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Offshoring and firm overlap: Welfare effects with non-sharp selection into offshoring

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Abstract

Using German establishment data, we provide evidence for selection of larger, more productive producers into offshoring. However, the selection is not sharp, and offshoring and nonoffshoring producers coexist over a wide range of the revenue distribution. To explain this overlap, we set up a model of offshoring, in which we decouple offshoring status from revenues through heterogeneity in two technology parameters. In an empirical analysis, we employ German establishment data to estimate key parameters of the model and show that disregarding the overlap has large quantitative effects. It lowers the estimated gains from offshoring by almost 50% and, at the same time, exaggerates the role of the extensive margin for explaining the evolution of German offshoring since the 1990s.

JEL CLASSIFICATION

F12; F14; L11

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1 | INTRODUCTION

Offshoring and its welfare effects have played a prominent role in academic research and the public debate since the fall of the iron curtain. In recent years, attention in the literature has shifted towards understanding the specific nature of firms that choose to offshore. Relying on models of heterogeneous firms, trade economists have pointed out that similar to exporters, offshoring firms are larger, more productive, and make higher profits than their nonoffshoring competitors (see Antràs, Garicano, & Rossi-Hansberg, 2006; Antràs & Helpman, 2004; Egger, Kreickemeier, & Wrona, 2015). Although, *grosso modo*, this pattern is consistent with the data (cf. Bernard, Jensen, Redding, & Schott, 2012; Hummels, Jørgensen, Munch, & Xiang, 2014; Moser, Urban, & Weder di Mauro, 2015), existing theoretical work misses the empirical fact that offshoring and nonoffshoring producers coexist over a wide range of the productivity distribution, as put forward by Tomiura (2007) and Antràs and Yeaple (2014) for Japanese and Spanish firms, respectively.

To explain this fact and to shed light on how it changes the conclusions we draw when it comes to the consequences of offshoring are the aim of this paper. For this purpose, we first reestablish two important patterns of offshoring from previous research using German establishment data: *Selection*, because offshoring is more common among producers from higher quantiles of the revenue distribution; *Overlap*, since there is coexistence of offshoring and nonoffshoring producers in the various quantiles of the revenue distribution. Based on empirical findings regarding important determinants of offshoring, we then construct a theoretical model that captures selection and overlap and use this model for a structural estimation of parameters, using German establishment data. With the parameter estimates at hand, we then study the nature and extent of the bias in the quantitative welfare effects of offshoring that originates from disregarding the overlap in the data and show how ignoring the overlap affects the relative importance of extensive and intensive margins for explaining observed changes in offshoring.

To construct our dataset, we combine information from three different sources. The first one is the Establishment Panel of the Institute for Employment Research (IAB), which along with other plant-level data provides information on offshoring activities of German producers for the years 1999, 2001, and 2003. As a second source of data input, we rely on the Employment Survey of the Federal Institute for Vocational Education and Training (BIBB) and the Federal Institute for Occupational Safety and Health (BAuA), which covers data on workers and, in particular, the activities they conduct in their workplace. We use the 2006 survey information to construct a measure of task content (the number of tasks and the share of tasks that are offshorable) for more than 300 occupations and employ the Linked Employer–Employee Database from the Institute for Employment Research (LIAB) to aggregate the task content at the occupation level to the plant level to merge workplace information from the BIBB/BAuA survey with employer information from the Establishment Panel. This gives a unique dataset for studying offshoring in the context of task production, and we use this dataset to show descriptive evidence on offshoring behavior and to identify key factors governing the offshoring decision of German producers.

Based on the empirical evidence, we set up a two-country model of offshoring, with labor being the only factor of production. The two countries differ in their levels of development and since offshoring is low-cost seeking, it is one directional and leads to production shifting from the more developed source country to the less developed host country. Following Acemoglu and Autor (2011), we model production as the assembly of tasks, with producers differing in the number of tasks performed in the production process. The number of tasks is directly linked to firm productivity, reflecting the idea that the usage of more tasks allows for a stronger division of labor in the production of goods. Hence, firm heterogeneity materializes because of differences in the task range—the number of tasks conducted divided by the total number of tasks available. Because of fixed costs and a positive link between task range and revenues, our model features selection into offshoring, similar to Antràs and Helpman (2004). To capture the overlap in the data, we add a second source of heterogeneity and assume, in line with German establishment data, that producers also differ in the share of tasks that can be offshored to the low-cost host country.[1] In the tradition of theoretical work building on the Melitz (2003) framework, we model firm heterogeneity as the outcome of a lottery, but acknowledge that firms draw two technology parameters: the task range and the share of offshorable tasks. The interaction of these two technology parameters determines the pattern of offshoring in our model.[2] The model predicts that establishments conducting more tasks and establishments using a larger share of offshorable tasks experience a higher probability to start offshoring, which finds strong support in our data.

In the theory section, we use this model to analyze how changes in variable and fixed offshoring costs affect offshoring and welfare in the source country. A decline in the variable cost of offshoring lowers the price of foreign workers. This makes offshoring attractive for a wider range of producers and increases the volume of tasks imported by incumbent offshoring firms—because the lower cost of foreign production makes them more competitive and because they substitute domestically produced tasks for imported ones. Both effects stimulate labor demand in the host country and lead to a rise in foreign wages. However, the increase in foreign wages is of second order and dominated by the initial drop in variable offshoring costs, so that the effective cost of employing foreign workers decreases. This reflects an appreciation of domestic relative to foreign labor and thus an improvement of the (double) factorial terms of trade for the source country of offshoring with positive welfare implications (cf. Ghironi & Melitz, 2005).[3] Things are different if the fixed cost of offshoring falls. Whereas this makes offshoring attractive for new producers, the higher foreign labor demand and the resulting increase in host country wages prompt incumbent offshoring producers to reduce the volume of imported tasks. The deterioration of the (double) factorial terms of trade counteracts the direct welfare gain from a lower offshoring fixed cost and this leads to the somewhat counterintuitive result that lifting a technology barrier can actually lower welfare of the source country of offshoring.[4]

In the empirical analysis, we employ the German establishment data to estimate key parameters of our theoretical model, using method of moments. Thereby, we consider two model variants: a flexible one, in which we allow for overlap; and a restrictive one, in which we rule out overlap by assumption. We find that the model with overlap provides a better fit with the data and show that disregarding the overlap significantly lowers the estimated cost saving from offshoring. This is intuitive, because the model without overlap presumes that all producers engaged in offshoring have high productivity and these are producers that require a comparably low cost saving to find offshoring attractive. The discrepancy regarding the estimated cost savings from offshoring generates quantitatively sizable differences in the welfare effects attributed to offshoring by the two models. The model with overlap associates the observed share of offshoring producers with an increase in German GDP per capita of 20.71%. The welfare gain attributed to offshoring falls to 10.93% and is therefore almost 50% lower in the model without overlap.

We finally use our model to decompose the observed increase of German offshoring openness vis-á-vis non-EMU countries from 7.01% in 1990 to 16.11% in 2013 into its intensive margin—capturing changes in the offshoring activity of incumbent offshoring producers; and its extensive margin—capturing changes in the mass of offshoring producers.[5] We show that both margins contributed significantly to the observed increase of German offshoring, with the intensive margin explaining about 38.23% of this increase. Disregarding the overlap, the model would attribute only 9.33% of the observed increase in German offshoring openness to the intensive margin and therefore considerably exaggerate the role played by the extensive margin. The model with (without) overlap suggests, moreover, that the increase in offshoring openness between 1990 and 2013 has entailed a welfare gain of

8.93% (7.86%), which explains almost one quarter of the overall increase in German GDP per capita over this period.

Shedding light on the overlap of offshoring and nonoffshoring firms, our analysis is closely related to Antràs, Fort, and Tintelnot (2017), who study the sourcing of firms in a multi-country model. They identify under which conditions importing exhibits complementarities across source markets so that larger firms end up importing from more countries. To reconcile the predictions of their model with the empirical observation that low-productivity firms do not import from strict subsets of source markets of high productivity firms, Antràs et al. (2017) allow firms to differ in two technology parameters, namely their core productivity and their fixed costs of market access. Whereas considering differences of productivity and fixed costs of market access as the two sources of heterogeneity would not change key predictions of our theoretical model, our dataset does not provide information on these two variables. For reasons of data availability, we therefore consider heterogeneity in two alternative technology parameters: the task range and the share of tasks that can be offshored.[6] As a further difference to Antràs et al. (2017), we account for dependencies in the distributions of technology parameters, and analyze to what extent such dependencies are important for describing the overlap in the data. Finally, we investigate how accounting for overlap changes the relative importance of the extensive and the intensive margins for explaining observed changes in offshoring—similar to Armenter and Koren's (2015) analysis in the context of exporting—and provide a detailed welfare analysis.[7]

By studying the effects of offshoring on source country welfare, our model contributes to a large body of literature that includes prominent contributions by Grossman and Rossi-Hansberg (2008), Rodriguez-Clare (2010), and more recently Acemoglu, Gancia, and Zilibotti (2015). Similar to Grossman and Rossi-Hansberg (2008), we associate offshoring with a relocation of task production to a low-cost country. However, focussing on the decision of heterogeneous firms to offshore while keeping the share of offshorable tasks constant, we follow Egger et al. (2015) and emphasize a specific adjustment channel, whose quantitative importance has been put forward by recent empirical evidence (cf. Bergin, Feenstra, & Hanson, 2011). Furthermore, since disregarding the overlap in the data leads to a downward bias in the welfare effects attributed to offshoring, our analysis points to a so far unexplored argument of why welfare effects of new-generation quantitative trade models are sometimes unrealistically small (cf. Caliendo & Parro, 2015; Costinot & Rodriguez-Clare, 2014).

The remainder of the paper is organized as follows. In Section 2, we introduce our dataset, report descriptives, illustrate the overlap of offshoring and nonoffshoring producers for Germany, and identify important factors explaining the offshoring decision. In Section 3, we set up a theoretical model that captures key features of the data, analyze the main adjustment margins, and study the welfare effects of offshoring in the presence of overlap. In Section 4 we employ our data to estimate key model parameters in a structural approach, discuss the goodness of fit of our model, quantify the welfare effects, and show to what extent accounting for the observed overlap of offshoring and nonoffshoring firms affects our results. We also apply our quantitative trade model to decompose the observed increase in German offshoring openness between 1990 and 2013 into its extensive and intensive margin and shed light on the welfare gains attributable to the increase in offshoring over this period. The last section concludes with a summary of the most important results.

2 | DATA SOURCES AND DESCRIPTIVES

We use data from three different sources. Information on production plants comes from the Establishment Panel of the Institute for Employment Research (IAB) in Nuremberg.[8] This database provides detailed establishment data on sales, input expenditures, the number of employees, etc. from employer surveys at an annual basis since 1993. Information on the offshoring activity of German producers is available in this dataset for 1999, 2001, and 2003, and hence we restrict our empirical analysis to these three years. Following Moser et al. (2015), we associate offshoring with the purchase of intermediates or other inputs from abroad in the previous business year. To capture the idea that offshoring is low-cost seeking, we restrict its definition to intermediate goods imports from non-EMU members.[9]

As a second data source, we use the BIBB/BAuA Employment Survey, which provides detailed information on the tasks performed and the occupations held by respondents for a representative sample of German employees with a working time of more than 10 hours per week (see Rohrbach-Schmidt, 2009, for a detailed description). Interviews have been conducted six times since 1979. Since the definition of tasks has changed over time and since using consistent task measures for more than a single year would result in a significant loss of data (cf. Becker & Muendler, 2015), we only consider the 2006 survey for our analysis. This survey covers 20,000 employees and allows us to distinguish 341 different occupations, according to the classification of the Federal Employment Agency (KldB, 1988), as well as 30 different tasks, which are listed in the Online Appendix (for access, see Supporting Information at the end of the paper). Interviewees can answer the question on whether they perform a certain task either with *often/sometimes/never* or with *yes/no*. We give answers *yes* and *often* a weight of one, the answer *sometimes* a weight of 0.5 and answers *never* or *no* a weight of zero, aggregate the thus weighted tasks for each interviewee, average over all individuals in an occupation, and divide the result by the total number of tasks reported by the BIBB/BAuA survey.[10] Following this procedure, we can assign a task range between 0 and 1 to 303 occupations in our dataset. Following Spitz-Oener (2006) and Becker, Ekholm, and Muendler (2013), we furthermore distinguish routine or nonroutine tasks and tasks requiring or not requiring face-to-face contact, classify routine tasks that do not need face-to-face communication as offshorable, as suggested by Levy and Murnane (2004) and Blinder (2006), and compute the share of offshorable tasks for each of the 303 occupations, for which we have determined the task range. The Online Appendix (see Supporting Information) gives an overview of which tasks are classified offshorable.[11]

To aggregate the task information from occupations to the firm level, we proceed in two steps. In a first step, we assign the task range and the share of offshorable tasks at the occupation level from BIBB/BAuA to the Establishment Panel. For this purpose, we make use of the Linked Employer–Employee (LIAB) database of the Institute for Employment Research, which provides record linkages for matching employees registered with the German social security system to the IAB Establishment Panel. The employee data contains the information on the occupation of workers, which we use for linking task information form BIBB/BAuA to firms in the Establishment Panel at the worker level. In a second step, we then compute the simple average of the two task variables (the task range and the share of offshorable tasks) across all workers within an establishment. Unfortunately, we lose some occupations through the matching procedure, because confidentiality rules of the IAB require that outside data matched to LIAB relies on at least three individual observations. Overall, we can generate task information for 268 occupations in the IAB Establishment Panel. Dropping establishments for which we lack task and/or other relevant plant-level information, we end up with a total number of 15,165 establishments and 24,342 establishment observations.

Table 1 summarizes the main descriptives of our dataset. The share of offshoring plants is with a value of 21.45% higher than the share of offshoring firms reported by Moser et al. (2015). The reason for this difference is that Moser et al. (2015) define offshoring by a qualitative increase of a firm's share of foreign intermediates in two consecutive periods with offshoring information, which is a more restrictive definition of offshoring than the one we use in our cross-section. The second row tells us that there is a lot of variation in the task range of German producers. Since we can only observe

TABLE 1 Descriptive statistics

	Mean	Median	STD.	Min.	Max.
Offshoring	0.215	0.005	0.411	0.000	1.000
Task range	0.271	0.272	0.039	0.092	0.407
Share of offshorable tasks	0.303	0.296	0.061	0.104	0.605
Log workforce size	3.003	2.890	1.888	0	10.786
Log revenues	14.717	14.509	2.173	7.601	23.148
Log revenues/worker	11.714	11.618	0.956	4.729	20.516

Note: Descriptives are computed based on 24,342 establishment observations over the years 1999, 2001, 2003. Workforce only covers regular employees and excludes apprentices, trainees, leased laborers, etc.

tasks conducted at home, the maximum task range of offshoring producers may be higher than indicated by Table 1. German producers also differ significantly in their share of offshorable tasks, and in some plants more than 60% of the tasks are vulnerable to offshoring.[12] Plants in our sample also feature large differences in the size of workforce as well as revenues and revenues per workers, which is the reason, why we report them in logs.

To illustrate the overlap of offshoring and nonoffshoring producers, we can rank the establishments in our dataset by their revenues and define decile intervals as a 10% fraction of the largest producers with revenues up to a decile position. This gives for the first decile interval the 10% fraction of producers with the lowest revenues in the dataset; for the second decile interval the 10% fraction of producers with revenues larger than the first decile and lower than or equal to the second decile; and so on. Averaging the share of offshoring producers over the respective decile intervals gives the profile in Figure 1, where black dots refer to the full sample of establishments from all sectors, whereas grey diamonds refer to the subsample of manufacturing producers. Figure 1 makes a strong case for selection, because the share of offshoring producers is larger in intervals reflecting higher revenues. However, the selection is not sharp, because offshoring and nonoffshoring producers coexist in all decile intervals. This highlights that overlap of offshoring and nonoffshoring producers in the revenue distribution is an important feature of the German establishment data.

The establishment data can also be used to identify key determinants of offshoring. For this purpose, we regress our binary offshoring variable on the task range, the share of offshorable tasks, other plant-level controls, and industry as well as region dummies, using a probit estimator. This shows the correlation of offshoring with key observables in our dataset, with the results of the analysis reported in Table 2.

From the results in Table 2, we can conclude that both the task range as well as the share of offshorable tasks are important determinants of offshoring. This result holds in the parsimonious specification of model (1), in which we only consider these two explanatory variables as well as in specifications in which we add log revenues and log revenues per worker as well as industry and region dummies as further controls: models (2) to (5). In model (6), we zoom in on the extensive margin of offshoring. For this purpose, restrict the sample of producers to those that are at least observed in two years and do not offshore in their initial year of observation. We then construct a dummy variable for switchers, which has a value of 1 if a firm starts to offshore in the second or third year of observation and a value of 0, otherwise. Evaluating the mean of the dummy variable shows that 11.35% of the 5,196 producers in this refined sample switch into offshoring. We then regress the binary variable for switchers on the determinants of offshoring in model (5) and find that the main insights regarding

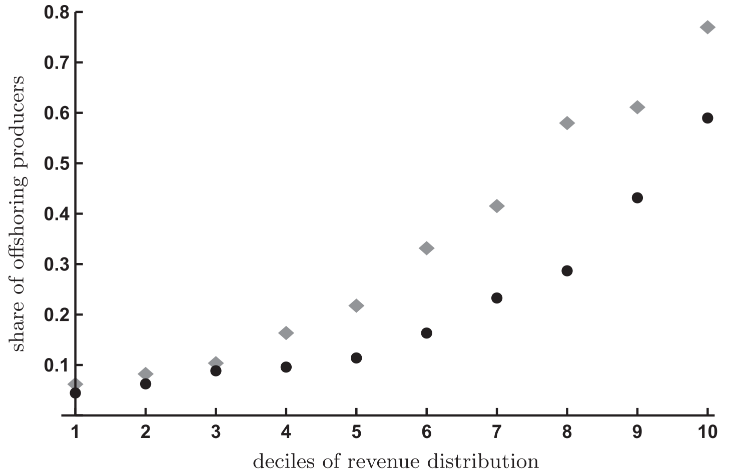

FIGURE 1 Share of offshoring producers. *Note:* The figure covers 24,342 German establishment observations for the years 1999, 2001, and 2003 from all size categories. •, refer to the full sample of producers; ♦, refer to manufacturing producers only. *Source*: IAB Establishment Panel. Descriptive statistics are based on own computations

the role of task range and the share of offshorable tasks for the probability of offshoring remain valid, when considering the extensive margin only.[13]

To assess the quantitative importance of the estimates, we can look at marginal effects. For the preferred specification in model (5), we find that evaluated at its mean, an increase in the task range by one standard deviation (or 3.91 percentage points) increases the probability to offshore by 2.25 percentage points (10.45% of its mean), whereas an increase in the share of offshorable tasks by one standard deviation (or 6.11 percentage points) increases the probability to offshore by 1.10 percentage points (5.10% of its mean). These effects are sizable even in comparison with the marginal effect of an increase in revenues. Increasing the mean of log revenues by one standard deviation (or 14.77%) increases the probability to offshore by 12.20 percentage points (56.73% of its mean).

In the next section, we use the insights from above as guidance for constructing a theoretical model that captures two important features of the German establishment: selection and overlap. Relying on a Melitz-type model in which the existence of fixed costs leads to selection of more productive producers with higher revenues into offshoring, we consider exogenous differences in task range as the major source of heterogeneity generating differences in productivities. To capture the overlap of offshoring and nonoffshoring producers outlined in Figure 1, we add differences in the share of offshorable tasks as a second source of heterogeneity. As shown below, it is the interaction of these two factors of heterogeneity that explains offshoring in our model and, in line with the results from the probit regressions, the model predicts that producers with a larger task range as well as producers using a larger share of offshorable tasks have a higher probability to offshore.

3 | A MODEL OF OFFSHORING AND FIRM OVERLAP

3.1 | Basic assumptions and intermediate results

We consider a static (one-period) world with two economies. Consumers in both countries have constant elasticity of substitution (CES) preferences over a continuum of differentiated and freely tradable goods $x(\omega)$. The representative consumer's utility is given by $U = \left[\int_{\omega \in \Omega} x(\omega)^{(\sigma-1)/\sigma} d\omega\right]^{\sigma/(\sigma-1)}$,

TABLE 2 Offshoring in the cross-section of firms

	Probit estimation					
Dependent variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Task range	2.526***	2.258***	2.474***	2.443***	2.437***	3.123**
	(0.238)	(0.261)	(0.290)	(0.313)	(0.314)	(0.761)
Share of offshorable tasks	4.352***	1.697***	1.961***	0.748**	0.761**	1.475*
	(0.156)	(0.210)	(0.218)	(0.246)	(0.247)	(0.593)
Log revenues				0.240***	0.238***	0.195***
				(0.005)	(0.006)	(0.015)
Log revenues per worker					0.007	−0.028
					(0.013)	(0.035)
Constant	−2.818***	−2.395***	−1.966***	−5.400***	−5.466***	−5.551***
	(0.094)	(0.127)	(0.141)	(0.178)	(0.213)	(0.578)
Dummies						
Industry	No	Yes	Yes	Yes	Yes	Yes
Region	No	No	Yes	Yes	Yes	Yes
Observations	24,342	24,342	24,342	24,342	24,342	5,196
Pseudo R^2	0.030	0.109	0.149	0.237	0.237	0.141
Log Likelihood	−12,271.7	−11,274.2	−10,773.9	−9,650.2	−9,650.0	−1,579.2
Log Likelihood (constant only)	−12,653.9	−12,653.9	−12,653.9	−12,653.9	−12,653.9	−1,838.7

Note: The dependent variable in models 1–5 is the offshoring dummy from Table 1. The dependent variable in model 6 is a binary variable for switchers in a subset of establishments that are observed in at least two years and do not offshore initially. Robust standard errors in parentheses:
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

where $\sigma > 1$ is the elasticity of substitution between different varieties ω and Ω is the set of available consumer goods. Maximizing U subject to the representative consumer's budget constraint $I = \int_{\omega\in\Omega} p(\omega)x(\omega)$ gives isoelastic demand for variety ω:

$$x(\omega) = \frac{I}{P}\left[\frac{p(\omega)}{P}\right]^{-\sigma}, \tag{1}$$

where I is aggregate income, $p(\omega)$ is the price of good ω, and $P = \left[\int_{\omega\in\Omega} p(\omega)^{1-\sigma} d\omega\right]^{1/(1-\sigma)}$ is a CES price index.

The two economies differ in their level of development and are populated by L and L^* units of labor, respectively, where an asterisk refers to the economy with the lower level of development. This is the host country of offshoring, whereas the more advanced economy is the source country of offshoring. Similar to Egger et al. (2015), we assume that the host country lacks the technology to operate its own firms. This implies that all (industrial) producers are headquartered in the source country and it makes the host country a labor reservoir that is inactive in the absence of offshoring.[14] Firms perform different tasks, which are combined in a Cobb–Douglas technology to produce output $y(\omega)$:

$$y(\omega)=\frac{z(\omega)}{1-z(\omega)}\exp\left[\frac{1}{z(\omega)}\int_0^{z(\omega)}\ln y(\omega,i)di\right], \tag{2}$$

where $y(\omega, i)$ denotes the output of task i and $z(\omega)$ is the task range of firm ω, that is, the number of tasks performed divided by the total number of tasks available. The technology in Equation 2 captures in a simple way the gains from labor division, as performing more tasks increases a firm's productivity. Assuming that task output equals labor input, the firm's total variable production costs are given by $C^v(\omega) = \int_0^{z(\omega)} \zeta(i)y(\omega, i)di$, where $\zeta(i)$ is the effective labor cost of task i, which is equal to the domestic wage w if a task is performed at home and equal to the foreign wage w^* multiplied by an iceberg trade cost parameter $\tau > 1$ if the task is performed abroad.

Profit maximization is a three-stage problem. At stage one, (risk-neutral) firms decide on market entry, which involves the investment of f_e units of labor. The investment allows firms to participate in a lottery, in which they draw task range z from a common distribution. At stage two, firms decide upon offshoring. This requires the investment of f units of labor and allows them to draw technology parameter s in a second lottery. After the investment, firms can put the share s of their tasks offshore.[15] At stage three, firms hire workers, produce, and sell their output in a monopolistically competitive market, facing consumer demand in Equation 1. Being a monopolist in their own market, firms consider $x(\omega) = y(\omega)$ and thus the impact of their employment decision on their own price. At the same time, firms are atomistic in the aggregate, and hence take income I and price index P as given. We solve the three-stage problem by backward induction.

At stage three firms make the employment decision for each task at home and abroad. Owing to the underlying Cobb–Douglas technology in Equation 2, profit maximization establishes the result that expenditures are the same for all tasks. The marginal production cost of firm ω is therefore given by

$$c(\omega)=\begin{cases}[1-z(\omega)]w & \text{if all tasks are produced at home}\\ [1-z(\omega)]w\kappa^{s(\omega)} & \text{if share } s(\omega) \text{ of tasks is produced offshore}\end{cases}, \tag{3}$$

where $\kappa \equiv \tau w^*/w$ denotes effective labor costs in the host relative to the source country of offshoring. Since offshoring has fixed costs, $\kappa < 1$ must hold in order to make it attractive for firms to shift task production abroad, and we can associate $\kappa^{-s(\omega)} > 1$ with the marginal cost saving effect of offshoring. Owing to an isoelastic demand function, profit maximization at stage three further establishes the well-known result that firms set their prices as a constant markup over their marginal costs: $p(\omega) = c(\omega)\sigma/(\sigma-1)$. In view of Equation 1, firm-level revenues, $r(\omega) = p(\omega)y(\omega)$ are then given by $r(\omega) = I[p(\omega)/P]^{1-\sigma}$, and relative revenues of two firms can be expressed as a decreasing function of their marginal cost differential:

$$\frac{r(\omega_1)}{r(\omega_2)}=\left[\frac{c(\omega_1)}{c(\omega_2)}\right]^{1-\sigma}. \tag{4}$$

In view of Equation 4, we can index revenues r by marginal costs c instead of ω from now on, in the understanding that marginal production costs are firm specific.[16]

At stage two firms make their offshoring decision. Offshoring requires the investment of $f > 0$ units of labor, which allows firms to participate in a lottery, in which they draw the share of offshorable tasks s. We assume that the distribution of s depends on the realization of z. To be more specific, a firm's probability to have at least some offshorable tasks is a positive function of the task range, and in the interest of tractability we assume $\Pr_z(s > 0) \equiv \nu_0 + \nu_1 z$, with $\nu_0, \nu_1 \geq 0$ and

$\nu \equiv \nu_0 + \nu_1 \in (0,1]$. We associate parameter ν_0 with a common offshorability factor and a positive value of ν_0 implies that even firms with the lowest possible task range have a positive probability that some of their tasks are offshorable. Parameter ν_1 captures a firm-specific offshorability factor with a positive value reflecting that firms with larger task range have a higher probability that some of their tasks are offshorable. Finally, we use the term "combined offshorability factor" to refer to $\nu = \nu_0 + \nu_1$. For firms with some offshorable tasks, the share of tasks that can be put offshore, s, is uniformly distributed over the interval (0, 1]. Hence, for a firm with task range z, the ex ante expected value of s is given by $\mathbb{E}_z[s] = (\nu_0 + \nu_1 z)/2$. The expected relative revenue gain from offshoring depends on the cost saving under all possible realizations of s. For $\nu_1 > 0$, it is larger for firms with a better z draw: $\mathbb{E}_z\left[\kappa^{s(1-\sigma)}\right] = \Pr_z(s > 0)\int_0^1 \kappa^{s(1-\sigma)}ds$, with $d\Pr_z(s > 0)/dz > 0$. In absolute terms, there is a second advantage that renders offshoring more attractive for firms with a better z draw. They make higher revenues at any possible realization of s, according to Equations 3 and 4, and hence can more easily cover the fixed cost of offshoring.

Being risk-neutral, firms will make the offshoring investment only if its expected return is sufficiently high, and since the expected return is higher *ceteris paribus* for firms that have drawn a larger value of z in the lottery, our model establishes for a sufficiently high fixed cost parameter f selection of high-productive firms into offshoring. For the moment, we simply assume selection, whereas in Section 3.3 we characterize the parameter domain that supports selection in our model. Accounting for Equations 3 and 4, the expected profit gain from offshoring of a firm with task range z can be expressed as $\Pr_z(s > 0)(1-z)^{1-\sigma} r(w)[\int_0^1 \kappa^{s(1-\sigma)}ds - 1]/\sigma - fw$, where $r(w)$ is the revenue of the least productive firm with $z = 0$ and $c = w$, which is a firm that does not offshore (see below). The marginal offshoring firm with task range $\bar{z}$, which is the firm that is indifferent between making and not making investment f, is therefore characterized by the following condition

$$\sigma f w = \left(\nu - \nu_1 \frac{\bar{c}}{w}\right)\left(\frac{\bar{c}}{w}\right)^{1-\sigma} r(w)\left[\frac{\kappa^{1-\sigma} - 1}{(1-\sigma)\ln\kappa} - 1\right]. \tag{5}$$

where $\bar{c} \equiv (1-\bar{z})w$ and $\nu = \nu_0 + \nu_1$ is the combined offshorability factor (see above).

At stage one, firms decide on firm entry. To enter the source country, they must make an initial investment of $f_e > 0$ units of labor. This investment gives them a single draw of task range z from a common distribution function. For tractability reasons, we assume that z is Pareto distributed over the unit interval with a probability density function $g_z(z) = k(1-z)^{k-1}$, $k > 0$. We consider a static model and, following Ghironi and Melitz (2005), abstract from fixed costs of production, so that all firms participating in the technology lottery start production, irrespective of their z draw. We do not allow for selection into production, because our dataset covers many small producers, which employ only few domestic workers. Free entry requires that firms make zero profits in expectation, and hence that aggregate operating profits, that is, total revenues R divided by σ, are equal to economy-wide expenditures for fixed costs, $M\bar{c}^k f + Mf_e$, where M is the mass of firms producing distinct varieties ω. The solution to the firms' problem at stage one gives the mass of firms entering the z-lottery, which is determined in general equilibrium and discussed in Section 3.3. To solve for the general equilibrium outcome, we first need to understand how the distributions of the two technology parameters z and s determine the distribution of marginal costs (and thus revenues) in our setting.

3.2 | The distribution of marginal costs

Even though our model features two forms of firm heterogeneity, we can conclude from Equation 3 that their combined effect on firm-level performance measures is captured by a single variable: the

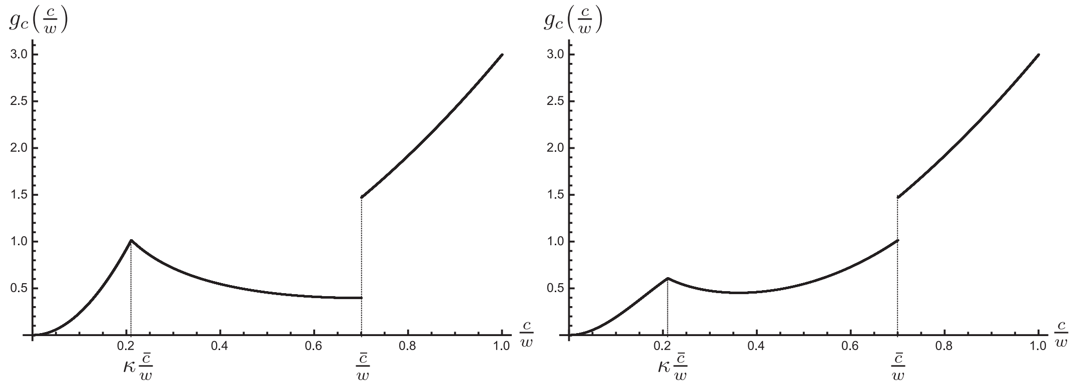

FIGURE 2 The probability density function $g_c\left(\frac{c}{w}\right)$. *Note:* Parameter values: $k = 3$, $\bar{c}/w = 0.7$, $\kappa = 0.3$, and $\nu_0 = 0.7$; $\nu_1 = 0.1$ (left panel); $\nu_0 = 0.1$; $\nu_1 = 0.7$ (right panel)

marginal cost of production. This implies that we can learn about the distribution of firms in their various performance measures, when we understand how the distributions of the two technology parameters z and s map into the distribution of marginal costs c. The marginal cost of nonoffshoring firms is given by $c = (1-z)w$, according to Equation 3. Nonoffshoring firms are either low-productivity producers with task range $z \leq \bar{z}$ or they are high productivity producers with task range $z \geq \bar{z}$ and no offshorable task. Owing to the inverse link between c and z, there is no difference between ranking nonoffshoring firms by their task range or the marginal costs—with the ordering of firms flipped—and for these firms we can therefore infer the distribution of marginal costs c from the distribution of task range z and the insights that a z-specific share of firms, $1-\Pr_z(s > 0)$, has not a single offshorable task.

Things are more complicated for offshoring firms, which are high-productivity firms with task range of $z \geq \bar{z}$, whose production process includes at least some offshorable tasks. The marginal cost of an offshoring firm is given by $c = (1-z)w\kappa^s$, according to Equation 3, and thus the product of two random variables. Therefore, the ranking of c cannot be inferred from the ranking of z in this case. Characterizing the distribution of marginal costs in the population of offshoring firms becomes even more sophisticated if $\nu_1 > 0$, because in this case the distributions of z and s are not independent. In the Online Appendix (see Supporting Information at end of paper), we show how we can link the distributions of z and s to compute the probability density function (pdf) of normalized marginal production costs c/w:

$$g_c\left(\frac{c}{w}\right)=\begin{cases} \left(1-\nu+\nu_1\frac{c}{w}\right)k\left(\frac{c}{w}\right)^{k-1}-\frac{1}{\ln\kappa}\left\{\nu\left(\frac{c}{w}\right)^{k-1}\left[\left(\frac{1}{\kappa}\right)^{k}-1\right]-\nu_1\frac{k(c/w)^k}{k+1}\left[\left(\frac{1}{\kappa}\right)^{k+1}-1\right]\right\} & \text{if } \frac{c}{w}\leq\kappa\frac{\bar{c}}{w} \\ (1-\nu+\nu_1\frac{c}{w})k\left(\frac{c}{w}\right)^{k-1}-\frac{1}{\ln\kappa}\left\{\nu\left(\frac{c}{w}\right)^{k-1}\left[\left(\frac{\bar{c}/w}{c/w}\right)^{k}-1\right]-\nu_1\frac{k(c/w)^k}{k+1}\left[\left(\frac{\bar{c}/w}{c/w}\right)^{k+1}-1\right]\right\} & \text{if } \frac{c}{w}\in\left(\kappa\frac{\bar{c}}{w},\frac{\bar{c}}{w}\right] \\ k\left(\frac{c}{w}\right)^{k-1} & \text{if } \frac{c}{w}>\frac{\bar{c}}{w} \end{cases}. \tag{6}$$

The probability density function of c/w is illustrated for two different sets of parameters in Figure 2.

As we can see from Equation 6 and Figure 2 the pdf of (normalized) marginal costs, $g_c(\frac{c}{w})$, has support on the unit interval and features a discontinuity at $\bar{c}/w$. This is because for firms with task range $z \geq \bar{z}$ investment into offshoring is attractive, and a subset of these firms detects to have at least some offshorable tasks and thus starts offshoring. Since offshoring firms experience a marginal cost saving and are thus shifted to a lower c/w and since the fraction of firms that is affected by this cost saving is discrete for any $z > 0$, selection into offshoring generates a discontinuity of the pdf at $\bar{c}/w$ in Figure 2. The kink of the pdf function at $\kappa\bar{c}/w$ is also rooted in the selection of high-productivity firms into offshoring. More specifically, since firms with $z < \bar{z}$ refuse to make the fixed cost investment for learning about the offshorability of their tasks, none of these firms is shifted towards lower marginal costs. This imposes a binding (selection) constraint on the number of firms that can be located in marginal cost interval $\left[\kappa\frac{\bar{c}}{w}, \frac{\bar{c}}{w}\right]$. For (normalized) marginal costs $c/w < \kappa\bar{c}/w$ the selection constraint is not binding, because the maximum possible cost saving from offshoring when shifting all tasks abroad is given by κ, and hence a firm with task range $z < \bar{z}$ could not be shifted to a (normalized) marginal cost lower than $\kappa\bar{c}/w$ even if it would make the investment into offshoring despite an expected profit loss.

3.3 | The general equilibrium

To solve for the general equilibrium, we choose source country labor as numéraire and set $w = 1$. As shown in the Online Appendix, using Equation 6, we can express economy-wide revenues as follows:

$$R = Mr(1)\left[\frac{k}{k-\sigma+1} + \bar{c}^{k-\sigma+1}\left(\frac{k\nu}{k-\sigma+1} - \frac{k\nu_1\bar{c}}{k-\sigma+2}\right)\left(\frac{\kappa^{1-\sigma}-1}{(1-\sigma)\ln\kappa} - 1\right)\right], \tag{7}$$

where $r(1)$ is the revenue of the least productive producer if $w = 1$ and $k > 2(\sigma-1)$ is assumed to ensure a finite positive value of both the mean and the variance of revenues (cf. Helpman, Melitz, & Yeaple, 2004). As outlined above, free entry establishes $R = M\sigma\left(f_e + \bar{c}^k f\right)$. Together with Equations 5 and 7, this gives a relationship between the marginal cost of the offshoring firm that is indifferent between making and not making investment f, $\bar{c}$, and the effective wage differential between the host and the source country of offshoring, κ, which we call "offshoring indifference condition" (OC):

$$\Gamma_1(\bar{c}, \kappa) \equiv \frac{\bar{c}^{\sigma-1}}{\nu - \nu_1\bar{c}}\frac{k}{k-\sigma+1} + \left\{\frac{\bar{c}^k}{\nu-\nu_1\bar{c}}\left[\frac{(\sigma-1)\nu}{k-\sigma+1} - \frac{(\sigma-2)\nu_1\bar{c}}{k-\sigma+2}\right] - \frac{f_e}{f}\right\}\left[\frac{\kappa^{1-\sigma}-1}{(1-\sigma)\ln\kappa} - 1\right] = 0. \tag{8}$$

As formally shown in the Online Appendix, $\Gamma_1(\cdot) = 0$ establishes a negative link between $\bar{c}$ and κ. The larger the relative effective labor costs in the host country are, the smaller is the cost saving effect of offshoring and the more productive the marginal firm that makes investment f must be in order to avoid in expectation losses from this investment. Intuitively, if the cost saving from offshoring vanishes owing to $\kappa = 1$, all firms prefer domestic production, resulting in $\bar{c} = 0$. In contrast, $\bar{c}$ reaches a maximum at low levels of κ.

A second link between $\bar{c}$ and κ can be determined, when noting from above that free entry into the technology lottery at stage one implies that all (disposable) income accrues to workers, $I = L + w^*L^*$. Since global income is equal to total consumption expenditures, we have $R = L + w^*L^*$. Furthermore, constant markup pricing establishes the well-known result that variable production costs are a constant fraction $(\sigma-1)/\sigma$ of a firm's revenues, with part of these costs accruing to imported tasks. As formally shown in the Online Appendix, the wage bill for workers in the host country of offshoring can thus be expressed as a function of aggregate revenues according to

$$w^*L^* = R\frac{\sigma-1}{\sigma}\frac{\bar{c}^{k-\sigma+1}\left(\nu-\nu_1\bar{c}\frac{k-\sigma+1}{k-\sigma+2}\right)\frac{1+\kappa^{1-\sigma}[(1-\sigma)\ln\kappa-1]}{[(1-\sigma)\ln\kappa]^2}}{1+\bar{c}^{k-\sigma+1}\left(\nu-\nu_1\bar{c}\frac{k-\sigma+1}{k-\sigma+2}\right)\left(\frac{\kappa^{1-\sigma}-1}{(1-\sigma)\ln\kappa}-1\right)}. \tag{9}$$

In combination with $R = L + w^*L^*$ this establishes a second implicit link between the two endogenous variables κ and $\bar{c}$, which reflects adjustments in the effective wage differential in response to changes in the attractiveness of offshoring that are enforced by labor market clearing in the two economies:

$$\Gamma_2(\kappa,\bar{c}) \equiv \kappa\left\{\frac{\sigma}{\sigma-1}\frac{1+\bar{c}^{k-\sigma+1}\left(\nu-\nu_1\bar{c}\frac{k-\sigma+1}{k-\sigma+2}\right)\left(\frac{\kappa^{1-\sigma}-1}{(1-\sigma)\ln\kappa}-1\right)}{\bar{c}^{k-\sigma+1}\left(\nu-\nu_1\bar{c}\frac{k-\sigma+1}{k-\sigma+2}\right)\frac{1+\kappa^{1-\sigma}[(1-\sigma)\ln\kappa-1]}{[(1-\sigma)\ln\kappa]^2}}-1\right\}-\frac{\tau L}{L^*}=0. \tag{10}$$

We refer to this implicit relationship by the term "labor market constraint" (LC) and formally show in the Online Appendix that $\Gamma_2(\cdot) = 0$ establishes a positive link between κ and $\bar{c}$. The larger is $\bar{c}$, the more firms are engaged in offshoring and the larger is *ceteris paribus* the demand for foreign workers. This drives up foreign wages and increases κ. If $\bar{c}$ falls to zero, there is no offshoring and, lacking access to occupations outside the production sector, wages in the host country and thus also κ fall to zero. In contrast, κ reaches a maximum at a high level of $\bar{c}$.

The equilibrium values of $\bar{c}$ and κ are jointly determined by the offshoring indifference condition and the labor market constraint. Thereby, our model features a unique interior equilibrium if offshoring cost parameters τ and f are sufficiently high.[17] The impact of changes in the two offshoring cost parameters is illustrated in Figure 3. A higher variable offshoring cost parameter τ implies for a given volume of offshoring that more foreign workers must be employed in order to provide the required amount of tasks for production in the source country. Therefore, the effective cost for employing foreign relative to domestic labor, κ, must increase to restore labor market clearing. This effect is captured by a counter-clockwise rotation of locus LC in Figure 3, which makes an interior solution with intersection of OC and LC at $\bar{c} < 1$ and $\kappa < 1$ more likely. A higher offshoring fixed cost parameter makes offshoring less attractive *ceteris paribus* and therefore lowers the cutoff cost level characterizing the firm that is indifferent between making and not making the investment of f. This effect is captured by a clockwise rotation of locus OC in Figure 3, which also makes the existence of an interior equilibrium more likely.

In an interior equilibrium as captured, for instance, by the intersection point of the solid OC and LC loci, an increase in either offshoring cost parameter lowers the cutoff cost level $\bar{c}$ and thus the share of offshoring firms in our model. The consequences of higher offshoring costs on the effective wage differential κ depend, however, on which offshoring cost parameter changes. If the fixed offshoring cost parameter increases, the provoked fall in host country labor demand unambiguously lowers the effective wage differential κ. Whereas this labor demand effect is also present when the variable offshoring parameter increases, it is counteracted and dominated by the initial increase in τ, so that the effective wage differential increases.

3.4 | Offshoring margins and welfare

With the general equilibrium outcome at hand, we can look in more detail at the adjustments of offshoring along two margins that play a prominent role in the trade literature: the extensive margin, capturing changes in the mass of offshoring firms; and the intensive margin, capturing changes in the volume of offshoring by incumbent offshoring firms. Looking at the extensive margin first, we can note that the share of firms that can offshore is c specific and depends on the firm's endogenous

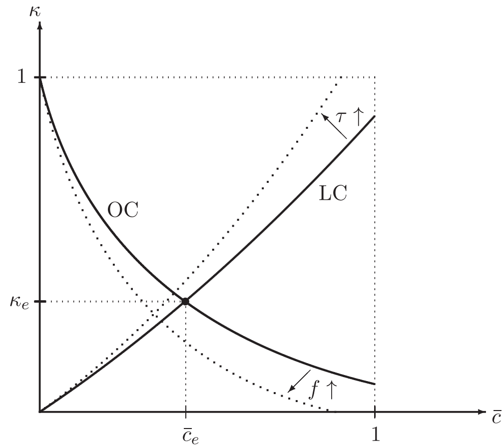

FIGURE 3 Equilibrium values of $\bar{c}$ and κ

decision on whether to make investment f or not. Denoting the share of offshoring firms in the total number of firms with the same marginal cost c by $\chi(c)$, we can compute

$$\chi(c)=\begin{cases} 1-\left[1-\frac{1}{\ln\kappa}\frac{\nu\left[\left(\frac{1}{\kappa}\right)^{k}-1\right]-\nu_1\frac{kc}{k+1}\left[\left(\frac{1}{\kappa}\right)^{k+1}-1\right]}{(1-\nu+\nu_1 c)k}\right]^{-1} & \text{if} \quad c\leq\kappa\bar{c} \\ 1-\left[1-\frac{1}{\ln\kappa}\frac{\nu\left[\left(\frac{\bar{c}}{c}\right)^{k}-1\right]-\nu_1\frac{kc}{k+1}\left[\left(\frac{\bar{c}}{c}\right)^{k+1}-1\right]}{(1-\nu+\nu_1 c)k}\right]^{-1} & \text{if} \quad c\in(\kappa\bar{c},\bar{c}] \\ 0 & \text{if} \quad c>\bar{c} \end{cases} \tag{11}$$

according to Equation 6. It is easily confirmed that $\chi'(c) < 0$ holds for all $c < \bar{c}$, implying that the share of offshoring firms decreases in c. The economy-wide share of offshoring firms is then given by the frequency-weighted mean of $\chi(c)$ and amounts to

$$\chi=\bar{c}^{k}\left[\nu-\nu_1\frac{k}{k+1}\bar{c}\right], \tag{12}$$

where $\nu = \nu_0 + \nu_1 < 1$. From Equation 12 we see that the share of offshoring firms, χ, increases in the cut-off level of marginal costs $\bar{c}$: $d\chi/d\bar{c} = k\bar{c}^{k-1}(\nu-\nu_1\bar{c}) > 0$. Since we know from Figure 3 that $d\bar{c}/df < 0$ and $d\bar{c}/d\tau < 0$, we can thus conclude that a decline in either offshoring cost parameter increases the share of offshoring firms and thus raises offshoring along the extensive margin.

To study adjustments of offshoring along the intensive margin, we can note that total task expenditures of offshoring firms are given by $[(\sigma-1)/\sigma]R[1-R^d/R]$, with

$$\frac{R^d}{R}=\frac{1-\bar{c}^{k-\sigma+1}\left(\nu-\nu_1\bar{c}\frac{k-\sigma+1}{k-\sigma+2}\right)}{1+\bar{c}^{k-\sigma+1}\left(\nu-\nu_1\bar{c}\frac{k-\sigma+1}{k-\sigma+2}\right)\left(\frac{\kappa^{1-\sigma}-1}{(1-\sigma)\ln\kappa}-1\right)}, \tag{13}$$

being the fraction of aggregate revenues accruing to nonoffshoring producers. In view of Equation 9, we can thus write the expenditure share of offshoring firms for imported tasks as follows

$$\rho\equiv\frac{w^*L^*}{[(\sigma-1)/\sigma]R[1-R^d/R]}=\frac{\kappa^{1-\sigma}}{\kappa^{1-\sigma}-1}-\frac{1}{(1-\sigma)\ln\kappa}, \tag{14}$$

with $\lim_{\kappa \to 0} \rho = 1$, $\lim_{\kappa \to 1} \rho = 1/2$, and $d\rho/d\kappa < 0$. From this we can conclude that incumbent offshoring firms expand their expenditure share for imported tasks if the effective cost of employing foreign labor, κ, decreases. From Figure 3 we know that $d\kappa/d\tau > 0$ and $d\kappa/df < 0$, and hence the response of offshoring to exogenous changes in the offshoring cost parameters along the intensive margin depends on the specific nature of the cost change. If the variable cost of offshoring decreases, the effective cost of foreign labor decreases despite an increase in the foreign labor demand and this triggers an expansion of offshoring along the intensive margin that complements the increase in offshoring along the extensive margin. If, however, the fixed cost of offshoring decreases, the effective cost of foreign labor increases owing to an increase in foreign labor demand, so that the increase in offshoring along the extensive margin is counteracted by a decline in offshoring along the intensive margin.

A distinction between the extensive and intensive margin of offshoring is important for understanding the welfare implications of offshoring in the source country.[18] Since preferences are homothetic, we can use the representative consumer in a normative interpretation and consider per-capita labor income ($\widehat{=}$ GDP per capita) as our preferred welfare measure. In view of $w = 1$, we can thus express source country welfare as the inverse of the consumer price index: $W = P^{-1}$. To determine the consumer price index, we can start from the observation that revenues are the product of prices and output. Therefore, accounting for Equation 1 and our previous insight that global consumption expenditure is equal to total source and host country labor income $L + w^*L^*$, revenues of the least productive firm can be expressed as

$$r(1) = \frac{L + w^* L^*}{P^{1-\sigma}} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma - 1}. \tag{15}$$

A second expression for the revenues of the least productive producer can be found when combining the indifference condition of the marginal offshoring firm in Equation 5 with the offshoring indifference condition $\Gamma_1(\cdot) = 0$:

$$r(1) = \sigma f \left[\frac{f_e}{f} - \frac{\bar{c}^k}{\nu - \nu_1 \bar{c}} \left(\nu \frac{\sigma - 1}{k - \sigma + 1} - \nu_1 \bar{c} \frac{\sigma - 2}{k - \sigma + 2} \right) \right] \frac{k - \sigma + 1}{k}. \tag{16}$$

The two Equations 15 and 16 jointly determine price index P and thus source country welfare

$$W = \left\{ \frac{L + \kappa L^*/\tau}{\sigma f} \left[\frac{f_e}{f} - \frac{\bar{c}^k}{\nu - \nu_1 \bar{c}} \left(\nu \frac{\sigma - 1}{k - \sigma + 1} - \nu_1 \bar{c} \frac{\sigma - 2}{k - \sigma + 2} \right) \right]^{-1} \frac{k}{k - \sigma + 1} \right\}^{\frac{1}{\sigma - 1}} \frac{\sigma - 1}{\sigma}. \tag{17}$$

A decline in τ induces an expansion of offshoring along both the intensive and extensive margin and therefore raises foreign labor demand. Whereas this leads to higher foreign wages, the increase in the foreign wage rate is not strong enough to dominate the initial decline in the variable offshoring cost. As a consequence, the effective foreign labor cost decreases, reflecting an appreciation of domestic relative to foreign labor and thus an improvement in the source country's (double) factorial terms of trade, with positive welfare consequences. Things are different if the fixed cost of offshoring decreases, because the expansion of offshoring along the extensive margin not only raises foreign wages but also the relative effective cost of employing workers in the host country. This induces a decline of offshoring along the intensive margin and worsens the (double) factorial terms of trade of the source country. The depreciation of domestic relative to foreign labor may be strong enough to dominate the source country's direct welfare gain from a lower offshoring fixed cost. In the Online Appendix, we provide a formal discussion of these effects and illustrate the possibility of welfare losses for the source country from a lower fixed offshoring cost by means of a numerical example.[19]

Welfare in the source country and the relative importance of the extensive and the intensive margin of offshoring are the two main targets of the empirical analysis conducted in Section 4. There, we use the formal structure of our model as guidance for estimating the main parameters of this model and for analyzing the aptitude of our model to capture important features of the data. Furthermore, we shed light on how important acknowledging the observed overlap is for quantifying the welfare effects of offshoring and for assessing the relative importance of the two margins of offshoring.

4 | AN EMPIRICAL ANALYSIS

Based on the theoretical model outlined in the previous section, we now employ the German establishment data to estimate four structural parameters, namely the common offshorability factor ν_0, measuring the size independent probability of firms that some of their tasks are offshorable, the specific offshorability factor ν_1, measuring how the probability of conducting offshorable tasks is influenced by the task range, the elasticity of substitution between different product varieties σ, and the Pareto shape parameter k. In addition, we estimate two general equilibrium variables, namely the effective labor costs in the host relative to the source country of offshoring, κ, and the marginal cost of the firm that is indifferent between making and not making the offshoring investment, $\bar{c}$. Since the six variables are treated parametrically by firms, we call them parameters in the subsequent analysis, while keeping in mind that κ and $\bar{c}$ are endogenous in general equilibrium and reflect realizations of trade costs. The six parameters jointly determine the observables in our dataset, and hence we cannot estimate them independently using linear specifications, but instead have to solve a system of equations.

To make this problem tractable, we first pin down k and $\bar{c}$ for all feasible realizations of ν_0 and ν_1 by enforcing equivalence of the share of offshoring producers and the average marginal costs of nonoffshoring producers in the model with the data. Since marginal costs are not directly observable, we construct a proxy for them, relying on the available task information. To be more specific, in line with our theoretical model we compute marginal costs from the observed task range in the data, relying on the functional relationship in Equation 3. As outlined in the theory section, the marginal costs thus defined depend on the range of tasks conducted at home and abroad. Since we can determine the task range only for the workplaces in Germany, we have to confine the computation of marginal costs to nonoffshoring producers. We normalize marginal costs by dividing them by their maximum level. This ensures that in line with our theory the maximum of the now normalized marginal costs is equal to one. We then compute for nonoffshoring producers the marginal cost average. From a theory point of view, the thus computed marginal cost average depends negatively on the fraction of offshoring firms. To obtain two independent expressions for the fraction of offshoring producers and the average marginal costs, we therefore multiply the latter by the share of nonoffshoring producers, $1-\chi$. Accounting for Equations 6 and 12, we then obtain

$$\widehat{\chi}=\bar{c}^{k}\left(\nu-\nu_1\bar{c}\frac{k}{k+1}\right),\qquad \widehat{c}^{d}_{avg}=\frac{k}{k+1}\left[1-\bar{c}^{k+1}\left(\nu-\nu_1\bar{c}\frac{k+1}{k+2}\right)\right], \tag{18}$$

where a hat notation is used to indicate empirically observed (or estimated) variables and $\nu=\nu_0+\nu_1$ has been considered. The two equations in 18 determine k and $\bar{c}$ as functions of the parameter tuple (ν_0, ν_1) and the observed values of $\widehat{\chi}$ and $\widehat{c}^{d}_{avg}$. To further reduce complexity of our estimation problem, we normalize revenues by dividing them by their economy-wide mean and enforce equivalence of the average of normalized revenues of nonoffshoring firms in the model with its observed counterpart. From Equation 13, we get

$$\widehat{r^d_{avg}/r_{avg}} = \frac{1-\bar{c}^{k-\sigma+1}\left(\nu-\nu_1\bar{c}\frac{k-\sigma+1}{k-\sigma+2}\right)}{1+\bar{c}^{k-\sigma+1}\left(\nu-\nu_1\bar{c}\frac{k-\sigma+1}{k-\sigma+2}\right)\left(\frac{\kappa^{1-\sigma}-1}{(1-\sigma)\ln\kappa}-1\right)}\frac{1}{1-\chi}, \tag{19}$$

with $r^d_{avg} \equiv R^d/[M(1-\chi)]$ and $r_{avg} \equiv R/M$. Accounting for the solutions of k and $\bar{c}$ from (18), we can then express σ as a function of the parameter tuple (ν_0,ν_1,κ). Following this approach reduces the estimation problem to one, in which we simultaneously estimate the three remaining parameters ν_0, ν_1, and κ, while recovering parameters $\bar{c}$, k, and σ from structural relationships imposed by our model. This procedure has the additional advantage that our model captures first moments of important variables in the data.

4.1 | Estimation of ν_0, ν_1, and κ

We use a minimum distance method-of-moments (MM) estimator outlined in Ferguson (1958) and Cameron and Trivedi (2005). This estimator is similar to other MM applications and builds on the idea to specify a vector of n_m observed population moments, $\mathbf{m}$, which is linked to a vector of n_x parameters of the model, $\mathbf{x}$, according to $\mathbf{m} = \boldsymbol{\mu}(\mathbf{x})$, where $\boldsymbol{\mu}(\mathbf{x})$ is a $n_m \times 1$ vector function. If the number of moments, n_m, is larger than the number of parameters, n_x, we can estimate the parameters $\mathbf{x}$ by minimizing the weighted squared distance between observed moments $\mathbf{m}$ and computed moments $\boldsymbol{\mu}(\mathbf{x})$, subject to a vector of constraints, **Cons**, that are imposed by the theoretical model:

$$\hat{\mathbf{x}}_{MD} = \mathrm{argmin}_{\mathbf{x}} \left(\hat{\mathbf{m}}-\boldsymbol{\mu}(\mathbf{x})\right)' \mathbf{W} \left(\hat{\mathbf{m}}-\boldsymbol{\mu}(\mathbf{x})\right), \quad s.t. \quad \mathbf{Cons}, \tag{20}$$

where $\mathbf{W}$ is a $n_m \times n_m$ positive-semidefinite weighting matrix and a hat indicates observed or estimated variables. The specific assumption of the MM estimator considered here is that $\mathbf{m}$ is a vector of reduced-form parameters, whose estimates $\hat{\mathbf{m}}$ are the means of subsets of observations. As weighting matrix $\mathbf{W}$, we use a diagonal matrix based on the inverse variances of the observations used to construct the reduced-form parameter estimates. This puts higher weight on more precisely measured moments and is the optimal weighting matrix for given reduced-form estimates $\hat{\mathbf{m}}$ (cf. Cameron & Trivedi, 2005).[20]

We consider four moments in Equation 20. The first one is the variance of normalized revenues over all firms. Combining Equations 4, 6, and 7, we can compute

$$\mu_1(\nu_0,\nu_1,\kappa) = \frac{(k-\sigma+1)^2}{k[k-2(\sigma-1)]}\frac{1-\bar{c}^{k-2(\sigma-1)}\left(\nu-\nu_1\bar{c}\frac{k-2(\sigma-1)}{k+1-2(\sigma-1)}\right)\left(1-\frac{\kappa^{2(1-\sigma)}-1}{2(1-\sigma)\ln\kappa}\right)}{\left[1-\bar{c}^{k-\sigma+1}\left(\nu-\nu_1\bar{c}\frac{k-\sigma+1}{k-\sigma+2}\right)\left(1-\frac{\kappa^{1-\sigma}-1}{(1-\sigma)\ln\kappa}\right)\right]^2}-1. \tag{21}$$

Targeting this moment allows us to acknowledge in the empirical application a formal condition on the relative size of k and σ imposed by our model: $k > 2(\sigma-1)$. If this condition were violated the variance of normalized revenues would go to infinity, and hence the minimum distance estimator would not select such a parameter constellation, irrespective of the considered weighting scheme.

With the remaining moments, we target the share of nonoffshoring producers over three decile intervals of the revenue distribution. To construct these intervals, we rank plants by their revenues and define groups that include the 10% fraction of producers with the highest revenues up to the respective decile. This gives ten disjoint intervals with increasing revenues. From the thus defined intervals, we select the interval 1 to acknowledge the observation that some offshorers have fairly low revenues and additionally choose intervals 5 and 9 to give also larger establishments a role in our estimation. To be more specific, choosing the first, fifth and ninth decile, we consider important information from the tails of the revenue distribution and information around the median observation. Thereby, we hope to capture key aspects of the revenue distribution, without using the full information of this distribution (as it is common, for instance, with maximum likelihood estimation).[21] To compute these three moments in the model, we make use of Equation 6 and determine the marginal cost corresponding to quantiles, $q = 1, 2, \ldots, 10$, in the revenue distribution according to $c_q = (1-q/10)^{1/k}$. With the marginal cost level at hand, we then compute the share of nonoffshoring producers up to a certain decile position, employing Equation 6 a second time:

$$sh_q^d = \begin{cases} 1-c_q^k & \text{if} \quad c_q \in (\bar{c},1] \\ 1-\bar{c}^k \left\{ \left(\frac{c_q}{\bar{c}}\right)^k + \nu \left[1-\left(\frac{c_q}{\bar{c}}\right)^k\right] - \nu_1 \bar{c} \frac{k}{k+1} \left[1-\left(\frac{c_q}{\bar{c}}\right)^{k+1}\right] \right\} & \text{if} \quad c_q \in [0,\bar{c}] \end{cases}. \tag{22}$$

The share of nonoffshoring producers for the three targeted revenue intervals can then be computed according to $10(sh_q^d - sh_{q-1}^d)$, and hence the theory values of the three remaining moments are given by $\mu_2(\nu_0, \nu_1, \kappa) = 10(sh_1^d - sh_0^d)$, $\mu_3(\nu_0, \nu_1, \kappa) = 10(sh_5^d - sh_4^d)$, and $\mu_4(\nu_0, \nu_1, \kappa) = 10(sh_9^d - sh_8^d)$, respectively.

Finally, in order for the estimated parameters to satisfy further parameter restrictions of the model, we specify the vector of constraints **Cons** in problem (20) as follows:

$$\mathbf{Cons} = \begin{bmatrix} k>0 \\ \sigma>1 \\ \bar{c}\in(0,1) \\ \kappa\in(0,1) \\ \nu_0,\nu_1 \geq 0 \\ \nu_0+\nu_1 \leq 1 \end{bmatrix}.$$

4.2 | Implementation of the estimation strategy

Since the moment conditions outlined above are highly nonlinear functions of the parameters of our model, we cannot solve the minimization problem (20) analytically. Therefore, we choose a numerical approach, consider a discrete parameter space with fine grid, and compute the theory moments for all possible combinations of ν_0, ν_1, κ, and the corresponding values of $\bar{c}$, k, σ resulting from Equations 18 and 19, which fulfill the parameter constraints. Equipped with these solutions, we then evaluate, which parameter combination minimizes our MM estimator. Since there are a few outliers in the revenue distribution and since we want to ensure that our results are not driven by these outliers, we drop the lowest and highest half percent of establishment observations in the revenue distribution and defer an analysis of the full sample to a robustness check in Section B4. Further details on how we implement our estimation procedure are given in the Online Appendix.

4.3 | Estimation results

Applying the MM estimator to our dataset gives the parameter values reported in Table 3, with bootstrapped standard errors from 50 replications in parentheses. In the upper panel, we report estimation results from the original sample, whereas in the lower panel we report the results when applying the weighting scheme provided by the Research Data Centre of the Institute for Employment Research in Nuremberg. This weighting scheme allows one to adjust for the overrepresentation of larger plants

TABLE 3 Estimation results for the model with overlap

Parameter values	***Unweighted data***				
	$\boldsymbol{\nu_0}$	$\boldsymbol{\nu_1}$	κ	k	σ	$\bar{c}$
Estimates	0.213 (0.00)	0.000 (0.00)	0.255 (0.01)	4.068 (0.01)	2.928 (0.01)	0.9996 (0.00)
Targets	m_1	m_2	m_3	m_4		
Computed	12.597 (0.40)	0.997 (0.00)	0.942 (0.00)	0.427 (0.01)		
Observed	10.379 (0.22)	0.952 (0.00)	0.883 (0.01)	0.569 (0.01)		
Difference	2.218 (0.30)	0.044 (0.00)	0.059 (0.01)	−0.143 (0.01)		
Parameter values	*Weighted data*					
	ν_0	ν_1	κ	k	σ	$\bar{c}$
Estimates	0.111 (0.00)	0.000 (0.00)	0.271 (0.01)	4.009 (0.00)	2.973 (0.03)	0.999 (0.00)
Targets	m_1	m_2	m_3	m_4		
Computed	36.822 (5.41)	0.999 (0.00)	0.977 (0.00)	0.777 (0.00)		
Observed	43.870 (0.58)	0.972 (0.00)	0.926 (0.00)	0.815 (0.00)		
Difference	−7.048 (5.34)	0.027 (0.00)	0.051 (0.00)	−0.038 (0.00)		

Note: We consider the variance of normalized revenues over all firms (μ_1) and the share of nonoffshoring producers in the first, fifth, and ninth decile of the revenue distribution (μ_2, μ_3, μ_4, respectively) as four data moments to estimate parameters ν_0, ν_1, and κ by means of the minimum-distance estimator in Equation 20. Furthermore, we retrieve parameters k, $\bar{c}$, and σ from Equations 18 and 19, which are used as constraints in our minimization problem. Estimations are based on 24,148 establishment observations from all industries. Bootstrapped standard errors (50 replications) in parentheses.

in the Establishment Panel, and hence using it is recommendable, when being interested in economy-wide effects of offshoring. Therefore, the lower panel captures the estimates from our preferred specification.

The estimates of ν_0 differ between the unweighted and weighted data. As outlined above, larger establishments are overrepresented in the unweighted sample, and hence the share of offshoring producers is upward biased. To be more specific, the share of offshoring producers falls by almost 50%, when using weighted instead of unweighted data. Because of this bias, we overestimate the propensity to offshore when considering the unweighted data. In contrast to ν_0, the other parameter estimates do not seem to be overly sensitive to data weighting. An estimate of $\nu_1 = 0$ indicates that dependencies in the distributions of task range and the share of offshorable tasks are not supported by the data. The estimate of k is within the range of estimates of Pareto shape parameters reported by other studies (cf. Corcos, Del Gatto, Mion, & Ottaviano, 2011; Arkolakis, 2010; Egger, Egger, & Kreickemeier, 2013). The value of σ is slightly lower than the one structurally estimated by Egger et al. (2013), relying on firm-level information for five European countries, but in the range of the parameter estimates reported by Broda and Weinstein (2006). The high estimate of $\bar{c}$ acknowledges that offshoring and non-offshoring establishments coexist over wide ranges of the revenue distribution. The estimated values are, however, lower than one because we observe selection in the establishment data.

Regarding the effective wage differential between the host and the source country of offshoring, κ, reliable estimates are not easy to find in the literature, mainly because information on labor costs for a large sample of countries is not easy to find. However, the US Bureau of Labor Statistics provides data on hourly labor compensation costs in manufacturing industries for several economies.[22] Using information on bilateral trade from the OECD STAN Database, this allows us to construct a sample of 32 host countries of German offshoring, for which we have information on both the value of intermediate goods imports and the hourly labor compensation costs.[23] We use this information to construct an intermediate-goods import-weighted measure of foreign labor compensation costs for the year 1999, which for non-EMU members amounts to 66.96% of the labor compensation costs reported for Germany in this year. For the subsample of Eastern European countries and countries outside the OECD, which covers the low-cost countries in the dataset, the respective value falls to 14.42%. Since offshoring in our model is low-cost seeking, we therefore think that an estimated value for κ of 0.27 is of reasonable magnitude.

To see how accounting for the overlap of offshoring and nonoffshoring producers affects our parameter estimates, we also apply the minimum distance estimator to a model variant, in which we impose the restriction $\nu_0 = 1$ and $\nu_1 = 0$. In this case, the probability of offshoring $\Pr_z(s > 0)$ equals one if a firm makes the offshoring investments f, and hence the model enforces an outcome without overlap. In all other respects, we keep the initial estimation approach. In particular, to make the parameter estimates directly comparable with those reported in Table 3, we consider the same moment conditions as in the model with overlap. The estimation results for the more restrictive model are reported in Table 4.

Contrasting the parameter estimates from Tables 3 and 4, we see that disregarding the overlap in the data by enforcing $\nu_0 = 1$ and $\nu_1 = 0$ leads to a considerably lower estimate of $\bar{c}$ and a considerably higher estimate of κ. This is intuitive, because a model without overlap associates offshoring producers with high-productivity plants, and hence a lower cost saving from offshoring is required *ceteris paribus* to make the producer with (a low) marginal cost $\bar{c}$ indifferent between offshoring and nonoffshoring. Both models do a fairly good job in explaining the targeted data moments. Unsurprisingly, the model with overlap is more successful in explaining the share of nonoffshoring firms in the three revenue decile intervals, but is at the same time somewhat less successful in explaining the variance of normalized revenues in the data.

TABLE 4 Estimation results for the model without overlap

Parameter values	***Unweighted data***				
	$\boldsymbol{\nu_0}$	$\boldsymbol{\nu_1}$	κ	k	σ	$\boldsymbol{\bar{c}}$
Estimates	1.000 (0.00)	0.000 (0.00)	0.463 (0.03)	2.491(0.01)	2.196(0.01)	0.537(0.00)
Targets	m_1	m_2	m_3	m_4		
Computed	10.351 (0.22)	1.000 (0.00)	1.000 (0.00)	0.000 (0.00)		
Observed	10.379 (0.22)	0.952 (0.00)	0.883 (0.01)	0.569 (0.01)		
Difference	−0.028 (0.06)	0.048 (0.00)	0.117 (0.01)	−0.569 (0.01)		
Parameter values	*Weighted data*					
	ν_0	ν_1	κ	k	σ	$\bar{c}$
Estimates	1.000 (0.00)	0.000 (0.00)	0.796 (0.01)	3.035 (0.00)	2.506 (0.00)	0.484 (0.00)
Targets	m_1	m_2	m_3	m_4		
Computed	42.204 (1.02)	1.000 (0.00)	1.000 (0.00)	0.894 (0.00)		
Observed	43.870 (0.58)	0.972 (0.00)	0.926 (0.00)	0.815 (0.00)		
Difference	−1.666 (0.92)	0.028 (0.00)	0.074 (0.00)	0.079 (0.00)		

Note: We set $\nu_0 = 1$, $\nu_1 = 0$, and consider the variance of normalized revenues over all firms (μ_1) and the share of nonoffshoring producers in the first, fifth, and ninth decile of the revenue distribution (μ_2, μ_3, μ_4, respectively) as four data moments to estimate parameter κ by means of the minimum-distance estimator in Equation 20. Furthermore, we retrieve parameters k, $\bar{c}$, and σ from Equations 18 and 19, which are used as constraints in our minimization problem. Estimations are based on 24,148 establishment observations from all industries. Bootstrapped standard errors (50 replications) in parentheses.

4.4 | Model fit

To shed further light on how well the two models capture important features of the data, we contrast computed and observed values for the share of offshoring producers, normalized revenues, and normalized marginal costs at the percentile level. Thereby, we focus on the parameter estimates for the weighted data, because these are the estimates we will use later to quantify economy-wide effects of offshoring. Starting with the share of offshoring producers, we rank plants according to their positions in the revenue distribution, define percentile intervals (as the highest 1% fraction of plants with revenues up to the respective percentile), and average the share of offshoring producers over these intervals. We then plot observed against computed shares of offshoring producers for each percentile interval. The outcome is displayed in Panel A of Figure 4, where we use black dots for the model with overlap and gray diamonds for the model without overlap. The figure shows that, not surprisingly, accounting for the overlap improves the fit of our model with the share of offshoring producers data. However, even the model with overlap is not able to fully capture the strong variation in the share of offshoring producers over percentile intervals.

In a second goodness of fit analysis, we look at the aptitude of our model to capture the variation of normalized marginal costs. For this purpose, we rank producers by their marginal costs and compute the average of these costs (divided by their maximum level) over percentile intervals. Since marginal costs are computed from the observed task range in the data and since we can determine the task range only for the workplaces in Germany, we restrict the sample of establishments to nonoffshoring producers and plot for these plants observed against computed marginal cost averages. Again, we use black dots for the model with overlap and grey diamonds for the model without overlap and display the results in Panel B of Figure 4. The model overestimates the variation of marginal costs in the data, primarily because it tries to explain the relative larger variation of revenues with variation in marginal costs only. The observation that the model with overlap underestimates the normalized marginal costs at low percentiles more strongly may indicate that it is more successful in capturing the high revenues of the most productive producers in our dataset.

To see whether this conjecture can be confirmed, we analyze in a third step the aptitude of our model to capture the variation of revenues among nonoffshoring producers. For this purpose, we rank nonoffshoring producers by their revenues and group them in percentile intervals. We then display observed and computed averages of normalized revenues, that is, revenues divided by their economy-wide mean, in Panel A of Figure 5, using black dots and grey diamonds to distinguish the model with overlap from the model without overlap. We see that the model cannot fully explain the extensive

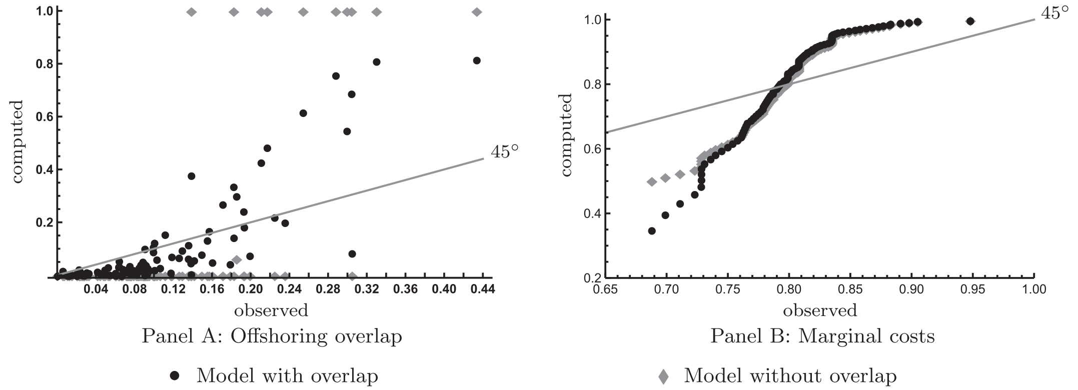

FIGURE 4 Model fit: overlap and normalized marginal costs. Panel A: Offshoring overlap; Panel B: Marginal costs. *Note:* ●, Model with overlap; ♦, Model without overlap

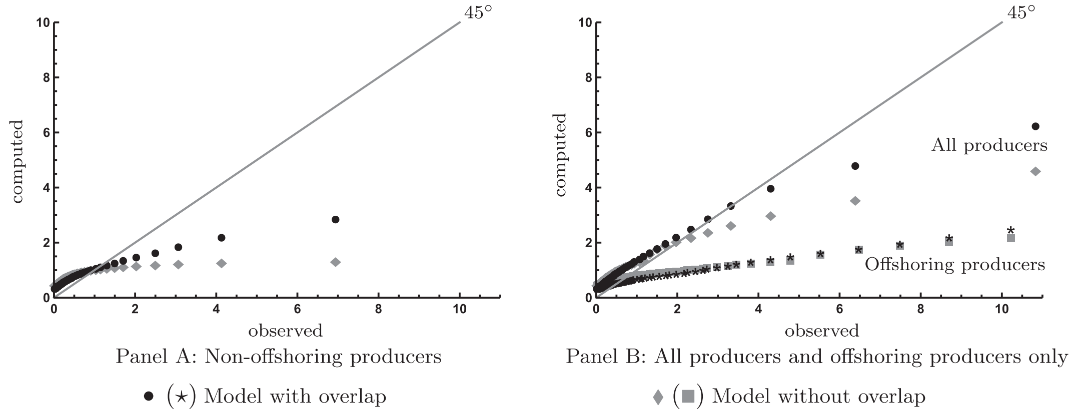

FIGURE 5 Model fit: normalized revenues. Panel A: Nonoffshoring producers; Panel B: All producers and offshoring producers only. *Note:* ● (★), Model with overlap; ♦ (■), Model without overlap

variation of normalized revenues in the data and find support for our conjecture that the model with overlap is more successful in capturing the high revenues of the most productive establishments in the data.

In a final goodness of fit analysis, we repeat the previous analysis for the full sample of offshoring and nonoffshoring producers (black dots and gray diamonds) and for the sample of offshoring firms only (black stars and gray squares). We display the result in Panel B of Figure 5. The finding that the model with overlap does a better job in explaining the high revenues of the most productive producers and is therefore more successful in capturing the variation of normalized revenues in the data remains valid when considering all producers. The goodness of fit for the sample of offshoring firms refers to an out-of-sample prediction of our model, since the revenues of offshoring firms have not been used as moments in the parameter estimation. Overall, the out-of-sample prediction is not overly successful, but the main insight that the model with overlap is better suited for explaining the high revenues of the most productive producers is still valid.[24]

4.5 | Welfare effects of offshoring

In a next step, we employ the parameter estimates from Tables 3 and 4 to quantify the welfare effects of offshoring in our model. Thereby, we focus on the weighted data in order to ensure that our results are not biased because of an overrepresentation of large establishments. Of course, the quantitative welfare effects presented here have to be interpreted with care, because the model outlined in Section 3 is too stylized to give a realistic picture of such effects. Still, the analysis in this and the next section provide a useful illustration of how firm overlap shapes the welfare effects of offshoring in a model with heterogeneous firms.

Welfare under autarky (superscript a) can be inferred from Equation 17 by setting the two general equilibrium variables $\bar{c}$ and κ at zero and one, respectively. According to Figure 3, this corresponds to the case of prohibitively high variable trade costs τ in our theoretical model. The welfare effects of offshoring can then be computed according to $\Delta W = 100\,(W/W^a - 1)$:

$$\Delta W = 100\left\{\left(1+\frac{\kappa L^*}{\tau L}\right)^{\frac{1}{\sigma-1}}\left[1-\frac{\bar{c}^k}{\nu-\nu_1\bar{c}}\left(\frac{\nu(\sigma-1)}{k-\sigma+1}-\frac{\nu_1\bar{c}(\sigma-2)}{k-\sigma+2}\right)\frac{f}{f_e}\right]^{\frac{1}{1-\sigma}}-1\right\}, \tag{23}$$

where ΔW can be interpreted as a change in GDP per capita relative to autarky. Combining Equations 5 and 16, and $\Gamma_2(\kappa, \bar{c}) = 0$, we can solve for theory-consistent values of f, f_e, and $\tau L/L^*$ as functions of the four structural parameters ν_0, ν_1, σ, k and the two general equilibrium variables κ and $\bar{c}$ (reflecting the level of variable trade costs). Substituting the resulting expressions into Equation 24, we then obtain the welfare effects of offshoring as function of the parameter estimates in Table 3.

Following this approach, we estimate a GDP per capita stimulus from the observed exposure to offshoring that amounts to 20.71%, with standard error 0.21, when relying on the parameter estimates in Table 3. In contrast, the welfare gain drops to 10.93%, with standard error 0.19, when employing the parameter estimates from Table 4. Hence, the welfare estimates from offshoring are reduced by almost 50% when disregarding the overlap of offshoring and nonoffshoring firms in the data. This sizable gap can be explained by the different κ-estimates from the two models, which reflect a fundamental bias from ignoring the overlap of offshoring and nonoffshoring producers in quantitative trade models. Since the model without overlap associates offshoring with the most productive producers, it underestimates the (marginal) cost saving from offshoring, that is, it overestimates the true value of κ. With the gains from offshoring directly linked to its (marginal) cost saving effect, this leads to a downward bias in the welfare estimates, when disregarding the overlap in the data.[25]

For an interpretation of the magnitudes of our welfare estimates, they can be put in perspective to estimates reported by other studies. An interesting point of departure in this respect is the multi-country Ricardian trade model of Eaton and Kortum (2002), which has become a benchmark in the quantitative trade literature. Eaton and Kortum compute the welfare effects of a country's movement from its observed trade openness to autarky and therefore consider a comparative static experiment of similar magnitude as ours. For Germany, they report a welfare loss of only 1.3% from moving to a closed economy. Alvarez and Lucas (2007) use an Eaton and Kortum (2002)-type model in a calibration exercise for 60 economies. They provide a recipe on how to use their setting for computing an upper bound of the welfare gain associated with a movement from autarky to free trade. For Germany, the upper bound of welfare gain is 19.6% of GDP in the overly optimistic case that all obstacles to trade are eliminated. As pointed out by Caliendo and Parro (2015) welfare estimates become significantly larger in quantitative trade models when accounting for intermediate goods. Costinot and Rodriguez-Clare (2014) analyze the role of intermediates systematically and show in an illustrative example that in the case of Germany, accounting for intermediates can lead to welfare estimates that are ten times higher than estimates from models, which do not account for intermediates. Our results indicate that estimates for welfare effects of offshoring can be increased as well when acknowledging the overlap of offshoring and nonoffshoring producers in the data.

4.6 | Offshoring at the turn of the millennium

To shed light on how German offshoring has evolved over the last 25 years, we use information from the OECD STAN and EBOPS databases and construct a comprehensive measure of offshoring, which accounts for the import of both goods and service inputs (see the Online Appendix for details). Dividing the resulting measure by GDP gives the German openness to offshoring, e_{off}, which has increased from 7.01% in 1990 to 16.17% in 2013. We can now use our model to decompose this increase into changes at the intensive margin—capturing changes in the offshoring activity of incumbent offshoring firms; and the extensive margin—capturing changes in the mass of offshoring firms. To do so, we specify a theory-consistent measure of offshoring openness $e_{\text{off}} = \kappa/(\tau L/L^*)$ and compute for each year values of the exogenous effective relative domestic labor supply $\tau L/L^*$ and the endogenous variables κ and $\bar{c}$ that are consistent with the observed e_{off} and the two implicit general equilibrium relationships $\Gamma_1(\bar{c}, \kappa) = 0$ and $\Gamma_2(\kappa, \bar{c}) = 0$.

We conduct these computations for both the model with overlap and the model without overlap and use the thus determined parameter estimates to derive theory-consistent values of offshoring openness for a counterfactual situation, in which the mass of offshoring firms stayed constant at the 1990 level. We present a detailed discussion on how we compute these variables and an overview of our parameter estimates in the Online Appendix and summarize the main insights from this decomposition exercise in Figure 6. The black line in this figure depicts the observed changes of German offshoring openness, whereas the solid and dashed gray lines capture the changes of offshoring that are attributed to the intensive margin by the models with and without overlap, respectively.

The figure shows an overall increase in German offshoring openness since the early 1990s. However, this increase has not been monotonic. There were ups and downs over the covered time span, with three notable dips in the early 1990s, the early 2000s and, most strongly, in 2009. Aside from a slight global decline in the trade to GDP ratio at the time, the first dip in offshoring openness captures two particularities of the German reunification. Eastern German producers were less inclined to offshore, and Western German producers gained access to cheap labor in the now larger domestic economy. The second dip picks up a general decline in the trade to GDP ratio in the aftermath of the dot-com crisis—maybe reinforced by a decline in the demand for cheap foreign labor after the drastic labor market reforms in Germany at the beginning of the new century. Finally, the dip of offshoring openness in 2009 captures the well documented sharp decline in globalization during the financial crisis.

According to the model with overlap, both the extensive and intensive margin have played a prominent role in explaining the evolution of German offshoring openness. The intensive margin contributed 38.23%, with standard error 0.61, to the overall increase in German offshoring openness over the period 1990 to 2013. The intensive margin seems much less important, however, if one relies on the model without overlap, explaining only 9.33%, with standard error 0.34, of the increase in German offshoring openness in this case. This difference is well in line with Armenter and Koren (2015), who calibrate a quantitative trade model along the lines of Melitz (2003) with sharp sorting of firms into export mode, using U.S. data, and compare it with an otherwise identical trade model that allows for overlap of exporters and non-exporters. In a counterfactual exercise they show that lowering the iceberg trade cost parameter leads to substantial differences of the two models regarding the relative importance of the extensive and intensive margin for explaining the increase in exporting activity, with the extensive margin being more important in the model without overlap.

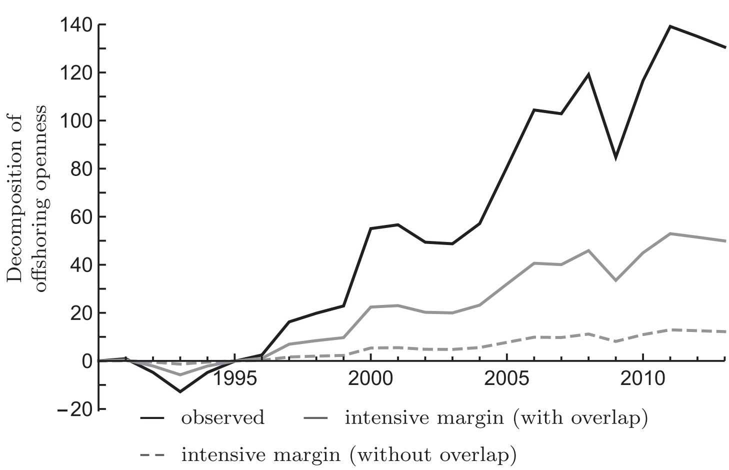

FIGURE 6 Changes in German offshoring openness between 1990 and 2013. *Note:* — , observed; —, intensive margin (with overlap); - - -, intensive margin (without overlap)

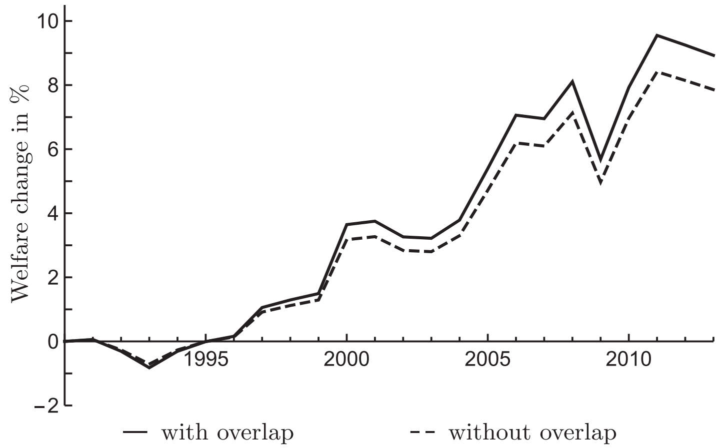

FIGURE 7 The welfare effects of offshoring between 1990 and 2013 *Note*: —, with overlap; - - -, without overlap.

We complete the discussion in this section by simulating the gains from offshoring over the period 1990 to 2013. The results of this exercise are depicted by Figure 7. In line with our insights from Section 4 the gains from offshoring are more pronounced when accounting for the observed overlap in the data. The welfare stimulus from the expansion of offshoring between 1990 and 2013 is 8.93%, with standard error 0.11, in the model with overlap and 7.86%, with standard error 0.08, in the model without overlap. To put the size of these effects into perspective, we can contrast the offshoring gains with the overall increase in German GDP per capita between 1990 and 2013, which amounts to 37.16%. According to our model, the exceptional increase in openness to offshoring after the fall of the Iron Curtain therefore explains almost one quarter of the overall increase in German GDP per capita according to our model.

Taking stock, the analysis in this section confirms our previous finding that ignoring the overlap leads to a downward bias in the welfare estimates of offshoring. Furthermore, the analysis shows that ignoring the overlap has the additional effect of exaggerating the contribution of the extensive margin to the observed increase of German offshoring openness since the early 1990s. Whereas we think that the differences of the two models regarding the decomposition of changes in offshoring into the extensive and intensive margin and the welfare effects associated with an observed change in Germany are informative about the importance of acknowledging firm overlap, given the stylized nature of our model one should not put too much emphasis on the specific level of the estimated effects.

5 | CONCLUDING REMARKS

This paper provides evidence on selection of offshoring producers and their coexistence with nonoffshoring producers over wide ranges of the revenue distribution, using German establishment data. To capture these patterns, we make use of insights from probit regressions for identifying the main determinants of offshoring and build a model, in which firms differ in the number of tasks they perform in the production process and the share of tasks they can offshore to a low-cost host country. Specific realizations of these two technology parameters are the outcome of a lottery and marginal production costs decline in the number of tasks performed and the share of tasks offshored. Offshoring is subject to fixed and variables costs, and not all producers find it attractive to make an investment into offshoring. This gives a model of heterogeneoues firms, in which some but not all firms of a certain revenue category conduct offshoring with the share of offshoring producers increasing in revenues, as suggested by the data.

In an empirical exercise, we estimate key parameters of the model with a method of moments approach, employing the German establishment data. Based on the parameter estimates, we show that access to offshoring has increased welfare in Germany by 20.71%. This welfare estimate falls by almost 50% when disregarding the overlap in the data. The reason for this sizable gap is that a model without overlap associates offshoring with high-productivity producers and thus with producers, which by assumption require just a small marginal cost saving for finding production shifting to a low-cost country attractive. Furthermore, in a decomposition analysis we show that the increase in German offshoring over the period 1990 to 2013 is to a large extent explained by an increase along the intensive margin, that is, by an expansion of offshoring by incumbent offshoring producers. This differs from the decomposition in the model without overlap, where the extensive margin, that is, the increase in offshoring owing to an increase in the number of offshoring producers, is considerably exaggerated. We show that the two main insights of a downward bias in the welfare effects and the exaggeration of the extensive margin of offshoring when ignoring the overlap in the data are robust to changes in the estimation strategy and the inclusion of outliers.

Elaborating on two important biases that materialize when ignoring the overlap of offshoring and nonoffshoring firms in the data, we hope to provide a stimulus for future research on the quantitative effects of offshoring. A promising avenue for extending the analysis in this paper is to allow for firms in the host country, which in the interest of tractability have been excluded in this paper. Such an extension would shed light on the crowding out of local production by foreign labor demand of offshoring firms and would provide a framework for a rigorous welfare analysis in the host country of offshoring. An analysis along these lines would thus be informative to what extent the welfare estimates in the host country are biased when ignoring the overlap in the data and thereby complement the analysis in this study.

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ENDNOTES

[1] Becker et al. (2013) point out that in order to be offshorable, a task must be routine (cf. Levy & Murnane, 2004) and lack the necessity of face-to-face contact (cf. Blinder, 2006). In our sample, 30.25% of tasks are offshorable in the average German establishment according to this criterion.

[2] It is well established that allowing for firm heterogeneity in more than just one dimension helps making the Melitz (2003) model better suited for explaining firm-level evidence in the context of trade. Prominent examples that provide extensions in this direction include Armenter and Koren (2015), Davis and Harrigan (2011), Eaton, Kortum, and Kramarz (2011), Hallak and Sivadasan (2013), Harrigan and Reshef (2015), and Helpman, Itskhoki, Muendler, and Redding (2017). In this paper, we assume that heterogeneity is rooted in two characteristics of the task composition (their number and offshorability) and assume, in line with Acemoglu and Autor (2011), Egger et al. (2015) and others, that task composition determines technology, which is exogenous to the firm. This differentiates our model from Bustos (2011) who studies endogenous technology choice in the context of trade.

[3] As pointed out by Baldwin 1955, p. 260): "The early classical writers refer to the terms on which a nation trades by comparing the number of units of productive services of a foreign country whose product exchanges for the product of one unit of the productive services of the home country. Being dominated by a real-cost theory of domestic value (although asserting its inapplicability in the international sector), it was only natural for the classical writers to express the terms of trade in this fashion." Viner 1937, p. 561) has introduced the term "double factorial terms of trade" to refer to these factor-based conditions of exchange. Ghironi and Melitz (2005) have adopted this criterion in a model featuring heterogeneous firms and external scale economies.

[4] Relying on relative effective labor costs when providing intuition for the welfare effects of offshoring acknowledges that trade involves the exchange of final against intermediate goods, so that changes in the relative price of exports and imports do not reflect changes in the terms of trade of consumer goods. We show in the Online Appendix (for access, see Supporting Information at the end of the paper) that a worsening of the factorial terms of trade for the source country is instrumental for the existence of welfare losses from offshoring in the source country.

[5] We measure offshoring openness by the import of intermediate goods and services relative to GDP.

[6] As a nice side effect of our modeling approach, the two sources of heterogeneity in our model are rooted in the marginal costs of production, which then subsume heterogeneity of firms in all relevant performance measures. This feature allows us to use the toolbox of heterogeneous firms models along the lines of Melitz (2003) for our analysis and makes our analysis akin to Harrigan and Reshef (2015), who consider differences in total factor productivity and the factor shares of skilled and unskilled workers as exogenous sources of firm heterogeneity. Since our data does not show evidence that offshroable and non-offshorable tasks differ in their skill composition, exogenous differences in factor shares appear to be a less important determinant for explaining the offshoring decisions of German producers.

[7] Rodriguez-Lopez (2014) also studies the overlap of offshoring and nonoffshoring firms. He formulates a probabilistic model of offshoring and shows that the interaction of a selection effect and an escape-competition effect produce a hump-shaped relationship between firm productivity and offshoring probability. To the extent that revenues are positively correlated with productivity, our data does not support a hump shape in this relationship.

[8] Please note that the data input is subject to data protection rules of the IAB. Therefore, not all data can be accessed through the authors. However, aggregated data as well as the program codes used are available from the authors upon request.

[9] Two remarks on the data input are in order. First, the IAB Establishment Panel provides plant-level information, which cannot be aggregated to the firm level. Since we cannot distinguish between plants (establishments) and firms, we use the two terms interchangeably. Second, the Establishment Panel does not provide information on the country of origin of imported intermediates, and hence we associate imports from low-income countries with those originating from non-EMU countries, as these are the countries with lower per-capita income on average.

[10] Our results do not change if we give answer *sometimes* a weight of 1.

[11] Using survey data from 2006 allows us to distinguish more tasks than in Spitz-Oener (2006) and Becker et al. (2013). In particular, we can capture a set of IT tasks that are not covered by previous studies. To make sure that our classification of these new tasks into offshorable and nonoffshorable ones does not drive our results, we have also considered the 1999 wave and the 19 tasks distinguished by Spitz-Oener (2006) as well as both the 1999 and 2006 waves and the 16 tasks distinguished by Becker et al. (2013). These modifications have only little effect on the evidence reported in this section.

[12]Whereas the variation in the task range and the share of offshorable tasks for the sample of establishments is sizable, differences in the means of these variables between sectors are rather small. For instance, distinguishing eight broad sector categories, the mean of task range has a minimum level of 0.229 in transport and communication and a maximum of 0.280 in services.

[13]Whereas Table 2 only reports robust standard errors, we have checked the significance of our estimates when clustering standard errors at the industry times region level.

[14]In the case of offshoring, the host country generates income from producing for firms in the source country and it uses the income from exporting the output of offshored production to finance the import of differentiated goods.

[15]One could alternatively assume that firms draw s together with z in the first-stage lottery. Provided that s is not revealed prior to the investment of stage two, this would give the same formal structure as in our model.

[16]It is an important feature of our model that marginal costs are negatively related to the task range. Whereas we cannot observe marginal costs in our dataset, we can make use of Equation 4 to establish a positive link between task range and revenues. In line with this theoretical prediction, we find evidence for a positive link between the range of tasks and the level revenues in our data.

[17]The critical levels of τ and f depend—among other model parameters—on the levels of ν_0 and ν_1. In the knife-edge case of $\nu_0 = 0$, a unique interior equilibrium is guaranteed for any combination of τ and f.

[18]Modeling the host country in a parsimonious way, our model lacks important features that make it suitable for studying host country welfare. Therefore, we focus on the source country of offshoring in our welfare analysis.

[19]Welfare losses in the source country do not go hand in hand with global welfare losses, because the host country benefits from higher labor demand.

[20]In a robustness analysis presented in Section B4 we analyze how our results change when relying on an estimate of the inverse variance–covariance matrix of moment conditions for constructing $\mathbf{W}$, as it is common in GMM applications.

[21]Of course, it is possible to add additional deciles from the revenue distributions and we know from Newey and Windmeijer (2009) that using more moment conditions can improve efficiency, but at the same time can make inference less accurate. Ziliak (1997) provides an early discussion of this efficiency–bias tradeoff in the choice of the number of moment conditions. In our application, the benefit from considering additional deciles of the revenue distributions as further sample moments should be fairly small if important features of the revenue distribution are already picked up by the first, fifth, and ninth decile.

[22]Labor compensation costs cover all payments made directly to the worker, social insurance expenditures, and labor-related taxes (cf. http://www.bls.gov/fls/ichcc.pdf for further details).

[23]The country sample includes Argentina, Australia, Austria, Belgium, Brasilia, Canada, Czech Republic, Denmark, Estland, Finland, France, Greece, Hungary, Ireland, Israel, Italy, Japan, Republic of Korea, Mexico, the Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Singapore, Slovakia, Spain, Sweden, Switzerland, Taiwan, the United Kingdom, and the United States.

[24]In the sample for offshoring firms, we can only report the first 94 percentiles of the revenue distribution if we limit log revenues to a value lower than 11.

[25]Using the unweighted establishment data, the share of offshoring producers is exaggerated and the welfare effects of offshoring therefore larger than in the our baseline scenario. In the model with overlap welfare effects would increase to 39.11%, with standard error 1.65, whereas in the model without overlap welfare effects would amount to 31.34%, with standard error 2.06. Hence, a drastic decline in the welfare effects of offshoring from disregarding overlap is also present when using the unweighted data.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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