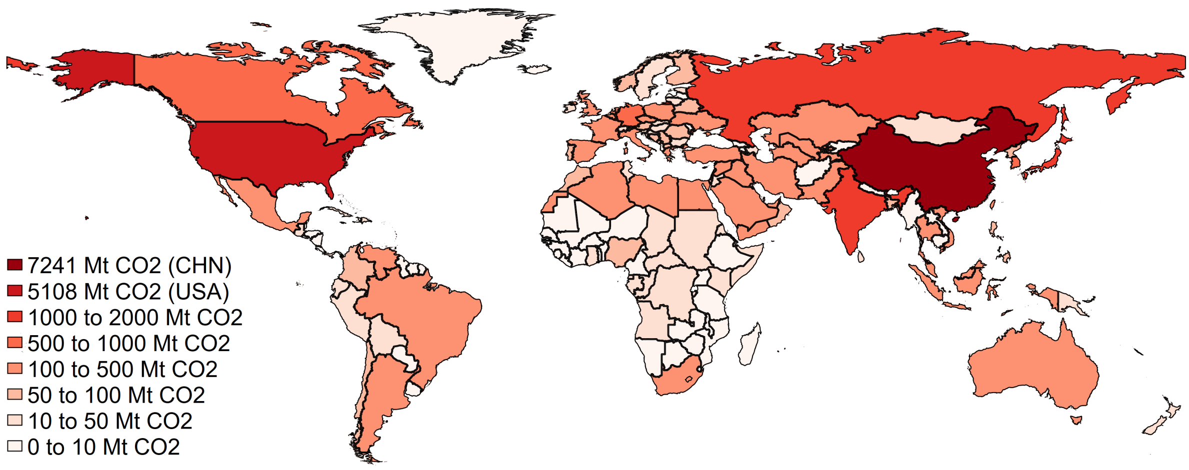


Table 4.2 additionally summarizes the gravity variables used in the trade cost estimation: country pairs are on average 7600 km apart, 2% share a common border, 11% share a common official language, and 23% are joint members of a regional trade agreement.

Table 4.2: Gravity Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Distance (in km)	19,321	7568.75	4334.84	8.45	19781.39
Contiguity	19,321	0.02	0.14	0	1
Common Language	19,321	0.11	0.31	0	1
RTA	19,321	0.23	0.42	0	1

4.3.4 Gravity Estimation

Estimates of bilateral trade costs can be obtained based on the gravity Equation (4.12) derived above. Approximating trade costs by a function of observable bilateral characteristics (captured by the vector $\mathbf{z}_{ij}$), collecting all (partly unobservable) importer- and exporter-specific terms and introducing an error term yields the following regression equation:

$$X_l^{ij} = \exp(\pi_l^i + \chi_l^j + \mathbf{z}'_{ij}\boldsymbol{\beta}_l) \times \varepsilon_l^{ij}. \tag{4.19}$$

Following the suggestions by Feenstra (2004) and Santos Silva and Tenreyro (2006), respectively, we capture π_l^i and χ_l^j by the inclusion of exporter and importer fixed effects and estimate the model in its multiplicative form (avoiding problems due to heteroskedasticity and zero trade flows) with the Poisson Pseudo Maximum Likelihood (PPML) estimator. The estimation results for all sectors are shown in Table D.1 in Appendix D.1. Based on these coefficient estimates, we can construct an estimated trade cost matrix.

4.3.5 Model Validation

In this subsection, we briefly discuss how our model fits the data from the baseline equilibrium, as well as how its global emission reactions to a policy shock compare to other models in the literature.

As structural gravity models always do, our model perfectly replicates the national (sectoral) production values. Unsurprisingly, the workhorse model in international trade also fits the sectoral bilateral trade flows very well, indicated by an average Pseudo-R^2 from the gravity regressions of 0.83. Importantly, national carbon emissions are also perfectly fitted in our framework. The sectoral distribution of a country's carbon emissions is closely proxied by the perfectly replicated distribution of sectoral energy expenditures.

In order to investigate whether the model predicts credible reactions to policy shocks (not only in terms of trade effects that are well established in the trade literature, but also in terms of emission changes), we simulate a counterfactual scenario in which all Annex I countries of the Kyoto Protocol reduce their emissions by 20% while all other countries undertake no climate policy and calculate the resulting leakage rate. This type of scenario has been investigated intensively in the literature and therefore can be compared nicely. Using 2011 baseline data, we find a leakage rate of 24.6%. Böhringer, Balistreri, and Rutherford (2012) implement the same scenario in a number of CGE models using data for 2004 and find a range of leakage rates from 5 to 19%. Larch and Wanner (2017) obtain a leakage rate of 12.5% for the base year 2007. Elliott, Foster, Kortum, Munson, Pérez Cervantes, and Weisbach (2010) consider the introduction of specific carbon tax rates rather than explicit reduction targets and—also using 2004 data—find leakage rates in the range of 15 to 25%, which increase in the level of the carbon tax. The prediction of our model hence are at the high end of a typical range of results. However, in comparing the models' predictions one should keep in mind that the Annex I countries covered a larger share of global emissions in 2004 than in 2011. Given the implied smaller coalition size in our case, leakage is expectedly somewhat higher in our simulation.[12]

[12]We re-calibrated our model to 2004 data and ran the same simulation, obtaining—as expected—a somewhat lower leakage rate of 21.3%.

4.4 Counterfactual Analysis: Unilateral Withdrawals from the Paris Agreement

We use the model framework developed in Section 4.2 to investigate the effects of unilateral withdrawals from the Paris Agreement. We consider each of the 139 countries in our data set in turn, i.e. we run 139 different model simulations in all of which *all countries but one* fulfill the targets specified in their NDCs while one country does not undertake any policies towards its reduction aim and instead endogenously adjusts to the policies undertaken by the committed countries. We start this section off by discussing the results for two particularly important and illustrative examples, the US and China, before comparing results across the world.

4.4.1 The US Withdrawal

As discussed in the introduction, the mere erasure of the US target would cut the overall emission reduction of the Paris Agreement by one fourth. But the calculation of this direct effect did not allow for an endogenous adjustment of the US to the climate policies of the Paris member countries, as the US were assumed to follow a BAU emission path rather than fulfill their NDC target. Simulating a US withdrawal as a counterfactual scenario in which all countries introduce carbon taxes that are sufficient to fulfill their reduction targets while the US introduces no carbon tax at all, we find that the US emissions *increase* by 5.7%. This implies a leakage rate of 9.4%, i.e. almost every tenth ton of CO_2 saved in the committed countries is offset by increased emissions in the US. Putting together the loss of the US target and the partial offset of the remaining countries' targets via leakage, we find that a US withdrawal from the Paris Agreement lowers the achieved global emission reduction by a third (32.7%). As shown in Section 4.2.2, we can decompose the US emission increase into three components. It could stem from an overall increase in production (scale effect), a shift towards the production of more energy-intensive goods (composition effect), or the use of more fossil fuel intensive production techniques for a given scale and composition of the economy (technique effect). We find a zero scale effect, a very small composition effect (0.3%) and a very strong technique effect (5.1%).[13] As explained above, the technique effect can occur either due to a carbon tax or due to changes in the world fossil fuel price. As the withdrawing country does not introduce a carbon tax, we can fully attribute the strong positive technique effect to a decline in the fossil fuel price in response to lower fossil fuel demand in the committed countries. US producers make use of this fall in the price to switch towards a more fossil fuel intensive production technique. These findings indicates that the leakage of carbon emissions into the US is almost entirely driven by the energy-market leakage channel. This insight relates to a strand of literature that stresses the role of the supply side in climate policies (cf. e.g. Sinn, 2008; Harstad, 2012; Jensen, Mohlin, Pittel, and Sterner, 2015). If achieving the reduction targets in the rest of the world via carbon taxes (i.e. a demand-side climate policy) induces strong leakage towards the US, climate policies that try to directly limit the *supply* of fossil fuels might be offset to a smaller extent.

4.4.2 A Potential Chinese Withdrawal

China has ratified the Paris Agreement and—different than the US—has not expressed an intention to withdraw. The scenario of a Chinese withdrawal is therefore a much more hypothetical one. Given China's role as the world's largest emitter and its very different economic structure compared to highly developed countries (as the US), we think it is nevertheless an illustrative example that is worth a closer look before moving on to comparing results across the world.

Given China's mild reduction target, we showed in the introduction that the direct

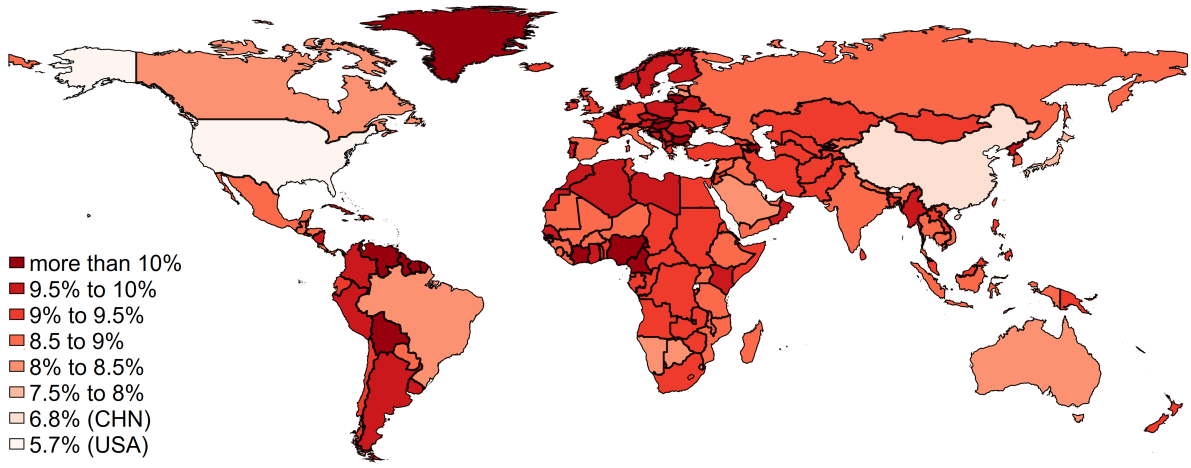
[13] Note that the decomposition relies on a total differential and therefore is a linear approximation around the baseline equilibrium. The three effects hence do not necessarily (and typically) exactly add up to the overall emission change.

effect of removing the Chinese NDC had a far less detrimental effect on the global emission reduction (8.2%) than the US case. But again, this number was based on China following its BAU emission path. In fact, we find that Chinese emissions increase by 6.8% in response to the other countries' carbon taxes if China does not introduce a climate policy of its own. Due to the very high level of Chinese emissions, this is equivalent to a 12.1% leakage rate, i.e. an even higher share of the rest of the world's emission reductions is offset than in the US withdrawal case. Putting the direct loss and the leakage effect together results in a total global emission reduction loss of 19.4% for a Chinese withdrawal from the Paris Agreement. Taking into account an endogenous reaction to the other countries' policies hence more than doubles the overall harm done to the effectiveness of the agreement in this case. As in the US case, the increase in Chinese emissions is almost entirely driven by the fall in the international price for fossil fuels (6.4%, compared to 0.1% scale and a 0.2% composition effect).

4.4.3 Results Across the World

We now turn to comparing the effects of unilateral withdrawals of all countries in our data set. Figure 4.4 shows the emission changes in every country if the rest of the world fulfills its targets and the respective country takes no climate policy action. Unsurprisingly, all countries endogenously react by increasing their emissions. As it turns out, the two examples considered so far (China and the US) are the countries with the smallest percentage emission increases. All other countries experience higher carbon emission increases in the range of 8.0 to almost 11.6%. Comparing the pattern to Figures 4.1 and 4.3, countries with a high overall level of emissions and/or very ambitious reduction targets appear to have lower increases of their emission levels. The reason is that countries with a high overall level of emissions and/or very ambitious reduction targets lead to larger reactions of world prices if they stick to their commitments and therefore reactions for other countries not sticking to their commitments will be larger.

Figure 4.4: National Emission Effects

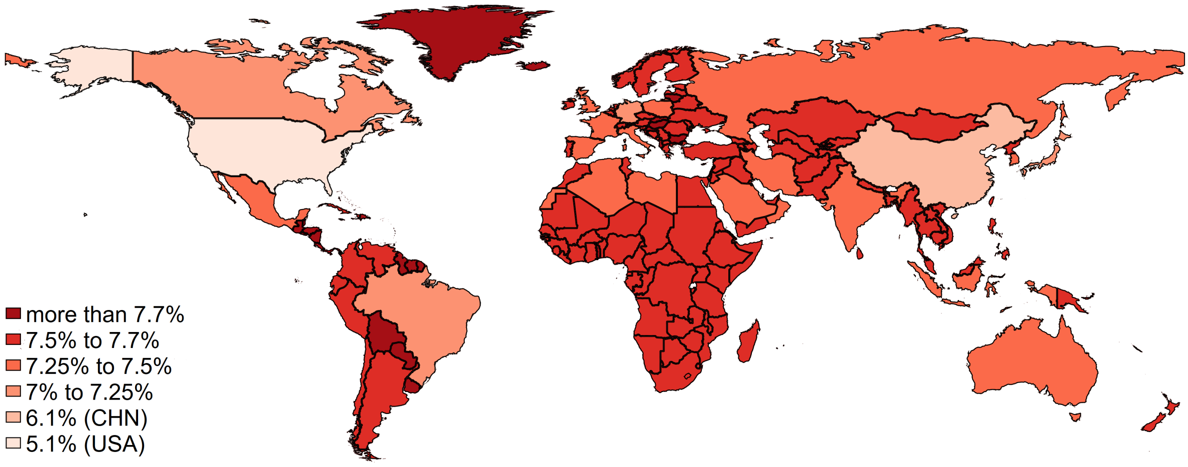


Notes: This figure shows the emission change in each country if the respective country withdraws from the Paris Agreement while the rest of the world fulfills its emission reduction targets. Emissions go up by 9.2% on average, ranging from 5.7% in the US to 11.6% in Trinidad and Tobago.

To dig a little deeper into the differences in national emission effects, we can again make use of the decomposition. Two characteristics of our exemplary considerations hold up as global patterns: the almost complete absence of a scale effect (0.01% on average) and the predominant role of the technique effect (accounting for 89% of the emission increase on average). Different from the Chinese and US cases, the composition effects are non-negligible for many other countries (0.9% on average, ranging up to 2.8%). Figures 4.5 and 4.6 depict the technique and composition effects in the withdrawing countries, respectively.

Just as for the overall emission effect, the technique effect is smallest in the US and China. If one of these major emitters of carbon emissions is absent from the Paris Agreement, the fall in the demand for fossil fuels is strongly attenuated. This implies less pressure on the international fossil fuel price and hence a smaller incentive to shift towards more fossil fuel intensive production techniques. On the other hand, if a small country with a mild reduction target drops out of the agreement, almost the complete sum of national targets is still in place. Therefore, the fossil fuel price goes down by almost the full extent by which it would have been lowered in the case of full global compliance with the Paris Agreement and therefore the withdrawing country faces a very strong incentive towards "dirtier" production techniques induced by the lower fossil fuel price.

Figure 4.5: Technique Effects

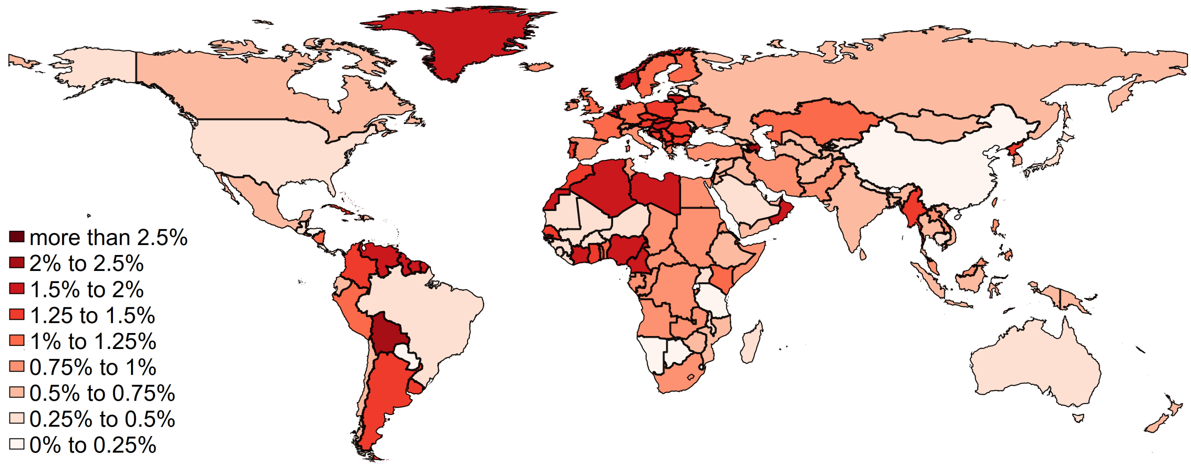


Notes: This figure shows the technique effect in each country if the respective country withdraws from the Paris Agreement while the rest of the world fulfills its emission reduction targets. The technique effect increases the withdrawing country's emissions by 7.6% on average, ranging from 5.1% in the US to slightly more than 7.7% for many countries.

More fossil fuel intensive production *techniques* for all goods are one reason why emissions in the withdrawing country can go up, another one is the possibility to specialize in the supply of goods from particularly emission-intensive *sectors*. This source of higher emissions is captured by the composition effect. While we found almost no compositional changes in China and the US in case of their withdrawals, it is evident from Figure 4.6 that the same is not true for many other countries. Even though the composition effects are not as strong as the technique effects, most countries make use to a noticeable extent of the possibility to shift production towards emission intensive sectors and then export these products to Paris Agreement member countries who partly pulled out of these sectors in order to achieve their emission reduction targets.

After this closer look on how the national emission increases of withdrawing countries come about, let us focus on the implications of these endogenous adjustments for the global emissions. As illustrated above for the Chinese and US case, the emission increase in the withdrawing country partly offsets the global emission reduction from the remaining reduction targets, a phenomenon that is captured by the leakage rate. Figure 4.7 displays the different leakage rates that occur in the 139 withdrawal scenarios. Even though the US and China experience the lowest percentage emission increase, their

Figure 4.6: Composition Effects



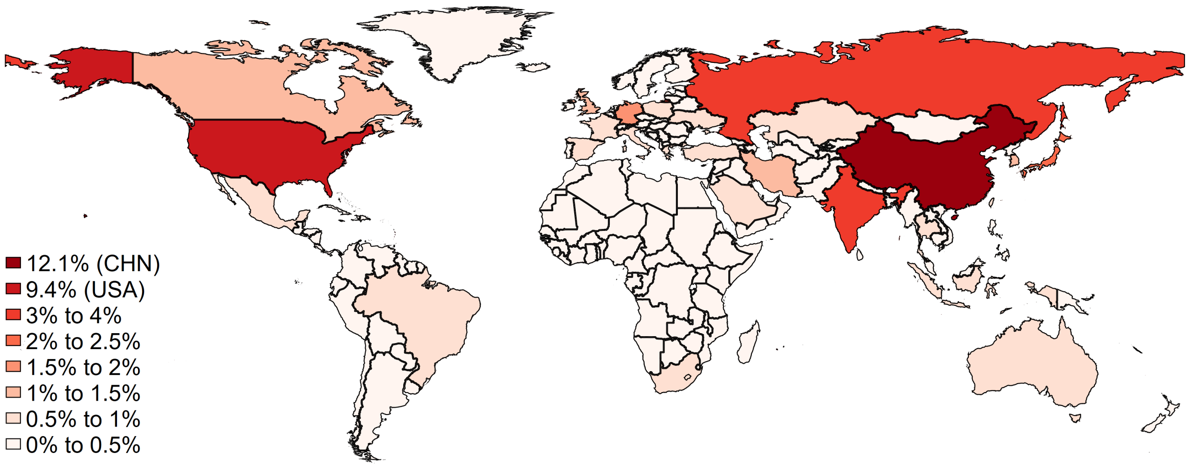
Notes: This figure shows the composition effect in each country if the respective country withdraws from the Paris Agreement while the rest of the world fulfills its emission reduction targets. The composition effect increases the withdrawing country's emissions by 0.9% on average, ranging from 0.03% in Namibia to 2.8% in Trinidad and Tobago.

very high levels of carbon emissions translates these comparatively small increases into the by far highest leakage rates. Already the withdrawals from the group of countries with the highest leakage rates after those two leading emitters (India, Russia, Japan, and Germany) offsets far lower shares of the world emission reduction (3.5, 3.1, 2.2, and 1.8%, respectively). As was illustrated by the consideration of the technique and composition effects above, leakage appears to be primarily driven by the energy market leakage channel, while leakage via the production shift and international trade channel plays a second-order role. For most countries, leakage is very small as their emissions make up only a small fraction of global emissions (the median leakage rate is 0.07%).

Figure 4.8 summarizes the relationship between countries' direct reduction losses and leakage highlighting the role of their national emission levels as well as their target reduction rates. It illustrates that while for leakage national emissions are the main driver, the direct reduction losses depend on both, national emission levels and the target. Starting from a vertical line of countries without a target, countries move in a clockwise direction when increasing their target reduction rate.

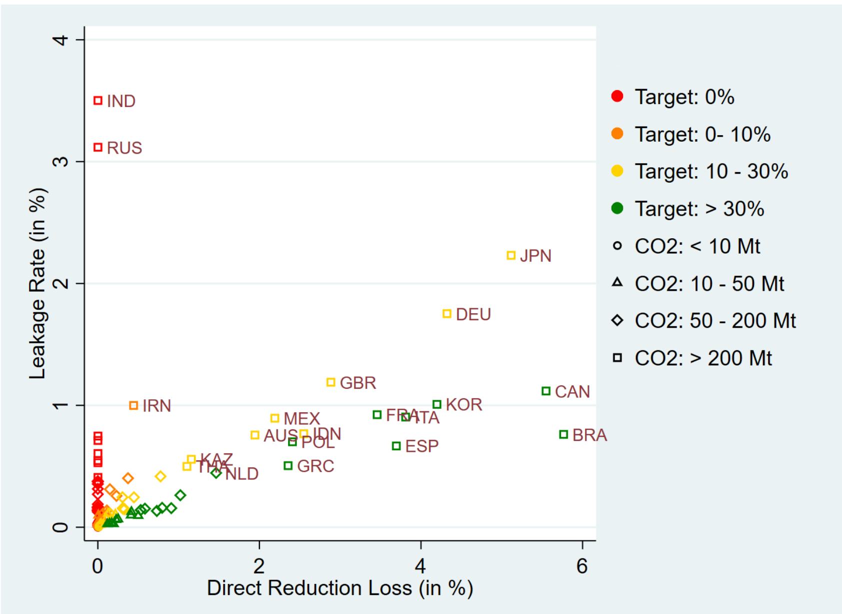
Putting together the direct emission reduction losses from removing a withdrawing country's reduction target and the additional leakage losses due to endogenous adjustment

Figure 4.7: Leakage Rates



Notes: This figure shows the leakage rates that occur in the 139 different unilateral withdrawal scenarios from the Paris Agreement. On average, 0.4% of the rest of the world's emission reduction is offset by emission increases in the withdrawing country. The leakage rates range between 0.0% for a number of very small countries and 12.1% for China.

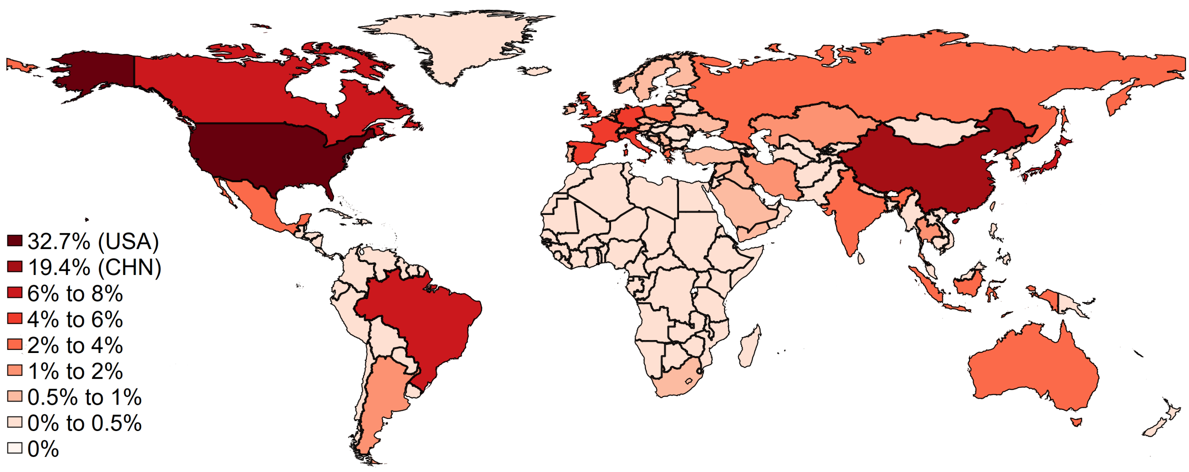
Figure 4.8: Direct Reduction Losses and Leakage



Notes: This figure shows the relationship between the leakage rate (in %) and the direct reduction losses (in %). Countries are depicted in different shapes and colors depending on their CO_2 emission levels and reduction targets, respectively. To be able to restrict the scale of the scatter plot, we leave out the US and China.

towards higher emissions in the withdrawing country, we can obtain the total loss in the global emission reduction of the Paris Agreement induced by unilateral withdrawals. These total reduction losses are shown in Figure 4.9 and (for the five countries with the strongest effects) in Table 4.3. The announced US withdrawal has by far the worst impact on the Paris Agreement's effectiveness to lower global emissions, followed by the also previously discussed Chinese case. All other unilateral withdrawals are significantly less harmful to the agreement's capacity to lower world emissions. Nevertheless, a group of countries including e.g. several European countries (Germany, Italy, France, Spain, the United Kingdom, and Poland), other large developed countries (Japan, Canada, and South Korea), as well as three of the four remaining BRICS states (Brazil, Russia, and India) would still perceptibly lower the overall reduction (all in the range of 3 to 7.2%). Two particularly noteworthy cases are India (3.5%) and Russia (3.1%) for both of which the zero target (i.e. the target to not do worse than the BAU path) implied a zero direct effect. Taking into account their endogenous adjustment, it becomes evident that a Russian or Indian withdrawal would indeed harm the effectiveness of the Paris Agreement significantly. For all African countries, as well as for smaller and/or poorer European, Asian, or South American countries, even the total effect remains rather small, pulling down the average across all countries to a 1.1% reduction loss.

Figure 4.9: Total Emission Reductions Lost



Notes: This figure shows the shares of the global emission reduction due to the Paris Agreement that is lost due to a unilateral withdrawal in the 139 different scenarios. On average, 1.1% of the global emission reduction are forgone. The loss shares range from 0.0% for a number of very small countries to 32.7% for the US.

Table 4.3: Top Five Total Reduction Losses

Withdrawing country	USA	CHN	JPN	CAN	BRA
World reduction lost (total effect)	32.7%	19.4%	7.2%	6.6%	6.5%

Table 4.4 summarizes the results for all major variables of interest across the 139 different withdrawal scenarios that have been graphically shown above.

Table 4.4: Unilateral Withdrawal Results

Variable	Obs	Mean	SD	Min	Max
Direct global reduction loss (in %)	139	0.72	2.51	0	25.75
Total global reduction loss (in %)	139	1.10	3.45	0.00	32.72
Leakage rate (in %)	139	0.41	1.36	0.00	12.13
Emission effect* (in %)	139	9.20	0.72	5.68	11.56
Scale effect* (in %)	139	0.01	0.05	-0.09	0.17
Composition effect* (in %)	139	0.91	0.54	0.03	2.84
Technique effect* (in %)	139	7.59	0.28	5.08	7.75

Notes: For the variables marked by an asterisk, the national values of the withdrawing countries are shown.

4.4.4 Sensitivity: Varying the Fossil Fuel Supply Elasticity

One crucial model parameter for which we need to rely on values from the literature is the fossil fuel supply elasticity. In this subsection, we investigate the sensitivity of our results with respect to the choice of η by considering the upper and lower bound of the range of elasticities used by Boeters and Bollen (2012) for their different fossil fuel types.

When increasing the fossil fuel supply elasticity from 2 to 4, the average global emission reduction loss decreases from 1.1% to 0.9%. The reduction loss induced by the US withdrawal still amounts to 29.5%. These somewhat lower effects are driven by lower leakage rates, which are cut in half on average (0.2% instead of 0.4%). Intuitively, the reason for the lower leakage and overall smaller emission reduction losses is that fossil fuel suppliers react more strongly to the falling prices by lowering the extracted quantities. This implies that the price in our new counterfactual equilibrium will decrease less, lowering the withdrawing country's incentive to shift to a more emission intensive production technique. Note that as a larger part of the reduction loss for China is due to leakage, a higher fossil fuel supply elasticity affects the Chinese withdrawal scenario specifically strongly: the reduction loss decreases from 19.4% to 14.2%.

When lowering the fossil fuel supply elasticity instead from 2 to 1, the average global emission reduction loss increases from 1.1% to 1.5%. In this case, a US withdrawal would eliminate 38.5% of the world emission reduction and a Chinese withdrawal would induce a 28.2% reduction loss. These larger effects are driven by relatively weaker quantity adjustments by fossil fuel suppliers in response to the falling fossil fuel price, inducing stronger leakage. Specifically, the average leakage rate almost doubles compared to the benchmark $\eta = 2$ case to 0.79%, with the maximum in the case of a Chinese withdrawal as high as 21.8%. Further details on the results for the different values of η are presented in Appendix D.3.

4.5 Model Extension: Multiple Fossil Fuels

The model developed in Section 4.2 incorporated one single fossil fuel resource used in energy production and assumed emissions to be proportional to the fossil fuel usage. In this section, we allow for multiple fossil fuels with varying carbon intensities and potentially different supply elasticities.

4.5.1 Model

Fossil fuels used in country i are now treated as a composite of different types of fossil fuels (specifically oil, gas, and coal):

$$E^i = A^i_E \left(\prod_{v \in \mathcal{V}} (R^i_v)^{\rho^i_v} \right)^{\xi^i_R} \prod_{f \in \mathcal{F}} (V^i_{Ef})^{\xi^i_f}, \tag{4.20}$$

with $\sum_{v\in\mathcal{V}} \rho_v^i = 1$. For each type of fossil fuel, supply is modeled with a separate CEFS function:

$$\widehat{R_v^W} = (\widehat{r_v})^{\eta_v}, \tag{4.21}$$

with $\sum_{i\in\mathcal{N}} R_v^i = R_v^W$. Fossil fuel types differ in their carbon intensity (κ_v). Hence, emissions are no longer simply proportional to R_i, but rather given by:

$$EM^i = \sum_{v\in\mathcal{V}} \kappa_v R_v^i. \tag{4.22}$$

Countries implement carbon taxes that are equal per ton of CO_2 across fossil fuel types. Therefore, the percentage tax is no longer simply given by λ^i, but by $\kappa_v\lambda^i/r_v$. Additionally using the Cobb-Douglas structure, the national aggregate fossil fuel price is then given by:

$$r^i = \prod_{v\in\mathcal{V}} \left(\frac{(1+\frac{\kappa_v\lambda^i}{r_v})r_v}{\rho_v^i} \right)^{\rho_v^i}. \tag{4.23}$$

Market clearing for each fossil fuel type pins down their respective world market prices:

$$r_v = \frac{1}{R_v^W} \sum_{i\in\mathcal{N}} \left(\frac{1}{1+\frac{\kappa_v\lambda^i}{r_v}} \right) \rho_v^i \xi_R^i \left(\alpha_{SE}^i Y_S^i + \sum_{l\in\mathcal{L}} \alpha_{lE}^i Y_l^i \right). \tag{4.24}$$

In order to achieve its emission target, country i sets the carbon tax according to:

$$\overline{EM^i} = \sum_{v\in\mathcal{V}} \kappa_v \frac{\rho_v^i \xi_R^i \left(\alpha_{SE}^i Y_S^i + \sum_{l\in\mathcal{L}} \alpha_{lE}^i Y_l^i\right)}{(1+\frac{\kappa_v\lambda^i}{r_v})r_v}. \tag{4.25}$$

In the absence of a target, there is no carbon tax levied (i.e. $\lambda^i = 0$). As there are multiple fossil fuels and countries can have different endowment shares for oil, gas, and coal (and the percentage tax rates vary across fossil fuel types), we also need to update the expression for a country's total income:

$$
\begin{aligned}
Y^i = \sum_{f\in\mathcal{F}} & \left[(\alpha^i_{Sf} + \xi^i_f \alpha^i_{SE}) Y^i_S + \sum_{l\in\mathcal{L}} (\alpha^i_{lf} + \xi^i_f \alpha^i_{lE}) Y^i_l \right] \\
&+ \sum_{v\in\mathcal{V}} \omega^i_v \sum_{j\in\mathcal{N}} \left(\frac{1}{1+\frac{\kappa_v \lambda^j}{r_v}}\right) \rho^j_v \xi^j_R \left(\alpha^j_{SE} Y^j_S + \sum_{l\in\mathcal{L}} \alpha^j_{lE} Y^j_l\right) \\
&+ \sum_{v\in\mathcal{V}} \left(\frac{\frac{\kappa_v \lambda^i}{r_v}}{1+\frac{\kappa_v \lambda^i}{r_v}}\right) \rho^i_v \xi^i_R \left(\alpha^i_{SE} Y^i_S + \sum_{l\in\mathcal{L}} \alpha^i_{lE} Y^i_l\right).
\end{aligned}
\tag{4.26}
$$

Further, the aggregate fossil fuel price is now country-specific (due to compositional differences) and already includes the tax, leading to the following new expression for the adjustment of the national energy price:

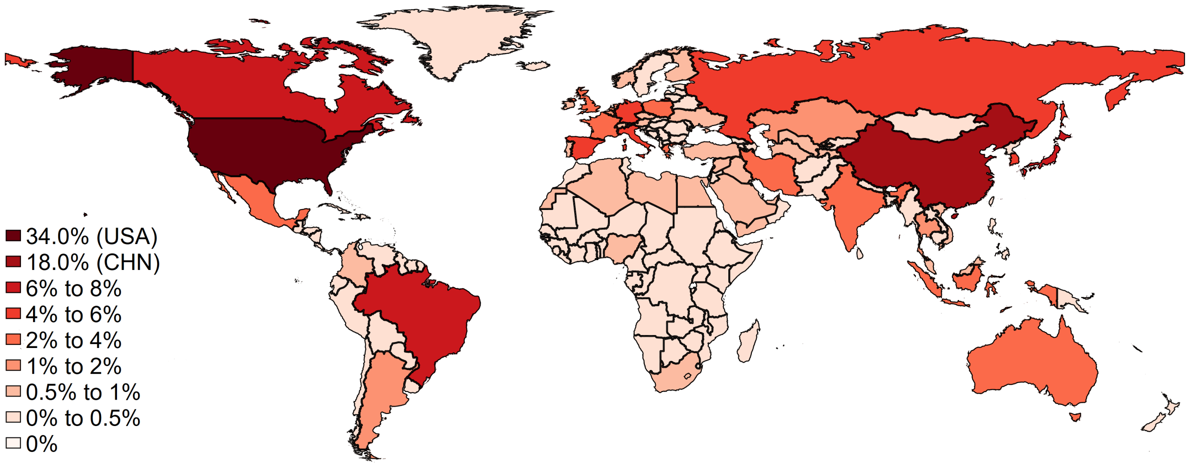
$$
\widehat{e}^i = (\widehat{r}_i)^{\xi^i_R} \prod_{f\in\mathcal{F}} \left[\frac{(\alpha^i_{Sf} + \xi^i_f \alpha^i_{SE}) Y^{i\prime}_S + \sum_{l\in\mathcal{L}} (\alpha^i_{lf} + \xi^i_f \alpha^i_{lE}) Y^{i\prime}_l}{(\alpha^i_{Sf} + \xi^i_f \alpha^i_{SE}) Y^i_S + \sum_{l\in\mathcal{L}} (\alpha^i_{lf} + \xi^i_f \alpha^i_{lE}) Y^i_l}\right]^{\xi^i_f}. \tag{4.27}
$$

As in the base model, we again can decompose the emission changes into scale, technique, and composition effect. Additionally, there is a substitution effect resulting from the change in the fossil fuel mix. See Appendices D.4.1 and D.4.2 for details on the decomposition and parametrization of the extended model, respectively.

4.5.2 Results

Figure 4.10 summarizes the most important results of the simulation of unilateral withdrawals from the Paris Agreement in our extended model framework, namely the total percentage loss for the world emission reduction (i.e. it reproduces Figure 4.9 from the main model results). Reassuringly, the overall pattern bears striking resemblance to our previous results. The US withdrawal still has by far the strongest effect, followed by China and then a group of countries with relatively similar effects including e.g. Japan, Canada, Brazil, and South Korea. On average, the incurred loss is slightly higher when additionally allowing for substitution between different fossil fuel sources. The largest differences occurs for Russia, whose withdrawal is associated with a 1.4 percentage points higher reduction loss, and China, whose withdrawal has a 1.4 percentage points *weaker* effect in the extended model.

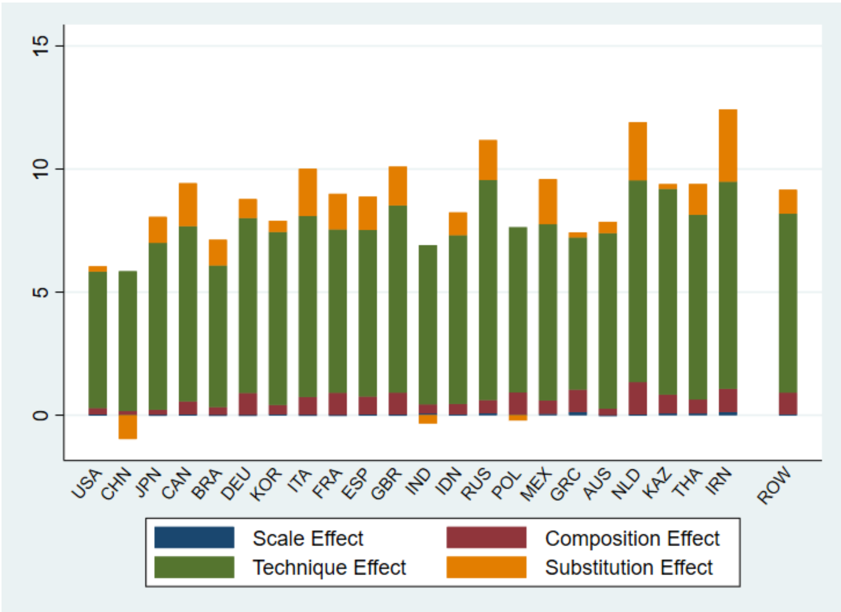
Figure 4.10: Total Emission Reductions Lost (Model Extension)



Notes: This figure shows the shares of the global emission reduction due to the Paris Agreement that is lost due to a unilateral withdrawal in the 139 different scenarios (in the extended model). On average, 1.1% of the global emission reduction are forgone. The loss shares range from 0.0% for a number of very small countries to 34.0% for the US.

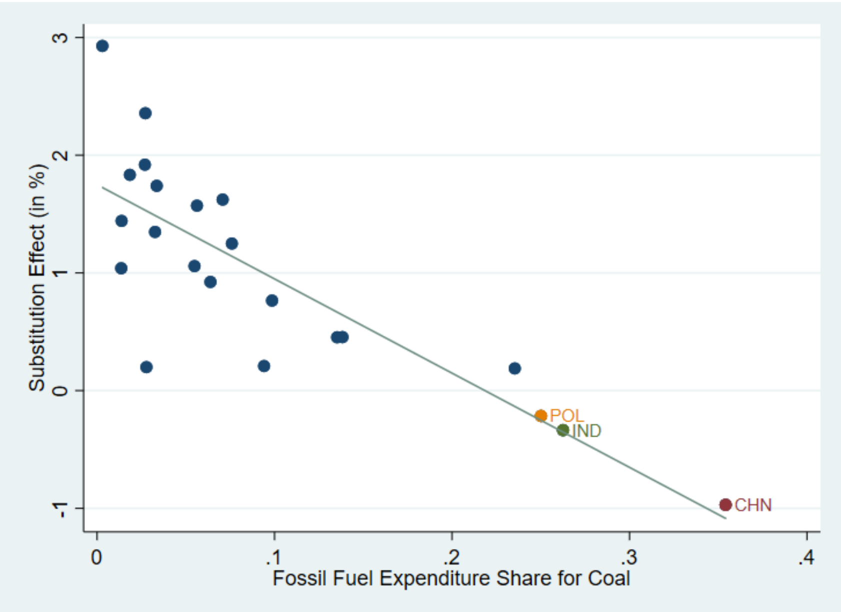
In order to gain a better insight into the differences in outcomes for the base and extended model, Figure 4.11 displays the decomposition of the withdrawing countries emission changes into scale, composition, technique, and substitution effect. As in the base model, the overall emission increases are primarily driven by the technique effects, i.e. generally more energy-intensive production. The new substitution effect in most cases additionally contributes to higher emissions in the non-committing countries. Hence, withdrawing countries shift within their fossil fuel mix from relatively cleaner gas and oil to the most emission intensive coal. This is because the price decrease on the international coal market is particularly strong as coal is the most heavily taxed fossil fuel in the committed countries. However, there are a few notable exceptions, like China, India, and Poland, where the substitution effect actually counteracts the overall emission increase. This only occurs in countries with a high coal-share in the initial fossil fuel mix. For example, if China does not participate in the Paris Agreement, there is a smaller price decrease on fossil fuels compared to a scenario in which all countries fulfill their targets due to a smaller drop in the fossil fuel demand. As China has a coal-intensive energy mix, this drop is smallest for coal. Hence, China substitutes away from coal to oil and gas, leading to a negative substitution effect. This relationship between the coal share and the substitution effect is illustrated in Figure 4.12.

Figure 4.11: Decomposition of Emission Changes (Model Extension)



Notes: This figure plots the decomposition of the emission changes into scale, composition, technique, and substitution effect for the 22 countries with the biggest reduction effect on world emissions and a rest of the world composite.

Figure 4.12: Scatter Plot of Substitution Effect against Coal Share



Notes: This figure plots the percentage substitution effect against the coal cost share in fossil fuel production for the 22 countries with the biggest reduction effect on world emissions.

4.6 Conclusions

In spite of potential problems of enforceability and an overall lack of ambition in the NDCs, the Paris Agreement has an important strength: its global coverage. This strength is currently at stake as not all signatory states have moved forward to ratification of the agreement and one major party—namely the US—has ratified, but already announced its withdrawal. In this paper, we analyze the consequences of unilateral withdrawals from the Paris Agreement on the achieved global emission reduction. To be able to account for both the direct effect of removing the withdrawing country's reduction target and the indirect effect of additional emission reductions due to carbon leakage, we develop an extended multi-sector structural gravity model featuring emissions from fossil fuel use, carbon taxes, and a constant elasticity fossil fuel supply function.

We find that single countries leaving the Paris Agreement can severely hurt the effectiveness of the treaty, the worst case being a US withdrawal which would eliminate one third of the overall emission reduction. Taking into account the endogenous emission adjustments beyond the mere absence of an emission target turns out to be of major importance, most notably in the Chinese case, in which the reduction loss more than doubles if carbon leakage is added to the direct effect. Using a decomposition of emission changes into scale, composition, and technique effects, we find that emission increases in withdrawing countries are mainly driven by a shift towards emission-intensive production techniques in response to a fall in the international fossil fuel price.

Both the overall magnitude of the reduction losses and the relative importance of the different leakage channels have significant policy implications. Most importantly, our findings imply that the global coverage is indeed crucial for the overall mitigation success of the agreement and therefore strong political efforts should be made to keep all large emitters on board. Further, if the global coverage breaks down, our findings on the strong energy market leakage channel suggest to consider new climate policy instruments that specifically tackle the fossil fuel supply.

Conclusions

The gravity model of international trade has become an integral part of empirical and quantitative trade economists' toolkit. It is used to estimate which factors determine bilateral trade flows and to quantify the effects of policy scenarios. Both types of gravity application rely on a solid theoretical foundation, either in informing the empirical specification or in enabling the computation of the counterfactual equilibrium.

This thesis contributes to both mentioned strands of the gravity literature. The first two chapters deal with econometric challenges arising in the estimation of in- and extensive margin gravity models. Specifically, they are concerned with nonlinear estimators in the presence of high-dimensional fixed effects, both with respect to the computational feasibility and the potential emergence of an incidental parameter problem. Crucially, the econometric advances turn out to matter decisively for the empirical results. The applications covered in the first two chapters can therefore be considered as cautionary tales concerning the temptation to circumvent some of the methodological difficulties by relying on linear estimators or less general sets of fixed effects. Interesting prospects for future research arise from incorporating aspects of the second chapter into the estimation of the intensive margin of trade. For instance, dynamics as introduced for the extensive margin in Chapter 2 may also be a relevant factor for intensive margin estimation. Furthermore, incidental parameter bias corrections are not unique to the extensive margin. While the specific large-sample PPML specification considered in Chapter 1 can be estimated without asymptotic bias, other specifications or estimators, such as Gamma PML, are not free from incidental parameter bias and require suitable corrections. An additional avenue for future research relating to the first two chapters of this dissertation is the transfer of the discussed methods to firm-level data sets and applications because they allow a much more fine-grained analysis of the functioning of trade policies.

The last two chapters of this thesis contribute to the role of gravity as a tool for general equilibrium policy analysis. More precisely, they incorporate environmental aspects into a gravity model. Gravity inherently focuses on international interconnectedness. This international perspective is crucial in the climate policy debate due to the threat of carbon leakage. The third chapter focuses on leakage due to production shifts, implying compositional changes in the sectoral structure, and on how carbon tariffs can be used to counteract this leakage tendency. The fourth chapter additionally considers carbon leakage via the international energy market in greater detail. In the context of the Paris Agreement, this leakage channel turns out to matter critically as countries that do not commit to emission reduction targets have a strong incentive to make use of falling fossil fuel prices and shift to carbon intensive production techniques in response to other countries' mitigation efforts. There is a plenitude of interesting directions for future research concerning the interplay of climate policy and international trade. To name just a few possible extensions of the model frameworks considered in Chapters 3 and 4, one could (i) incorporate trade in intermediate goods to capture more details of the international input-output linkages, (ii) include damages from global warming into the production function to link the model more closely to the science of climate change, and (iii) develop a dynamic model which could generate insights on the roles of directed technical change, trade induced growth effects, and optimal resource extraction paths of fossil fuel owners in the international efforts against climate change.

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Appendix A

Currency Unions and Trade: A PPML Re-assessment with High-dimensional Fixed Effects

This Appendix elaborates on several important considerations such as how to obtain multi-way clustered standard errors and how to verify before estimation that valid estimates do indeed exist. It is in part intended to serve as additional technical documentation for interested readers seeking to work with or extend the machinery used in `ppml_panel_sg` or implement the proposed procedure in other software packages such as Matlab or R.[1] All procedures described here can be verified to reproduce results produced by other widely-used routines. See the supporting material included with Zylkin (2017) for examples. Further, we provide some additional results and robustness checks.

A.1 Iteratively Re-weighted Least Squares Algorithm

The IRLS version of the algorithm is analogous to typical IRLS estimation in that it repeatedly utilizes weighted least squares estimation (of a particular form specific to the estimator being used), which is continuously updated as new estimates are produced, until both weights and estimates eventually converge. An IRLS approach is thus easily embedded within the broad approach described in the paper.

For IRLS estimation of a PPML model, it is necessary to first define an adjusted dependent variable—call it $\widetilde{X}_{ijt}$—which is given by:

$$\widetilde{X}_{ijt} = \frac{X_{ijt} - \widehat{X}_{ijt}}{\widehat{X}_{ijt}} + \widehat{\mathbf{b}}'\mathbf{w}_{ijt}.$$

For PPML, the relevant weighting matrix for the estimation is simply given by the conditional mean $\widehat{X}_{ijt}$. Thus, given $\widehat{X}_{ijt}$ and $\widetilde{X}_{ijt}$, an updated value for $\widehat{\mathbf{b}}$ can be simply

[1] We use Stata because it is the most widely used software by trade economists running gravity regressions. However, the procedure described here can be easily implemented in other software packages as well.

computed as:

$$\widehat{\mathbf{b}} = \left[\mathbf{W}'\widehat{\mathbf{X}}\mathbf{W}\right]^{-1}\mathbf{W}'\widehat{\mathbf{X}}\widetilde{\mathbf{X}},$$

where $\widehat{\mathbf{X}}$ is a diagonal weighting matrix with elements $\widehat{X}_{ijt}$ on its main diagonal and $\mathbf{W}$ is the matrix of main covariates $\mathbf{w}_{ijt}$. As in a more-typical IRLS loop, the weighting matrix is updated repeatedly as each new iteration of $\widehat{\mathbf{b}}$ implies a new conditional mean.[2] What must be added here are the intermediate steps needed to compute Ψ, Φ, and D, which follow from (1.5b)-(1.5d). Iterating repeatedly on these objects, along with $\widehat{\mathbf{b}}$, will eventually converge to the correct conditional mean, weighting matrix, and PPML estimates for $\widehat{\mathbf{b}}$. Since the algorithm requires repeated iteration anyway, the IRLS method is always the most efficient approach versus solving the first-order condition for $\widehat{\mathbf{b}}$ exactly each time through the loop.[3]

A.2 Three-way Within Transformation

A useful prior for the rest of these notes is the notion of a three-way "within-transformation", generalizing the two-way procedures of Abowd, Creecy, and Kramarz (2002) and Guimarães and Portugal (2010) and as may be applied via the `hdfe` algorithm of Correia (2016b).

Let each of the "main" (non-fixed effect) regressors of the vector $\mathbf{w}_{ijt}$ on the right hand side be denoted by w^k_{ijt}, with superscript k indexing the kth regressor. The idea is to (iteratively) regress each w^k_{ijt} on the complete set of fixed effects. Doing so results in a new set of "partialed-out" (or "within-transformed") versions of w^k_{ijt}, which have been removed of any partial correlation with the set of fixed effects. For the current three-way

[2]For clarity, $\widetilde{X}_{ijt}$ is derived from a first-order Taylor approximation of the PPML FOC for $\widehat{\mathbf{b}}$ around $\widehat{\mathbf{b}}^0$, where $\widehat{\mathbf{b}}^0$ denotes the current guess for $\widehat{\mathbf{b}}$. The use of $\widehat{X}$ as a weighting matrix also follows from this approximation. For a reference, see Nelder and Wedderburn (1972).

[3]The adoption of IRLS in `ppml_panel_sg` was inspired by the use of a similar principle—albeit in an altogether very different procedure—in the latest version of `Guimaraes2016`, by Guimarães (2016).

HDFE context—with it, jt, and ij fixed effects—the needed within-transformation for each w_{ijt}^k is given by the following system of equations:

$$\sum_j \left(w_{ijt}^k - \widetilde{\lambda}_{it}^k - \widetilde{\psi}_{jt}^k - \widetilde{\mu}_{ij}^k \right) = 0 \quad \forall i, t, \tag{A.1a}$$

$$\sum_i \left(w_{ijt}^k - \widetilde{\lambda}_{it}^k - \widetilde{\psi}_{jt}^k - \widetilde{\mu}_{ij}^k \right) = 0 \quad \forall j, t, \tag{A.1b}$$

$$\sum_t \left(w_{ijt}^k - \widetilde{\lambda}_{it}^k - \widetilde{\psi}_{jt}^k - \widetilde{\mu}_{ij}^k \right) = 0 \quad \forall i, j, \tag{A.1c}$$

where (A.1a)-(A.1c) are derived from the first-order conditions from an OLS regression of w^k on a set of fixed effects $\{\widetilde{\lambda}_{it}^k, \widetilde{\psi}_{it}^k, \widetilde{\mu}_{ij}^k\}$. Either by using "zig-zag" iteration methods or via the more sophisticated algorithm of Correia (2016b), this system is easily solved even for a large number of fixed effects. The resulting, now-transformed regressors, which we will denote as $\widetilde{w}^k$, are given by:

$$\widetilde{w}_{ijt}^k = w_{ijt}^k - \widetilde{\lambda}_{it}^k - \widetilde{\psi}_{jt}^k - \widetilde{\mu}_{ij}^k.$$

Variations of this within-transformation procedure will come into play in the discussion that follows of how we construct standard errors as well as how we implement the "check for existence" recommended by Santos Silva and Tenreyro (2010b). Thus, these basic mechanics will be helpful to keep in mind.

A.3 Standard Errors

The construction of standard errors largely follows the exposition in the Appendix of Figueiredo, Guimarães, and Woodward (2015), which we extend to the case of three-way HDFEs with multi-way clustering. Let $\sum_{i,j,t}$ denote a sum over all observations and let $\mathbf{x}_{ijt}$ denote the vector of all covariates associated with observation ijt, including all $0/1$ dummy variables associated with each fixed effect. The estimated "robust" variance-covariance (VCV) matrix for our PPML estimates that we need to construct is given by

$$\widehat{\mathbf{V}}_{rob} = \underbrace{\left[\sum_{i,j,t} \widehat{X}_{ijt}\mathbf{x}_{ijt}\mathbf{x}'_{ijt}\right]^{-1}}_{\widehat{\mathbf{V}}} \times \underbrace{\left[\sum_{i,j,t} \left(X_{ijt} - \widehat{X}_{ijt}\right)^2 \mathbf{x}_{ijt}\mathbf{x}'_{ijt}\right]}_{\mathbf{M}} \times \underbrace{\left[\sum_{i,j,t} \widehat{X}_{ijt}\mathbf{x}_{ijt}\mathbf{x}'_{ijt}\right]^{-1}}_{\widehat{\mathbf{V}}}, \quad \text{(A.2)}$$

where $\widehat{\mathbf{V}}$ is proportional to the usual (uncorrected) Poisson MLE VCV matrix and $\widehat{X}_{ijt}$ is the conditional mean from our regression. The middle term, $\mathbf{M}$, provides a heteroscedasticity correction.

While we can compute the matrix $\sum_{i,j,t} \widehat{X}_{ijt}\mathbf{x}_{ijt}\mathbf{x}'_{ijt}$, inversion of this matrix is potentially infeasible due to the large dimension of $\mathbf{x}_{ijt}$. The problem is simplified, however, by recognizing we are only interested in the submatrix of $\widehat{\mathbf{V}}$ that pertains to $\widehat{\mathbf{b}}$, the coefficients for our non-fixed effect regressors. Call this submatrix $\widehat{\mathbf{V}}^*$. To obtain $\widehat{\mathbf{V}}^*$, we make use of the following two "tricks": (i) the $\widehat{\mathbf{V}}$ that appears in (A.2) is proportional to the VCV matrix that would be produced by *any* weighted least squares regression using $\mathbf{x}_{ijt}$ as covariates and $\sqrt{\widehat{X}_{ijt}}$ as weights; (ii) By the Frish-Waugh-Lovell theorem, the dimensionality of an HDFE linear regression can be easily reduced by first applying a within-transformation (a weighted one in this case).

We thus proceed in two steps. First, using a weighted version of our within-transformation procedure, we regress each weighted regressor $\sqrt{\widehat{X}_{ijt}}w^k_{ijt}$ on a set of exporter-time, importer-time, and exporter-importer fixed effects, which themselves must also be weighted by $\sqrt{\widehat{X}_{ijt}}$. The system of equations associated with this operation may be written as

$$\sum_j \widehat{X}_{ijt}\left(w^k_{ijt} - \widetilde{\lambda}^{k*}_{it} - \widetilde{\psi}^{k*}_{jt} - \widetilde{\mu}^{k*}_{ij}\right) = 0 \quad \forall i,t, \quad \text{(A.3a)}$$

$$\sum_i \widehat{X}_{ijt}\left(w^k_{ijt} - \widetilde{\lambda}^{k*}_{it} - \widetilde{\psi}^{k*}_{jt} - \widetilde{\mu}^{k*}_{ij}\right) = 0 \quad \forall j,t, \quad \text{(A.3b)}$$

$$\sum_t \widehat{X}_{ijt}\left(w^k_{ijt} - \widetilde{\lambda}^{k*}_{it} - \widetilde{\psi}^{k*}_{jt} - \widetilde{\mu}^{k*}_{ij}\right) = 0 \quad \forall i,j, \quad \text{(A.3c)}$$

where $\{\widetilde{\lambda}^{k*}_{it}, \widetilde{\psi}^{k*}_{it}, \widetilde{\mu}^{k*}_{ij}\}$ are the fixed effects terms we now need to solve for. Despite the presence of $\widehat{X}_{ijt}$ in (A.3a)-(A.3c), the basic principles and methods to solve are no different than with (A.1a)-(A.1c).

The transformed regressors we need for our auxiliary regression—call these $\widetilde{w}_i^{k*}$—are given by

$$\widetilde{w}_{ijt}^{k*} = \sqrt{\widehat{X}_{ijt}} \left(w_{ijt}^{k} - \widetilde{\lambda}_{it}^{k*} - \widetilde{\psi}_{jt}^{k*} - \widetilde{\mu}_{ij}^{k*} \right).$$

With these residuals in hand, the second step is to now perform the following OLS regression:

$$X_{ijt} = \sum_k a_k \widetilde{w}_{ijt}^{k*} + u_i. \tag{A.4}$$

The estimates obtained from this regression are irrelevant. The main point is that, after employing the two "tricks" mentioned above, the VCV matrix from (A.4) will be equal to $s^2 \times \widehat{\mathbf{V}}^*$, where s^2 is the usual mean squared error from the linear regression.

Finally, now that we have $\widehat{\mathbf{V}}^*$, the full, heteroscedasticity-robust VCV matrix for our main regressors can be computed as

$$\widehat{\mathbf{V}}_{rob}^* = \widehat{\mathbf{V}}^* \times \mathbf{M}^* \times \widehat{\mathbf{V}}^*,$$

where the middle term,

$$\mathbf{M}^* = \left[\sum_{i,j,t} \frac{\left(X_{ijt} - \widehat{X}_{ijt} \right)^2}{\widehat{X}_{ijt}} \widetilde{\mathbf{w}}_{ijt}^* \widetilde{\mathbf{w}}_{ijt}^{*\prime} \right],$$

must be adjusted to take into account the fact that each $\widetilde{w}_{ijt}^{k*}$ is weighted by $\sqrt{\widehat{X}_{ijt}}$.

Multi-way clustering. The multi-way clustered VCV matrix takes the form

$$\widehat{\mathbf{V}}_{clus}^* = \widehat{\mathbf{V}}^* \mathbf{M}_{clus}^* \widehat{\mathbf{V}}^*,$$

where $\widehat{\mathbf{V}}^*$ is calculated in the exact same way as described above. For the matrix $\mathbf{M}^*_{clus}$, we follow Cameron, Gelbach, and Miller (2011), taking into account that we are still dealing only with a submatrix of the overall matrix $\widehat{\mathbf{V}}$, and calculate it as follows:

$$\mathbf{M}^*_{clus} = \sum_{||\mathbf{r}||=k, \mathbf{r}\in R} (-1)^{k+1} \tilde{\mathbf{M}}^*_{\mathbf{r}},$$

with

$$\tilde{\mathbf{M}}^*_{\mathbf{r}} = \sum_{l} \sum_{m} \frac{\left(X_l - \widehat{X}_l\right)}{\sqrt{\widehat{X}_l}} \frac{\left(X_m - \widehat{X}_m\right)}{\sqrt{\widehat{X}_m}} \tilde{\mathbf{w}}^*_l \tilde{\mathbf{w}}^{*\prime}_m I_{\mathbf{r}}(l,m) \quad \mathbf{r} \in R,$$

where the set $R \equiv \{\mathbf{r} : r_d \in \{0,1\}, d = 1, 2, ..., D, \mathbf{r} \neq \mathbf{0}\}$, where D is the number of dimensions of clustering and the elements of R index whether two observations are joint members of at least one cluster. l and m denote specific ijt-observations. $I_{\mathbf{r}}(l,m)$ takes the value one if observations l and m are both members of all clusters for which $r_d = 1$. $||\mathbf{r}||$ denotes the ℓ_1-norm of the vector $\mathbf{r}$.

A.4 Check for Existence

As illuminated in Santos Silva and Tenreyro (2010b), depending on the configuration of the data, estimates from Poisson regressions may not actually exist. Specifically, if two or more regressors are perfectly collinear over the subsample where the dependent variable is non-zero, researchers are advised to carefully investigate each "implicated" regressor to see if it can be included in their model. Otherwise, estimation routines may result in spurious estimates, or even no estimates at all.[4]

With multiple high-dimensional fixed effects, implementing the checks favoured by Santos Silva and Tenreyro (2010b) may seem a daunting task, since collinearity checks

[4]Note this is a different issue altogether than the standard issue of "perfect collinearity" and can be significantly more difficult to detect. See Santos Silva and Tenreyro (2010b) for a simple example of a model with non-collinear regressors that does not have a solution.

across all the different fixed effects to determine whether one or more are "implicated" may be computationally expensive and/or conceptually difficult, especially when there are more than two HDFEs. In addition, it is also necessary to check whether each individual regressor is collinear over $X_{ijt} > 0$ with the complete set of fixed effects, as well as whether any subset of fixed effect and non-fixed effect regressors are collinear over $X_{ijt} > 0$.

Fortunately, however, it turns out these issues are quickly and easily resolved by (i) applying the within-transformation technique described above and (ii) recognizing that fixed effects themselves only present an issue under easily-identifiable circumstances. To see this, let "$\widetilde{w}^k_{ijt|X>0}$" denote the within-transformed version of each non-fixed effect regressor w_k after performing a within-transformation (only this time restricted to the subsample $X_{ijt} > 0$). After applying the within-transformation, these $\widetilde{w}^k_{ijt|X>0}$'s now only contain the residual variation in each w^k_{ijt} over $X_{ijt} > 0$ that is uncorrelated with the set of fixed effects. Thus, any individual $\widetilde{w}^k_{ijt|X>0}$ that is uniformly zero should be considered "implicated", since this only occurs if w^k_{ijt} is perfectly collinear with the set of fixed effects over $X_{ijt} > 0$. Furthermore, it is now a simple matter to apply a standard collinearity check among the remaining $\widetilde{w}^k_{ijt|X>0}$ to test for joint collinearity over $X_{ijt} > 0$, taking into account all possible correlations with the set of fixed effects.

That still leaves the matter of collinearity among the potentially very many fixed effects, which may seem the most difficult step of all. However, Santos Silva and Tenreyro (2010b) also clarify that it should always be possible to include any regressor that has "reasonable overlap" in the values that it takes over both the $X_{ijt} > 0$ and $X_{ijt} = 0$ samples. While there is no hard-and-fast rule that may be applied to determine how much overlap is "reasonable", the condition they include with their `ppml` command is to check whether the mean value of each w^k_{ijt} over $X_{ijt} > 0$ lies between the maximum and minimum values it takes over $X_{ijt} = 0$. Setting aside the more general (and comparably benign) issue of collinearity over *all* X_{ijt}, the only situation where any of our fixed effects would fail this condition would be if a country did not engage in exporting or importing in a given year or if a pair of countries never trades during the sample.[5] Thus, `ppml_panel_sg` drops all observations for pairs of countries who never trade, exporters who do not export anything in a given year, and importers who do not import anything in the given year.[6]

A.5 Time Trends

For time trends, let α_{ij} be the time trend coefficient and let $t = 0, 1, 2, 3...$ be the time trend itself. The estimating equation is now given by:

$$X_{ijt} = \exp\left(\lambda_{it} + \psi_{jt} + \mu_{ij} + \alpha_{ij}t + \mathbf{b}'\mathbf{w}_{ijt}\right) + \nu_{ijt}. \tag{A.5}$$

The PPML first-order condition for α_{ij} is

$$\sum_t \left(X_{ijt} - \widehat{X}_{ijt}\right) t = 0,$$

which again amounts to a summation of actual and fitted flows, only this time multiplied by the trend at time t (which we are here taking to be one and the same).

Now suppose we have an initial guess value α_{ij}^0 for the time trend and we want to obtain the next value in a converging sequence α_{ij}^1. To obtain α_{ij}^1 we may write:

$$\sum_t \left(X_{ijt} - \widehat{X}_{ijt}^0 e^{d\alpha_{ij}t}\right) t = 0, \tag{A.6}$$

[5]When multiple fixed effects are collinear over the whole sample (as is always the case in this context), these manifest as redundant FOC's that do not affect the existence or uniqueness of a solution for $\widehat{\mathbf{b}}$. Thus, even though one might construct examples where one or more of the fixed effect dummies do not take on both 0 and 1 over each subsample, these scenarios can always be resolved by accounting for general collinearity.

[6]Ultimately, whether or not these observations are dropped or kept does not affect much. What standard Stata commands will do is try to force the conditional mean for these observations to zero, by (wrongly) estimating large, negative values for their associated fixed effects. Stata users should be reassured that, despite this oddity, other estimates are usually fine so long as the main set of non-fixed effect regressors meets the conditions described above.

where $d\alpha_{ij} = \alpha_{ij}^1 - \alpha_{ij}^0$ is the change in α_{ij} from one iteration to another and $\widehat{X}_{ijt}^0$ are current fitted values. The idea is that when the α_{ij}'s converge, $d\alpha_{ij} = 0$ implies that the first-order condition is satisfied. We want to obtain a new value for $d\alpha_{ij}$ based on (A.6) that will allow us to update $\alpha_{ij}^1 = \alpha_{ij}^0 + d\alpha_{ij}$, but unfortunately (A.6) is nonlinear in $d\alpha_{ij}$ and cannot be solved analytically. Thus, we instead derive a first-order Taylor Series expansion around $d\alpha_{ij} = 0$:

$$\sum_t \left(X_{ijt} - \widehat{X}_{ijt}^0\right) t - d\alpha_{ij} \sum_t \widehat{X}_{ijt}^0 t^2 = 0, \tag{A.7}$$

since $f'(0)$ in this case is $-\sum \widehat{X}_{ijt}^0 t^2$. We then solve (A.7) to obtain $d\alpha_{ij}$, update $\alpha_{ij}^1 = \alpha_{ij}^0 + d\alpha_{ij}$, iterate on all other first-order conditions, and repeat until convergence. The system of equations we now need to solve to obtain standard errors is:

$$\sum_j \widehat{X}_{ijt} \left(w_{ijt}^k - \widetilde{\lambda}_{it}^{k*} - \widetilde{\psi}_{jt}^{k*} - \widetilde{\mu}_{ij}^{k*} - \widetilde{\alpha}_{ij}^{k*} t\right) = 0 \quad \forall i, t, \tag{A.8a}$$

$$\sum_i \widehat{X}_{ijt} \left(w_{ijt}^k - \widetilde{\lambda}_{it}^{k*} - \widetilde{\psi}_{jt}^{k*} - \widetilde{\mu}_{ij}^{k*} - \widetilde{\alpha}_{ij}^{k*} t\right) = 0 \quad \forall j, t, \tag{A.8b}$$

$$\sum_t \widehat{X}_{ijt} \left(w_{ijt}^k - \widetilde{\lambda}_{it}^{k*} - \widetilde{\psi}_{jt}^{k*} - \widetilde{\mu}_{ij}^{k*} - \widetilde{\alpha}_{ij}^{k*} t\right) = 0 \quad \forall i, j, \tag{A.8c}$$

$$\sum_t \widehat{X}_{ijt} \left(w_{ijt}^k - \widetilde{\lambda}_{it}^{k*} - \widetilde{\psi}_{jt}^{k*} - \widetilde{\mu}_{ij}^{k*} - \widetilde{\alpha}_{ij}^{k*} t\right) t = 0 \quad \forall i, j, \tag{A.8d}$$

which is again our weighted within-transformation exercise from before only with the last set of equations representing the first-order conditions from a linear time trend.

A.6 Computation Times

Table A.1: Comparison of Computation Times

	1948-2013		1985-2013		1995-2013		1948-2005		1985-2005		1995-2005	
	HDFE PPML	Standard PPML	HDFE PPML	Standard PPML	HDFE PPML	Standard PPML	HDFE PPML	Standard PPML	HDFE PPML	Standard PPML	HDFE PPML	Standard PPML
5	0:00:05	0:01:04	0:00:02	0:00:11	0:00:02	0:00:08	0:00:04	0:00:54	0:00:02	0:00:06	0:00:02	0:00:05
10	0:00:08	0:06:47	0:00:08	0:00:55	0:00:06	0:00:35	0:00:09	0:04:26	0:00:02	0:00:33	0:00:03	0:00:14
15	0:00:14	0:25:19	0:00:07	0:03:51	0:00:07	0:01:50	0:00:14	0:18:16	0:00:06	0:02:08	0:00:04	0:00:46
20	0:00:34	1:19:04	0:00:12	0:11:14	0:00:13	0:05:08	0:00:27	0:55:35	0:00:09	0:06:13	0:00:05	0:02:22
25	0:00:49	4:07:49	0:00:20	0:25:19	0:00:25	0:11:23	0:00:46	2:56:44	0:00:15	0:14:24	0:00:22	0:06:02
30	0:01:00	10:02:02	0:00:32	1:06:18	0:00:28	0:28:04	0:01:06	7:12:47	0:00:23	0:33:39	0:00:15	0:13:32
35	0:01:29	20:28:41	0:00:41	2:50:11	0:00:32	0:59:14	0:01:20	14:14:27	0:00:33	1:12:04	0:00:39	0:25:30
40	0:01:44	n.c.	0:00:57	6:03:55	0:00:37	2:46:06	0:01:34	n.c.	0:00:41	3:00:26	0:00:27	0:52:57
45	0:02:08	n.c.	0:01:16	13:00:35	0:00:50	6:05:37	0:02:04	n.c.	0:00:57	6:57:02	0:00:34	2:24:56
50	0:02:08	n.c.	0:01:28	21:26:31	0:01:03	10:24:28	0:01:52	n.c.	0:01:01	11:36:54	0:00:38	4:32:44
55	0:01:47	n.c.	0:01:45	n.c.	0:01:38	17:23:56	0:02:05	n.c.	0:01:16	19:37:42	0:00:51	8:01:50
60	0:01:28	n.c.	0:01:39	n.c.	0:02:05	n.c.	0:01:16	n.c.	0:01:25	n.c.	0:00:54	13:00:53
65	0:01:03	n.c.	0:01:45	n.c.	0:01:15	n.c.	0:01:04	n.c.	0:01:34	n.c.	0:00:52	20:52:58
70	0:01:13	n.c.	0:01:29	n.c.	0:01:21	n.c.	0:01:01	n.c.	0:01:31	n.c.	0:01:05	n.c.
75	0:00:58	n.c.	0:01:19	n.c.	0:01:24	n.c.	0:01:09	n.c.	0:01:38	n.c.	0:01:17	n.c.

Notes: This table reports computation times for different sample sizes (both in terms of countries and years considered) for the `ppml`-command of Santos Silva and Tenreyro (2011), in columns labelled 'Standard PPML' and the HDFE `ppml_panel_sg`-command of Zylkin (2017), in columns labelled 'HDFE PPML'. The first column of the table lists the number of countries included in each specification in increasing order. Computation times are given in hh:mm:ss. "n.c." refers to situations where we did not achieve convergence after 24 hours. All estimations performed on a cluster with 2 cores à 3.06MHz and allocated 15GB RAM each. Note that the Stata's maximum number of variables of 32,767 precludes estimations with PPML for example for the full data set form 1948-2013 at the latest for more than 127 countries as one needs to generate $N \times (N-1) + (N \times T \times 2)$ dummies. The exact speed gains as well as the applicable constraints depend on specific soft- and hardware used to implement the procedure. The speed of the `ppml`-command can be improved by using re-scaled trade flows instead of their original values. Nonetheless, the results in this table indicate clear speed and feasibility improvements of the HDFE `ppml_panel_sg`-command.

A.7 Further OLS Estimation Results

Table A.2: OLS Estimation of Different Subsamples

	1948-2013	1985-2013	1995-2013	1948-2005	1985-2005	1995-2005
			All countries			
EMU	0.429	0.444	0.476	0.172	0.176	0.177
	(0.021)***	(0.022)***	(0.028)***	(0.032)***	(0.030)***	(0.037)***
	{0.149}***	{0.135}***	{0.121}***	{0.158}	{0.140}	{0.120}
All Non-EMU CUs	0.298	0.235	0.301	0.290	0.076	0.167
	(0.025)***	(0.088)***	(0.132)**	(0.026)***	(0.107)	(0.167)
	{0.097}***	{0.183}	{0.224}	{0.091}***	{0.170}	{0.209}
			Industrial countries plus present/future EU			
EMU	-0.010	-0.052	0.043	-0.088	-0.158	-0.074
	(0.021)	(0.022)**	(0.025)*	(0.032)***	(0.031)***	(0.036)**
	{0.098}	{0.074}	{0.042}	{0.107}	{0.095}	{0.068}
All Non-EMU CUs	0.537	-0.151	-0.444	0.532	0.300	0.059
	(0.049)***	(0.250)	(0.329)	(0.049)***	(0.275)	(0.302)
	{0.196}***	{0.732}	{0.460}	{0.181}***	{0.644}	{0.440}
			Upper income (GDP p/c $\geq$ $ 12,736)			
EMU	0.107	0.138	0.163	-0.017	-0.007	-0.085
	(0.026)***	(0.027)***	(0.033)***	(0.037)	(0.035)	(0.041)**
	{0.103}	{0.094}	{0.099}	{0.123}	{0.104}	{0.108}
All Non-EMU CUs	0.456			0.378		
	(0.138)***			(0.123)***		
	{0.350}			{0.277}		
			Rich Big (GDP$\geq$$ 10bn, GDP p/c$\geq$$ 10k)			
EMU	0.109	0.098	0.094	0.051	0.016	-0.066
	(0.023)***	(0.024)***	(0.029)***	(0.032)	(0.030)	(0.032)**
	{0.093}	{0.078}	{0.081}	{0.117}	{0.088}	{0.090}
All Non-EMU CUs	1.041			0.990		
	(0.100)***			(0.093)***		
	{0.263}***			{0.239}***		
			OECD			
EMU	0.058	-0.001	-0.027	0.035	-0.038	-0.077
	(0.017)***	(0.015)	(0.019)	(0.023)	(0.018)**	(0.018)***
	{0.093}	{0.053}	{0.032}	{0.086}	{0.048}	{0.039}*
All Non-EMU CUs	0.991			0.947		
	(0.129)***			(0.120)***		
	{0.664}			{0.615}		
			Present/future EU			
EMU	-0.267	-0.217	-0.037	-0.312	-0.289	-0.099
	(0.024)***	(0.023)***	(0.024)	(0.036)***	(0.032)***	(0.029)***
	{0.112}**	{0.096}**	{0.046}	{0.123}**	{0.125}**	{0.078}
All Non-EMU CUs	0.814			0.736		
	(0.065)***			(0.065)***		
	{0.417}*			{0.407}*		

Notes: This table reports estimates obtained from linear specifications that correspond to the PPML estimates from Table 1.3 of the main text. RTAs and CurCol are included in the regressions, but their coefficient estimates are not shown for brevity. Robust standard errors in parentheses. Standard errors clustered by exporter, importer, and year in curly brackets. * $p < 0.10$, ** $p < .05$, *** $p < .01$. See text for further details.

Table A.3: OLS with Time Trends, Leads, and Lags

	Intervals (1)	Trends (2)	Lags (3)	Leads (4)
EMU	0.431	0.361	0.225	0.055
	(0.042)***	(0.047)***	(0.057)***	(0.073)
	{0.169}**	{0.128}**	{0.148}	{0.141}
All Non-EMU CUs	0.348	0.076	0.238	0.275
	(0.051)***	(0.065)	(0.081)***	(0.073)***
	{0.106}***	{0.116}	{0.087}**	{0.098}**
RTAs	0.414	0.053	0.207	0.325
	(0.019)***	(0.022)**	(0.025)***	(0.028)***
	{0.084}***	{0.067}	{0.109}*	{0.115}**
CurCol	0.321	-0.015	-0.076	0.341
	(0.069)***	(0.074)	(0.101)	(0.103)***
	{0.154}*	{0.135}	{0.132}	{0.111}***
EMU$_{t-4}$			0.141	
			(0.068)**	
			{0.105}	
All Non-EMU CUs$_{t-4}$			0.075	
			(0.073)	
			{0.124}	
RTAs$_{t-4}$			0.358	
			(0.027)***	
			{0.103}***	
CurCol$_{t-4}$			0.358	
			(0.089)***	
			{0.119}***	
EMU$_{t+4}$				0.280
				(0.063)***
				{0.137}*
All Non-EMU CUs$_{t+4}$				0.127
				(0.082)
				{0.114}
RTAs$_{t+4}$				0.183
				(0.026)***
				{0.084}**
CurCol$_{t+4}$				-0.136
				(0.117)
				{0.080}
N	221,170	221,170	217,462	196,559
# of Clusters				
Exporters	212	212	212	211
Importers	212	212	212	211
Years	17	17	16	16
R^2	0.864	0.914	0.865	0.866

Notes: Column (1) of this table reproduces the results of column (2) of Table 1.1 but using the data in four year intervals. In addition, we add bilateral linear time trend in column (2) and lags and leads in columns (3) and (4), respectively. Robust standard errors in parentheses. Standard errors clustered by exporter, importer, and year in curly brackets. * $p < 0.10$, ** $p < .05$, *** $p < .01$. See text for further details.

Appendix B

Persistent Zeros: The Extensive Margin of Trade

B.1 Stylized Facts

Figure B.1: Determinants of the Extensive margin of Trade — Gravity and Persistence (1990–1991).

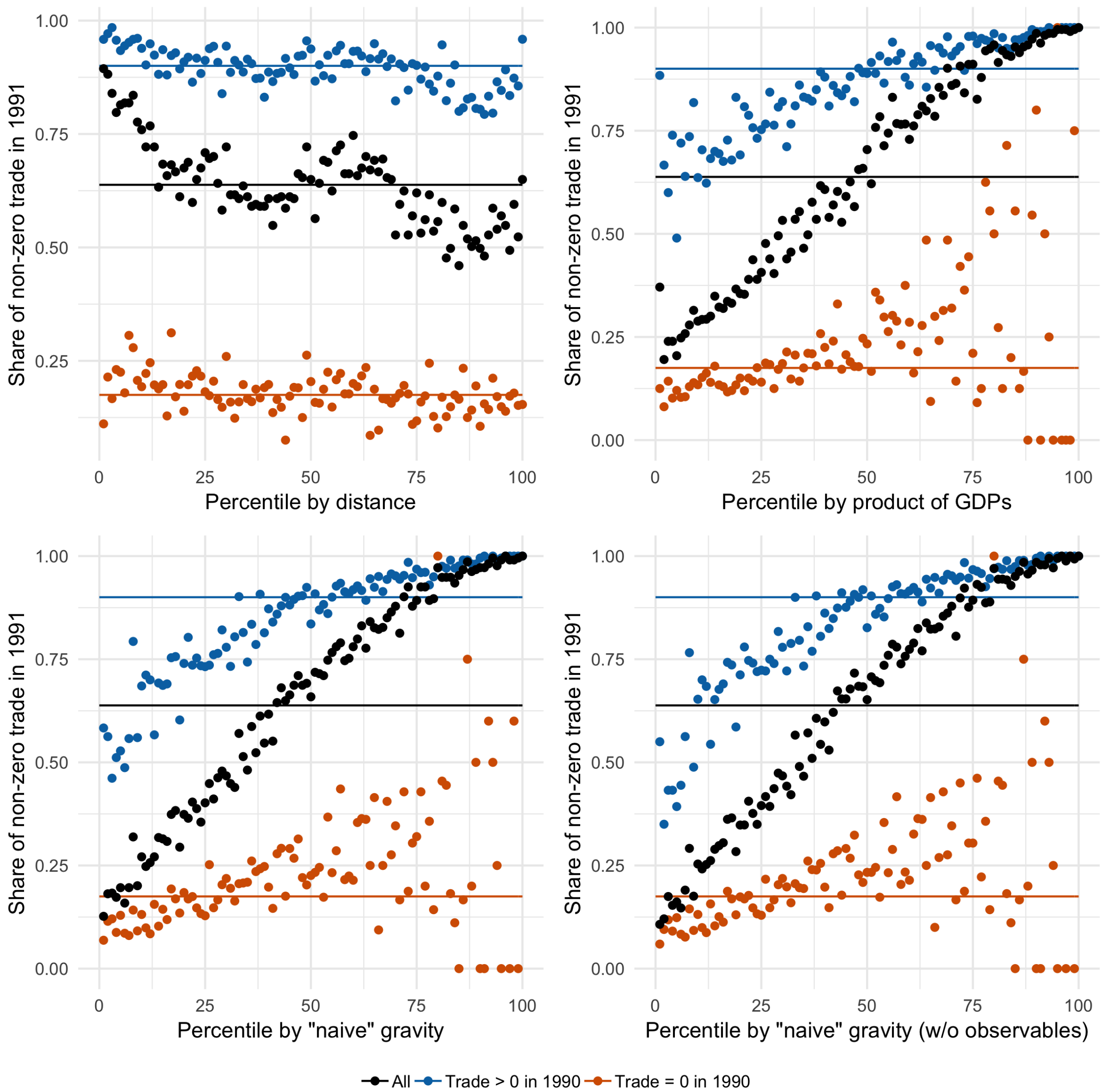
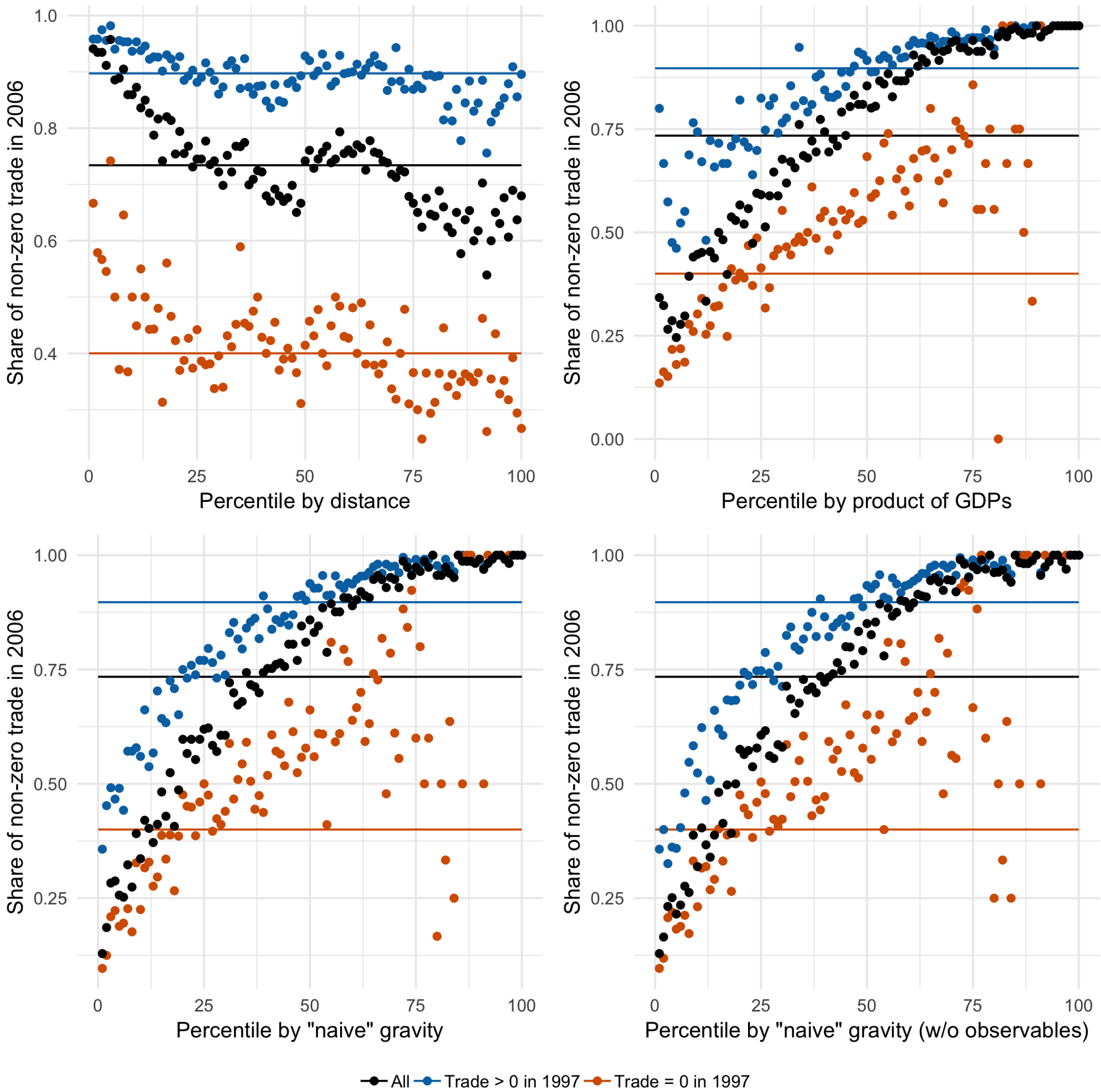


Figure B.2: Determinants of the Extensive Margin of Trade — Gravity and Persistence (1997–2006).



B.2 Computational and Econometric Details

B.2.1 Computational Details

In this section we briefly demonstrate how the method of alternating projections (MAP) works in the context of logit and probit models with a two- or three-way error component, and how it can be efficiently embedded into a standard Newton-Raphson optimization routine (see Stammann, 2018, for further details).

First, note that $\mathbb{M}\,\mathbf{v}$ is essentially a weighted within transformation, where $\mathbf{v}$ is an arbitrary $n \times 1$ vector, and $\mathbb{M} = \mathbf{I}_n - \mathbb{P} = \mathbf{I}_n - \mathbf{D}(\mathbf{D}'\boldsymbol{\Omega}\mathbf{D})^{-1}\mathbf{D}'\boldsymbol{\Omega}$. The computation of $\mathbb{M}$ is problematic even in moderately large data sets, and since $\mathbb{M}$ is non-sparse, there is also no general scalar expression to compute $\mathbb{M}\,\mathbf{v}$. Thus Stammann (2018) proposes to calculate $\mathbb{M}\,\mathbf{v}$ using a simple iterative approach based on the MAP tracing back to Von Neumann (1950) and Halperin (1962).[1] Let $\mathbf{D}_k$, denote the dummy variables corresponding to the k-th group, $k \in \{1, 2, 3\}$. Further, let $\mathbb{M}_{\mathbf{D}_k}\,\mathbf{v}$, with $\mathbb{M}_{\mathbf{D}_k} = \mathbf{I}_n - \mathbf{D}_k(\mathbf{D}_k'\boldsymbol{\Omega}\mathbf{D}_k)^{-1}\mathbf{D}_k'\boldsymbol{\Omega}$. The corresponding scalar expressions of $\mathbb{M}_{\mathbf{D}_k}\,\mathbf{v}$ are summarized in table (B.1).

Table B.1: Scalar Transformations

group	$\mathbb{M}_{\mathbf{D}_k}\,\mathbf{v}$
importer-time ($k = 1$)	$\mathbf{v}_{ijt} - \frac{\sum_{j=1}^{J} \omega_{ijt} v_{ijt}}{\sum_{j=1}^{J} \omega_{ijt}}$
exporter-time ($k = 2$)	$\mathbf{v}_{ijt} - \frac{\sum_{i=1}^{I} \omega_{ijt} v_{ijt}}{\sum_{i=1}^{I} \omega_{ijt}}$
dyadic ($k = 3$)	$\mathbf{v}_{ijt} - \frac{\sum_{t=1}^{T} \omega_{ijt} v_{ijt}}{\sum_{t=1}^{T} \omega_{ijt}}$

The MAP can be summarized by algorithm 1, where $K = 2$ in the case of two-way fixed effects and $K = 3$ in the case of three-way fixed effects. Thus, the MAP only requires

[1] The MAP has been introduced to econometrics by Guimarães and Portugal (2010) and Gaure (2013) in the context of linear models with multi-way fixed effects.

to repeatedly apply weighted one-way within transformations (see Stammann, 2018)). The entire optimization routine is sketched by algorithm 2.

Algorithm 1 MAP: Neumann-Halperin

```
Initialize 𝕄 v = v.
repeat
    for k = 1, ..., K do
        Compute 𝕄_{D_k} 𝕄 v and update 𝕄 v such that 𝕄 v = 𝕄_{D_k} 𝕄 v
until convergence.
```

Algorithm 2 Efficient Newton-Raphson using the MAP

```
Initialize β^0, η^0, and r = 0.
repeat
    Set r = r + 1.
    Given η̂^{r−1} compute ν̂ and Ω̂.
    Given ν̂ and Ω̂ compute \widehat{𝕄ν} and \widehat{𝕄X} using the MAP
    Compute β^r − β^{r−1} = ((\widehat{𝕄X})'Ω̂(\widehat{𝕄X}))^{−1} (\widehat{𝕄X})'Ω̂(\widehat{𝕄ν})
    Compute η̂^r = η̂^{r−1} + ν̂ − \widehat{𝕄ν} + \widehat{𝕄X}(β^r − β^{r−1})
until convergence.
```

B.2.2 Neyman-Scott Variance Example

In this section we study two variants of the classical Neyman and Scott (1948) variance example to support the form of the bias terms, and to illustrate the functionality of the bias corrections. To the best of our knowledge, the variance example of Neyman and Scott (1948) has not been investigated for our specific error components. We start with the more general three-way fixed effects case which nests the two-way error structure.

Three-way Fixed Effects

Let $i = 1, \ldots, I$, $j = 1, \ldots, J$ and $t = 1, \ldots, T$. Consider the following linear three-way fixed effects model:

$$y_{ijt} = \mathbf{x}'_{ijt}\boldsymbol{\beta} + \lambda_{it} + \psi_{jt} + \mu_{ij} + u_{ijt} \, . \tag{B.1}$$

According to Balazsi, Matyas, and Wansbeek (2018), the appropriate within transformation corresponding to equation (B.1) is given by

$$z_{ijt} - \bar{z}_{ij\cdot} - \bar{z}_{\cdot jt} - \bar{z}_{i\cdot t} + \bar{z}_{\cdot\cdot t} + \bar{z}_{\cdot j\cdot} + \bar{z}_{i\cdot\cdot} - \bar{z}_{\cdot\cdot\cdot} \ ,$$

where $\bar{z}_{ij\cdot} = \frac{1}{T}\sum_{t=1}^{T} z_{ijt}$, $\bar{z}_{\cdot jt} = \frac{1}{I}\sum_{i=1}^{I} z_{ijt}$, $\bar{z}_{i\cdot t} = \frac{1}{J}\sum_{j=1}^{J} z_{ijt}$, $\bar{z}_{\cdot\cdot t} = \frac{1}{IJ}\sum_{i=1}^{I}\sum_{j=1}^{J} z_{ijt}$, $\bar{z}_{\cdot j\cdot} = \frac{1}{IT}\sum_{i=1}^{I}\sum_{t=1}^{T} z_{ijt}$, $\bar{z}_{i\cdot\cdot} = \frac{1}{JT}\sum_{j=1}^{J}\sum_{t=1}^{T} z_{ijt}$, and $\bar{z}_{\cdot\cdot\cdot} = \frac{1}{IJT}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} z_{ijt}$.

This result is helpful to study the following variant of the Neyman and Scott (1948) variance example

$$y_{ijt}|\boldsymbol{\lambda}, \boldsymbol{\psi}, \boldsymbol{\mu} \sim \mathcal{N}(\lambda_{it} + \psi_{jt} + \mu_{ij}, \beta) \ ,$$

where we can now easily form the uncorrected variance estimator

$$\hat{\beta}_{I,J,T} = \frac{1}{IJT}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T}(y_{ijt} - \bar{y}_{ij\cdot} - \bar{y}_{\cdot jt} - \bar{y}_{i\cdot t} + \bar{y}_{\cdot\cdot t} + \bar{y}_{\cdot j\cdot} + \bar{y}_{i\cdot\cdot} - \bar{y}_{\cdot\cdot\cdot})^2 \qquad \text{(B.2)}$$

and the (degrees-of-freedom)-corrected counterpart

$$\hat{\beta}^{cor}_{I,J,T} = \frac{IJT}{(I-1)(J-1)(T-1)}\hat{\beta}_{I,J,T} \ .$$

Taking the expectation of (B.2) (conditional on the fixed effects) yields

$$\begin{aligned}\bar{\beta}_{I,J,T} = \mathbb{E}_{\alpha}[\hat{\beta}_{I,J,T}] &= \beta^0\left(\frac{(I-1)(J-1)(T-1)}{IJT}\right) \qquad \text{(B.3)}\\ &= \beta^0\left(1 - \frac{1}{I} - \frac{1}{J} - \frac{1}{T} + \frac{1}{IT} + \frac{1}{JT} + \frac{1}{IJ} - \frac{1}{IJT}\right) \ ,\end{aligned}$$

where β^0 is the true variance parameter. Thus, the three leading bias terms, which drive the main part of the asymptotic bias, are $\overline{\mathbf{B}}^{\beta}_{1,\infty} = -\beta^0$, $\overline{\mathbf{B}}^{\beta}_{2,\infty} = -\beta^0$, and $\overline{\mathbf{B}}^{\beta}_{3,\infty} = -\beta^0$.

Analytical Bias Correction. Using equation (B.3), we can form the analytically bias-corrected estimator

$$\tilde{\beta}^{a}_{I,J,T} = \hat{\beta}_{I,J,T} - \frac{\widehat{\mathbf{B}}^{\beta}_{1,I,J,T}}{I} - \frac{\widehat{\mathbf{B}}^{\beta}_{2,I,J,T}}{J} - \frac{\widehat{\mathbf{B}}^{\beta}_{3,I,J,T}}{T} \ , \tag{B.4}$$

where we set $\widehat{\mathbf{B}}^{\beta}_{1,I,J,T} = -\hat{\beta}_{I,J,T}$, $\widehat{\mathbf{B}}^{\beta}_{2,I,J,T} = -\hat{\beta}_{I,J,T}$, and $\widehat{\mathbf{B}}^{\beta}_{3,I,J,T} = -\hat{\beta}_{I,J,T}$ to reduce the order of the bias in equation (B.3) at costs of introducing higher order terms (see equation (B.6)). Thus, we can rewrite the analytically bias-corrected estimator (B.4)

$$\tilde{\beta}^{a}_{I,J,T} = \hat{\beta}_{I,J,T} \left(1 + \frac{1}{I} + \frac{1}{J} + \frac{1}{T}\right) \ . \tag{B.5}$$

Taking the expectation of (B.5) yields

$$\begin{aligned}\bar{\beta}^{a}_{I,J,T} = \mathbb{E}_{\alpha}[\tilde{\beta}^{a}_{I,J,T}] &= \beta^{0} \left(1 - \frac{1}{I} - \frac{1}{J} - \frac{1}{T} + \frac{1}{IT} + \frac{1}{JT} + \frac{1}{IJ} - \frac{1}{IJT}\right) \left(1 + \frac{1}{I} + \frac{1}{J} + \frac{1}{T}\right) \\ &= \beta^{0} \left(1 - \frac{1}{IT} - \frac{1}{JT} - \frac{1}{T^2} - \frac{3}{IJ} + \frac{1}{I^3} + \frac{1}{J^3} + \frac{4}{IJT} + \frac{1}{IT^2} + \frac{1}{JT^2} \right. \\ &\qquad \left. - \frac{1}{I^3 T} - \frac{1}{J^3 T} - \frac{1}{IJT^2}\right) \ .\end{aligned} \tag{B.6}$$

Split-Panel Jackknife. As an alternative to equation (B.5) we can also form the following SPJ estimator

$$\hat{\beta}^{spj}_{I,J,T} = 4\hat{\beta}_{I,J,T} - \hat{\beta}_{I/2,J,T} - \hat{\beta}_{I,J/2,T} - \hat{\beta}_{I,J,T/2} \ ,$$

where $\hat{\beta}_{I/2,J,T}$ denotes the half panel estimator based on splitting the panel by exporters. This estimator also reduces the order of the bias in equation (B.3) as we see from its expected value

$$\begin{aligned}\bar{\beta}^{spj}_{I,J,T} = E_{\phi}[\hat{\beta}^{spj}_{I,J,T}] &= 4\bar{\beta}_{I,J,T} - \bar{\beta}_{I/2,J,T} - \bar{\beta}_{I,J/2,T} - \bar{\beta}_{I,J,T/2} \\ &= \beta^{0} \left(1 - \frac{1}{IT} - \frac{1}{JT} - \frac{1}{IJ} + \frac{2}{IJT}\right) \ .\end{aligned} \tag{B.7}$$

Numerical Results. Table B.2 shows numerical results for the uncorrected and the bias-corrected estimators in finite samples, where we assume symmetry, i.e. $I = J = N$. The results demonstrate that the bias corrections are effective in reducing the bias.

Table B.2: Bias - Three-way Fixed Effects

N	T	$(\bar{\beta}_{I,J,T} - \beta^0)/\beta^0$	$(\bar{\beta}^{a}_{I,J,T} - \beta^0)/\beta^0$	$(\bar{\beta}^{spj}_{I,J,T} - \beta^0)/\beta^0$
10	10	-0.271	-0.052	-0.028
25	10	-0.171	-0.021	-0.009
25	25	-0.115	-0.009	-0.005
50	10	-0.136	-0.015	-0.004
50	25	-0.078	-0.004	-0.002
50	50	-0.059	-0.002	-0.001

Two-way Fixed Effects

In the following we briefly review the example with two-way fixed effects:

$$y_{ijt} | \boldsymbol{\lambda}, \boldsymbol{\psi} \sim \mathcal{N}(\lambda_{it} + \psi_{jt}, \beta) \; .$$

Since it is a subcase of three-way fixed effects example, all previous results simplify by dropping the terms that exhibit T.

The uncorrected variance estimator is[2]

$$\hat{\beta}_{I,J,T} = \frac{1}{IJT} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} (y_{ijt} - \bar{y}_{\cdot jt} - \bar{y}_{i \cdot t} + \bar{y}_{\cdot\cdot t})^2$$

and the (degrees-of-freedom)-corrected variance estimator is

$$\hat{\beta}^{cor}_{I,J,T} = \frac{IJ}{(I-1)(J-1)} \hat{\beta}_{I,J,T} \; .$$

[2]We draw on the appropriate demeaning formula for the two-way fixed effects model $y_{ijt} = \boldsymbol{x}'_{ijt}\boldsymbol{\beta} + \lambda_{it} + \psi_{jt} + u_{ijt}$, which is given by $z_{ijt} - \bar{z}_{\cdot jt} - \bar{z}_{i \cdot t} + \bar{z}_{\cdot\cdot t}$.

Taking the expected value yields

$$\bar{\beta}_{I,J,T} = \mathbb{E}_\alpha[\hat{\beta}_{I,J,T}] = \beta^0 \left(\frac{(I-1)^2}{IJ} \right) \tag{B.8}$$
$$= \beta^0 \left(1 - \frac{1}{I} - \frac{1}{J} + \frac{1}{IJ} \right) \; .$$

Analytical Bias Correction. Based on equation (B.8) we can form the following analytically bias-corrected estimator

$$\tilde{\beta}^a_{I,J,T} = \hat{\beta}_{I,J,T} \left(1 + \frac{1}{I} + \frac{1}{J} \right) \; ,$$

which has the expected value

$$\bar{\beta}^a_{I,J,T} = \mathbb{E}_\alpha[\tilde{\beta}^a_{I,J,T}] = \beta^0 \left(1 - \frac{3}{IJ} + \frac{1}{I^3} + \frac{1}{J^3} \right) \; .$$

Split-Panel Jackknife. A suitable split-panel jackknife estimator is

$$\hat{\beta}^{spj}_{I,J,T} = 4\hat{\beta}_{I,J,T} - \hat{\beta}_{I/2,J,T} - \hat{\beta}_{I,J/2,T} \; ,$$

which has the expected value

$$\bar{\beta}^{spj}_{I,J,T} = \mathbb{E}_\alpha[\hat{\beta}^{spj}_{I,J,T}] = 3\bar{\beta}_{I,J,T} - \bar{\beta}_{I/2,J,T} - \bar{\beta}_{I,J/2,T}$$
$$= \beta^0 \left(1 - \frac{1}{IJ} \right) \; .$$

Numerical Results. The numerical results in table B.3 demonstrate that the bias corrections work.

Table B.3: Bias - Two-way Fixed Effects

N	$(\bar{\beta}_{I,J,T} - \beta^0)/\beta^0$	$(\bar{\beta}^{a}_{I,J,T} - \beta^0)/\beta^0$	$(\bar{\beta}^{spj}_{I,J,T} - \beta^0)/\beta^0$
10	-0.190	-0.028	-0.010
25	-0.078	-0.005	-0.002
50	-0.040	-0.001	-0.000
100	-0.020	-0.000	-0.000

B.2.3 Asymptotic Bias Corrections

For the following expressions we draw on the results of Fernández-Val and Weidner (2016), who have already derived the asymptotic distributions of the MLE estimators for structural parameters and APEs in classical two-way fixed effects models based on it-panels. As outlined in Cruz-Gonzalez, Fernández-Val, and Weidner (2017) the bias corrections of Fernández-Val and Weidner (2016) can easily be adjusted to two-way fixed effects models based on pseudo-panels with an ij-structure (i corresponds to importer and j to exporter), and importer and exporter fixed effects. We give an intuitive explanation. Since only J observations are informative per exporter fixed effects, we get a bias of order J for including exporter fixed effects, and vice versa a bias of order I for including importer fixed effects. Further, since there are no predetermined regressors in an ij-structure, we get two symmetric bias terms

$$\overline{\mathbf{B}}_{1,\infty} = \text{plim}_{I,J\to\infty}\left[\frac{1}{2J}\sum_{j=1}^{J}\frac{\sum_{i=1}^{I}\mathbb{E}_{\alpha}[H_{ij}\partial_{\eta^2}F_{ij}(\mathbb{M}\,\mathbf{X})_{ij}]}{\sum_{i=1}^{I}\mathbb{E}_{\alpha}[\omega_{ij}]}\right], \tag{B.9}$$

$$\overline{\mathbf{B}}_{2,\infty} = \text{plim}_{I,J\to\infty}\left[\frac{1}{2I}\sum_{i=1}^{I}\frac{\sum_{j=1}^{J}\mathbb{E}_{\alpha}[H_{ij}\partial_{\eta^2}F_{ij}(\mathbb{M}\,\mathbf{X})_{ij}]}{\sum_{j=1}^{J}\mathbb{E}_{\alpha}[\omega_{ij}]}\right], \tag{B.10}$$

where ω_{ij} is the ij-th diagonal entry of $\mathbf{\Omega}$, and $\mathbb{M} = \mathbf{I}_{IJ} - \mathbf{D}(\mathbf{D}'\mathbf{\Omega}\mathbf{D})^{-1}\mathbf{D}'\mathbf{\Omega}$. $\partial_{\iota^2}g(\cdot)$ denotes the second order partial derivative of an arbitrary function $g(\cdot)$ with respect to some parameter ι. The explicit expressions of H_{ijt} and $\partial_{\eta^2}F_{ijt}$ are reported in table 2.1. Equations (B.9) and (B.10) are essentially $\overline{\mathbf{D}}_{\infty}$ from Fernández-Val and Weidner (2016) with adjusted indices. The same adjustment can be transferred to the APEs.

In the following we apply the same logic to derive the asymptotic bias terms in our two-and three-way error structure.

Two-way Fixed Effects

We get a bias of order J for including exporter-time fixed effects, since J observations are informative per exporter-time fixed effect. In the same way we get a bias of order I for including importer-time fixed effects. As in the case of the ij-structure of Cruz-Gonzalez, Fernández-Val, and Weidner (2017) there are no predetermined regressors, leading to two symmetric bias terms in the distributions of the structural parameters and the APEs, respectively.

Asymptotic distribution of $\hat{\boldsymbol{\beta}}$:

$$\sqrt{IJ}(\widehat{\boldsymbol{\beta}}_{I,J,T} - \boldsymbol{\beta}^0) \to_d \overline{\mathbf{W}}_\infty^{-1} \mathcal{N}(\kappa \overline{\mathbf{B}}_{1,\infty} + \kappa^{-1} \overline{\mathbf{B}}_{2,\infty}, \overline{\mathbf{W}}_\infty), \quad \text{with} \tag{B.11}$$
$$\overline{\mathbf{B}}_{1,\infty} = \text{plim}_{I,J\to\infty} \left[\frac{1}{2J} \sum_{t=1}^{T} \sum_{j=1}^{J} \frac{\sum_{i=1}^{I} \mathbb{E}_\alpha[H_{ijt} \partial_{\eta^2} F_{ijt} (\mathbb{M}\,\mathbf{X})_{ijt}]}{\sum_{i=1}^{I} \mathbb{E}_\alpha[\omega_{ijt}]} \right],$$
$$\overline{\mathbf{B}}_{2,\infty} = \text{plim}_{I,J\to\infty} \left[\frac{1}{2I} \sum_{t=1}^{T} \sum_{i=1}^{I} \frac{\sum_{j=1}^{J} \mathbb{E}_\alpha[H_{ijt} \partial_{\eta^2} F_{ijt} (\mathbb{M}\,\mathbf{X})_{ijt}]}{\sum_{j=1}^{J} \mathbb{E}_\alpha[\omega_{ijt}]} \right],$$
$$\overline{\mathbf{W}}_\infty = \text{plim}_{I,J\to\infty} \left[-\frac{1}{IJ} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \mathbb{E}_\alpha[\omega_{ijt} (\mathbb{M}\,\mathbf{X})_{ijt} (\mathbb{M}\,\mathbf{X})'_{ijt}] \right],$$

where $\sqrt{J/I} \to \kappa$ as $I, J \to \infty$.

Asymptotic distribution of $\hat{\boldsymbol{\delta}}$:

$$r(\hat{\boldsymbol{\delta}} - \boldsymbol{\delta} - I^{-1} \overline{\mathbf{B}}^{\delta}_{1,\infty} - J^{-1} \overline{\mathbf{B}}^{\delta}_{2,\infty}) \to_d \mathcal{N}(0, \overline{\mathbf{V}}_\infty), \quad \text{with} \tag{B.12}$$
$$\overline{\mathbf{B}}^{\delta}_{1,\infty} = \text{plim}_{I,J\to\infty} \left[\frac{1}{2JT} \sum_{t=1}^{T} \sum_{j=1}^{J} \frac{\sum_{i=1}^{I} - \mathbb{E}_\alpha[H_{ijt} \partial_{\eta^2} F_{ijt}] \, \mathbb{E}_\alpha \left(\mathbb{P}\, \boldsymbol{\Psi} \right)_{ijt} + \mathbb{E}_\alpha[\partial_{\eta^2} \boldsymbol{\Delta}_{ijt}]}{\sum_{i=1}^{I} \mathbb{E}_\alpha[\omega_{ijt}]} \right],$$
$$\overline{\mathbf{B}}^{\delta}_{2,\infty} = \text{plim}_{I,J\to\infty} \left[\frac{1}{2IT} \sum_{t=1}^{T} \sum_{i=1}^{I} \frac{\sum_{j=1}^{J} - \mathbb{E}_\alpha[H_{ijt} \partial_{\eta^2} F_{ijt}] \, \mathbb{E}_\alpha \left(\mathbb{P}\, \boldsymbol{\Psi} \right)_{ijt} + \mathbb{E}_\alpha[\partial_{\eta^2} \boldsymbol{\Delta}_{ijt}]}{\sum_{j=1}^{J} \mathbb{E}_\alpha[\omega_{ijt}]} \right],$$
$$\overline{\mathbf{V}}^{\delta}_\infty = \text{plim}_{I,J\to\infty} \frac{r^2}{I^2 J^2 T^2} \mathbb{E}_\alpha \left[\left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \bar{\boldsymbol{\Delta}}_{ijt} \right) \left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \bar{\boldsymbol{\Delta}}_{ijt} \right)' + \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \boldsymbol{\Gamma}_{ijt} \boldsymbol{\Gamma}'_{ijt} \right],$$

where $\bar{\boldsymbol{\Delta}}_{ijt} = \boldsymbol{\Delta}_{ijt} - \boldsymbol{\delta}$, $\boldsymbol{\Delta}_{ijt} = [\Delta^1_{ijt}, \ldots, \Delta^m_{ijt}]'$, $\boldsymbol{\delta} = [\delta_1, \ldots, \delta_m]'$, $\delta_k = \frac{1}{IJT} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \Delta^k_{ijt}$,

$\boldsymbol{\Psi}_{ijt} = \partial_\eta \boldsymbol{\Delta}_{ijt}/\omega_{ijt}$, and

$$\boldsymbol{\Gamma}_{ijt} = \left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \partial_\beta \boldsymbol{\Delta}_{ijt} - (\mathbb{P}\,\mathbf{X})_{ijt}\, \partial_\eta \boldsymbol{\Delta}_{ijt} \right)' \mathbf{W}^{-1} (\mathbb{M}\,\mathbf{X})_{ijt}\, \omega_{ijt} \boldsymbol{\nu}_{ijt} - (\mathbb{P}\,\boldsymbol{\Psi})_{ijt}\, \partial_\eta \ell_{ijt} \,.$$

r is a convergence rate. $\partial_\iota g(\cdot)$ denotes the first order partial derivative of an arbitrary function $g(\cdot)$ with respect to some parameter ι. The expression $\overline{\mathbf{V}}_\infty^\delta$ can be modified by assuming that $\{\lambda_{it}\}_{IT}$ and $\{\psi_{jt}\}_{JT}$ are independent sequences, and λ_{it} and ψ_{jt} are independent for all it, jt:

$$\overline{\mathbf{V}}_\infty^\delta = \text{plim}_{I,J\to\infty} \frac{r^2}{I^2 J^2 T^2}\, \mathbb{E}_\alpha \left(\sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{j=1}^{J} \sum_{r=1}^{J} \bar{\boldsymbol{\Delta}}_{ijt} \bar{\boldsymbol{\Delta}}_{irt}' + \sum_{j=1}^{J} \sum_{t=1}^{T} \sum_{i \neq p}^{I} \bar{\boldsymbol{\Delta}}_{ijt} \bar{\boldsymbol{\Delta}}_{pjt}' \right.$$
$$\left. + \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \boldsymbol{\Gamma}_{ijt} \boldsymbol{\Gamma}_{ijt}' \right) \,.$$

Three-way Fixed Effects

With the inclusion of pair fixed effects, we introduce an additional bias of order T, since only T observations are informative per pair fixed effect. Another difference that occurs in contrast to the two-way fixed effects case is that predetermined regressors are now possible. To deal with this issue we adapt the asymptotic bias terms $\overline{\mathbf{B}}_\infty$ and $\overline{\mathbf{B}}_\infty^\delta$ of Fernández-Val and Weidner (2016) to the new structure.

Conjectured asymptotic distribution of $\hat{\boldsymbol{\beta}}$:

$$\sqrt{IJT}(\widehat{\boldsymbol{\beta}}_{I,J,T} - \boldsymbol{\beta}^0) \to_d \overline{\mathbf{W}}_\infty^{-1} \mathcal{N}(\kappa_1 \overline{\mathbf{B}}_{1,\infty} + \kappa_2 \overline{\mathbf{B}}_{2,\infty} + \kappa_3 \overline{\mathbf{B}}_{3,\infty}, \overline{\mathbf{W}}_\infty), \quad \text{with}$$

$$\overline{\mathbf{B}}_{1,\infty} = \text{plim}_{I,J,T\to\infty} \left[\frac{1}{2JT} \sum_{t=1}^{T} \sum_{j=1}^{J} \frac{\sum_{i=1}^{I} \mathbb{E}_\alpha [H_{ijt} \partial_{\eta^2} F_{ijt} (\mathbb{M}\,\mathbf{X})_{ijt}]}{\sum_{i=1}^{I} \mathbb{E}_\alpha [\omega_{ijt}]} \right],$$

$$\overline{\mathbf{B}}_{2,\infty} = \text{plim}_{I,J,T\to\infty} \left[\frac{1}{2IT} \sum_{t=1}^{T} \sum_{i=1}^{I} \frac{\sum_{j=1}^{J} \mathbb{E}_\alpha [H_{ijt} \partial_{\eta^2} F_{ijt} (\mathbb{M}\,\mathbf{X})_{ijt}]}{\sum_{j=1}^{J} \mathbb{E}_\alpha [\omega_{ijt}]} \right],$$

$$\overline{\mathbf{B}}_{3,\infty} = \text{plim}_{I,J,T\to\infty} \left[\frac{1}{2IJ} \sum_{i=1}^{I} \sum_{j=1}^{J} \left(\sum_{t=1}^{T} \mathbb{E}_\alpha [\omega_{ijt}] \right)^{-1} \left(\sum_{t=1}^{T} \mathbb{E}_\alpha [H_{ijt} \partial_{\eta^2} F_{ijt} (\mathbb{M}\,\mathbf{X})_{ijt}] \right.\right.$$
$$\left.\left. + 2 \sum_{\tau=t+1}^{T} \mathbb{E}_\alpha [H_{ijt} (Y_{ijt} - F_{ijt}) \omega_{ijt} (\mathbb{M}\,\mathbf{X})_{ijt}] \right) \right],$$

$$\overline{\mathbf{W}}_\infty = \text{plim}_{I,J,T\to\infty} \left[-\frac{1}{IJT} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \mathbb{E}_\alpha [\omega_{ijt} (\mathbb{M}\,\mathbf{X})_{ijt} (\mathbb{M}\,\mathbf{X})'_{ijt}] \right].$$

where $\sqrt{(JT)/I} \to \kappa_1$, $\sqrt{(IT)/J} \to \kappa_2$, and $\sqrt{(IJ)/T} \to \kappa_3$ as $I, J, T \to \infty$. The second term in the numerator of $\overline{\mathbf{B}}_{3,\infty}$ is dropped if all regressors are assumed to be strictly exogenous.

Conjectured asymptotic distribution of $\hat{\boldsymbol{\delta}}$:

$$r(\hat{\boldsymbol{\delta}} - \boldsymbol{\delta} - I^{-1} \overline{\mathbf{B}}^\delta_{1,\infty} - J^{-1} \overline{\mathbf{B}}^\delta_{2,\infty} - T^{-1} \overline{\mathbf{B}}^\delta_{3,\infty}) \to_d \mathcal{N}(0, \overline{\mathbf{V}}^\delta_\infty), \quad \text{with}$$

$$\overline{\mathbf{B}}^\delta_{1,\infty} = \text{plim}_{I,J,T\to\infty} \left[\frac{1}{2JT} \sum_{t=1}^{T} \sum_{j=1}^{J} \frac{\sum_{i=1}^{I} - \mathbb{E}_\alpha [H_{ijt} \partial_{\eta^2} F_{ijt}] \, \mathbb{E}_\alpha \left(\mathbb{P}\,\boldsymbol{\Psi} \right)_{ijt} + \mathbb{E}_\alpha [\partial_{\eta^2} \boldsymbol{\Delta}_{ijt}]}{\sum_{i=1}^{I} \mathbb{E}_\alpha [\omega_{ijt}]} \right],$$

$$\overline{\mathbf{B}}^\delta_{2,\infty} = \text{plim}_{I,J,T\to\infty} \left[\frac{1}{2IT} \sum_{t=1}^{T} \sum_{i=1}^{I} \frac{\sum_{j=1}^{J} - \mathbb{E}_\alpha [H_{ijt} \partial_{\eta^2} F_{ijt}] \, \mathbb{E}_\alpha \left(\mathbb{P}\,\boldsymbol{\Psi} \right)_{ijt} + \mathbb{E}_\alpha [\partial_{\eta^2} \boldsymbol{\Delta}_{ijt}]}{\sum_{j=1}^{J} \mathbb{E}_\alpha [\omega_{ijt}]} \right],$$

$$\overline{\mathbf{B}}^\delta_{3,\infty} = \text{plim}_{I,J,T\to\infty} \left[\frac{1}{2IJ} \sum_{i=1}^{I} \sum_{j=1}^{J} \left(\sum_{t=1}^{T} \mathbb{E}_\alpha [\omega_{ijt}] \right)^{-1} \left(\sum_{t=1}^{T} - \mathbb{E}_\alpha [H_{ijt} \partial_{\eta^2} F_{ijt}] \, \mathbb{E}_\alpha [(\mathbb{P}\,\boldsymbol{\Psi})_{ijt}] \right.\right.$$
$$\left.\left. + \mathbb{E}_\alpha [\partial_{\eta^2} \boldsymbol{\Delta}_{ijt}] + 2 \sum_{\tau=t+1}^{T} \mathbb{E}_\alpha [\partial_\eta \ell_{ijt-l} \omega_{ijt} \left(\mathbb{M}\,\boldsymbol{\Psi} \right)_{ijt}] \right) \right].$$

$$\overline{\mathbf{V}}^\delta_\infty = \text{plim}_{I,J,T\to\infty} \frac{r^2}{I^2 J^2 T^2} \mathbb{E}_\alpha \left[\left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \bar{\boldsymbol{\Delta}}_{ijt} \right) \left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \bar{\boldsymbol{\Delta}}_{ijt} \right)' \right.$$
$$\left. + \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} \boldsymbol{\Gamma}_{ijt} \boldsymbol{\Gamma}'_{ijt} + 2 \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{s>t}^{T} \bar{\boldsymbol{\Delta}}_{ijt} \boldsymbol{\Gamma}'_{ijs} \right],$$

r is a convergence rate. The second term in the numerator of $\overline{\mathbf{B}}_{3,\infty}$ and the last term in $\overline{\mathbf{V}}_{\infty}^{\delta}$ are dropped if all regressors are assumed to be strictly exogenous. The expression $\overline{\mathbf{V}}_{\infty}^{\delta}$ can be further modified by assuming that $\{\lambda_{it}\}_{IT}$, $\{\psi_{jt}\}_{JT}$ and $\{\mu_{ij}\}_{IJ}$ are independent sequences, and λ_{it}, ψ_{jt} and μ_{ij} are independent for all it, jt, ij:

$$\widehat{\mathbf{V}}^{\delta} = \text{plim}_{I,J,T\to\infty} \frac{r^2}{I^2J^2T^2}\,\mathbb{E}_{\alpha}\left(\sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{r=1}^{J}\bar{\mathbf{\Delta}}_{ijt}\bar{\mathbf{\Delta}}_{irt}' + \sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i\neq p}^{I}\bar{\mathbf{\Delta}}_{ijt}\bar{\mathbf{\Delta}}_{pjt}' \right.$$
$$\left. + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s\neq t}^{T}\bar{\mathbf{\Delta}}_{ijt}\bar{\mathbf{\Delta}}_{ijs}' + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T}\mathbf{\Gamma}_{ijt}\mathbf{\Gamma}_{ijt}' + 2\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{s>t}^{T}\bar{\mathbf{\Delta}}_{ijt}\mathbf{\Gamma}_{ijs}'\right) ,$$

B.2.4 Bias-corrected Ordinary Least Squares

Consider the three-way fixed effects linear probability model

$$y_{ijt} = \lambda_{it} + \psi_{jt} + \mu_{ij} + \mathbf{x}_{ijt}'\boldsymbol{\beta} + \epsilon_{ijt} ,$$

which can also be rewritten in matrix notation:

$$\mathbf{y} = \mathbf{D}\boldsymbol{\alpha} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} . \tag{B.13}$$

We first deal with the computational burden. Applying the three-way fixed effects residual projection $\mathbb{M} = \mathbf{I}_{IJT} - \mathbf{D}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'$ to (B.13), leads to the following concentrated regression:

$$\mathbb{M}\mathbf{y} = \mathbb{M}\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} . \tag{B.14}$$

The demeaning can be efficiently carried out by using the method of alternating projections (see Gaure, 2013).

Hahn and Moon (2006) have derived the bias of dynamic linear models with individual and time fixed effects. They show that there is only a bias of order $1/T$ stemming from the inclusion of individual effects in combination with predetermined regressors. Transferring their result to our problem with the three-way error component suggests that the inclusion of pair fixed effects in combination with predetermined regressors leads to the same order of the bias. Thus, the linear probability model needs only to be bias-corrected if not all regressors are strictly exogenous. This is, for example, the case in a dynamic model, where we include $\mathbf{y}_{t-1}$ to our set of regressors.

An estimator of the bias is given by

$$\widehat{\mathbf{B}} = \left(\frac{1}{IJT} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} (\mathbb{M}\mathbf{X})_{ijt} (\mathbb{M}\mathbf{X})'_{ijt} \right)^{-1} \left(- \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{l=1}^{L} \frac{1}{T-l} \sum_{t=l+1}^{T} \mathbf{X}_{ijt} \hat{\boldsymbol{\epsilon}}_{ijt-l} \right) ,$$

where $\hat{\boldsymbol{\epsilon}}$ is the residual of (B.14) and L is a bandwidth parameter.[3] This yields the bias-corrected estimator

$$\hat{\boldsymbol{\beta}} - \frac{\widehat{\mathbf{B}}}{IJT} , \tag{B.15}$$

where $\hat{\boldsymbol{\beta}} = \left((\mathbb{M}\mathbf{X})'(\mathbb{M}\mathbf{X}) \right)^{-1} (\mathbb{M}\mathbf{X})'\mathbb{M}\mathbf{y}$.

[3]The residuals of equation (B.13) and equation (B.14) are identical (see Gaure, 2013).

B.3 Monte Carlo Results — Dynamic Model

B.3.1 Two-way Fixed Effects

Table B.4: Dynamic: Two-way FEs — x, $N = 50$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
	N = 50; T = 10									
MLE	5	2	5	0.95	0.14	0	1	1	0.97	0.95
ABC	-0	2	2	0.99	0.95	-0	1	1	0.98	0.95
SPJ	-1	2	2	0.96	0.90	-0	1	1	0.96	0.95
LPM						-0	1	1	0.89	0.91
	N = 50; T = 20									
MLE	5	1	5	0.97	0.00	0	1	1	0.97	0.95
ABC	-0	1	1	1.01	0.95	-0	1	1	0.98	0.95
SPJ	-1	1	1	0.97	0.88	-0	1	1	0.96	0.94
LPM						-0	1	1	0.88	0.92
	N = 50; T = 30									
MLE	5	1	5	0.93	0.00	0	1	1	0.97	0.94
ABC	-0	1	1	0.97	0.94	-0	1	1	0.98	0.95
SPJ	-1	1	1	0.93	0.86	-0	1	1	0.96	0.94
LPM						-0	1	1	0.90	0.92
	N = 50; T = 40									
MLE	5	1	5	0.98	0.00	0	1	1	1.00	0.96
ABC	-0	1	1	1.03	0.95	-0	1	1	1.01	0.96
SPJ	-1	1	1	0.98	0.83	-0	1	1	0.98	0.94
LPM						-0	1	1	0.92	0.92
	N = 50; T = 50									
MLE	5	1	5	0.92	0.00	0	1	1	0.95	0.93
ABC	-0	1	1	0.96	0.94	-0	1	1	0.95	0.94
SPJ	-1	1	1	0.94	0.80	-0	1	1	0.93	0.92
LPM						-0	1	1	0.86	0.90

Table B.5: Dynamic: Two-way FEs — x, $N = 100$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
	N = 100; T = 10									
MLE	2	1	3	0.97	0.12	0	1	1	0.95	0.94
ABC	-0	1	1	0.99	0.94	-0	1	1	0.95	0.94
SPJ	-0	1	1	0.97	0.94	-0	1	1	0.94	0.93
LPM						-0	1	1	0.79	0.87
	N = 100; T = 20									
MLE	2	1	2	0.96	0.01	0	1	1	0.90	0.92
ABC	-0	1	1	0.98	0.94	-0	1	1	0.90	0.92
SPJ	-0	1	1	0.96	0.93	-0	1	1	0.89	0.91
LPM						-0	1	1	0.73	0.82
	N = 100; T = 30									
MLE	2	0	2	0.97	0.00	0	0	0	0.92	0.93
ABC	-0	0	0	0.99	0.95	-0	0	0	0.92	0.93
SPJ	-0	0	0	0.98	0.93	-0	0	0	0.91	0.92
LPM						-0	0	1	0.75	0.83
	N = 100; T = 40									
MLE	2	0	2	0.97	0.00	0	0	0	0.89	0.92
ABC	-0	0	0	0.99	0.95	-0	0	0	0.89	0.92
SPJ	-0	0	0	0.99	0.92	-0	0	0	0.88	0.92
LPM						-0	0	0	0.73	0.81
	N = 100; T = 50									
MLE	2	0	2	0.99	0.00	0	0	0	0.92	0.93
ABC	-0	0	0	1.00	0.95	-0	0	0	0.92	0.94
SPJ	-0	0	0	0.99	0.93	-0	0	0	0.91	0.93
LPM						-0	0	0	0.74	0.83

Table B.6: Dynamic: Two-way FEs — x, $N = 150$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
					N = 150; T = 10					
MLE	2	1	2	0.98	0.12	-0	1	1	0.91	0.92
ABC	-0	1	1	0.99	0.95	-0	1	1	0.91	0.93
SPJ	-0	1	1	0.99	0.94	-0	1	1	0.91	0.93
LPM						-0	1	1	0.67	0.80
					N = 150; T = 20					
MLE	2	0	2	0.99	0.01	0	0	0	0.91	0.92
ABC	-0	0	0	1.00	0.95	-0	0	0	0.90	0.93
SPJ	-0	0	0	0.98	0.93	-0	0	0	0.90	0.92
LPM						-0	0	0	0.67	0.76
					N = 150; T = 30					
MLE	2	0	2	1.01	0.00	0	0	0	0.86	0.91
ABC	-0	0	0	1.02	0.95	-0	0	0	0.86	0.90
SPJ	-0	0	0	1.01	0.95	-0	0	0	0.86	0.91
LPM						-0	0	0	0.63	0.73
					N = 150; T = 40					
MLE	2	0	2	0.99	0.00	0	0	0	0.88	0.91
ABC	0	0	0	1.00	0.95	0	0	0	0.88	0.91
SPJ	-0	0	0	0.98	0.94	0	0	0	0.88	0.91
LPM						-0	0	0	0.66	0.75
					N = 150; T = 50					
MLE	2	0	2	1.02	0.00	0	0	0	0.90	0.93
ABC	-0	0	0	1.03	0.96	-0	0	0	0.90	0.93
SPJ	-0	0	0	1.02	0.95	-0	0	0	0.90	0.93
LPM						-0	0	0	0.67	0.73

Table B.7: Dynamic: Two-way FEs — y_{t-1}, $N = 50$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
	N = 50; T = 10									
MLE	5	4	7	0.99	0.81	0	4	4	0.99	0.95
ABC	-0	4	4	1.03	0.95	-0	4	4	1.01	0.95
SPJ	-1	4	4	1.00	0.94	-0	4	4	0.98	0.94
LPM						5	4	7	0.97	0.76
	N = 50; T = 20									
MLE	5	3	6	0.96	0.65	-0	3	3	0.96	0.94
ABC	-0	3	3	1.00	0.95	-0	3	3	0.97	0.95
SPJ	-1	3	3	0.97	0.93	-0	3	3	0.94	0.94
LPM						5	3	6	0.96	0.56
	N = 50; T = 30									
MLE	5	3	6	0.95	0.48	0	3	3	0.94	0.92
ABC	0	3	3	0.99	0.95	0	3	3	0.96	0.93
SPJ	-1	3	3	0.97	0.93	0	3	3	0.94	0.93
LPM						6	3	6	0.94	0.40
	N = 50; T = 40									
MLE	5	2	5	0.98	0.38	0	2	2	0.99	0.95
ABC	-0	2	2	1.02	0.95	-0	2	2	1.01	0.95
SPJ	-1	2	2	1.01	0.94	-0	2	2	0.99	0.95
LPM						6	2	6	0.97	0.27
	N = 50; T = 50									
MLE	5	2	5	0.92	0.31	0	2	2	0.93	0.93
ABC	-0	2	2	0.96	0.94	-0	2	2	0.95	0.93
SPJ	-1	2	2	0.94	0.92	-0	2	2	0.92	0.93
LPM						6	2	6	0.93	0.21

Table B.8: Dynamic: Two-way FEs — y_{t-1}, $N = 100$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
					N = 100; T = 10					
MLE	2	2	3	0.96	0.80	0	2	2	0.94	0.94
ABC	0	2	2	0.98	0.94	0	2	2	0.95	0.94
SPJ	-0	2	2	0.97	0.94	0	2	2	0.95	0.94
LPM						5	2	6	0.91	0.30
					N = 100; T = 20					
MLE	2	2	3	0.99	0.63	0	2	2	0.99	0.94
ABC	-0	1	1	1.01	0.95	-0	2	2	1.00	0.94
SPJ	-0	2	2	0.99	0.94	-0	2	2	0.98	0.94
LPM						6	2	6	0.96	0.06
					N = 100; T = 30					
MLE	2	1	3	0.97	0.52	0	1	1	0.97	0.94
ABC	-0	1	1	0.99	0.94	-0	1	1	0.98	0.94
SPJ	-0	1	1	0.96	0.94	-0	1	1	0.96	0.93
LPM						6	1	6	0.94	0.01
					N = 100; T = 40					
MLE	2	1	3	0.99	0.42	0	1	1	0.97	0.94
ABC	-0	1	1	1.01	0.95	-0	1	1	0.98	0.94
SPJ	-0	1	1	0.99	0.94	-0	1	1	0.96	0.94
LPM						6	1	6	0.94	0.00
					N = 100; T = 50					
MLE	2	1	3	0.94	0.31	0	1	1	0.92	0.93
ABC	-0	1	1	0.96	0.93	-0	1	1	0.92	0.93
SPJ	-0	1	1	0.95	0.93	-0	1	1	0.91	0.92
LPM						6	1	6	0.90	0.00

Table B.9: Dynamic: Two-way FEs — y_{t-1}, $N = 150$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
					N = 150; T = 10					
MLE	2	1	2	0.98	0.79	0	2	2	0.96	0.94
ABC	0	1	1	0.99	0.95	0	2	2	0.97	0.94
SPJ	-0	1	1	0.98	0.95	0	2	2	0.95	0.94
LPM						6	2	6	0.92	0.04
					N = 150; T = 20					
MLE	2	1	2	0.98	0.66	-0	1	1	1.00	0.95
ABC	-0	1	1	1.00	0.95	-0	1	1	1.00	0.95
SPJ	-0	1	1	0.99	0.95	-0	1	1	0.99	0.95
LPM						5	1	6	0.96	0.00
					N = 150; T = 30					
MLE	2	1	2	0.98	0.53	0	1	1	0.99	0.95
ABC	0	1	1	1.00	0.95	0	1	1	0.99	0.95
SPJ	-0	1	1	0.98	0.95	0	1	1	0.98	0.95
LPM						6	1	6	0.94	0.00
					N = 150; T = 40					
MLE	2	1	2	0.96	0.42	-0	1	1	0.96	0.94
ABC	-0	1	1	0.97	0.94	-0	1	1	0.96	0.94
SPJ	-0	1	1	0.96	0.94	-0	1	1	0.95	0.94
LPM						6	1	6	0.91	0.00
					N = 150; T = 50					
MLE	2	1	2	0.94	0.34	-0	1	1	0.93	0.93
ABC	-0	1	1	0.95	0.94	-0	1	1	0.94	0.94
SPJ	-0	1	1	0.94	0.94	-0	1	1	0.93	0.94
LPM						6	1	6	0.90	0.00

B.3.2 Three-way Fixed Effects

Table B.10: Dynamic: Three-way FEs — x, $N = 50$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
	N = 50; T = 10									
MLE	29	3	29	0.82	0.00	4	2	4	1.01	0.33
ABC (1)	-1	2	2	1.02	0.94	-1	2	2	1.09	0.94
ABC (2)	-1	2	2	1.01	0.93	-1	2	2	1.08	0.93
SPJ	-14	3	14	0.62	0.00	4	2	5	0.87	0.32
LPM (1)						0	2	2	0.94	0.93
LPM (2)						-0	2	2	0.94	0.93
	N = 50; T = 20									
MLE	16	1	16	0.87	0.00	3	1	3	0.97	0.36
ABC (1)	-0	1	1	0.98	0.94	-0	1	1	1.00	0.95
ABC (2)	-0	1	1	0.97	0.93	-0	1	1	0.99	0.95
SPJ	-5	1	5	0.86	0.04	1	1	1	0.91	0.89
LPM (1)						-0	1	1	0.90	0.93
LPM (2)						-0	1	1	0.90	0.92
	N = 50; T = 30									
MLE	12	1	12	0.92	0.00	2	1	2	1.00	0.48
ABC (1)	-0	1	1	1.01	0.95	-0	1	1	1.01	0.95
ABC (2)	-0	1	1	1.01	0.95	-0	1	1	1.01	0.94
SPJ	-3	1	3	0.93	0.15	-0	1	1	0.96	0.95
LPM (1)						-0	1	1	0.89	0.92
LPM (2)						-0	1	1	0.89	0.90
	N = 50; T = 40									
MLE	10	1	10	0.89	0.00	1	1	2	0.97	0.53
ABC (1)	-0	1	1	0.97	0.94	-0	1	1	0.98	0.93
ABC (2)	-0	1	1	0.97	0.94	-0	1	1	0.97	0.93
SPJ	-2	1	2	0.88	0.27	-0	1	1	0.91	0.91
LPM (1)						-0	1	1	0.84	0.89
LPM (2)						-0	1	1	0.84	0.86
	N = 50; T = 50									
MLE	9	1	9	0.90	0.00	1	1	1	1.01	0.61
ABC (1)	-0	1	1	0.97	0.94	-0	1	1	1.01	0.96
ABC (2)	-0	1	1	0.97	0.93	-0	1	1	1.01	0.96
SPJ	-2	1	2	0.90	0.33	-0	1	1	0.94	0.94
LPM (1)						-0	1	1	0.86	0.88
LPM (2)						-0	1	1	0.86	0.87

Table B.11: Dynamic: Three-way FEs — x, $N = 100$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
	N = 100; T = 10									
MLE	24	1	24	0.89	0.00	4	1	4	1.04	0.02
ABC (1)	0	1	1	1.05	0.95	-0	1	1	1.08	0.94
ABC (2)	0	1	1	1.05	0.96	-1	1	1	1.08	0.91
SPJ	-9	1	9	0.70	0.00	6	1	6	0.89	0.00
LPM (1)						0	1	1	0.88	0.91
LPM (2)						-0	1	1	0.87	0.91
	N = 100; T = 20									
MLE	13	1	13	0.89	0.00	2	1	2	0.96	0.02
ABC (1)	0	1	1	0.98	0.93	0	1	1	0.98	0.95
ABC (2)	0	1	1	0.98	0.94	-0	1	1	0.97	0.94
SPJ	-3	1	3	0.86	0.01	1	1	1	0.89	0.54
LPM (1)						-0	1	1	0.85	0.89
LPM (2)						-0	1	1	0.85	0.87
	N = 100; T = 30									
MLE	9	1	9	0.91	0.00	2	0	2	0.96	0.05
ABC (1)	0	0	0	0.97	0.95	0	0	0	0.96	0.94
ABC (2)	-0	0	0	0.97	0.94	-0	0	0	0.96	0.94
SPJ	-1	1	2	0.91	0.14	0	0	1	0.93	0.86
LPM (1)						-0	0	1	0.82	0.86
LPM (2)						-0	0	1	0.82	0.81
	N = 100; T = 40									
MLE	7	0	7	0.91	0.00	1	0	1	0.94	0.12
ABC (1)	0	0	0	0.96	0.94	0	0	0	0.94	0.93
ABC (2)	-0	0	0	0.96	0.94	-0	0	0	0.94	0.92
SPJ	-1	0	1	0.92	0.32	0	0	0	0.91	0.91
LPM (1)						-0	0	1	0.79	0.81
LPM (2)						-0	0	1	0.79	0.73
	N = 100; T = 50									
MLE	6	0	6	0.94	0.00	1	0	1	1.00	0.17
ABC (1)	0	0	0	0.99	0.94	0	0	0	1.00	0.95
ABC (2)	-0	0	0	0.98	0.94	-0	0	0	1.00	0.95
SPJ	-1	0	1	0.95	0.48	0	0	0	0.96	0.94
LPM (1)						-0	0	0	0.80	0.76
LPM (2)						-0	0	1	0.80	0.69

Table B.12: Dynamic: Three-way FEs — x, $N = 150$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
	N = 150; T = 10									
MLE	23	1	23	0.86	0.00	3	1	4	1.06	0.00
ABC (1)	1	1	1	1.01	0.82	-0	1	1	1.09	0.94
ABC (2)	0	1	1	1.00	0.88	-0	1	1	1.07	0.90
SPJ	-7	1	7	0.67	0.00	6	1	6	0.89	0.00
LPM (1)						0	1	1	0.84	0.88
LPM (2)						-0	1	1	0.83	0.90
	N = 150; T = 20									
MLE	11	0	11	0.94	0.00	2	0	2	0.97	0.00
ABC (1)	0	0	0	1.02	0.89	0	0	0	0.97	0.94
ABC (2)	0	0	0	1.01	0.93	-0	0	0	0.97	0.94
SPJ	-2	0	2	0.89	0.00	1	0	1	0.90	0.16
LPM (1)						-0	0	0	0.81	0.88
LPM (2)						-0	0	0	0.81	0.81
	N = 150; T = 30									
MLE	8	0	8	0.92	0.00	2	0	2	0.96	0.00
ABC (1)	0	0	0	0.98	0.91	0	0	0	0.97	0.93
ABC (2)	0	0	0	0.98	0.95	-0	0	0	0.97	0.95
SPJ	-1	0	1	0.91	0.06	0	0	1	0.92	0.73
LPM (1)						-0	0	0	0.79	0.80
LPM (2)						-0	0	0	0.79	0.66
	N = 150; T = 40									
MLE	6	0	6	0.95	0.00	1	0	1	0.95	0.01
ABC (1)	0	0	0	1.00	0.94	0	0	0	0.95	0.92
ABC (2)	-0	0	0	1.00	0.95	-0	0	0	0.95	0.94
SPJ	-1	0	1	0.94	0.22	0	0	0	0.92	0.87
LPM (1)						-0	0	0	0.75	0.68
LPM (2)						-0	0	0	0.75	0.54
	N = 150; T = 50									
MLE	5	0	5	0.95	0.00	1	0	1	0.97	0.02
ABC (1)	0	0	0	0.99	0.93	0	0	0	0.97	0.93
ABC (2)	-0	0	0	0.99	0.94	-0	0	0	0.97	0.94
SPJ	-1	0	1	0.95	0.38	0	0	0	0.95	0.91
LPM (1)						-0	0	0	0.76	0.61
LPM (2)						-0	0	0	0.76	0.45

Table B.13: Dynamic: Three-way FEs — y_{t-1}, $N = 50$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
					N = 50; T = 10					
MLE	-62	5	62	0.95	0.00	-70	4	71	1.02	0.00
ABC (1)	-6	4	7	1.14	0.81	-7	5	8	1.11	0.76
ABC (2)	-7	5	9	1.05	0.68	-8	5	10	1.02	0.62
SPJ	24	6	25	0.77	0.01	-11	6	12	0.94	0.48
LPM (1)						2	5	5	1.02	0.95
LPM (2)						3	5	6	0.94	0.89
					N = 50; T = 20					
MLE	-27	4	27	0.94	0.00	-36	3	37	0.95	0.00
ABC (1)	-3	3	4	1.05	0.87	-3	3	5	1.00	0.85
ABC (2)	-1	3	3	1.00	0.94	-1	3	4	0.96	0.93
SPJ	5	4	6	0.89	0.69	-2	4	4	0.89	0.89
LPM (1)						8	3	9	0.95	0.28
LPM (2)						11	4	12	0.91	0.09
					N = 50; T = 30					
MLE	-16	3	16	0.97	0.00	-25	3	25	0.97	0.00
ABC (1)	-2	3	3	1.06	0.88	-2	3	3	1.01	0.87
ABC (2)	-0	3	3	1.03	0.95	-0	3	3	0.98	0.95
SPJ	2	3	3	0.95	0.88	-1	3	3	0.92	0.93
LPM (1)						10	3	11	0.96	0.03
LPM (2)						13	3	13	0.94	0.00
					N = 50; T = 40					
MLE	-11	2	11	0.96	0.01	-19	2	19	0.95	0.00
ABC (1)	-2	2	3	1.03	0.86	-2	2	3	0.99	0.85
ABC (2)	-0	2	2	1.01	0.95	-0	2	2	0.97	0.95
SPJ	1	2	3	0.93	0.92	-0	3	3	0.90	0.92
LPM (1)						11	2	12	0.95	0.01
LPM (2)						13	2	13	0.93	0.00
					N = 50; T = 50					
MLE	-7	2	8	0.94	0.07	-15	2	15	0.92	0.00
ABC (1)	-2	2	3	1.01	0.89	-2	2	3	0.95	0.87
ABC (2)	-0	2	2	0.99	0.95	-0	2	2	0.93	0.93
SPJ	0	2	2	0.92	0.92	-0	2	2	0.87	0.90
LPM (1)						12	2	12	0.92	0.00
LPM (2)						14	2	14	0.91	0.00

Table B.14: Dynamic: Three-way FEs — y_{t-1}, $N = 100$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
					N = 100; T = 10					
MLE	-63	3	63	0.98	0.00	-70	2	70	1.04	0.00
ABC (1)	-6	2	7	1.13	0.22	-8	2	8	1.10	0.09
ABC (2)	-8	2	8	1.04	0.08	-9	2	10	1.01	0.03
SPJ	21	3	21	0.80	0.00	-11	3	11	0.94	0.02
LPM (1)						2	2	3	1.00	0.84
LPM (2)						4	3	4	0.92	0.66
					N = 100; T = 20					
MLE	-29	2	29	0.96	0.00	-37	2	37	0.96	0.00
ABC (1)	-3	2	4	1.03	0.42	-4	2	4	0.99	0.37
ABC (2)	-1	2	2	0.99	0.86	-2	2	2	0.95	0.83
SPJ	4	2	5	0.91	0.26	-2	2	3	0.90	0.80
LPM (1)						8	2	9	0.95	0.00
LPM (2)						11	2	11	0.91	0.00
					N = 100; T = 30					
MLE	-18	1	18	0.97	0.00	-25	1	25	0.96	0.00
ABC (1)	-3	1	3	1.03	0.50	-3	1	3	0.98	0.49
ABC (2)	-1	1	1	1.00	0.93	-1	1	2	0.95	0.92
SPJ	2	1	2	0.94	0.72	-1	1	2	0.90	0.90
LPM (1)						10	1	10	0.95	0.00
LPM (2)						13	1	13	0.92	0.00
					N = 100; T = 40					
MLE	-13	1	13	1.01	0.00	-19	1	19	1.01	0.00
ABC (1)	-2	1	2	1.06	0.57	-2	1	2	1.04	0.56
ABC (2)	-0	1	1	1.04	0.94	-0	1	1	1.02	0.94
SPJ	1	1	2	0.98	0.86	-0	1	1	0.96	0.93
LPM (1)						11	1	11	0.98	0.00
LPM (2)						13	1	13	0.96	0.00
					N = 100; T = 50					
MLE	-10	1	10	0.98	0.00	-15	1	15	0.97	0.00
ABC (1)	-2	1	2	1.03	0.61	-2	1	2	0.99	0.62
ABC (2)	-0	1	1	1.01	0.95	-0	1	1	0.98	0.94
SPJ	1	1	1	0.98	0.91	-0	1	1	0.95	0.93
LPM (1)						12	1	12	0.94	0.00
LPM (2)						14	1	14	0.93	0.00

Table B.15: Dynamic: Three-way FEs — y_{t-1}, $N = 150$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
					N = 150; T = 10					
MLE	-63	2	64	0.95	0.00	-70	1	70	1.02	0.00
ABC (1)	-7	1	7	1.09	0.01	-8	2	9	1.08	0.00
ABC (2)	-8	2	9	1.01	0.00	-10	2	10	1.00	0.00
SPJ	20	2	20	0.78	0.00	-11	2	11	0.92	0.00
LPM (1)						2	2	3	0.98	0.71
LPM (2)						3	2	4	0.90	0.42
					N = 150; T = 20					
MLE	-30	1	30	0.99	0.00	-37	1	37	1.00	0.00
ABC (1)	-4	1	4	1.07	0.05	-4	1	4	1.03	0.03
ABC (2)	-2	1	2	1.02	0.69	-2	1	2	0.99	0.61
SPJ	4	1	4	0.92	0.05	-2	1	2	0.90	0.61
LPM (1)						8	1	8	0.96	0.00
LPM (2)						11	1	11	0.92	0.00
					N = 150; T = 30					
MLE	-19	1	19	0.98	0.00	-25	1	25	0.97	0.00
ABC (1)	-3	1	3	1.04	0.15	-3	1	3	0.99	0.13
ABC (2)	-1	1	1	1.01	0.89	-1	1	1	0.97	0.87
SPJ	2	1	2	0.96	0.47	-0	1	1	0.92	0.90
LPM (1)						10	1	10	0.93	0.00
LPM (2)						13	1	13	0.91	0.00
					N = 150; T = 40					
MLE	-14	1	14	1.01	0.00	-19	1	19	0.99	0.00
ABC (1)	-2	1	2	1.06	0.20	-2	1	2	1.01	0.19
ABC (2)	-0	1	1	1.03	0.92	-0	1	1	0.99	0.90
SPJ	1	1	1	0.96	0.76	-0	1	1	0.93	0.92
LPM (1)						11	1	11	0.96	0.00
LPM (2)						13	1	13	0.94	0.00
					N = 150; T = 50					
MLE	-11	1	11	0.97	0.00	-15	1	15	0.95	0.00
ABC (1)	-2	1	2	1.01	0.30	-2	1	2	0.97	0.30
ABC (2)	-0	1	1	0.99	0.92	-0	1	1	0.95	0.91
SPJ	1	1	1	0.96	0.84	-0	1	1	0.92	0.92
LPM (1)						12	1	12	0.92	0.00
LPM (2)						14	1	14	0.90	0.00

B.4 Further Monte Carlo Results — Static Model

Although the main focus of our article is on the dynamic two- and three-way fixed effects model, the static counterparts are also highly relevant for applied work. For this reason, we study the finite sample properties of MLE, ABC, SPJ and LPM for these model specifications, too. In the following we briefly sketch the designs. Let $i = 1, \ldots, N$, $j = 1, \ldots, N$, $t = 1, \ldots, T$, $\beta_y = 0.5$, $\beta = 1$.

Design — Two-way Fixed Effects.

$$y_{ijt} = \mathbf{1}[\beta x_{ijt} + \lambda_{it} + \psi_{jt} \geq \epsilon_{ijt}] \ ,$$

where $\lambda_{it} \sim \text{iid.}\, \mathcal{N}(0, 1/16)$, $\psi_{jt} \sim \text{iid.}\, \mathcal{N}(0, 1/16)$, and $\epsilon_{ijt} \sim \text{iid.}\, \mathcal{N}(0, 1)$. Further, $x_{ijt} = 0.5x_{ijt-1} + \lambda_{it} + \psi_{jt} + \nu_{ijt}$, where $\nu_{ijt} \sim \text{iid.}\, \mathcal{N}(0, 0.5)$, $x_{ij0} \sim \text{iid.}\, \mathcal{N}(0, 1)$.

Design — Three-way Fixed Effects.

$$y_{ijt} = \mathbf{1}[\beta x_{ijt} + \lambda_{it} + \psi_{jt} + \mu_{ij} \geq \epsilon_{ijt}] \ ,$$

where $\lambda_{it} \sim \text{iid.}\, \mathcal{N}(0, 1/24)$, $\psi_{jt} \sim \text{iid.}\, \mathcal{N}(0, 1/24)$, $\mu_{ij} \sim \text{iid.}\, \mathcal{N}(0, 1/24)$, and $\epsilon_{ijt} \sim \text{iid.}\, \mathcal{N}(0, 1)$. Further, $x_{ijt} = 0.5x_{ijt-1} + \lambda_{it} + \psi_{jt} + \mu_{ij} + \nu_{ijt}$, where $\nu_{ijt} \sim \text{iid.}\, \mathcal{N}(0, 0.5)$, $x_{ij0} \sim \text{iid.}\, \mathcal{N}(0, 1)$.

Note that, unlike in the dynamic three-way fixed effects model, the OLS estimator of the linear probability model (LPM) does not require a bias correction for the specifications considered in this section.

We now review the key results of the simulation experiments.

Results — Two-way Fixed Effects. Static (see Tables B.16, B.17, B.18): although MLE shows a distortion in the structural parameter estimates, the bias does not carry over to the estimates of APEs. The bias corrections ABC and SPJ work well. They reduce the biases of the structural parameters and APEs to 1 or zero percent, and bring the CPs close to the nominal level. Overall, ABC, SPJ and MLE work similarly well if APEs are of interest. In terms of structural parameters, ABC exhibits a lower bias and better CPs than SPJ in samples with smaller N. LPM shows no distortion of the APEs in all settings, but we observe that with increasing N, the standard errors are underestimated, resulting in too low CPs.

Note that MLE is consistent under fixed T asymptotics. This is also evident from the simulation results, where the properties of the estimator do not change with T.

Results — Three-way Fixed Effects. Static (see Tables B.19, B.20, B.21): we find a considerable distortion in the MLE estimates of the structural parameters, which decreases with rising T, but is not negligibly small even at $T = 50$. ABC and SPJ both reduce this bias considerably, but ABC works better in samples with smaller T. While the CPs of ABC quickly converge to the nominal level, the CPs of SPJ are still far away from 95 percent even at $T = 50$. If we look at the APEs, we see that all estimators have either a very small bias of 1 percent or none at all. With increasing T, their CPs are also getting closer to 95 percent.

Table B.16: Static: Two-way FEs — x, $N = 50$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
					N = 50; T = 10					
MLE	5	2	5	0.97	0.10	0	1	1	0.98	0.94
ABC	-0	1	1	1.01	0.94	-0	1	1	0.99	0.94
SPJ	-1	1	2	0.98	0.93	-0	1	1	0.96	0.93
LPM						0	1	1	0.96	0.93
					N = 50; T = 20					
MLE	5	1	5	0.99	0.01	0	1	1	1.06	0.96
ABC	-0	1	1	1.03	0.96	-0	1	1	1.07	0.97
SPJ	-1	1	1	0.98	0.91	-0	1	1	1.04	0.95
LPM						-0	1	1	1.05	0.96
					N = 50; T = 30					
MLE	5	1	5	0.98	0.00	0	1	1	1.01	0.95
ABC	-0	1	1	1.02	0.95	-0	1	1	1.03	0.95
SPJ	-1	1	1	1.00	0.89	-0	1	1	1.00	0.95
LPM						0	1	1	0.99	0.94
					N = 50; T = 40					
MLE	5	1	5	0.94	0.00	0	1	1	0.98	0.95
ABC	-0	1	1	0.97	0.94	-0	1	1	0.99	0.95
SPJ	-1	1	1	0.95	0.84	-0	1	1	0.97	0.94
LPM						-0	1	1	0.97	0.94
					N = 50; T = 50					
MLE	5	1	5	0.97	0.00	0	1	1	1.02	0.95
ABC	-0	1	1	1.01	0.96	-0	1	1	1.04	0.96
SPJ	-1	1	1	0.98	0.83	-0	1	1	1.00	0.95
LPM						0	1	1	1.00	0.95

Table B.17: Static: Two-way FEs — x, $N = 100$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
	N = 100; T = 10									
MLE	2	1	2	0.95	0.13	0	1	1	0.96	0.94
ABC	-0	1	1	0.97	0.94	-0	1	1	0.96	0.93
SPJ	-0	1	1	0.95	0.93	-0	1	1	0.95	0.93
LPM						0	1	1	0.85	0.90
	N = 100; T = 20									
MLE	2	1	2	0.98	0.00	0	0	0	0.99	0.96
ABC	-0	1	1	1.00	0.95	-0	0	0	1.00	0.95
SPJ	-0	1	1	0.99	0.94	-0	0	0	0.99	0.95
LPM						-0	0	0	0.89	0.92
	N = 100; T = 30									
MLE	2	0	2	1.00	0.00	0	0	0	1.03	0.95
ABC	0	0	0	1.02	0.96	-0	0	0	1.03	0.95
SPJ	-0	0	0	1.00	0.95	-0	0	0	1.03	0.96
LPM						0	0	0	0.92	0.93
	N = 100; T = 40									
MLE	2	0	2	0.98	0.00	0	0	0	0.97	0.94
ABC	-0	0	0	1.00	0.94	-0	0	0	0.97	0.94
SPJ	-0	0	0	0.98	0.93	-0	0	0	0.96	0.94
LPM						-0	0	0	0.87	0.91
	N = 100; T = 50									
MLE	2	0	2	1.00	0.00	0	0	0	0.99	0.95
ABC	-0	0	0	1.02	0.96	-0	0	0	0.99	0.95
SPJ	-0	0	0	1.02	0.94	-0	0	0	0.99	0.95
LPM						-0	0	0	0.88	0.92

Table B.18: Static: Two-way FEs — x, $N = 150$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
	N = 150; T = 10									
MLE	1	0	2	0.99	0.12	0	0	0	1.02	0.96
ABC	-0	0	0	1.01	0.96	-0	0	0	1.02	0.96
SPJ	-0	0	0	1.00	0.95	-0	0	0	1.01	0.95
LPM						-0	0	0	0.84	0.90
	N = 150; T = 20									
MLE	1	0	2	0.95	0.01	0	0	0	0.95	0.94
ABC	0	0	0	0.96	0.94	0	0	0	0.95	0.94
SPJ	-0	0	0	0.95	0.93	0	0	0	0.95	0.94
LPM						0	0	0	0.79	0.86
	N = 150; T = 30									
MLE	1	0	2	1.01	0.00	0	0	0	0.96	0.95
ABC	-0	0	0	1.03	0.95	-0	0	0	0.97	0.94
SPJ	-0	0	0	1.02	0.94	-0	0	0	0.96	0.95
LPM						-0	0	0	0.79	0.88
	N = 150; T = 40									
MLE	1	0	2	0.99	0.00	0	0	0	0.97	0.94
ABC	-0	0	0	1.00	0.95	-0	0	0	0.97	0.94
SPJ	-0	0	0	0.99	0.94	-0	0	0	0.96	0.94
LPM						-0	0	0	0.80	0.88
	N = 150; T = 50									
MLE	1	0	2	0.99	0.00	0	0	0	0.95	0.94
ABC	-0	0	0	1.00	0.94	-0	0	0	0.95	0.94
SPJ	-0	0	0	0.99	0.94	-0	0	0	0.95	0.94
LPM						0	0	0	0.78	0.88

Table B.19: Static: Three-way FEs — x, $N = 50$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
					N = 50; T = 10					
MLE	22	2	22	0.85	0.00	1	1	2	1.00	0.89
ABC	-1	2	2	1.03	0.88	-1	1	2	1.07	0.86
SPJ	-12	2	12	0.72	0.00	-0	2	2	0.88	0.91
LPM						0	1	1	1.04	0.96
					N = 50; T = 20					
MLE	12	1	12	0.92	0.00	0	1	1	1.00	0.94
ABC	-1	1	1	1.02	0.92	-0	1	1	1.03	0.93
SPJ	-4	1	4	0.88	0.08	-1	1	1	0.92	0.89
LPM						-0	1	1	1.04	0.96
					N = 50; T = 30					
MLE	10	1	10	0.94	0.00	0	1	1	1.02	0.94
ABC	-0	1	1	1.02	0.94	-0	1	1	1.04	0.94
SPJ	-2	1	2	0.93	0.28	-0	1	1	0.96	0.89
LPM						0	1	1	1.01	0.95
					N = 50; T = 40					
MLE	8	1	8	0.93	0.00	0	1	1	1.02	0.95
ABC	-0	1	1	0.99	0.92	-0	1	1	1.03	0.94
SPJ	-2	1	2	0.94	0.40	-0	1	1	0.99	0.90
LPM						-0	1	1	0.98	0.94
					N = 50; T = 50					
MLE	8	1	8	0.96	0.00	0	1	1	1.04	0.94
ABC	-0	1	1	1.03	0.93	-0	1	1	1.06	0.95
SPJ	-1	1	2	0.95	0.46	-0	1	1	0.99	0.91
LPM						0	1	1	0.99	0.94

Table B.20: Static: Three-way FEs — x, $N = 100$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
	N = 100; T = 10									
MLE	18	1	18	0.89	0.00	1	1	1	1.05	0.90
ABC	-1	1	1	1.05	0.80	-1	1	1	1.09	0.70
SPJ	-8	1	8	0.74	0.00	0	1	1	0.89	0.87
LPM						-0	1	1	1.04	0.96
	N = 100; T = 20									
MLE	9	1	9	0.93	0.00	0	0	1	1.01	0.92
ABC	-0	1	1	1.00	0.92	-0	0	1	1.03	0.92
SPJ	-2	1	2	0.94	0.01	-0	1	1	0.96	0.91
LPM						0	0	0	0.96	0.93
	N = 100; T = 30									
MLE	7	0	7	0.95	0.00	0	0	0	1.05	0.95
ABC	-0	0	0	1.01	0.93	-0	0	0	1.06	0.95
SPJ	-1	0	1	0.93	0.21	-0	0	0	0.98	0.92
LPM						-0	0	0	0.97	0.95
	N = 100; T = 40									
MLE	6	0	6	0.96	0.00	0	0	0	1.00	0.94
ABC	-0	0	0	1.00	0.94	-0	0	0	1.01	0.94
SPJ	-1	0	1	0.95	0.44	-0	0	0	0.95	0.92
LPM						-0	0	0	0.93	0.93
	N = 100; T = 50									
MLE	5	0	5	0.94	0.00	0	0	0	0.99	0.94
ABC	-0	0	0	0.98	0.94	-0	0	0	1.00	0.94
SPJ	-1	0	1	0.94	0.57	-0	0	0	0.97	0.92
LPM						-0	0	0	0.91	0.93

Table B.21: Static: Three-way FEs — x, $N = 150$

	Coefficients					APE				
	Bias	SD	RMSE	SE/SD	CP .95	Bias	SD	RMSE	SE/SD	CP .95
					N = 150; T = 10					
MLE	16	1	16	0.87	0.00	0	0	1	1.04	0.87
ABC	-1	1	1	1.02	0.77	-1	0	1	1.07	0.51
SPJ	-7	1	7	0.76	0.00	1	1	1	0.91	0.73
LPM						-0	0	0	0.95	0.94
					N = 150; T = 20					
MLE	8	0	8	0.92	0.00	0	0	0	1.00	0.91
ABC	-0	0	0	0.99	0.91	-0	0	0	1.01	0.89
SPJ	-2	0	2	0.89	0.00	-0	0	0	0.93	0.91
LPM						-0	0	0	0.93	0.93
					N = 150; T = 30					
MLE	6	0	6	0.93	0.00	0	0	0	0.97	0.93
ABC	-0	0	0	0.97	0.93	-0	0	0	0.98	0.92
SPJ	-1	0	1	0.93	0.08	-0	0	0	0.92	0.90
LPM						-0	0	0	0.88	0.92
					N = 150; T = 40					
MLE	5	0	5	0.95	0.00	0	0	0	1.01	0.93
ABC	-0	0	0	0.99	0.94	-0	0	0	1.02	0.94
SPJ	-1	0	1	0.93	0.33	-0	0	0	0.98	0.93
LPM						-0	0	0	0.90	0.93
					N = 150; T = 50					
MLE	4	0	4	0.98	0.00	0	0	0	1.05	0.95
ABC	-0	0	0	1.01	0.94	-0	0	0	1.05	0.95
SPJ	-0	0	0	0.97	0.51	-0	0	0	1.00	0.94
LPM						-0	0	0	0.92	0.92

B.5 Application

Table B.22: Logit Estimation: Coefficients

	Dependent variable: y_{ijt}				
	(1)	(2)	(3)	(4)	(5)
Lagged DV	-	-	2.869^{***}	-	1.929^{***}
	[-]	[-]	[2.985]	[-]	[1.798]
	(-)	(-)	(0.008)	(-)	(0.009)
log(Distance)	-	-1.454^{***}	-0.980^{***}	-	-
	[-1.181^{***}]	[-1.494]	[-1.012]	[-]	[-]
	(0.005)	(0.006)	(0.007)	(-)	(-)
Land border	-	0.621^{***}	0.231^{***}	-	-
	[0.660^{***}]	[0.643]	[0.244]	[-]	[-]
	(0.026)	(0.029)	(0.033)	(-)	(-)
Legal	-	0.262^{***}	0.169^{***}	-	-
	[0.172^{***}]	[0.269]	[0.176]	[-]	[-]
	(0.007)	(0.008)	(0.009)	(-)	(-)
Language	-	0.737^{***}	0.514^{***}	-	-
	[0.663^{***}]	[0.757]	[0.529]	[-]	[-]
	(0.009)	(0.01)	(0.012)	(-)	(-)
Colonial ties	-	1.345^{***}	1.002^{***}	-	-
	[0.342^{***}]	[1.443]	[1.102]	[-]	[-]
	(0.036)	(0.061)	(0.07)	(-)	(-)
Currency union	-	1.137^{***}	0.775^{***}	0.578^{***}	0.421^{***}
	[0.660^{***}]	[1.173]	[0.807]	[0.64]	[0.497]
	(0.021)	(0.027)	(0.031)	(0.06)	(0.064)
FTA	-	1.059^{***}	0.664^{***}	0.130^{*}	0.072
	[0.955^{***}]	[1.077]	[0.674]	[0.123]	[0.054]
	(0.031)	(0.036)	(0.04)	(0.07)	(0.075)
WTO	-	0.228^{***}	0.187^{***}	0.095^{***}	0.087^{***}
	[0.462^{***}]	[0.232]	[0.191]	[0.105]	[0.102]
	(0.009)	(0.014)	(0.016)	(0.028)	(0.031)
Fixed effects	i, j, t	it, jt	it, jt	it, jt, ij	it, jt, ij
Sample size	1204671	1204671	1171794	1204671	1171794
- perf. class.	12298	147760	141537	370617	374067
Deviance	8.857×10^5	6.976×10^5	5.2×10^5	4.728×10^5	4.184×10^5

Notes: Uncorrected coefficients in square brackets. Standard errors in parenthesis.

Table B.23: Logit Estimation: APEs

	Dependent variable: y_{ijt}				
	(1)	(2)	(3)	(4)	(5)
Lagged DV	-	-	0.331***	-	0.168***
	[-]	[-]	[0.332]	[-]	[0.13]
	(-)	(-)	(0.002)	(-)	(0.049)
log(Distance)	-	-0.138***	-0.067***	-	-
	[-0.140***]	[-0.137]	[-0.067]	[-]	[-]
	(0.005)	(0.005)	(0.001)	(-)	(-)
Land border	-	0.058***	0.016***	-	-
	[0.077***]	[0.059]	[0.016]	[-]	[-]
	(0.004)	(0.004)	(0.003)	(-)	(-)
Legal	-	0.025***	0.012***	-	-
	[0.020***]	[0.025]	[0.012]	[-]	[-]
	(0.001)	(0.001)	(0.001)	(-)	(-)
Language	-	0.069***	0.035***	-	-
	[0.078***]	[0.069]	[0.035]	[-]	[-]
	(0.003)	(0.001)	(0.001)	(-)	(-)
Colonial ties	-	0.122***	0.069***	-	-
	[0.040***]	[0.127]	[0.074]	[-]	[-]
	(0.004)	(0.006)	(0.006)	(-)	(-)
Currency union	-	0.104***	0.053***	0.041***	0.027***
	[0.077***]	[0.104]	[0.054]	[0.04]	[0.028]
	(0.004)	(0.003)	(0.002)	(0.006)	(0.009)
FTA	-	0.098***	0.046***	0.009	0.004
	[0.110***]	[0.097]	[0.045]	[0.008]	[0.003]
	(0.005)	(0.004)	(0.003)	(0.006)	(0.006)
WTO	-	0.022***	0.013***	0.007**	0.005*
	[0.056***]	[0.021]	[0.013]	[0.006]	[0.006]
	(0.002)	(0.002)	(0.001)	(0.003)	(0.003)
Fixed effects	i, j, t	it, jt	it, jt	it, jt, ij	it, jt, ij
Sample size	1204671	1204671	1171794	1204671	1171794
- perf. class.	12298	147760	141537	370617	374067
Deviance	8.857×10^5	6.976×10^5	5.2×10^5	4.728×10^5	4.184×10^5

Notes: Uncorrected average partial effects in square brackets. Standard errors in parenthesis.

Table B.24: Probit Estimation with Different Bandwidths: Coefficients

	Dependent variable: y_{ijt}				
	(1)	(2)	(3)	(4)	(5)
Lagged DV	0.961***	1.112***	1.140***	1.154***	1.161***
	(0.036)	(0.037)	(0.039)	(0.04)	(0.04)
Currency union	0.228***	0.217***	0.214***	0.214***	0.216***
	(0.05)	(0.048)	(0.048)	(0.048)	(0.047)
FTA	0.035	0.037	0.038	0.042	0.043
	(0.056)	(0.054)	(0.053)	(0.053)	(0.053)
WTO	0.041	0.039	0.039	0.040	0.042*
	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
Trim	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$

Notes: All columns include Origin × Year, Destination × Year and Origin × Destination fixed effects. Standard errors in parenthesis.

Table B.25: Probit Estimation with Different Bandwidths: Average Partial Effects

	Dependent variable: y_{ijt}				
	(1)	(2)	(3)	(4)	(5)
Lagged DV	0.144***	0.173***	0.179***	0.182***	0.183***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Currency union	0.026***	0.025***	0.024***	0.024***	0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
FTA	0.004	0.004	0.004	0.005	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
WTO	0.005**	0.004**	0.004**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Trim	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$

Notes: All columns include Origin × Year, Destination × Year and Origin × Destination fixed effects. Standard errors in parenthesis.

Table B.26: Logit Estimation with Different Bandwidths: Coefficients

	Dependent variable: y_{ijt}				
	(1)	(2)	(3)	(4)	(5)
lagged DV	1.606***	1.879***	1.929***	1.953***	1.965***
	(0.037)	(0.038)	(0.039)	(0.04)	(0.04)
Currency Union	0.448***	0.426***	0.421***	0.421***	0.425***
	(0.057)	(0.054)	(0.054)	(0.054)	(0.053)
FTA	0.065	0.069	0.072	0.077	0.080
	(0.063)	(0.061)	(0.06)	(0.06)	(0.06)
WTO	0.091***	0.087***	0.087***	0.088***	0.091***
	(0.028)	(0.027)	(0.027)	(0.027)	(0.027)
Trim	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$

Notes: All columns include Origin × Year, Destination × Year and Origin × Destination fixed effects. Standard errors in parenthesis.

Table B.27: Logit Estimation with Different Bandwidths: Average Partial Effects

	Dependent variable: y_{ijt}				
	(1)	(2)	(3)	(4)	(5)
lagged DV	0.133***	0.162***	0.168***	0.170***	0.172***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Currency Union	0.028***	0.027***	0.027***	0.027***	0.027***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
FTA	0.004	0.004	0.004	0.005	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
WTO	0.006***	0.005***	0.005***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Trim	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$

Notes: All columns include Origin × Year, Destination × Year and Origin × Destination fixed effects. Standard errors in parenthesis.

Table B.28: Probit vs. OLS estimation: Average Partial Effects with Two-way Fixed Effects

	Dependent variable: y_{ijt}			
	(1)	(2)	(3)	(5)
Lagged DV	-	-	0.599***	0.346***
	(-)	(-)	(0.001)	(0.003)
log(Distance)	-0.133***	-0.135***	-0.053***	-0.066***
	(0.001)	(0.005)	(0)	(0.001)
Land border	0.014***	0.035***	0.003*	0.015***
	(0.002)	(0.004)	(0.002)	(0.003)
Legal	0.008***	0.023***	0.002***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Language	0.098***	0.071***	0.040***	0.035***
	(0.001)	(0.001)	(0.001)	(0.001)
Colonial ties	0.021***	0.107***	0.008***	0.061***
	(0.003)	(0.007)	(0.002)	(0.005)
Currency union	0.107***	0.103***	0.046***	0.053***
	(0.003)	(0.003)	(0.002)	(0.002)
FTA	-0.155***	0.090***	-0.063***	0.045***
	(0.002)	(0.004)	(0.002)	(0.003)
WTO	-0.010***	0.026***	-0.008***	0.013***
	(0.001)	(0.002)	(0.001)	(0.001)
Estimator	OLS	Probit	OLS	Probit
bias corrected	-	true	-	true
Sample size	1204671	1204671	1171794	1171794

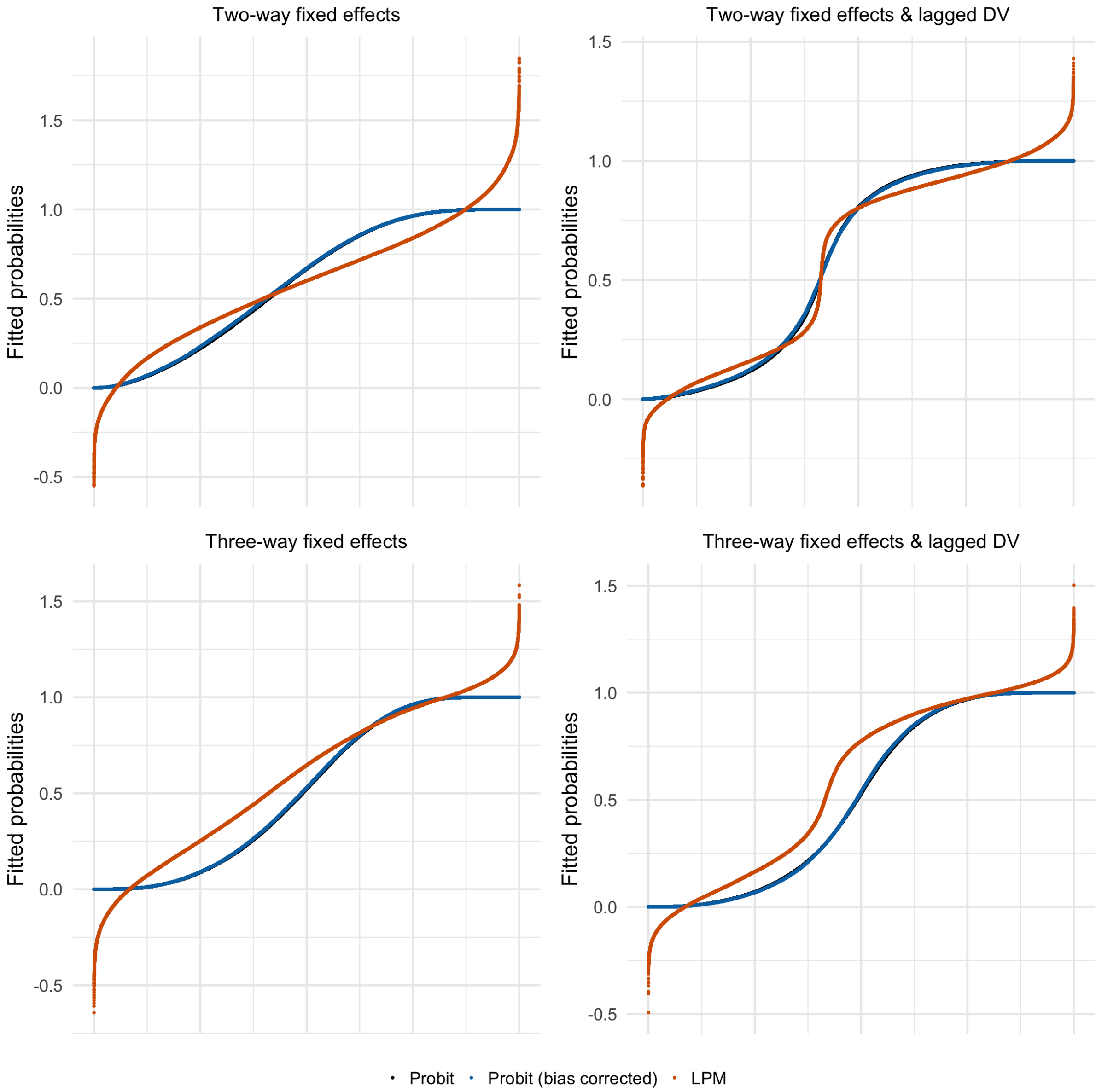
Notes: All columns include Origin × Year, Destination × Year and Origin × Destination fixed effects. Standard errors in parenthesis.

Table B.29: LPM Estimation with Different Bandwidths: Average Partial Effects

	Dependent variable: y_{ijt}				
	(1)	(2)	(3)	(4)	(5)
Lagged DV	0.444***	0.466***	0.474***	0.480***	0.485***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Currency union	0.008***	0.008**	0.008**	0.008**	0.008**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
FTA	-0.065***	-0.062***	-0.062***	-0.061***	-0.061***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
WTO	0.008***	0.008***	0.008***	0.008***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Trim	$L = 0$	$L = 1$	$L = 2$	$L = 3$	$L = 4$

Notes: All columns include Origin × Year, Destination × Year and Origin × Destination fixed effects. Standard errors in parenthesis.

Figure B.3: Fitted Probabilities



Appendix C

Carbon Tariffs: An Analysis of the Trade, Welfare, and Emission Effects

C.1 Detailed Model Derivations

This part of the Appendix gives some further details on the derivations of our model. The calibration of the utility function is described and additional explanations on the production structure, the implementation of counterfactual scenarios, the calculation of the changes in variables of interest, the emission decomposition, and the model extension are provided.

C.1.1 Calibration of μ^j

In order to calibrate μ^j, we exactly follow the procedure used and described by Shapiro and Walker (2015). Specifically, we take the derivative of the direct utility function with respect to world emissions and equalize this marginal utility of an additional unit of world emissions to the part of total social costs in the world accruing to the country (which we denote by SCC^j):

$$\frac{\partial\left(\frac{Y^j}{P^j}\left[\frac{1}{1+\left(\frac{1}{\mu^j}\sum_{i=1}^{N}E^i\right)^2}\right]\right)}{\partial\left(\sum_{i=1}^{N}E^i\right)} = SCC^j, \tag{C.1}$$

where we used the fact that $\left(U_S^j\right)^{\gamma_S^j}\left[\prod_{l\in\mathcal{L}}(U_l^j)^{\gamma_l^j}\right] = Y^j/P^j$. Calculating the derivative on the left-hand side leads to:

$$-\frac{Y^j}{P^j}\frac{\frac{2}{(\mu^j)^2}\sum_{i=1}^{N}E^i}{\left[1+\left(\frac{1}{\mu^j}\sum_{i=1}^{N}E^i\right)^2\right]^2} = sc^W\frac{sc^jY^j/P^j}{\sum_i sc^jY^i/P^i}, \tag{C.2}$$

where sc^W denotes the world social costs, which we take from the Interagency Working Group on the Social Cost of Carbon (2013), and sc^j captures the distribution across countries according to Boyer and Nordhaus (2000), as in Shapiro and Walker (2015). We take national real income values from the Penn World Table 9.0.

C.1.2 Production Structure

With the production structure given by equation (3.11), the cost function can be derived as

$$c_l^i(e^i, \mathbf{v}^i, q_l^i) = \frac{1}{A_l^i}\left[\prod_{f\in\mathcal{F}}\left(\frac{v_f^i}{\alpha_{lf}^i}\right)^{\alpha_{lf}^i}\right]\left(\frac{e^i}{\alpha_{lE}^i}\right)^{\alpha_{lE}^i} q_{,l}^i\,. \tag{C.3}$$

where $\mathbf{v}^i$ is a vector that collects all factor prices of country i. Under the assumption of perfect competition, the price in country i equals minimal unit costs and, rearranging slightly, is hence given by

$$p_l^i = \frac{1}{A_l^i}\left(\frac{e^i}{\alpha_{lE}^i}\right)^{\alpha_{lE}^i}\prod_{f\in\mathcal{F}}\left(\frac{v_f^i}{\alpha_{lf}^i}\right)^{\alpha_{lf}^i}. \tag{C.4}$$

According to Shepard's lemma, the conditional demand for the input factor energy in tradable sector l, x_{lE}^i, is given by the partial derivative of the cost function (C.3):

$$x_{lE}^i(e^i, \mathbf{v}^i, q_l^i) = \frac{\partial c(e^i, \mathbf{v}^i, q_l^i)}{\partial e^i} = \frac{\alpha_{lE}^i}{e^i} p_l^i q_l^i = \frac{\alpha_{lE}^i}{e^i} Y_l^i. \tag{C.5}$$

Analogous expressions hold for the non-tradable sector S. Additionally, factor market clearing ensures that the following expression holds:

$$E^i = x_{SE}^i + \sum_{l\in\mathcal{L}} x_{lE}^i. \tag{C.6}$$

From equations (C.5) and (C.6), the equilibrium amount of energy can be derived:

$$E^i = \frac{\alpha_{SE}^i Y_S^i + \sum_{l\in\mathcal{L}} \alpha_{lE}^i Y_l^i}{e^i}. \tag{C.7}$$

For all other factors, the amount is given and the price is flexible and hence an expression for the equilibrium factor price v_f^i is of interest. Following the same procedure as for energy, but solving for the factor price v_f^i instead of the factor endowments V_f^i, yields

$$v_f^i = \frac{\alpha_{Sf}^i Y_S^i + \sum_{l\in\mathcal{L}} \alpha_{lf}^i Y_l^i}{V_f^i}. \tag{C.8}$$

C.1.3 Calculating Counterfactual Changes

Using the production structure given by equation (3.11), inserting $E_l^i = \alpha_{lE}^i Y_l^i / e^i$ into (3.11) and adding the counterfactual subscript, we obtain the following expression for sectoral GDP:

$$Y_{l,c}^i = p_{l,c}^i A_l^i \left(\frac{\alpha_{lE}^i Y_{l,c}^i}{e_c^i} \right)^{\alpha_{lE}^i} \prod_{f \in \mathcal{F}} (V_{lf,c}^i)^{\alpha_{lf}^i}. \tag{C.9}$$

This again represents a system of LN equations, but at the same time adds the $(1+F)LN$ unknown variables $p_{l,c}^i$ and $V_{lf,c}^i$ and the LN unknown parameters A_l^i.

In order to obtain different expressions for $V_{lf,c}^i$, we make use of the fact that the equation for the factor prices given by (C.8) also has to hold on the sectoral level:

$$v_f^i = \frac{\alpha_{lf}^i Y_l^i}{V_{lf}^i}. \tag{C.10}$$

Solving for V_{lf}^i and substituting equation (C.8) for v_f^i gives

$$V_{lf}^i = \frac{\alpha_{lf}^i Y_l^i V_f^i}{\alpha_{Sf}^i Y_S^i + \sum_{m \in \mathcal{L}} \alpha_{mf}^i Y_m^i}. \tag{C.11}$$

Now the expression for (counterfactual) sectoral GDP can be restated as

$$Y_{l,c}^i = p_{l,c}^i A_l^i \left(\frac{\alpha_{lE}^i Y_{l,c}^i}{e_c^i} \right)^{\alpha_{lE}^i} \prod_{f \in \mathcal{F}} \left(\frac{\alpha_{lf}^i Y_{l,c}^i V_f^i}{\alpha_{Sf}^i Y_{S,c}^i + \sum_{m \in \mathcal{L}} \alpha_{mf}^i Y_{m,c}^i} \right)^{\alpha_{lf}^i}. \tag{C.12}$$

Following Dekle, Eaton, and Kortum (2007, 2008), rewriting (C.12) as the counterfactual *change* in sectoral GDP will turn out to be of use:

$$\frac{Y_{l,c}^i}{Y_{l,b}^i} = \left(\frac{p_{l,c}^i}{p_{l,b}^i} \right) \left(\frac{Y_{l,c}^i e_b^i}{Y_{l,b}^i e_c^i} \right)^{\alpha_{lE}^i} \prod_{f \in \mathcal{F}} \left(\frac{Y_{l,c}^i \left(\alpha_{Sf}^i Y_{S,b}^i + \sum_{m \in \mathcal{L}} \alpha_{mf}^i Y_{m,b}^i \right)}{Y_{l,b}^i \left(\alpha_{Sf}^i Y_{S,c}^i + \sum_{m \in \mathcal{L}} \alpha_{mf}^i Y_{m,c}^i \right)} \right)^{\alpha_{lf}^i}. \tag{C.13}$$

This equation can be restated using scaled equilibrium prices:

$$\frac{Y_{l,c}^i}{Y_{l,b}^i} = \left(\frac{\psi_{l,c}^i}{\psi_{l,b}^i} \right)^{\frac{1}{1-\sigma_l}} \left(\frac{Y_{l,c}^i e_b^i}{Y_{l,b}^i e_c^i} \right)^{\alpha_{lE}^i} \prod_{f \in \mathcal{F}} \left(\frac{Y_{l,c}^i \left(\alpha_{Sf}^i Y_{S,b}^i + \sum_{m \in \mathcal{L}} \alpha_{mf}^i Y_{m,b}^i \right)}{Y_{l,b}^i \left(\alpha_{Sf}^i Y_{S,c}^i + \sum_{m \in \mathcal{L}} \alpha_{mf}^i Y_{m,c}^i \right)} \right)^{\alpha_{lf}^i}, \tag{C.14}$$

which simplifies to equation (3.16) in the main text.

To derive equation (3.17), we start off with the constant real energy price condition, $e^i_c/P^i_c = e^i_b/P^i_b$, and therefore require an expression for the change of a country's overall price index:

$$\frac{P^i_c}{P^i_b} = \frac{\left(p^i_{S,c}\right)^{\gamma^i_S} \prod_{l\in\mathcal{L}}(P^i_{l,c})^{\gamma^i_l}}{\left(p^i_{S,b}\right)^{\gamma^i_S} \prod_{l\in\mathcal{L}}(P^i_{l,b})^{\gamma^i_l}}. \tag{C.15}$$

We hence need the counterfactual sectoral price indexes to obtain counterfactual nominal energy price. These are given by equation (3.5) and can be reformulated as:

$$P^i_{l,c} = \left[\sum_{j=1}^{N}(T^{ji}_{l,c}\tau^{ji}_{l,c})^{1-\sigma_l}\psi^j_{l,c}\right]^{\frac{1}{1-\sigma_l}}. \tag{C.16}$$

Further, counterfactual prices in the non-tradable sector are given by:

$$p^i_{S,c} = \frac{1}{A^i_S}\left(\frac{e^i_c}{\alpha^i_{SE}}\right)^{\alpha^i_{SE}} \prod_{f\in\mathcal{F}}\left(\frac{v^i_{f,c}}{\alpha^i_{Sf}}\right)^{\alpha^i_{Sf}}. \tag{C.17}$$

To solve for the overall price change, we in fact only need the ratio of $p^i_{S,c}/p^i_{S,b}$, which is given by:

$$\frac{p^i_{S,c}}{p^i_{S,b}} = \left(\frac{e^i_c}{e^i_b}\right)^{\alpha^i_{SE}} \prod_{f\in\mathcal{F}}\left(\frac{\alpha^i_{Sf}Y^i_{S,c} + \sum_{l\in\mathcal{L}}\alpha^i_{lf}Y^i_{l,c}}{\alpha^i_{Sf}Y^i_{S,b} + \sum_{l\in\mathcal{L}}\alpha^i_{lf}Y^i_{l,b}}\right)^{\alpha^i_{Sf}}, \tag{C.18}$$

where we substituted $v^i_{f,c}$ and $v^i_{f,b}$ using equation (C.8) into the non-tradable counterpart of (C.4).

C.1.4 Counterfactual Percentage Changes

The effect of counterfactual scenarios on trade flows could in general be investigated on a sectoral and bilateral level. As this would imply the depiction of LN^2 numbers, we instead only present the effect on a country's aggregate trade flows. Due to the balanced trade assumption, it does not make any difference if the percentage change in total imports or total exports is analyzed and the counterfactual percentage changes in a country's normalized international trade flows can hence be obtained as

$$\Delta X^i \equiv \left[\frac{\sum_{l\in\mathcal{L}}\sum_{j\neq i} X^{ij}_{l,c}/Y^i_c}{\sum_{l\in\mathcal{L}}\sum_{j\neq i} X^{ij}_{l,b}/Y^i_b} - 1\right] \times 100, \tag{C.19}$$

where the values of sectoral, bilateral exports between countries i and j in the baseline ($X^{ij}_{l,b}$) and counterfactual ($X^{ij}_{l,c}$) can be obtained using equations (3.7) to (3.9) for the benchmark and counterfactual case, respectively.

As emissions are proportional to energy use, the counterfactual percentage change in a country's level of carbon emissions is equal to the percentage change in energy use and hence given by

$$\Delta E^i \equiv \left[\frac{E^i_c}{E^i_b} - 1\right] \times 100 = \left[\frac{e^i_b\left(\alpha^i_{SE}Y^i_{S,c} + \sum_{l\in\mathcal{L}}\alpha^i_{lE}Y^i_{l,c}\right)}{e^i_c\left(\alpha^i_{SE}Y^i_{S,b} + \sum_{l\in\mathcal{L}}\alpha^i_{lE}Y^i_{l,b}\right)} - 1\right] \times 100, \tag{C.20}$$

using the factor market clearing condition for energy, i.e. $E^i = (\alpha^i_{SE}Y^i_S + \sum_{l\in\mathcal{L}}\alpha^i_{lE}Y^i_l)/e^i$.

Real income is defined as total income divided by the consumer price index, i.e.

$$\mathfrak{R}^i = \frac{Y^i}{P^i} = \frac{Y^i}{(p^i_S)^{\gamma^i_S}\prod_{l\in\mathcal{L}}(P^i_l)^{\gamma^i_l}}. \tag{C.21}$$

The percentage change of real income is then given by

$$\Delta\mathfrak{R}^i \equiv \left(\frac{Y^i_c/P^i_c}{Y^i_b/P^i_b} - 1\right) \times 100 = \left(\frac{Y^i_c\prod_{l\in\mathcal{L}}(P^i_{l,b})^{\gamma^i_l}}{Y^i_b\prod_{l\in\mathcal{L}}(P^i_{l,c})^{\gamma^i_l}}\left(\frac{p^i_{S,c}}{p^i_{S,b}}\right)^{-\gamma^i_S} - 1\right) \times 100. \tag{C.22}$$

Additionally accounting for the social costs of carbon, the change in welfare can be calculated using the total utility function (3.2):

$$\Delta U^i = \left\{\left(\frac{U^i_{S,c}}{U^i_{S,b}}\right)^{\gamma^i_S}\left[\prod_{l\in\mathcal{L}}\left(\frac{U^i_{l,c}}{U^i_{l,b}}\right)^{\gamma^i_l}\right]\left[\frac{1+\left(\frac{1}{\mu^i}\sum_{j=1}^N E^j_b\right)^2}{1+\left(\frac{1}{\mu^i}\sum_{j=1}^N E^j_c\right)^2}\right] - 1\right\} \times 100.$$

Noting that the dual representation for the first part is the change in real income, and utilizing for the second part the factor market clearing condition for energy, we can write the change in welfare as:

$$\Delta U^i = \left[\frac{Y_c^i \prod_{l\in\mathcal{L}} (P_{l,b}^i)^{\gamma_l^i}}{Y_b^i \prod_{l\in\mathcal{L}} (P_{l,c}^i)^{\gamma_l^i}} \left(\frac{p_{S,c}^i}{p_{S,b}^i} \right)^{-\gamma_S^i} \times \right. \\ \left. \left[\frac{1 + \left(\frac{1}{\mu^i} \sum_{j=1}^N \frac{\alpha_{SE}^j Y_{S,b}^j + \sum_{l\in\mathcal{L}} \alpha_{lE}^j Y_{l,b}^j}{e_b^j} \right)^2}{1 + \left(\frac{1}{\mu^i} \sum_{j=1}^N \frac{\alpha_{SE}^j Y_{S,c}^j + \sum_{l\in\mathcal{L}} \alpha_{lE}^j Y_{l,c}^j}{e_c^j} \right)^2} \right] - 1 \right] \times 100. \tag{C.23}$$

C.1.5 Two-Sector Decomposition

In this subsection, we show a decomposition of the emission effects in scale, composition and technique effects for the case of two (tradable) sectors in order to follow closely the theoretical decomposition of Copeland and Taylor (2003). We call the these sectors clean (C) and dirty (D) subsequently, i.e. $\gamma_S^i = 0$ for all i and $\mathcal{L} = \{C, D\}$.

Starting from $E^i = \sum_{l\in\{C,D\}} \alpha_{lE}^i Y_l^i / e^i$, a country's carbon emissions can be re-expressed in terms of the dirty production share, real value of production and the real energy price as follows:

$$E^i = \left\{ \alpha_{CE}^i (1 - \kappa_D^i) + \alpha_{DE}^i \kappa_D^i \right\} \frac{\tilde{Y}^i}{P^i} \left(\frac{e^i}{P^i} \right)^{-1}, \tag{C.24}$$

where $\tilde{Y}^i \equiv \sum_{l\in\{C,D\}} Y_l^i$ is the total nominal income without tariff revenues and $\kappa_D^i \equiv Y_D^i / \tilde{Y}^i$ denotes the dirty production share. Note that the expression in curly brackets exactly equals the definition of the production-share-weighted average energy cost share $\bar{\alpha}_E^i$ in the main text. We could hence apply our multi-sectoral decomposition here. But given that the sectoral energy cost shares do not change in our model and the sectoral composition is fully captured by one parameter (κ_D^i) in the two sector case, we can equivalently follow Copeland and Taylor (2003) and capture the composition effect via changes in the dirty production share:

$$dE^i = \underbrace{\frac{\partial E^i}{\partial (\tilde{Y}^i / P^i)} d(\tilde{Y}^i / P^i)}_{\text{scale effect}} + \underbrace{\frac{\partial E^i}{\partial \kappa_D^i} d\kappa_D^i}_{\text{composition effect}} + \underbrace{\frac{\partial E^i}{\partial (e^i / P^i)} d(e^i / P^i)}_{\text{technique effect}}. \tag{C.25}$$

Scale effect. The effect of a ceteris paribus increase of a country's production on its emissions is positive and directly proportional to the rise in production:

$$\frac{\partial E^i}{\partial(\tilde{Y}^i/P^i)} = \left(\alpha^i_{CE}(1-\kappa^i_D)+\alpha^i_{DE}\kappa^i_D\right)\left(\frac{e^i}{P^i}\right)^{-1} > 0$$
$$\text{and } \frac{\partial E^i}{\partial(\tilde{Y}^i/P^i)}\frac{(\tilde{Y}^i/P^i)}{E^i} = 1. \tag{C.26}$$

Composition effect. The effect of an increase of the dirty production share on emissions is always positive:

$$\frac{\partial E^i}{\partial \kappa^i_D} = \left(\frac{\tilde{Y}^i}{e^i}\right)\left(\alpha^i_{DE}-\alpha^i_{CE}\right) > 0 \text{ if } \alpha^i_{DE} > \alpha^i_{CE}\ \forall\, i. \tag{C.27}$$

Technique effect. The effect of an increase of the real energy price on emissions is always negative and inversely proportional to the rise of the real energy price:

$$\frac{\partial E^i}{\partial(e^i/P^i)} = -\left(\alpha^i_{CE}(1-\kappa^i_D)+\alpha^i_{DE}\kappa^i_D\right)\frac{\tilde{Y}^i/P^i}{(e^i/P^i)^2} < 0$$
$$\text{and } \frac{\partial E^i}{\partial(e^i/P^i)}\frac{(e^i/P^i)}{E^i} = -1. \tag{C.28}$$

C.1.6 Incorporating Energy Production

The general production functions stay the same in the extended model:

$$q^i_l = A^i_l (E^i_l)^{\alpha^i_{lE}} \prod_{f\in\mathcal{F}} (V^i_{lf})^{\alpha^i_{lf}}, \tag{C.29}$$

$$q^i_S = A^i_S (E^i_S)^{\alpha^i_{SE}} \prod_{f\in\mathcal{F}} (V^i_{Sf})^{\alpha^i_{Sf}}. \tag{C.30}$$

As before, factor market clearing for energy holds and ensures that the following expression holds:

$$E^i = \frac{\alpha^i_{SE}Y^i_S + \sum_{l\in\mathcal{L}}\alpha^i_{lE}Y^i_l}{e^i}. \tag{C.31}$$

What is new in the extended framework is a production function for energy:

$$E^i = E_S^i + \sum_{l\in\mathcal{L}} E_l^i = A_E^i (R^i)^{\xi_R^i} \prod_{f\in\mathcal{F}} (V_{Ef}^i)^{\xi_f^i}, \tag{C.32}$$

where R is a freely internationally tradable input resource and the E subscript denotes the energy sector which is neither part of the $l \in \mathcal{L}$ tradable sectors nor of the non-tradable sector S. It follows from the Cobb-Douglas production structure that ξ_R^i is the resource cost share in energy production.

The extended production structure changes the factor market clearing conditions to:

$$V_f^i = V_{Ef}^i + V_{Sf}^i + \sum_{l\in\mathcal{L}} V_{lf}^i. \tag{C.33}$$

It also leads to a new expression for the equilibrium factor prices:

$$\begin{aligned} v_f^i &= \frac{\alpha_{Sf}^i Y_S^i + \sum_{l\in\mathcal{L}} \alpha_{lf}^i Y_l^i + \xi_f^i E^i e^i}{V_f^i} \\ &= \frac{\left(\alpha_{Sf}^i + \xi_f^i \alpha_{SE}^i\right) Y_S^i + \sum_{l\in\mathcal{L}} (\alpha_{lf}^i + \xi_f^i \alpha_{lE}^i) Y_l^i}{V_f^i}. \end{aligned} \tag{C.34}$$

We can furthermore add an international resource factor market clearing condition:

$$\sum_{i=1}^{N} R^i = \overline{R^W}, \tag{C.35}$$

assuming the world resource endowment $\overline{R^W}$ and the use of it to be constant.

The expression for the energy price that is implied by the general production function (C.29) stays the same as in the benchmark model:

$$e^i = \frac{\alpha_{SE}^i Y_S^i + \sum_{l\in\mathcal{L}} \alpha_{lE}^i Y_l^i}{E^i}. \tag{C.36}$$

From (C.32), we can then derive a country's resource use as follows:

$$R^i = \frac{\xi_R^i}{r} e^i E^i = \frac{\xi_R^i}{r} \left(\alpha_{SE}^i Y_S^i + \sum_{l \in \mathcal{L}} \alpha_{lE}^i Y_l^i \right), \tag{C.37}$$

where r denotes the international resource price. Summing both sides over all countries and solving for r yields:

$$r = \frac{1}{\overline{R^W}} \sum_{i=1}^{N} \xi_R^i \left(\alpha_{SE}^i Y_S^i + \sum_{l \in \mathcal{L}} \alpha_{lE}^i Y_l^i \right). \tag{C.38}$$

The benchmark resource price r_b can hence be calculated from the data. The international character of the resource factor implies that factor income associated with production in a certain country no longer incurs only in that country. Hence, total national income is defined in terms of factor incomes and tariff revenues as follows:

$$Y^i = \sum_{f \in \mathcal{F}} v_f^i V_f^i + \omega^i r \overline{R^W} + \sum_{j=1}^{N} \sum_{l \in \mathcal{L}} (\tau_l^{ji} - 1) X_l^{ji}, \tag{C.39}$$

where ω^i is the ressource endowment share of country i (and hence $\sum_{i=1}^N \omega^i = 1$).

Using (C.34) and (C.38), (C.39) can be rewritten as

$$\begin{aligned} Y^i \;\; = \;\; & \sum_{f \in \mathcal{F}} \left[\left(\alpha_{Sf}^i + \xi_f^i \alpha_{SE}^i \right) Y_S^i + \sum_{l \in \mathcal{L}} (\alpha_{lf}^i + \xi_f^i \alpha_{lE}^i) Y_l^i \right] \\ & + \omega^i \sum_{j=1}^{N} \xi_R^j \left(\alpha_{SE}^j Y_S^j + \sum_{l \in \mathcal{L}} \alpha_{lE}^j Y_l^j \right) + \sum_{j=1}^{N} \sum_{l \in \mathcal{L}} (\tau_l^{ji} - 1) X_l^{ji}, \end{aligned} \tag{C.40}$$

where

$$X_l^{ji} = \frac{\psi_l^j (T_l^{ji})^{1-\sigma_l} (\tau_l^{ji})^{-\sigma_l}}{\sum_{k=1}^N \psi_l^k (T_l^{ki} \tau_l^{ki})^{1-\sigma_l}} \gamma_l^i Y^i.$$

Using this new expression for total income, (3.13) can again be solved for scaled equilibrium prices in the benchmark scenario.

In the system of equations (3.14) to (3.17) that needs to be solved to conduct counterfactual analyses in the base model, (3.14) stays the same and (3.15) is substituted by the counterfactual equivalent of (C.40) in the extended model:

$$\begin{aligned} Y_c^i &= \sum_{f\in\mathcal{F}}\left[\left(\alpha_{Sf}^i+\xi_f^i\alpha_{SE}^i\right)\gamma_S^iY_c^i+\sum_{l\in\mathcal{L}}(\alpha_{lf}^i+\xi_f^i\alpha_{lE}^i)Y_{l,c}^i\right] \\ &\quad +\omega^i\sum_{j=1}^N\xi_R^j\left(\alpha_{SE}^j\gamma_S^jY_c^j+\sum_{l\in\mathcal{L}}\alpha_{lE}^jY_{l,c}^j\right)+\sum_{j=1}^N\sum_{l\in\mathcal{L}}(\tau_{l,c}^{ji}-1)X_{l,c}^{ji}. \end{aligned} \tag{C.41}$$

Additionally, we need a new analogue for equation (3.16). It evolves from the expression for sectoral GDP:

$$Y_l^i = p_l^iA_l^i\left(\frac{\alpha_{lE}^iY_l^i}{e^i}\right)^{\alpha_{lE}^i}\prod_{f\in\mathcal{F}}(V_{lf}^i)^{\alpha_{lf}^i}. \tag{C.42}$$

We again need an expression for the sectoral use of factors, V_{lf}^i. It still has to hold that

$$v_f^i = \frac{\alpha_{lf}^iY_l^i}{V_{lf}^i}. \tag{C.43}$$

Solving for V_{lf}^i and substituting (C.34) for v_f^i gives

$$V_{lf}^i = \frac{\alpha_{lf}^iY_l^iV_f^i}{\left(\alpha_{Sf}^i+\xi_f^i\alpha_{SE}^i\right)Y_S^i+\sum_{l\in\mathcal{L}}(\alpha_{lf}^i+\xi_f^i\alpha_{lE}^i)Y_l^i}. \tag{C.44}$$

Using this expression in equation (C.42) and – as in the base model – considering the counterfactual *change* in sectoral GDP yields:

$$\begin{aligned} \left(\frac{\psi_{l,c}^i}{\psi_{l,b}^i}\right)^{\frac{1}{\sigma_l-1}} &= \left(\frac{e_b^i}{e_c^i}\right)^{\alpha_{lE}^i} \\ &\quad\times\prod_{f\in\mathcal{F}}\left(\frac{\left(\alpha_{Sf}^i+\xi_f^i\alpha_{SE}^i\right)\gamma_S^iY_b^i+\sum_{m\in\mathcal{L}}(\alpha_{mf}^i+\xi_f^i\alpha_{mE}^i)Y_{m,b}^i}{\left(\alpha_{Sf}^i+\xi_f^i\alpha_{SE}^i\right)\gamma_S^iY_c^i+\sum_{m\in\mathcal{L}}(\alpha_{mf}^i+\xi_f^i\alpha_{mE}^i)Y_{m,c}^i}\right)^{\alpha_{lf}^i}. \end{aligned} \tag{C.45}$$

Equations (3.14), (C.41), and (C.45) hence correspond to equations (3.14) to (3.16) in the base model. We additionally need an equivalent for equation (3.17) to solve for e_c^i.[1]

We can derive an expression for the energy price by cost minimization using the production function given in (C.32). Specifically, we minimize the costs for producing energy,

[1]Also, additional parameters (ξ_R^i, ξ_f^i and ω^i) have to be obtained from the data, as described in Section 3.4.2.

$rR^i + \sum_{f \in \mathcal{F}} v_f^i V_{Ef}^i$, under the constraint of the factor usage for producing one unit of energy, i.e. $1 = A_E^i (R^i)^{\xi_R^i} \prod_{f \in \mathcal{F}} (V_{Ef}^i)^{\xi_f^i}$:

$$e^i = \frac{1}{A_E^i} \left(\frac{r}{\xi_R^i} \right)^{\xi_R^i} \prod_{f \in \mathcal{F}} \left(\frac{v_f^i}{\xi_f^i} \right)^{\xi^i}, \tag{C.46}$$

where the right-hand side are marginal costs of energy production.

Considering the *change* of the energy price and additionally using (C.34), we can obtain the following expression for the energy price in the counterfactual scenario:

$$e_c^i = \prod_{f \in \mathcal{F}} \left(\frac{\left(\alpha_{Sf}^i + \xi_f^i \alpha_{SE}^i \right) \gamma_S^i Y_c^i + \sum_{l \in \mathcal{L}} (\alpha_{lf}^i + \xi_f^i \alpha_{lE}^i) Y_{l,c}^i}{\left(\alpha_{Sf}^i + \xi_f^i \alpha_{SE}^i \right) \gamma_S^i Y_b^i + \sum_{l \in \mathcal{L}} (\alpha_{lf}^i + \xi_f^i \alpha_{lE}^i) Y_{l,b}^i} \right)^{\xi_f^i} \left(\frac{r_c}{r_b} \right)^{\xi_R^i} e_b^i, \tag{C.47}$$

with

$$r_c = \frac{1}{\overline{\overline{R^W}}} \sum_{i=1}^{N} \xi_R^i \left(\alpha_{SE}^i \gamma_S^i Y_c^i + \sum_{l \in \mathcal{L}} \alpha_{lE}^i Y_{l,c}^i \right). \tag{C.48}$$

We can then jointly solve equations (3.14), (C.41), (C.45), (C.47), and (C.48), for Y_c^i, $Y_{l,c}^i$, $\psi_{l,c}^i$, r_c, and e_c^i.

C.2 Data

This part of the Appendix gives some further details on the data used in this paper. First, the 128 regions and the countries which are aggregated to one region are given. Afterwards, the grouping of the industries of the GTAP 8 database into the fifteen sectors used in this work is presented and the computation of sectoral expenditure is displayed. Then, we show descriptive statistics for the gravity variables followed by a short description of our additional data source for implicit carbon taxes (OECD, 2016). We also compare these tax values to the ones we obtain based on the GTAP data. Finally, the voluntary national emission reduction pledges made in Appendix II of the Copenhagen Accord are shown.

C.2.1 Regions

The 128 regions are:[2]

Albania, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahrain, Bangladesh, Belarus, Belgium, Bolivia, Botswana, Brazil, Bulgaria, Cambodia, Cameroon, Canada, Caribbean (Aruba, Anguilla, Netherland Antilles, Antigua and Barbuda, Bahamas, Barbados, Cuba, Cayman Islands, Dominica, Dominican Republic, Grenada, Haiti, Jamaica, Saint Kitts and Nevis, Saint Lucia, Montserrat, Puerto Rico, Turks and Caicos Islands, Trinidad and Tobago, Saint Vincent and the Grenadines, Virgin Islands British, Virgin Islands U.S.), **Central Africa** (Central African Republic, Congo, Gabon, Equatorial Guinea, Sao Tome and Principe, Chad), **Chile, China, Colombia, Costa Rica, Cote d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Ecuador, Egypt, El Salvador, Estonia, Ethiopia, Finland, France, Georgia, Germany, Ghana, Greece, Guatemala, Honduras, Hong Kong, Hungary, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Kazakhstan, Kenya, Kuwait, Kyrgyzstan, Lao People's Democratic Republic, Latvia,**

[2]In parentheses, we indicate which countries are aggregated to give the respective region. The aggregated countries and regions finally used in the analysis are written in bold.

Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Malta, Mauritius, Mexico, Mongolia, Morocco, Mozambique, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Nigeria, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Rest of Central America (Belize)**, Rest of East Asia** (Macao, Democratic People's Republic of Korea)**, Rest of Eastern Africa** (Burundi, Comoros, Djibouti, Eritrea, Mayotte, Rwanda, Sudan, Somalia, Seychelles)**, Rest of Eastern Europe** (Moldova)**, Rest of EFTA** (Iceland, Lichtenstein)**, Rest of Europe** (Andorra, Bosnia and Herzegovina, Faroe Islands, Gibraltar, Monaco, Macedonia, San Marino, Serbia, Guernsey, Isle of Man, Jersey, Montenegro, Vatican)**, Rest of Former Soviet Union** (Tajikistan, Turkmenistan, Uzbekistan)**, Rest of North Africa** (Algeria, Lybia, Western Sahara)**, Rest of North America** (Bermuda, Greenland, Saint Pierre and Miquelon)**, Rest of Oceania** (American Samoa, Cook Islands, Fiji, Federated States of Micronesia, Guam, Kiribati, Marshall Islands, Northern Mariana Islands, New Caledonia, Niue, Nauru, Palau, Papua New Guinea, French Polynesia, Solomon Islands, Tokelau, Tonga, Tuvalu, Vanuatu, Wallis and Futuna, Samoa, Pitcairn, United States Minor Outlying Islands)**, Rest of South African Customs Union** (Lesotho, Swaziland)**, Rest of South America** (Falkland Islands, French Guiana, Guyana, Suriname, South Georgia and the South Sandwich Islands)**, Rest of Southeast Asia** (Brunei Darussalam, Myanmar, Timor Leste)**, Rest of South Asia** (Afghanistan, Bhutan, Maldives)**, Rest of Western Africa** (Benin, Burkina Faso, Cape Verde, Guinea, Gambia, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Saint Helena, Sierra Leone, Togo)**, Rest of Western Asia** (Iraq, Jordan, Lebanon, Palestine, Syria, Yemen)**, Romania, Russia, Saudi Arabia, Senegal, Singapore, Slovakia, Slovenia, South Africa, South Central Africa** (Angola, Congo Democratic Republic), **South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Tanzania, Thailand, Tunisia, Turkey, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States of America, Uruguay, Vietnam, Venezuela, Zambia, Zimbabwe.**

C.2.2 Sectors

The 15 sectors comprise the following GTAP 8 industries:

Agriculture: pdr (Paddy rice), wht (Wheat), gro (Cereal grains nec), v_f (Vegetables, fruit, nuts), osd (Oil seeds), c_b (Sugar cane, sugar beet), pfb (Plant-based fibers), ocr (Crops nec), ctl (Cattle, sheep, goats, horses), oap (Animal products nec), rmk (Raw milk), wol (Wool, silk-worn cocoons), frs (Forestry), fsh (Fishing).

Apparel: wap (Wearing apparel), lea (Leather products).

Chemical: crp (Chemical, rubber, plastic prods).

Equipment: mvh (Motor vehicles and parts), otn (Transport equipment nec).

Food: cmt (Meat: cattle, sheep, goats, horse), omt (Meat products nec), vol (Vegetable oils and fats), mil (Dairy products), pcr (Processed rice), sgr (Sugar), ofd (Food products nec), b_t (Beverages and tobacco products).

Machinery: ele (Electronic equipment), ome (Machinery and equipment nec).

Metal: i_s (Ferrous metals), nfm (Metals nec), fmp (Metal products).

Mineral: p_c (Petroleum, coal products), nmm (Mineral products nec).

Mining: coa (Coal), oil (Oil), gas (Gas), omn (Minerals nec).

Non-Tradables: ely (Electricity), gdt (Gas manufacture, distribution), wtr (Water), cns (Construction), osg (PubAdmin/Defence/Health/Educat), dwe (Dwellings).

Other: omf (Manufactures nec).

Paper: ppp (Paper products, publishing).

Service: trd (Trade), otp (Transport nec), wtp (Sea transport), atp (Air transport), cmn (Communication), ofi (Financial Services nec), isr (Insurance), obs (Business services nec), ros (Recreation and other services).

Textile: tex (Textiles).

Wood: lum (Wood products).

C.2.3 Calculation of Sectoral Expenditures

In GTAP notation, r and s refer to regions and i to sectors. Then, sectoral expenditures can be calculated as follows:[3]

$$\begin{aligned} \mathfrak{X}_l^j &= \mathfrak{X}_i^r \\ &= \sum_s VXMD(i,s,r) + VDPM(r,i) + VDGM(r,i) + VDFM(r,i), \end{aligned}$$

where $VXMD(i,s,r)$ denotes the value of exports of commodity i from source s to destination r, $VDPM(r,i)$ is the value of private household's purchases of domestic commodity i in region r, $VDGM(r,i)$ denotes the value of government's expenditure on domestic commodity i in region r, and $VDFM(r,i)$ is the value of purchases of domestic commodity i in region r.

C.2.4 Descriptive Statistics of Gravity Variables

Table C.1 shows the descriptive statistics for all gravity variables. As both the RTA and the CEPII data are given on a country level, we aggregated them to the GTAP 8 regional level. For the distance variable, the mean distance was used for aggregation. All of the other variables are binary. For these variables, we again took the mean when aggregating the countries and then rounded these variables to zero or one.

22 percent of the country-pairs in the data set had signed some kind of common RTA

[3]For a good introduction to the GTAP model and database and the included variables, see Hertel (1997).

Table C.1: Descriptive Statistics for Gravity Variables

	Variable	Mean	S.D.	Min	Max
WTO					
	RTA	0.22	0.41	0	1
CEPII					
	$DIST$	7,585	4,346	132	19,781
	$CONTIG$	0.02	0.15	0	1
	$COLONY$	0.01	0.12	0	1
	$COMCOL$	0.07	0.26	0	1
	$COMLANG$	0.13	0.33	0	1
GTAP					
	$X^{ij}_{agriculture}$	21.89	186.21	0	8,074
	$X^{ij}_{apparel}$	24.13	388.84	0	39,618
	$X^{ij}_{chemicals}$	107.21	871.50	0	33,201
	$X^{ij}_{equipment}$	95.63	1,184.58	0	75,321
	X^{ij}_{food}	40.51	289.15	0	12,659
	$X^{ij}_{machinery}$	206.03	2,125.12	0	144,059
	X^{ij}_{metal}	75.60	560.13	0	31,767
	$X^{ij}_{mineral}$	44.06	330.14	0	14,025
	X^{ij}_{mining}	93.67	1,037.74	0	51,876
	X^{ij}_{other}	16.39	295.58	0	31,932
	X^{ij}_{paper}	15.92	176.90	0	15,277
	$X^{ij}_{service}$	143.65	867.00	0	32,857
	$X^{ij}_{textile}$	20.11	183.81	0	13,135
	X^{ij}_{wood}	15.18	224.30	0	18,745

Notes: We have information for 128 countries, leading to $128 \times 127 = 16,256$ observations (excluding intra-trade flows). Distances are given in kilometers and trade flows in million US-$.

in 2007. The average weighted distance between two countries is 7,585 km, ranging from 132 to 19,781 km. Only two percent have a common land border. One percent had a direct colonial link and seven percent a common colonizer at some point in the past. 13 percent share a common language.[4] Average bilateral sectoral trade flows range between 15.2 million US-$ in the wood sector and 206 million US-$ for machinery. In all sectors, there are country-pairs that do not trade at all. As explained in Section 3.4.1 of the main manuscript, these zero trade flows are unproblematic for the estimation with our preferred PPML estimator.

C.2.5 Implicit Carbon Taxes

The OECD (2016) provides data on the effective carbon rates for 41 OECD and G20 countries. The rates are distinguished between non-road and road emissions. We calculate one national number from this by weighting the two values with the corresponding national emission shares.

The effective carbon prices in OECD (2016) are given in 2012 Euros. We make them compatible with the rest of our data by converting them to 2012 US-$ using the exchange rate obtained from the OECD (0.778 US-$/Euro) and to 2007 US-$ using US inflation data also obtained from the OECD (with an average inflation rate from 2007 to 2012 of 2.2 percent).

For the calculation of the carbon tariffs, we make use of the implicit carbon tax differentials between all country-pairs. We therefore need carbon tax data for all countries. We use the average of the non-OECD countries for which the OECD (2016) provides data as the value for all other non-OECD countries in our data set. The resulting implicit carbon tax data are highly correlated with the measure we obtain from GTAP (with a correlation coefficient of 0.78), though somewhat lower on average. Table C.2 shows

[4] We construct the variable for common language ($COMLANG$) to be one if either the two countries share an official language or if one language is spoken by at least nine percent of the population in both countries.

descriptive statistics for both sources.

Table C.2: Implicit Carbon Taxes

	Obs.	Mean	S.D.	Min.	Max.
GTAP	128	25.6	31.8	-13.1	138.4
OECD	128	19.3	23.0	0	104.4

Notes: The values are given in US-$/t CO_2.

C.2.6 Appendix II of the Copenhagen Accord

Table C.3 shows the voluntary emission reduction pledges made in Appendix II of the Copenhagen Accord, adjusted to the base year of our model (2007).

Table C.3: National Pledges Made in the Copenhagen Accord (Appendix II)

Brazil	27.8%	Chile	26.7%	China	37.1%
Costa Rica	53.4%	India	19.5%	Indonesia	13.9%
Israel	22.7%	Kyrgyzstan	18.8%	Mexico	33.2%
Singapore	6.1%	South Afr.	43.8%	South Korea	27.2%
Thailand	9.2%				

C.3 Detailed Results

This section of the Appendix gives some further detailed results for the regressions and counterfactual scenarios. Tables C.4 and C.5 give the PPML and OLS estimation results, respectively. Figure C.1 illustrates the real income effects for all countries in our first counterfactual scenario (pure product-based carbon tariffs in our base model). Tables C.6 to C.15 give the exact results for all countries in the counterfactual scenarios discussed in Section 3.6.2 of the main paper. Specifically, the implicit carbon taxes (λ^i), the percentage changes in trade flows (ΔX^i), real income ($\Delta \mathfrak{R}^i$), welfare (ΔU^i), and emissions (ΔE^i), as well as the percentage scale, composition, and technique effects (PSE, PCE, and PTE, respectively) are shown. For our Copenhagen Accord scenarios, we additionally show our exact log decomposition, i.e. the log scale, composition, and technique effects (LSE, LCE, and LTE, respectively). In all results tables, bootstrapped standard errors are given in parentheses.

In the tables, country codes are given rather than country names. We therefore provide an alphabetical list of all the country codes here: ALB (Albania), ARE (United Arab Emirates), ARG (Argentina), ARM (Armenia), AUS (Australia), AUT (Austria), AZE (Azerbaijan), BEL (Belgium), BGD (Bangladesh), BGR (Bulgaria), BHR (Bahrain), BLR (Belarus), BOL (Bolivia), BRA (Brazil), BWA (Botswana), CAN (Canada), CHE (Switzerland), CHL (Chile), CHN (China), CIV (Cote d'Ivoire), CMR (Cameroon), COL (Colombia), CRI (Costa Rica), CYP (Cyprus), CZE (Czech Republic), DEU (Germany), DNK (Denmark), ECU (Ecuador), EGY (Egypt), ESP (Spain), EST (Estonia), ETH (Ethiopia), FIN (Finland), FRA (France), GBR (United Kingdom), GEO (Georgia), GHA (Ghana), GRC (Greece), GTM (Guatemala), HKG (Hong Kong), HND (Honduras), HRV (Croatia), HUN (Hungary), IDN (Indonesia), IND (India), IRL (Ireland), IRN (Iran), ISR (Israel), ITA (Italy), JPN (Japan), KAZ (Kazakhstan), KEN (Kenya), KGZ (Kyrgyzstan), KHM (Cambodia), KOR (South Korea), KWT (Kuwait), LAO (Laos), LKA (Sri Lanka), LTU (Lithuania), LUX (Luxembourg), LVA (Latvia), MAR (Morocco), MDG (Madagascar), MEX (Mexico), MLT (Malta), MNG (Mongolia), MOZ (Mozambique), MUS (Mauritius), MWI (Malawi), MYS (Malaysia), NAM (Namibia), NGA (Nigeria), NIC (Nicaragua), NLD (Netherlands), NOR (Norway), NPL (Nepal), NZL (New Zealand), OMN (Oman), PAK (Pakistan), PAN (Panama), PER (Peru), PHL (Philippines), POL (Po-land), PRT (Portugal), PRY (Paraguay), QAT (Qatar), ROU (Romania), RUS (Russia), SAU (Saudi Arabia), SEN (Senegal), SGP (Singapore), SLV (El Salvador), SVK (Slovakia), SVN (Slovenia), SWE (Sweden), THA (Thailand), TUN (Tunisia), TUR (Turkey), TWN (Taiwan), TZA (Tanzania), UGA (Uganda), UKR (Ukraine), URY (Uruguay), USA (U.S.A.), VEN (Venezuela), VNM (Vietnam), XAC (South Central Africa), XCA (Rest of Central America), XCB (Caribbean), XCF (Central Africa), XEA (Rest of East Asia), XEC (Rest of Eastern Africa), XEE (Rest of Eastern Europe), XEF (Rest of EFTA), XER (Rest of Europe), XNA (Rest of North America), XNF (Rest of North Africa), XOC (Rest of Oceania), XSA (Rest of South Asia), XSC (Rest of South African Customs Union), XSE (Rest of Southeast Asia), XSM (Rest of South America), XSU (Rest of Former Soviet Union), XWF (Rest of Western Africa), XWS (Rest of Western Asia), ZAF (South Africa), ZMB (Zambia), ZWE (Zimbabwe).

C.3.1 Regression Results

As was described in Section 3.4, the gravity equation resulting from the model developed in Section 4.2 is estimated both with OLS and PPML. The PPML results are given in Table C.4 and are in line with the usual findings. Distance significantly reduces bilateral trade flows in all sectors. Regional trade agreements, contiguity, and common language have the expected positive effects on trade. However, the magnitude and significance vary strongly across sectors. The two variables for colonial links do not show a robust effect across sectors, but also tend to be positive. Table C.5 shows the results obtained by OLS estimation of the log-linearized gravity equation.

Table C.4: Estimation Results for the Gravity Equation (PPML)

dep. var.	(1) $X_{agr.}$	(2) $X_{apr.}$	(3) $X_{che.}$	(4) $X_{equ.}$	(5) X_{food}	(6) $X_{mac.}$	(7) $X_{met.}$	(8) $X_{mine.}$	(9) $X_{mini.}$	(10) $X_{oth.}$	(11) $X_{pap.}$	(12) $X_{ser.}$	(13) $X_{tex.}$	(14) X_{wood}
$\ln DIST$	-1.14**	-0.93**	-0.92**	-0.60**	-0.92**	-0.77**	-0.93**	-1.22**	-1.33**	-0.50**	-0.95**	-0.35**	-1.08**	-0.93**
	(0.052)	(0.083)	(0.038)	(0.063)	(0.040)	(0.040)	(0.043)	(0.062)	(0.11)	(0.099)	(0.046)	(0.032)	(0.052)	(0.098)
RTA	0.22*	0.053	0.40**	0.87**	0.52**	0.20**	0.19*	0.11	0.100	0.26	0.45**	0.14*	0.26**	0.43**
	(0.088)	(0.11)	(0.069)	(0.099)	(0.067)	(0.071)	(0.085)	(0.11)	(0.16)	(0.20)	(0.091)	(0.059)	(0.087)	(0.15)
$CONT.$	0.36**	0.35**	0.17*	0.50**	0.44**	0.20**	0.51**	0.41**	0.16	0.10	0.61**	0.36**	0.10	0.71**
	(0.096)	(0.12)	(0.076)	(0.094)	(0.080)	(0.075)	(0.076)	(0.099)	(0.25)	(0.14)	(0.080)	(0.078)	(0.091)	(0.12)
$LANG$	0.32**	0.45**	0.024	0.084	0.29**	0.18*	0.098	0.24*	0.036	0.19	0.25**	0.14*	0.52**	0.12
	(0.11)	(0.11)	(0.093)	(0.11)	(0.083)	(0.089)	(0.098)	(0.11)	(0.20)	(0.14)	(0.098)	(0.060)	(0.086)	(0.13)
$COL.$	0.17	0.27^{+}	0.27*	-0.11	0.48**	0.11	0.43**	0.13	0.87**	0.24^{+}	0.21*	0.030	0.050	0.29**
	(0.16)	(0.15)	(0.11)	(0.14)	(0.093)	(0.11)	(0.10)	(0.12)	(0.23)	(0.14)	(0.10)	(0.070)	(0.15)	(0.10)
$COMC.$	0.49**	-0.45*	0.20^{+}	0.47^{+}	0.74**	0.088	0.49*	0.43*	0.71^{+}	1.31**	0.72**	-0.25^{+}	-0.54**	0.63**
	(0.16)	(0.19)	(0.12)	(0.25)	(0.14)	(0.16)	(0.21)	(0.20)	(0.41)	(0.29)	(0.16)	(0.15)	(0.14)	(0.15)
Obs.	16,256	16,256	16,256	16,256	16,256	16,256	16,256	16,256	16,256	16,256	16,256	16,256	16,256	16,256
Pseudo-R^2	0.776	0.962	0.901	0.936	0.849	0.906	0.846	0.769	0.641	0.929	0.920	0.886	0.894	0.849

Notes: All regressions include importer and exporter fixed effects and a constant, the coefficients of which are not shown. Robust standard errors are given in parentheses. $^{+}$, * and ** denote statistical significance at the 10, 5 and 1 percent level, respectively.

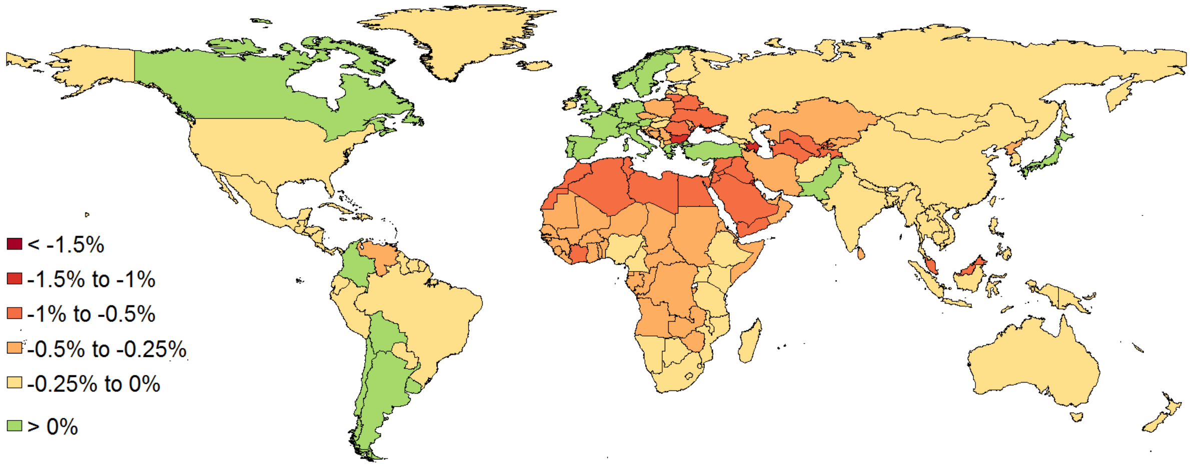
Table C.5: Estimation Results for the Gravity Equation (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
dep. var.	$x_{agr.}$	$x_{apr.}$	$x_{che.}$	$x_{equ.}$	x_{food}	$x_{mac.}$	$x_{met.}$	$x_{mine.}$	$x_{mini.}$	$x_{oth.}$	$x_{pap.}$	$x_{ser.}$	$x_{tex.}$	x_{wood}
ln $DIST$	-1.17**	-0.92**	-1.37**	-1.08**	-1.31**	-1.22**	-1.59**	-1.43**	-1.34**	-0.89**	-1.41**	-0.075**	-1.19**	-1.41**
	(0.028)	(0.025)	(0.027)	(0.031)	(0.028)	(0.027)	(0.034)	(0.031)	(0.050)	(0.025)	(0.028)	(0.0082)	(0.029)	(0.033)
RTA	0.33**	0.32**	0.46**	0.67**	0.34**	0.44**	0.45**	0.23**	0.11	0.27**	0.31**	0.023+	0.51**	0.37**
	(0.044)	(0.035)	(0.040)	(0.049)	(0.042)	(0.042)	(0.053)	(0.046)	(0.074)	(0.039)	(0.043)	(0.012)	(0.042)	(0.049)
$CONT.$	1.24**	1.26**	0.90**	1.10**	0.99**	0.79**	0.77**	1.38**	1.02**	0.79**	0.99**	0.31**	1.01**	0.89**
	(0.11)	(0.11)	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)	(0.13)	(0.15)	(0.10)	(0.11)	(0.050)	(0.11)	(0.11)
$LANG$	0.29**	0.31**	0.42**	0.23**	0.41**	0.44**	0.37**	0.32**	-0.029	0.37**	0.41**	-0.035*	0.32**	0.33**
	(0.052)	(0.042)	(0.049)	(0.057)	(0.052)	(0.050)	(0.063)	(0.058)	(0.088)	(0.047)	(0.052)	(0.015)	(0.051)	(0.056)
$COL.$	1.02**	0.73**	0.59**	0.83**	0.94**	0.88**	0.88**	0.63**	1.30**	0.84**	0.78**	0.25**	0.69**	0.93**
	(0.12)	(0.11)	(0.11)	(0.12)	(0.13)	(0.11)	(0.12)	(0.11)	(0.16)	(0.10)	(0.11)	(0.045)	(0.11)	(0.11)
$COMC.$	0.50**	0.19**	0.77**	0.75**	0.77**	0.66**	0.85**	0.69**	0.40**	0.50**	0.71**	-0.019	0.47**	0.68**
	(0.072)	(0.061)	(0.071)	(0.089)	(0.074)	(0.076)	(0.093)	(0.088)	(0.12)	(0.070)	(0.084)	(0.021)	(0.073)	(0.088)
Obs.	13,663	13,459	13,727	12,016	14,435	13,112	11,597	12,945	9,114	12,187	11,779	16,243	11,981	10,307
R^2	0.749	0.833	0.824	0.796	0.791	0.845	0.747	0.777	0.588	0.817	0.803	0.969	0.791	0.750

Notes: All regressions include importer and exporter fixed effects and a constant, the coefficients of which are not shown. Robust standard errors are given in parentheses. $^+$, * and ** denote statistical significance at the 10, 5 and 1 percent level, respectively. The lower case x for the dependent variables indicates that the natural logarithm of the trade flows has been taken for the regressions.

C.3.2 Counterfactual Analyses

Figure C.1: Percentage Changes in Real Income (Pure Carbon Tariffs)



Notes: This figure shows the percentage changes in real income due to the counterfactual introduction of product-based carbon tariffs in our base model. Green represents an increase in a country's real income, while red represents a reduction. The values range between -1.6 percent for Bahrain and 0.29 percent for Norway.

Table C.6: Pure Carbon Tariffs (Product-Based)

Country	λ^i	ΔX^i	$\Delta \Re^i$	ΔU^i	ΔE^i	PSE	PCE
ALB	70.41	-1.52	-0.01	0.00	-0.76	-0.61	-0.14
		(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.03)
ARE	-0.17	-3.34	-0.44	-0.43	-2.87	-0.44	-2.44
		(0.04)	(0.01)	(0.01)	(0.11)	(0.01)	(0.10)
ARG	28.84	-1.17	0.04	0.05	0.38	-0.11	0.49
		(0.02)	(0.01)	(0.01)	(0.07)	(0.00)	(0.07)
ARM	58.38	-1.89	-0.09	-0.09	-1.34	-0.79	-0.55
		(0.02)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
AUS	0.58	-1.63	-0.14	-0.14	-0.40	-0.14	-0.27
		(0.02)	(0.01)	(0.01)	(0.08)	(0.01)	(0.07)
AUT	99.13	-0.83	0.13	0.14	0.53	-0.21	0.74
		(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.02)
AZE	-0.09	-5.85	-1.33	-1.32	-5.79	-1.33	-4.52
		(0.16)	(0.06)	(0.06)	(0.30)	(0.06)	(0.25)
BEL	88.87	-0.83	0.11	0.12	0.49	-0.06	0.55
		(0.01)	(0.01)	(0.01)	(0.10)	(0.01)	(0.10)
BGD	5.71	-1.55	-0.18	-0.17	-1.23	-0.21	-1.03
		(0.03)	(0.01)	(0.01)	(0.06)	(0.01)	(0.06)
BGR	4.14	-4.63	-1.41	-1.41	-6.97	-1.43	-5.62
		(0.14)	(0.03)	(0.03)	(0.17)	(0.03)	(0.14)
BHR	-0.09	-4.52	-1.55	-1.55	-5.12	-1.55	-3.62
		(0.18)	(0.07)	(0.07)	(0.26)	(0.07)	(0.19)
BLR	21.56	-2.47	-0.79	-0.78	-3.41	-0.86	-2.58
		(0.08)	(0.04)	(0.04)	(0.16)	(0.04)	(0.13)
BOL	31.25	-1.57	0.00	0.01	-0.15	-0.42	0.27
		(0.02)	(0.01)	(0.01)	(0.08)	(0.02)	(0.06)
BRA	22.06	-0.92	-0.03	-0.02	-0.07	-0.05	-0.02
		(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
BWA	1.03	-2.87	-0.22	-0.20	-0.38	-0.22	-0.16
		(0.05)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
CAN	30.51	-1.02	0.03	0.03	0.29	-0.08	0.36
		(0.02)	(0.01)	(0.01)	(0.06)	(0.00)	(0.06)
CHE	75.84	-0.85	0.01	0.02	-0.33	-0.09	-0.25
		(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
CHL	35.00	-1.20	0.06	0.06	0.55	-0.14	0.69
		(0.03)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
CHN	4.35	-1.22	-0.06	-0.06	-0.36	-0.07	-0.29
		(0.03)	(0.01)	(0.01)	(0.05)	(0.01)	(0.04)
CIV	2.59	-2.54	-0.69	-0.68	-5.05	-0.69	-4.39
		(0.08)	(0.03)	(0.03)	(0.32)	(0.04)	(0.29)
CMR	15.50	-1.48	-0.21	-0.20	-1.71	-0.26	-1.46
		(0.04)	(0.01)	(0.01)	(0.15)	(0.01)	(0.14)
COL	31.26	-1.03	0.03	0.04	0.49	-0.09	0.58
		(0.01)	(0.00)	(0.00)	(0.03)	(0.01)	(0.03)
CRI	18.50	-0.95	-0.07	-0.06	-0.44	-0.13	-0.31
		(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)
CYP	64.69	-1.73	-0.01	0.00	-0.76	-0.74	-0.02
		(0.02)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)

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Table C.6 – *Continued from previous page*

Country	λ^i	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
CZE	18.57	-2.45	-0.39	-0.39	-3.34	-0.44	-2.91
		(0.06)	(0.01)	(0.01)	(0.12)	(0.01)	(0.11)
DEU	61.59	-1.07	0.01	0.01	-0.23	-0.11	-0.12
		(0.03)	(0.00)	(0.00)	(0.04)	(0.00)	(0.03)
DNK	84.76	-1.05	0.09	0.10	0.08	-0.27	0.35
		(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)
ECU	11.48	-1.40	-0.21	-0.20	-1.35	-0.25	-1.11
		(0.05)	(0.02)	(0.02)	(0.16)	(0.02)	(0.14)
EGY	-0.02	-3.49	-0.81	-0.80	-4.24	-0.81	-3.46
		(0.16)	(0.05)	(0.05)	(0.30)	(0.05)	(0.25)
ESP	54.66	-1.14	0.00	0.01	-0.24	-0.13	-0.12
		(0.03)	(0.00)	(0.00)	(0.04)	(0.01)	(0.04)
EST	29.12	-1.80	-0.13	-0.13	-0.62	-0.33	-0.29
		(0.03)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
ETH	5.92	-1.56	-0.16	-0.15	-0.52	-0.18	-0.34
		(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
FIN	52.58	-1.35	-0.06	-0.05	-0.71	-0.19	-0.51
		(0.05)	(0.01)	(0.01)	(0.07)	(0.01)	(0.06)
FRA	113.02	-0.78	0.17	0.18	1.12	-0.08	1.20
		(0.01)	(0.01)	(0.01)	(0.08)	(0.00)	(0.08)
GBR	92.31	-0.95	0.14	0.15	0.71	-0.10	0.81
		(0.02)	(0.01)	(0.01)	(0.07)	(0.00)	(0.07)
GEO	18.46	-1.90	-0.16	-0.15	-0.52	-0.28	-0.24
		(0.04)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
GHA	1.55	-1.99	-0.38	-0.36	-3.20	-0.38	-2.82
		(0.03)	(0.01)	(0.01)	(0.12)	(0.01)	(0.11)
GRC	62.69	-2.42	0.07	0.08	-0.22	-0.67	0.46
		(0.02)	(0.02)	(0.02)	(0.10)	(0.02)	(0.08)
GTM	27.86	-0.87	-0.01	0.00	-0.16	-0.18	0.02
		(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
HKG	-2.05	-1.88	-0.24	-0.24	-0.32	-0.24	-0.08
		(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
HND	8.58	-1.29	-0.13	-0.12	-0.41	-0.16	-0.25
		(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
HRV	46.45	-2.26	-0.31	-0.31	-1.63	-0.48	-1.16
		(0.09)	(0.02)	(0.02)	(0.07)	(0.01)	(0.06)
HUN	57.83	-1.26	-0.03	-0.03	-0.60	-0.27	-0.33
		(0.02)	(0.01)	(0.01)	(0.06)	(0.01)	(0.06)
IDN	1.88	-1.64	-0.11	-0.11	-0.35	-0.14	-0.21
		(0.03)	(0.01)	(0.01)	(0.11)	(0.01)	(0.10)
IND	16.81	-1.50	-0.01	0.00	-0.13	-0.11	-0.02
		(0.02)	(0.01)	(0.01)	(0.03)	(0.00)	(0.03)
IRL	51.95	-1.70	-0.09	-0.08	-1.01	-0.23	-0.78
		(0.03)	(0.01)	(0.01)	(0.10)	(0.00)	(0.10)
IRN	6.43	-2.74	-0.41	-0.41	-1.46	-0.50	-0.97
		(0.07)	(0.04)	(0.04)	(0.18)	(0.04)	(0.14)
ISR	27.57	-1.80	-0.11	-0.11	-0.88	-0.27	-0.61
		(0.04)	(0.02)	(0.02)	(0.24)	(0.02)	(0.22)

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Table C.6 – *Continued from previous page*

Country	λ^i	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
ITA	124.51	-1.13	0.22	0.23	1.34	-0.09	1.44
		(0.02)	(0.01)	(0.01)	(0.13)	(0.01)	(0.13)
JPN	41.75	-0.81	0.05	0.05	0.30	-0.02	0.33
		(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
KAZ	0.18	-2.95	-0.48	-0.47	-2.36	-0.48	-1.88
		(0.07)	(0.03)	(0.03)	(0.20)	(0.03)	(0.18)
KEN	3.71	-1.55	-0.24	-0.22	-2.23	-0.25	-1.99
		(0.04)	(0.01)	(0.01)	(0.18)	(0.01)	(0.16)
KGZ	11.83	-2.08	-0.27	-0.27	-0.81	-0.51	-0.30
		(0.02)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
KHM	15.97	-0.72	-0.02	-0.01	-0.14	-0.12	-0.02
		(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
KOR	17.34	-0.95	-0.06	-0.05	-0.37	-0.10	-0.27
		(0.02)	(0.00)	(0.00)	(0.04)	(0.01)	(0.03)
KWT	0.03	-4.61	-1.32	-1.31	-5.87	-1.32	-4.61
		(0.12)	(0.04)	(0.04)	(0.18)	(0.04)	(0.15)
LAO	12.33	-0.80	-0.08	-0.07	-0.76	-0.13	-0.63
		(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)
LKA	-0.86	-2.21	-0.38	-0.37	-1.88	-0.39	-1.50
		(0.04)	(0.02)	(0.02)	(0.15)	(0.02)	(0.13)
LTU	29.15	-2.47	-0.53	-0.53	-3.55	-0.60	-2.97
		(0.07)	(0.02)	(0.02)	(0.15)	(0.02)	(0.13)
LUX	84.77	-0.81	0.07	0.07	-0.30	-0.27	-0.03
		(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
LVA	40.98	-1.29	-0.05	-0.05	-0.32	-0.23	-0.09
		(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
MAR	0.03	-3.24	-0.56	-0.55	-4.87	-0.56	-4.33
		(0.11)	(0.04)	(0.03)	(0.39)	(0.04)	(0.36)
MDG	1.64	-2.10	-0.20	-0.18	-1.52	-0.20	-1.32
		(0.02)	(0.01)	(0.01)	(0.08)	(0.01)	(0.07)
MEX	-0.15	-1.57	-0.19	-0.18	-1.01	-0.19	-0.82
		(0.03)	(0.02)	(0.02)	(0.23)	(0.02)	(0.21)
MLT	63.22	-1.16	-0.03	-0.02	-0.42	-0.47	0.05
		(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
MNG	5.06	-1.92	-0.24	-0.23	-0.64	-0.37	-0.26
		(0.10)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MOZ	5.28	-1.87	-0.23	-0.21	-0.77	-0.23	-0.54
		(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
MUS	7.40	-1.66	-0.17	-0.16	-0.72	-0.22	-0.50
		(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
MWI	4.51	-1.82	-0.24	-0.23	-1.19	-0.26	-0.93
		(0.03)	(0.01)	(0.00)	(0.04)	(0.01)	(0.04)
MYS	-13.12	-2.94	-0.58	-0.57	-3.70	-0.58	-3.13
		(0.08)	(0.04)	(0.04)	(0.38)	(0.04)	(0.34)
NAM	2.58	-2.17	-0.21	-0.20	-0.27	-0.21	-0.05
		(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NGA	12.96	-2.58	-0.13	-0.12	0.00	-0.23	0.22
		(0.11)	(0.01)	(0.01)	(0.21)	(0.01)	(0.20)

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Table C.6 – *Continued from previous page*

Country	λ^i	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
NIC	44.39	-1.47	-0.04	-0.03	-0.57	-0.75	0.18
		(0.02)	(0.01)	(0.01)	(0.09)	(0.02)	(0.07)
NLD	107.53	-0.79	0.23	0.24	1.36	-0.07	1.42
		(0.01)	(0.01)	(0.01)	(0.05)	(0.00)	(0.05)
NOR	138.42	-1.34	0.29	0.30	2.13	-0.31	2.45
		(0.02)	(0.00)	(0.00)	(0.03)	(0.01)	(0.03)
NPL	3.94	-1.69	-0.19	-0.18	-0.74	-0.20	-0.54
		(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
NZL	0.77	-1.53	-0.16	-0.16	-0.66	-0.16	-0.50
		(0.03)	(0.01)	(0.01)	(0.14)	(0.01)	(0.13)
OMN	0.98	-4.03	-0.46	-0.46	-2.23	-0.48	-1.76
		(0.06)	(0.01)	(0.01)	(0.10)	(0.01)	(0.09)
PAK	35.01	-2.07	0.06	0.07	-0.03	-0.49	0.47
		(0.04)	(0.02)	(0.02)	(0.12)	(0.03)	(0.09)
PAN	3.35	-1.47	-0.16	-0.15	-0.35	-0.17	-0.18
		(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
PER	19.54	-1.02	-0.07	-0.06	-0.48	-0.10	-0.38
		(0.02)	(0.00)	(0.00)	(0.06)	(0.01)	(0.06)
PHL	11.75	-1.01	-0.05	-0.05	-0.34	-0.12	-0.22
		(0.02)	(0.01)	(0.01)	(0.10)	(0.01)	(0.08)
POL	24.58	-2.14	-0.27	-0.27	-2.23	-0.37	-1.86
		(0.07)	(0.02)	(0.02)	(0.16)	(0.02)	(0.14)
PRT	79.44	-1.08	0.11	0.12	0.33	-0.19	0.52
		(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)
PRY	29.02	-0.78	-0.02	-0.02	-0.18	-0.16	-0.02
		(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
QAT	-0.05	-3.59	-0.44	-0.44	-3.46	-0.45	-3.03
		(0.08)	(0.01)	(0.01)	(0.12)	(0.01)	(0.11)
ROU	4.61	-3.25	-0.66	-0.66	-4.94	-0.67	-4.29
		(0.10)	(0.03)	(0.03)	(0.23)	(0.03)	(0.20)
RUS	22.00	-1.73	-0.14	-0.14	-0.71	-0.23	-0.47
		(0.03)	(0.01)	(0.01)	(0.03)	(0.01)	(0.03)
SAU	-0.03	-3.74	-0.60	-0.59	-2.48	-0.60	-1.90
		(0.03)	(0.03)	(0.03)	(0.18)	(0.03)	(0.15)
SEN	10.09	-2.05	-0.39	-0.37	-2.44	-0.42	-2.02
		(0.06)	(0.02)	(0.02)	(0.16)	(0.02)	(0.14)
SGP	5.14	-1.52	-0.28	-0.28	-1.74	-0.33	-1.42
		(0.04)	(0.02)	(0.02)	(0.14)	(0.02)	(0.13)
SLV	22.96	-0.92	-0.05	-0.04	-0.32	-0.20	-0.11
		(0.02)	(0.00)	(0.00)	(0.06)	(0.01)	(0.05)
SVK	42.45	-1.68	-0.21	-0.21	-2.08	-0.34	-1.75
		(0.03)	(0.01)	(0.01)	(0.07)	(0.01)	(0.07)
SVN	52.40	-1.49	-0.07	-0.06	-0.53	-0.25	-0.28
		(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
SWE	138.13	-0.66	0.23	0.24	1.75	-0.07	1.83
		(0.01)	(0.01)	(0.01)	(0.07)	(0.00)	(0.07)
THA	13.03	-1.13	-0.05	-0.04	-0.26	-0.13	-0.13
		(0.03)	(0.01)	(0.01)	(0.04)	(0.01)	(0.04)

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Table C.6 – *Continued from previous page*

Country	λ^i	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
TUN	0.97	-3.50	-0.58	-0.57	-3.66	-0.59	-3.09
		(0.07)	(0.02)	(0.02)	(0.13)	(0.02)	(0.12)
TUR	89.49	-2.10	0.26	0.27	1.08	-0.36	1.45
		(0.03)	(0.00)	(0.00)	(0.03)	(0.02)	(0.04)
TWN	12.80	-1.07	-0.06	-0.05	-0.30	-0.10	-0.19
		(0.03)	(0.01)	(0.01)	(0.06)	(0.01)	(0.05)
TZA	1.73	-1.83	-0.19	-0.18	-0.61	-0.20	-0.41
		(0.03)	(0.00)	(0.00)	(0.02)	(0.00)	(0.01)
UGA	29.73	-1.14	-0.05	-0.03	-0.33	-0.19	-0.14
		(0.03)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
UKR	15.14	-2.69	-0.60	-0.59	-2.12	-0.73	-1.40
		(0.07)	(0.03)	(0.03)	(0.10)	(0.03)	(0.07)
URY	30.50	-0.82	0.00	0.01	0.02	-0.09	0.12
		(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
USA	13.92	-0.92	-0.03	-0.03	-0.17	-0.04	-0.13
		(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
VEN	6.43	-2.04	-0.45	-0.44	-3.59	-0.46	-3.15
		(0.04)	(0.01)	(0.01)	(0.11)	(0.01)	(0.10)
VNM	-4.19	-2.19	-0.24	-0.23	-0.87	-0.26	-0.61
		(0.06)	(0.01)	(0.01)	(0.05)	(0.01)	(0.04)
XAC	2.05	-3.66	-0.30	-0.29	-1.88	-0.31	-1.58
		(0.04)	(0.01)	(0.01)	(0.26)	(0.01)	(0.24)
XCA	19.15	-0.99	-0.10	-0.10	-0.81	-0.16	-0.65
		(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)
XCB	14.15	-1.27	-0.15	-0.14	-0.97	-0.17	-0.80
		(0.03)	(0.01)	(0.01)	(0.06)	(0.01)	(0.05)
XCF	3.16	-3.07	-0.30	-0.29	-2.35	-0.30	-2.05
		(0.04)	(0.01)	(0.01)	(0.21)	(0.01)	(0.20)
XEA	1.39	-1.78	-0.28	-0.28	-1.31	-0.30	-1.02
		(0.03)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
XEC	1.46	-2.53	-0.33	-0.32	-1.71	-0.34	-1.38
		(0.06)	(0.02)	(0.02)	(0.14)	(0.02)	(0.12)
XEE	10.09	-2.33	-0.28	-0.28	-0.55	-0.34	-0.21
		(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
XEF	20.62	-1.80	-0.20	-0.19	-1.33	-0.25	-1.08
		(0.04)	(0.01)	(0.01)	(0.04)	(0.01)	(0.04)
XER	30.38	-2.23	-0.27	-0.26	-1.71	-0.49	-1.22
		(0.05)	(0.02)	(0.02)	(0.11)	(0.02)	(0.09)
XNA	46.67	-1.05	-0.06	-0.05	-0.84	-0.19	-0.64
		(0.01)	(0.00)	(0.00)	(0.04)	(0.01)	(0.04)
XNF	0.03	-4.31	-0.84	-0.83	-5.77	-0.84	-4.97
		(0.10)	(0.04)	(0.04)	(0.36)	(0.04)	(0.32)
XOC	9.26	-1.43	-0.15	-0.14	-0.77	-0.17	-0.60
		(0.04)	(0.01)	(0.01)	(0.12)	(0.01)	(0.11)
XSA	19.74	-1.22	-0.10	-0.10	-0.97	-0.19	-0.79
		(0.01)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)
XSC	4.32	-1.77	-0.21	-0.19	-1.39	-0.21	-1.18
		(0.03)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)

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Table C.6 – *Continued from previous page*

Country	λ^i	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
XSE	17.86	-1.34	-0.06	-0.06	-0.28	-0.32	0.04
		(0.03)	(0.01)	(0.01)	(0.11)	(0.01)	(0.10)
XSM	23.04	-1.23	-0.11	-0.11	-1.23	-0.14	-1.09
		(0.04)	(0.01)	(0.01)	(0.06)	(0.00)	(0.06)
XSU	1.73	-3.40	-0.77	-0.77	-2.07	-0.81	-1.27
		(0.15)	(0.04)	(0.04)	(0.14)	(0.05)	(0.09)
XWF	2.00	-2.59	-0.26	-0.25	-1.27	-0.27	-1.00
		(0.03)	(0.01)	(0.01)	(0.11)	(0.01)	(0.10)
XWS	1.43	-3.51	-0.67	-0.66	-2.21	-0.69	-1.52
		(0.09)	(0.04)	(0.04)	(0.19)	(0.04)	(0.15)
ZAF	8.35	-1.66	-0.13	-0.11	-0.54	-0.16	-0.37
		(0.04)	(0.01)	(0.01)	(0.11)	(0.01)	(0.10)
ZMB	2.63	-2.20	-0.29	-0.27	-1.23	-0.29	-0.94
		(0.06)	(0.01)	(0.01)	(0.05)	(0.01)	(0.05)
ZWE	0.23	-2.73	-0.41	-0.39	-1.19	-0.42	-0.77
		(0.08)	(0.01)	(0.01)	(0.06)	(0.01)	(0.04)

Notes: λ^i denotes the implicit carbon taxes, ΔX^i denotes the percentage changes in trade flows, $\Delta \mathfrak{R}^i$ the percentage changes in real income, ΔU^i the percentage changes in welfare, ΔE^i the percentage changes in carbon emissions, PSE the percentage scale effects, and PCE the percentage composition effects. The numbers in parentheses below the reported values give the corresponding bootstrapped standard errors.

Table C.7: Pure Carbon Tariffs (Product-Based, with OECD carbon tax data)

Country	λ^i	ΔX^i	$\Delta \Re^i$	ΔU^i	ΔE^i	PSE	PCE
ALB	8.53	-2.17	-0.43	-0.42	-2.42	-0.45	-1.98
		(0.04)	(0.01)	(0.01)	(0.05)	(0.01)	(0.04)
ARE	8.53	-1.42	-0.15	-0.14	-0.97	-0.17	-0.81
		(0.04)	(0.00)	(0.00)	(0.04)	(0.00)	(0.03)
ARG	32.96	-1.41	0.16	0.17	1.26	-0.11	1.37
		(0.04)	(0.01)	(0.01)	(0.15)	(0.00)	(0.15)
ARM	8.53	-1.08	-0.10	-0.10	-0.51	-0.14	-0.38
		(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
AUS	21.18	-0.79	0.02	0.02	0.53	-0.04	0.57
		(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.03)
AUT	56.24	-0.52	0.06	0.07	0.25	-0.08	0.32
		(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
AZE	8.53	-2.48	-0.44	-0.44	-1.97	-0.51	-1.47
		(0.06)	(0.02)	(0.02)	(0.08)	(0.02)	(0.07)
BEL	40.64	-1.43	-0.21	-0.20	-2.25	-0.26	-1.99
		(0.04)	(0.01)	(0.01)	(0.07)	(0.01)	(0.06)
BGD	8.53	-0.75	-0.06	-0.05	-0.37	-0.10	-0.26
		(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.02)
BGR	8.53	-2.80	-0.83	-0.82	-4.19	-0.85	-3.37
		(0.09)	(0.02)	(0.02)	(0.11)	(0.02)	(0.09)
BHR	8.53	-2.14	-0.60	-0.59	-2.01	-0.62	-1.40
		(0.09)	(0.02)	(0.02)	(0.07)	(0.02)	(0.05)
BLR	8.53	-2.32	-0.86	-0.86	-3.68	-0.89	-2.81
		(0.07)	(0.04)	(0.04)	(0.16)	(0.04)	(0.13)
BOL	8.53	-1.20	-0.24	-0.23	-1.14	-0.29	-0.84
		(0.07)	(0.02)	(0.02)	(0.12)	(0.02)	(0.09)
BRA	3.83	-1.00	-0.08	-0.08	-0.48	-0.08	-0.39
		(0.01)	(0.01)	(0.01)	(0.07)	(0.01)	(0.07)
BWA	8.53	-1.45	-0.09	-0.08	-0.20	-0.11	-0.09
		(0.05)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
CAN	10.73	-0.73	-0.04	-0.04	-0.19	-0.07	-0.12
		(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
CHE	104.36	-0.45	0.10	0.11	0.59	-0.17	0.76
		(0.01)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)
CHL	12.47	-1.01	-0.07	-0.06	-0.16	-0.12	-0.04
		(0.02)	(0.01)	(0.01)	(0.07)	(0.01)	(0.07)
CHN	3.98	-0.84	-0.05	-0.05	-0.31	-0.05	-0.26
		(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
CIV	8.53	-1.32	-0.31	-0.30	-2.32	-0.32	-2.01
		(0.04)	(0.02)	(0.01)	(0.14)	(0.02)	(0.13)
CMR	8.53	-1.14	-0.20	-0.19	-1.73	-0.21	-1.52
		(0.03)	(0.01)	(0.01)	(0.10)	(0.01)	(0.09)
COL	8.53	-0.80	-0.07	-0.07	-0.57	-0.09	-0.48
		(0.02)	(0.00)	(0.00)	(0.05)	(0.00)	(0.04)
CRI	8.53	-0.69	-0.07	-0.06	-0.39	-0.09	-0.30
		(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
CYP	8.53	-1.56	-0.19	-0.19	-0.60	-0.22	-0.38
		(0.04)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)

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Table C.7 – *Continued from previous page*

Country	λ^i	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
CZE	33.20	-1.26	-0.11	-0.11	-1.15	-0.25	-0.90
		(0.02)	(0.01)	(0.01)	(0.05)	(0.01)	(0.05)
DEU	58.67	-0.63	0.08	0.09	0.50	-0.04	0.54
		(0.01)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)
DNK	80.28	-0.81	0.12	0.13	0.41	-0.28	0.69
		(0.02)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)
ECU	8.53	-0.85	-0.11	-0.10	-0.64	-0.14	-0.50
		(0.03)	(0.01)	(0.01)	(0.07)	(0.01)	(0.06)
EGY	8.53	-2.14	-0.45	-0.44	-2.52	-0.48	-2.05
		(0.12)	(0.03)	(0.03)	(0.16)	(0.03)	(0.14)
ESP	43.36	-0.75	0.02	0.03	-0.01	-0.08	0.07
		(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
EST	29.09	-1.30	-0.07	-0.06	-0.50	-0.34	-0.15
		(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
ETH	8.53	-0.90	-0.08	-0.07	-0.27	-0.11	-0.16
		(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FIN	48.75	-0.81	0.04	0.05	0.12	-0.11	0.23
		(0.02)	(0.00)	(0.00)	(0.03)	(0.01)	(0.02)
FRA	65.84	-0.44	0.09	0.10	0.55	-0.03	0.58
		(0.01)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)
GBR	75.53	-0.73	0.14	0.14	0.80	-0.07	0.88
		(0.01)	(0.00)	(0.01)	(0.06)	(0.00)	(0.06)
GEO	8.53	-1.31	-0.13	-0.12	-0.36	-0.17	-0.19
		(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
GHA	8.53	-0.97	-0.14	-0.13	-1.13	-0.17	-0.97
		(0.03)	(0.01)	(0.01)	(0.09)	(0.01)	(0.08)
GRC	60.44	-2.08	0.17	0.18	0.14	-0.66	0.81
		(0.04)	(0.01)	(0.01)	(0.07)	(0.02)	(0.05)
GTM	8.53	-0.66	-0.05	-0.04	-0.15	-0.08	-0.07
		(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
HKG	8.53	-0.78	-0.07	-0.07	-0.10	-0.09	-0.02
		(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HND	8.53	-0.67	-0.06	-0.05	-0.18	-0.09	-0.09
		(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
HRV	8.53	-2.82	-0.67	-0.67	-3.04	-0.68	-2.38
		(0.11)	(0.02)	(0.02)	(0.11)	(0.02)	(0.09)
HUN	35.41	-0.99	-0.08	-0.08	-0.87	-0.21	-0.66
		(0.02)	(0.01)	(0.01)	(0.05)	(0.01)	(0.05)
IDN	2.37	-1.13	-0.12	-0.11	-0.58	-0.12	-0.46
		(0.02)	(0.01)	(0.01)	(0.11)	(0.01)	(0.10)
IND	2.93	-1.10	-0.16	-0.14	-0.80	-0.16	-0.64
		(0.02)	(0.01)	(0.01)	(0.05)	(0.01)	(0.05)
IRL	71.87	-0.55	0.10	0.11	0.36	-0.18	0.53
		(0.02)	(0.00)	(0.00)	(0.03)	(0.01)	(0.03)
IRN	8.53	-1.58	-0.22	-0.22	-0.83	-0.29	-0.54
		(0.04)	(0.02)	(0.02)	(0.08)	(0.02)	(0.06)
ISR	79.60	-1.67	0.31	0.31	3.08	-0.36	3.45
		(0.05)	(0.02)	(0.02)	(0.32)	(0.04)	(0.29)

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Table C.7 – *Continued from previous page*

Country	λ^i	ΔX^i	$\Delta \Re^i$	ΔU^i	ΔE^i	PSE	PCE
ITA	60.42	-0.50	0.09	0.09	0.49	-0.02	0.52
		(0.01)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)
JPN	34.77	-0.58	0.04	0.04	0.23	-0.02	0.25
		(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
KAZ	8.53	-1.43	-0.12	-0.11	-0.55	-0.21	-0.34
		(0.02)	(0.01)	(0.01)	(0.07)	(0.01)	(0.06)
KEN	8.53	-0.81	-0.11	-0.10	-1.06	-0.13	-0.93
		(0.03)	(0.01)	(0.01)	(0.09)	(0.01)	(0.08)
KGZ	8.53	-1.21	-0.15	-0.14	-0.40	-0.25	-0.15
		(0.03)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
KHM	8.53	-0.51	-0.04	-0.03	-0.13	-0.06	-0.07
		(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
KOR	28.41	-0.73	0.05	0.05	0.23	-0.05	0.27
		(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
KWT	8.53	-2.23	-0.53	-0.53	-2.39	-0.54	-1.86
		(0.06)	(0.01)	(0.01)	(0.07)	(0.01)	(0.06)
LAO	8.53	-0.54	-0.06	-0.05	-0.62	-0.08	-0.53
		(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
LKA	8.53	-0.86	-0.10	-0.09	-0.50	-0.14	-0.36
		(0.03)	(0.01)	(0.01)	(0.05)	(0.01)	(0.04)
LTU	8.53	-2.68	-0.76	-0.76	-4.93	-0.77	-4.19
		(0.08)	(0.03)	(0.03)	(0.17)	(0.03)	(0.15)
LUX	95.30	-0.75	0.10	0.10	-0.56	-0.47	-0.09
		(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
LVA	8.53	-1.45	-0.15	-0.14	-0.35	-0.16	-0.19
		(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
MAR	8.53	-1.76	-0.29	-0.28	-2.62	-0.30	-2.33
		(0.07)	(0.02)	(0.02)	(0.20)	(0.02)	(0.18)
MDG	8.53	-0.99	-0.08	-0.07	-0.66	-0.10	-0.56
		(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
MEX	2.68	-0.87	-0.09	-0.09	-0.48	-0.09	-0.39
		(0.02)	(0.01)	(0.01)	(0.10)	(0.01)	(0.09)
MLT	8.53	-1.32	-0.17	-0.16	-0.38	-0.19	-0.19
		(0.03)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
MNG	8.53	-1.60	-0.19	-0.18	-0.81	-0.56	-0.25
		(0.06)	(0.00)	(0.00)	(0.02)	(0.01)	(0.00)
MOZ	8.53	-1.08	-0.11	-0.10	-0.34	-0.12	-0.22
		(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
MUS	8.53	-1.00	-0.09	-0.09	-0.44	-0.13	-0.31
		(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
MWI	8.53	-1.00	-0.12	-0.11	-0.61	-0.14	-0.47
		(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.02)
MYS	8.53	-0.68	-0.06	-0.06	-0.36	-0.10	-0.26
		(0.02)	(0.00)	(0.00)	(0.04)	(0.01)	(0.03)
NAM	8.53	-1.19	-0.10	-0.09	-0.16	-0.11	-0.05
		(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NGA	8.53	-1.88	-0.12	-0.11	-0.50	-0.16	-0.34
		(0.08)	(0.01)	(0.00)	(0.10)	(0.01)	(0.09)

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Table C.7 – *Continued from previous page*

Country	λ^i	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
NIC	8.53	-0.73	-0.12	-0.11	-0.51	-0.17	-0.34
		(0.02)	(0.01)	(0.01)	(0.04)	(0.01)	(0.03)
NLD	88.67	-0.73	0.21	0.21	1.22	-0.09	1.31
		(0.01)	(0.00)	(0.00)	(0.03)	(0.01)	(0.03)
NOR	92.96	-0.90	0.21	0.22	1.55	-0.19	1.74
		(0.01)	(0.00)	(0.00)	(0.03)	(0.01)	(0.02)
NPL	8.53	-0.75	-0.06	-0.05	-0.25	-0.10	-0.15
		(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
NZL	30.53	-0.69	0.06	0.06	0.80	-0.05	0.85
		(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
OMN	8.53	-1.88	-0.18	-0.18	-0.89	-0.23	-0.66
		(0.04)	(0.00)	(0.00)	(0.03)	(0.01)	(0.03)
PAK	8.53	-0.96	-0.10	-0.09	-0.48	-0.17	-0.31
		(0.02)	(0.01)	(0.01)	(0.04)	(0.01)	(0.03)
PAN	8.53	-0.79	-0.06	-0.05	-0.20	-0.12	-0.08
		(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PER	8.53	-0.82	-0.08	-0.07	-0.61	-0.09	-0.52
		(0.02)	(0.00)	(0.00)	(0.07)	(0.01)	(0.06)
PHL	8.53	-0.67	-0.06	-0.05	-0.46	-0.09	-0.38
		(0.02)	(0.01)	(0.01)	(0.07)	(0.01)	(0.06)
POL	28.61	-1.52	-0.12	-0.12	-1.13	-0.29	-0.85
		(0.04)	(0.01)	(0.01)	(0.12)	(0.01)	(0.11)
PRT	48.43	-0.73	0.04	0.05	0.03	-0.12	0.15
		(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.02)
PRY	8.53	-0.94	-0.09	-0.09	-0.13	-0.11	-0.02
		(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
QAT	8.53	-1.58	-0.16	-0.16	-1.23	-0.18	-1.05
		(0.06)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)
ROU	8.53	-1.95	-0.38	-0.38	-2.93	-0.39	-2.54
		(0.07)	(0.02)	(0.02)	(0.14)	(0.02)	(0.12)
RUS	0.00	-1.97	-0.41	-0.41	-1.85	-0.41	-1.45
		(0.03)	(0.01)	(0.01)	(0.08)	(0.01)	(0.07)
SAU	8.53	-1.85	-0.24	-0.24	-1.03	-0.27	-0.77
		(0.02)	(0.01)	(0.01)	(0.06)	(0.01)	(0.05)
SEN	8.53	-1.35	-0.25	-0.24	-1.63	-0.27	-1.36
		(0.04)	(0.01)	(0.01)	(0.09)	(0.01)	(0.08)
SGP	8.53	-0.78	-0.13	-0.13	-0.81	-0.14	-0.66
		(0.03)	(0.01)	(0.01)	(0.06)	(0.01)	(0.05)
SLV	8.53	-0.66	-0.07	-0.07	-0.39	-0.10	-0.29
		(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)
SVK	39.97	-0.90	-0.04	-0.04	-0.54	-0.16	-0.38
		(0.01)	(0.01)	(0.01)	(0.05)	(0.00)	(0.05)
SVN	67.84	-0.60	0.07	0.07	-0.18	-0.30	0.12
		(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
SWE	69.34	-0.35	0.11	0.12	0.76	0.00	0.76
		(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)
THA	8.53	-0.70	-0.08	-0.07	-0.41	-0.10	-0.31
		(0.02)	(0.01)	(0.01)	(0.04)	(0.01)	(0.03)

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Table C.7 – *Continued from previous page*

Country	λ^i	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
TUN	8.53	-1.91	-0.30	-0.29	-2.03	-0.32	-1.72
		(0.04)	(0.01)	(0.01)	(0.07)	(0.01)	(0.06)
TUR	39.23	-1.17	0.05	0.05	0.05	-0.17	0.22
		(0.02)	(0.00)	(0.00)	(0.03)	(0.01)	(0.02)
TWN	8.53	-0.77	-0.08	-0.07	-0.52	-0.10	-0.42
		(0.02)	(0.01)	(0.01)	(0.05)	(0.01)	(0.05)
TZA	8.53	-0.87	-0.07	-0.06	-0.22	-0.10	-0.13
		(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
UGA	8.53	-1.10	-0.10	-0.09	-0.51	-0.11	-0.40
		(0.03)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
UKR	8.53	-1.91	-0.45	-0.45	-1.58	-0.53	-1.06
		(0.07)	(0.02)	(0.02)	(0.08)	(0.03)	(0.06)
URY	8.53	-1.40	-0.26	-0.26	-2.43	-0.27	-2.16
		(0.06)	(0.01)	(0.01)	(0.16)	(0.01)	(0.15)
USA	5.69	-0.73	-0.03	-0.03	-0.18	-0.03	-0.15
		(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
VEN	8.53	-1.01	-0.16	-0.16	-1.25	-0.18	-1.07
		(0.03)	(0.00)	(0.00)	(0.04)	(0.01)	(0.04)
VNM	8.53	-0.84	-0.04	-0.04	-0.24	-0.15	-0.08
		(0.02)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)
XAC	8.53	-1.92	-0.14	-0.13	-0.81	-0.15	-0.66
		(0.03)	(0.00)	(0.00)	(0.12)	(0.01)	(0.11)
XCA	8.53	-0.77	-0.10	-0.10	-0.74	-0.12	-0.62
		(0.02)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)
XCB	8.53	-0.93	-0.12	-0.11	-0.76	-0.13	-0.63
		(0.02)	(0.01)	(0.01)	(0.05)	(0.01)	(0.04)
XCF	8.53	-1.67	-0.14	-0.13	-1.08	-0.15	-0.93
		(0.02)	(0.01)	(0.01)	(0.10)	(0.01)	(0.10)
XEA	8.53	-1.23	-0.17	-0.16	-1.05	-0.29	-0.76
		(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
XEC	8.53	-1.23	-0.14	-0.13	-0.77	-0.15	-0.62
		(0.04)	(0.01)	(0.01)	(0.06)	(0.01)	(0.05)
XEE	8.53	-1.43	-0.17	-0.17	-0.35	-0.21	-0.14
		(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
XEF	8.53	-1.55	-0.20	-0.19	-1.21	-0.21	-1.00
		(0.04)	(0.01)	(0.01)	(0.04)	(0.01)	(0.03)
XER	8.53	-1.87	-0.36	-0.36	-1.99	-0.39	-1.61
		(0.06)	(0.01)	(0.01)	(0.09)	(0.01)	(0.08)
XNA	8.53	-1.30	-0.27	-0.26	-2.46	-0.28	-2.19
		(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
XNF	8.53	-2.36	-0.43	-0.42	-3.02	-0.44	-2.59
		(0.07)	(0.02)	(0.02)	(0.17)	(0.02)	(0.15)
XOC	8.53	-1.00	-0.11	-0.11	-0.71	-0.13	-0.59
		(0.03)	(0.01)	(0.01)	(0.09)	(0.01)	(0.08)
XSA	8.53	-0.99	-0.12	-0.12	-1.06	-0.15	-0.92
		(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
XSC	8.53	-1.10	-0.12	-0.11	-0.93	-0.13	-0.81
		(0.04)	(0.00)	(0.00)	(0.04)	(0.00)	(0.03)

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Table C.7 – *Continued from previous page*

Country	λ^i	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
XSE	8.53	-1.00	-0.11	-0.10	-0.58	-0.17	-0.41
		(0.04)	(0.01)	(0.01)	(0.06)	(0.01)	(0.05)
XSM	8.53	-1.19	-0.16	-0.15	-1.69	-0.16	-1.53
		(0.03)	(0.00)	(0.00)	(0.06)	(0.00)	(0.06)
XSU	8.53	-1.81	-0.30	-0.29	-0.89	-0.46	-0.43
		(0.06)	(0.02)	(0.02)	(0.06)	(0.02)	(0.04)
XWF	8.53	-1.33	-0.12	-0.11	-0.56	-0.13	-0.43
		(0.01)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)
XWS	8.53	-2.08	-0.38	-0.37	-1.32	-0.42	-0.90
		(0.06)	(0.02)	(0.02)	(0.09)	(0.02)	(0.07)
ZAF	13.67	-1.13	-0.03	-0.02	0.08	-0.11	0.19
		(0.03)	(0.01)	(0.01)	(0.04)	(0.01)	(0.03)
ZMB	8.53	-1.12	-0.13	-0.12	-0.53	-0.13	-0.40
		(0.04)	(0.01)	(0.00)	(0.03)	(0.01)	(0.03)
ZWE	8.53	-1.32	-0.17	-0.16	-0.61	-0.27	-0.35
		(0.06)	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)

Notes: λ^i denotes the implicit carbon taxes (obtained from the OECD (2016) data), ΔX^i denotes the percentage changes in trade flows, $\Delta \mathfrak{R}^i$ the percentage changes in real income, ΔU^i the percentage changes in welfare, ΔE^i the percentage changes in carbon emissions, PSE the percentage scale effects, and PCE the percentage composition effects. The numbers in parentheses below the reported values give the corresponding bootstrapped standard errors.

Table C.8: Pure Carbon Tariffs (Production-Based)

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
ALB	-2.38	-0.11	-0.09	-1.07	-0.74	-0.33
	(0.02)	(0.01)	(0.01)	(0.05)	(0.01)	(0.05)
ARE	-3.53	-0.65	-0.63	-4.86	-0.65	-4.24
	(0.07)	(0.02)	(0.02)	(0.21)	(0.02)	(0.19)
ARG	-2.09	-0.11	-0.09	-0.41	-0.23	-0.19
	(0.04)	(0.01)	(0.01)	(0.05)	(0.01)	(0.04)
ARM	-2.93	-0.31	-0.28	-2.64	-0.76	-1.89
	(0.04)	(0.01)	(0.01)	(0.04)	(0.01)	(0.04)
AUS	-1.92	-0.17	-0.17	-0.91	-0.18	-0.73
	(0.03)	(0.01)	(0.01)	(0.15)	(0.01)	(0.14)
AUT	-1.43	0.25	0.27	1.21	-0.40	1.62
	(0.03)	(0.00)	(0.00)	(0.05)	(0.01)	(0.05)
AZE	-4.87	-2.00	-1.97	-9.44	-2.00	-7.60
	(0.14)	(0.06)	(0.06)	(0.33)	(0.06)	(0.28)
BEL	-1.24	0.30	0.32	1.60	-0.11	1.72
	(0.02)	(0.02)	(0.02)	(0.19)	(0.01)	(0.18)
BGD	-2.46	-0.41	-0.38	-3.82	-0.43	-3.41
	(0.06)	(0.01)	(0.01)	(0.14)	(0.01)	(0.13)
BGR	-9.62	-2.98	-2.97	-13.57	-2.99	-10.90
	(0.19)	(0.07)	(0.07)	(0.34)	(0.07)	(0.29)
BHR	-5.21	-2.07	-2.05	-6.76	-2.07	-4.79
	(0.23)	(0.09)	(0.09)	(0.33)	(0.09)	(0.25)
BLR	-5.46	-1.84	-1.83	-7.67	-1.92	-5.87
	(0.15)	(0.08)	(0.08)	(0.33)	(0.08)	(0.26)
BOL	-3.08	-0.24	-0.22	-0.56	-0.52	-0.03
	(0.06)	(0.02)	(0.02)	(0.12)	(0.03)	(0.09)
BRA	-0.93	0.01	0.03	-0.06	-0.05	-0.01
	(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.01)
BWA	-5.44	-0.51	-0.48	-1.56	-0.52	-1.05
	(0.09)	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)
CAN	-1.56	0.00	0.00	0.05	-0.13	0.18
	(0.03)	(0.01)	(0.01)	(0.06)	(0.01)	(0.06)
CHE	-0.96	0.17	0.19	-0.11	-0.16	0.05
	(0.01)	(0.01)	(0.01)	(0.06)	(0.01)	(0.06)
CHL	-1.80	0.02	0.04	0.50	-0.21	0.71
	(0.03)	(0.00)	(0.00)	(0.05)	(0.01)	(0.04)
CHN	-3.41	-0.19	-0.19	-0.96	-0.19	-0.76
	(0.07)	(0.01)	(0.01)	(0.11)	(0.01)	(0.09)
CIV	-1.83	-0.53	-0.50	-4.79	-0.54	-4.27
	(0.06)	(0.03)	(0.02)	(0.28)	(0.03)	(0.26)
CMR	-1.39	-0.28	-0.24	-3.52	-0.37	-3.17
	(0.03)	(0.01)	(0.01)	(0.20)	(0.01)	(0.19)
COL	-1.65	0.05	0.06	0.76	-0.14	0.90
	(0.01)	(0.00)	(0.00)	(0.05)	(0.01)	(0.05)
CRI	-1.29	-0.05	-0.03	-0.35	-0.17	-0.18
	(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)
CYP	-3.21	-0.25	-0.23	-1.26	-0.97	-0.29
	(0.03)	(0.01)	(0.01)	(0.03)	(0.02)	(0.03)

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Table C.8 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
CZE	-4.80	-0.72	-0.71	-5.25	-0.77	-4.51
	(0.10)	(0.02)	(0.02)	(0.18)	(0.02)	(0.16)
DEU	-1.59	0.11	0.14	0.24	-0.13	0.37
	(0.04)	(0.01)	(0.01)	(0.05)	(0.00)	(0.06)
DNK	-1.49	0.15	0.18	0.43	-0.32	0.76
	(0.02)	(0.00)	(0.01)	(0.03)	(0.01)	(0.04)
ECU	-2.41	-0.40	-0.38	-2.37	-0.44	-1.94
	(0.03)	(0.02)	(0.02)	(0.24)	(0.03)	(0.22)
EGY	-8.64	-1.97	-1.94	-9.19	-1.97	-7.36
	(0.21)	(0.10)	(0.10)	(0.60)	(0.10)	(0.51)
ESP	-1.69	0.09	0.12	0.24	-0.14	0.38
	(0.04)	(0.01)	(0.01)	(0.05)	(0.00)	(0.05)
EST	-5.55	-0.68	-0.67	-1.98	-0.84	-1.15
	(0.11)	(0.02)	(0.02)	(0.05)	(0.01)	(0.03)
ETH	-4.32	-0.55	-0.51	-3.02	-0.58	-2.45
	(0.10)	(0.00)	(0.00)	(0.05)	(0.00)	(0.04)
FIN	-2.06	0.09	0.12	0.16	-0.24	0.40
	(0.06)	(0.01)	(0.01)	(0.06)	(0.01)	(0.06)
FRA	-1.72	0.31	0.34	1.94	-0.23	2.17
	(0.02)	(0.01)	(0.01)	(0.15)	(0.01)	(0.15)
GBR	-1.62	0.25	0.27	1.19	-0.19	1.38
	(0.03)	(0.01)	(0.01)	(0.12)	(0.01)	(0.13)
GEO	-4.96	-0.66	-0.63	-2.31	-0.78	-1.54
	(0.10)	(0.01)	(0.02)	(0.05)	(0.02)	(0.04)
GHA	-3.77	-0.74	-0.71	-6.15	-0.75	-5.44
	(0.08)	(0.03)	(0.02)	(0.34)	(0.03)	(0.32)
GRC	-4.28	-0.19	-0.16	-0.39	-0.67	0.28
	(0.05)	(0.03)	(0.03)	(0.14)	(0.03)	(0.10)
GTM	-1.93	-0.09	-0.07	-0.56	-0.33	-0.23
	(0.04)	(0.00)	(0.00)	(0.03)	(0.01)	(0.02)
HKG	-2.15	-0.20	-0.20	-0.25	-0.20	-0.05
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
HND	-3.26	-0.41	-0.39	-1.91	-0.45	-1.46
	(0.05)	(0.01)	(0.01)	(0.04)	(0.01)	(0.03)
HRV	-2.80	-0.03	-0.02	-0.14	-0.35	0.22
	(0.04)	(0.01)	(0.02)	(0.06)	(0.01)	(0.06)
HUN	-1.91	0.01	0.02	-0.43	-0.37	-0.07
	(0.02)	(0.01)	(0.01)	(0.07)	(0.01)	(0.07)
IDN	-3.61	-0.31	-0.29	-1.23	-0.33	-0.90
	(0.07)	(0.03)	(0.02)	(0.25)	(0.03)	(0.22)
IND	-3.38	-0.28	-0.23	-1.07	-0.34	-0.73
	(0.07)	(0.02)	(0.01)	(0.07)	(0.02)	(0.06)
IRL	-1.43	0.07	0.09	-1.66	-0.18	-1.49
	(0.02)	(0.01)	(0.01)	(0.13)	(0.00)	(0.13)
IRN	-8.51	-1.84	-1.82	-6.28	-1.88	-4.49
	(0.09)	(0.10)	(0.10)	(0.45)	(0.11)	(0.35)
ISR	-2.38	-0.21	-0.21	-2.94	-0.44	-2.51
	(0.05)	(0.03)	(0.03)	(0.40)	(0.03)	(0.37)

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Table C.8 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
ITA	-2.30	0.37	0.40	2.25	-0.26	2.52
	(0.04)	(0.02)	(0.02)	(0.23)	(0.01)	(0.23)
JPN	-1.33	0.12	0.13	0.62	-0.04	0.67
	(0.03)	(0.01)	(0.01)	(0.06)	(0.00)	(0.06)
KAZ	-8.47	-1.57	-1.56	-6.93	-1.58	-5.44
	(0.14)	(0.06)	(0.06)	(0.47)	(0.06)	(0.42)
KEN	-2.66	-0.39	-0.36	-3.56	-0.41	-3.16
	(0.05)	(0.02)	(0.02)	(0.26)	(0.02)	(0.25)
KGZ	-8.83	-1.43	-1.41	-2.67	-1.58	-1.11
	(0.12)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)
KHM	-1.96	-0.17	-0.14	-1.22	-0.38	-0.84
	(0.03)	(0.01)	(0.00)	(0.03)	(0.00)	(0.02)
KOR	-1.28	-0.01	0.01	-0.22	-0.10	-0.12
	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
KWT	-3.10	-1.42	-1.41	-6.93	-1.43	-5.58
	(0.12)	(0.05)	(0.04)	(0.23)	(0.05)	(0.19)
LAO	-0.91	-0.04	-0.02	-1.07	-0.15	-0.92
	(0.02)	(0.01)	(0.01)	(0.06)	(0.00)	(0.06)
LKA	-4.01	-0.64	-0.62	-2.79	-0.65	-2.15
	(0.09)	(0.02)	(0.02)	(0.15)	(0.02)	(0.13)
LTU	-2.77	-0.45	-0.45	-3.78	-0.63	-3.17
	(0.07)	(0.02)	(0.02)	(0.16)	(0.02)	(0.14)
LUX	-1.22	0.14	0.16	-0.43	-0.33	-0.11
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LVA	-2.69	-0.21	-0.20	-1.39	-0.46	-0.93
	(0.04)	(0.01)	(0.01)	(0.03)	(0.00)	(0.03)
MAR	-4.81	-0.91	-0.87	-8.38	-0.91	-7.54
	(0.17)	(0.06)	(0.06)	(0.63)	(0.06)	(0.58)
MDG	-2.08	-0.23	-0.20	-3.73	-0.24	-3.50
	(0.05)	(0.01)	(0.00)	(0.17)	(0.01)	(0.17)
MEX	-1.68	-0.20	-0.19	-1.38	-0.21	-1.17
	(0.07)	(0.03)	(0.02)	(0.30)	(0.03)	(0.27)
MLT	-2.38	-0.27	-0.25	-1.46	-0.80	-0.67
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
MNG	-13.08	-2.51	-2.48	-6.72	-2.53	-4.29
	(0.45)	(0.04)	(0.04)	(0.09)	(0.04)	(0.07)
MOZ	-2.97	-0.75	-0.71	-5.45	-0.77	-4.71
	(0.07)	(0.02)	(0.02)	(0.12)	(0.02)	(0.11)
MUS	-3.54	-0.52	-0.48	-2.73	-0.57	-2.17
	(0.04)	(0.01)	(0.01)	(0.07)	(0.01)	(0.07)
MWI	-1.90	-0.27	-0.23	-1.25	-0.29	-0.95
	(0.03)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)
MYS	-4.09	-0.81	-0.79	-5.18	-0.81	-4.41
	(0.06)	(0.05)	(0.05)	(0.47)	(0.05)	(0.43)
NAM	-2.84	-0.32	-0.28	-1.42	-0.33	-1.09
	(0.04)	(0.00)	(0.00)	(0.03)	(0.00)	(0.02)
NGA	-3.77	-0.47	-0.43	-3.47	-0.53	-2.95
	(0.13)	(0.02)	(0.02)	(0.47)	(0.02)	(0.45)

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Table C.8 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
NIC	-2.00	-0.09	-0.07	-0.44	-0.67	0.23
	(0.03)	(0.02)	(0.02)	(0.12)	(0.03)	(0.09)
NLD	-1.39	0.39	0.41	2.07	-0.19	2.27
	(0.03)	(0.01)	(0.01)	(0.12)	(0.00)	(0.12)
NOR	-2.10	0.37	0.39	3.18	-0.59	3.79
	(0.04)	(0.00)	(0.01)	(0.08)	(0.02)	(0.10)
NPL	-3.18	-0.40	-0.38	-2.31	-0.41	-1.90
	(0.05)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)
NZL	-1.35	-0.11	-0.11	-0.79	-0.11	-0.68
	(0.03)	(0.01)	(0.01)	(0.16)	(0.01)	(0.15)
OMN	-6.34	-1.09	-1.07	-5.36	-1.10	-4.30
	(0.09)	(0.03)	(0.03)	(0.20)	(0.03)	(0.18)
PAK	-3.68	-0.23	-0.21	-1.19	-0.63	-0.56
	(0.09)	(0.02)	(0.02)	(0.15)	(0.04)	(0.11)
PAN	-9.00	-1.55	-1.54	-5.10	-1.56	-3.60
	(0.11)	(0.02)	(0.02)	(0.08)	(0.02)	(0.06)
PER	-1.20	-0.03	-0.02	-0.43	-0.12	-0.31
	(0.01)	(0.00)	(0.00)	(0.06)	(0.01)	(0.06)
PHL	-1.92	-0.17	-0.15	-1.22	-0.24	-0.99
	(0.04)	(0.02)	(0.01)	(0.18)	(0.02)	(0.16)
POL	-5.13	-0.75	-0.75	-5.03	-0.84	-4.22
	(0.13)	(0.04)	(0.04)	(0.33)	(0.04)	(0.29)
PRT	-1.70	0.22	0.24	1.15	-0.25	1.40
	(0.02)	(0.01)	(0.01)	(0.06)	(0.01)	(0.07)
PRY	-1.76	-0.13	-0.12	-1.32	-0.31	-1.01
	(0.05)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)
QAT	-3.90	-0.85	-0.83	-7.97	-0.85	-7.18
	(0.12)	(0.03)	(0.03)	(0.31)	(0.03)	(0.28)
ROU	-5.21	-1.01	-1.00	-7.24	-1.02	-6.29
	(0.13)	(0.04)	(0.04)	(0.33)	(0.04)	(0.29)
RUS	-4.14	-0.72	-0.72	-3.16	-0.80	-2.38
	(0.08)	(0.02)	(0.02)	(0.12)	(0.03)	(0.09)
SAU	-3.77	-1.06	-1.05	-5.13	-1.07	-4.11
	(0.09)	(0.05)	(0.05)	(0.28)	(0.05)	(0.23)
SEN	-3.44	-0.63	-0.59	-3.69	-0.68	-3.03
	(0.07)	(0.02)	(0.02)	(0.21)	(0.02)	(0.19)
SGP	-0.87	-0.08	-0.08	-1.11	-0.14	-0.97
	(0.04)	(0.01)	(0.01)	(0.10)	(0.01)	(0.09)
SLV	-1.49	-0.07	-0.05	-0.34	-0.24	-0.10
	(0.03)	(0.01)	(0.01)	(0.08)	(0.01)	(0.07)
SVK	-2.21	-0.11	-0.11	-1.76	-0.37	-1.39
	(0.03)	(0.01)	(0.01)	(0.09)	(0.01)	(0.08)
SVN	-2.70	-0.12	-0.11	-0.54	-0.37	-0.17
	(0.03)	(0.01)	(0.01)	(0.02)	(0.00)	(0.02)
SWE	-2.20	0.40	0.43	3.08	-0.59	3.69
	(0.04)	(0.00)	(0.00)	(0.07)	(0.02)	(0.08)
THA	-2.48	-0.22	-0.20	-0.97	-0.31	-0.67
	(0.06)	(0.02)	(0.01)	(0.09)	(0.02)	(0.08)

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Table C.8 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
TUN	-5.87	-1.09	-1.05	-6.97	-1.09	-5.94
	(0.10)	(0.03)	(0.03)	(0.25)	(0.03)	(0.23)
TUR	-2.66	0.31	0.32	1.74	-0.34	2.09
	(0.05)	(0.01)	(0.01)	(0.05)	(0.02)	(0.06)
TWN	-1.53	-0.12	-0.10	-0.90	-0.19	-0.71
	(0.05)	(0.01)	(0.01)	(0.12)	(0.02)	(0.10)
TZA	-3.28	-0.40	-0.36	-2.14	-0.41	-1.74
	(0.09)	(0.01)	(0.01)	(0.08)	(0.01)	(0.07)
UGA	-1.58	-0.08	-0.05	-0.71	-0.35	-0.36
	(0.03)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)
UKR	-10.61	-2.97	-2.97	-9.09	-3.03	-6.25
	(0.27)	(0.10)	(0.10)	(0.32)	(0.10)	(0.23)
URY	-1.11	0.03	0.05	0.18	-0.14	0.31
	(0.02)	(0.00)	(0.00)	(0.03)	(0.01)	(0.02)
USA	-1.33	-0.04	-0.04	-0.39	-0.06	-0.34
	(0.03)	(0.00)	(0.00)	(0.05)	(0.00)	(0.04)
VEN	-3.27	-0.93	-0.91	-7.68	-0.94	-6.80
	(0.06)	(0.03)	(0.03)	(0.26)	(0.03)	(0.24)
VNM	-8.41	-1.38	-1.36	-7.40	-1.39	-6.09
	(0.17)	(0.04)	(0.04)	(0.20)	(0.04)	(0.17)
XAC	-1.33	-0.26	-0.23	-2.87	-0.27	-2.61
	(0.04)	(0.02)	(0.01)	(0.32)	(0.02)	(0.31)
XCA	-1.04	-0.04	-0.02	-0.75	-0.19	-0.56
	(0.02)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)
XCB	-1.51	-0.18	-0.15	-1.52	-0.21	-1.32
	(0.04)	(0.01)	(0.01)	(0.10)	(0.01)	(0.09)
XCF	-1.75	-0.23	-0.20	-2.10	-0.24	-1.86
	(0.03)	(0.01)	(0.01)	(0.16)	(0.01)	(0.15)
XEA	-10.15	-2.15	-2.13	-8.05	-2.16	-6.02
	(0.12)	(0.02)	(0.02)	(0.06)	(0.02)	(0.06)
XEC	-1.81	-0.17	-0.14	-0.65	-0.18	-0.47
	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.02)
XEE	-8.37	-1.41	-1.40	-2.84	-1.45	-1.41
	(0.18)	(0.04)	(0.04)	(0.07)	(0.04)	(0.04)
XEF	-3.04	-0.73	-0.70	-8.91	-0.81	-8.16
	(0.05)	(0.02)	(0.02)	(0.19)	(0.02)	(0.18)
XER	-6.44	-1.16	-1.14	-5.43	-1.32	-4.16
	(0.15)	(0.05)	(0.04)	(0.24)	(0.05)	(0.20)
XNA	-1.48	-0.05	-0.03	-1.33	-0.31	-1.03
	(0.01)	(0.01)	(0.00)	(0.07)	(0.01)	(0.06)
XNF	-4.11	-1.54	-1.51	-12.17	-1.54	-10.79
	(0.12)	(0.09)	(0.09)	(0.79)	(0.09)	(0.72)
XOC	-1.42	-0.12	-0.10	-0.89	-0.16	-0.73
	(0.03)	(0.01)	(0.01)	(0.14)	(0.01)	(0.13)
XSA	-1.64	-0.11	-0.09	-1.48	-0.27	-1.21
	(0.02)	(0.00)	(0.00)	(0.07)	(0.01)	(0.06)
XSC	-1.22	-0.11	-0.07	-0.67	-0.12	-0.55
	(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)

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Table C.8 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE
XSE	-2.96	-0.44	-0.42	-2.05	-0.61	-1.45
	(0.07)	(0.02)	(0.02)	(0.20)	(0.02)	(0.17)
XSM	-0.68	0.06	0.08	-0.26	-0.09	-0.18
	(0.01)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)
XSU	-14.84	-4.06	-4.04	-10.00	-4.07	-6.18
	(0.11)	(0.13)	(0.13)	(0.37)	(0.13)	(0.26)
XWF	-3.04	-0.34	-0.30	-1.92	-0.34	-1.58
	(0.04)	(0.01)	(0.00)	(0.12)	(0.01)	(0.12)
XWS	-7.29	-1.90	-1.87	-5.84	-1.91	-4.01
	(0.15)	(0.10)	(0.10)	(0.42)	(0.11)	(0.33)
ZAF	-5.13	-0.55	-0.52	-2.88	-0.57	-2.32
	(0.14)	(0.04)	(0.04)	(0.44)	(0.04)	(0.41)
ZMB	-1.08	-0.05	-0.02	-0.80	-0.07	-0.73
	(0.04)	(0.00)	(0.01)	(0.02)	(0.00)	(0.02)
ZWE	-11.99	-2.12	-2.09	-5.31	-2.13	-3.25
	(0.32)	(0.06)	(0.06)	(0.16)	(0.06)	(0.10)

Notes: ΔX^i denotes the percentage changes in trade flows, $\Delta \mathfrak{R}^i$ the percentage changes in real income, ΔU^i the percentage changes in welfare, ΔE^i the percentage changes in carbon emissions, PSE the percentage scale effects, and PCE the percentage composition effects. The numbers in parentheses below the reported values give the corresponding bootstrapped standard errors.

Table C.9: Pure Carbon Tariffs (Product-Based, Extended Model)

Country	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
ALB	-1.51	0.06	0.06	0.18	-0.54	0.02	0.69
	(0.01)	(0.00)	(0.00)	(0.04)	(0.01)	(0.03)	(0.01)
ARE	-3.31	-0.24	-0.24	-2.17	-0.29	-2.21	0.34
	(0.05)	(0.01)	(0.01)	(0.10)	(0.01)	(0.11)	(0.02)
ARG	-1.12	0.02	0.02	0.74	-0.11	0.53	0.31
	(0.02)	(0.00)	(0.00)	(0.10)	(0.00)	(0.08)	(0.02)
ARM	-1.87	0.02	0.03	-0.15	-0.67	-0.12	0.64
	(0.02)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
AUS	-1.63	-0.12	-0.12	-0.17	-0.12	-0.26	0.21
	(0.02)	(0.00)	(0.00)	(0.06)	(0.00)	(0.07)	(0.01)
AUT	-0.82	0.12	0.12	0.72	-0.23	0.71	0.24
	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
AZE	-6.06	-0.41	-0.41	-3.96	-0.61	-3.87	0.53
	(0.17)	(0.02)	(0.02)	(0.25)	(0.03)	(0.25)	(0.03)
BEL	-0.82	0.08	0.09	0.45	-0.09	0.45	0.09
	(0.01)	(0.00)	(0.00)	(0.09)	(0.00)	(0.09)	(0.00)
BGD	-1.56	-0.10	-0.10	-0.91	-0.13	-0.96	0.18
	(0.03)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)	(0.01)
BGR	-4.69	-0.50	-0.49	-5.30	-0.54	-5.33	0.57
	(0.14)	(0.01)	(0.01)	(0.14)	(0.01)	(0.14)	(0.01)
BHR	-4.64	-0.36	-0.35	-3.40	-0.61	-3.22	0.42
	(0.20)	(0.02)	(0.02)	(0.19)	(0.03)	(0.19)	(0.03)
BLR	-2.53	-0.13	-0.13	-2.12	-0.22	-2.24	0.34
	(0.08)	(0.01)	(0.01)	(0.10)	(0.01)	(0.11)	(0.01)
BOL	-1.50	0.02	0.02	0.74	-0.35	0.50	0.58
	(0.02)	(0.00)	(0.00)	(0.03)	(0.01)	(0.04)	(0.03)
BRA	-0.90	-0.02	-0.01	0.04	-0.04	-0.05	0.13
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
BWA	-2.85	-0.20	-0.19	-0.12	-0.20	-0.16	0.24
	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
CAN	-0.98	0.01	0.01	0.52	-0.08	0.37	0.22
	(0.02)	(0.00)	(0.00)	(0.07)	(0.00)	(0.06)	(0.01)
CHE	-0.85	0.02	0.02	-0.30	-0.08	-0.30	0.08
	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
CHL	-1.18	0.02	0.02	0.66	-0.18	0.68	0.16
	(0.03)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
CHN	-1.21	-0.03	-0.03	-0.24	-0.04	-0.32	0.12
	(0.03)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.01)
CIV	-2.67	-0.27	-0.26	-4.24	-0.36	-4.22	0.33
	(0.09)	(0.01)	(0.01)	(0.28)	(0.02)	(0.28)	(0.02)
CMR	-1.48	-0.10	-0.09	-1.10	-0.16	-1.22	0.28
	(0.04)	(0.00)	(0.00)	(0.12)	(0.01)	(0.13)	(0.02)
COL	-0.99	0.01	0.01	0.72	-0.10	0.57	0.25
	(0.01)	(0.00)	(0.00)	(0.04)	(0.00)	(0.03)	(0.02)
CRI	-0.95	-0.05	-0.04	-0.37	-0.11	-0.36	0.11
	(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)
CYP	-1.72	0.06	0.06	0.06	-0.66	0.03	0.69
	(0.02)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)	(0.02)

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Table C.9 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
CZE	-2.47	-0.21	-0.21	-2.87	-0.26	-2.92	0.31
	(0.06)	(0.01)	(0.01)	(0.11)	(0.01)	(0.11)	(0.01)
DEU	-1.07	0.02	0.02	-0.12	-0.09	-0.17	0.14
	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.01)
DNK	-1.03	0.09	0.09	0.58	-0.26	0.38	0.45
	(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)	(0.01)
ECU	-1.41	-0.11	-0.11	-0.86	-0.15	-1.01	0.30
	(0.05)	(0.01)	(0.01)	(0.12)	(0.01)	(0.13)	(0.02)
EGY	-3.68	-0.28	-0.28	-3.14	-0.39	-3.21	0.47
	(0.17)	(0.01)	(0.01)	(0.22)	(0.02)	(0.23)	(0.03)
ESP	-1.13	0.01	0.02	-0.14	-0.11	-0.16	0.13
	(0.03)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)
EST	-1.80	-0.09	-0.09	-0.22	-0.29	-0.28	0.36
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
ETH	-1.54	-0.13	-0.13	-0.33	-0.15	-0.35	0.17
	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
FIN	-1.35	-0.01	-0.01	-0.56	-0.15	-0.57	0.16
	(0.05)	(0.00)	(0.00)	(0.07)	(0.01)	(0.07)	(0.01)
FRA	-0.77	0.13	0.13	1.16	-0.12	1.15	0.13
	(0.01)	(0.00)	(0.00)	(0.08)	(0.00)	(0.08)	(0.00)
GBR	-0.93	0.11	0.12	0.94	-0.12	0.80	0.25
	(0.02)	(0.00)	(0.00)	(0.08)	(0.00)	(0.07)	(0.01)
GEO	-1.87	-0.11	-0.10	-0.22	-0.22	-0.22	0.22
	(0.04)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
GHA	-1.96	-0.18	-0.18	-2.59	-0.19	-2.69	0.30
	(0.03)	(0.00)	(0.00)	(0.10)	(0.00)	(0.10)	(0.01)
GRC	-2.40	0.09	0.10	0.66	-0.64	0.61	0.68
	(0.02)	(0.01)	(0.00)	(0.07)	(0.02)	(0.07)	(0.02)
GTM	-0.86	0.01	0.01	0.11	-0.17	0.02	0.25
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
HKG	-1.87	-0.23	-0.23	-0.07	-0.23	-0.08	0.23
	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HND	-1.29	-0.10	-0.09	-0.25	-0.12	-0.25	0.13
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
HRV	-2.30	-0.12	-0.12	-1.02	-0.32	-1.13	0.43
	(0.09)	(0.01)	(0.01)	(0.06)	(0.01)	(0.06)	(0.01)
HUN	-1.26	0.01	0.01	-0.31	-0.23	-0.32	0.24
	(0.02)	(0.00)	(0.00)	(0.06)	(0.00)	(0.06)	(0.01)
IDN	-1.62	-0.09	-0.08	-0.11	-0.10	-0.20	0.19
	(0.04)	(0.00)	(0.00)	(0.08)	(0.01)	(0.09)	(0.02)
IND	-1.47	0.01	0.01	0.02	-0.09	-0.05	0.16
	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.01)
IRL	-1.70	-0.07	-0.07	-0.76	-0.21	-0.78	0.23
	(0.03)	(0.01)	(0.01)	(0.10)	(0.00)	(0.10)	(0.00)
IRN	-2.74	-0.16	-0.15	-0.67	-0.25	-0.73	0.31
	(0.08)	(0.01)	(0.01)	(0.12)	(0.02)	(0.13)	(0.02)
ISR	-1.78	-0.05	-0.05	-0.60	-0.21	-0.60	0.22
	(0.04)	(0.01)	(0.01)	(0.22)	(0.01)	(0.22)	(0.01)

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Table C.9 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
ITA	-1.10	0.16	0.16	1.42	-0.15	1.40	0.17
	(0.02)	(0.00)	(0.00)	(0.13)	(0.01)	(0.13)	(0.01)
JPN	-0.79	0.03	0.03	0.28	-0.04	0.30	0.02
	(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
KAZ	-3.04	-0.26	-0.26	-1.76	-0.32	-1.77	0.34
	(0.08)	(0.01)	(0.01)	(0.16)	(0.01)	(0.17)	(0.02)
KEN	-1.53	-0.12	-0.11	-1.96	-0.13	-1.99	0.16
	(0.04)	(0.01)	(0.00)	(0.16)	(0.00)	(0.17)	(0.01)
KGZ	-2.07	-0.08	-0.08	-0.23	-0.32	-0.23	0.32
	(0.02)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
KHM	-0.71	-0.01	0.00	-0.04	-0.10	-0.03	0.09
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
KOR	-0.95	-0.02	-0.02	-0.27	-0.06	-0.29	0.08
	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
KWT	-4.72	-0.36	-0.36	-3.90	-0.56	-3.86	0.51
	(0.13)	(0.01)	(0.01)	(0.14)	(0.02)	(0.15)	(0.02)
LAO	-0.79	-0.05	-0.05	-0.65	-0.10	-0.67	0.12
	(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)
LKA	-2.20	-0.23	-0.22	-1.43	-0.23	-1.47	0.28
	(0.04)	(0.01)	(0.01)	(0.13)	(0.01)	(0.14)	(0.01)
LTU	-2.48	-0.17	-0.16	-2.93	-0.24	-2.94	0.25
	(0.07)	(0.01)	(0.01)	(0.13)	(0.01)	(0.13)	(0.01)
LUX	-0.81	0.08	0.08	-0.01	-0.26	-0.03	0.27
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
LVA	-1.29	-0.03	-0.03	-0.09	-0.21	-0.08	0.20
	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
MAR	-3.25	-0.27	-0.26	-3.95	-0.27	-4.14	0.46
	(0.12)	(0.01)	(0.01)	(0.34)	(0.01)	(0.35)	(0.03)
MDG	-2.08	-0.16	-0.16	-1.16	-0.17	-1.26	0.27
	(0.02)	(0.01)	(0.01)	(0.06)	(0.01)	(0.07)	(0.02)
MEX	-1.59	-0.13	-0.13	-0.76	-0.14	-0.83	0.21
	(0.04)	(0.01)	(0.01)	(0.21)	(0.01)	(0.21)	(0.01)
MLT	-1.15	0.01	0.02	0.08	-0.43	0.11	0.39
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
MNG	-1.92	-0.15	-0.15	-0.11	-0.28	-0.15	0.31
	(0.10)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
MOZ	-1.86	-0.15	-0.15	-0.28	-0.16	-0.31	0.20
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
MUS	-1.66	-0.12	-0.12	-0.34	-0.17	-0.48	0.31
	(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.03)	(0.02)
MWI	-1.81	-0.20	-0.19	-0.84	-0.21	-0.93	0.31
	(0.04)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.02)
MYS	-3.05	-0.29	-0.29	-3.08	-0.35	-3.06	0.32
	(0.08)	(0.01)	(0.01)	(0.33)	(0.02)	(0.33)	(0.02)
NAM	-2.15	-0.19	-0.19	-0.04	-0.19	-0.03	0.19
	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NGA	-2.54	-0.16	-0.16	0.55	-0.21	0.42	0.34
	(0.11)	(0.01)	(0.01)	(0.18)	(0.01)	(0.19)	(0.01)

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Table C.9 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
NIC	-1.48	0.04	0.05	0.51	-0.67	0.50	0.69
	(0.02)	(0.00)	(0.00)	(0.07)	(0.01)	(0.07)	(0.01)
NLD	-0.75	0.15	0.15	1.65	-0.13	1.52	0.26
	(0.01)	(0.00)	(0.00)	(0.06)	(0.01)	(0.06)	(0.01)
NOR	-1.23	0.14	0.15	3.13	-0.37	2.84	0.65
	(0.02)	(0.00)	(0.00)	(0.05)	(0.01)	(0.04)	(0.03)
NPL	-1.68	-0.16	-0.15	-0.52	-0.17	-0.53	0.18
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
NZL	-1.53	-0.13	-0.13	-0.46	-0.13	-0.51	0.18
	(0.03)	(0.00)	(0.00)	(0.12)	(0.01)	(0.13)	(0.01)
OMN	-3.95	-0.25	-0.25	-1.44	-0.30	-1.49	0.35
	(0.06)	(0.01)	(0.01)	(0.09)	(0.01)	(0.10)	(0.02)
PAK	-2.04	0.07	0.07	0.79	-0.47	0.78	0.48
	(0.03)	(0.00)	(0.00)	(0.07)	(0.02)	(0.07)	(0.02)
PAN	-1.46	-0.11	-0.11	-0.17	-0.12	-0.17	0.12
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PER	-1.01	-0.05	-0.04	-0.33	-0.08	-0.42	0.17
	(0.02)	(0.00)	(0.00)	(0.05)	(0.00)	(0.06)	(0.01)
PHL	-1.00	-0.03	-0.03	-0.25	-0.09	-0.25	0.09
	(0.02)	(0.00)	(0.00)	(0.09)	(0.00)	(0.09)	(0.00)
POL	-2.16	-0.13	-0.13	-1.83	-0.24	-1.87	0.29
	(0.07)	(0.01)	(0.01)	(0.14)	(0.01)	(0.15)	(0.01)
PRT	-1.07	0.09	0.10	0.50	-0.21	0.50	0.21
	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)	(0.01)
PRY	-0.77	-0.01	-0.01	-0.02	-0.15	-0.01	0.14
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
QAT	-3.57	-0.21	-0.21	-2.69	-0.28	-2.72	0.30
	(0.08)	(0.01)	(0.01)	(0.10)	(0.01)	(0.11)	(0.02)
ROU	-3.30	-0.29	-0.29	-4.26	-0.32	-4.25	0.31
	(0.10)	(0.01)	(0.01)	(0.21)	(0.01)	(0.21)	(0.01)
RUS	-1.74	-0.04	-0.04	-0.26	-0.13	-0.41	0.28
	(0.03)	(0.00)	(0.00)	(0.05)	(0.00)	(0.03)	(0.01)
SAU	-3.65	-0.23	-0.23	-1.47	-0.29	-1.45	0.27
	(0.04)	(0.01)	(0.01)	(0.14)	(0.01)	(0.15)	(0.02)
SEN	-2.03	-0.20	-0.19	-2.01	-0.23	-2.01	0.24
	(0.06)	(0.01)	(0.01)	(0.14)	(0.01)	(0.14)	(0.01)
SGP	-1.53	-0.11	-0.11	-1.30	-0.15	-1.36	0.21
	(0.04)	(0.00)	(0.00)	(0.12)	(0.01)	(0.12)	(0.01)
SLV	-0.92	-0.03	-0.02	-0.13	-0.18	-0.13	0.18
	(0.02)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)	(0.00)
SVK	-1.68	-0.07	-0.07	-1.76	-0.19	-1.77	0.21
	(0.03)	(0.00)	(0.00)	(0.06)	(0.00)	(0.06)	(0.00)
SVN	-1.49	-0.05	-0.05	-0.25	-0.23	-0.29	0.26
	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
SWE	-0.64	0.16	0.17	1.66	-0.14	1.73	0.08
	(0.01)	(0.00)	(0.00)	(0.06)	(0.00)	(0.06)	(0.00)
THA	-1.11	-0.01	-0.01	-0.08	-0.10	-0.14	0.16
	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.01)

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Table C.9 – *Continued from previous page*

Country	ΔX^i	$\Delta \Re^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
TUN	-3.54	-0.33	-0.33	-2.88	-0.38	-2.98	0.48
	(0.08)	(0.01)	(0.01)	(0.11)	(0.01)	(0.12)	(0.02)
TUR	-2.05	0.19	0.20	1.56	-0.42	1.48	0.51
	(0.03)	(0.00)	(0.00)	(0.05)	(0.02)	(0.04)	(0.02)
TWN	-1.06	-0.03	-0.02	-0.21	-0.08	-0.22	0.08
	(0.03)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)	(0.01)
TZA	-1.80	-0.17	-0.16	-0.38	-0.17	-0.41	0.20
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
UGA	-1.11	-0.03	-0.03	0.07	-0.17	-0.12	0.36
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.02)	(0.02)
UKR	-2.73	-0.14	-0.14	-1.17	-0.28	-1.19	0.30
	(0.08)	(0.01)	(0.01)	(0.07)	(0.01)	(0.07)	(0.01)
URY	-0.82	0.00	0.00	0.00	-0.09	0.00	0.09
	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
USA	-0.91	-0.02	-0.02	-0.08	-0.03	-0.16	0.10
	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
VEN	-2.16	-0.16	-0.16	-2.87	-0.23	-2.95	0.30
	(0.04)	(0.01)	(0.01)	(0.08)	(0.01)	(0.09)	(0.02)
VNM	-2.19	-0.16	-0.16	-0.52	-0.18	-0.55	0.22
	(0.06)	(0.01)	(0.01)	(0.03)	(0.01)	(0.04)	(0.02)
XAC	-3.63	-0.28	-0.27	-1.27	-0.27	-1.34	0.33
	(0.05)	(0.01)	(0.01)	(0.23)	(0.01)	(0.24)	(0.02)
XCA	-1.00	-0.06	-0.06	-0.65	-0.12	-0.69	0.16
	(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)
XCB	-1.30	-0.07	-0.07	-0.70	-0.10	-0.81	0.21
	(0.03)	(0.00)	(0.00)	(0.04)	(0.00)	(0.05)	(0.01)
XCF	-3.06	-0.23	-0.23	-1.90	-0.25	-1.97	0.32
	(0.04)	(0.01)	(0.01)	(0.20)	(0.01)	(0.21)	(0.02)
XEA	-1.80	-0.18	-0.17	-0.87	-0.21	-0.95	0.29
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
XEC	-2.57	-0.21	-0.20	-1.32	-0.25	-1.38	0.31
	(0.07)	(0.01)	(0.01)	(0.12)	(0.01)	(0.13)	(0.02)
XEE	-2.31	-0.18	-0.18	-0.20	-0.24	-0.19	0.24
	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
XEF	-1.80	-0.13	-0.12	-0.86	-0.17	-0.89	0.20
	(0.04)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.00)
XER	-2.25	-0.10	-0.09	-1.09	-0.33	-1.14	0.38
	(0.05)	(0.01)	(0.01)	(0.09)	(0.01)	(0.09)	(0.01)
XNA	-1.07	0.00	0.01	-0.43	-0.14	-0.55	0.26
	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.01)
XNF	-4.40	-0.30	-0.29	-4.31	-0.42	-4.35	0.46
	(0.12)	(0.01)	(0.01)	(0.32)	(0.02)	(0.33)	(0.03)
XOC	-1.43	-0.11	-0.11	-0.52	-0.13	-0.61	0.22
	(0.04)	(0.00)	(0.00)	(0.10)	(0.01)	(0.11)	(0.01)
XSA	-1.22	-0.05	-0.05	-0.66	-0.14	-0.78	0.26
	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.01)
XSC	-1.77	-0.17	-0.16	-1.09	-0.18	-1.21	0.30
	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.02)

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Table C.9 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
XSE	-1.29	-0.06	-0.06	0.39	-0.28	0.25	0.42
	(0.03)	(0.01)	(0.01)	(0.08)	(0.01)	(0.09)	(0.01)
XSM	-1.22	-0.06	-0.06	-1.12	-0.09	-1.17	0.14
	(0.04)	(0.00)	(0.00)	(0.06)	(0.00)	(0.06)	(0.00)
XSU	-3.60	-0.22	-0.22	-1.10	-0.36	-1.08	0.34
	(0.16)	(0.01)	(0.01)	(0.07)	(0.02)	(0.08)	(0.02)
XWF	-2.58	-0.22	-0.21	-0.92	-0.23	-1.02	0.33
	(0.03)	(0.01)	(0.01)	(0.09)	(0.01)	(0.10)	(0.02)
XWS	-3.69	-0.24	-0.24	-1.35	-0.37	-1.30	0.33
	(0.10)	(0.01)	(0.01)	(0.13)	(0.02)	(0.13)	(0.02)
ZAF	-1.65	-0.10	-0.09	-0.27	-0.13	-0.38	0.24
	(0.05)	(0.01)	(0.00)	(0.09)	(0.01)	(0.09)	(0.02)
ZMB	-2.17	-0.21	-0.20	-0.66	-0.21	-0.80	0.34
	(0.06)	(0.01)	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)
ZWE	-2.71	-0.22	-0.21	-0.70	-0.24	-0.72	0.26
	(0.08)	(0.01)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)

Notes: ΔX^i denotes the percentage changes in trade flows, $\Delta \mathfrak{R}^i$ the percentage changes in real income, ΔU^i the percentage changes in welfare, ΔE^i the percentage changes in carbon emissions, PSE the percentage scale effects, PCE the percentage composition effects, and PTE the percentage technique effects. The numbers in parentheses below the reported values give the corresponding bootstrapped standard errors.

Table C.10: Pure Carbon Tariffs (Product-Based, Extended Model, with EIA Data for National Resource Shares)

Country	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
ALB	-1.50	0.05	0.06	0.18	-0.54	0.03	0.69
	(0.01)	(0.00)	(0.00)	(0.04)	(0.01)	(0.03)	(0.01)
ARE	-3.33	-0.25	-0.24	-2.21	-0.29	-2.26	0.34
	(0.05)	(0.01)	(0.01)	(0.10)	(0.01)	(0.11)	(0.02)
ARG	-1.12	0.03	0.03	0.71	-0.11	0.50	0.31
	(0.02)	(0.00)	(0.00)	(0.10)	(0.00)	(0.08)	(0.02)
ARM	-1.87	0.02	0.03	-0.15	-0.67	-0.12	0.64
	(0.02)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
AUS	-1.61	-0.12	-0.12	-0.14	-0.12	-0.24	0.21
	(0.02)	(0.00)	(0.00)	(0.06)	(0.00)	(0.07)	(0.01)
AUT	-0.82	0.12	0.12	0.72	-0.23	0.71	0.23
	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
AZE	-6.18	-0.41	-0.41	-4.13	-0.61	-4.04	0.52
	(0.17)	(0.01)	(0.01)	(0.23)	(0.02)	(0.24)	(0.03)
BEL	-0.82	0.08	0.09	0.45	-0.09	0.45	0.09
	(0.02)	(0.00)	(0.00)	(0.09)	(0.00)	(0.09)	(0.00)
BGD	-1.57	-0.10	-0.10	-0.92	-0.13	-0.97	0.18
	(0.03)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)	(0.01)
BGR	-4.69	-0.50	-0.50	-5.31	-0.54	-5.34	0.58
	(0.14)	(0.01)	(0.01)	(0.14)	(0.01)	(0.14)	(0.01)
BHR	-4.61	-0.35	-0.35	-3.39	-0.60	-3.21	0.41
	(0.21)	(0.02)	(0.02)	(0.19)	(0.03)	(0.19)	(0.03)
BLR	-2.50	-0.13	-0.13	-2.08	-0.22	-2.20	0.34
	(0.08)	(0.01)	(0.01)	(0.11)	(0.01)	(0.11)	(0.01)
BOL	-1.50	0.02	0.02	0.73	-0.35	0.50	0.58
	(0.02)	(0.00)	(0.00)	(0.03)	(0.01)	(0.04)	(0.03)
BRA	-0.90	-0.02	-0.01	0.03	-0.04	-0.06	0.13
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
BWA	-2.87	-0.20	-0.19	-0.12	-0.20	-0.16	0.24
	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
CAN	-0.98	0.01	0.01	0.52	-0.08	0.37	0.22
	(0.02)	(0.00)	(0.00)	(0.07)	(0.00)	(0.06)	(0.01)
CHE	-0.85	0.02	0.02	-0.30	-0.08	-0.30	0.08
	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
CHL	-1.18	0.02	0.03	0.65	-0.17	0.66	0.16
	(0.03)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
CHN	-1.21	-0.03	-0.03	-0.25	-0.04	-0.32	0.12
	(0.03)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.01)
CIV	-2.69	-0.27	-0.26	-4.29	-0.37	-4.26	0.34
	(0.09)	(0.01)	(0.01)	(0.27)	(0.02)	(0.28)	(0.02)
CMR	-1.51	-0.09	-0.08	-1.15	-0.16	-1.27	0.28
	(0.04)	(0.00)	(0.00)	(0.12)	(0.01)	(0.13)	(0.02)
COL	-0.98	0.01	0.01	0.71	-0.10	0.56	0.25
	(0.01)	(0.00)	(0.00)	(0.04)	(0.00)	(0.03)	(0.02)
CRI	-0.94	-0.04	-0.04	-0.36	-0.11	-0.36	0.11
	(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)
CYP	-1.72	0.06	0.07	0.06	-0.66	0.03	0.69

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Table C.10 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
	(0.02)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)	(0.02)
CZE	-2.46	-0.21	-0.21	-2.87	-0.26	-2.91	0.31
	(0.06)	(0.01)	(0.01)	(0.11)	(0.01)	(0.11)	(0.01)
DEU	-1.06	0.02	0.02	-0.12	-0.09	-0.17	0.14
	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.01)
DNK	-1.03	0.09	0.10	0.58	-0.26	0.38	0.45
	(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)	(0.01)
ECU	-1.43	-0.09	-0.09	-0.90	-0.15	-1.05	0.30
	(0.06)	(0.00)	(0.00)	(0.11)	(0.01)	(0.13)	(0.02)
EGY	-3.73	-0.28	-0.27	-3.22	-0.40	-3.30	0.47
	(0.17)	(0.01)	(0.01)	(0.22)	(0.02)	(0.23)	(0.03)
ESP	-1.13	0.01	0.02	-0.14	-0.11	-0.16	0.13
	(0.03)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)
EST	-1.79	-0.09	-0.09	-0.21	-0.29	-0.28	0.36
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
ETH	-1.55	-0.13	-0.12	-0.33	-0.15	-0.35	0.17
	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
FIN	-1.34	-0.01	-0.01	-0.55	-0.15	-0.56	0.16
	(0.05)	(0.00)	(0.00)	(0.06)	(0.01)	(0.07)	(0.01)
FRA	-0.77	0.13	0.13	1.16	-0.12	1.15	0.13
	(0.01)	(0.00)	(0.00)	(0.08)	(0.00)	(0.08)	(0.00)
GBR	-0.93	0.12	0.12	0.93	-0.12	0.80	0.25
	(0.02)	(0.00)	(0.00)	(0.08)	(0.00)	(0.07)	(0.01)
GEO	-1.87	-0.11	-0.10	-0.22	-0.22	-0.22	0.22
	(0.04)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
GHA	-1.98	-0.18	-0.17	-2.59	-0.19	-2.69	0.30
	(0.03)	(0.00)	(0.00)	(0.10)	(0.00)	(0.10)	(0.01)
GRC	-2.39	0.09	0.10	0.66	-0.63	0.62	0.68
	(0.02)	(0.00)	(0.00)	(0.07)	(0.02)	(0.07)	(0.02)
GTM	-0.86	0.01	0.01	0.11	-0.17	0.02	0.25
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
HKG	-1.87	-0.23	-0.23	-0.07	-0.23	-0.08	0.23
	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HND	-1.28	-0.10	-0.09	-0.25	-0.12	-0.25	0.13
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
HRV	-2.30	-0.12	-0.12	-1.02	-0.31	-1.13	0.42
	(0.09)	(0.01)	(0.01)	(0.06)	(0.01)	(0.06)	(0.01)
HUN	-1.25	0.01	0.01	-0.30	-0.23	-0.32	0.24
	(0.02)	(0.00)	(0.00)	(0.06)	(0.00)	(0.06)	(0.01)
IDN	-1.62	-0.09	-0.08	-0.11	-0.10	-0.20	0.19
	(0.04)	(0.00)	(0.00)	(0.08)	(0.01)	(0.09)	(0.02)
IND	-1.47	0.00	0.01	0.04	-0.09	-0.03	0.16
	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.02)	(0.01)
IRL	-1.69	-0.07	-0.06	-0.76	-0.21	-0.78	0.23
	(0.03)	(0.01)	(0.01)	(0.10)	(0.00)	(0.10)	(0.00)
IRN	-2.72	-0.16	-0.16	-0.63	-0.25	-0.69	0.31
	(0.08)	(0.01)	(0.01)	(0.13)	(0.02)	(0.13)	(0.02)
ISR	-1.78	-0.05	-0.05	-0.59	-0.21	-0.60	0.22
	(0.04)	(0.01)	(0.01)	(0.22)	(0.01)	(0.22)	(0.01)

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Table C.10 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
ITA	-1.10	0.16	0.16	1.42	-0.15	1.40	0.17
	(0.02)	(0.00)	(0.00)	(0.13)	(0.01)	(0.13)	(0.01)
JPN	-0.79	0.03	0.03	0.28	-0.04	0.30	0.02
	(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.03)	(0.00)
KAZ	-3.00	-0.27	-0.27	-1.71	-0.32	-1.73	0.34
	(0.08)	(0.01)	(0.01)	(0.17)	(0.01)	(0.18)	(0.02)
KEN	-1.54	-0.12	-0.11	-1.98	-0.13	-2.01	0.17
	(0.04)	(0.00)	(0.00)	(0.16)	(0.00)	(0.17)	(0.01)
KGZ	-2.05	-0.10	-0.10	-0.22	-0.33	-0.23	0.33
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
KHM	-0.72	0.00	0.01	-0.04	-0.10	-0.02	0.09
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
KOR	-0.95	-0.02	-0.02	-0.27	-0.06	-0.29	0.08
	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
KWT	-4.83	-0.36	-0.36	-4.07	-0.57	-4.02	0.52
	(0.13)	(0.01)	(0.01)	(0.14)	(0.01)	(0.14)	(0.02)
LAO	-0.79	-0.05	-0.05	-0.66	-0.10	-0.68	0.12
	(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)
LKA	-2.21	-0.23	-0.22	-1.44	-0.23	-1.49	0.28
	(0.04)	(0.01)	(0.01)	(0.13)	(0.01)	(0.14)	(0.01)
LTU	-2.46	-0.16	-0.16	-2.89	-0.24	-2.90	0.25
	(0.07)	(0.01)	(0.01)	(0.13)	(0.01)	(0.13)	(0.01)
LUX	-0.81	0.08	0.08	-0.01	-0.26	-0.03	0.27
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
LVA	-1.28	-0.03	-0.03	-0.09	-0.21	-0.08	0.20
	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
MAR	-3.26	-0.27	-0.26	-3.99	-0.27	-4.18	0.46
	(0.12)	(0.01)	(0.01)	(0.34)	(0.01)	(0.35)	(0.03)
MDG	-2.11	-0.15	-0.15	-1.18	-0.17	-1.28	0.27
	(0.02)	(0.00)	(0.00)	(0.05)	(0.01)	(0.07)	(0.02)
MEX	-1.59	-0.13	-0.13	-0.77	-0.14	-0.84	0.21
	(0.04)	(0.01)	(0.01)	(0.21)	(0.01)	(0.21)	(0.01)
MLT	-1.15	0.01	0.02	0.08	-0.42	0.11	0.39
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
MNG	-1.86	-0.21	-0.21	-0.11	-0.30	-0.14	0.33
	(0.10)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
MOZ	-1.86	-0.15	-0.15	-0.28	-0.16	-0.32	0.20
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
MUS	-1.67	-0.11	-0.11	-0.34	-0.17	-0.48	0.31
	(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.03)	(0.02)
MWI	-1.83	-0.19	-0.18	-0.85	-0.21	-0.94	0.31
	(0.04)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.02)
MYS	-3.06	-0.29	-0.29	-3.13	-0.35	-3.11	0.32
	(0.09)	(0.01)	(0.01)	(0.33)	(0.02)	(0.33)	(0.02)
NAM	-2.16	-0.19	-0.18	-0.04	-0.19	-0.03	0.19
	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NGA	-2.55	-0.14	-0.13	0.50	-0.21	0.37	0.34
	(0.11)	(0.01)	(0.01)	(0.18)	(0.01)	(0.19)	(0.01)

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Table C.10 – *Continued from previous page*

Country	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
NIC	-1.47	0.05	0.05	0.51	-0.67	0.50	0.68
	(0.02)	(0.00)	(0.00)	(0.07)	(0.01)	(0.07)	(0.01)
NLD	-0.75	0.15	0.16	1.64	-0.13	1.51	0.26
	(0.01)	(0.00)	(0.00)	(0.07)	(0.01)	(0.06)	(0.01)
NOR	-1.25	0.18	0.19	3.02	-0.36	2.74	0.64
	(0.02)	(0.00)	(0.00)	(0.06)	(0.01)	(0.05)	(0.03)
NPL	-1.69	-0.16	-0.15	-0.52	-0.17	-0.54	0.18
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
NZL	-1.53	-0.13	-0.13	-0.46	-0.13	-0.51	0.18
	(0.03)	(0.00)	(0.00)	(0.12)	(0.01)	(0.13)	(0.01)
OMN	-4.08	-0.23	-0.22	-1.55	-0.29	-1.61	0.35
	(0.06)	(0.00)	(0.00)	(0.08)	(0.01)	(0.09)	(0.01)
PAK	-2.04	0.07	0.07	0.80	-0.47	0.79	0.48
	(0.03)	(0.00)	(0.00)	(0.07)	(0.02)	(0.07)	(0.02)
PAN	-1.46	-0.11	-0.11	-0.17	-0.12	-0.17	0.12
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PER	-1.01	-0.04	-0.04	-0.34	-0.08	-0.43	0.17
	(0.02)	(0.00)	(0.00)	(0.05)	(0.00)	(0.06)	(0.01)
PHL	-1.01	-0.03	-0.02	-0.25	-0.09	-0.25	0.09
	(0.02)	(0.00)	(0.00)	(0.09)	(0.00)	(0.09)	(0.00)
POL	-2.15	-0.13	-0.13	-1.81	-0.24	-1.86	0.29
	(0.07)	(0.01)	(0.01)	(0.14)	(0.01)	(0.15)	(0.01)
PRT	-1.07	0.10	0.10	0.50	-0.21	0.50	0.21
	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)	(0.01)
PRY	-0.77	-0.01	-0.01	-0.02	-0.15	-0.01	0.14
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
QAT	-3.53	-0.25	-0.24	-2.70	-0.29	-2.72	0.32
	(0.08)	(0.01)	(0.01)	(0.10)	(0.01)	(0.10)	(0.02)
ROU	-3.31	-0.29	-0.29	-4.27	-0.32	-4.26	0.31
	(0.10)	(0.01)	(0.01)	(0.21)	(0.01)	(0.21)	(0.01)
RUS	-1.70	-0.05	-0.05	-0.19	-0.13	-0.34	0.28
	(0.03)	(0.00)	(0.00)	(0.04)	(0.00)	(0.03)	(0.01)
SAU	-3.82	-0.22	-0.22	-1.66	-0.30	-1.64	0.27
	(0.04)	(0.01)	(0.01)	(0.13)	(0.01)	(0.14)	(0.02)
SEN	-2.04	-0.19	-0.19	-2.03	-0.23	-2.03	0.24
	(0.06)	(0.01)	(0.01)	(0.14)	(0.01)	(0.14)	(0.01)
SGP	-1.53	-0.11	-0.11	-1.32	-0.15	-1.38	0.21
	(0.04)	(0.00)	(0.00)	(0.11)	(0.01)	(0.12)	(0.01)
SLV	-0.92	-0.02	-0.02	-0.12	-0.18	-0.12	0.18
	(0.02)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)	(0.00)
SVK	-1.68	-0.07	-0.07	-1.74	-0.19	-1.76	0.21
	(0.03)	(0.00)	(0.00)	(0.06)	(0.00)	(0.07)	(0.00)
SVN	-1.48	-0.05	-0.04	-0.25	-0.23	-0.29	0.26
	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
SWE	-0.64	0.16	0.17	1.64	-0.14	1.70	0.08
	(0.01)	(0.00)	(0.00)	(0.06)	(0.00)	(0.06)	(0.00)
THA	-1.11	-0.01	-0.01	-0.09	-0.10	-0.15	0.16
	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.01)

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Table C.10 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
TUN	-3.56	-0.33	-0.32	-2.91	-0.38	-3.01	0.48
	(0.08)	(0.01)	(0.01)	(0.11)	(0.01)	(0.12)	(0.02)
TUR	-2.05	0.19	0.20	1.56	-0.42	1.48	0.51
	(0.03)	(0.00)	(0.00)	(0.05)	(0.02)	(0.05)	(0.02)
TWN	-1.07	-0.03	-0.02	-0.21	-0.08	-0.22	0.08
	(0.03)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)	(0.01)
TZA	-1.82	-0.17	-0.16	-0.39	-0.17	-0.41	0.20
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
UGA	-1.13	-0.02	-0.02	0.07	-0.17	-0.12	0.36
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.02)	(0.02)
UKR	-2.68	-0.16	-0.16	-1.10	-0.29	-1.12	0.30
	(0.08)	(0.01)	(0.01)	(0.07)	(0.01)	(0.07)	(0.01)
URY	-0.82	0.00	0.00	-0.02	-0.09	-0.02	0.09
	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
USA	-0.91	-0.02	-0.02	-0.07	-0.03	-0.14	0.10
	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
VEN	-2.09	-0.18	-0.17	-2.73	-0.22	-2.80	0.30
	(0.04)	(0.01)	(0.01)	(0.09)	(0.01)	(0.10)	(0.02)
VNM	-2.21	-0.16	-0.15	-0.53	-0.18	-0.56	0.22
	(0.06)	(0.01)	(0.01)	(0.03)	(0.01)	(0.04)	(0.02)
XAC	-3.68	-0.25	-0.24	-1.44	-0.26	-1.51	0.33
	(0.04)	(0.00)	(0.00)	(0.23)	(0.01)	(0.24)	(0.02)
XCA	-0.99	-0.06	-0.06	-0.64	-0.12	-0.68	0.16
	(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)
XCB	-1.30	-0.07	-0.06	-0.70	-0.10	-0.81	0.21
	(0.03)	(0.00)	(0.00)	(0.04)	(0.00)	(0.05)	(0.01)
XCF	-3.10	-0.22	-0.21	-1.99	-0.24	-2.06	0.32
	(0.04)	(0.01)	(0.01)	(0.19)	(0.01)	(0.20)	(0.02)
XEA	-1.80	-0.18	-0.17	-0.87	-0.21	-0.95	0.29
	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
XEC	-2.60	-0.20	-0.20	-1.37	-0.25	-1.42	0.31
	(0.07)	(0.01)	(0.01)	(0.11)	(0.01)	(0.12)	(0.02)
XEE	-2.31	-0.18	-0.18	-0.19	-0.24	-0.19	0.24
	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
XEF	-1.80	-0.12	-0.12	-0.86	-0.17	-0.89	0.20
	(0.04)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.00)
XER	-2.23	-0.11	-0.10	-1.06	-0.33	-1.11	0.38
	(0.05)	(0.01)	(0.01)	(0.09)	(0.01)	(0.09)	(0.01)
XNA	-1.05	0.00	0.01	-0.41	-0.14	-0.53	0.26
	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.01)
XNF	-4.56	-0.29	-0.29	-4.59	-0.43	-4.62	0.47
	(0.12)	(0.01)	(0.01)	(0.30)	(0.02)	(0.30)	(0.03)
XOC	-1.44	-0.11	-0.11	-0.52	-0.13	-0.61	0.22
	(0.04)	(0.00)	(0.00)	(0.10)	(0.01)	(0.11)	(0.01)
XSA	-1.22	-0.05	-0.05	-0.65	-0.14	-0.77	0.26
	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.01)
XSC	-1.77	-0.16	-0.16	-1.09	-0.18	-1.21	0.30
	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.02)

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Table C.10 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
XSE	-1.32	-0.03	-0.03	0.36	-0.28	0.22	0.42
	(0.03)	(0.00)	(0.00)	(0.08)	(0.01)	(0.09)	(0.01)
XSM	-1.22	-0.06	-0.06	-1.12	-0.09	-1.17	0.14
	(0.04)	(0.00)	(0.00)	(0.06)	(0.00)	(0.06)	(0.00)
XSU	-3.54	-0.23	-0.23	-1.07	-0.36	-1.05	0.34
	(0.16)	(0.01)	(0.01)	(0.08)	(0.02)	(0.08)	(0.02)
XWF	-2.59	-0.21	-0.21	-0.93	-0.23	-1.03	0.33
	(0.03)	(0.00)	(0.00)	(0.09)	(0.01)	(0.10)	(0.02)
XWS	-3.70	-0.24	-0.24	-1.36	-0.37	-1.32	0.33
	(0.10)	(0.01)	(0.01)	(0.13)	(0.02)	(0.13)	(0.02)
ZAF	-1.63	-0.10	-0.10	-0.22	-0.13	-0.33	0.25
	(0.04)	(0.01)	(0.01)	(0.09)	(0.01)	(0.09)	(0.02)
ZMB	-2.19	-0.21	-0.20	-0.68	-0.21	-0.81	0.35
	(0.06)	(0.01)	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)
ZWE	-2.72	-0.23	-0.22	-0.71	-0.24	-0.73	0.26
	(0.08)	(0.01)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)

Notes: ΔX^i denotes the percentage changes in trade flows, $\Delta \mathfrak{R}^i$ the percentage changes in real income, ΔU^i the percentage changes in welfare, ΔE^i the percentage changes in carbon emissions, PSE the percentage scale effects, PCE the percentage composition effects, and PTE the percentage technique effects. The numbers in parentheses below the reported values give the corresponding bootstrapped standard errors.

Table C.11: Pure Carbon Tariffs (Production-Based, Extended Model)

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
ALB	-2.37	0.00	0.01	0.21	-0.62	-0.15	0.97
	(0.02)	(0.01)	(0.01)	(0.07)	(0.01)	(0.05)	(0.02)
ARE	-3.48	-0.36	-0.35	-3.50	-0.38	-3.87	0.76
	(0.07)	(0.01)	(0.01)	(0.17)	(0.01)	(0.19)	(0.04)
ARG	-2.05	-0.06	-0.05	0.42	-0.16	-0.08	0.65
	(0.04)	(0.00)	(0.00)	(0.06)	(0.01)	(0.05)	(0.03)
ARM	-2.91	-0.06	-0.05	-1.65	-0.51	-1.64	0.51
	(0.04)	(0.01)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)
AUS	-1.89	-0.13	-0.13	-0.35	-0.13	-0.72	0.50
	(0.04)	(0.01)	(0.01)	(0.11)	(0.01)	(0.13)	(0.03)
AUT	-1.42	0.20	0.21	1.58	-0.44	1.56	0.47
	(0.03)	(0.00)	(0.00)	(0.05)	(0.01)	(0.05)	(0.01)
AZE	-5.20	-0.56	-0.55	-6.46	-0.80	-6.61	0.96
	(0.15)	(0.02)	(0.02)	(0.27)	(0.02)	(0.29)	(0.04)
BEL	-1.23	0.20	0.22	1.51	-0.20	1.52	0.20
	(0.02)	(0.01)	(0.01)	(0.17)	(0.01)	(0.18)	(0.01)
BGD	-2.49	-0.17	-0.16	-3.11	-0.20	-3.28	0.38
	(0.06)	(0.01)	(0.01)	(0.11)	(0.01)	(0.12)	(0.02)
BGR	-9.79	-1.20	-1.20	-10.08	-1.26	-10.18	1.37
	(0.20)	(0.03)	(0.03)	(0.29)	(0.03)	(0.29)	(0.03)
BHR	-5.35	-0.51	-0.50	-4.04	-0.78	-4.09	0.82
	(0.26)	(0.02)	(0.02)	(0.23)	(0.03)	(0.24)	(0.04)
BLR	-5.62	-0.37	-0.36	-4.81	-0.48	-5.12	0.80
	(0.17)	(0.02)	(0.02)	(0.21)	(0.02)	(0.22)	(0.03)
BOL	-2.99	-0.16	-0.14	0.74	-0.38	0.24	0.88
	(0.06)	(0.00)	(0.00)	(0.04)	(0.02)	(0.06)	(0.05)
BRA	-0.87	0.02	0.03	0.24	-0.03	-0.06	0.32
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)
BWA	-5.41	-0.46	-0.44	-0.94	-0.46	-1.05	0.57
	(0.09)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
CAN	-1.50	-0.01	-0.01	0.64	-0.10	0.21	0.53
	(0.03)	(0.00)	(0.00)	(0.08)	(0.00)	(0.06)	(0.03)
CHE	-0.96	0.17	0.19	-0.14	-0.16	-0.08	0.09
	(0.01)	(0.01)	(0.01)	(0.05)	(0.00)	(0.05)	(0.01)
CHL	-1.75	-0.02	-0.01	0.63	-0.23	0.64	0.22
	(0.03)	(0.00)	(0.00)	(0.04)	(0.01)	(0.05)	(0.01)
CHN	-3.38	-0.11	-0.11	-0.59	-0.12	-0.80	0.33
	(0.07)	(0.01)	(0.01)	(0.08)	(0.01)	(0.10)	(0.02)
CIV	-1.94	-0.12	-0.10	-3.84	-0.20	-4.13	0.50
	(0.07)	(0.00)	(0.00)	(0.24)	(0.01)	(0.25)	(0.02)
CMR	-1.41	-0.05	-0.03	-2.18	-0.16	-2.68	0.68
	(0.04)	(0.00)	(0.00)	(0.15)	(0.01)	(0.17)	(0.03)
COL	-1.55	0.00	0.01	1.33	-0.14	0.89	0.58
	(0.01)	(0.00)	(0.00)	(0.06)	(0.01)	(0.05)	(0.03)
CRI	-1.27	-0.02	-0.01	-0.31	-0.14	-0.31	0.14
	(0.02)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)	(0.00)
CYP	-3.19	-0.11	-0.10	-0.21	-0.83	-0.25	0.87
	(0.03)	(0.01)	(0.01)	(0.03)	(0.02)	(0.03)	(0.02)

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Table C.11 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
CZE	-4.82	-0.43	-0.43	-4.43	-0.49	-4.53	0.60
	(0.10)	(0.01)	(0.01)	(0.16)	(0.01)	(0.16)	(0.02)
DEU	-1.57	0.11	0.12	0.40	-0.13	0.26	0.27
	(0.04)	(0.00)	(0.00)	(0.06)	(0.00)	(0.05)	(0.01)
DNK	-1.45	0.14	0.15	1.30	-0.31	0.80	0.80
	(0.02)	(0.00)	(0.00)	(0.05)	(0.01)	(0.04)	(0.03)
ECU	-2.38	-0.25	-0.24	-1.35	-0.26	-1.75	0.66
	(0.03)	(0.01)	(0.01)	(0.16)	(0.01)	(0.19)	(0.04)
EGY	-9.04	-0.83	-0.81	-6.67	-1.05	-6.76	1.15
	(0.23)	(0.04)	(0.03)	(0.45)	(0.05)	(0.47)	(0.07)
ESP	-1.67	0.08	0.10	0.30	-0.15	0.27	0.18
	(0.04)	(0.00)	(0.00)	(0.04)	(0.01)	(0.04)	(0.01)
EST	-5.55	-0.54	-0.54	-1.01	-0.71	-1.15	0.85
	(0.11)	(0.02)	(0.02)	(0.04)	(0.01)	(0.03)	(0.02)
ETH	-4.27	-0.44	-0.42	-2.04	-0.46	-2.38	0.80
	(0.10)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.01)
FIN	-2.03	0.09	0.10	0.26	-0.24	0.24	0.27
	(0.07)	(0.00)	(0.00)	(0.06)	(0.01)	(0.06)	(0.01)
FRA	-1.70	0.24	0.25	2.13	-0.30	2.10	0.33
	(0.02)	(0.00)	(0.01)	(0.15)	(0.01)	(0.15)	(0.01)
GBR	-1.57	0.20	0.22	1.74	-0.21	1.38	0.56
	(0.03)	(0.00)	(0.01)	(0.14)	(0.01)	(0.13)	(0.02)
GEO	-4.93	-0.44	-0.42	-1.48	-0.56	-1.51	0.59
	(0.10)	(0.01)	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)
GHA	-3.74	-0.38	-0.36	-4.80	-0.37	-5.07	0.66
	(0.08)	(0.01)	(0.01)	(0.30)	(0.01)	(0.32)	(0.02)
GRC	-4.24	-0.12	-0.11	0.45	-0.60	0.35	0.70
	(0.05)	(0.01)	(0.01)	(0.09)	(0.02)	(0.10)	(0.02)
GTM	-1.92	-0.05	-0.04	0.01	-0.29	-0.23	0.53
	(0.04)	(0.00)	(0.00)	(0.02)	(0.01)	(0.02)	(0.02)
HKG	-2.14	-0.18	-0.18	-0.03	-0.18	-0.05	0.20
	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HND	-3.26	-0.29	-0.28	-1.40	-0.32	-1.45	0.37
	(0.05)	(0.00)	(0.00)	(0.03)	(0.01)	(0.03)	(0.01)
HRV	-2.77	0.03	0.03	0.63	-0.29	0.22	0.69
	(0.05)	(0.01)	(0.01)	(0.08)	(0.00)	(0.06)	(0.02)
HUN	-1.90	0.06	0.06	-0.11	-0.32	-0.14	0.36
	(0.02)	(0.00)	(0.00)	(0.07)	(0.01)	(0.07)	(0.01)
IDN	-3.58	-0.21	-0.20	-0.54	-0.22	-0.82	0.50
	(0.07)	(0.01)	(0.01)	(0.18)	(0.01)	(0.20)	(0.03)
IND	-3.36	-0.15	-0.13	-0.59	-0.22	-0.75	0.37
	(0.08)	(0.01)	(0.01)	(0.05)	(0.01)	(0.05)	(0.02)
IRL	-1.42	0.11	0.12	-1.59	-0.14	-1.59	0.13
	(0.02)	(0.01)	(0.01)	(0.14)	(0.00)	(0.14)	(0.01)
IRN	-8.98	-0.71	-0.70	-3.56	-0.92	-3.66	1.02
	(0.09)	(0.03)	(0.03)	(0.30)	(0.04)	(0.31)	(0.05)
ISR	-2.35	-0.02	-0.02	-2.67	-0.25	-2.68	0.26
	(0.05)	(0.01)	(0.01)	(0.37)	(0.01)	(0.37)	(0.01)

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Table C.11 – *Continued from previous page*

Country	ΔX^i	$\Delta\Re^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
ITA	-2.26	0.26	0.28	2.51	-0.37	2.46	0.42
	(0.04)	(0.01)	(0.01)	(0.23)	(0.01)	(0.23)	(0.01)
JPN	-1.29	0.09	0.09	0.58	-0.07	0.62	0.04
	(0.03)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)	(0.00)
KAZ	-8.76	-0.93	-0.92	-5.13	-1.11	-5.08	1.05
	(0.15)	(0.02)	(0.02)	(0.38)	(0.03)	(0.40)	(0.06)
KEN	-2.63	-0.20	-0.18	-3.19	-0.21	-3.26	0.28
	(0.05)	(0.01)	(0.00)	(0.25)	(0.01)	(0.26)	(0.01)
KGZ	-8.83	-0.80	-0.79	-0.83	-0.95	-0.91	1.03
	(0.12)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
KHM	-1.93	-0.09	-0.08	-0.82	-0.28	-0.83	0.30
	(0.03)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
KOR	-1.26	0.02	0.03	-0.17	-0.08	-0.19	0.09
	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
KWT	-3.12	-0.41	-0.40	-4.59	-0.50	-4.83	0.75
	(0.12)	(0.02)	(0.02)	(0.17)	(0.02)	(0.18)	(0.03)
LAO	-0.87	-0.01	0.00	-1.05	-0.09	-1.09	0.14
	(0.02)	(0.00)	(0.00)	(0.06)	(0.00)	(0.06)	(0.00)
LKA	-3.99	-0.41	-0.39	-2.23	-0.41	-2.20	0.38
	(0.09)	(0.01)	(0.01)	(0.13)	(0.01)	(0.14)	(0.01)
LTU	-2.77	-0.05	-0.04	-3.38	-0.22	-3.39	0.24
	(0.07)	(0.01)	(0.01)	(0.13)	(0.01)	(0.13)	(0.01)
LUX	-1.22	0.15	0.16	-0.07	-0.31	-0.10	0.34
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LVA	-2.68	-0.12	-0.12	-0.86	-0.37	-0.92	0.44
	(0.04)	(0.01)	(0.01)	(0.03)	(0.00)	(0.03)	(0.00)
MAR	-4.83	-0.40	-0.38	-7.11	-0.40	-7.35	0.66
	(0.18)	(0.02)	(0.02)	(0.56)	(0.02)	(0.58)	(0.04)
MDG	-2.05	-0.17	-0.15	-2.95	-0.16	-3.38	0.61
	(0.05)	(0.00)	(0.00)	(0.14)	(0.00)	(0.17)	(0.03)
MEX	-1.69	-0.12	-0.11	-0.88	-0.13	-1.21	0.46
	(0.07)	(0.01)	(0.01)	(0.26)	(0.01)	(0.27)	(0.03)
MLT	-2.37	-0.12	-0.11	-0.54	-0.65	-0.57	0.68
	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)	(0.03)	(0.01)
MNG	-13.30	-1.60	-1.58	-3.43	-1.72	-3.70	1.99
	(0.44)	(0.04)	(0.04)	(0.06)	(0.04)	(0.07)	(0.03)
MOZ	-3.02	-0.29	-0.27	-3.99	-0.34	-4.12	0.48
	(0.07)	(0.01)	(0.01)	(0.10)	(0.01)	(0.10)	(0.01)
MUS	-3.55	-0.36	-0.34	-1.68	-0.43	-2.09	0.84
	(0.04)	(0.00)	(0.00)	(0.03)	(0.00)	(0.06)	(0.04)
MWI	-1.85	-0.22	-0.20	-0.54	-0.22	-0.99	0.67
	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.05)	(0.03)
MYS	-4.21	-0.40	-0.39	-4.09	-0.46	-4.23	0.61
	(0.07)	(0.01)	(0.01)	(0.41)	(0.02)	(0.42)	(0.03)
NAM	-2.80	-0.26	-0.24	-1.10	-0.25	-1.06	0.20
	(0.04)	(0.00)	(0.00)	(0.03)	(0.00)	(0.02)	(0.00)
NGA	-3.70	-0.45	-0.44	-1.86	-0.41	-2.35	0.92
	(0.13)	(0.01)	(0.01)	(0.40)	(0.01)	(0.42)	(0.04)

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Table C.11 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
NIC	-2.00	-0.02	-0.01	0.44	-0.59	0.40	0.62
	(0.03)	(0.00)	(0.00)	(0.09)	(0.02)	(0.09)	(0.02)
NLD	-1.33	0.26	0.28	2.89	-0.28	2.54	0.62
	(0.02)	(0.01)	(0.01)	(0.15)	(0.01)	(0.14)	(0.02)
NOR	-1.88	0.12	0.13	5.35	-0.65	4.59	1.37
	(0.04)	(0.00)	(0.00)	(0.18)	(0.02)	(0.15)	(0.04)
NPL	-3.16	-0.31	-0.30	-1.78	-0.32	-1.88	0.42
	(0.05)	(0.00)	(0.00)	(0.02)	(0.00)	(0.03)	(0.01)
NZL	-1.32	-0.08	-0.08	-0.59	-0.07	-0.76	0.24
	(0.03)	(0.00)	(0.00)	(0.14)	(0.00)	(0.15)	(0.01)
OMN	-6.29	-0.62	-0.61	-3.57	-0.68	-3.75	0.86
	(0.09)	(0.02)	(0.02)	(0.18)	(0.01)	(0.20)	(0.04)
PAK	-3.65	-0.06	-0.05	-0.26	-0.46	-0.33	0.53
	(0.09)	(0.01)	(0.01)	(0.10)	(0.02)	(0.10)	(0.02)
PAN	-9.02	-1.03	-1.02	-3.59	-1.04	-3.52	0.97
	(0.12)	(0.01)	(0.01)	(0.06)	(0.01)	(0.06)	(0.01)
PER	-1.16	-0.02	-0.01	-0.16	-0.08	-0.42	0.34
	(0.01)	(0.00)	(0.00)	(0.05)	(0.00)	(0.07)	(0.02)
PHL	-1.90	-0.09	-0.07	-1.07	-0.15	-1.07	0.15
	(0.04)	(0.00)	(0.00)	(0.17)	(0.01)	(0.17)	(0.01)
POL	-5.19	-0.42	-0.42	-4.15	-0.54	-4.23	0.63
	(0.13)	(0.02)	(0.02)	(0.29)	(0.02)	(0.29)	(0.03)
PRT	-1.68	0.15	0.17	1.30	-0.31	1.31	0.30
	(0.02)	(0.00)	(0.00)	(0.06)	(0.01)	(0.06)	(0.01)
PRY	-1.74	-0.09	-0.08	-0.97	-0.26	-0.99	0.28
	(0.05)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)
QAT	-3.97	-0.36	-0.35	-6.12	-0.47	-6.45	0.82
	(0.13)	(0.01)	(0.01)	(0.25)	(0.02)	(0.27)	(0.04)
ROU	-5.27	-0.45	-0.45	-6.22	-0.49	-6.27	0.55
	(0.14)	(0.02)	(0.02)	(0.29)	(0.02)	(0.29)	(0.02)
RUS	-4.29	-0.27	-0.27	-1.96	-0.40	-2.21	0.66
	(0.08)	(0.01)	(0.01)	(0.07)	(0.01)	(0.08)	(0.03)
SAU	-3.89	-0.39	-0.38	-2.93	-0.42	-3.24	0.74
	(0.09)	(0.02)	(0.02)	(0.20)	(0.02)	(0.22)	(0.04)
SEN	-3.41	-0.34	-0.32	-3.06	-0.39	-3.08	0.41
	(0.07)	(0.01)	(0.01)	(0.20)	(0.01)	(0.20)	(0.01)
SGP	-0.86	0.04	0.04	-1.19	-0.02	-1.26	0.09
	(0.04)	(0.00)	(0.00)	(0.11)	(0.00)	(0.11)	(0.01)
SLV	-1.48	-0.04	-0.03	-0.20	-0.21	-0.21	0.21
	(0.03)	(0.00)	(0.00)	(0.08)	(0.00)	(0.08)	(0.00)
SVK	-2.20	0.01	0.02	-1.54	-0.24	-1.55	0.26
	(0.04)	(0.01)	(0.01)	(0.08)	(0.00)	(0.08)	(0.00)
SVN	-2.70	-0.09	-0.09	-0.12	-0.34	-0.20	0.42
	(0.03)	(0.01)	(0.01)	(0.02)	(0.00)	(0.02)	(0.00)
SWE	-2.18	0.28	0.29	3.59	-0.71	3.69	0.62
	(0.04)	(0.00)	(0.00)	(0.09)	(0.02)	(0.09)	(0.02)
THA	-2.46	-0.09	-0.09	-0.52	-0.18	-0.68	0.34
	(0.06)	(0.01)	(0.01)	(0.07)	(0.01)	(0.08)	(0.02)

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Table C.11 – *Continued from previous page*

Country	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
TUN	-5.95	-0.61	-0.59	-5.39	-0.69	-5.71	1.03
	(0.11)	(0.01)	(0.01)	(0.22)	(0.02)	(0.24)	(0.03)
TUR	-2.58	0.20	0.21	2.18	-0.43	2.04	0.58
	(0.04)	(0.00)	(0.00)	(0.07)	(0.02)	(0.07)	(0.03)
TWN	-1.52	-0.03	-0.02	-0.77	-0.11	-0.79	0.13
	(0.05)	(0.00)	(0.00)	(0.11)	(0.01)	(0.11)	(0.01)
TZA	-3.23	-0.33	-0.31	-1.60	-0.33	-1.73	0.46
	(0.08)	(0.01)	(0.01)	(0.06)	(0.01)	(0.07)	(0.01)
UGA	-1.51	-0.06	-0.04	0.28	-0.29	-0.32	0.89
	(0.03)	(0.00)	(0.00)	(0.02)	(0.00)	(0.04)	(0.04)
UKR	-10.97	-1.04	-1.04	-5.34	-1.17	-5.34	1.17
	(0.28)	(0.04)	(0.04)	(0.19)	(0.04)	(0.19)	(0.04)
URY	-1.10	0.03	0.04	0.06	-0.13	0.06	0.13
	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)
USA	-1.31	-0.02	-0.01	-0.14	-0.03	-0.38	0.27
	(0.03)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.01)
VEN	-3.52	-0.33	-0.32	-6.07	-0.43	-6.36	0.74
	(0.06)	(0.01)	(0.01)	(0.19)	(0.01)	(0.21)	(0.04)
VNM	-8.61	-0.75	-0.74	-5.76	-0.85	-5.83	0.93
	(0.17)	(0.02)	(0.02)	(0.15)	(0.02)	(0.16)	(0.04)
XAC	-1.11	-0.33	-0.31	-1.76	-0.19	-2.27	0.72
	(0.03)	(0.02)	(0.02)	(0.27)	(0.01)	(0.30)	(0.04)
XCA	-1.04	0.01	0.02	-0.59	-0.14	-0.69	0.24
	(0.02)	(0.00)	(0.00)	(0.05)	(0.00)	(0.05)	(0.01)
XCB	-1.54	-0.05	-0.03	-0.93	-0.09	-1.32	0.48
	(0.05)	(0.00)	(0.00)	(0.06)	(0.00)	(0.08)	(0.02)
XCF	-1.61	-0.23	-0.21	-1.28	-0.17	-1.84	0.73
	(0.03)	(0.01)	(0.01)	(0.13)	(0.01)	(0.16)	(0.04)
XEA	-10.34	-1.55	-1.53	-5.65	-1.67	-5.60	1.62
	(0.12)	(0.02)	(0.02)	(0.08)	(0.02)	(0.06)	(0.02)
XEC	-1.73	-0.12	-0.10	0.16	-0.10	-0.52	0.78
	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.04)
XEE	-8.34	-0.95	-0.95	-1.29	-1.00	-1.35	1.07
	(0.18)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
XEF	-3.07	-0.24	-0.23	-7.96	-0.33	-7.97	0.34
	(0.05)	(0.01)	(0.01)	(0.18)	(0.01)	(0.18)	(0.01)
XER	-6.54	-0.62	-0.61	-3.88	-0.82	-3.95	0.90
	(0.15)	(0.02)	(0.02)	(0.19)	(0.03)	(0.20)	(0.03)
XNA	-1.49	0.05	0.07	-0.47	-0.21	-0.81	0.55
	(0.01)	(0.00)	(0.00)	(0.04)	(0.00)	(0.05)	(0.02)
XNF	-4.47	-0.47	-0.45	-9.24	-0.65	-9.55	0.98
	(0.16)	(0.02)	(0.02)	(0.72)	(0.04)	(0.73)	(0.06)
XOC	-1.40	-0.08	-0.07	-0.44	-0.10	-0.76	0.42
	(0.03)	(0.00)	(0.00)	(0.11)	(0.00)	(0.13)	(0.02)
XSA	-1.62	-0.03	-0.02	-0.83	-0.19	-1.20	0.56
	(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.06)	(0.02)
XSC	-1.17	-0.09	-0.07	-0.06	-0.08	-0.64	0.66
	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)	(0.04)

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Table C.11 – *Continued from previous page*

Country	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE
XSE	-2.90	-0.35	-0.34	-0.71	-0.45	-1.07	0.81
	(0.07)	(0.01)	(0.01)	(0.14)	(0.01)	(0.16)	(0.04)
XSM	-0.65	0.07	0.08	-0.38	-0.06	-0.46	0.14
	(0.01)	(0.00)	(0.01)	(0.07)	(0.00)	(0.07)	(0.00)
XSU	-15.87	-1.46	-1.45	-5.18	-2.05	-4.99	1.85
	(0.12)	(0.04)	(0.04)	(0.18)	(0.06)	(0.20)	(0.08)
XWF	-3.01	-0.27	-0.26	-1.07	-0.27	-1.60	0.81
	(0.04)	(0.00)	(0.00)	(0.08)	(0.00)	(0.12)	(0.04)
XWS	-7.78	-0.75	-0.74	-3.20	-1.05	-3.24	1.09
	(0.18)	(0.03)	(0.03)	(0.26)	(0.05)	(0.27)	(0.06)
ZAF	-5.16	-0.39	-0.37	-2.05	-0.44	-2.27	0.67
	(0.15)	(0.02)	(0.02)	(0.37)	(0.02)	(0.39)	(0.04)
ZMB	-1.04	0.00	0.02	-0.62	0.00	-0.76	0.14
	(0.04)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
ZWE	-12.00	-1.31	-1.29	-3.12	-1.36	-3.02	1.26
	(0.33)	(0.04)	(0.04)	(0.10)	(0.04)	(0.10)	(0.04)

Notes: ΔX^i denotes the percentage changes in trade flows, $\Delta\mathfrak{R}^i$ the percentage changes in real income, ΔU^i the percentage changes in welfare, ΔE^i the percentage changes in carbon emissions, PSE the percentage scale effects, PCE the percentage composition effects, and PTE the percentage technique effects. The numbers in parentheses below the reported values give the corresponding bootstrapped standard errors.

Table C.12: Copenhagen Accord (Appendix I, Without Tariffs)

	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
ALB	-0.05	-0.05	0.09	5.19	-0.05	5.24	0.00	-0.01	1.01	0.00
	(0.01)	(0.02)	(0.03)	(0.14)	(0.02)	(0.12)	(0.00)	(0.01)	(0.01)	(0.00)
ARE	-0.08	0.34	0.44	4.42	0.34	4.06	0.00	0.08	0.92	0.00
	(0.01)	(0.02)	(0.02)	(0.27)	(0.02)	(0.25)	(0.00)	(0.00)	(0.00)	(0.00)
ARG	-0.21	0.19	0.32	3.11	0.19	2.92	0.00	0.06	0.94	0.00
	(0.01)	(0.03)	(0.03)	(0.38)	(0.03)	(0.35)	(0.00)	(0.00)	(0.00)	(0.00)
ARM	0.00	0.04	0.17	1.34	0.04	1.30	0.00	0.03	0.97	0.00
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
AUS	0.24	-0.77	-0.77	-23.02	-0.77	-2.92	-25.14	0.03	0.11	0.86
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.21)	(0.27)	(0.00)	(0.01)	(0.01)
AUT	0.17	-1.52	-1.38	-37.91	-1.52	-5.00	-50.69	0.03	0.11	0.86
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.07)	(0.09)	(0.00)	(0.00)	(0.00)
AZE	-0.25	1.04	1.18	6.90	1.04	5.80	0.00	0.16	0.84	0.00
	(0.04)	(0.02)	(0.02)	(0.19)	(0.02)	(0.16)	(0.00)	(0.00)	(0.00)	(0.00)
BEL	-0.03	-1.41	-1.27	-22.94	-1.41	-3.72	-23.18	0.05	0.15	0.80
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)	(0.18)	(0.00)	(0.01)	(0.01)
BGD	-0.06	0.01	0.14	1.87	0.01	1.86	0.00	0.01	0.99	0.00
	(0.01)	(0.00)	(0.00)	(0.08)	(0.00)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)
BGR	-0.11	-0.01	0.03	0.00	-0.01	4.24	-4.23	-	-	-
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.06)	(0.06)	-	-	-
BHR	-0.05	2.09	2.19	7.72	2.09	5.51	0.00	0.28	0.72	0.00
	(0.01)	(0.13)	(0.13)	(0.50)	(0.13)	(0.36)	(0.00)	(0.00)	(0.00)	(0.00)
BLR	-0.07	0.24	0.28	0.00	0.24	3.10	-3.35	-	-	-
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.07)	(0.07)	-	-	-
BOL	-0.32	0.45	0.58	4.07	0.45	3.61	0.00	0.11	0.89	0.00
	(0.05)	(0.03)	(0.03)	(0.28)	(0.03)	(0.24)	(0.00)	(0.00)	(0.00)	(0.00)
BRA	-0.25	0.04	0.17	1.72	0.04	1.67	0.00	0.02	0.98	0.00
	(0.01)	(0.01)	(0.01)	(0.25)	(0.01)	(0.23)	(0.00)	(0.01)	(0.01)	(0.00)
BWA	-0.01	-0.10	0.10	0.07	-0.10	0.17	0.00	-1.51	2.51	0.00
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.13)	(0.13)	(0.00)
CAN	0.08	-0.89	-0.89	-16.66	-0.89	-1.14	-17.57	0.05	0.06	0.89
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)	(0.12)	(0.00)	(0.01)	(0.01)
CHE	-0.08	-0.37	-0.22	-15.94	-0.37	1.82	-20.68	0.02	-0.10	1.08
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.08)	(0.00)	(0.00)	(0.00)
CHL	-0.29	0.04	0.13	1.65	0.04	1.61	0.00	0.03	0.97	0.00
	(0.01)	(0.02)	(0.01)	(0.22)	(0.02)	(0.21)	(0.00)	(0.01)	(0.01)	(0.00)
CHN	-0.41	0.06	0.07	1.36	0.06	1.30	0.00	0.05	0.95	0.00
	(0.01)	(0.01)	(0.01)	(0.16)	(0.01)	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)
CIV	-0.22	0.88	1.08	10.75	0.88	9.79	0.00	0.09	0.91	0.00
	(0.01)	(0.03)	(0.02)	(0.40)	(0.03)	(0.37)	(0.00)	(0.00)	(0.00)	(0.00)
CMR	-0.12	0.41	0.61	8.13	0.41	7.70	0.00	0.05	0.95	0.00
	(0.02)	(0.01)	(0.01)	(0.28)	(0.01)	(0.27)	(0.00)	(0.00)	(0.00)	(0.00)
COL	-0.16	0.19	0.28	4.47	0.19	4.27	0.00	0.04	0.96	0.00
	(0.01)	(0.02)	(0.02)	(0.42)	(0.02)	(0.40)	(0.00)	(0.00)	(0.00)	(0.00)
CRI	-0.14	-0.11	-0.01	2.99	-0.11	3.10	0.00	-0.04	1.04	0.00
	(0.02)	(0.00)	(0.00)	(0.20)	(0.00)	(0.20)	(0.00)	(0.00)	(0.00)	(0.00)
CYP	-0.05	-2.33	-2.21	-57.38	-2.33	-7.58	-111.8	0.03	0.09	0.88
	(0.02)	(0.02)	(0.02)	(0.00)	(0.02)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)

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Table C.12 – *Continued from previous page*

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
CZE	-0.04	-0.72	-0.68	-15.67	-0.72	1.37	-19.34	0.04	-0.08	1.04
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.08)	(0.00)	(0.00)	(0.00)
DEU	-0.18	-0.56	-0.41	-10.65	-0.56	2.25	-13.81	0.05	-0.20	1.15
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.09)	(0.00)	(0.01)	(0.01)
DNK	-0.14	-0.44	-0.30	-10.05	-0.44	2.16	-13.08	0.04	-0.20	1.16
	(0.02)	(0.00)	(0.01)	(0.00)	(0.00)	(0.06)	(0.07)	(0.00)	(0.01)	(0.01)
ECU	-0.25	0.30	0.39	4.92	0.30	4.60	0.00	0.06	0.94	0.00
	(0.02)	(0.03)	(0.03)	(0.44)	(0.03)	(0.40)	(0.00)	(0.00)	(0.00)	(0.00)
EGY	-0.28	0.78	0.98	6.65	0.78	5.83	0.00	0.12	0.88	0.00
	(0.01)	(0.04)	(0.04)	(0.38)	(0.04)	(0.34)	(0.00)	(0.00)	(0.00)	(0.00)
ESP	1.06	-2.68	-2.54	-54.23	-2.68	-9.88	-91.65	0.03	0.13	0.83
	(0.01)	(0.02)	(0.02)	(0.00)	(0.02)	(0.61)	(1.25)	(0.00)	(0.01)	(0.01)
EST	-0.04	-0.45	-0.41	-8.48	-0.45	0.71	-9.55	0.05	-0.08	1.03
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.03)	(0.03)	(0.00)	(0.00)	(0.00)
ETH	-0.07	-0.15	0.05	0.48	-0.15	0.63	0.00	-0.31	1.31	0.00
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
FIN	0.73	-2.41	-2.27	-39.35	-2.41	-10.91	-43.35	0.05	0.23	0.72
	(0.05)	(0.02)	(0.02)	(0.00)	(0.02)	(0.27)	(0.42)	(0.00)	(0.01)	(0.01)
FRA	0.01	-0.97	-0.83	-24.86	-0.97	-0.99	-30.47	0.03	0.03	0.93
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.11)	(0.14)	(0.00)	(0.00)	(0.00)
GBR	0.04	-0.83	-0.69	-21.08	-0.83	-0.64	-24.86	0.04	0.03	0.94
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)	(0.12)	(0.00)	(0.00)	(0.00)
GEO	-0.01	-0.09	0.04	0.57	-0.09	0.66	0.00	-0.16	1.16	0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
GHA	-0.10	0.21	0.41	5.22	0.21	5.00	0.00	0.04	0.96	0.00
	(0.01)	(0.01)	(0.01)	(0.22)	(0.01)	(0.21)	(0.00)	(0.00)	(0.00)	(0.00)
GRC	0.90	-4.84	-4.70	-43.30	-4.84	-10.50	-50.21	0.09	0.20	0.72
	(0.08)	(0.03)	(0.03)	(0.00)	(0.03)	(0.17)	(0.24)	(0.00)	(0.00)	(0.00)
GTM	-0.10	-0.14	0.00	0.71	-0.14	0.84	0.00	-0.19	1.19	0.00
	(0.02)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)	(0.01)	(0.01)	(0.00)
HKG	-0.07	-0.13	-0.13	-0.06	-0.13	0.08	0.00	2.35	-1.35	0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.13)	(0.13)	(0.00)
HND	-0.11	-0.23	-0.10	0.41	-0.23	0.64	0.00	-0.57	1.57	0.00
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)
HRV	0.50	-4.00	-3.97	-48.44	-4.00	-9.46	-68.58	0.06	0.15	0.79
	(0.08)	(0.02)	(0.02)	(0.00)	(0.02)	(0.09)	(0.14)	(0.00)	(0.00)	(0.00)
HUN	-0.08	-0.51	-0.47	-6.83	-0.51	3.10	-10.10	0.07	-0.43	1.36
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.07)	(0.08)	(0.00)	(0.01)	(0.01)
IDN	-0.35	0.12	0.25	2.09	0.12	1.97	0.00	0.06	0.94	0.00
	(0.02)	(0.02)	(0.02)	(0.27)	(0.02)	(0.25)	(0.00)	(0.00)	(0.00)	(0.00)
IND	-0.19	0.20	0.45	2.07	0.20	1.87	0.00	0.10	0.90	0.00
	(0.02)	(0.02)	(0.02)	(0.21)	(0.02)	(0.19)	(0.00)	(0.00)	(0.00)	(0.00)
IRL	0.07	-0.93	-0.79	-47.60	-0.93	-7.79	-74.32	0.01	0.13	0.86
	(0.03)	(0.01)	(0.00)	(0.00)	(0.01)	(0.07)	(0.12)	(0.00)	(0.00)	(0.00)
IRN	-0.46	0.67	0.77	3.91	0.67	3.22	0.00	0.18	0.82	0.00
	(0.02)	(0.06)	(0.06)	(0.34)	(0.06)	(0.27)	(0.00)	(0.00)	(0.00)	(0.00)
ISR	-0.13	0.28	0.28	6.36	0.28	6.07	0.00	0.05	0.95	0.00
	(0.01)	(0.03)	(0.03)	(0.50)	(0.03)	(0.47)	(0.00)	(0.00)	(0.00)	(0.00)

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Table C.12 – *Continued from previous page*

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
ITA	0.41	-1.51	-1.37	-32.31	-1.51	-3.93	-39.80	0.04	0.10	0.86
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.26)	(0.38)	(0.00)	(0.01)	(0.01)
JPN	1.13	-1.50	-1.48	-34.38	-1.50	-4.26	-43.72	0.04	0.10	0.86
	(0.04)	(0.01)	(0.01)	(0.00)	(0.01)	(0.33)	(0.49)	(0.00)	(0.01)	(0.01)
KAZ	-0.10	-0.04	0.05	0.00	-0.04	2.15	-2.11	-	-	-
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.08)	-	-	-
KEN	-0.08	0.17	0.37	4.99	0.17	4.81	0.00	0.04	0.96	0.00
	(0.01)	(0.01)	(0.01)	(0.31)	(0.01)	(0.30)	(0.00)	(0.00)	(0.00)	(0.00)
KGZ	-0.02	0.02	0.16	0.45	0.02	0.42	0.00	0.05	0.95	0.00
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
KHM	-0.03	-0.21	-0.08	0.13	-0.21	0.34	0.00	-1.67	2.67	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.12)	(0.12)	(0.00)
KOR	-0.44	0.37	0.49	4.47	0.37	4.09	0.00	0.08	0.92	0.00
	(0.03)	(0.04)	(0.03)	(0.38)	(0.04)	(0.34)	(0.00)	(0.00)	(0.00)	(0.00)
KWT	-0.09	1.58	1.68	8.58	1.58	6.89	0.00	0.19	0.81	0.00
	(0.01)	(0.08)	(0.07)	(0.43)	(0.08)	(0.34)	(0.00)	(0.00)	(0.00)	(0.00)
LAO	0.00	0.09	0.22	3.21	0.09	3.12	0.00	0.03	0.97	0.00
	(0.00)	(0.00)	(0.00)	(0.14)	(0.00)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
LKA	-0.12	0.05	0.18	2.25	0.05	2.20	0.00	0.02	0.98	0.00
	(0.02)	(0.01)	(0.01)	(0.16)	(0.01)	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)
LTU	-0.07	0.06	0.10	0.00	0.06	5.16	-5.22	-	-	-
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.10)	(0.10)	-	-	-
LUX	-0.01	-1.17	-1.03	-31.94	-1.17	-1.00	-43.76	0.03	0.03	0.94
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
LVA	-0.01	-0.26	-0.23	0.00	-0.26	0.51	-0.24	-	-	-
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	-	-	-
MAR	-0.55	0.60	0.80	12.48	0.60	11.81	0.00	0.05	0.95	0.00
	(0.06)	(0.02)	(0.02)	(0.40)	(0.02)	(0.39)	(0.00)	(0.00)	(0.00)	(0.00)
MDG	-0.04	-0.07	0.13	2.42	-0.07	2.49	0.00	-0.03	1.03	0.00
	(0.01)	(0.00)	(0.00)	(0.06)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
MEX	-0.43	0.06	0.15	3.91	0.06	3.85	0.00	0.02	0.98	0.00
	(0.01)	(0.03)	(0.03)	(0.67)	(0.03)	(0.64)	(0.00)	(0.01)	(0.01)	(0.00)
MLT	-0.03	-0.60	-0.48	-40.04	-0.60	-5.83	-56.12	0.01	0.12	0.87
	(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.01)	(0.03)	(0.00)	(0.00)	(0.00)
MNG	-0.02	-0.18	-0.05	0.05	-0.18	0.23	0.00	-3.55	4.55	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.70)	(0.70)	(0.00)
MOZ	-0.02	-0.06	0.14	0.68	-0.06	0.74	0.00	-0.08	1.08	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
MUS	-0.04	-0.17	0.03	1.15	-0.17	1.32	0.00	-0.15	1.15	0.00
	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
MWI	-0.02	-0.10	0.10	1.94	-0.10	2.05	0.00	-0.05	1.05	0.00
	(0.00)	(0.00)	(0.01)	(0.07)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
MYS	-0.12	0.11	0.24	2.54	0.11	2.42	0.00	0.04	0.96	0.00
	(0.01)	(0.02)	(0.02)	(0.28)	(0.02)	(0.26)	(0.00)	(0.00)	(0.00)	(0.00)
NAM	-0.02	-0.15	0.05	-0.23	-0.15	-0.08	0.00	0.66	0.34	0.00
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
NGA	-0.15	0.00	0.20	3.99	0.00	3.99	0.00	0.00	1.00	0.00
	(0.02)	(0.01)	(0.01)	(0.24)	(0.01)	(0.24)	(0.00)	(0.00)	(0.00)	(0.00)

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Table C.12 – *Continued from previous page*

	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
NIC	-0.09	0.31	0.45	3.77	0.31	3.45	0.00	0.08	0.92	0.00
	(0.02)	(0.02)	(0.02)	(0.18)	(0.02)	(0.16)	(0.00)	(0.00)	(0.00)	(0.00)
NLD	0.22	-1.88	-1.74	-30.72	-1.88	-9.68	-27.92	0.05	0.28	0.67
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.13)	(0.17)	(0.00)	(0.00)	(0.00)
NOR	0.82	-3.20	-3.06	-54.75	-3.20	-20.36	-70.40	0.04	0.29	0.67
	(0.09)	(0.03)	(0.02)	(0.00)	(0.03)	(0.29)	(0.57)	(0.00)	(0.00)	(0.00)
NPL	-0.02	-0.09	0.04	0.68	-0.09	0.77	0.00	-0.13	1.13	0.00
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
NZL	0.82	-1.41	-1.41	-40.22	-1.41	-8.51	-50.90	0.03	0.17	0.80
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.44)	(0.71)	(0.00)	(0.01)	(0.01)
OMN	-0.10	0.36	0.46	3.63	0.36	3.25	0.00	0.10	0.90	0.00
	(0.02)	(0.01)	(0.01)	(0.15)	(0.01)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
PAK	-0.15	0.22	0.36	2.25	0.22	2.02	0.00	0.10	0.90	0.00
	(0.02)	(0.02)	(0.01)	(0.14)	(0.02)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
PAN	-0.03	-0.35	-0.26	-0.27	-0.35	0.08	0.00	1.31	-0.31	0.00
	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.04)	(0.04)	(0.00)
PER	-0.25	0.14	0.23	4.11	0.14	3.97	0.00	0.03	0.97	0.00
	(0.01)	(0.02)	(0.02)	(0.43)	(0.02)	(0.41)	(0.00)	(0.00)	(0.00)	(0.00)
PHL	-0.21	0.09	0.22	3.37	0.09	3.28	0.00	0.03	0.97	0.00
	(0.02)	(0.02)	(0.01)	(0.28)	(0.02)	(0.26)	(0.00)	(0.00)	(0.00)	(0.00)
POL	-0.06	-0.65	-0.61	-12.15	-0.65	1.48	-14.76	0.05	-0.11	1.06
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.08)	(0.00)	(0.01)	(0.01)
PRT	0.59	-2.64	-2.50	-48.00	-2.64	-8.81	-70.74	0.04	0.14	0.82
	(0.06)	(0.01)	(0.01)	(0.00)	(0.01)	(0.29)	(0.52)	(0.00)	(0.00)	(0.00)
PRY	-0.05	-0.12	-0.02	-0.18	-0.12	-0.06	0.00	0.66	0.34	0.00
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.06)	(0.06)	(0.00)
QAT	-0.02	0.42	0.52	5.60	0.42	5.15	0.00	0.08	0.92	0.00
	(0.01)	(0.02)	(0.02)	(0.28)	(0.02)	(0.26)	(0.00)	(0.00)	(0.00)	(0.00)
ROU	-0.16	-0.07	-0.03	0.00	-0.07	5.25	-5.18	-	-	-
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.10)	(0.09)	-	-	-
RUS	-0.05	0.01	0.01	-0.13	0.01	2.14	-2.28	-0.10	-16.59	17.69
	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.08)	(0.01)	(0.59)	(0.59)
SAU	-0.28	0.75	0.85	4.71	0.75	3.92	0.00	0.16	0.84	0.00
	(0.03)	(0.06)	(0.06)	(0.38)	(0.06)	(0.31)	(0.00)	(0.00)	(0.00)	(0.00)
SEN	-0.24	0.40	0.60	6.96	0.40	6.53	0.00	0.06	0.94	0.00
	(0.03)	(0.00)	(0.01)	(0.14)	(0.00)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
SGP	-0.08	0.47	0.47	4.74	0.47	4.25	0.00	0.10	0.90	0.00
	(0.01)	(0.05)	(0.05)	(0.46)	(0.05)	(0.40)	(0.00)	(0.00)	(0.00)	(0.00)
SLV	-0.10	0.06	0.15	3.89	0.06	3.83	0.00	0.01	0.99	0.00
	(0.02)	(0.01)	(0.01)	(0.24)	(0.01)	(0.23)	(0.00)	(0.00)	(0.00)	(0.00)
SVK	-0.02	-0.66	-0.62	-9.90	-0.66	1.64	-12.06	0.06	-0.16	1.09
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.08)	(0.00)	(0.01)	(0.01)
SVN	0.01	-1.40	-1.37	-42.39	-1.40	-1.03	-69.38	0.03	0.02	0.96
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.03)	(0.05)	(0.00)	(0.00)	(0.00)
SWE	0.01	-0.92	-0.78	-18.93	-0.92	-0.83	-21.21	0.04	0.04	0.92
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.13)	(0.16)	(0.00)	(0.01)	(0.01)
THA	-0.23	0.24	0.33	2.76	0.24	2.52	0.00	0.09	0.91	0.00
	(0.01)	(0.03)	(0.03)	(0.29)	(0.03)	(0.26)	(0.00)	(0.00)	(0.00)	(0.00)

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Table C.12 – *Continued from previous page*

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
TUN	-0.13	0.10	0.30	6.25	0.10	6.14	0.00	0.02	0.98	0.00
	(0.03)	(0.01)	(0.01)	(0.14)	(0.01)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
TUR	-0.30	0.17	0.27	4.20	0.17	4.02	0.00	0.04	0.96	0.00
	(0.01)	(0.01)	(0.01)	(0.27)	(0.01)	(0.26)	(0.00)	(0.00)	(0.00)	(0.00)
TWN	-0.44	0.26	0.39	4.08	0.26	3.80	0.00	0.07	0.93	0.00
	(0.02)	(0.03)	(0.03)	(0.37)	(0.03)	(0.34)	(0.00)	(0.00)	(0.00)	(0.00)
TZA	-0.03	-0.08	0.11	0.52	-0.08	0.61	0.00	-0.16	1.16	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)
UGA	-0.05	-0.03	0.16	1.88	-0.03	1.92	0.00	-0.02	1.02	0.00
	(0.01)	(0.00)	(0.01)	(0.07)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)
UKR	-0.24	-0.06	-0.02	0.00	-0.06	1.95	-1.89	-	-	-
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.05)	(0.04)	-	-	-
URY	-0.09	0.11	0.20	3.18	0.11	3.06	0.00	0.04	0.96	0.00
	(0.02)	(0.01)	(0.01)	(0.22)	(0.01)	(0.20)	(0.00)	(0.00)	(0.00)	(0.00)
USA	0.03	-0.62	-0.60	-17.00	-0.62	-0.86	-18.70	0.03	0.05	0.92
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.13)	(0.16)	(0.00)	(0.01)	(0.01)
VEN	-0.05	0.70	0.80	7.77	0.70	7.01	0.00	0.09	0.91	0.00
	(0.03)	(0.03)	(0.03)	(0.41)	(0.03)	(0.37)	(0.00)	(0.00)	(0.00)	(0.00)
VNM	-0.23	-0.10	0.04	0.63	-0.10	0.73	0.00	-0.16	1.16	0.00
	(0.03)	(0.00)	(0.01)	(0.02)	(0.00)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)
XAC	-0.14	0.06	0.26	5.21	0.06	5.15	0.00	0.01	0.99	0.00
	(0.01)	(0.01)	(0.01)	(0.32)	(0.01)	(0.31)	(0.00)	(0.00)	(0.00)	(0.00)
XCA	-0.01	0.11	0.20	5.41	0.11	5.29	0.00	0.02	0.98	0.00
	(0.00)	(0.01)	(0.01)	(0.24)	(0.01)	(0.22)	(0.00)	(0.00)	(0.00)	(0.00)
XCB	-0.21	0.38	0.50	5.12	0.38	4.72	0.00	0.08	0.92	0.00
	(0.02)	(0.04)	(0.03)	(0.48)	(0.04)	(0.44)	(0.00)	(0.00)	(0.00)	(0.00)
XCF	-0.19	0.10	0.29	5.71	0.10	5.61	0.00	0.02	0.98	0.00
	(0.01)	(0.01)	(0.01)	(0.31)	(0.01)	(0.30)	(0.00)	(0.00)	(0.00)	(0.00)
XEA	-0.01	0.02	0.14	1.71	0.02	1.70	0.00	0.01	0.99	0.00
	(0.00)	(0.01)	(0.01)	(0.15)	(0.01)	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)
XEC	-0.27	0.18	0.38	3.33	0.18	3.14	0.00	0.06	0.94	0.00
	(0.01)	(0.02)	(0.01)	(0.28)	(0.02)	(0.26)	(0.00)	(0.00)	(0.00)	(0.00)
XEE	0.00	-0.21	-0.17	0.25	-0.21	0.46	0.00	-0.82	1.82	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.04)	(0.04)	(0.00)
XEF	0.03	-1.36	-1.22	-25.00	-1.36	-11.93	-15.82	0.05	0.44	0.51
	(0.02)	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
XER	-0.40	0.51	0.64	6.68	0.51	6.13	0.00	0.08	0.92	0.00
	(0.04)	(0.01)	(0.01)	(0.14)	(0.01)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
XNA	-0.10	0.86	1.00	11.77	0.86	10.82	0.00	0.08	0.92	0.00
	(0.02)	(0.01)	(0.01)	(0.10)	(0.01)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)
XNF	-0.41	1.23	1.43	12.64	1.23	11.28	0.00	0.10	0.90	0.00
	(0.03)	(0.05)	(0.05)	(0.60)	(0.05)	(0.54)	(0.00)	(0.00)	(0.00)	(0.00)
XOC	-0.23	0.14	0.24	4.44	0.14	4.29	0.00	0.03	0.97	0.00
	(0.01)	(0.01)	(0.01)	(0.37)	(0.01)	(0.36)	(0.00)	(0.00)	(0.00)	(0.00)
XSA	-0.04	0.15	0.28	4.41	0.15	4.25	0.00	0.03	0.97	0.00
	(0.01)	(0.00)	(0.00)	(0.10)	(0.00)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)
XSC	-0.01	-0.08	0.12	2.05	-0.08	2.13	0.00	-0.04	1.04	0.00
	(0.00)	(0.00)	(0.00)	(0.08)	(0.00)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)

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Table C.12 – *Continued from previous page*

	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
XSE	-0.10	0.12	0.25	2.99	0.12	2.87	0.00	0.04	0.96	0.00
	(0.01)	(0.01)	(0.01)	(0.18)	(0.01)	(0.17)	(0.00)	(0.00)	(0.00)	(0.00)
XSM	-0.09	0.26	0.35	7.68	0.26	7.40	0.00	0.04	0.96	0.00
	(0.02)	(0.01)	(0.01)	(0.30)	(0.01)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)
XSU	-0.29	0.79	0.92	3.04	0.79	2.23	0.00	0.26	0.74	0.00
	(0.02)	(0.03)	(0.03)	(0.14)	(0.03)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)
XWF	-0.13	-0.03	0.17	2.76	-0.03	2.79	0.00	-0.01	1.01	0.00
	(0.01)	(0.00)	(0.00)	(0.09)	(0.00)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)
XWS	-0.45	0.57	0.70	3.77	0.57	3.18	0.00	0.15	0.85	0.00
	(0.02)	(0.05)	(0.05)	(0.35)	(0.05)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)
ZAF	-0.20	0.09	0.29	2.81	0.09	2.72	0.00	0.03	0.97	0.00
	(0.02)	(0.02)	(0.02)	(0.44)	(0.02)	(0.42)	(0.00)	(0.00)	(0.00)	(0.00)
ZMB	-0.09	0.05	0.25	1.86	0.05	1.81	0.00	0.03	0.97	0.00
	(0.01)	(0.00)	(0.00)	(0.08)	(0.00)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)
ZWE	-0.04	0.08	0.28	1.17	0.08	1.09	0.00	0.07	0.93	0.00
	(0.01)	(0.00)	(0.00)	(0.05)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: ΔX^i denotes the percentage changes in trade flows, $\Delta\mathfrak{R}^i$ the percentage changes in real income, ΔU^i the percentage changes in welfare, ΔE^i the percentage changes in carbon emissions, PSE the percentage scale effects, PCE the percentage composition effects, PTE the percentage technique effects, LSE the log scale effects, LCE the log composition effects, and LTE the log technique effects. Note that for countries with constant emissions, these log changes are not defined. The numbers in parentheses below the reported values give the corresponding bootstrapped standard errors.

Table C.13: Copenhagen Accord (Appendix I, With Tariffs)

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
ALB	-4.92	-1.31	-1.17	-1.75	-1.31	-0.44	0.00	0.75	0.25	0.00
	(0.07)	(0.04)	(0.04)	(0.11)	(0.04)	(0.08)	(0.00)	(0.03)	(0.03)	(0.00)
ARE	-3.88	-0.17	-0.06	1.20	-0.17	1.37	0.00	-0.14	1.14	0.00
	(0.14)	(0.01)	(0.01)	(0.11)	(0.01)	(0.11)	(0.00)	(0.02)	(0.02)	(0.00)
ARG	-2.21	-0.14	0.00	1.26	-0.14	1.41	0.00	-0.11	1.11	0.00
	(0.06)	(0.01)	(0.01)	(0.16)	(0.01)	(0.15)	(0.00)	(0.02)	(0.02)	(0.00)
ARM	-2.16	-0.26	-0.11	-0.12	-0.26	0.15	0.00	2.27	-1.27	0.00
	(0.03)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.17)	(0.17)	(0.00)
AUS	-0.29	-0.69	-0.69	-23.02	-0.80	-1.33	-27.14	0.03	0.05	0.92
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.15)	(0.20)	(0.00)	(0.01)	(0.01)
AUT	-0.19	-1.45	-1.30	-37.91	-1.66	-4.27	-51.63	0.04	0.09	0.87
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.04)	(0.06)	(0.00)	(0.00)	(0.00)
AZE	-6.72	-0.33	-0.19	1.09	-0.33	1.42	0.00	-0.31	1.31	0.00
	(0.08)	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)
BEL	-0.20	-1.33	-1.18	-22.94	-1.44	-2.87	-24.23	0.06	0.11	0.83
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.08)	(0.11)	(0.00)	(0.00)	(0.00)
BGD	-1.82	-0.23	-0.08	0.50	-0.23	0.73	0.00	-0.45	1.45	0.00
	(0.07)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)
BGR	-0.39	0.17	0.21	0.00	0.00	5.24	-5.23	-	-	-
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.07)	(0.06)	-	-	-
BHR	-5.17	0.26	0.37	1.68	0.26	1.42	0.00	0.15	0.85	0.00
	(0.27)	(0.03)	(0.03)	(0.17)	(0.03)	(0.13)	(0.00)	(0.01)	(0.01)	(0.00)
BLR	-0.20	0.36	0.40	0.00	0.28	3.64	-3.92	-	-	-
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.07)	(0.07)	-	-	-
BOL	-3.46	-0.24	-0.10	1.13	-0.24	1.37	0.00	-0.22	1.22	0.00
	(0.14)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.00)	(0.02)	(0.02)	(0.00)
BRA	-2.33	-0.16	-0.02	0.73	-0.16	0.89	0.00	-0.22	1.22	0.00
	(0.05)	(0.01)	(0.01)	(0.11)	(0.01)	(0.11)	(0.00)	(0.04)	(0.04)	(0.00)
BWA	-3.52	-0.38	-0.16	-0.40	-0.38	-0.02	0.00	0.96	0.04	0.00
	(0.08)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
CAN	-0.28	-0.83	-0.83	-16.66	-0.92	-0.49	-18.31	0.05	0.03	0.92
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.04)	(0.00)	(0.00)	(0.00)
CHE	-0.14	-0.30	-0.15	-15.94	-0.35	2.51	-21.53	0.02	-0.14	1.12
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)	(0.00)	(0.00)	(0.00)
CHL	-2.79	-0.30	-0.20	0.77	-0.30	1.07	0.00	-0.39	1.39	0.00
	(0.06)	(0.01)	(0.01)	(0.04)	(0.01)	(0.04)	(0.00)	(0.02)	(0.02)	(0.00)
CHN	-2.16	-0.07	-0.06	0.56	-0.07	0.62	0.00	-0.12	1.12	0.00
	(0.05)	(0.01)	(0.01)	(0.08)	(0.01)	(0.08)	(0.00)	(0.03)	(0.03)	(0.00)
CIV	-3.72	-0.24	-0.02	2.41	-0.24	2.66	0.00	-0.10	1.10	0.00
	(0.10)	(0.03)	(0.03)	(0.09)	(0.03)	(0.07)	(0.00)	(0.02)	(0.02)	(0.00)
CMR	-3.08	-0.31	-0.10	2.08	-0.31	2.40	0.00	-0.15	1.15	0.00
	(0.07)	(0.02)	(0.02)	(0.08)	(0.02)	(0.07)	(0.00)	(0.01)	(0.01)	(0.00)
COL	-2.74	-0.19	-0.08	1.39	-0.19	1.57	0.00	-0.13	1.13	0.00
	(0.07)	(0.01)	(0.01)	(0.14)	(0.01)	(0.14)	(0.00)	(0.02)	(0.02)	(0.00)
CRI	-2.46	-0.48	-0.38	0.65	-0.48	1.13	0.00	-0.74	1.74	0.00
	(0.05)	(0.02)	(0.02)	(0.05)	(0.02)	(0.03)	(0.00)	(0.09)	(0.09)	(0.00)
CYP	-1.92	-2.37	-2.23	-57.38	-3.51	-7.32	-109.8	0.04	0.09	0.87
	(0.08)	(0.02)	(0.02)	(0.00)	(0.02)	(0.01)	(0.05)	(0.00)	(0.00)	(0.00)

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Table C.13 – *Continued from previous page*

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
CZE	-0.26	-0.65	-0.61	-15.67	-0.78	2.24	-20.29	0.05	-0.13	1.08
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.07)	(0.07)	(0.00)	(0.00)	(0.00)
DEU	-0.32	-0.50	-0.34	-10.65	-0.56	2.98	-14.61	0.05	-0.26	1.21
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.15)	(0.16)	(0.00)	(0.01)	(0.01)
DNK	-0.28	-0.36	-0.21	-10.05	-0.45	2.81	-13.78	0.04	-0.26	1.22
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.07)	(0.00)	(0.01)	(0.01)
ECU	-3.12	-0.23	-0.13	1.60	-0.23	1.83	0.00	-0.15	1.15	0.00
	(0.08)	(0.01)	(0.01)	(0.08)	(0.01)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)
EGY	-4.13	-0.21	0.01	1.45	-0.21	1.66	0.00	-0.14	1.14	0.00
	(0.15)	(0.01)	(0.02)	(0.07)	(0.01)	(0.08)	(0.00)	(0.01)	(0.01)	(0.00)
ESP	0.02	-2.59	-2.44	-54.23	-2.88	-8.53	-94.10	0.04	0.11	0.85
	(0.01)	(0.02)	(0.02)	(0.00)	(0.01)	(0.58)	(1.21)	(0.00)	(0.01)	(0.01)
EST	-0.16	-0.37	-0.33	-8.48	-0.46	0.97	-9.82	0.05	-0.11	1.06
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
ETH	-2.22	-0.43	-0.21	-0.35	-0.43	0.08	0.00	1.22	-0.22	0.00
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.04)	(0.04)	(0.00)
FIN	0.09	-2.34	-2.19	-39.35	-2.61	-9.89	-44.70	0.05	0.21	0.74
	(0.05)	(0.02)	(0.02)	(0.00)	(0.01)	(0.26)	(0.40)	(0.00)	(0.01)	(0.01)
FRA	-0.27	-0.90	-0.75	-24.86	-1.01	-0.19	-31.49	0.04	0.01	0.96
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.06)	(0.00)	(0.00)	(0.00)
GBR	-0.24	-0.76	-0.60	-21.08	-0.86	0.08	-25.72	0.04	0.00	0.97
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.05)	(0.00)	(0.00)	(0.00)
GEO	-2.82	-0.48	-0.34	-0.48	-0.48	0.01	0.00	1.01	-0.01	0.00
	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
GHA	-2.45	-0.28	-0.06	1.23	-0.28	1.52	0.00	-0.23	1.23	0.00
	(0.08)	(0.02)	(0.02)	(0.11)	(0.02)	(0.10)	(0.00)	(0.04)	(0.04)	(0.00)
GRC	-1.28	-4.77	-4.62	-43.30	-5.62	-9.39	-50.83	0.10	0.17	0.72
	(0.08)	(0.02)	(0.02)	(0.00)	(0.01)	(0.21)	(0.35)	(0.00)	(0.00)	(0.00)
GTM	-2.42	-0.42	-0.27	-0.11	-0.42	0.31	0.00	3.84	-2.84	0.00
	(0.05)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.50)	(0.50)	(0.00)
HKG	-2.21	-0.42	-0.42	-0.43	-0.42	-0.01	0.00	0.97	0.03	0.00
	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
HND	-2.28	-0.52	-0.38	-0.40	-0.52	0.12	0.00	1.30	-0.30	0.00
	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.00)	(0.03)	(0.03)	(0.00)
HRV	-0.55	-3.93	-3.90	-48.44	-4.51	-8.62	-69.24	0.07	0.14	0.79
	(0.06)	(0.02)	(0.02)	(0.00)	(0.02)	(0.06)	(0.12)	(0.00)	(0.00)	(0.00)
HUN	-0.25	-0.42	-0.38	-6.83	-0.54	4.10	-11.13	0.08	-0.57	1.49
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.07)	(0.07)	(0.00)	(0.01)	(0.01)
IDN	-2.38	-0.11	0.04	1.04	-0.11	1.15	0.00	-0.11	1.11	0.00
	(0.08)	(0.01)	(0.01)	(0.10)	(0.01)	(0.10)	(0.00)	(0.01)	(0.01)	(0.00)
IND	-2.14	-0.09	0.19	0.68	-0.09	0.77	0.00	-0.13	1.13	0.00
	(0.07)	(0.01)	(0.01)	(0.10)	(0.01)	(0.09)	(0.00)	(0.03)	(0.03)	(0.00)
IRL	-0.24	-0.86	-0.71	-47.60	-1.07	-7.34	-74.93	0.02	0.12	0.87
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.07)	(0.13)	(0.00)	(0.00)	(0.00)
IRN	-4.09	-0.08	0.02	1.29	-0.08	1.37	0.00	-0.06	1.06	0.00
	(0.11)	(0.02)	(0.02)	(0.12)	(0.02)	(0.10)	(0.00)	(0.02)	(0.02)	(0.00)
ISR	-3.33	-0.36	-0.36	1.15	-0.36	1.52	0.00	-0.32	1.32	0.00
	(0.10)	(0.01)	(0.01)	(0.10)	(0.01)	(0.10)	(0.00)	(0.03)	(0.03)	(0.00)

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Table C.13 – *Continued from previous page*

	ΔX^i	$\Delta \Re^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
ITA	-0.17	-1.43	-1.27	-32.31	-1.59	-3.00	-41.02	0.04	0.08	0.88
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.20)	(0.28)	(0.00)	(0.01)	(0.01)
JPN	-0.87	-1.39	-1.36	-34.38	-1.64	-2.53	-46.11	0.04	0.06	0.90
	(0.05)	(0.01)	(0.01)	(0.00)	(0.00)	(0.23)	(0.35)	(0.00)	(0.01)	(0.01)
KAZ	-0.12	0.03	0.13	0.00	-0.03	2.47	-2.44	-	-	-
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.12)	(0.12)	-	-	-
KEN	-2.01	-0.19	0.03	1.51	-0.19	1.71	0.00	-0.13	1.13	0.00
	(0.07)	(0.01)	(0.01)	(0.05)	(0.01)	(0.05)	(0.00)	(0.01)	(0.01)	(0.00)
KGZ	-2.82	-0.46	-0.31	-0.48	-0.46	-0.02	0.00	0.95	0.05	0.00
	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
KHM	-1.36	-0.38	-0.23	-0.34	-0.38	0.04	0.00	1.12	-0.12	0.00
	(0.03)	(0.01)	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)
KOR	-2.98	-0.14	-0.01	1.32	-0.14	1.46	0.00	-0.11	1.11	0.00
	(0.11)	(0.01)	(0.01)	(0.13)	(0.01)	(0.13)	(0.00)	(0.02)	(0.02)	(0.00)
KWT	-5.51	0.02	0.13	1.75	0.02	1.73	0.00	0.01	0.99	0.00
	(0.22)	(0.03)	(0.03)	(0.20)	(0.03)	(0.17)	(0.00)	(0.02)	(0.02)	(0.00)
LAO	-1.51	-0.18	-0.04	0.67	-0.18	0.85	0.00	-0.27	1.27	0.00
	(0.05)	(0.01)	(0.01)	(0.04)	(0.01)	(0.04)	(0.00)	(0.02)	(0.02)	(0.00)
LKA	-2.22	-0.34	-0.20	0.36	-0.34	0.70	0.00	-0.96	1.96	0.00
	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.00)	(0.07)	(0.07)	(0.00)
LTU	-0.19	0.18	0.22	0.00	0.10	5.99	-6.10	-	-	-
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.11)	(0.11)	-	-	-
LUX	-0.20	-1.10	-0.95	-31.94	-1.25	-0.98	-43.66	0.03	0.03	0.94
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LVA	0.00	-0.22	-0.18	0.00	-0.22	0.68	-0.45	-	-	-
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	-	-	-
MAR	-5.32	-0.48	-0.26	2.41	-0.48	2.90	0.00	-0.20	1.20	0.00
	(0.13)	(0.06)	(0.06)	(0.35)	(0.06)	(0.30)	(0.00)	(0.06)	(0.06)	(0.00)
MDG	-2.67	-0.33	-0.12	0.26	-0.33	0.60	0.00	-1.29	2.29	0.00
	(0.03)	(0.01)	(0.01)	(0.05)	(0.01)	(0.04)	(0.00)	(0.36)	(0.36)	(0.00)
MEX	-2.83	-0.28	-0.18	1.87	-0.28	2.16	0.00	-0.15	1.15	0.00
	(0.06)	(0.01)	(0.01)	(0.18)	(0.01)	(0.19)	(0.00)	(0.01)	(0.01)	(0.00)
MLT	-0.64	-0.58	-0.45	-40.04	-1.07	-5.60	-55.76	0.02	0.11	0.87
	(0.03)	(0.02)	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
MNG	-3.48	-0.60	-0.46	-0.71	-0.60	-0.11	0.00	0.85	0.15	0.00
	(0.28)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)
MOZ	-2.70	-0.41	-0.19	-0.30	-0.41	0.11	0.00	1.36	-0.36	0.00
	(0.08)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.00)	(0.08)	(0.08)	(0.00)
MUS	-2.62	-0.51	-0.29	-0.22	-0.51	0.29	0.00	2.32	-1.32	0.00
	(0.06)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.00)	(0.26)	(0.26)	(0.00)
MWI	-2.54	-0.50	-0.28	0.09	-0.50	0.59	0.00	-5.45	6.45	0.00
	(0.07)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.00)	(4.50)	(4.50)	(0.00)
MYS	-1.92	-0.21	-0.07	0.74	-0.21	0.95	0.00	-0.28	1.28	0.00
	(0.07)	(0.01)	(0.01)	(0.11)	(0.01)	(0.11)	(0.00)	(0.04)	(0.04)	(0.00)
NAM	-2.83	-0.46	-0.24	-0.67	-0.46	-0.22	0.00	0.68	0.32	0.00
	(0.05)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
NGA	-5.51	-0.43	-0.21	1.72	-0.43	2.16	0.00	-0.25	1.25	0.00
	(0.28)	(0.01)	(0.01)	(0.14)	(0.01)	(0.14)	(0.00)	(0.02)	(0.02)	(0.00)

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Table C.13 – *Continued from previous page*

	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
NIC	-2.53	-0.40	-0.25	0.72	-0.40	1.12	0.00	-0.55	1.55	0.00
	(0.07)	(0.02)	(0.02)	(0.06)	(0.02)	(0.04)	(0.00)	(0.09)	(0.09)	(0.00)
NLD	-0.05	-1.81	-1.65	-30.72	-1.94	-9.03	-28.78	0.05	0.26	0.69
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.09)	(0.12)	(0.00)	(0.00)	(0.00)
NOR	0.18	-3.14	-2.98	-54.75	-3.44	-19.62	-71.54	0.04	0.28	0.68
	(0.08)	(0.02)	(0.02)	(0.00)	(0.02)	(0.31)	(0.62)	(0.00)	(0.00)	(0.00)
NPL	-1.85	-0.32	-0.18	-0.12	-0.32	0.21	0.00	2.79	-1.79	0.00
	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.16)	(0.16)	(0.00)
NZL	-0.29	-1.32	-1.32	-40.22	-1.62	-5.67	-55.26	0.03	0.11	0.85
	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.49)	(0.80)	(0.00)	(0.01)	(0.01)
OMN	-5.62	-0.26	-0.15	0.78	-0.26	1.05	0.00	-0.34	1.34	0.00
	(0.16)	(0.01)	(0.01)	(0.05)	(0.01)	(0.04)	(0.00)	(0.03)	(0.03)	(0.00)
PAK	-2.10	-0.18	-0.03	0.53	-0.18	0.72	0.00	-0.34	1.34	0.00
	(0.09)	(0.01)	(0.01)	(0.04)	(0.01)	(0.04)	(0.00)	(0.03)	(0.03)	(0.00)
PAN	-2.12	-0.61	-0.51	-0.76	-0.61	-0.15	0.00	0.80	0.20	0.00
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
PER	-2.66	-0.19	-0.09	1.47	-0.19	1.67	0.00	-0.13	1.13	0.00
	(0.07)	(0.01)	(0.01)	(0.13)	(0.01)	(0.14)	(0.00)	(0.01)	(0.01)	(0.00)
PHL	-1.99	-0.22	-0.08	1.02	-0.22	1.24	0.00	-0.22	1.22	0.00
	(0.05)	(0.01)	(0.01)	(0.05)	(0.01)	(0.06)	(0.00)	(0.01)	(0.01)	(0.00)
POL	-0.32	-0.57	-0.53	-12.15	-0.69	2.29	-15.63	0.05	-0.17	1.12
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)	(0.12)	(0.00)	(0.01)	(0.01)
PRT	-0.48	-2.54	-2.39	-48.00	-2.95	-7.55	-72.55	0.05	0.12	0.83
	(0.04)	(0.01)	(0.01)	(0.00)	(0.00)	(0.27)	(0.50)	(0.00)	(0.00)	(0.00)
PRY	-1.90	-0.35	-0.25	-0.55	-0.35	-0.19	0.00	0.65	0.35	0.00
	(0.05)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
QAT	-4.22	-0.10	0.01	1.78	-0.10	1.88	0.00	-0.06	1.06	0.00
	(0.19)	(0.01)	(0.01)	(0.12)	(0.01)	(0.12)	(0.00)	(0.01)	(0.01)	(0.00)
ROU	-0.27	0.03	0.07	0.00	-0.05	6.22	-6.17	-	-	-
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.15)	(0.14)	-	-	-
RUS	-0.05	0.08	0.08	-0.13	0.04	2.50	-2.67	-0.34	-19.34	20.68
	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.12)	(0.12)	(0.02)	(0.92)	(0.91)
SAU	-5.29	-0.02	0.09	1.55	-0.02	1.57	0.00	-0.01	1.01	0.00
	(0.09)	(0.02)	(0.02)	(0.18)	(0.02)	(0.15)	(0.00)	(0.02)	(0.02)	(0.00)
SEN	-3.77	-0.52	-0.30	1.06	-0.52	1.59	0.00	-0.50	1.50	0.00
	(0.07)	(0.04)	(0.04)	(0.17)	(0.04)	(0.14)	(0.00)	(0.14)	(0.14)	(0.00)
SGP	-2.29	-0.13	-0.13	1.21	-0.13	1.33	0.00	-0.10	1.10	0.00
	(0.10)	(0.01)	(0.01)	(0.16)	(0.01)	(0.15)	(0.00)	(0.03)	(0.03)	(0.00)
SLV	-2.37	-0.38	-0.28	1.28	-0.38	1.67	0.00	-0.30	1.30	0.00
	(0.07)	(0.02)	(0.02)	(0.06)	(0.02)	(0.04)	(0.00)	(0.03)	(0.03)	(0.00)
SVK	-0.20	-0.57	-0.53	-9.90	-0.69	2.61	-13.11	0.07	-0.25	1.18
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.08)	(0.00)	(0.01)	(0.01)
SVN	-0.32	-1.34	-1.30	-42.39	-1.57	-0.70	-69.66	0.03	0.01	0.96
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.03)	(0.00)	(0.00)	(0.00)
SWE	-0.23	-0.84	-0.68	-18.93	-0.96	0.16	-22.37	0.05	-0.01	0.96
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.10)	(0.00)	(0.00)	(0.00)
THA	-1.99	-0.14	-0.04	0.83	-0.14	0.97	0.00	-0.16	1.16	0.00
	(0.07)	(0.01)	(0.01)	(0.12)	(0.01)	(0.11)	(0.00)	(0.04)	(0.04)	(0.00)

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Table C.13 – *Continued from previous page*

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
TUN	-4.73	-0.85	-0.64	-0.27	-0.85	0.59	0.00	3.18	-2.18	0.00
	(0.07)	(0.03)	(0.03)	(0.18)	(0.03)	(0.16)	(0.00)	(40.6)	(40.6)	(0.00)
TUR	-3.62	-0.40	-0.30	0.77	-0.40	1.18	0.00	-0.53	1.53	0.00
	(0.10)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.00)	(0.04)	(0.04)	(0.00)
TWN	-2.56	-0.14	-0.01	1.51	-0.14	1.66	0.00	-0.10	1.10	0.00
	(0.09)	(0.01)	(0.01)	(0.13)	(0.01)	(0.12)	(0.00)	(0.01)	(0.01)	(0.00)
TZA	-2.15	-0.34	-0.12	-0.16	-0.34	0.18	0.00	2.10	-1.10	0.00
	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.00)	(0.20)	(0.20)	(0.00)
UGA	-2.89	-0.37	-0.15	0.28	-0.37	0.65	0.00	-1.34	2.34	0.00
	(0.08)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.18)	(0.18)	(0.00)
UKR	-0.41	0.03	0.07	0.00	-0.05	2.26	-2.20	-	-	-
	(0.03)	(0.00)	(0.00)	(0.00)	(0.01)	(0.07)	(0.06)	-	-	-
URY	-2.21	-0.25	-0.15	0.87	-0.25	1.12	0.00	-0.29	1.29	0.00
	(0.06)	(0.01)	(0.01)	(0.04)	(0.01)	(0.05)	(0.00)	(0.01)	(0.01)	(0.00)
USA	-0.31	-0.58	-0.55	-17.00	-0.63	-0.43	-19.21	0.03	0.02	0.94
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.08)	(0.00)	(0.00)	(0.00)
VEN	-3.60	-0.12	-0.02	1.35	-0.12	1.47	0.00	-0.09	1.09	0.00
	(0.08)	(0.02)	(0.02)	(0.21)	(0.02)	(0.20)	(0.00)	(0.03)	(0.03)	(0.00)
VNM	-2.14	-0.29	-0.15	0.04	-0.29	0.33	0.00	-7.33	8.33	0.00
	(0.09)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(246)	(246)	(0.00)
XAC	-6.13	-0.43	-0.21	2.35	-0.43	2.79	0.00	-0.18	1.18	0.00
	(0.19)	(0.01)	(0.01)	(0.06)	(0.01)	(0.05)	(0.00)	(0.01)	(0.01)	(0.00)
XCA	-2.65	-0.47	-0.37	0.69	-0.47	1.17	0.00	-0.69	1.69	0.00
	(0.07)	(0.01)	(0.01)	(0.05)	(0.01)	(0.04)	(0.00)	(0.07)	(0.07)	(0.00)
XCB	-3.05	-0.22	-0.08	1.03	-0.22	1.25	0.00	-0.21	1.21	0.00
	(0.09)	(0.01)	(0.01)	(0.15)	(0.01)	(0.15)	(0.00)	(0.04)	(0.04)	(0.00)
XCF	-4.97	-0.39	-0.18	2.02	-0.39	2.42	0.00	-0.20	1.20	0.00
	(0.03)	(0.01)	(0.01)	(0.04)	(0.01)	(0.03)	(0.00)	(0.01)	(0.01)	(0.00)
XEA	-2.45	-0.36	-0.23	0.14	-0.36	0.50	0.00	-2.62	3.62	0.00
	(0.18)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.00)	(3.18)	(3.18)	(0.00)
XEC	-3.58	-0.29	-0.07	0.86	-0.29	1.16	0.00	-0.34	1.34	0.00
	(0.12)	(0.01)	(0.01)	(0.07)	(0.01)	(0.09)	(0.00)	(0.02)	(0.02)	(0.00)
XEE	-3.35	-0.78	-0.74	-0.80	-0.78	-0.01	0.00	0.98	0.02	0.00
	(0.04)	(0.01)	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
XEF	-0.28	-1.30	-1.14	-25.00	-1.46	-11.72	-15.99	0.05	0.43	0.52
	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
XER	-4.81	-0.63	-0.49	0.59	-0.63	1.23	0.00	-1.06	2.06	0.00
	(0.09)	(0.04)	(0.04)	(0.15)	(0.04)	(0.11)	(0.00)	(0.50)	(0.50)	(0.00)
XNA	-4.02	-0.35	-0.20	0.47	-0.35	0.82	0.00	-0.77	1.77	0.00
	(0.03)	(0.02)	(0.02)	(0.14)	(0.02)	(0.12)	(0.00)	(1.59)	(1.59)	(0.00)
XNF	-7.00	-0.24	-0.02	2.16	-0.24	2.41	0.00	-0.11	1.11	0.00
	(0.14)	(0.01)	(0.01)	(0.12)	(0.01)	(0.13)	(0.00)	(0.01)	(0.01)	(0.00)
XOC	-3.36	-0.35	-0.25	1.15	-0.35	1.51	0.00	-0.31	1.31	0.00
	(0.07)	(0.01)	(0.01)	(0.03)	(0.01)	(0.03)	(0.00)	(0.02)	(0.02)	(0.00)
XSA	-2.69	-0.32	-0.17	0.51	-0.32	0.83	0.00	-0.62	1.62	0.00
	(0.04)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.05)	(0.05)	(0.00)
XSC	-2.36	-0.39	-0.17	0.41	-0.39	0.80	0.00	-0.95	1.95	0.00
	(0.04)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.06)	(0.06)	(0.00)

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Table C.13 – *Continued from previous page*

	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
XSE	-3.11	-0.34	-0.20	0.63	-0.34	0.97	0.00	-0.54	1.54	0.00
	(0.17)	(0.01)	(0.01)	(0.03)	(0.01)	(0.04)	(0.00)	(0.04)	(0.04)	(0.00)
XSM	-3.44	-0.34	-0.24	1.00	-0.34	1.34	0.00	-0.35	1.35	0.00
	(0.12)	(0.02)	(0.02)	(0.10)	(0.02)	(0.09)	(0.00)	(0.05)	(0.05)	(0.00)
XSU	-4.73	-0.25	-0.11	0.32	-0.25	0.58	0.00	-0.80	1.80	0.00
	(0.16)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.00)	(0.11)	(0.11)	(0.00)
XWF	-3.78	-0.44	-0.22	0.74	-0.44	1.18	0.00	-0.60	1.60	0.00
	(0.03)	(0.01)	(0.02)	(0.09)	(0.01)	(0.08)	(0.00)	(0.11)	(0.11)	(0.00)
XWS	-4.66	-0.32	-0.18	0.93	-0.32	1.26	0.00	-0.35	1.35	0.00
	(0.21)	(0.03)	(0.03)	(0.05)	(0.03)	(0.06)	(0.00)	(0.03)	(0.03)	(0.00)
ZAF	-2.70	-0.24	-0.02	0.93	-0.24	1.18	0.00	-0.26	1.26	0.00
	(0.09)	(0.01)	(0.01)	(0.16)	(0.01)	(0.16)	(0.00)	(0.05)	(0.05)	(0.00)
ZMB	-2.86	-0.36	-0.15	0.28	-0.36	0.64	0.00	-1.31	2.31	0.00
	(0.10)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.00)	(0.20)	(0.20)	(0.00)
ZWE	-2.89	-0.35	-0.13	-0.06	-0.35	0.29	0.00	5.61	-4.61	0.00
	(0.13)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.00)	(2.27)	(2.27)	(0.00)

Notes: ΔX^i denotes the percentage changes in trade flows, $\Delta\mathfrak{R}^i$ the percentage changes in real income, ΔU^i the percentage changes in welfare, ΔE^i the percentage changes in carbon emissions, PSE the percentage scale effects, PCE the percentage composition effects, PTE the percentage technique effects, LSE the log scale effects, LCE the log composition effects, and LTE the log technique effects. Note that for countries with constant emissions, these log changes are not defined. The numbers in parentheses below the reported values give the corresponding bootstrapped standard errors.

Table C.14: Copenhagen Accord (Appendices I and II, Without Tariffs)

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
ALB	-0.06	0.01	0.29	6.43	0.01	6.42	0.00	0.00	1.00	0.00
	(0.02)	(0.02)	(0.02)	(0.09)	(0.02)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)
ARE	-0.13	0.69	0.90	8.33	0.69	7.59	0.00	0.09	0.91	0.00
	(0.02)	(0.04)	(0.04)	(0.48)	(0.04)	(0.44)	(0.00)	(0.00)	(0.00)	(0.00)
ARG	-0.44	0.58	0.84	8.09	0.58	7.47	0.00	0.07	0.93	0.00
	(0.05)	(0.07)	(0.07)	(0.96)	(0.07)	(0.88)	(0.00)	(0.00)	(0.00)	(0.00)
ARM	0.00	0.08	0.36	2.12	0.08	2.04	0.00	0.04	0.96	0.00
	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)
AUS	0.10	-0.79	-0.79	-23.02	-0.79	-1.54	-26.89	0.03	0.06	0.91
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.11)	(0.00)	(0.00)	(0.00)
AUT	0.16	-1.55	-1.24	-37.91	-1.55	-4.28	-51.77	0.03	0.09	0.88
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.03)	(0.04)	(0.00)	(0.00)	(0.00)
AZE	-0.38	1.72	2.01	10.88	1.72	9.00	0.00	0.17	0.83	0.00
	(0.05)	(0.06)	(0.06)	(0.43)	(0.06)	(0.36)	(0.00)	(0.00)	(0.00)	(0.00)
BEL	-0.05	-1.41	-1.11	-22.94	-1.41	-2.98	-24.12	0.05	0.12	0.83
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.09)	(0.00)	(0.00)	(0.00)
BGD	-0.20	0.06	0.35	5.80	0.06	5.74	0.00	0.01	0.99	0.00
	(0.03)	(0.01)	(0.01)	(0.14)	(0.01)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
BGR	-0.13	0.02	0.09	0.00	0.02	5.24	-5.26	-	-	-
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.08)	(0.07)	-	-	-
BHR	-0.09	3.74	3.96	13.71	3.74	9.61	0.00	0.29	0.71	0.00
	(0.01)	(0.23)	(0.23)	(0.88)	(0.23)	(0.61)	(0.00)	(0.00)	(0.00)	(0.00)
BLR	-0.07	0.31	0.39	0.00	0.31	4.01	-4.33	-	-	-
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.06)	-	-	-
BOL	-0.69	1.20	1.49	9.82	1.20	8.52	0.00	0.13	0.87	0.00
	(0.05)	(0.06)	(0.06)	(0.63)	(0.06)	(0.56)	(0.00)	(0.00)	(0.00)	(0.00)
BRA	0.57	-1.52	-1.26	-27.77	-1.52	-3.67	-31.33	0.05	0.12	0.84
	(0.02)	(0.01)	(0.00)	(0.00)	(0.01)	(0.38)	(0.51)	(0.00)	(0.01)	(0.01)
BWA	-0.05	-0.28	0.14	0.41	-0.28	0.69	0.00	-0.70	1.70	0.00
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.00)	(0.05)	(0.05)	(0.00)
CAN	0.03	-0.89	-0.89	-16.66	-0.89	-0.24	-18.64	0.05	0.01	0.94
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.00)	(0.00)	(0.00)
CHE	-0.09	-0.38	-0.07	-15.94	-0.38	2.43	-21.39	0.02	-0.14	1.12
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.00)	(0.00)	(0.00)
CHL	0.64	-1.62	-1.43	-26.67	-1.62	-4.65	-27.92	0.05	0.15	0.79
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.11)	(0.14)	(0.00)	(0.00)	(0.00)
CHN	1.11	-2.37	-2.35	-37.10	-2.37	-2.51	-51.31	0.05	0.05	0.89
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.26)	(0.40)	(0.00)	(0.01)	(0.01)
CIV	-0.30	1.40	1.84	16.62	1.40	15.01	0.00	0.09	0.91	0.00
	(0.01)	(0.06)	(0.06)	(0.84)	(0.06)	(0.76)	(0.00)	(0.00)	(0.00)	(0.00)
CMR	-0.18	0.72	1.15	13.34	0.72	12.53	0.00	0.06	0.94	0.00
	(0.02)	(0.03)	(0.03)	(0.60)	(0.03)	(0.56)	(0.00)	(0.00)	(0.00)	(0.00)
COL	-0.25	0.38	0.58	8.20	0.38	7.78	0.00	0.05	0.95	0.00
	(0.01)	(0.04)	(0.04)	(0.83)	(0.04)	(0.79)	(0.00)	(0.00)	(0.00)	(0.00)
CRI	0.21	-1.82	-1.63	-53.41	-1.82	-7.11	-95.73	0.02	0.10	0.88
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.08)	(0.16)	(0.00)	(0.00)	(0.00)
CYP	-0.06	-2.47	-2.21	-57.38	-2.47	-7.41	-111.9	0.03	0.09	0.88
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)

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Table C.14 – *Continued from previous page*

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
CZE	-0.05	-0.74	-0.67	-15.67	-0.74	2.34	-20.44	0.04	-0.14	1.09
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.07)	(0.00)	(0.00)	(0.00)
DEU	-0.21	-0.58	-0.27	-10.65	-0.58	3.02	-14.63	0.05	-0.26	1.21
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.15)	(0.16)	(0.00)	(0.01)	(0.01)
DNK	-0.15	-0.45	-0.14	-10.05	-0.45	2.87	-13.85	0.04	-0.27	1.22
	(0.02)	(0.00)	(0.01)	(0.00)	(0.00)	(0.06)	(0.06)	(0.00)	(0.01)	(0.00)
ECU	-0.40	0.62	0.82	9.02	0.62	8.35	0.00	0.07	0.93	0.00
	(0.02)	(0.06)	(0.06)	(0.84)	(0.06)	(0.77)	(0.00)	(0.00)	(0.00)	(0.00)
EGY	-0.46	1.20	1.63	10.07	1.20	8.77	0.00	0.12	0.88	0.00
	(0.01)	(0.07)	(0.07)	(0.65)	(0.07)	(0.57)	(0.00)	(0.00)	(0.00)	(0.00)
ESP	0.99	-2.71	-2.41	-54.23	-2.71	-9.23	-92.96	0.04	0.12	0.84
	(0.01)	(0.02)	(0.01)	(0.00)	(0.02)	(0.54)	(1.12)	(0.00)	(0.01)	(0.01)
EST	-0.05	-0.48	-0.41	-8.48	-0.48	1.03	-9.85	0.05	-0.12	1.06
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)
ETH	-0.10	-0.22	0.21	0.99	-0.22	1.21	0.00	-0.22	1.22	0.00
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)
FIN	0.69	-2.45	-2.15	-39.35	-2.45	-9.89	-44.93	0.05	0.21	0.74
	(0.05)	(0.02)	(0.01)	(0.00)	(0.02)	(0.21)	(0.31)	(0.00)	(0.00)	(0.00)
FRA	-0.02	-0.99	-0.69	-24.86	-0.99	-0.33	-31.33	0.03	0.01	0.95
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.05)	(0.00)	(0.00)	(0.00)
GBR	0.01	-0.85	-0.54	-21.08	-0.85	0.05	-25.70	0.04	0.00	0.97
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.00)	(0.00)	(0.00)
GEO	-0.01	-0.10	0.19	0.96	-0.10	1.06	0.00	-0.10	1.10	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)
GHA	-0.16	0.39	0.82	8.61	0.39	8.19	0.00	0.05	0.95	0.00
	(0.02)	(0.02)	(0.01)	(0.39)	(0.02)	(0.38)	(0.00)	(0.00)	(0.00)	(0.00)
GRC	0.82	-4.90	-4.60	-43.30	-4.90	-10.03	-50.89	0.09	0.19	0.73
	(0.07)	(0.02)	(0.02)	(0.00)	(0.02)	(0.14)	(0.19)	(0.00)	(0.00)	(0.00)
GTM	-0.19	-0.20	0.08	1.52	-0.20	1.73	0.00	-0.13	1.13	0.00
	(0.03)	(0.02)	(0.02)	(0.05)	(0.02)	(0.06)	(0.00)	(0.01)	(0.01)	(0.00)
HKG	-0.16	-0.33	-0.33	-0.03	-0.33	0.30	0.00	10.76	-9.76	0.00
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(1.45)	(1.45)	(0.00)
HND	-0.18	-0.34	-0.05	0.84	-0.34	1.19	0.00	-0.41	1.41	0.00
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.00)	(0.02)	(0.02)	(0.00)
HRV	0.46	-4.03	-3.96	-48.44	-4.03	-8.71	-69.93	0.06	0.14	0.80
	(0.08)	(0.02)	(0.02)	(0.00)	(0.02)	(0.04)	(0.05)	(0.00)	(0.00)	(0.00)
HUN	-0.09	-0.53	-0.46	-6.83	-0.53	4.23	-11.27	0.08	-0.59	1.51
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.07)	(0.07)	(0.00)	(0.01)	(0.01)
IDN	0.01	-0.85	-0.57	-13.89	-0.85	-0.95	-14.05	0.06	0.06	0.88
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.05)	(0.00)	(0.00)	(0.00)
IND	0.57	-1.78	-1.25	-19.46	-1.78	-2.02	-19.49	0.08	0.09	0.82
	(0.02)	(0.01)	(0.00)	(0.00)	(0.01)	(0.08)	(0.09)	(0.00)	(0.00)	(0.00)
IRL	0.08	-0.93	-0.62	-47.60	-0.93	-7.45	-74.97	0.01	0.12	0.87
	(0.03)	(0.01)	(0.00)	(0.00)	(0.01)	(0.04)	(0.07)	(0.00)	(0.00)	(0.00)
IRN	-0.75	1.19	1.39	6.61	1.19	5.36	0.00	0.18	0.82	0.00
	(0.04)	(0.12)	(0.12)	(0.70)	(0.12)	(0.56)	(0.00)	(0.00)	(0.00)	(0.00)
ISR	0.22	-0.70	-0.70	-22.67	-0.70	-6.72	-19.78	0.03	0.27	0.70
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.18)	(0.23)	(0.00)	(0.01)	(0.01)

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Table C.14 – *Continued from previous page*

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
ITA	0.37	-1.53	-1.23	-32.31	-1.53	-3.25	-40.75	0.04	0.08	0.88
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.19)	(0.27)	(0.00)	(0.01)	(0.00)
JPN	0.65	-1.57	-1.52	-34.38	-1.57	-2.23	-46.66	0.04	0.05	0.91
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.18)	(0.26)	(0.00)	(0.00)	(0.00)
KAZ	-0.18	-0.01	0.19	0.00	-0.01	4.14	-4.14	-	-	-
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.24)	(0.23)	-	-	-
KEN	-0.17	0.36	0.79	9.68	0.36	9.29	0.00	0.04	0.96	0.00
	(0.02)	(0.02)	(0.02)	(0.56)	(0.02)	(0.54)	(0.00)	(0.00)	(0.00)	(0.00)
KGZ	0.09	-2.27	-1.99	-18.78	-2.27	-2.16	-17.73	0.11	0.11	0.78
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.03)	(0.03)	(0.00)	(0.00)	(0.00)
KHM	-0.06	-0.66	-0.38	0.14	-0.66	0.81	0.00	-4.76	5.76	0.00
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.00)	(0.51)	(0.51)	(0.00)
KOR	0.45	-2.31	-2.05	-27.20	-2.31	-3.47	-29.54	0.07	0.11	0.82
	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.15)	(0.19)	(0.00)	(0.00)	(0.00)
KWT	-0.17	2.82	3.03	15.01	2.82	11.86	0.00	0.20	0.80	0.00
	(0.02)	(0.13)	(0.13)	(0.73)	(0.13)	(0.57)	(0.00)	(0.00)	(0.00)	(0.00)
LAO	-0.02	0.29	0.57	12.18	0.29	11.86	0.00	0.02	0.98	0.00
	(0.01)	(0.01)	(0.01)	(0.47)	(0.01)	(0.45)	(0.00)	(0.00)	(0.00)	(0.00)
LKA	-0.40	0.18	0.47	6.40	0.18	6.20	0.00	0.03	0.97	0.00
	(0.04)	(0.01)	(0.01)	(0.35)	(0.01)	(0.34)	(0.00)	(0.00)	(0.00)	(0.00)
LTU	-0.07	0.11	0.18	0.00	0.11	6.33	-6.44	-	-	-
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.10)	(0.09)	-	-	-
LUX	-0.01	-1.20	-0.89	-31.94	-1.20	-0.91	-43.84	0.03	0.02	0.94
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
LVA	-0.01	-0.30	-0.22	0.00	-0.30	0.62	-0.32	-	-	-
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	-	-	-
MAR	-0.62	0.76	1.19	15.27	0.76	14.40	0.00	0.05	0.95	0.00
	(0.06)	(0.02)	(0.02)	(0.58)	(0.02)	(0.55)	(0.00)	(0.00)	(0.00)	(0.00)
MDG	-0.05	-0.08	0.35	5.04	-0.08	5.12	0.00	-0.02	1.02	0.00
	(0.01)	(0.00)	(0.01)	(0.10)	(0.00)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)
MEX	0.65	-1.37	-1.18	-33.18	-1.37	-3.97	-41.75	0.03	0.10	0.87
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.30)	(0.43)	(0.00)	(0.01)	(0.01)
MLT	-0.03	-0.73	-0.47	-40.04	-0.73	-5.67	-56.17	0.01	0.11	0.87
	(0.00)	(0.02)	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)
MNG	-0.09	-0.51	-0.22	0.33	-0.51	0.85	0.00	-1.54	2.54	0.00
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.00)	(0.21)	(0.21)	(0.00)
MOZ	-0.07	-0.09	0.34	1.81	-0.09	1.90	0.00	-0.05	1.05	0.00
	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
MUS	-0.08	-0.31	0.12	2.48	-0.31	2.80	0.00	-0.13	1.13	0.00
	(0.01)	(0.01)	(0.01)	(0.07)	(0.01)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)
MWI	-0.04	-0.15	0.28	4.32	-0.15	4.48	0.00	-0.04	1.04	0.00
	(0.01)	(0.01)	(0.01)	(0.13)	(0.01)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
MYS	-0.53	0.55	0.82	10.17	0.55	9.56	0.00	0.06	0.94	0.00
	(0.02)	(0.06)	(0.06)	(0.90)	(0.06)	(0.84)	(0.00)	(0.00)	(0.00)	(0.00)
NAM	-0.08	-0.32	0.10	-0.43	-0.32	-0.11	0.00	0.75	0.25	0.00
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.02)	(0.02)	(0.00)
NGA	-0.22	0.09	0.52	6.50	0.09	6.40	0.00	0.01	0.99	0.00
	(0.02)	(0.01)	(0.01)	(0.45)	(0.01)	(0.43)	(0.00)	(0.00)	(0.00)	(0.00)

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Table C.14 – *Continued from previous page*

	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
NIC	-0.17	0.63	0.91	7.14	0.63	6.48	0.00	0.09	0.91	0.00
	(0.03)	(0.02)	(0.02)	(0.22)	(0.02)	(0.20)	(0.00)	(0.00)	(0.00)	(0.00)
NLD	0.21	-1.89	-1.59	-30.72	-1.89	-9.06	-28.79	0.05	0.26	0.69
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.08)	(0.10)	(0.00)	(0.00)	(0.00)
NOR	0.80	-3.21	-2.91	-54.75	-3.21	-19.74	-71.69	0.04	0.28	0.68
	(0.09)	(0.02)	(0.02)	(0.00)	(0.02)	(0.25)	(0.50)	(0.00)	(0.00)	(0.00)
NPL	-0.05	-0.27	0.02	2.01	-0.27	2.28	0.00	-0.13	1.13	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
NZL	0.63	-1.49	-1.49	-40.22	-1.49	-6.81	-53.59	0.03	0.14	0.83
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.34)	(0.54)	(0.00)	(0.01)	(0.01)
OMN	-0.18	0.72	0.94	6.76	0.72	5.99	0.00	0.11	0.89	0.00
	(0.03)	(0.03)	(0.03)	(0.32)	(0.03)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)
PAK	-0.61	0.69	0.98	6.87	0.69	6.13	0.00	0.10	0.90	0.00
	(0.03)	(0.04)	(0.04)	(0.44)	(0.04)	(0.39)	(0.00)	(0.00)	(0.00)	(0.00)
PAN	-0.05	-0.57	-0.37	-0.39	-0.57	0.17	0.00	1.44	-0.44	0.00
	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.00)	(0.04)	(0.04)	(0.00)
PER	-0.39	0.36	0.56	8.63	0.36	8.24	0.00	0.04	0.96	0.00
	(0.02)	(0.04)	(0.04)	(0.99)	(0.04)	(0.94)	(0.00)	(0.00)	(0.00)	(0.00)
PHL	-0.54	0.37	0.65	9.77	0.37	9.37	0.00	0.04	0.96	0.00
	(0.02)	(0.05)	(0.05)	(0.93)	(0.05)	(0.87)	(0.00)	(0.00)	(0.00)	(0.00)
POL	-0.09	-0.66	-0.58	-12.15	-0.66	2.45	-15.84	0.05	-0.19	1.14
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.11)	(0.12)	(0.00)	(0.01)	(0.01)
PRT	0.54	-2.68	-2.38	-48.00	-2.68	-7.97	-72.26	0.04	0.13	0.83
	(0.06)	(0.01)	(0.01)	(0.00)	(0.01)	(0.22)	(0.40)	(0.00)	(0.00)	(0.00)
PRY	-0.11	-0.22	-0.02	-0.28	-0.22	-0.06	0.00	0.77	0.23	0.00
	(0.02)	(0.01)	(0.01)	(0.03)	(0.01)	(0.03)	(0.00)	(0.07)	(0.07)	(0.00)
QAT	-0.04	0.79	1.00	10.01	0.79	9.15	0.00	0.08	0.92	0.00
	(0.01)	(0.03)	(0.03)	(0.49)	(0.03)	(0.45)	(0.00)	(0.00)	(0.00)	(0.00)
ROU	-0.19	-0.06	0.01	0.00	-0.06	6.57	-6.50	-	-	-
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.18)	(0.17)	-	-	-
RUS	-0.01	0.06	0.06	-0.13	0.06	3.26	-3.46	-0.48	-25.17	26.65
	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.18)	(0.18)	(0.02)	(1.35)	(1.38)
SAU	-0.41	1.28	1.50	7.66	1.28	6.30	0.00	0.17	0.83	0.00
	(0.05)	(0.11)	(0.11)	(0.71)	(0.11)	(0.58)	(0.00)	(0.00)	(0.00)	(0.00)
SEN	-0.33	0.64	1.07	10.27	0.64	9.57	0.00	0.07	0.93	0.00
	(0.04)	(0.01)	(0.01)	(0.33)	(0.01)	(0.31)	(0.00)	(0.00)	(0.00)	(0.00)
SGP	0.06	-0.37	-0.37	-6.12	-0.37	2.10	-8.35	0.06	-0.33	1.27
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.28)	(0.31)	(0.00)	(0.04)	(0.04)
SLV	-0.16	0.19	0.38	7.37	0.19	7.17	0.00	0.03	0.97	0.00
	(0.02)	(0.01)	(0.01)	(0.38)	(0.01)	(0.37)	(0.00)	(0.00)	(0.00)	(0.00)
SVK	-0.03	-0.67	-0.59	-9.90	-0.67	2.75	-13.28	0.06	-0.26	1.20
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.08)	(0.00)	(0.01)	(0.01)
SVN	0.00	-1.43	-1.36	-42.39	-1.43	-0.60	-70.06	0.03	0.01	0.96
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
SWE	-0.01	-0.95	-0.64	-18.93	-0.95	0.23	-22.47	0.05	-0.01	0.97
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.06)	(0.07)	(0.00)	(0.00)	(0.00)
THA	-0.21	-0.74	-0.55	-9.23	-0.74	1.40	-10.88	0.08	-0.14	1.07
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.18)	(0.00)	(0.02)	(0.02)

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Table C.14 – *Continued from previous page*

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
TUN	-0.15	0.17	0.60	7.74	0.17	7.56	0.00	0.02	0.98	0.00
	(0.03)	(0.01)	(0.01)	(0.07)	(0.01)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)
TUR	-0.38	0.26	0.46	5.62	0.26	5.35	0.00	0.05	0.95	0.00
	(0.01)	(0.03)	(0.02)	(0.43)	(0.03)	(0.40)	(0.00)	(0.00)	(0.00)	(0.00)
TWN	-1.15	0.94	1.21	12.99	0.94	11.93	0.00	0.08	0.92	0.00
	(0.02)	(0.08)	(0.08)	(0.93)	(0.08)	(0.84)	(0.00)	(0.00)	(0.00)	(0.00)
TZA	-0.07	-0.14	0.29	1.12	-0.14	1.26	0.00	-0.12	1.12	0.00
	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
UGA	-0.09	-0.03	0.40	3.42	-0.03	3.45	0.00	-0.01	1.01	0.00
	(0.01)	(0.00)	(0.01)	(0.12)	(0.00)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)
UKR	-0.29	-0.05	0.03	0.00	-0.05	2.65	-2.60	-	-	-
	(0.03)	(0.01)	(0.01)	(0.00)	(0.01)	(0.09)	(0.09)	-	-	-
URY	-0.19	0.38	0.58	8.27	0.38	7.85	0.00	0.05	0.95	0.00
	(0.03)	(0.02)	(0.02)	(0.44)	(0.02)	(0.42)	(0.00)	(0.00)	(0.00)	(0.00)
USA	-0.04	-0.63	-0.58	-17.00	-0.63	-0.25	-19.42	0.03	0.01	0.95
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)	(0.00)	(0.00)	(0.00)
VEN	-0.03	1.33	1.53	14.14	1.33	12.64	0.00	0.10	0.90	0.00
	(0.06)	(0.06)	(0.06)	(0.77)	(0.06)	(0.68)	(0.00)	(0.00)	(0.00)	(0.00)
VNM	-0.80	-0.31	-0.02	1.90	-0.31	2.22	0.00	-0.16	1.16	0.00
	(0.07)	(0.02)	(0.02)	(0.07)	(0.02)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)
XAC	-0.23	0.21	0.64	9.32	0.21	9.09	0.00	0.02	0.98	0.00
	(0.01)	(0.02)	(0.02)	(0.70)	(0.02)	(0.68)	(0.00)	(0.00)	(0.00)	(0.00)
XCA	-0.02	0.32	0.52	11.16	0.32	10.81	0.00	0.03	0.97	0.00
	(0.00)	(0.01)	(0.01)	(0.23)	(0.01)	(0.23)	(0.00)	(0.00)	(0.00)	(0.00)
XCB	-0.29	0.64	0.91	8.23	0.64	7.54	0.00	0.08	0.92	0.00
	(0.04)	(0.06)	(0.05)	(0.74)	(0.06)	(0.68)	(0.00)	(0.00)	(0.00)	(0.00)
XCF	-0.27	0.23	0.66	9.12	0.23	8.87	0.00	0.03	0.97	0.00
	(0.01)	(0.02)	(0.01)	(0.62)	(0.02)	(0.60)	(0.00)	(0.00)	(0.00)	(0.00)
XEA	-0.07	0.02	0.29	7.95	0.02	7.92	0.00	0.00	1.00	0.00
	(0.02)	(0.01)	(0.01)	(0.14)	(0.01)	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)
XEC	-0.48	0.39	0.82	6.23	0.39	5.81	0.00	0.07	0.93	0.00
	(0.02)	(0.03)	(0.03)	(0.51)	(0.03)	(0.47)	(0.00)	(0.00)	(0.00)	(0.00)
XEE	0.00	-0.24	-0.16	0.37	-0.24	0.61	0.00	-0.65	1.65	0.00
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.02)	(0.02)	(0.00)
XEF	0.01	-1.40	-1.10	-25.00	-1.40	-11.36	-16.53	0.05	0.42	0.53
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
XER	-0.47	0.69	0.95	8.45	0.69	7.71	0.00	0.08	0.92	0.00
	(0.04)	(0.01)	(0.01)	(0.19)	(0.01)	(0.18)	(0.00)	(0.00)	(0.00)	(0.00)
XNA	-0.13	1.28	1.59	17.19	1.28	15.71	0.00	0.08	0.92	0.00
	(0.02)	(0.00)	(0.00)	(0.10)	(0.00)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)
XNF	-0.46	1.63	2.07	16.23	1.63	14.36	0.00	0.11	0.89	0.00
	(0.04)	(0.09)	(0.09)	(0.99)	(0.09)	(0.88)	(0.00)	(0.00)	(0.00)	(0.00)
XOC	-0.42	0.33	0.52	8.41	0.33	8.05	0.00	0.04	0.96	0.00
	(0.01)	(0.03)	(0.03)	(0.77)	(0.03)	(0.74)	(0.00)	(0.00)	(0.00)	(0.00)
XSA	-0.12	0.39	0.68	11.08	0.39	10.65	0.00	0.04	0.96	0.00
	(0.02)	(0.01)	(0.01)	(0.31)	(0.01)	(0.31)	(0.00)	(0.00)	(0.00)	(0.00)
XSC	-0.07	-0.23	0.20	8.10	-0.23	8.35	0.00	-0.03	1.03	0.00
	(0.02)	(0.02)	(0.03)	(0.28)	(0.02)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)

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Table C.14 – *Continued from previous page*

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
XSE	-0.32	0.42	0.68	8.51	0.42	8.06	0.00	0.05	0.95	0.00
	(0.03)	(0.02)	(0.02)	(0.49)	(0.02)	(0.46)	(0.00)	(0.00)	(0.00)	(0.00)
XSM	-0.17	0.61	0.81	15.47	0.61	14.77	0.00	0.04	0.96	0.00
	(0.03)	(0.01)	(0.01)	(0.41)	(0.01)	(0.40)	(0.00)	(0.00)	(0.00)	(0.00)
XSU	-0.54	1.51	1.80	5.65	1.51	4.08	0.00	0.27	0.73	0.00
	(0.03)	(0.07)	(0.07)	(0.32)	(0.07)	(0.24)	(0.00)	(0.00)	(0.00)	(0.00)
XWF	-0.16	0.01	0.44	4.19	0.01	4.18	0.00	0.00	1.00	0.00
	(0.02)	(0.00)	(0.00)	(0.20)	(0.00)	(0.20)	(0.00)	(0.00)	(0.00)	(0.00)
XWS	-0.78	0.95	1.24	6.09	0.95	5.10	0.00	0.16	0.84	0.00
	(0.02)	(0.08)	(0.07)	(0.47)	(0.08)	(0.38)	(0.00)	(0.00)	(0.00)	(0.00)
ZAF	0.57	-2.01	-1.59	-43.78	-2.01	-9.90	-57.05	0.04	0.18	0.78
	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.67)	(1.14)	(0.00)	(0.01)	(0.01)
ZMB	-0.21	0.19	0.61	4.22	0.19	4.02	0.00	0.04	0.96	0.00
	(0.02)	(0.00)	(0.01)	(0.14)	(0.00)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)
ZWE	-0.14	0.26	0.69	3.21	0.26	2.94	0.00	0.08	0.92	0.00
	(0.02)	(0.01)	(0.02)	(0.09)	(0.01)	(0.10)	(0.00)	(0.01)	(0.01)	(0.00)

Notes: ΔX^i denotes the percentage changes in trade flows, $\Delta \mathfrak{R}^i$ the percentage changes in real income, ΔU^i the percentage changes in welfare, ΔE^i the percentage changes in carbon emissions, PSE the percentage scale effects, PCE the percentage composition effects, PTE the percentage technique effects, LSE the log scale effects, LCE the log composition effects, and LTE the log technique effects. Note that for countries with constant emissions, these log changes are not defined. The numbers in parentheses below the reported values give the corresponding bootstrapped standard errors.

Table C.15: Copenhagen Accord (Appendices I and II, With Tariffs)

	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
ALB	-5.66	-1.54	-1.24	-1.81	-1.54	-0.28	0.00	0.85	0.15	0.00
	(0.45)	(0.40)	(0.40)	(1.21)	(0.40)	(1.17)	(0.00)	(222)	(222)	(0.00)
ARE	-7.10	-0.29	-0.07	2.21	-0.29	2.51	0.00	-0.13	1.13	0.00
	(0.76)	(0.36)	(0.36)	(1.22)	(0.36)	(1.02)	(0.00)	(3.28)	(3.28)	(0.00)
ARG	-4.24	-0.30	-0.03	1.92	-0.30	2.22	0.00	-0.16	1.16	0.00
	(0.76)	(0.25)	(0.25)	(0.46)	(0.25)	(0.44)	(0.00)	(0.22)	(0.22)	(0.00)
ARM	-3.11	-0.39	-0.09	-0.25	-0.39	0.14	0.00	1.54	-0.54	0.00
	(0.35)	(0.37)	(0.37)	(0.57)	(0.37)	(0.61)	(0.00)	(138)	(138)	(0.00)
AUS	-0.11	-0.74	-0.74	-23.02	-0.79	-0.69	-27.98	0.03	0.03	0.94
	(0.40)	(0.22)	(0.22)	(0.00)	(0.21)	(0.81)	(0.90)	(0.01)	(0.03)	(0.03)
AUT	-0.04	-1.50	-1.19	-37.91	-1.62	-3.71	-52.57	0.03	0.08	0.89
	(0.13)	(0.18)	(0.18)	(0.00)	(0.18)	(0.48)	(1.00)	(0.00)	(0.01)	(0.01)
AZE	-10.31	-0.46	-0.16	1.94	-0.46	2.40	0.00	-0.24	1.24	0.00
	(1.59)	(0.70)	(0.71)	(1.70)	(0.70)	(1.21)	(0.00)	(11.6)	(11.6)	(0.00)
BEL	-0.13	-1.36	-1.04	-22.94	-1.41	-2.32	-24.96	0.05	0.09	0.86
	(0.11)	(0.20)	(0.20)	(0.00)	(0.20)	(0.97)	(1.30)	(0.01)	(0.04)	(0.04)
BGD	-4.56	-0.69	-0.39	0.56	-0.69	1.25	0.00	-1.25	2.25	0.00
	(0.54)	(0.34)	(0.34)	(0.69)	(0.34)	(0.67)	(0.00)	(29.9)	(29.9)	(0.00)
BGR	-0.37	0.18	0.26	0.00	0.03	6.10	-6.13	-	-	-
	(0.21)	(0.34)	(0.34)	(0.00)	(0.30)	(1.13)	(1.31)	-	-	-
BHR	-8.66	0.53	0.75	3.14	0.53	2.60	0.00	0.17	0.83	0.00
	(0.88)	(0.48)	(0.48)	(1.82)	(0.48)	(1.37)	(0.00)	(3.92)	(3.92)	(0.00)
BLR	-0.15	0.42	0.50	0.00	0.36	4.46	-4.84	-	-	-
	(0.23)	(0.25)	(0.25)	(0.00)	(0.24)	(0.77)	(0.93)	-	-	-
BOL	-6.50	-0.58	-0.28	1.49	-0.58	2.08	0.00	-0.39	1.39	0.00
	(1.55)	(0.55)	(0.55)	(0.59)	(0.55)	(0.81)	(0.00)	(0.54)	(0.54)	(0.00)
BRA	-0.08	-1.47	-1.20	-27.77	-1.57	-2.30	-33.15	0.05	0.07	0.88
	(0.21)	(0.09)	(0.09)	(0.00)	(0.08)	(0.67)	(0.90)	(0.00)	(0.02)	(0.02)
BWA	-7.72	-0.95	-0.51	-0.91	-0.95	0.04	0.00	1.04	-0.04	0.00
	(0.76)	(0.67)	(0.68)	(0.75)	(0.67)	(0.66)	(0.00)	(24.0)	(24.0)	(0.00)
CAN	-0.15	-0.86	-0.86	-16.66	-0.90	0.23	-19.18	0.05	-0.01	0.96
	(0.60)	(0.22)	(0.22)	(0.00)	(0.22)	(0.20)	(0.24)	(0.01)	(0.01)	(0.01)
CHE	-0.12	-0.34	-0.02	-15.94	-0.36	2.97	-22.06	0.02	-0.17	1.15
	(0.08)	(0.26)	(0.26)	(0.00)	(0.26)	(1.12)	(1.47)	(0.01)	(0.06)	(0.07)
CHL	-0.45	-1.54	-1.34	-26.67	-1.84	-2.83	-30.08	0.06	0.09	0.85
	(0.92)	(0.65)	(0.65)	(0.00)	(0.62)	(1.56)	(1.55)	(0.02)	(0.05)	(0.04)
CHN	-0.01	-2.32	-2.29	-37.10	-2.42	-1.81	-52.31	0.05	0.04	0.91
	(1.08)	(0.04)	(0.04)	(0.00)	(0.05)	(0.45)	(0.77)	(0.00)	(0.01)	(0.01)
CIV	-5.21	-0.31	0.13	3.82	-0.31	4.15	0.00	-0.08	1.08	0.00
	(0.80)	(0.42)	(0.42)	(1.47)	(0.42)	(1.31)	(0.00)	(0.29)	(0.29)	(0.00)
CMR	-4.50	-0.45	-0.01	3.50	-0.45	3.96	0.00	-0.13	1.13	0.00
	(0.71)	(0.57)	(0.58)	(1.77)	(0.57)	(1.44)	(0.00)	(2.72)	(2.72)	(0.00)
COL	-4.38	-0.31	-0.11	1.98	-0.31	2.30	0.00	-0.16	1.16	0.00
	(0.76)	(0.23)	(0.23)	(0.40)	(0.23)	(0.26)	(0.00)	(0.17)	(0.17)	(0.00)
CRI	-0.55	-1.78	-1.58	-53.41	-2.20	-6.20	-96.89	0.03	0.08	0.89
	(0.25)	(0.50)	(0.50)	(0.00)	(0.50)	(0.62)	(1.36)	(0.01)	(0.01)	(0.01)
CYP	-1.21	-2.52	-2.25	-57.38	-3.23	-7.13	-110.9	0.04	0.09	0.87
	(0.02)	(0.33)	(0.33)	(0.00)	(0.33)	(0.37)	(1.06)	(0.00)	(0.00)	(0.01)

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Table C.15 – *Continued from previous page*

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
CZE	-0.19	-0.69	-0.61	-15.67	-0.77	3.01	-21.20	0.05	-0.17	1.13
	(0.13)	(0.29)	(0.29)	(0.00)	(0.29)	(0.94)	(1.21)	(0.02)	(0.05)	(0.06)
DEU	-0.28	-0.53	-0.21	-10.65	-0.57	3.57	-15.25	0.05	-0.31	1.26
	(0.16)	(0.11)	(0.11)	(0.00)	(0.11)	(0.19)	(0.16)	(0.01)	(0.02)	(0.01)
DNK	-0.22	-0.40	-0.08	-10.05	-0.45	3.39	-14.43	0.04	-0.31	1.27
	(0.12)	(0.24)	(0.24)	(0.00)	(0.24)	(0.55)	(0.63)	(0.02)	(0.05)	(0.05)
ECU	-4.86	-0.39	-0.19	2.30	-0.39	2.70	0.00	-0.17	1.17	0.00
	(1.23)	(0.40)	(0.40)	(0.70)	(0.40)	(0.87)	(0.00)	(0.21)	(0.21)	(0.00)
EGY	-5.91	-0.33	0.12	2.04	-0.33	2.38	0.00	-0.16	1.16	0.00
	(0.82)	(0.30)	(0.30)	(1.05)	(0.30)	(0.81)	(0.00)	(6.17)	(6.17)	(0.00)
ESP	0.37	-2.65	-2.34	-54.23	-2.82	-8.18	-94.97	0.04	0.11	0.85
	(0.11)	(0.08)	(0.08)	(0.00)	(0.08)	(0.75)	(1.65)	(0.00)	(0.01)	(0.01)
EST	-0.11	-0.43	-0.35	-8.48	-0.48	1.22	-10.07	0.05	-0.14	1.08
	(0.05)	(0.35)	(0.35)	(0.00)	(0.35)	(0.22)	(0.30)	(0.04)	(0.02)	(0.03)
ETH	-3.34	-0.68	-0.24	-0.58	-0.68	0.10	0.00	1.17	-0.17	0.00
	(0.55)	(0.44)	(0.44)	(0.85)	(0.44)	(0.68)	(0.00)	(17.5)	(17.5)	(0.00)
FIN	0.33	-2.41	-2.09	-39.35	-2.55	-9.13	-46.00	0.05	0.19	0.76
	(0.23)	(0.20)	(0.20)	(0.00)	(0.19)	(0.21)	(0.51)	(0.00)	(0.00)	(0.01)
FRA	-0.17	-0.94	-0.62	-24.86	-1.00	0.30	-32.14	0.04	-0.01	0.98
	(0.08)	(0.12)	(0.12)	(0.00)	(0.12)	(0.14)	(0.21)	(0.00)	(0.00)	(0.01)
GBR	-0.11	-0.81	-0.49	-21.08	-0.86	0.60	-26.39	0.04	-0.03	0.99
	(0.17)	(0.18)	(0.18)	(0.00)	(0.18)	(0.16)	(0.21)	(0.01)	(0.01)	(0.01)
GEO	-3.93	-0.70	-0.40	-0.72	-0.70	-0.02	0.00	0.97	0.03	0.00
	(0.50)	(0.48)	(0.48)	(0.57)	(0.48)	(0.66)	(0.00)	(5.00)	(5.00)	(0.00)
GHA	-3.69	-0.42	0.02	2.03	-0.42	2.47	0.00	-0.21	1.21	0.00
	(0.50)	(0.38)	(0.38)	(0.68)	(0.38)	(0.39)	(0.00)	(0.66)	(0.66)	(0.00)
GRC	-0.68	-4.85	-4.54	-43.30	-5.38	-9.06	-51.75	0.10	0.17	0.74
	(0.06)	(0.21)	(0.21)	(0.00)	(0.21)	(0.71)	(1.24)	(0.00)	(0.01)	(0.01)
GTM	-4.14	-0.75	-0.45	-0.36	-0.75	0.39	0.00	2.07	-1.07	0.00
	(0.55)	(0.36)	(0.36)	(0.55)	(0.36)	(0.61)	(0.00)	(30.0)	(30.0)	(0.00)
HKG	-4.49	-1.04	-1.04	-1.01	-1.04	0.03	0.00	1.03	-0.03	0.00
	(0.42)	(0.39)	(0.39)	(0.57)	(0.39)	(0.25)	(0.00)	(1.83)	(1.83)	(0.00)
HND	-3.76	-0.87	-0.58	-0.76	-0.87	0.11	0.00	1.14	-0.14	0.00
	(0.44)	(0.50)	(0.50)	(0.79)	(0.50)	(0.62)	(0.00)	(21.3)	(21.3)	(0.00)
HRV	-0.21	-3.97	-3.90	-48.44	-4.33	-8.03	-70.67	0.07	0.13	0.81
	(0.22)	(0.34)	(0.34)	(0.00)	(0.34)	(0.47)	(0.95)	(0.01)	(0.01)	(0.01)
HUN	-0.20	-0.46	-0.39	-6.83	-0.54	5.02	-12.11	0.08	-0.69	1.62
	(0.12)	(0.25)	(0.25)	(0.00)	(0.25)	(0.81)	(0.96)	(0.04)	(0.11)	(0.12)
IDN	-0.42	-0.79	-0.49	-13.89	-0.90	0.17	-15.29	0.06	-0.01	0.95
	(0.22)	(0.12)	(0.12)	(0.00)	(0.11)	(1.06)	(1.17)	(0.01)	(0.07)	(0.07)
IND	-0.29	-1.68	-1.13	-19.46	-1.84	-1.21	-20.40	0.09	0.06	0.86
	(0.30)	(0.11)	(0.11)	(0.00)	(0.10)	(0.19)	(0.22)	(0.00)	(0.01)	(0.01)
IRL	-0.09	-0.88	-0.57	-47.60	-0.99	-7.11	-75.50	0.02	0.11	0.87
	(0.14)	(0.22)	(0.22)	(0.00)	(0.22)	(0.34)	(0.65)	(0.00)	(0.01)	(0.01)
IRN	-6.73	-0.11	0.09	2.16	-0.11	2.28	0.00	-0.05	1.05	0.00
	(1.27)	(0.18)	(0.18)	(0.86)	(0.18)	(0.82)	(0.00)	(0.68)	(0.68)	(0.00)
ISR	-0.37	-0.60	-0.60	-22.67	-0.86	-5.60	-21.02	0.03	0.22	0.74
	(0.18)	(0.36)	(0.36)	(0.00)	(0.35)	(0.32)	(0.58)	(0.01)	(0.01)	(0.02)

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Table C.15 – *Continued from previous page*

	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
ITA	0.04	-1.48	-1.16	-32.31	-1.57	-2.52	-41.76	0.04	0.07	0.89
	(0.18)	(0.09)	(0.09)	(0.00)	(0.09)	(0.20)	(0.33)	(0.00)	(0.01)	(0.01)
JPN	0.04	-1.52	-1.46	-34.38	-1.61	-1.63	-47.50	0.04	0.04	0.92
	(0.39)	(0.07)	(0.07)	(0.00)	(0.07)	(0.43)	(0.69)	(0.00)	(0.01)	(0.01)
KAZ	-0.10	0.07	0.27	0.00	0.02	4.54	-4.57	-	-	-
	(0.83)	(0.37)	(0.37)	(0.00)	(0.35)	(0.58)	(0.79)	-	-	-
KEN	-3.31	-0.31	0.13	2.94	-0.31	3.26	0.00	-0.11	1.11	0.00
	(0.46)	(0.33)	(0.33)	(0.73)	(0.33)	(0.45)	(0.00)	(0.20)	(0.20)	(0.00)
KGZ	-1.10	-2.25	-1.96	-18.78	-2.83	-2.17	-17.03	0.14	0.11	0.76
	(0.25)	(0.49)	(0.49)	(0.00)	(0.45)	(0.27)	(0.63)	(0.02)	(0.01)	(0.03)
KHM	-2.97	-1.12	-0.82	-1.18	-1.12	-0.06	0.00	0.95	0.05	0.00
	(0.47)	(0.56)	(0.56)	(0.68)	(0.56)	(0.92)	(0.00)	(22.0)	(22.0)	(0.00)
KOR	-0.22	-2.22	-1.95	-27.20	-2.37	-2.66	-30.54	0.08	0.08	0.84
	(0.11)	(0.07)	(0.08)	(0.00)	(0.07)	(0.28)	(0.37)	(0.00)	(0.01)	(0.01)
KWT	-9.30	0.10	0.32	3.24	0.10	3.14	0.00	0.03	0.97	0.00
	(1.90)	(0.79)	(0.80)	(2.97)	(0.79)	(2.25)	(0.00)	(2.08)	(2.08)	(0.00)
LAO	-4.61	-0.75	-0.45	1.52	-0.75	2.29	0.00	-0.49	1.49	0.00
	(0.78)	(0.90)	(0.90)	(2.44)	(0.90)	(2.13)	(0.00)	(12.3)	(12.3)	(0.00)
LKA	-4.72	-0.80	-0.50	1.27	-0.80	2.08	0.00	-0.64	1.64	0.00
	(0.57)	(0.47)	(0.47)	(0.60)	(0.47)	(0.82)	(0.00)	(2.15)	(2.15)	(0.00)
LTU	-0.16	0.20	0.28	0.00	0.14	7.02	-7.18	-	-	-
	(0.10)	(0.33)	(0.33)	(0.00)	(0.32)	(1.43)	(1.52)	-	-	-
LUX	-0.10	-1.16	-0.84	-31.94	-1.22	-0.91	-43.80	0.03	0.02	0.94
	(0.01)	(0.25)	(0.25)	(0.00)	(0.25)	(0.39)	(0.44)	(0.01)	(0.01)	(0.01)
LVA	0.00	-0.27	-0.19	0.00	-0.27	0.76	-0.48	-	-	-
	(0.08)	(0.33)	(0.33)	(0.00)	(0.33)	(0.65)	(0.59)	-	-	-
MAR	-6.32	-0.56	-0.11	3.09	-0.56	3.66	0.00	-0.18	1.18	0.00
	(0.51)	(0.26)	(0.26)	(0.57)	(0.26)	(0.53)	(0.00)	(0.10)	(0.10)	(0.00)
MDG	-4.70	-0.61	-0.17	0.46	-0.61	1.08	0.00	-1.33	2.33	0.00
	(0.64)	(0.46)	(0.47)	(0.55)	(0.46)	(0.48)	(0.00)	(36.8)	(36.8)	(0.00)
MEX	0.27	-1.33	-1.13	-33.18	-1.43	-2.91	-43.24	0.04	0.07	0.89
	(0.25)	(0.42)	(0.42)	(0.00)	(0.41)	(1.45)	(1.65)	(0.01)	(0.04)	(0.03)
MLT	-0.35	-0.71	-0.44	-40.04	-0.96	-5.53	-56.04	0.02	0.11	0.87
	(0.01)	(0.34)	(0.34)	(0.00)	(0.34)	(0.64)	(1.06)	(0.01)	(0.01)	(0.01)
MNG	-10.75	-1.78	-1.49	-1.96	-1.78	-0.18	0.00	0.91	0.09	0.00
	(0.84)	(0.79)	(0.80)	(1.05)	(0.79)	(0.97)	(0.00)	(2.29)	(2.29)	(0.00)
MOZ	-5.11	-0.88	-0.43	-0.73	-0.88	0.15	0.00	1.21	-0.21	0.00
	(0.63)	(0.67)	(0.67)	(1.91)	(0.67)	(1.49)	(0.00)	(5.39)	(5.39)	(0.00)
MUS	-4.69	-0.98	-0.53	-0.42	-0.98	0.56	0.00	2.32	-1.32	0.00
	(0.57)	(0.72)	(0.72)	(1.06)	(0.72)	(0.98)	(0.00)	(11.4)	(11.4)	(0.00)
MWI	-4.49	-0.92	-0.47	0.22	-0.92	1.15	0.00	-4.12	5.12	0.00
	(0.57)	(0.79)	(0.79)	(0.62)	(0.79)	(0.74)	(0.00)	(71.7)	(71.7)	(0.00)
MYS	-4.99	-0.44	-0.17	3.39	-0.44	3.85	0.00	-0.13	1.13	0.00
	(0.64)	(0.20)	(0.20)	(0.63)	(0.20)	(0.60)	(0.00)	(0.08)	(0.08)	(0.00)
NAM	-5.41	-0.97	-0.53	-1.35	-0.97	-0.38	0.00	0.72	0.28	0.00
	(0.84)	(0.64)	(0.64)	(1.03)	(0.64)	(0.83)	(0.00)	(11.2)	(11.2)	(0.00)
NGA	-8.38	-0.65	-0.21	2.83	-0.65	3.50	0.00	-0.23	1.23	0.00
	(0.54)	(0.50)	(0.51)	(1.90)	(0.50)	(2.11)	(0.00)	(1.98)	(1.98)	(0.00)

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Table C.15 – *Continued from previous page*

	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
NIC	-4.55	-0.88	-0.59	0.25	-0.88	1.15	0.00	-3.50	4.50	0.00
	(0.53)	(0.73)	(0.74)	(0.81)	(0.73)	(0.60)	(0.00)	(80.3)	(80.3)	(0.00)
NLD	0.06	-1.85	-1.53	-30.72	-1.92	-8.55	-29.48	0.05	0.24	0.70
	(0.14)	(0.22)	(0.22)	(0.00)	(0.22)	(0.54)	(0.82)	(0.01)	(0.02)	(0.02)
NOR	0.49	-3.19	-2.88	-54.75	-3.33	-19.18	-72.67	0.04	0.27	0.69
	(0.37)	(0.24)	(0.24)	(0.00)	(0.24)	(0.25)	(0.48)	(0.00)	(0.00)	(0.00)
NPL	-4.28	-0.90	-0.60	-0.67	-0.90	0.23	0.00	1.34	-0.34	0.00
	(0.61)	(0.63)	(0.63)	(0.70)	(0.63)	(0.70)	(0.00)	(16.4)	(16.4)	(0.00)
NZL	0.15	-1.44	-1.44	-40.22	-1.57	-5.27	-55.99	0.03	0.11	0.86
	(0.27)	(0.39)	(0.39)	(0.00)	(0.39)	(1.58)	(2.23)	(0.01)	(0.03)	(0.03)
OMN	-10.40	-0.47	-0.25	1.48	-0.47	1.96	0.00	-0.32	1.32	0.00
	(1.35)	(0.70)	(0.70)	(1.18)	(0.70)	(0.88)	(0.00)	(27.3)	(27.3)	(0.00)
PAK	-5.17	-0.54	-0.24	1.13	-0.54	1.68	0.00	-0.48	1.48	0.00
	(0.81)	(0.32)	(0.32)	(0.54)	(0.32)	(0.36)	(0.00)	(46.9)	(46.9)	(0.00)
PAN	-3.09	-0.98	-0.78	-1.23	-0.98	-0.25	0.00	0.80	0.20	0.00
	(0.33)	(0.49)	(0.49)	(1.16)	(0.49)	(0.99)	(0.00)	(46.1)	(46.1)	(0.00)
PER	-4.73	-0.35	-0.15	2.28	-0.35	2.64	0.00	-0.16	1.16	0.00
	(0.84)	(0.24)	(0.24)	(0.51)	(0.24)	(0.38)	(0.00)	(0.18)	(0.18)	(0.00)
PHL	-4.20	-0.42	-0.13	3.47	-0.42	3.91	0.00	-0.12	1.12	0.00
	(0.26)	(0.16)	(0.16)	(0.94)	(0.16)	(0.93)	(0.00)	(0.07)	(0.07)	(0.00)
POL	-0.25	-0.60	-0.52	-12.15	-0.67	3.09	-16.56	0.05	-0.24	1.18
	(0.16)	(0.22)	(0.22)	(0.00)	(0.21)	(0.58)	(0.65)	(0.02)	(0.04)	(0.04)
PRT	-0.12	-2.61	-2.29	-48.00	-2.84	-6.97	-73.83	0.04	0.11	0.85
	(0.18)	(0.22)	(0.22)	(0.00)	(0.22)	(0.22)	(0.29)	(0.00)	(0.00)	(0.00)
PRY	-3.76	-0.76	-0.56	-1.13	-0.76	-0.37	0.00	0.67	0.33	0.00
	(0.72)	(0.67)	(0.67)	(1.62)	(0.67)	(2.07)	(0.00)	(24.2)	(24.2)	(0.00)
QAT	-7.66	-0.18	0.04	3.04	-0.18	3.23	0.00	-0.06	1.06	0.00
	(0.75)	(0.42)	(0.43)	(1.74)	(0.42)	(1.50)	(0.00)	(4.71)	(4.71)	(0.00)
ROU	-0.25	0.02	0.10	0.00	-0.04	7.41	-7.37	-	-	-
	(0.20)	(0.22)	(0.22)	(0.00)	(0.21)	(0.90)	(0.98)	-	-	-
RUS	0.05	0.11	0.11	-0.13	0.09	3.60	-3.82	-0.69	-27.70	29.39
	(0.79)	(0.17)	(0.17)	(0.00)	(0.16)	(0.68)	(0.73)	(1.26)	(5.12)	(5.54)
SAU	-8.62	-0.03	0.19	2.53	-0.03	2.56	0.00	-0.01	1.01	0.00
	(2.53)	(0.39)	(0.39)	(0.49)	(0.39)	(0.78)	(0.00)	(0.17)	(0.17)	(0.00)
SEN	-5.05	-0.71	-0.26	1.63	-0.71	2.36	0.00	-0.44	1.44	0.00
	(0.61)	(0.47)	(0.47)	(0.75)	(0.47)	(0.65)	(0.00)	(2.71)	(2.71)	(0.00)
SGP	-0.38	-0.22	-0.22	-6.12	-0.45	2.89	-9.10	0.07	-0.45	1.38
	(0.36)	(0.41)	(0.41)	(0.00)	(0.36)	(1.26)	(1.52)	(0.06)	(0.19)	(0.22)
SLV	-3.82	-0.63	-0.42	1.93	-0.63	2.57	0.00	-0.33	1.33	0.00
	(0.44)	(0.39)	(0.39)	(0.76)	(0.39)	(0.80)	(0.00)	(0.90)	(0.90)	(0.00)
SVK	-0.14	-0.60	-0.52	-9.90	-0.68	3.53	-14.13	0.07	-0.33	1.27
	(0.10)	(0.28)	(0.28)	(0.00)	(0.28)	(1.13)	(1.38)	(0.03)	(0.10)	(0.12)
SVN	-0.16	-1.39	-1.31	-42.39	-1.51	-0.36	-70.33	0.03	0.01	0.97
	(0.04)	(0.37)	(0.37)	(0.00)	(0.37)	(0.23)	(0.63)	(0.01)	(0.00)	(0.01)
SWE	-0.14	-0.89	-0.57	-18.93	-0.96	0.98	-23.37	0.05	-0.05	1.00
	(0.14)	(0.20)	(0.20)	(0.00)	(0.19)	(0.40)	(0.51)	(0.01)	(0.02)	(0.02)
THA	-0.55	-0.64	-0.43	-9.23	-0.78	2.14	-11.65	0.08	-0.22	1.14
	(0.17)	(0.18)	(0.18)	(0.00)	(0.16)	(0.28)	(0.38)	(0.02)	(0.03)	(0.03)

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Table C.15 – *Continued from previous page*

	ΔX^i	$\Delta \mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
TUN	-5.62	-1.02	-0.57	-0.14	-1.02	0.89	0.00	7.49	-6.49	0.00
	(0.55)	(0.40)	(0.40)	(0.97)	(0.40)	(0.68)	(0.00)	(245)	(245)	(0.00)
TUR	-4.63	-0.52	-0.31	1.10	-0.52	1.63	0.00	-0.48	1.48	0.00
	(0.29)	(0.14)	(0.14)	(0.30)	(0.14)	(0.28)	(0.00)	(0.29)	(0.29)	(0.00)
TWN	-5.68	-0.21	0.07	4.87	-0.21	5.09	0.00	-0.04	1.04	0.00
	(0.29)	(0.22)	(0.22)	(0.71)	(0.22)	(0.56)	(0.00)	(0.06)	(0.06)	(0.00)
TZA	-3.76	-0.62	-0.18	-0.36	-0.62	0.26	0.00	1.71	-0.71	0.00
	(0.61)	(0.47)	(0.47)	(0.48)	(0.47)	(0.52)	(0.00)	(22.8)	(22.8)	(0.00)
UGA	-4.72	-0.62	-0.17	0.48	-0.62	1.10	0.00	-1.30	2.30	0.00
	(0.51)	(0.54)	(0.54)	(0.40)	(0.54)	(0.37)	(0.00)	(248)	(248)	(0.00)
UKR	-0.41	0.03	0.11	0.00	-0.04	2.93	-2.89	-	-	-
	(0.33)	(0.26)	(0.26)	(0.00)	(0.25)	(0.37)	(0.38)	-	-	-
URY	-4.27	-0.51	-0.31	1.26	-0.51	1.78	0.00	-0.41	1.41	0.00
	(0.62)	(0.58)	(0.58)	(1.49)	(0.58)	(1.09)	(0.00)	(18.5)	(18.5)	(0.00)
USA	-0.13	-0.61	-0.56	-17.00	-0.63	0.05	-19.78	0.03	0.00	0.97
	(1.17)	(0.12)	(0.12)	(0.00)	(0.12)	(0.17)	(0.08)	(0.01)	(0.01)	(0.00)
VEN	-5.60	-0.22	-0.02	1.80	-0.22	2.02	0.00	-0.13	1.13	0.00
	(1.54)	(0.52)	(0.52)	(3.76)	(0.52)	(3.30)	(0.00)	(21.1)	(21.1)	(0.00)
VNM	-5.96	-0.96	-0.66	-0.35	-0.96	0.62	0.00	2.76	-1.76	0.00
	(0.63)	(0.28)	(0.28)	(0.65)	(0.28)	(0.80)	(0.00)	(45.2)	(45.2)	(0.00)
XAC	-9.70	-0.67	-0.22	4.13	-0.67	4.83	0.00	-0.17	1.17	0.00
	(0.84)	(0.74)	(0.74)	(1.91)	(0.74)	(2.58)	(0.00)	(0.54)	(0.54)	(0.00)
XCA	-4.53	-0.88	-0.68	0.50	-0.88	1.39	0.00	-1.77	2.77	0.00
	(0.46)	(0.86)	(0.86)	(1.59)	(0.86)	(1.23)	(0.00)	(7.97)	(7.97)	(0.00)
XCB	-4.34	-0.32	-0.04	1.50	-0.32	1.82	0.00	-0.21	1.21	0.00
	(0.38)	(0.30)	(0.30)	(1.02)	(0.30)	(0.99)	(0.00)	(9.71)	(9.71)	(0.00)
XCF	-7.30	-0.57	-0.13	3.19	-0.57	3.78	0.00	-0.18	1.18	0.00
	(0.78)	(0.50)	(0.50)	(0.72)	(0.50)	(1.05)	(0.00)	(0.16)	(0.16)	(0.00)
XEA	-6.38	-1.66	-1.39	-1.62	-1.66	0.04	0.00	1.03	-0.03	0.00
	(0.37)	(0.44)	(0.44)	(1.16)	(0.44)	(0.90)	(0.00)	(10.2)	(10.2)	(0.00)
XEC	-6.04	-0.46	-0.02	1.73	-0.46	2.21	0.00	-0.27	1.27	0.00
	(0.77)	(0.43)	(0.43)	(0.66)	(0.43)	(0.41)	(0.00)	(1.26)	(1.26)	(0.00)
XEE	-4.19	-1.01	-0.93	-1.03	-1.01	-0.02	0.00	0.98	0.02	0.00
	(0.48)	(0.42)	(0.42)	(0.47)	(0.42)	(0.12)	(0.00)	(0.99)	(0.99)	(0.00)
XEF	-0.14	-1.36	-1.04	-25.00	-1.44	-11.18	-16.72	0.05	0.41	0.54
	(0.17)	(0.45)	(0.45)	(0.00)	(0.45)	(0.43)	(0.84)	(0.02)	(0.02)	(0.03)
XER	-5.83	-0.75	-0.48	0.92	-0.75	1.68	0.00	-0.83	1.83	0.00
	(0.49)	(0.46)	(0.46)	(0.66)	(0.46)	(0.58)	(0.00)	(11.1)	(11.1)	(0.00)
XNA	-5.30	-0.48	-0.16	0.91	-0.48	1.40	0.00	-0.53	1.53	0.00
	(0.53)	(0.61)	(0.61)	(3.48)	(0.61)	(3.14)	(0.00)	(3.96)	(3.96)	(0.00)
XNF	-8.65	-0.29	0.15	2.97	-0.29	3.27	0.00	-0.10	1.10	0.00
	(1.79)	(0.44)	(0.44)	(1.79)	(0.44)	(1.38)	(0.00)	(4.77)	(4.77)	(0.00)
XOC	-5.39	-0.56	-0.35	2.40	-0.56	2.98	0.00	-0.24	1.24	0.00
	(0.78)	(0.49)	(0.49)	(0.32)	(0.49)	(0.56)	(0.00)	(0.22)	(0.22)	(0.00)
XSA	-5.34	-0.71	-0.41	1.24	-0.71	1.96	0.00	-0.58	1.58	0.00
	(0.75)	(0.57)	(0.57)	(2.36)	(0.57)	(2.13)	(0.00)	(19.6)	(19.6)	(0.00)
XSC	-5.67	-1.14	-0.70	0.20	-1.14	1.35	0.00	-5.70	6.70	0.00
	(0.61)	(0.68)	(0.68)	(0.60)	(0.68)	(0.59)	(0.00)	(443)	(443)	(0.00)

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Table C.15 – *Continued from previous page*

	ΔX^i	$\Delta\mathfrak{R}^i$	ΔU^i	ΔE^i	PSE	PCE	PTE	LSE	LCE	LTE
XSE	-7.11	-0.74	-0.47	1.98	-0.74	2.75	0.00	-0.38	1.38	0.00
	(0.88)	(0.38)	(0.39)	(0.51)	(0.38)	(0.50)	(0.00)	(0.31)	(0.31)	(0.00)
XSM	-6.23	-0.64	-0.44	1.50	-0.64	2.15	0.00	-0.43	1.43	0.00
	(0.85)	(0.68)	(0.68)	(2.76)	(0.68)	(2.26)	(0.00)	(10.2)	(10.2)	(0.00)
XSU	-8.39	-0.41	-0.11	0.69	-0.41	1.10	0.00	-0.59	1.59	0.00
	(1.78)	(0.27)	(0.27)	(0.38)	(0.27)	(0.25)	(0.00)	(16.2)	(16.2)	(0.00)
XWF	-5.31	-0.63	-0.19	1.04	-0.63	1.69	0.00	-0.61	1.61	0.00
	(0.57)	(0.40)	(0.40)	(0.90)	(0.40)	(0.93)	(0.00)	(115)	(115)	(0.00)
XWS	-7.20	-0.50	-0.20	1.52	-0.50	2.03	0.00	-0.33	1.33	0.00
	(0.86)	(0.30)	(0.30)	(1.16)	(0.30)	(1.01)	(0.00)	(13.1)	(13.1)	(0.00)
ZAF	-0.26	-1.94	-1.51	-43.78	-2.12	-7.93	-60.32	0.04	0.14	0.82
	(0.11)	(0.24)	(0.24)	(0.00)	(0.23)	(0.90)	(1.43)	(0.00)	(0.02)	(0.02)
ZMB	-5.06	-0.62	-0.18	0.69	-0.62	1.32	0.00	-0.91	1.91	0.00
	(0.67)	(0.52)	(0.52)	(1.09)	(0.52)	(0.93)	(0.00)	(14.5)	(14.5)	(0.00)
ZWE	-6.26	-0.88	-0.43	-0.36	-0.88	0.53	0.00	2.47	-1.47	0.00
	(0.95)	(0.73)	(0.73)	(0.94)	(0.73)	(0.27)	(0.00)	(31.2)	(31.2)	(0.00)

Notes: ΔX^i denotes the percentage changes in trade flows, $\Delta\mathfrak{R}^i$ the percentage changes in real income, ΔU^i the percentage changes in welfare, ΔE^i the percentage changes in carbon emissions, PSE the percentage scale effects, PCE the percentage composition effects, PTE the percentage technique effects, LSE the log scale effects, LCE the log composition effects, and LTE the log technique effects. Note that for countries with constant emissions, these log changes are not defined. The numbers in parentheses below the reported values give the corresponding bootstrapped standard errors.

Appendix D

The Consequences of Unilateral Withdrawals from the Paris Agreement

D.1 Estimation Results

Table D.1: Gravity Estimation Results

	(1) agricult.	(2) apparel	(3) chemical	(4) equipm.	(5) food	(6) machin.	(7) metal
$\ln DIST$	-1.202	-0.789	-0.885	-0.563	-0.920	-0.768	-0.865
	(0.127)***	(0.137)***	(0.073)***	(0.129)***	(0.093)***	(0.076)***	(0.083)***
$BRDR$	0.331	0.361	0.187	0.660	0.474	0.204	0.550
	(0.166)**	(0.177)**	(0.138)	(0.216)***	(0.152)***	(0.127)	(0.119)***
$LANG$	-0.078	0.455	0.208	0.064	0.375	0.077	-0.000
	(0.211)	(0.209)**	(0.181)	(0.134)	(0.127)***	(0.178)	(0.235)
RTA	0.113	0.154	0.263	0.670	0.461	0.169	0.084
	(0.136)	(0.210)	(0.106)**	(0.166)***	(0.129)***	(0.143)	(0.223)
N	19182	19182	19182	19182	19182	19182	19182

	(8) mineral	(9) mining	(10) other	(11) paper	(12) service	(13) textile	(14) wood
$\ln DIST$	-1.233	-1.331	-0.810	-1.006	-0.352	-0.994	-0.872
	(0.124)***	(0.224)***	(0.292)***	(0.084)***	(0.053)***	(0.091)***	(0.194)***
$BRDR$	0.553	0.087	-0.058	0.619	0.256	0.147	0.735
	(0.214)***	(0.360)	(0.280)	(0.152)***	(0.094)***	(0.147)	(0.210)***
$LANG$	-0.050	0.199	0.106	0.259	0.255	0.297	0.062
	(0.194)	(0.355)	(0.316)	(0.184)	(0.071)***	(0.180)*	(0.284)
RTA	0.005	0.026	-0.162	0.227	0.006	0.337	0.389
	(0.168)	(0.244)	(0.420)	(0.145)	(0.077)	(0.182)*	(0.252)
N	19182	19182	19182	19182	19182	19182	19182

Notes: All regressions include importer and exporter fixed effects. Standard errors clustered by exporter and importer are given in parentheses. * $p < 0.10$, ** $p < .05$, *** $p < .01$.

D.2 Parametrization

In this section, we briefly describe how the model parameters can be obtained from the data. The Cobb-Douglas utility parameters γ_l^i and γ_S^i can be calculated as the sectoral expenditure shares. For the factor cost shares in the sectoral production functions, we first obtain the energy cost share by dividing firms' expenditure on intermediate inputs from the six GTAP energy sectors (coal, electricity, gas, gas manufacture and distribution, oil, and petroleum and coal products) by the firms' total costs. We then distribute the remaining cost share to the five GTAP factors (natural resources, capital, skilled labor, unskilled labor, and land) according to the reported relative expenses for these factors. The factor cost shares of the energy production function are determined in a similar way. First, we obtain the fossil fuel cost share. To ensure that we fit national emission levels, we multiply the world price of fossil fuels per ton of carbon with the country's carbon emissions and divide by the energy sectors' total costs. The remaining cost share is again distributed between the GTAP factors according to the factor expenditures. Finally, the national fossil fuel endowment shares are calculated by dividing a country's total revenue from the natural resource factor by the sum of these revenues in all countries.

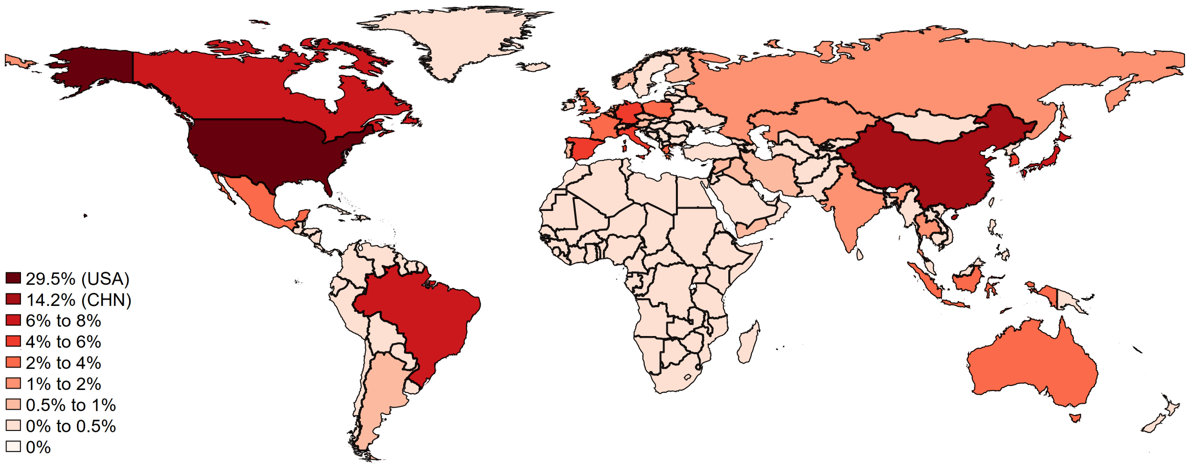
Table D.2 shows the implemented reduction targets illustrated in Figure 4.1 and used in our counterfactual analyses.

Table D.2: Implemented Reduction Targets (%)

ALB	11.50	ETH	0	MEX	22.00	THA	20
ARE	0	FIN	36.34	MLT	54.29	TTO	0
ARG	18.00	FRA	35.33	MNG	14.00	TUN	0
ARM	0	GBR	22.78	MOZ	0	TUR	0
AUS	22.05	GEO	15.00	MUS	0	TWN	0
AUT	48.64	GHA	15.00	MWI	0	TZA	0
AZE	16.62	GIN	0	MYS	0	UGA	6.60
BEL	39.84	GRC	44.07	NAM	8.86	UKR	0
BEN	0	GTM	11.20	NGA	20	URY	0
BFA	6.60	HKG	48.43	NIC	0	USA	20.98
BGD	5.00	HND	0	NLD	33.31	VEN	0
BGR	11.36	HRV	36.38	NOR	38.20	VNM	8.00
BHR	0	HUN	9.87	NPL	0	XAC	1.73
BLR	0	IDN	29.00	NZL	34.23	XCA	0
BOL	0	IND	0	OMN	0	XCB	0.64
BRA	64.92	IRL	38.86	PAK	0	XCF	8.98
BRN	0	IRN	4.00	PAN	0	XEA	8.00
BWA	0	ISR	0	PER	20	XEC	0.36
CAN	44.46	ITA	38.65	PHL	0	XEE	0
CHE	49.45	JAM	7.80	POL	33.46	XEF	0
CHL	0	JOR	1.50	PRI	44.47	XER	12.38
CHN	5.02	JPN	19.30	PRT	53.27	XNA	25.10
CIV	0	KAZ	19.82	PRY	10	XNF	4.78
CMR	0	KEN	0	QAT	0	XOC	0.42
COL	20	KGZ	12.62	ROU	0	XSA	0.66
CRI	44.00	KHM	0	RUS	0	XSC	5.00
CYP	61.53	KOR	37.00	RWA	0	XSE	0
CZE	17.82	KWT	0	SAU	0	XSM	0
DEU	23.19	LAO	0	SEN	5.00	XSU	0
DNK	21.45	LKA	0	SGP	0	XWF	0.59
DOM	0	LTU	0	SLV	0	XWS	8.05
ECU	9.00	LUX	39.54	SVK	9.17	ZAF	0
EGY	0	LVA	0	SVN	44.83	ZMB	0
ESP	50.98	MAR	13.00	SWE	31.71	ZWE	0
EST	0	MDG	0	TGO	0		

D.3 Sensitivity: Different Fossil Fuel Supply Elasticities

Figure D.1: Total Emission Reductions Lost ($\eta = 4$)

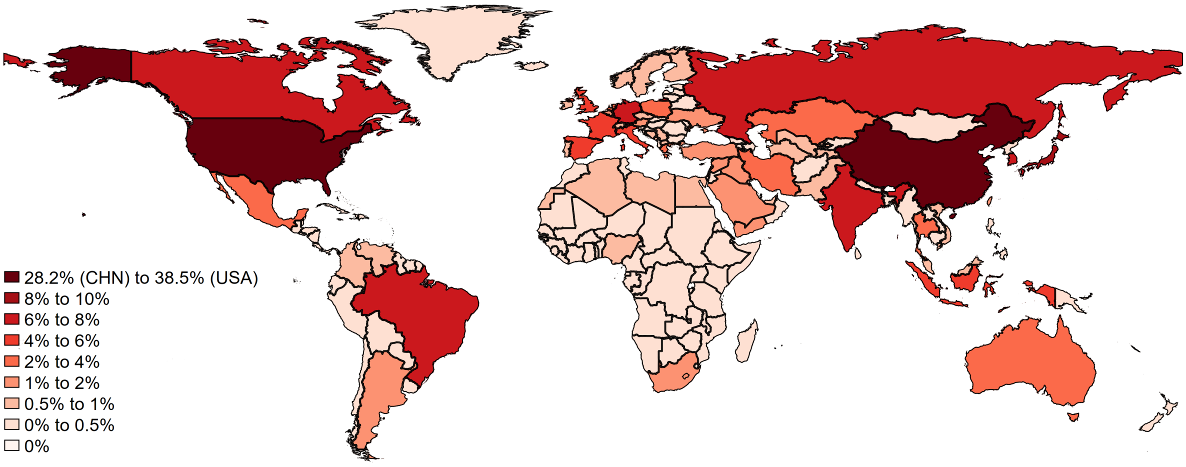


Notes: This figure shows the shares of the global emission reduction due to the Paris Agreement that is lost due to a unilateral withdrawal in the 139 different scenarios with a fossil fuel supply elasticity of $\eta = 4$. On average, 0.9% of the global emission reduction are forgone. The loss shares range from 0.0% for a number of very small countries to 29.5% for the US.

Table D.3: Top Five Total Reduction Losses ($\eta = 4$)

Withdrawing country	USA	CHN	JPN	BRA	CAN
World reduction lost (total effect)	29.5%	14.2%	6.2%	6.1%	6.1%

Figure D.2: Total Emission Reductions Lost ($\eta = 1$)



Notes: This figure shows the shares of the global emission reduction due to the Paris Agreement that is lost due to a unilateral withdrawal in the 139 different scenarios with a fossil fuel supply elasticity of $\eta = 1$. On average, 1.5% of the global emission reduction are forgone. The loss shares range from 0.0% for a number of very small countries to 38.5% for the US.

Table D.4: Top Five Total Reduction Losses ($\eta = 1$)

Withdrawing country	USA	CHN	JPN	CAN	DEU
World reduction lost (total effect)	38.5%	28.2%	9.3%	7.6%	7.6%

D.4 Model Extension

D.4.1 Decomposition

Taking into account multiple fossil fuel types, country i's emissions can be expressed as:

$$EM^i = \sum_{v\in\mathcal{V}} \kappa_v \frac{\rho_v^i \xi_R^i \left(\alpha_{SE}^i Y_S^i + \sum_{l\in\mathcal{L}} \alpha_{lE}^i Y_l^i\right)}{(1+\frac{\kappa_v \lambda^i}{r_v})r_v} = \xi_R^i \bar{\alpha}_E^i \frac{\tilde{Y}^i}{P^i} \bar{\kappa}^i \left(\frac{r^i}{P^i}\right)^{-1},$$

where $\bar{\kappa}^i \equiv \sum_{v\in\mathcal{V}} \frac{\kappa_v \rho_v^i r^i}{(1+\frac{\kappa_v\lambda^i}{r_v})r_v}$ captures the average carbon intensity of a country's fossil fuel mix.

As in the base model, we can take the total differential and hence decompose the emission changes into different effects, namely scale, composition, and technique, as well as a new additional substitution effect, which captures shifts between different types of fossil fuel (e.g. substitution of coal with less emission-intensive fossil fuels to fulfill emission targets):

$$dEM^i = \underbrace{\frac{\partial EM^i}{\partial(\tilde{Y}^i/P^i)} d(\tilde{Y}^i/P^i)}_{\text{scale effect}} + \underbrace{\frac{\partial EM^i}{\partial \bar{\alpha}_E^i} d\bar{\alpha}_E^i}_{\text{composition effect}} + \underbrace{\frac{\partial EM^i}{\partial(r^i/P^i)} d(r^i/P^i)}_{\text{technique effect}} + \underbrace{\frac{\partial EM^i}{\partial \bar{\kappa}^i} d\bar{\kappa}^i}_{\text{substitution effect}}.$$

Scale Effect. A country's emissions increase proportionally with the size of the economy:

$$\frac{\partial EM^i}{\partial(\tilde{Y}^i/P^i)} = \frac{\xi_R^i \bar{\alpha}_E^i \bar{\kappa}^i}{r^i/P^i} > 0 \quad \text{and} \quad \frac{\partial EM^i}{\partial(\tilde{Y}^i/P^i)} \frac{(\tilde{Y}^i/P^i)}{EM^i} = 1.$$

Composition Effect. An increase in the average energy intensity of production in a country proportionately increases the country's carbon emissions:

$$\frac{\partial EM^i}{\partial \bar{\alpha}_E^i} = \frac{\xi_R^i \tilde{Y}^i \bar{\kappa}^i}{r^i} > 0 \quad \text{and} \quad \frac{\partial EM^i}{\partial \bar{\alpha}_E^i} \frac{\bar{\alpha}_E^i}{EM^i} = 1.$$

Technique Effect. An increase in the national fossil fuel resource price proportionately *lowers* a country's carbon emissions:

$$\frac{\partial EM^i}{\partial (r/P^i)} = -\frac{\xi_R^i \bar{\alpha}_E^i \bar{\kappa}^i \tilde{Y}^i / P^i}{(r^i/P^i)^2} < 0 \quad \text{and} \quad \frac{\partial EM^i}{\partial (r^i/P^i)} \frac{r^i/P^i}{EM^i} = -1.$$

Substitution Effect. An increase in the average carbon intensity of a country's fossil fuel mix proportionately increases the country's carbon emissions:

$$\frac{\partial R^i}{\partial \bar{\kappa}^i} = \frac{\xi_R^i \bar{\alpha}_E^i \tilde{Y}^i}{r^i} > 0 \quad \text{and} \quad \frac{\partial R^i}{\partial \bar{\kappa}^i} \frac{\bar{\kappa}^i}{R^i} = 1.$$

The decomposition in the extended model hence captures the different emission channels very similarly to the base model, but allows to further differentiate the part of the change that takes place conditional on economic size and sectoral structure. While countries could simply produce more or less fossil fuel intensively (in response to a changing fossil fuel price) in the base model, they can still do so in the model extension, but can additionally shift between different fossil fuels based on relative price changes between them. We follow Pothen and Hübler (2018) in calling this latter channel the "substitution effect".

D.4.2 Parametrization

We consider three different fossil fuel types, namely *oil*, *gas*, and *coal* (i.e. $\mathcal{V} = \{oil, gas, coal\}$). The GTAP fossil fuel sectors are: oil, gas, coa, p_c (Petroleum, coal products), and gdt (Gas manufacture, distribution). We collect gas and gdt in our gas resource and split p_c between our $coal$ and oil resources according to the respective input expenditure shares for the GTAP oil and coa sectors.

For the carbon intensities of the different fossil fuels (κ_v), we rely on intensities given by the US EIA (https://www.eia.gov/tools/faqs/faq.php?id=73&t=11, accessed on August 16th, 2019). For $coal$, we use the average over anthracite, bituminous, lignite, and subbituminous coal. For oil, we use the average over "diesel fuel and heating oil" and "gasoline (without ethanol)". For gas, we use the value of "natural gas".

Out of the five GTAP fossil fuel sectors, only coa, oil, and gas use the natural resource factor. Hence we can obtain fuel type specific endowment shares as $\omega_v^i = NVFA^i_{NatRes,v}/\sum_j NVFA^j_{NatRes,v}$, where $NVFA^i_{NatRes,v}$ is expenditure on the GTAP natural resource factor ($NatRes$) for fossil type v in country i (using the GTAP labeling for the $NVFA$ variable).

We calculate the fossil fuel production expenditure shares ξ_R^i and ρ_v^i in such a way as to exactly fit national carbon emissions from each fossil fuel type. We start by obtaining the emissions (EM_v^i) from the data. Then, resource quantities by fuel type can be obtained as $R_v^i = EM_v^i/\kappa_v$. We obtain the fossil fuel world market prices as $r_v = (\sum_i NVFA^i_{NatRes,v})/(\sum_i EM_v^i)$. Then, the fossil fuel type cost shares in fossil fuel production and the fossil fuel cost share in energy production can be obtained as $\rho_v^i = (r_v R_v^i)/(\sum_u r_u R_u^i)$ and $\xi_R^i = (\sum_v r_v R_v^i)/(\alpha^i_{SE} Y^i_S + \sum_l \alpha^i_{lE} Y^i_l)$, respectively.