Essays on Foreign Ownership, Multinational Business Groups and Wages

Dissertation
zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft
der Rechts- und Wirtschaftswissenschaftlichen Fakultät
der Universität Bayreuth

Vorgelegt
von
Stefan Kornitzky
aus
Burgkunstadt

Dekan:	Prof. Dr. André Meyer
Erstberichterstatter:	Prof. Dr. Hartmut Egger
Zweitberichterstatterin:	Prof. Dr. Elke Jahn
Tag der mündlichen Prüfung:	09.11.2023

Für meine Familie

Acknowledgements

I would like to thank the people that helped, supported and accompanied me during the process of writing this thesis. In particular, I would like to express my gratitude to my first supervisor Hartmut Egger for his patience, help and the many interesting discussions during my time at his chair. His motivation to improve on our knowledge as well as his interest in virtually every topic imaginable in and outside of economic research have made an impression on me that I will always remember on my further path of life. I would also like to thank my second supervisor Elke Jahn for her support and many helpful comments. Her extraordinary attention to detail and outstanding knowledge of German administrative data were invaluable for this thesis.

My grateful thanks also extend to my colleagues at the Department of Economics and the Chair of Economics II. Specifically, I would like to thank Philipp Meier for the pleasant time and many interesting discussions we had while sharing an office and Heidi Frohnhöfer for her support and many conversations about things outside of research.

In addition, I would like to thank all the children and adults at my home town tennis club Baur SV Burgkunstadt, whom I coached and worked for in my spare time, for providing me the necessary distraction from research, as well as my former coach, my fellow team members and all volunteers for sharing my passion for the sport of tennis.

Finally, I would like to thank my family. Special thanks go to my brother, who always accompanies and still sincerely impresses me, to my parents for teaching me the values that made me become the person I am today, and to my partner Julia for her continuous encouragement, her love and for being a role model.

Abstract

This thesis aims to advance the literature on the effects of foreign firm ownership and the organization structure of multinational business groups by shedding light on three distinct research questions:

(i) How does the acquisition of German plants by foreign owners affect workers' wages?

(ii) How does foreign ownership influence the task composition in German plants?

(iii) How does the position in business group hierarchies affect workers' wages?

To answer these research questions, this thesis presents new empirical and theoretical evidence in three separate chapters.

After a short introduction in Chapter 1, Chapter 2 evaluates the effect of foreign takeover on wages of workers in German establishments using rich linked employer-employee data from 2003 to 2014. To identify a causal effect of foreign takeover, propensity-score matching is combined with a difference-in-difference estimator. The results show that a takeover by a foreign investor leads to a wage premium of 4.0 log points in the year after ownership change, which further increases to 6.3 log points three years after acquisition. The wage premium is largest for high-skilled workers, which is consistent with three theoretical arguments, namely rent appropriation by managers, technology protection, and training on new technology. The analysis also shows that the wage premium does not pick up an exporter effect due to a platform investment of the foreign owner, that the wage premium takes about four years before it fully develops, that the wage premium does not vanish after foreign divestment, and that the wage increase is specific to foreign acquisition instead of ownership change per se.

Chapter 3 investigates the effect of foreign takeover on the task composition in German plants in the period from 2000 to 2019. The empirical analysis presents descriptive evidence that foreign-owned establishments in Germany are more intensive in routine tasks. Combining propensity-score matching with a difference-in-difference estimator, this chapter shows that foreign takeover leads to a reduction in the non-routine analytical task share of 0.2 percentage points. This is consistent with the theoretical argument that in multinational firms non-routine tasks are less easily performed abroad. The analysis also demonstrates that this effect cannot be attributed to foreign owners changing the hierarchical organization of plants by adding or dropping layers.

In Chapter 4 firm-level data on ownership linkages are merged with administrative data on German workers to analyze how the position in a business group hierarchy affects workers' wages. To acknowledge that ownership linkages are not one-directional, an index, which measures hierarchical distance to the ultimate owner and accounts for the complex network structure of business groups is proposed. After controlling for unobserved heterogeneity, the analysis documents a positive effect of larger hierarchical distance to the ultimate owner of a business group on workers' wages. To explain this finding, a monitoring-based theory of business groups is presented. This model predicts higher wages to prevent shirking by workers if a larger hierarchical distance to the ultimate owner is associated with lower monitoring efficiency.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Motivated by the growing importance of multinational firm activity in the global economy, a large number of studies in international economics have analysed the effects of foreign firm ownership on various outcomes. In general, this research has shown that foreign-owned firms differ from their domestic counterparts in many dimensions, for instance with regard to productivity,[1] job security and firm survival prospects,[2] management practices,[3] or organizational structure.[4] Another prominent strand of this literature has analysed the effect of foreign ownership on wages, documenting that foreign-owned firms pay higher wages to their workforce. This finding is generally referred to as the foreign ownership or multinational wage premium.[5] In this thesis, I contribute to the literature, which aims to shed light on the effects of multinational firm activity, by investigating three distinct research questions in three separate articles. In the remainder of the introductory section, I briefly summarize the content of these articles, which are presented in Chapters 2–4, whereas a detailed discussion on how each of the three articles contribute to the literature is delegated to the respective chapter.

Chapter 2 analyzes the effect of foreign takeover on wages of workers in German establishments in the period from 2003 to 2014.[6] Combining propensity-score matching with a difference-in-difference estimator, I show that a takeover by a foreign investor leads to a wage premium of 4.0 log points in the year after ownership change, which further increases to 6.3 log points three years after acquisition. The wage premium is largest for high-skilled workers, which is consistent with three theoretical arguments, namely rent appropriation by managers, technology protection, and training on new technology. The analysis also shows that the wage premium does not pick up an exporter effect due to a platform investment of the foreign owner, that the wage premium takes about four years before it fully develops, that the wage premium does not vanish after foreign divestment, and that the wage increase is specific to foreign acquisition instead of ownership change per se. Because the question of how to regulate foreign takeovers has been discussed quite intensively in the German public over recent years, the findings presented in this chapter might be of particular interest for policymakers as well as employers and employees.

[1] See, e.g., Bandick (2011); Bastos et al. (2018); Bircan (2019).

[2] See, e.g., Bernard and Sjöholm (2003); Girma and Görg (2004); Bandick and Görg (2010).

[3] See, e.g., Bloom et al. (2012b).

[4] See, e.g., Altomonte and Rungi (2013); Bastos et al. (2018).

[5] See, e.g., Aitken et al. (1996); Lipsey and Sjöholm (2004); Girma and Görg (2007); Görg et al. (2007); Hijzen et al. (2013).

[6] This chapter is based on Egger et al. (2020), which has been published in The World Economy. When working on this chapter, I have benefited from comments by participants at two research seminars at the University of Bayreuth, the Bavarian Graduate Program in Economics (BGPE)-Workshop in Regensburg and the 21st Annual Conference of the European Trade Study Group (ETSG) in Bern.

Chapter 3 builds on Chapter 2 and investigates the effect of foreign takeover on the task composition in German plants in the period from 2000 to 2019.[7] First, using descriptive evidence, the empirical analysis illustrates that foreign-owned establishments in Germany are more intensive in routine tasks. Second, combining propensity-score matching with a difference-in-difference estimator, this chapter shows that foreign takeover leads to a reduction in the non-routine analytical task share of 0.2 percentage points. This result is consistent with the theoretical argument that in multinational firms non-routine tasks are less easily performed abroad. This finding also cannot be attributed to foreign owners changing the hierarchical organization of plants by adding or dropping layers. The analysis of the impact of foreign acquisition on plants' task composition presented in this chapter might be particularly helpful to establish a more complete picture of the effects of foreign ownership on firms and workers.

In Chapter 4, firm-level data on ownership linkages are merged with administrative data on German workers to analyze how the position in a multinational business group hierarchy affects the wages paid to workers.[8] To acknowledge that ownership linkages are not one-directional, an index accounting for the complex network structure of business groups to measure hierarchical distance of firms to their ultimate owner is proposed. The analysis documents a positive effect of larger hierarchical distance to the ultimate owner of a business group on workers' wages. To explain this finding, a monitoring-based theory of business groups is developed. This model predicts higher wages to prevent shirking by workers if a larger hierarchical distance to the ultimate owner is associated with lower monitoring efficiency. Because the largest multinational firms across the globe are organized as business groups and account for a major part of economic activity, the procedure to link global firm data with plant- and individual-level administrative data presented in this chapter might also motivate further research in this area.

Finally, Chapter 5 concludes with a brief summary of the most important results.

[7] When working on this chapter, I have benefited from comments by Hartmut Egger, Elke Jahn, Philipp Meier, Marco Molitor, Marc-Andreas Muendler and Leandro Navarro.

[8] This chapter is based on Egger et al. (2022), which has been published in the Journal of Economic Behavior & Organization. When working on this chapter, I have benefited from comments by participants at the biannual workshop of the Bavarian Graduate Program in Economics in 2020, the annual conferences of the European Economic Association in 2021 as well as seminars at the Institute for Employment Research in Nuremberg and the University of Bayreuth.

Chapter 2

Reassessing the Foreign Ownership Wage Premium in Germany

2.1 Introduction

Empirical evidence reported by Aitken et al. (1996) that foreign direct investment leads to higher wage payments has sparked a lot of interest among economists and has started a new strand of empirical research in international trade, documenting the existence of a foreign ownership wage premium (Girma et al., 2001; Velde and Morrissey, 2003; Lipsey and Sjöholm, 2004). With access to detailed firm-level data, the causal relationship between foreign ownership and wage premia has become an important topic in this strand of research over the last decade (Girma and Görg, 2007; Heyman et al., 2007; Balsvik, 2011). This chapter provides new evidence for a foreign ownership wage premium in Germany.

We contribute to the literature in two important ways. First, we estimate the foreign ownership wage premium in Germany, using a longitudinal linked employer-employee data set that covers an observation window spanning the years 2003 to 2014. This long time span not only allows us to separate the impact effect of foreign takeover in the period of ownership change from lagged adjustment effects in subsequent years, but also to estimate the foreign ownership wage premium by skill groups. Second, we test three channels put forward by previous research, which give rise to a foreign ownership wage premium. In particular, we consider *rent appropriation by managers*, *technology protection*, and *training on new technology* as distinct arguments justifying the existence of a foreign ownership wage premium. Finally, we control for an *export platform* motive of foreign takeover to ensure that our estimates do not accidentally pick up an exporter wage premium.

To estimate a causal effect of foreign takeover on wages paid by German establishments, we combine propensity-score matching with a difference-in-difference estimator. We associate the probability of a worker in our sample to be treated – defined by staying in an establishment acquired by a foreign investor – with the product of two probabilities: the probability that the employer is target of a foreign takeover and the probability of the worker to remain employed in the same establishment. As both, worker and establishment characteristics, matter for the treatment, we follow Martins (2004) and Hijzen et al. (2013) and combine establishment information with data on worker characteristics in the propensity-score matching. To construct our control group, we match to each treated worker the nearest observational neighbour from establishments that are not subject to foreign takeover.

Using a difference-in-difference approach we then shed light on the effect of treatment on wages distinguishing between an impact effect in the year after takeover and a lagged adjustment effect arising in the second and the third year after takeover. We use data from the year prior to acquisition to determine the control group and build our analysis on a four-year window around the takeover. Because we rely on takeover events from different years, choosing the same four-year observation window for all acquisitions is important (see Egger et al., 2008). In our baseline specification, we estimate an average wage premium from foreign takeover of 4.0 log points, which further grows to 6.3 log points three years after ownership change. When analysing the impact of ownership change for different skill groups, we find that the wage premium is larger for high-skilled than for low- and medium-skilled workers. We also provide evidence that foreign takeover exerts a lagged adjustment effect particularly on the wages of medium- and high-skilled workers.

To shed light on the economic mechanisms that can explain a foreign ownership wage premium, we rely on insights from previous research and distinguish three arguments. First, managers receive a higher remuneration after a successful acquisition (see Heyman et al., 2011). If rent appropriation by managers plays a role, we would expect to find a transitory increase of manager wages. Second, as a result of knowledge transfer by the investor, foreign takeover may lead to the use of new technology requiring training of workers (see Fosfuri et al., 2001; Görg et al., 2007). If training of workers requires time, we would expect to observe a lagged adjustment of wages. Third, foreign-owned plants may have an incentive to protect their technology by reducing knowledge dissipation through worker turnover (see Glass and Saggi, 2002). Workers should thus receive wage premia as long as foreign-owned plants possess a technology advantage.

Using information on manager status and *product* as well as *process innovation* we analyse these different explanations empirically and find support for the relevance of all three channels. Our results also indicate that none of the considered channels can simultaneously explain the immediate wage premium in the year after takeover and the lagged adjustment effect in consecutive periods. Because previous research suggests that an important motive for foreign investment can be market access in nearby countries, we also account for the initial export status of acquired plants to control for an *export platform* motive. We thus ensure that the estimated wage premia do not incorrectly pick up an exporter wage premium due to an expansion of trade with Eastern Europe after the millennium (cf. Dauth et al., 2014).[1] Since the estimated wage premium from foreign takeover does not differ for initial exporters and non-exporters, this concern seems not to be justified.

We complement our empirical analysis by three extensions. First, we analyse whether wages increase because it takes time before the full effect of foreign takeover materialises, or because foreign takeover affects not only the wage level but also the wage growth of workers in German plants. To distinguish between these two interpretations, we expand the observation window around the takeover events to six years. Our results indicate that the growth of wages, which we observe after ownership change, is temporary and washes out after four years. Moreover, our results indicate that reaching the full effect of foreign takeover on wages takes longer for high-skilled workers. Second, we investigate whether foreign takeover causes a persistent wage increase that lasts even after divestment and (re-)acquisition of a foreign-owned plant by a German investor. We find support for a persistent effect, consistent with the view that foreign investment provides a one-time knowledge transfer and a permanent improvement of technology. In a third extension, we conduct a placebo test and estimate the effect of a takeover of German plants by German investors. For low- and medium-skilled workers, we find negative and mostly insignificant effects. For high-skilled workers, we only document insignificant estimates. Thus, a wage premium from takeover only exists in our

[1] The platform argument has been put forward by Motta and Norman (1996), Yeaple (2003), Ekholm et al. (2007), and Neary (2009) as an important motive for foreign investment. It has been used to explain the finding that foreign investment increased in times of falling trade costs. Bernard and Jensen (1995, 1999) were the first providing evidence that exporters pay higher wages than non-exporters. The existence of an exporter wage premium has been empirically confirmed by Schank et al. (2007) and Wagner (2007).

data if the investor comes from abroad. Finally, in two sensitivity tests, we show that our results are robust to changes in the matching procedure.

The remainder of this chapter is organised as follows. In Section 2.2 we introduce the data set and present descriptive statistics. In Section 2.3 we describe our empirical methodology and in Section 2.4 we present and discuss our estimation results. Section 2.5 presents extensions of our analysis and robustness checks and Section 2.6 concludes.

2.2 Data and descriptive statistics

For our empirical analysis, we rely on two data sources provided by the Institute for Employment Research (IAB). The first data set is the IAB Establishment Panel, which consists of a stratified one percent random sample of establishments that employ at least one employee covered by the social security system at June 30 of a year. Since 1993, the IAB Establishment Panel surveys the same establishments from all industries in West Germany and since 1996 in East Germany. Response rates of repeatedly interviewed establishments – which account for about seven percent of the German workforce – are above 80 percent. From the survey questions, we use information about (change in) plant size, industry affiliation, exporting share, location and profitability. Crucial to our analysis, the IAB Establishment Panel also provides information on majority ownership of establishments, differentiating between East German, West German, foreign and public owners as well as a residual group, for which no majority owner is found. Relying on this information, we identify foreign takeover as a change in the majority ownership from German to non-German in two subsequent years.

As a second data set we use the Integrated Employment Biographies (IEB) of the IAB, which cover about 80 percent of the German workforce. This data set contains administrative data on all employees who are subject to social security contributions. The IEB provides information about age, gender, nationality, tenure, occupation, education and the daily wage of workers employed in the plants of the IAB Establishment Panel.

The IEB can be linked to the IAB Establishment Panel by a unique identifier, which allows constructing a linked employer-employee data-set (LIAB) with highly reliable information on workers, wages and establishments.[2] The IEB does not contain detailed information on hours worked. In addition, since worker information comes from social security records, wages are top-coded at the social security contribution ceiling. To deal with these drawbacks, we use only full-time workers aged 16–65 years in our analysis and impute wages above the social security contribution ceiling using Tobit regressions (see, e.g. Schafer, 1997; Gartner, 2004; Baumgarten, 2013; Dustmann et al., 2014).[3] Furthermore, we have information on the education level, which is missing or inconsistent for some workers. To mitigate this problem, we impute missing or implausible information on education, relying on information from previous periods.

Due to the low number of takeovers prior to 2003, we use establishment and worker information for the years 2003 to 2014. Furthermore, we concentrate on establishments located in West Germany, because economic conditions and wages in East Germany still differ substantially from those in West Germany. Another reason for focusing on West Germany only is that we want to avoid attributing the effects of foreign takeover to more general (wage) adjustments during the ongoing transition and catch-up process of East Germany. We also drop establishments, which we do not observe over four consecutive years around the takeover. We use information from the year prior to takeover

[2] For further details on the LIAB, see Alda et al. (2005) and Klosterhuber et al. (2016).

[3] In 2003, the social security contribution ceiling was 167.67 Euro for daily wages and 12.5 percent of the wages of full-time workers are top-coded.

to match workers and the three years afterwards to distinguish the impact effect in the year after ownership change from lagged adjustment effects of foreign acquisition. Because we are interested in the wage impact of foreign takeover over a time span of three years, we only keep workers employed at an establishment over the four-year time horizon (stayers). We also drop workers changing their education over time or employees with a monthly wage below the social security threshold.[4] Finally, we drop one percent of workers with the highest wages in each year to avoid that outliers influence our results.

Table 2.1: Descriptives of key covariates

	Acquired	*(S.D.)*	*Non-Acquired Domestic*	*(S.D.)*
(a) Plant-Characteristics				
Plants	152		6,219	
Plant-Years	608		56,052	
Log Employment	4.485	(1.726)	3.400	(1.580)
ΔLog Employment	-0.013	(0.207)	0.014	(0.179)
Agriculture and Energy	0.018	(0.133)	0.031	(0.173)
Manufacturing	0.479	(0.500)	0.276	(0.447)
Construction	0.033	(0.179)	0.107	(0.310)
Retail and Repair	0.192	(0.395)	0.185	(0.388)
Services and Finance	0.278	(0.448)	0.400	(0.490)
Profitability	0.493	(0.500)	0.413	(0.492)
(b) Worker-Characteristics				
Workers	24,946		489,686	
Worker-Years	99,784		3,502,568	
Log Wage	4.851	(0.463)	4.810	(0.504)
Age	42.8	(9.1)	42.8	(9.5)
Female	0.187	(0.390)	0.197	(0.398)
Low-skilled	0.142	(0.349)	0.123	(0.329)
Medium-skilled	0.744	(0.436)	0.759	(0.427)
High-skilled	0.114	(0.317)	0.117	(0.322)

Notes: Plant-characteristics are plant-year averages which are taken from the IAB Establishment Panel survey. Worker-characteristics are worker-year averages which come from the IEB. ΔLog Employment is the difference in log employment before ownership change. We classify workers with no vocational training, no high-school degree (Abitur) or workers lacking education information and conducting simple tasks as low-skilled; workers with a high-school degree and/or vocational training or workers lacking education information and conducting specialised tasks as medium-skilled; workers with a degree from a university or a university of applied sciences or workers lacking education information and conducting highly-complex tasks as high-skilled. The dummy variable profitability is one if a plant evaluates its previous profits as very good or good. Further matching variables (not listed) are eight West German federal state dummies for Schleswig-Holstein (including Hamburg), Lower Saxony (including Bremen), North Rhine-Westphalia, Hesse, Rhineland-Palatinate (including Saarland), Baden-Württemberg, Bavaria and Berlin.

Table 2.1 reports descriptive statistics of the key variables used when matching workers from acquired to workers in non-acquired establishments. We identify 152 foreign takeovers and 24,946 stayers in the acquired establishments over our sample period. The descriptive statistics are in line

[4]The limit was 400 Euro per month from 2003 to 2012 and 450 Euro in 2013 and 2014.

with previous findings that establishments acquired by foreign investors differ from non-acquired establishments in various dimensions (see Gelübcke, 2013). Targeted establishments are bigger, more prevalent in manufacturing and less prevalent in services than in other industries. Moreover, foreign takeover targets exhibit better profits. At the worker level, Table 2.1 shows that acquired and non-acquired establishments differ slightly with regard to gender and skill composition and that employees in establishments that are target of foreign takeover receive higher wages. Overall, the descriptive statistics suggest that foreign investors do not choose establishments and their workforce randomly, which is why we perform propensity score matching to deal with selection.

2.3 Estimation strategy

2.3.1 Baseline specification

To estimate the effect of foreign acquisition on wages, we use information from a four-year window around a takeover event. Specifically, to construct our control group, we use data one year prior to the change in ownership, whereas we use information from three years after foreign takeover to distinguish the impact effect of ownership change from lagged adjustment effects. Thus, we consider foreign acquisitions in the years 2004 to 2012. Despite the long observation period, we observe only 152 foreign takeovers. To avoid problems from small sample size, we therefore follow Martins (2004), Heyman et al. (2007) and Hijzen et al. (2013) and build our analysis on individual worker data. All workers in an establishment subject to a foreign takeover are part of the *treatment group* if they are continuously employed in the same establishment over the four-year window around ownership change. Accordingly,

$$D_{ij} = \begin{cases} 1 & \text{if } i \text{ employed in } j \text{ from } t=0 \text{ to } t=3 \text{ and } j \text{ foreign-acquired} \\ 0 & \text{if } i \text{ employed in } j \text{ from } t=0 \text{ to } t=3 \text{ and } j \text{ domestic \& non-acquired} \end{cases}$$

defines the treatment indicator D_{ij} which is equal to one if worker i from establishment j that has been acquired by a foreign investor between $t = 0$ and $t = 1$ stays in this establishment over the period $t = 0$ to $t = 3$.[5] In contrast, the treatment indicator is zero if worker i's plant j remains domestically owned over the four-year observation window, which defines our *control group*. However, to identify a causal effect of foreign takeover on wages, we have to take into account that acquired and non-acquired establishments differ in several dimensions, including their workforce (see Table 2.1). Since previous research shows that establishment characteristics and worker characteristics are determinants of both foreign takeover (see Girma and Görg, 2007; Heyman et al., 2007; Bandick and Görg, 2010) and wage payments (Bayard and Troske, 1999; Idson and Oi, 1999; Winter-Ebmer and Zweimüller, 1999), estimates of the effects of foreign takeover that do not account for pre-existing establishment and worker differences are vulnerable to a selection bias.

To overcome the problem of selection bias, we use nearest-neighbour propensity-score matching to define a suitable control group (see e.g. Rosenbaum and Rubin, 1983). We use the variables reported in Table 2.1 to construct the treatment and control group. To determine the nearest neighbour of a worker in the treatment group, we proceed in two steps. We first estimate the probability that a worker i is employed in plant j in the year prior to foreign takeover ($t = 0$) and stays in the plant until year $t = 3$. We then match workers from the treatment group to workers with the smallest absolute distance in their propensity scores in the control group.

[5] Since we do not know the exact date of ownership change, we refer to period $t = 0$ as the year prior to takeover and to period $t = 1$ as the year after takeover.

We model the probability of workers to be treated,

$$P(D_{ij} = 1) = \Phi(\beta \cdot \mathbf{X}_{j,0} + \gamma \cdot \mathbf{X}_{i,0}), \tag{2.1}$$

as a function of a vector of establishment-level covariates, $\mathbf{X}_{j,0}$, and a vector of worker-level covariates, $\mathbf{X}_{i,0}$, measured in period $t = 0$ (with β, γ the respective vectors of coefficients). Establishment-level covariates include the log of employment to control for plant size, the change in log employment prior to takeover to capture business conditions, as well as a dummy that is one if a plant reports very good or good profits as proxy for profitability, five sector-dummies indicating establishments' industry affiliation and eight federal state-dummies determining establishments' location.[6]

Worker-level covariates include information on log wage, age and gender to control for worker heterogeneity. Conditioning on worker characteristics prior to an ownership change ensures that we compare two workers – one in a foreign-acquired and the other in a domestic establishment – with similar earnings potential before the takeover event. To minimise differences in workers' education level, we also match on workers' skill levels. Finally, we match observations from the same year to minimise the risk that estimates of the foreign ownership wage premium pick up macroeconomic changes that have been quite substantial over the observation period.

Table 2.12 in the Appendix reports the mean values of the covariates in the treatment and control group before and after matching. We also show two diagnostics for evaluating the matching quality based on individual covariates (see Girma and Görg, 2007; Hijzen et al., 2013; Balsvik and Saethre, 2016). The first one is the standardised (percentage) bias put forward by Rosenbaum and Rubin (1985). The reduction of the mean standardised bias from 14.8 percent in the unmatched to 4.2 percent in the matched sample indicates a fairly good matching result. As a second diagnostics, we report the normalised difference of covariate means introduced by Imbens and Wooldridge (2009), who suggest an upper limit of one quarter to consider a variable as sufficiently balanced. This criterion is fulfilled for all of our covariates.

We estimate the causal effect of foreign takeover on the wages of stayers using a difference-in-difference (DID) approach. We estimate the treatment effect separately for the year after a foreign takeover and the two subsequent years using a baseline DID model of the following form:

$$w_{ijt} = \alpha_i + \lambda_t + \sum_{s=1}^{3} \nu_s \cdot d_t^s \cdot D_{ij} + \epsilon_{ijt}, \tag{2.2}$$

where w_{ijt} is the log daily wage of worker i in plant j and year t after ownership change, α_i is a worker fixed effect to control for time-invariant unobserved heterogeneity and λ_t is a time-fixed effect.[7] Furthermore, d_t^s is a time dummy equal to one if $t = s$ and D_{ij} is the treatment indicator equal to one for each stayer, whose plant j has been acquired between $t = 0$ and $t = 1$, and zero otherwise. Parameters ν_s are the coefficients for the interaction term of the time dummies with the treatment indicator. Finally, ϵ_{ijt} is the error term. Since the estimates of ν_s represent the wage premium s periods after a worker experiences a foreign takeover, Equation (2.2) allows to estimate the effect of ownership change at three points in time. Hence, we can determine if the effect of foreign takeover on wages is immediate or takes time to develop (see Balsvik and Haller, 2010; Hijzen et al., 2013).

The coefficients ν_s capture a causal average treatment effect of foreign takeover on workers if the following three assumptions hold. The first one is the *Conditional Independence Assumption*

[6] Due to the low number of affected workers in some federal states we assign Bremen (538 stayers) to Lower Saxony, Saarland (11 stayers) to Rhineland-Palatinate and Hamburg (554 stayers) to Schleswig-Holstein.

[7] Since all workers in our sample are stayers, we cannot estimate a separate establishment fixed effect. Put differently, the average worker fixed effect within an establishment is the establishment fixed effect.

(CIA), which states that conditional on the covariates in Table 2.1 the assignment of workers into treatment and control group is random. We take the CIA into account by matching on establishment characteristics, such as establishment size, employment growth, industry, establishments' location and profitability, as well as worker characteristics, such as age, gender, skill dummies and the log daily wage.

The second assumption is the *Stable Unit-Treatment Value Assumption* (SUTVA). In our context, this assumption requires that untreated workers' wages are not affected by other workers staying in a foreign acquired establishment. We are confident that the SUTVA holds because the number of foreign takeovers compared to the total German establishment population is small (see Table 2.1). Thus, we do not expect an effect of a foreign takeover on the wages of untreated workers, e.g. due to an increase in equilibrium wages for all workers.

Third, in the absence of treatment, the wages of both treated and untreated workers have to follow the same path, which is referred to as the *Common Trend Assumption* (CTA). With data from only one pre-acquisition period, it is not possible to test if the CTA holds prior to takeover (see e.g. Mora and Reggio, 2012). However, our matching approach ensures that workers in the treatment and control group are similar in their skills as well as their wages prior to acquisition. To the extent that wages of workers with similar characteristics follow a common trend in a competitive labour market, it is likely that our matching approach does not violate the CTA. As suggested by Pischke (2005), we investigate pre-treatment trends graphically. Since examining a pre-trend requires at least two observations for each worker prior to a foreign takeover, we restrict the sample to all matched worker-pairs, which we observe from period $t = -1$ to period $t = 3$. This decreases the sample to 15,581 stayers in 117 foreign-acquired plants.

Figure 2.1: Average wages in treated and matched control group

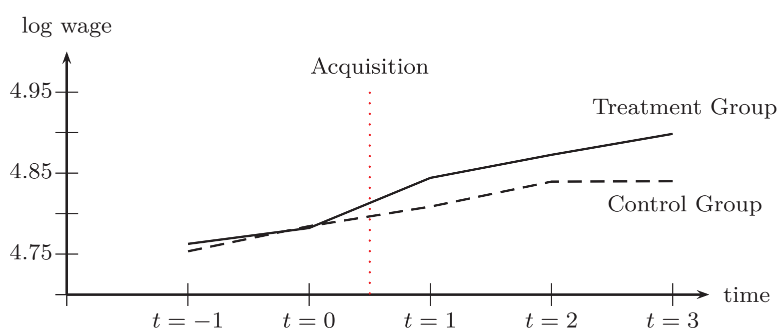


Figure 2.1 depicts the wage trend of treated and untreated workers. The graph shows that wages grow similarly prior to foreign acquisition and that our matching is successful in eliminating differences in average wages between treatment and control group. A test on the equality of means confirms that average wages in period $t = 0$ do not differ significantly between groups. Finally, a simple linear regression of the wage increase between $t = -1$ and $t = 0$ additionally shows that the growth in wages prior to acquisition is similar. These results suggest that the wage premium from foreign takeover does not pick up pre-existing differences in the compositions of treatment and control group. As illustrated by Figure 2.1, workers in establishments that are subject to foreign takeover experience a considerably steeper wage profile after ownership changes.

2.3.2 Heterogeneity of the foreign wage premium

Combining propensity-score matching with a difference-in-difference approach allows to estimate a causal effect of a foreign takeover on wages. However, if the wage premium from foreign takeover differs between heterogeneous workers or plants, estimates from the pooled sample are less informative. From a policy perspective, heterogeneity in the wage premium is particularly relevant if some workers benefit from a foreign investment while others lose. There are two approaches to analyse if the wage premium varies across workers. First, we can split the sample by observable differences of workers and estimate the model in Equation (2.2) separately for the sub-samples. We follow this approach to analyse if pooling over skill groups is justified in our model.

Second, we can include interaction terms in the difference-in-difference regression and estimate a model of the following form,

$$w_{ijt} = \alpha_i + \lambda_t + \sum_{s=1}^{3} \nu_s \cdot d_t^s \cdot D_{ij} + \sum_{s=1}^{3} \eta_s \cdot d_t^s \cdot I_i + \sum_{s=1}^{3} \pi_s \cdot d_t^s \cdot D_{ij} \cdot I_i + \rho_{ijt}, \tag{2.3}$$

where I_i is an indicator variable for worker i, which is one if worker i belongs to a certain sub-group and zero otherwise, and ρ_{ijt} is an error term. Accordingly, coefficients η_s measure the wage differential s years after ownership change for workers with $I_i = 1$ compared to workers with $I_i = 0$. π_s is the additional wage gain s years after acquisiton from foreign takeover between years $t = 0$ and $t = 1$ for workers from this group. In general, I_i can vary across workers differing in individual characteristics within an establishment (such as the manager status) or can be the same for all workers from the same establishment but differ between establishments (such as the export status of the employer).

2.4 Results

This section presents results from our difference-in-difference estimation for the matched sample of treated and untreated workers. The estimates reported in Table 2.2 rely on the baseline specification in Equation (2.2). In the first column, we report our finding for the pooled sample of all workers. The estimates show that workers receive a wage premium of 4.0 log points in the year after ownership change, with the wage premium further increasing to 6.3 log points after three years. A simple Wald test, which compares the equality of coefficients, shows that the difference between the premia in $t = 3$ and $t = 1$ is significant. These results are similar in size to previous estimates for Germany (see Andrews et al., 2009; Hijzen et al., 2013) and in line with findings from other studies arguing that the impact of ownership change takes time to develop (see Balsvik and Haller, 2010; Hijzen et al., 2013).

Columns (2) to (4) of Table 2.2 show the estimates of foreign takeover by skill groups. We find that the immediate wage impact in the period of ownership change with 3.1 log points is less pronounced for low- and medium-skilled workers than for high skilled workers, who obtain a sizeable wage premium of 11.3 log points right after a foreign takeover. This indicates that foreign takeover exerts a stronger positive wage effect if workers are better educated. The wage premium of low-skilled workers is positive but insignificantly different from zero in $t = 2$ and reaches 2.6 log points in the third year after takeover. The wage premium for medium skilled workers increases to 5.2 log points while the wage premium for high skilled workers noticeably rises to 18.1 log points after 3 years. The differences in the wage premia between periods $t = 3$ and $t = 1$ for medium- and high-skilled workers are significant. Thus, wages even grow stronger after the ownership change – particularly for workers with higher skill levels.

Table 2.2: The foreign ownership wage premium

	All workers	*Low-skilled*	*Med.-skilled*	*High-skilled*
	(1)	*(2)*	*(3)*	*(4)*
Acquisition $t = 1$	0.040***	0.031***	0.031***	0.113***
	(0.010)	(0.011)	(0.009)	(0.022)
Acquisition $t = 2$	0.042***	0.008	0.030***	0.167***
	(0.012)	(0.014)	(0.010)	(0.028)
Acquisition $t = 3$	0.063***	0.026*	0.052***	0.181***
	(0.014)	(0.016)	(0.012)	(0.030)
Constant	4.780***	4.641***	4.763***	5.062***
	(0.004)	(0.005)	(0.004)	(0.009)
Observations	199,384	28,368	148,352	22,664

Notes: Dependent variable is the log daily wage. The estimation includes time dummies and worker fixed effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

With the results in Table 2.2 at hand, we investigate three main channels highlighted in the literature explaining positive wage effects of a foreign takeover. A first potential explanation is the *rent appropriation by managers* hypothesis. Evidence for this hypothesis has been put forward by Heyman et al. (2011). Using Swedish linked employer-employee data, they find that the foreign ownership wage premium for high-skilled workers disappears when additionally controlling for individuals' manager status. Manasse and Turrini (2001) discuss a theoretical argument for managers' rent appropriation by arguing that manager income is directly linked to profits, implying that this group benefits disproportionately from cross-border activity (see Kong et al., 2018, for supportive evidence). In the context of foreign acquisition, incentives for rent appropriation by managers exist in particular if performance-based contracts stipulate higher remuneration upon successful takeover.[8]

To investigate to what extent the skill bias in the foreign takeover effect reported in Table 2.2 captures differences in the positions of workers with different skill levels in a plant's hierarchy, we estimate the model outlined in Equation (2.3), in which we additionally interact the treatment indicators with the manager status of workers. For this purpose, we use occupation codes from the German nomenclature in 1988 (KldB 1988) available in the LIAB.[9] We convert these codes into the international standard classification of occupations (ISCO-88 COM) and, following Caliendo et al. (2015), assign employees to three hierarchical layers: *workers*, *supervisors* and *managers or directors*. We then refer to *managers or directors* simply as *managers*.[10] Of course, formal education and hierarchical position in a plant are highly correlated. Still, distinguishing between skill groups and management status is not the same, because low-skilled workers can be managers of an establishment, while high-skilled university graduates can end up working in the production

[8]The *rent appropriation by managers* hypothesis is also supported by findings that top executives experience a strong income increase after a successful acquisition (cf. Schmidt and Fowler, 1990; Datta et al., 2002; Girma et al., 2006). Guest (2009) extends the analysis to international acquisitions and shows that the payment increase for managers is temporary. Whereas studies on the link between acquisition and manager remuneration typically focus on the effects in acquiring firms, one may argue that if there are rents to share, managers of acquired plants should also benefit from a takeover.

[9]The occupation codes capture the job a worker currently performs.

[10]Accordingly, our manager category comprises workers from ISCO-88 COM codes 111-131 and 211-247.

process. In our sample, about 13.4 percent of workers are managers, with the fraction varying between 1.3 percent among low-skilled workers, 7.9 percent among medium-skilled workers and 63.4 percent among high-skilled workers. Table 2.3 summarises the estimation results when additionally taking into account the manager status of workers.

Table 2.3: The foreign ownership wage premium for managers

	All workers	*Low-skilled*	*Med.-skilled*	*High-skilled*
	(1)	*(2)*	*(3)*	*(4)*
Acquisition $t = 1$	0.031***	0.027**	0.028***	0.100***
	(0.009)	(0.011)	(0.008)	(0.028)
Acquisition $t = 2$	0.032***	0.008	0.030***	0.140***
	(0.010)	(0.013)	(0.009)	(0.031)
Acquisition $t = 3$	0.051***	0.027*	0.049***	0.154***
	(0.012)	(0.015)	(0.012)	(0.029)
Manager×Acquisition $t = 1$	0.072***	0.060*	0.035*	0.014
	(0.019)	(0.036)	(0.020)	(0.034)
Manager×Acquisition $t = 2$	0.087***	0.033	0.015	0.039
	(0.021)	(0.032)	(0.018)	(0.039)
Manager×Acquisition $t = 3$	0.097***	0.023	0.036*	0.042
	(0.026)	(0.039)	(0.022)	(0.046)
Constant	4.780***	4.641***	4.763***	5.062***
	(0.004)	(0.005)	(0.004)	(0.009)
Observations	199,384	28,368	148,352	22,664

Notes: Dependent variable is the log daily wage. The estimation includes time dummies and worker fixed effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Column (1) in Table 2.3 shows that the wage premium of 3.1 log points for non-managers is considerable lower than for managers who receive a wage premium of 10.3 log points in the year after acquisition. Similar to the baseline results in Table 2.2, the wage premium increases for non-managers to 5.1 log points and for managers to 14.8 log points three periods after the ownership change. This result is well in line with the *rent appropriation by managers* hypothesis.[11]

Columns (2) to (4) show that for non-managers the initial ranking of wage gains from our baseline specification is unaffected with the wage premia ranging from 2.7 to 10.0 log points in the first and 2.7 to 15.4 log points in the third year after ownership change. Moreover, we find an additional and immediate wage gain of 3.5 log points for medium-skilled managers, which stays fairly stable over the three-year, post-treatment observation window. Our results for the low-skilled group indicate that in the first year after ownership change low-skilled managers receive an additional positive wage premium of 6.0 log points. In the second and third year after takeover for low-skilled workers and over the whole post-treatment observation window for the group of high-skilled workers, we estimate a positive effect of manager status on the foreign ownership wage premium, which is, however, not

[11] Since most managers are high-skilled (about 55 percent in our sample), our estimated manager premia could in fact simply control for high skills. To make sure that this is not the case, we have estimated an additional specification controlling for high-skilled workers and their interaction with the acquisition dummy. This lowers the estimated manager premium but does not eliminate it. Also, including a further interaction between acquisition, high-skilled workers, and manager status does not change this result.

statistically significant. Summing up our results, we find that after separating the wage gain by manager status, wage premia for non-managers decrease in all skill groups – with high-skilled workers still receiving the largest wage increase – but remain economically and statistically significant. This differentiates our results from Heyman et al. (2011) and indicates that the *rent appropriation by manager* hypothesis does not provide a satisfying explanation for the skill bias in the wage effects reported in Table 2.2.

In a next step, we investigate to what extent the wage effects reported in Table 2.2 capture an incentive of firms to reduce job turnover and technology dissipation (*technology protection*), as argued for instance by Glass and Saggi (2002). An incentive to reduce worker turnover exists in particular if the acquired plant developed an innovation in particular around the event of foreign takeover. Otherwise, competitors could have targeted workers with valuable knowledge from the respective plant already prior to foreign acquisition. Such an innovation can be triggered by the investor, because after ownership change firm assets are jointly used, which gives the acquired plant access to the know-how of the foreign owner (see Barba Navaretti and Venables, 2004). This technology transfer may be associated with *process innovation* and evidence for it is provided by Bloom et al. (2012a,b). However, there could also be a *product innovation* in the acquired plant.

Table 2.4: The foreign ownership wage premium with product innovation

	All workers	*Low-skilled*	*Med.-skilled*	*High-skilled*
	(1)	*(2)*	*(3)*	*(4)*
Acquisition $t = 1$	0.028***	0.019*	0.024***	0.068***
	(0.007)	(0.010)	(0.007)	(0.015)
Acquisition $t = 2$	0.034***	-0.000	0.028***	0.113***
	(0.008)	(0.011)	(0.008)	(0.020)
Acquisition $t = 3$	0.046***	0.010	0.042***	0.118***
	(0.012)	(0.013)	(0.012)	(0.023)
Product Innovation	0.019	0.013	0.009	0.076**
×Acquisition $t = 1$	(0.017)	(0.021)	(0.019)	(0.030)
Product Innovation	0.005	-0.002	-0.010	0.095***
×Acquisition $t = 2$	(0.020)	(0.026)	(0.018)	(0.036)
Product Innovation	0.030	0.022	0.015	0.126***
×Acquisition $t = 3$	(0.022)	(0.029)	(0.021)	(0.038)
Constant	4.780***	4.641***	4.763***	5.062***
	(0.003)	(0.004)	(0.003)	(0.005)
Observations	199,384	28,368	148,352	22,664

Notes: Dependent variable is the log daily wage. The estimation includes time dummies and worker-fixed effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

To test this *technology protection* hypothesis, we investigate both *product* and *process innovation*. We capture *product innovation* by a survey question asking if the plant introduced a completely new activity or product over the two preceding years. From this question, we derive a dummy variable, which is one if a plant reports *product innovation* in the two years prior to takeover and zero otherwise. 30 of 152 acquired plants (accounting for 9,975 stayers) report *product innovation* according to this criterion. Table 2.4 reports the results after adding the interaction of this dummy with the treatment indicators to the model outlined in Equation (2.3). In Column (1), we see little evidence for an impact of *product innovation* on the foreign ownership wage premium when considering the pooled sample of all workers – although the estimates of the acquisition dummies are somewhat reduced. This picture does not change, when zooming in on the subgroups of low- and medium-skilled workers. However, for high-skilled workers the estimated foreign ownership premium increases by 7.6 to 12.6 log point in plants reporting *product innovation*, with the estimated effects being highly statistically significant. This suggests that concerns of job turnover and technology dissipation can explain part of the skill bias in the estimated wage effects of foreign takeover.

Table 2.5: The foreign ownership wage premium with process innovation

	All workers	*Low-skilled*	*Med.-skilled*	*High-skilled*
	(1)	*(2)*	*(3)*	*(4)*
Acquisition $t = 1$	0.027*	0.018	0.013	0.097***
	(0.015)	(0.016)	(0.015)	(0.036)
Acquisition $t = 2$	0.057***	0.014	0.039***	0.168***
	(0.014)	(0.021)	(0.014)	(0.034)
Acquisition $t = 3$	0.045**	0.009	0.034*	0.120***
	(0.019)	(0.024)	(0.019)	(0.035)
Process Innovation	0.016	0.015	0.022	0.025
× Acquisition $t = 1$	(0.019)	(0.020)	(0.018)	(0.044)
Process Innovation	-0.017	-0.006	-0.011	0.007
× Acquisition $t = 2$	(0.020)	(0.026)	(0.018)	(0.047)
Process innovation	0.021	0.020	0.021	0.086*
× Acquisition $t = 3$	(0.025)	(0.030)	(0.024)	(0.047)
Constant	4.780***	4.641***	4.763***	5.062***
	(0.004)	(0.005)	(0.004)	(0.008)
Observations	199,384	28,368	148,352	22,664

Notes: Dependent variable is the log daily wage. The estimation includes time dummies and worker-fixed effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

To investigate the role of *process innovation*, we rely on information about new investment and create a dummy variable, which is one if a plant reports positive investment in the period of foreign takeover and zero otherwise. The idea is that firms with modern technology are more receptive to the know-how provided by the new owner. Two-thirds of the acquired plants (accounting for 20,893 stayers) report *process innovation* according to this definition. Table 2.5 displays the results from estimating Equation (2.3) when controlling for the interaction of the *process innovation* dummy with the treatment indicators. From these estimates we see that in acquired plants *process innovation* exerts a statistically significant effect only three years after ownership change for the subgroup of high-skilled workers. However, the small insignificant coefficient in $t = 2$ and the following increase in $t = 3$ for high-skilled workers is in line with installment of new technology and training of the workforce after foreign takeover. This is because according to the *training on new technology* hypothesis, foreign takeover and technology transfer should lead to lagged positive wage effects as training to use technology productively takes time (see Fosfuri et al., 2001; Görg et al., 2007).[12]

[12]The lack of strong supportive evidence for *technology protection* in the context of *process innovation* could come from using a rather imprecise proxy for technology transfer. Therefore, we have run an additional specification, in

In a final step, we analyse to what extent the estimated foreign ownership premium actually captures a wage premium from exporting (see Bernard and Jensen, 1995; Schank et al., 2007) because the main reason for the investment decision is a platform motive (*export platform* hypothesis). This concern is of particular relevance for the years after the millennium, because the trade literature points to the opening up of Eastern Europe as a historic event providing evidence for platform investment (see Motta and Norman, 1996; Ekholm et al., 2007; Neary, 2009). To account for the *export platform* hypothesis, we consider the initial exporter status of establishments and interact it with the treatment indicator. The exporter dummy is one if the plant generated positive revenues abroad in the year prior to acquisition. 70 acquired plants (accounting for 17,539 stayers) report positive exports prior to the takeover event.

Table 2.6: The foreign ownership wage premium for exporters

	All workers	*Low-skilled*	*Med.-skilled*	*High-skilled*
	(1)	*(2)*	*(3)*	*(4)*
Acquisition $t = 1$	0.057***	0.038*	0.049**	0.132***
	(0.021)	(0.023)	(0.023)	(0.028)
Acquisition $t = 2$	0.053***	0.010	0.045**	0.157***
	(0.017)	(0.016)	(0.018)	(0.041)
Acquisition $t = 3$	0.064***	0.036*	0.055**	0.157***
	(0.021)	(0.019)	(0.023)	(0.031)
Exporter×Acquisition $t = 1$	-0.023	-0.010	-0.025	-0.029
	(0.024)	(0.026)	(0.025)	(0.040)
Exporter×Acquisition $t = 2$	-0.015	-0.002	-0.023	0.013
	(0.023)	(0.025)	(0.021)	(0.053)
Exporter×Acquisition $t = 3$	-0.002	-0.013	-0.005	0.033
	(0.028)	(0.028)	(0.027)	(0.048)
Constant	4.780***	4.641***	4.763***	5.062***
	(0.004)	(0.005)	(0.004)	(0.009)
Observations	199,384	28,368	148,352	22,664

Notes: Dependent variable is the log daily wage. The estimation includes time dummies and worker fixed effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Table 2.6 displays the wage effects for workers employed by initial exporters and non-exporters. Our results indicate that the wage premium is not significantly different between workers employed by exporters and non-exporters. Dividing the sample by skill groups shows that we observe the same ranking of wage premia as in our baseline specification, i.e. high-skilled workers receiving the highest premium and low-skilled workers the lowest one. From the results in Table 2.6, we therefore conclude that the estimated wage premia do not pick up an exporter effect.

Summing up, our estimation results illustrate that *rent appropriation* (Heyman et al., 2011),

which we associate positive investment with *process innovation* only if the plant additionally reports expenditures for IT infrastructure. This captures the idea that foreign-owned plants use IT more productively or that the foreign owner implements new management practices that may require intensive communication with the parent (cf. Bloom and Van Reenen, 2010; Bloom et al., 2012b; Javorcik and Poelhekke, 2017). Using this alternative measure as a proxy for *process innovation* gives slightly stronger results and significant effects of the interaction term for medium- and high-skilled workers. The general picture from Table 2.5 does not change after this refinement.

technology protection (Glass and Saggi, 2002), and *training on technology* (Fosfuri et al., 2001; Görg et al., 2007) are relevant channels for explaining the wage effects of foreign takeover in German plants. However, a single hypothesis does not explain the whole pattern of the observed wage effects and our finding of a positive impact and a lagged adjustment effect therefore suggests that different theoretical hypotheses have to be combined to better understand wage effects of foreign acquisition. As discussed, platform investment to access Eastern European markets may also be an important motive for foreign takeover. However, there is no evidence from our analysis that we falsely attribute an exporter premium to a foreign ownership effect.

Whereas we consider different channels for explaining the wage premium of foreign takeover above, lacking the necessary data we cannot shed light on two further channels that may be similarly important. The first one is rooted in a general rent-sharing argument, stressing that employers as well as employees benefit from increasing profits. In a study for the UK, Conyon et al. (2004) show that mergers lead to higher profitability and higher wages, providing support for this argument in the context of acquisitions. However, they exclude international mergers from their data set. Rent sharing in the context of international ownership has been put forward by Budd et al. (2005) who provide evidence for international rent-sharing in multinational firms. According to their results, wages in German plants should increase if the acquiring firm has higher profits than its target. Egger and Kreickemeier (2013) additionally show that international rent-sharing can rationalise evidence on residual wage premia in the context of North-South investment.[13]

A second channel we cannot address in this chapter, is the changing demand for skill types after foreign takeover, which can be an important factor for explaining the skill bias in the wage effects reported in Table 2.2. Hummels et al. (2014) show a differential effect of offshoring on skilled and unskilled workers in Danish firms and argue that such a differential effect can exist if firms face skill-specific, upward-sloping labour supply curves. Egger et al. (2019) elaborate on this argument in a general equilibrium framework with monopsonistic labour market competition and demonstrate that in such a setting one can also explain that a major part of vertical foreign investment is observed between similar countries. However, due to not having information on the acquirer's profitability and lacking the data necessary to estimate labour supply at the firm-level, we cannot further analyse these two additional channels.

2.5 Extensions

Section 2.4 documents a sizeable effect on wages in the year after foreign takeover as well as evidence for a lagged adjustment effect, suggesting additional wage growth in later years for medium- and high-skilled workers. There are two possible interpretations of the lagged adjustment in wages. On the one hand, additional positive wage effects may arise because it takes some time before the full effect of ownership change materialises – for instance, due to increased training in the period right after ownership change (see Fosfuri et al., 2001; Görg et al., 2007). On the other hand, the lagged adjustment in wages is also consistent with the idea that foreign takeover does not only increase the level but also the growth rate of wages.

To discriminate between these two interpretations, we expand the time window around the ownership change to six years. Expanding the observation window reduces the number of takeover events to 50 and the number of treated stayers to 9,289. It also somewhat increases the mean standardised bias of matching. Still, this exercise has the advantage of showing a more long-run perspective of wage adjustments due to ownership change. Table 2.7 reports the results and shows

[13] Relying on Chinese data, Greaney and Li (2017) find support that foreign-owned plants pay higher wages because of rent-sharing and to reduce worker turnover.

Table 2.7: The foreign ownership wage premium over five years

	All workers	*Low-skilled*	*Med.-skilled*	*High-skilled*
	(1)	*(2)*	*(3)*	*(4)*
Acquisition $t = 1$	0.055***	0.060***	0.043**	0.135***
	(0.017)	(0.019)	(0.017)	(0.032)
Acquisition $t = 2$	0.063***	0.041*	0.047***	0.219***
	(0.017)	(0.022)	(0.015)	(0.043)
Acquisition $t = 3$	0.095***	0.065***	0.080***	0.251***
	(0.022)	(0.021)	(0.022)	(0.038)
Acquisition $t = 4$	0.117***	0.071**	0.103***	0.300***
	(0.026)	(0.029)	(0.025)	(0.037)
Acquisition $t = 5$	0.100***	0.050	0.081**	0.323***
	(0.035)	(0.040)	(0.034)	(0.067)
Constant	4.799***	4.679***	4.786***	5.075***
	(0.009)	(0.010)	(0.009)	(0.017)
Observations	111,468	15,468	85,188	10,812

Notes: Dependent variable is the log daily wage. The estimation includes time dummies and worker fixed effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

that – despite the reduction in the number of observations – the general picture regarding the effects of foreign takeover on wages in the first three years after ownership change remains by and large unaffected. Furthermore, looking at periods four and five after ownership change reveals that the wage growth is temporary and washes out after four years. For low- and medium-skilled workers we even observe a decline in the estimated wage premium after four years. High-skilled workers receive a higher wage premium in $t = 5$ as compared to $t = 4$, but the estimates do not differ significantly, indicating that the wage premia for high-skilled workers also stop increasing after four years. This suggests that foreign takeover affects the level and not the growth rate of wages, with the level effect requiring about four years before materialising fully.

Another question related to the timing of wage effects recently addressed by Javorcik and Poelhekke (2017) is whether the benefit from foreign ownership is *"due to a one-time knowledge transfer or [... due to] continuous injections of knowledge"* (p. 501). To rephrase the question in our context: Are higher wages due to foreign ownership temporary or do they persist and continue to exist even after foreign investors sell back domestic plants? To elaborate on this question, we investigate the wage effect of foreign divestments, i.e. (re-)acquisitions of foreign-owned plants by German investors. During the sample period, we identify 97 foreign divestments with 8,752 stayers. Using our propensity-score matching approach with employees in continuously foreign-owned plants as controls, we can estimate an equation similar to (2.2) to shed light on the effect of foreign divestments.

Column (1) in Table 2.8 shows that foreign divestment does not have a significant effect on wages. The estimates in Column (2) suggest that low-skilled workers are worse off after foreign divestment. However, the wage loss is small and only significant in $t = 2$. Medium- and high-skilled wages are not affected significantly in any period. Overall, these results imply that at least for medium- and high-skilled workers the positive wage effect of foreign ownership does not vanish within three years after takeover by a domestic owner.

Table 2.8: The wage effect of foreign divestments

	All workers	*Low-skilled*	*Med.-skilled*	*High-skilled*
	(1)	*(2)*	*(3)*	*(4)*
Divestment $t = 1$	-0.005	-0.014	0.000	-0.028
	(0.009)	(0.009)	(0.011)	(0.023)
Divestment $t = 2$	0.002	-0.021*	0.007	0.001
	(0.011)	(0.012)	(0.012)	(0.034)
Divestment $t = 3$	0.008	-0.014	0.009	0.036
	(0.012)	(0.012)	(0.013)	(0.037)
Constant	4.778***	4.578***	4.769***	5.127***
	(0.003)	(0.003)	(0.004)	(0.010)
Observations	70,016	11,640	50,328	8,048

Notes: Dependent variable is the log daily wage. The estimation includes time dummies and worker-fixed effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

The results in Table 2.8 also indicate that the wage premia reported in Table 2.2 are due to foreign takeover and not the result of a general acquisition effect. To further elaborate on this finding, we consider as a Placebo test takeovers of West German plants by East or West German investors. Thereby, we use the IAB Establishment Panel to identify whether the majority owner of an establishment is from West or East Germany and classify a German takeover as an event, in which ownership in two consecutive years switches from West German to East German or vice versa. We identify 81 intra-German takeovers with 2,721 stayers over our sample period. The matching for this placebo is similarly successful as for our main specification. Table 2.9 presents the results.

Table 2.9: The wage premium from intra-German takeovers

	All workers	*Low-skilled*	*Med.-skilled*	*High-skilled*
	(1)	*(2)*	*(3)*	*(4)*
Acquisition $t = 1$	-0.004	-0.003	-0.009	0.023
	(0.012)	(0.018)	(0.012)	(0.025)
Acquisition $t = 2$	-0.022*	-0.017	-0.027**	-0.003
	(0.012)	(0.023)	(0.013)	(0.033)
Acquisition $t = 3$	-0.050	-0.088	-0.047	0.003
	(0.036)	(0.070)	(0.031)	(0.027)
Constant	4.366***	4.298***	4.351***	4.581***
	(0.005)	(0.010)	(0.005)	(0.009)
Observations	21,736	4,424	14,896	2,416

Notes: Dependent variable is the log daily wage. Estimation includes relative time dummies and controls for worker fixed effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

To the extent that our estimates so far only capture a general takeover effect, stayers in domestic-acquired establishments should experience a wage increase similar to stayers in foreign-acquired establishments. However, Table 2.9 shows that this is clearly not the case. For low- and high-skilled workers we find no significant effect of a German takeover. Medium-skilled workers even lose from a takeover by a German investor after two years. Summing up, the insignificant and negative coefficients in Table 2.9 support the findings from foreign divestment that the wage premia in Table 2.2 do not capture a general takeover, but rather a genuine foreign takeover effect.

To ensure that our results are robust to changing the set of covariates used for matching, we control for three additional variables in the propensity-score estimation. The first one is a dummy variable that is one if the establishment has already existed prior to 1990. This dummy controls for selection of older targets by foreign investors, which can pay higher wages because they are already well-established in the market (see Heyman et al., 2007). As a second matching variable, we add a dummy that is one if wages paid by the establishment are subject to collective labour agreements. Accounting for this dummy helps ruling out a selection bias because foreign investors aim to avoid wage pressure from unions.[14] As a final control variable, we add the share of female workers because recent research by Vahter and Masso (2018) suggests that foreign investors require stronger commitment and higher flexibility from workers, which potentially leads to selection of establishments with fewer women, who might be less flexible due to family responsibilities. We compute the share of female workers in $t = 0$ as the share of females among the total workforce in an establishment. If foreign investors acquire establishments, which are older, covered by collective agreements and/or employ an below-average share of women, our matching would suffer from omitted variable bias when not controlling for these covariates.[15]

Table 2.10: Additional matching covariates

	All workers	*Low-skilled*	*Med.-skilled*	*High-skilled*
	(1)	*(2)*	*(3)*	*(4)*
Acquisition $t = 1$	0.037***	0.028**	0.028***	0.107***
	(0.010)	(0.011)	(0.009)	(0.022)
Acquisition $t = 2$	0.038***	0.011	0.024**	0.165***
	(0.012)	(0.015)	(0.010)	(0.028)
Acquisition $t = 3$	0.060***	0.027*	0.049***	0.174***
	(0.014)	(0.015)	(0.012)	(0.030)
Constant	4.757***	4.626***	4.740***	5.031***
	(0.004)	(0.005)	(0.004)	(0.009)
Observations	199,496	28,400	148,432	22,664

Notes: Nearest-neighbour propensity-score matching includes a dummy indicating if the plant has already existed prior to 1990, a dummy for workers under collective labour agreements and the establishment share of females in addition to baseline covariates in Table 2.12. The dependent variable in the difference-in-difference estimation is the log daily wage. The estimation includes time dummies and worker fixed effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Table 2.10 shows the results after adding the three additional matching variables and confirms

[14]The turmoil after the takeover of the German automotive supplier Grohmann Engineering by Tesla is a prominent example in this case.

[15]Despite adding three new covariates, matching is similarly successful as in our main specification. The mean standardised bias slightly increases to 6.5 percent, while normalised differences are smaller than one quarter for all covariates.

our initial findings. Thus, selection by firm age, coverage by collective agreements or gender composition does not drive our results. Matching with a more extensive set of covariates leaves the initial ranking of wage premia unaffected. Moreover, the wage premia are similar in size, ranging from 2.8 to 10.7 log points in the period after takeover and 2.7 to 17.4 log points after three years.

In a further extension reported in Table 2.11, we refine our matching approach by introducing a caliper of 0.05. This implies that stayers are matched to controls only within a range of 0.05 of their respective propensity scores and excludes observations for which no match is found within this range.[16]

Table 2.11: The foreign ownership wage premium with caliper matching

	All workers	*Low-skilled*	*Med.-skilled*	*High-skilled*
	(1)	*(2)*	*(3)*	*(4)*
Acquisition $t = 1$	0.036***	0.021*	0.024**	0.122***
	(0.010)	(0.011)	(0.010)	(0.030)
Acquisition $t = 2$	0.035***	-0.005	0.020**	0.173***
	(0.011)	(0.010)	(0.009)	(0.035)
Acquisition $t = 3$	0.057***	0.015	0.043***	0.187***
	(0.013)	(0.013)	(0.012)	(0.037)
Constant	4.752***	4.611***	4.735***	5.033***
	(0.004)	(0.004)	(0.004)	(0.012)
Observations	174,856	25,240	128,704	20,912

Notes: Propensity-score matching is conducted with a caliper of 0.05. The dependent variable in the difference-in-difference estimation is the log daily wage. The estimation includes time dummies and worker fixed effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Table 2.11 confirms our baseline results that foreign takeover leads to an immediate wage increase for all workers. The reported coefficients vary between 2.1 and 12.2 log points in $t = 1$ and 1.5 to 18.7 log points in $t = 3$ and are comparable in size to the estimates relying on nearest-neighbour matching without a caliper reported in Table 2.2. However, the estimated low-skilled wage premium in period $t = 3$ is no longer significant. Overall, we nonetheless conclude that the finding of a significant foreign ownership wage premium is robust to refinements of the matching procedure.[17]

[16]The standardised bias of caliper matching is 6.1 percent and normalised differences are less than 0.13 for all variables. The number of establishments subject to foreign takeover remains unaffected, whereas the number of treated workers falls to 21,857, which implies a decrease by 3,066 observations.

[17]The finding of a significant foreign ownership wage premium also remains unchanged when conducting matching with replacement, when matching separately for each skill group or after excluding workers lacking reliable education information. Since we cannot rule out that plants in the control group are multinationals themselves, our estimated wage premia may be compressed due to a comparison of foreign-owned multinationals with domestic-owned multinationals. To make sure that this is not the case, we have conducted a robustness check, in which we confine the control group to standalone plants only. This modification does hardly affect our results and is available upon request. Furthermore, the results are robust to including part-time workers or to restricting the sample to establishments with more than ten full-time workers, which is the threshold at which employment protection legislation in Germany limits the scope of establishments to lay off workers.

2.6 Conclusion

This chapter provides new evidence on the foreign ownership wage premium from a large German employer-employee data set. Using information on ownership change of German establishments, we observe 152 foreign takeover events over the period 2003 to 2014. To identify a causal effect of foreign acquisition, we combine propensity-score matching with a difference-in-difference estimator. We then analyse workers' wages in the year after ownership change as well as in two subsequent periods to distinguish impact effects from lagged adjustment effects. Similar to previous studies, we conduct our analysis at the worker level and consider employees staying in the same establishment over a four-year window around ownership change.

Based on this data set, we provide evidence for the existence of a foreign ownership wage premium in the year after takeover. On average, this wage premium amounts to 4.0 log points and varies considerably by skill group. We find evidence for a lagged adjustment effect, in particular for medium- and high-skilled workers. Moreover, high-skilled workers experience the highest wage stimulus from ownership change over the whole observation period. In further estimations, we distinguish possible explanations for the existence of a foreign ownership wage premium. We find support for the *rent appropriation by managers* hypothesis, the *technology protection* hypothesis, and the *training on new technology* hypothesis. We also show that the wage premium is of similar size for initial exporters and non-exporters, indicating that our results do not falsely pick up an exporter wage premium. Expanding the observation window around takeover events reveals that foreign takeover increases the level but not the growth rate of wages, with the level effect requiring roughly four years before materialising fully. We also show that the wage gains from foreign takeover are persistent and do not vanish after divestment. In a placebo test, we analyse takeovers by German investors and show that intra-German takeovers – if at all – affect wages negatively. Finally, we also document that our results are robust to changes in the matching procedure.

Drawing a nuanced picture of the foreign ownership wage premium, we think that our results are of interest for policy makers, who set the rules and conditions for foreign investment. In this respect, our finding that workers' positions in the hierarchy of establishments explains part of the wage premium is disconcerting, as it suggests that foreign takeover gives the management of acquired establishments scope for rent appropriation. At the same time, it is comforting that the wage increase after foreign takeover seems to be persistent and is not eliminated when the foreign owner decides to sell back the plant to German investors. Moreover, we believe that distinguishing immediate impact and lagged adjustment effects of foreign takeover within a single framework is a promising avenue for future research.

2.7 Appendix

Table 2.12: Balancing test for the matching procedure

Variable	*Sample*	*Mean*		*Stand.*	*Bias*	*Normal.*
		Treated	*Control*	*bias %*	*reduction*	*diff.*
(a) Plant-Characteristics						
Log Employment	Unmatched	6.841	6.982	-8.3		
Log Employment	Matched	6.841	6.569	16.0	-92.3	0.133
ΔLog Employment	Unmatched	-0.012	0.009	-17.3		
ΔLog Employment	Matched	-0.012	-0.013	0.4	97.6	0.002
Profitability	Unmatched	0.580	0.531	9.8		
Profitability	Matched	0.580	0.555	5.0	49.2	0.035
Manufacturing	Unmatched	0.758	0.681	17.1		
Manufacturing	Matched	0.758	0.783	-5.6	67.2	-0.041
Construction	Unmatched	0.005	0.031	-19.2		
Construction	Matched	0.005	0.008	-2.2	88.5	-0.025
Trade and Repair	Unmatched	0.051	0.076	-10.3		
Trade and Repair	Matched	0.051	0.045	2.1	79.3	0.017
Services and Finance	Unmatched	0.180	0.183	-1.0		
Services and Finance	Matched	0.180	0.157	5.9	-498.3	0.041
Lower Saxony	Unmatched	0.173	0.136	10.5		
Lower Saxony	Matched	0.173	0.149	6.8	35.0	0.048
North Rhine-Westphalia	Unmatched	0.094	0.231	-37.9		
North Rhine-Westphalia	Matched	0.094	0.107	-3.6	90.4	-0.031
Hesse	Unmatched	0.217	0.072	42.0		
Hesse	Matched	0.217	0.203	3.9	90.7	0.022
Rhineland-Palatinate	Unmatched	0.042	0.073	-13.5		
Rhineland-Palatinate	Matched	0.042	0.054	-5.2	61.5	-0.040
Baden-Württemberg	Unmatched	0.278	0.137	35.3		
Baden-Württemberg	Matched	0.278	0.312	-8.3	76.5	-0.051
Bavaria	Unmatched	0.104	0.265	-42.5		
Bavaria	Matched	0.104	0.086	4.5	89.4	0.041
Berlin	Unmatched	0.028	0.022	3.9		
Berlin	Matched	0.028	0.021	4.3	-9.5	0.031
(b) Worker-Characteristics						
Log Wage	Unmatched	4.779	4.761	4.1		
Log Wage	Matched	4.779	4.782	-0.5	86.8	-0.006
Age	Unmatched	41.3	41.3	-0.7		
Age	Matched	41.3	41.3	-0.4	43.6	-0.003
Female	Unmatched	0.187	0.197	-2.7		
Female	Matched	0.187	0.180	1.6	40.6	0.012
Medium Skill	Unmatched	0.744	0.759	-3.6		
Medium Skill	Matched	0.744	0.740	1.0	71.5	0.007
High Skill	Unmatched	0.114	0.117	-1.2		
High Skill	Matched	0.114	0.120	-2.1	-73.4	-0.014
Sample				*Mean bias*	*Median bias*	
Unmatched				14.8	10.3	
Matched				4.2	3.9	

Notes: All variables are measured in $t = 0$ and averaged at the worker-level in the treated and control group respectively. Due to the low number of takeovers in small Federal States we assign the city state of Bremen to Lower Saxony, Saarland to Rhineland-Palatinate and the city state of Hamburg to Schleswig-Holstein. The omitted Federal State is Schleswig-Holstein including Hamburg, the omitted sector is agriculture, hunting and forestry.

Chapter 3

How Does Foreign Ownership Influence the Task Composition in German Plants?

3.1 Introduction

A number of studies in international economics have shifted the discussion about the main factors determining distributional consequences of trade from skills to the tasks workers perform (see e.g. Blinder, 2006; Acemoglu and Autor, 2011; Kemeny and Rigby, 2012; Becker and Muendler, 2015). This literature has argued that workers' tasks are the important margin that separates winners and losers of globalisation. Despite the fact that these insights link the tasks workers perform to multinational firm activity, the question of how foreign takeover affects the organization of production in general and the composition of tasks performed by the workforce in particular has received comparably little attention (e.g. Hakkala et al., 2014).[1] This is surprising because firm organisation has been shown to matter for growth or productivity of firms (e.g. Garicano and Rossi-Hansberg, 2015; Bastos et al., 2018). To fill this gap, in this chapter I use survey information to identify the tasks performed by the workforce of German plants (Spitz-Oener, 2006; Antonczyk et al., 2009; Gathmann and Schönberg, 2010; Becker et al., 2013). Using this task information, I attempt to provide a more complete picture of the effects of foreign ownership by analysing for the first time the task composition within foreign-acquired plants in Germany.

In my analysis, I rely on a large German administrative linked employer-employee dataset for the years 2000 to 2019. This dataset contains information on foreign plant ownership and, thus, allows to identify foreign takeovers of German plants taking place during the sample period. Additionally, making use of occupational-level survey information, the data also enables me to measure the task composition of the workforce of a given plant. For this purpose, I use and aggregate four waves of a widely-used German employment survey conducted by the Federal Institute for Vocational Education and Training (BIBB) and the Federal Institute for Occupational Safety and Health (BAuA). I use thirteen questions from the German employment survey to generate occupational-

[1] So far, academic research has focussed on the effects of foreign ownership on (among others) wages paid to workers (see e.g. Aitken et al., 1996; Lipsey and Sjöholm, 2004; Girma and Görg, 2007; Görg et al., 2007; Hijzen et al., 2013; Egger et al., 2020), plant survival (see e.g. Bernard and Sjöholm, 2003; Girma and Görg, 2004; Bandick and Görg, 2010) or firm productivity (see e.g. Bandick, 2011). One attempt addressing how multinationality affects the task composition in firms has been put forward by Becker et al. (2013). However, focussing on the decision of multinational firms to offshore production and its impact on firm organization in the parent firm, they do not address the consequences for the subsidiary.

level measures for five different task categories: (non-routine) analytic, interactive and manual and (routine) cognitive and manual.[2] Subsequently, I construct a task measure, the share of a *given* task sub-category among *all* tasks conducted, for each establishment by making use of workers' occupations. More precisely, I aggregate the task shares, which I assign to each employee making use of her occupation, from the worker- to the plant-level (Antonczyk et al., 2009; Hakkala et al., 2014).

In the empirical analysis I, first, show that foreign-owned plants in Germany are less (more) intensive in non-routine (routine) tasks. In particular, foreign-owned plants demonstrate a significantly lower share in the non-routine analytical task sub-category. In a second step, I implement a two-step estimator with propensity-score matching in step one and difference-in-difference estimation for the matched sample in step two to discern the effect of foreign acquisition on the task composition. Thereby, I rely on more than 390 foreign acquisitions taking place in Germany in the period from 2000 to 2019. Using takeovers to identify the effects of foreign ownership better enables me to tackle selection of acquisition targets, an issue, which has been prominently discussed in the literature as "cherry-picking" (see e.g. Girma and Görg, 2007; Gelübcke, 2013). Specifically, I use propensity-score matching to control for the endogeneity involved in selecting foreign acquisition targets (Girma and Görg, 2007; Hakkala et al., 2014; Bastos et al., 2018; Egger et al., 2020).

Applying the two-step estimator, I find that foreign takeover leads to a statistically significant reduction of 0.2 percentage points - about one percent relative to the mean - in the non-routine analytical task share. This finding is in line with the argument that foreign multinationals might be less willing to locate knowledge-intensive non-routine analytical tasks in a foreign plant (see Antràs et al., 2006; Hakkala et al., 2014). The result of a negative effect of foreign acquisition on non-routine analytical tasks lends support to the hypothesis that foreign multinationals want to keep knowledge-intensive tasks in close proximity to the headquarters (Antràs et al., 2006; Oldenski, 2012).

I also investigate whether the effect of foreign acquisition on the task composition can be attributed to plants changing their hierarchical organization after takeover (Bastos et al., 2018). This argument builds on the literature on firms as knowledge hierarchies, which stresses the tradeoff between knowledge acquisition and communication costs as crucial determinant of firms' hierarchical organization (Garicano, 2000; Caliendo et al., 2015; Gumpert et al., 2022). In this literature, foreign takeovers can affect the number of hierarchical layers through at least two channels. First, superior I.T. technology and more advanced management practices of foreign multinationals can decrease communication costs (Bloom et al., 2012a,b). Second, foreign acquisition can lead to an increase in the scale of production resulting from improved productivity or higher demand after ownership change (Bastos et al., 2018). Both of these channels - decreasing communication costs or increasing production scale - make hierarchical plant organization with more layers feasible. However, I find no statistically significant effect of foreign takeover on the number of hierarchical layers in acquired establishments. This result suggests that foreign owners do not reorganize targeted plants in Germany substantially by adding or dropping layers after ownership change. In addition, this shows that arguments from the literature on firms as knowledge hierarchies, which indicate that foreign owners might increase the number of layers to facilitate communication with the foreign headquarters and to make efficient use of existing knowledge, might not apply to FDI in a highly-industrialised country like Germany (Bastos et al., 2018).

The remainder of this chapter is organized as follows. In Section 3.2, I summarize previous research when discussing the expected effect of foreign acquisition on plants' task composition. In

[2] The distinction is that routine tasks are well defined and expressible in rules allowing computers to perform the respective tasks (Spitz-Oener, 2006).

Section 3.3, I introduce the dataset, explain how I construct a measure for the task composition of plants and present descriptive statistics. In Section 3.4, I present results from regressing task shares on foreign ownership to assess whether the task composition in domestic plants differs from the task composition in foreign-owned plants. In Section 3.5, I present the estimation strategy using propensity-score matching combined with a difference-in-difference estimator to identify a causal effect of foreign takeover on the task composition and report estimation results. In Section 3.6, I report robustness checks and investigate potential further mechanisms explaining the effect of foreign takeover on the task composition in acquired plants. Section 3.7 concludes.

3.2 Foreign ownership and the task composition

One well-known fear of globalisation is that the presence of multinational firms leads to detrimental outcomes for the local workforce, for instance because multinationals are able to relocate low-skilled jobs to low-wage countries. Therefore, the literature has discussed the effects of foreign acquisition on the employment and skill composition of firms very extensively (Girma and Görg, 2004; Almeida, 2007; Huttunen, 2007; Hijzen et al., 2013). Still, the results of this line of research have been far from leading to a uniform conclusion. Most studies find no or very marginal effects of foreign ownership on the skill composition of the workforce or the total employment of low-skilled workers.[3]

Recently, several authors have, however, pointed out the importance of distinguishing *skills*, which are based on formal education, from *tasks* performed in an occupation (Autor et al., 2003; Spitz-Oener, 2006; Acemoglu and Autor, 2011). Recent studies on offshoring have also shifted attention away from skills towards tasks as the important margin separating winners and losers of globalisation and production shifting (Blinder, 2006).

In their paper, Becker et al. (2013) analyse the effect of offshoring from German multinationals on their onshore workforce composition and find that offshoring from Germany to low-income countries leads to particularly strong changes in the German workforce composition in favor of non-routine tasks. They argue that this result supports the view that tasks offshored to low-income countries are often conducted by low-skilled workers. Because low-skilled workers in the offshore operations more often carry out routine tasks, offshoring results in a relative increase in non-routine tasks in the onshore operations.[4] In addition, Hakkala et al. (2014) show that takeover increases the importance of non-routine tasks in Swedish firms. Because both, Germany and Sweden, are highly-industrialised, high-wage countries with a well-educated workforce, their analysis suggests that non-routine tasks could become more important in German firms after foreign takeover as well.

An additional and differentiated argument linking foreign ownership and the task composition has been brought forward by Antràs et al. (2006). In their theoretical analysis, Antràs et al. (2006) suggest that foreign multinationals are less inclined to locate non-routine tasks, for instance knowledge-intensive tasks like research and development, in a foreign plant. Instead, multinationals might want to keep non-routine, less predictable tasks in close range to their headquarters. The reason for keeping non-routine tasks in close range is that non-routine tasks are more costly to offshore because when problems arise, managers at the (onshore) headquarters location must

[3] Girma and Görg (2004) provide evidence that foreign acquisition reduces employment growth in particular for low-skilled workers in the UK, while Almeida (2007) finds no effect of foreign takeover on the skill composition in Portugal. Huttunen (2007) documents a small decrease in the share of high-skilled workers in Finland and Hijzen et al. (2013) report positive effects of foreign acquisition on the employment of both low- and high-skilled workers in Portugal and a negative effect of foreign takeover on low-skilled employment in Brazil.

[4] In this chapter, Germany, however, is the host and not the home country of FDI. As the dataset unfortunately provides no information on the nationality of foreign acquirers, it is not possible to distinguish FDI from low-, medium-, or high-income countries.

intervene at the location of the foreign subsidiary to fix them. As a result, Antràs et al. (2006) show that offshoring leads to a relative increase in non-routine (routine) tasks for the onshore (offshore) workforce. Notably, this does not imply that routine tasks are always conducted in low-wage countries, but rather in the host country of foreign direct investment, which can be either a high- or a low-wage destination. Oldenski (2012) provides support for the prediction of this model by analysing the case of offshoring by U.S. multinationals. She finds that U.S. multinationals are more likely to offshore production stages, which are more intensive in routine tasks, to a foreign affiliate. This finding suggests that foreign takeover could also lead to a decrease in non-routine tasks in acquired establishments in Germany. Summing up, there is no clear-cut expectation about the effect of foreign takeover on the task composition in German plants. My empirical analysis below aims to give a more definite answer to this question.

3.3 Data source and descriptives

For my empirical analysis, I rely on three data sources. The first dataset is the IAB Establishment Panel, which consists of a stratified one percent random sample of establishments that employ at least one employee covered by the social security system at 30th of June each year. Since 1993, the IAB Establishment Panel surveys a sample of establishments from all industries in West Germany and since 1996 also in East Germany. From the survey questions I use information about industry affiliation or location of German plants. Crucial to my analysis, the IAB Establishment Panel also provides information on majority ownership of establishments.[5] Relying on this information, I am able to identify a foreign takeover as change in the majority ownership from German to non-German in two subsequent years.

As a second dataset, I use the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB), which cover about 80% of the German workforce. This dataset contains administrative and, therefore, very reliable information about age, gender, education or occupation of workers employed in plants of the IAB Establishment Panel. The IEB does not contain exact information on hours worked and since worker information comes from social security records, wages are top-coded at the social security contribution ceiling. To deal with these issues, I only consider full-time workers between 16 and 65 years of age and impute wages above the social security contribution ceiling, using the two-step Tobit procedure suggested by Card et al. (2013).[6] The IEB can be linked to the IAB Establishment Panel making use of a unique identifier, which allows to construct a linked employer-employee dataset (LIAB) with highly reliable information on workers and establishments.[7]

As a third dataset, I use four waves of the BIBB-BAuA employment surveys. These surveys cover between 20.000 and 34.000 individuals in each wave.[8] The employment surveys are particular

[5] Starting in 2000, the IAB Establishment Panel records the majority owner for each establishment surveyed. Between 1996 and 1999, ownership was only recorded for establishments located in East Germany. This is why my analysis starts in 2000.

[6] This procedure has been implemented for the IEB data by Dauth and Eppelsheimer (2020).

[7] For further details on the LIAB, see e.g. Alda et al. (2005); Klosterhuber et al. (2016).

[8] The BIBB-BAuA carries out the employment survey every six to seven years since 1979. In this chapter, I use the survey waves from 1998/1999, 2005/2006, 2011/2012 and 2017/2018 and, for better readability, refer to these waves as 1999, 2006, 2012 and 2018. Dengler et al. (2014) have introduced an alternative task operationalisation based on the BERUFENET, which is constructed similar to U.S. O*NET. The dataset is available from the German Federal employment agency and provides expert assessments about the tasks workers in a given occupation have to perform. However, the classification is only available after 2011 and is therefore not suited to analyse the period before 2010. Still, I checked the correlation between this task classification and the one based on survey-data used in this chapter. The correlations between task shares in the analytical, interactive, non-routine and routine manual categories, which

well suited to analyse the task composition of occupations because the information comes from workers self-reporting the tasks they perform at their workplace regularly. Since it has been shown by Becker and Muendler (2015) that the tasks performed in occupations vary quite considerably over time, using four waves which span the whole window of my analysis, also helps in capturing the time-variation of tasks.[9]

Table 3.1 shows the assignment of reported tasks into the routine and non-routine category. Using the distinction introduced by Spitz-Oener (2006), I can further disaggregate routine and non-routine tasks into five task sub-categories: (Non-routine) analytical, interactive and manual as well as (routine) cognitive and manual tasks.

Table 3.1: The classification of tasks

Tasks	Non-routine Analytical	Non-routine Interactive	Non-routine Manual	Routine Cognitive	Routine Manual
Develop, research and construct	X				
Gather information and document	X				
Apply legal knowledge	X				
Measure, inspect, and control quality				X	
Purchase, procure, and sell		X			
Advertise, marketing, and public relations		X			
Organize, plan, and prepare (others' work)		X			
Train, teach, instruct, and educate		X			
Consult and inform		X			
Manufacture and produce goods					X
Oversee and control machinery and technical processes					X
Repair and maintain			X		
Nurse, taking care, cure			X		

Notes: The Table shows the classification of 13 tasks, which are reported in each of the four waves 1999, 2006, 2012 and 2018 of the BIBB-BAuA Employment Survey into five task sub-categories. The classification of tasks as routine and non-routine follows Spitz-Oener (2006) and Becker et al. (2013).

To construct a measure for the task composition of each plant, I proceed in several steps. First, for each respondent in the employment survey, I record whether she sometimes or often performs one of the 13 tasks reported in Table 3.1. In the next step, I aggregate the waves from 1999 and 2006 as well as the waves from 2012 and 2018, respectively. Aggregating two waves enables me to increase the number of respondents and, therefore, results in a better coverage of each occupation. The reason for not aggregating all four waves is that in the years 1999 and 2006 occupations in the employment survey were recorded making use of the older classification of occupations (KldB 1988), whereas in 2012 and 2018 the survey uses the newer classification (KldB 2010). Then, by

lie between 0.58 and 0.82, indicate that both approaches to assigning task shares overall are well in line.

[9] The new classification of occupations 2010 (KldB 2010) replaced the previous classification of occupations 1988 (KldB 1988) during my sample period. The dataset contains both occupation codes. However, as employers were obliged to report workers' occupations making use of the KldB 2010 for job spells from the end of 2011 onwards, I make use of the KldB 1988 for the years 2000 to 2010 and apply the KldB 2010 for the years 2011 to 2019 to assign task measures to workers.

averaging over all respondents in a given occupation, I calculate the total number as well as the number of tasks performed in each of the five sub-categories, out of the answers to the 13 questions regarding the performed tasks in the employment survey.

Table 3.2 illustrates this procedure by showing the three occupations with the highest task measures (in each task sub-category) for the aggregated waves 1999 & 2006 as well as for 2012 & 2018. The ranking is based on the number of tasks workers perform on average. Exemplary, winegrowers and ship's officers with an average of 10.7 conduct the highest number of tasks among all occupations. This average can be split up into 7.8 (9) non-routine and 2.9 (1.7) routine tasks for winegrowers (ship's officers).

With the average number of tasks in a given occupation at hand, I generate a measure for the task composition in each occupation. I normalize the number of tasks in a task sub-category (analytical, interactive, non-routine manual, routine cognitive, routine manual) by the total number of tasks performed. In doing so, I follow Antonczyk et al. (2009), who argue that this proxies the share of working time a worker uses to perform tasks in a certain sub-category. For instance, the non-routine interactive task measure for winegrowers is about 0.4 ($\approx \frac{4.3}{10.7}$).[10] Subsequently, I merge the thus constructed task content of occupations with LIAB using occupation codes of workers. Finally, I aggregate the task-content to the establishment-level by averaging over all (full-time) employees.

Table 3.3 reports descriptive statistics of the dataset and shows the task measure for each task sub-category. During the sample period, I identify 394 foreign takeovers. The descriptive statistics are in line with previous findings that establishments, which are acquired by foreign investors, differ from non-acquired domestic establishments in several dimensions (see e.g. Almeida, 2007; Gelübcke, 2013; Egger et al., 2020).

The variable profitability, which indicates whether plants evaluate their profits as good or very good, shows that acquired plants exhibit a better profit situation. In addition, as shown by the higher average share of plants with a positive employment expectation, acquisition targets more often predict an increase in employment. The descriptives also demonstrate that acquired establishments have a bigger workforce, are more prevalent in manufacturing and more often engage in exporting. Moreover, average wages and the share of high-skilled workers in acquired plants are higher. Finally, Table 3.3 shows a marked difference in the number of hierarchical layers between acquired and non-acquired plants. This variable measures the total number of the four hierarchical layers production workers, supervisors, senior staff and directors, which are occupied by workers in a plant (Caliendo et al., 2015). The mean of 2.98 demonstrates that foreign-acquired establishments on average have almost one additional hierarchical layer in comparison to non-acquired domestic plants.

Regarding the task composition, the workforce in acquired plants also demonstrates a higher (lower) share of routine (non-routine) tasks. This higher share of routine tasks results from a higher share of routine cognitive and routine manual tasks. Overall, the descriptive statistics suggest that foreign investors do not pick acquisition targets randomly. Therefore, I perform propensity-score matching in the empirical analysis to deal with selection bias.

[10] Spitz-Oener (2006) measures the share of tasks of a *given sub-category* which on average is being carried out by workers in that occupation. A value of 0.4 in non-routine interactive tasks, for instance, means that on average workers in that occupation carry out 40% of all tasks from the non-routine interactive sub-category. A value of 0.4 in non-routine interactive tasks in Antonczyk et al. (2009), however, means that on average out of *all tasks* conducted by workers in a given occupation, 40% fall into the non-routine interactive sub-category. Normalizing by the total number of tasks conducted also means that the task measures for the five task sub-categories add up to one.

Table 3.2: The top three occupations in each task category

	1999 & 2006		2012 & 2018	
Rank	Occupation	Measure	Occupation	Measure
		Total number of tasks		
1	Winegrowers	10.7	Ship's officers	10.7
2	Dentists	9.4	Occ. in viniculture	10.5
3	Scenery, sign painters	9.1	Artisans in ceramics	9.6
		Non-routine tasks		
1	Winegrowers	7.8	Ship's officers	9
2	Dentists	7.5	Occ. in education	7.8
3	Ministers of religion	7.2	Occ. in viniculture	7.8
		Routine tasks		
1	Textile finishers	3	Occ. in metalworking	2.8
2	Spoolers, twisters	3	Occ. in viniculture	2.8
3	Mineral preparers	3	Occ. in ind. glass-making	2.7
		Non-routine analytical tasks		
1	Mechanical engineers	2.3	Ship's officers	3
2	Memb. of Parl.	2.2	Occ. in economics	2.7
3	Veterinarian	2.2	Occ. in constr. scheduling	2.6
		Non-routine interactive tasks		
1	Ministers of religion	4.3	Ship's officers	4.7
2	Winegrowers	4.3	Managing directors	4.3
3	Sports teachers	4.1	Occ. in theology	4.2
		Non-routine manual tasks		
1	Winegrowers	1.8	Occ. in animal husbandry	1.7
2	Metal drawers	1.7	Occ. in animal care	1.5
3	Dentists	1.7	Occ. in vet. medicine	1.4
		Routine cognitive tasks		
1	Jewel preparers	1	Ship's officers	1
2	Vulcanisers	1	Occ. in philology	1
3	Metal finishers	1	Occ. in music. instrument making	1
		Routine manual tasks		
1	Textile finishers	2	Occ. in metalworking	1.8
2	Other beverage makers	2	Occ. in viniculture	1.8
3	Winegrowers	2	Occ. in ind. glass-making	1.7

Notes: The Table shows the three occupations with the highest average number of tasks performed in a given task category. The average is constructed using 13 tasks, which are reported in each of the four waves 1999, 2006, 2012 and 2018 of the BIBB-BAuA Employment Survey. The classification of tasks as routine and non-routine is according to Spitz-Oener (2006) and Becker et al. (2013).

3.4 Reduced form estimation

In this section, I analyse the correlation between foreign ownership and plants' task composition to investigate whether foreign-owned differ from domestic plants with regard to the tasks performed. More specifically, in a first step, I use OLS to estimate a model of the form:

Table 3.3: Descriptive statistics of plant characteristics and task shares

	Acquired	*(S.D.)*	*Non-Acquired Domestic*	*(S.D.)*
(a) Plant characteristics				
Plants	394		27,326	
Plant-Years	3,027		157,566	
East German	0.403	(0.491)	0.391	(0.488)
Profitability	0.457	(0.498)	0.398	(0.489)
Positive empl. expectation	0.222	(0.415)	0.155	(0.362)
Employment $<$ 10	0.137	(0.344)	0.377	(0.485)
10 $\leq$ Employment $<$ 50	0.281	(0.449)	0.361	(0.310)
50 $\leq$ Employment $<$ 250	0.412	(0.492)	0.199	(0.399)
250 $\leq$ Employment $<$ 1000	0.132	(0.339)	0.052	(0.221)
Employment $\geq$ 1000	0.038	(0.191)	0.011	(0.105)
Exporter	0.538	(0.499)	0.228	(0.419)
Log avg. wage	4.689	(0.371)	4.427	(0.378)
Log avg. wage squared	22.120	(3.415)	19.739	(3.330)
Share of medium-skilled	0.747	(0.203)	0.815	(0.209)
Share of high-skilled	0.186	(0.209)	0.134	(0.200)
Number of hierarchical layers	2.982	(1.004)	2.111	(1.068)
Agriculture, foresting, fishing	0.003	(0.054)	0.019	(0.136)
Manufacturing	0.547	(0.498)	0.293	(0.455)
Mining and construction	0.054	(0.226)	0.122	(0.328)
Retail and warehousing	0.231	(0.421)	0.237	(0.425)
Finance and insurance services	0.123	(0.328)	0.143	(0.350)
Public and private services	0.043	(0.203)	0.186	(0.389)
Private households	0.000	(0.000)	0.000	(0.009)
Year	2009.161	(5.312)	2008.958	(5.639)
(b) Task shares				
Share non-routine	0.745	(0.085)	0.771	(0.085)
Share routine	0.255	(0.085)	0.229	(0.085)
Share non-routine analytical	0.216	(0.052)	0.210	(0.058)
Share non-routine interactive	0.412	(0.071)	0.428	(0.070)
Share non-routine manual	0.118	(0.037)	0.134	(0.047)
Share routine cognitive	0.115	(0.022)	0.108	(0.025)
Share routine manual	0.140	(0.066)	0.121	(0.063)

Notes: Plant characteristics are plant-year averages taken from the IAB Establishment Panel survey. The dummy variable profitability is one if a plant evaluates its profits as very good or good. The dummy variable positive employment expectation is one if a plant expects an increase in its workforce. I classify workers with no vocational training, no high-school degree (Abitur) or workers lacking education information as low-skilled; workers with a high-school degree and/or vocational training as medium-skilled; workers with a degree from a university (of applied sciences) as high-skilled. The variable hierarchical layers ranges from one to four and counts the number of hierarchical layers (production workers, supervisors, senior staff and directors) occupied by workers in a given plant. The variable is constructed following Caliendo et al. (2015).Task measures are plant-year average shares of (non-routine) analytic, interactive, manual, (routine) cognitive and manual tasks taken from the BIBB-BAuA employment surveys 1999, 2006, 2012 and 2018. The construction of task shares follows Antonczyk et al. (2009).

$$y_{jt} = \alpha + \mu_t + \beta \cdot \mathbf{X}_{jt} + \epsilon_{jt}, \tag{3.1}$$

where y_{jt} are task shares (of the respective task sub-categories) measuring the task composition of establishment j in year t. α is a constant and μ_t comprises year dummies for every calendar year in the sample period. $\mathbf{X}_{jt}$ are the characteristics of plant j in year t given in Table 3.3 with β as the corresponding vector of coefficients. Finally, ϵ_{jt} is the error term.

The first column of Table 3.4 shows results from simply regressing the share of non-routine tasks on foreign ownership. This unconditional comparison indicates that there is a significant difference in the task shares between foreign and domestic establishments. The non-routine task share is 2.4 percentage points lower in foreign-owned than in domestic plants. As task shares together add up to one, the reverse can be observed for routine tasks, where foreign-owned establishments exhibit a 2.4 percentage points higher share.

Descriptive statistics in Table 3.3, though, demonstrate that foreign-owned establishments differ substantially from German establishments in various dimensions. Hence, a simple unconditional comparison quite likely suffers from omitted variable bias. Therefore, in column (2) I include all plant characteristics presented in Table 3.3 to account for the effect of such omitted variables. The results show that after including the set of control variables, the foreign ownership coefficient becomes insignificant and close to zero. This indicates that there remains no difference in the routine and non-routine task composition between foreign and domestic plants after including year dummies and plant controls.

Table 3.4: Foreign ownership and the task composition

Dependent variable:	Non-routine	Non-routine
Average task share	(1)	(2)
Foreign ownership	-0.024*** (0.005)	-0.001 (0.003)
Year Dummies	No	Yes
Plant Controls	No	Yes
Adj. R^2	0.001	0.564
Observations	160,593	160,593

Notes: Dependent variable is the plant-averaged share for non-routine tasks. Column (2) includes year dummies and plant controls. Plant controls are dummies for East Germany, (very good/good) profitability, positive employment expectation, five establishment size categories, exporting status and seven industries as well as the log average wage and its square, the share of medium- and high-skilled employees and the number of hierarchical layers. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

However, it is important to keep in mind that the non-routine task share is constructed from analytical, interactive and (non-routine) manual tasks, while the routine task share is constructed from cognitive and (routine) manual tasks. Therefore, no statistically significant difference in task shares could be the result of aggregation. Thus, I take one additional step and decompose the non-routine and routine task shares into the five task sub-categories. This allows to analyse whether the finding of no difference in routine and non-routine tasks masks heterogeneity between foreign and domestic establishments across the five task sub-categories. In doing so, the data at hand also allow me to address one important shortcoming of the study by Hakkala et al. (2014), who analyse the effect of foreign ownership on task shares in Sweden. In their study, they only distinguish routine from non-routine and interactive tasks. In my analysis I am, however, able to disaggregate routine and non-routine tasks into all of the five task sub-categories introduced in Table 3.1: non-routine analytical, interactive and manual tasks as well as routine cognitive and manual tasks. In Table 3.5, I, therefore, regress plant-level task shares on an indicator variable for foreign ownership and the set of controls. Columns (1) to (5) separately show the results for the analytical, interactive, non-routine manual, cognitive and routine manual task categories.

Table 3.5: Foreign ownership and the task composition by task categories

Dependent variable:	Non-routine Analytical	Non-routine Interactive	Non-routine Manual	Routine Cognitive	Routine Manual
Average task share	(1)	(2)	(3)	(4)	(5)
Foreign ownership	-0.003**	0.002	-0.000	-0.000	0.001
	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
Year Dummies	Yes	Yes	Yes	Yes	Yes
Plant Controls	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.690	0.430	0.538	0.456	0.566
Observations	160,593	160,593	160,593	160,593	160,593

Notes: Dependent variable is the plant-averaged share for non-routine (analytical, interactive, manual) and routine (cognitive and manual) tasks. All columns control for year dummies. Plant controls are dummies for East Germany, (very good/good) profitability, positive employment expectation, five establishment size categories, exporting status and seven industries as well as the log average wage and its square, the share of medium- and high-skilled employees and the number of hierarchical layers. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

The results indicate that there is no significant difference in task shares in foreign-owned and domestic establishments in the non-routine interactive and manual as well as in the routine cognitive and manual task categories. However, Column (1) shows that foreign-owned establishments have a 0.3 percentage points lower analytical task share. This suggests that splitting up routine and non-routine tasks into the respective sub-categories can be important when analysing the effect of foreign ownership on plants' task composition.

However, as acquisition targets are selected by foreign investors along various observable and unobservable dimensions, results in Table 3.4 and Table 3.5 can only be interpreted as correlation. In order to identify a causal effect of foreign ownership, in the next section I, therefore, follow the literature and use nearest-neighbour propensity-score matching to identify a control group, which is (ex-ante) comparable to foreign-acquired establishments. Using propensity-score matching I can make the sample of foreign-acquired and domestic plants in the control group more homogeneous. A more homogeneous sample also helps to address potential bias from time-variant omitted variables influencing, both, foreign takeover and the task composition.[11]

[11] One example for this could be a one-time investment into a superior IT-infrastructure in a given establishment prior to a foreign takeover. Having a good IT-infrastructure at the same time increases the likelihood of being acquired and can change the tasks workers have to conduct subsequently. I address such biases by making treatment and control

3.5 Matching and difference-in-difference estimation

I begin the analysis in this section by introducing the estimation strategy to identify the effect of foreign takeover on the task composition of the workforce in acquired plants and report the estimation results afterwards.

3.5.1 Estimation strategy

When estimating the effect of foreign ownership, I have to overcome the problem of selection bias, which has been prominently discussed as "cherry-picking" in the literature on multinational firms (Almeida, 2007; Girma and Görg, 2007; Heyman et al., 2007; Balsvik, 2011; Gelübcke, 2013; Egger et al., 2020). Table 3.3 shows that foreign investors do not acquire German establishments with average observable characteristics. Acquired plants differ from domestic non-acquired plants in several dimensions. A simple comparison of foreign-owned and domestic plants that does not account for pre-existing establishment differences, thus, would suffer from selection bias.

First, I drop establishments experiencing multiple ownership changes and plants remaining foreign-owned throughout the whole observation window. Then, I follow previous research, which uses foreign acquisitions of domestic plants to estimate the effect of foreign ownership. Specifically, I identify foreign acquisitions of German establishments as change in majority ownership from German to foreign in two subsequent years $t-1$ and t and define the treatment indicator D_{jt}:

$$D_{jt} = \begin{cases} 1 & \text{if plant } j \text{ is foreign-acquired between } t-1 \text{ and } t \\ 0 & \text{if plant } j \text{ is domestic in } t-1 \text{ and } t \end{cases}$$

For defining this dummy, I only consider two years around a takeover event. Accordingly, I associate plants for which $D_{jt} = 1$ with the group of treated and plants for which $D_{jt} = 0$ with the group of untreated observations. Moreover, I eliminate plants, which become foreign-acquired in later sample years from the group of untreated observations.

In a next step, I use nearest-neighbour propensity-score matching without replacement to define a suitable control group (Rosenbaum and Rubin, 1983, 1985). For this purpose, I determine the probability that an establishment will be foreign-acquired between two years $t-1$ and t and estimate the following probit model for the whole sample period.

$$P(D_{jt} = 1) = \Phi(\beta \cdot \mathbf{X}_{jt-1}), \tag{3.2}$$

where $\mathbf{X}_{jt-1}$ is a (row) vector of the establishment-level covariates reported in Table 3.3 with β as the corresponding (column) vector of coefficients measured in pre-acquisition period $t-1$. I follow Bastos et al. (2018) and conduct exact matching on the number of hierarchical layers to account for plants' hierarchical organization of production prior to ownership change, seven industries, and year. Choosing these variables for exact matching ensures that plants from the treatment and matched control group have the same number of hierarchical layers, are active in the same industry and matched in the same year. This is important because the literature on knowledge hierarchies has stressed that the hierarchical organization of establishments is a key determinant of the tasks performed by its workforce (Garicano, 2000). Once a plant acquired between $t-1$ and t is matched with a control, I keep all years of data for the matched plant pair in my sample. Considering all years an establishment is in the sample has two advantages over restricting the analysis to one or two years around the takeover event. First, a bigger sample size enables me to estimate the effects of foreign acquisition on the task composition more precisely. And second, this approach also allows

group more similar through propensity-score matching.

the task composition to adjust over a longer post-acquisition period (Hakkala et al., 2014; Bastos et al., 2018).[12]

To ensure that the matching procedure is successful in eliminating pre-existing differences between acquired and non-acquired plants, I compare averages of all covariates used in estimating the propensity-score before and after matching. I report the results in Appendix 3.8.1 and show two diagnostics commonly used to assess matching quality. The first one is the mean standardized percentage bias introduced by Rosenbaum and Rubin (1985). Matching reduces this bias considerably from 30.0 percent to 1.2 percent. I also report the normalized difference between covariates introduced by Imbens and Wooldridge (2009) and Imbens and Rubin (2015) who suggest an upper limit of 0.25 to consider a variable as balanced. This threshold is not surpassed by any of the matching covariates. Because I match exactly on the number of layers, industries and year, there remains no difference in these covariates after matching. The two diagnostics, therefore, indicate that the matching procedure results in a very well balanced sample.

With the matched sample of foreign-acquired and domestic control plants at hand, I then conduct difference-in-difference estimation to identify the effect of foreign takeover on the task composition in German plants. For this purpose, I consider all years in which plants from the treatment and (matched) control group are observable in my dataset. This requires to define the treatment indicator also for periods that have not been used for matching. To do so, I follow the simple rule to set $D_{jt} = 0$ for all periods t a plant j from the control group is observed. For plants in the treatment group I set $D_{jt} = 0$ prior to their foreign acquisition and $D_{jt} = 1$ after their foreign acquisition. Then, I estimate a model of the following form:

$$y_{jt} = \alpha_j + \mu_t + \eta \cdot D_{jt} \cdot + \epsilon_{jt}, \tag{3.3}$$

where y_{jt} are task shares (of the respective task sub-categories) measuring the task composition of establishment j in year t, α_j is a plant fixed-effect to control for any remaining, time-invariant unobserved heterogeneity of plants, and μ_t are year dummies for every calendar year in our sample period. D_{jt} is the treatment indicator equal to one for each establishment j, which has been acquired between two subsequent years $t-1$ and t, and zero for all non-acquired domestic plants from the matched control group. Coefficient η captures the effect of foreign ownership on the task composition. Finally, ϵ_{jt} is the error term.

The coefficient η captures an average treatment effect of foreign takeover on the task composition if three assumptions hold. The first one is the *conditional independence assumption* (CIA), which states that the assignment of plants into the treatment (foreign-acquired) and control (domestic non-acquired) group conditional on the matching covariates in Table 3.3 has to be random. I take the CIA into account by matching on a large set of establishment covariates, which have been shown to determine the foreign takeover decision. Specifically, I include a dummy for East Germany to control for the non-random selection of plants across locations (Girma and Görg, 2007; Egger et al., 2020); a dummy for good/very good profitability to account for investors choosing more or less profitable plants (Gelübcke, 2013; Egger et al., 2020); a dummy for positive employment expectation to control for employment developing differently across plants (Gelübcke, 2013; Egger et al., 2020); plant size categories to account for the selection of smaller or bigger establishments (Gelübcke, 2013; Hijzen et al., 2013; Egger et al., 2020); an exporter dummy to control for whether plants engaged in exporting (Bandick and Görg, 2010); and industry dummies to account for the selection of acquisition targets in certain industries (Bandick and Görg, 2010; Gelübcke, 2013; Hijzen

[12] In Appendix 3.8.2 I present results when only considering one respectively two years after foreign acquisition. Even though the smaller sample size leads to less precise estimates, the results from the restricted samples are broadly in line with the results in my main analysis.

et al., 2013; Egger et al., 2020). Additionally, I include the log average wage and its square to control for foreign investors selecting establishments with above- or below-average wages (Girma and Görg, 2007; Hijzen et al., 2013; Bastos et al., 2018); the share of medium-/high-skilled workers to account for plants' skill intensity (Bandick and Görg, 2010); and year dummies to control for the state of the business cycle (Girma and Görg, 2007; Bastos et al., 2018). Using this large set of matching covariates which have been shown to determine the foreign takeover decision, I am confident that the CIA holds.

The second assumption is the *stable unit treatment value assumption* (SUTVA). In my analysis, this assumption requires that the task composition in untreated plants is not affected by some other plants becoming foreign-acquired. It is very likely that the SUTVA holds because the total number of foreign takeovers over the long period of my analysis is very small compared to the total German establishment population. Thus, I do not expect an effect of foreign takeover on the task composition in non-acquired plants for instance due to worker movements.

Finally, the third assumption, which is referred to as *common trend assumption* (CTA), is that, in the absence of foreign takeover, the task composition in treated and untreated establishments has to follow the same path. To investigate whether the CTA holds, I follow Egger et al. (2020) and restrict my sample to all matched plant pairs, which can be observed in periods $t-2$ and $t-1$. Then, I first compare average shares in each task sub-category by testing the equality of means in the treatment and matched control group before takeover. These tests confirm that task shares in each of the five task sub-categories do not differ significantly between treatment and matched control group in both pre-acquisition periods. Additionally, a simple linear regression of the change in each task sub-category between $t-2$ and $t-1$ shows that the trend in task shares does not differ between treated and untreated plants. This suggests that the effect of foreign acquisition does not follow from task shares in the treatment and matched control group developing differently already prior to ownership change.[13]

3.5.2 Estimation results

In the following section, I present the results from estimating the effect of foreign takeover on the task composition in acquired plants.

Table 3.6: The effect of foreign acquisition on the task composition

Dependent variable:	Non-routine Analytical	Non-routine Interactive	Non-routine Manual	Routine Cognitive	Routine Manual
Average task share	(1)	(2)	(3)	(4)	(5)
Foreign	-0.002*	0.001	-0.000	0.000	0.001
acquisition	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Observations	6,900	6,900	6,900	6,900	6,900

Notes: Dependent variable is the plant-averaged share for non-routine (analytical, interactive, manual) and routine (cognitive and manual) tasks. The estimation includes year dummies and plant fixed effects. Standard errors in parentheses are clustered at the plant-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

[13] As suggested by Pischke (2005), I also illustrate the trends in task shares graphically. Figure 3.1 in Appendix 3.8.4 depicts the trend in the task shares for treated and matched control plants for all five task sub-categories.

Table 3.6 shows the results from estimating Equation (3.3) for the five task sub-categories. The effects for the five sub-categories again confirm that disaggregating routine and non-routine tasks is important when analysing the effect of foreign takeover on the task composition. There is no significant impact of foreign acquisition on plant-level task shares when distinguishing between the cognitive, interactive or manual sub-categories. However, foreign acquisition reduces the analytical task share in acquired plants by 0.2 percentage points. One can use the average of 21% non-routine analytical tasks among all domestic plants to assess the magnitude of this estimate. Foreign acquisition results in a relative decrease of the non-routine analytical task share by about one percent relative to this average.

Despite the fact that the reduction in the analytical task share appears to be modest quantitatively, one has to keep the tasks forming the analytical sub-category, in mind when putting this result in perspective: *develop, research and construct* (R&D), *gather information and document* and *apply legal knowledge*. Stressing these tasks is important, because there already exists a large literature on the importance of, in particular, R&D-activity for economic growth. This research has shown that the returns to R&D can be substantial. Thus, even a small reduction in the analytical task share in acquired plants could matter economically. For instance, in case foreign owners reduce the analytical task share by relocating activities like product innovation or basic research to their home country, this could result in substantial negative impacts on growth at the plant-, industry-, or even national level.[14] However, the data at hand unfortunately do not allow to analyse, which activities are replaced or reduced after foreign takeover in further detail. Therefore, I have to leave this question to future research.

Summing up, a negative impact of foreign acquisition on the analytical task share indeed speaks in favor of the hypothesis introduced before that foreign owners might be less inclined to locate knowledge-intensive tasks (like *develop, research and construct*) in a foreign plant. The negative impact of foreign ownership on the analytical task share, to the contrary, indicates that foreign owners could be more inclined to keep non-routine analytical tasks in close proximity or relocate such tasks to their headquarters. This, subsequently, would explain restructuring of acquired plants in Germany in favor of non-analytical tasks.

From a policy perspective, this result is especially interesting. This is because the public discussion on FDI in Germany has long since revolved around the question on whether foreign acquisitions, if left unregulated, lead to knowledge dissipation or losses of certain jobs performing specific tasks domestically. Policymakers, employers and employees have constantly expressed worries that Germany over time could lose its strategic advantage in some key industries, particularly in the important manufacturing sector which is fundamental to Germany's economic success. In my analysis, I also find that the majority of foreign acquisitions takes place in manufacturing. Against the background that foreign takeovers lead to a decrease in non-routine analytical (knowledge-intensive) tasks, taking the recurrent worries of all actors seriously, might indeed be important for Germany's economic development and future competitiveness.

3.6 Robustness checks and channel of influence

The purpose of this section is twofold. In subsection 3.6.1, I analyse the robustness of my results when considering an alternative definition of task shares and study whether the main results also exist after domestic takeover. In subsection 3.6.2, I shed light on a potential explanation for a

[14] The survey of the literature in Nadiri (1993) suggests that R&D-activites in general have very sizable positive rates of return between 20% and 100%. For instance, Kim (2011) measures the economic growth effect of R&D in Korea and finds that R&D stocks account for about one third of total growth.

negative effect of foreign acquisition on the non-routine analytical task share when estimating the effect of foreign takeover on the number of hierarchical layers in acquired plants.

3.6.1 Robustness checks

In the following section, I investigate whether the negative impact of foreign acquisition on non-routine analytical tasks is robust to an alternative definition of task shares. Additionally, when analysing domestic acquisitions taking place during the sample period, I also examine whether my result can be attributed to a general takeover instead of a foreign ownership effect.

To begin with, I follow Becker et al. (2013), who calculate a different measure for the task composition. Becker et al. (2013) standardize the average number of tasks (in each task sub-category) from Table 3.2 in a *given* occupation by the difference between the maximum and minimum number of tasks among *all* occupations. As a result, task shares (in each task sub-category) vary from zero to one and do not add up to one in each occupation.

Table 3.7: The effect of foreign acquisition on standardized task shares

Dependent variable:	Non-routine Analytical	Non-routine Interactive	Non-routine Manual	Routine Cognitive	Routine Manual
Average task share	(1)	(2)	(3)	(4)	(5)
Foreign acquisition	-0.008** (0.004)	-0.003 (0.004)	-0.006 (0.004)	-0.006 (0.004)	-0.003 (0.004)
Observations	6,900	6,900	6,900	6,900	6,900

Notes: Dependent variable is the plant-averaged standardized share for non-routine (analytical, interactive, manual) and routine (cognitive and manual) tasks. The estimation includes year dummies and plant fixed effects. Standard errors in parentheses are clustered at the plant-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Table 3.7 shows the results from estimating Equation (3.3) using standardized task shares as outcome variable. The main conclusion from Table 3.6 remains intact. When decomposing the effect into task sub-categories, there is no significant effect on standardized shares in cognitive, interactive and (routine/non-routine) manual tasks. However, the results still indicate a statistically significant decrease in the standardized analytical task measure.

Additionally, as has been argued in previous literature on multinational firms and foreign ownership, one also has to guard the analysis against the possibility that the estimates only capture a general takeover effect, which is independent of the nationality of the acquirer (see e.g. Egger et al., 2020). Therefore, in another robustness check, I identify 241 domestic acquisitions of foreign-owned plants in Germany between 2000 and 2019. I then match acquired establishments to plants, which constantly remain foreign-owned and estimate the effect of domestic takeover on the plant-level task composition. In case takeovers, irrespective of the nationality of the acquirer, lead to a decrease in acquired plants' analytical task share, I should also find a negative effect of domestic acquisition on the analytical task share.

Table 3.8 shows the results from this exercise. I find no impact of domestic takeovers on the aggregated non-routine or routine task shares in acquired plants. The same holds true when investigating the five task sub-categories separately. Thus, the observation that foreign ownership decreases the non-routine analytical task share in German plants seems not to be caused by a general restructuring effect after any type of acquisition, but instead applies to foreign takeover only.

Table 3.8: The effect of domestic acquisition on task shares

Dependent variable:	Non-routine Analytical	Non-routine Interactive	Non-routine Manual	Routine Cognitive	Routine Manual
Average task share	(1)	(2)	(3)	(4)	(5)
Domestic acquisition	-0.001 (0.002)	0.000 (0.002)	0.000 (0.002)	0.001 (0.001)	-0.000 (0.002)
Observations	3,024	3,024	3,024	3,024	3,024

Notes: Dependent variable is the plant-averaged share for non-routine (analytical, interactive, manual) and routine (cognitive and manual) tasks. The estimation includes year dummies and plant fixed effects. Standard errors in parentheses are clustered at the plant-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Finally, another argument explaining the negative effect of foreign takeover on knowledge-intensive non-routine analytical tasks might be that new foreign owners only restructure plants, which are not productive enough. Following this argument, I should not observe a negative effect of ownership change on the analytical task share in acquired plants, which are close to the technological frontier and therefore very profitable. To investigate, whether the average negative effect results from foreign owners decreasing the share of non-routine analytical tasks only at relatively unproductive plants, I repeat the analysis from Table 3.6, but additionally include an interaction between foreign acquisition and a dummy that indicates whether a plants' profitability is very good or good. The expectation underlying this analysis is that the impact of foreign takeover on the analytical task share should be stronger (more negative) in unproductive plants. If this argument applies, I expect the interaction term between foreign acquisition and very good/good profitability to turn out positive, while the effect for acquired plants without very good/good profitability should be even more negative. The results, which are available upon request, however, do not confirm this hypothesis. Both, the acquisition and interaction term are negative and statistically insignificant when I separate the effect of foreign takeover between relatively profitable and less profitable plants.

3.6.2 Channel of influence

In this subsection, I investigate whether hierarchical reorganization of production in acquired plants can explain the effect of foreign takeover on the non-routine analytical task content. This argument comes from research on plants' hierarchical organization. The concept of hierarchical layers within establishments used in this literature has been introduced by Caliendo et al. (2015), who assign workers to either of four layers making use of their occupation codes. In ascending order these four hierarchical layers are production workers, supervisors, senior staff and directors.[15]

[15] The assignment of occupations to hierarchical layers from Caliendo et al. (2015) has been converted to the German classification of occupations (KldB) by Gumpert et al. (2022). The occupation of plastics processors, for instance, belongs to the lowest hierarchical layer of production workers; electrical engineers are classified as supervisors; foremen and master technicians are senior staff; and directors or executives of a company are assigned to the highest layer of directors. Caliendo et al. (2015) show that the assignment to four hierarchical layers fits theoretical predictions well. They find firms to be hierarchical in the sense that workers in higher layers earn more and that firms employ fewer workers in higher layers. I would like to thank Anna Gumpert, Henrike Steimer and Manfred Antoni for sharing their

Analysing plants' hierarchical organization could be important because changes to a plant's hierarchy - either due to an increase or a decrease in the number of hierarchical layers after foreign acquisition - would likely also change plants' task composition. This is because reorganization by introducing (or eliminating) layers in the vertical hierarchy goes along with hiring (or firing) employees in occupations with task profiles differing from the incumbent workforce. Evidence from the literature suggests that foreign acquisition could result in a higher number of hierarchical layers.

For instance, studying multi-establishment firms in Germany, Gumpert et al. (2022) show that larger geographic distance to the headquarters induces German establishments to operate with more hierarchical layers. According to their analysis, this is the consequence of more distant owners allocating more knowledge to the German establishment and its workforce. Similarly, Bastos et al. (2018) find that foreign acquisition in Portugal leads to an expansion in the scale of production and an increase in the number of hierarchical layers.

Whereas existing results are suggestive of foreign acquisition making firms more hierarchical, they seem to overlook an important counteracting effect. Larger business networks may choose stronger hierarchical specialization across firms, reducing the number of vertical layers in each firm (see Egger et al., 2022, for a detailed study on the vertical structure of business groups).

Given that a change in the hierarchical structure after foreign takeover exists, the theory of knowledge hierarchies establishes a relationship between these changes and the task composition in plants. Therefore, in the subsequent, I investigate whether hierarchical reorganization after ownership change could be responsible for the negative effect of foreign acquisition on the non-routine analytical task share.

For this purpose, I match foreign-acquired to domestic control plants and run the regression in Equation (3.3), where I use the number of hierarchical layers as dependent variable.[16] The first column of Table 3.9 shows the results for the pooled sample of all plants and indicates that foreign acquisition does not lead to reorganization within plants by adding or dropping hierarchical layers. However, reorganization by adding or dropping layers is obviously limited by the number of layers establishments already had prior to ownership change. Therefore, as the pooled sample of all plants might mask heterogeneity between plants differing in the initial number of layers, in Columns (2) to (5) I split the sample by the number of layers in the year before ownership change.

Table 3.9: The effect of foreign acquisition on the number of hierarchical layers

Dependent variable:	All	One layer	Two layers	Three layers	Four layers
Number of layers	(1)	(2)	(3)	(4)	(5)
Foreign	-0.017	0.139	0.068	-0.101	-0.053
acquisition	(0.040)	(0.086)	(0.105)	(0.066)	(0.053)
Observations	6,887	967	1,110	2,334	2,476

Notes: Dependent variable is the number of hierarchical layers. The estimation includes year dummies and plant fixed effects. Standard errors in parentheses are clustered at the plant-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

The results show that there is no statistically significant effect on the number of layers in either of one- ,two-, three-, or four-layered plants. All estimates are close to zero and suggest

correspondence table with me.

[16] When analysing the effect of foreign ownership on the number of hierarchical layers, I do not match on the number of hierarchical layers.

that foreign owners do not substantially change the hierarchical organization of plants in Germany after acquisition. The finding of a negative effect of foreign takeover on the non-routine analytical task share, therefore, cannot be attributed to hierarchical reorganization acting against non-routine analytical tasks.

In Appendix 3.8.4, I also check, whether evidence for hierarchical reorganization of plants after acquisition differs depending on the type of targeted plant. More specifically, one might expect that in case a foreign investor acquires plants belonging to multi-establishment firms in Germany, communication and, therefore, the introduction of an additional hierarchical layer, could be achieved at only one of several plants belonging to the multinational network. In such a case there could be changes in the hierarchical structure of firms outside of individual plants. To eliminate such cases, in Table 3.14 I, therefore, confine the sample to single-establishment firms. The reason for analysing this restricted sample is that a foreign investor, arguably, can only restructure the management of acquired single plants by increasing or decreasing the number of hierarchical layers at the given plant. Using independent plants, thus, shields the estimates against the possibility that restucturing happens in other plants of a multi-establishment network.[17] Using this restricted sample, however, does not alter the conclusion. I find no significant effect of foreign ownership on the number of hierarchical layers. Therefore, the main result of a negative effect of foreign takeover on the non-routine analytical task share does not appear to be caused by foreign owners hierarchically restructuring plants in favor of non-analytical tasks.

3.7 Conclusion

This chapter provides first and new evidence for the effect of foreign ownership on the task composition of the workforce in German plants. Using rich administrative linked employer-employee data, I identify more than 390 foreign takeovers taking place in Germany in the very recent period from 2000 to 2019. To estimate the effect of foreign acquisition on the task composition of the workforce in acquired plants, I combine propensity-score matching with a difference-in-difference estimator.

In my empirical analysis, I first show descriptive evidence suggesting that, as compared to domestic establishments, foreign-owned plants are less intensive in non-routine tasks, particularly in the non-routine analytical task category. Making use of propensity-score matching combined with a difference-in-difference estimator in a second step, I estimate the effect of foreign takeover on the task composition within targeted plants. Using the matched sample, I identify a statistically significant impact of foreign acquisition on the share of non-routine analytical tasks. Foreign takeover reduces the non-routine analytical task share in acquired plants by 0.2 percentage points or about one percent relative to its mean. This result is consistent with the theoretical argument from the literature that foreign multinationals are less inclined to locate non-routine, less predictable tasks abroad, because in case unexpected problems occur, problem solving is more costly.

In several robustness checks, I then demonstrate that the negative effect of foreign acquisition on the non-routine analytical task share is robust to changing the construction of the task measure. Additionally, I present evidence consistent with the argument that my main result cannot be attributed to a general takeover effect, but can only be observed in the case of foreign acquisitions. Finally, I also show that the negative effect of foreign takeover on the non-routine analytical task

[17] An example would be the acquisition of two plants belonging to the same firm by a foreign investor. In this example, one plant could be responsible for production, whereas the other plant is the central office and, therefore, responsible for communicating with the foreign headquarters. Then, foreign takeover might lead to a reorganization by adding one management layer at the German central office. This, in turn, could cause an underestimation of the effect of foreign ownership on hierarchical organization when not restricting the sample to independent single plants.

share cannot be attributed to hierarchical restructuring. This is important, because if hierarchical restructuring takes place after acquisition, this could affect the task composition within plants substantially.

The analysis in this chapter is particularly interesting against the background of the ongoing public discussion about the effect of foreign takeovers in German key industries. The results show that foreign ownership decreases the non-routine analytical task share, which consists of *develop, research and construct*, *gather information and document* and *apply legal knowledge*. As these are tasks that could potentially have substantial consequences for growth at the plant-, industry-, or even national level, the evidence presented in this chapter might be of particular interest for policymakers deciding on the regulation of FDI activity in Germany.

Overall, I believe that this chapter has shown that a further and in-depth analysis of the effects of foreign ownership on the task composition and within-plant organization is a promising avenue for future research.

3.8 Empirical appendix

3.8.1 Balancing test

Table 3.10: Balancing test for the matching procedure

Variable	*Sample*	*Mean*		*Stand.*	*Bias*	*Normal.*
		Treated	*Control*	*bias %*	*reduction*	*diff.*
Plant characteristics						
East Germany	Unmatched	0.355	0.399	-9.0		
East Germany	Matched	0.355	0.312	8.9	1.3	0.065
Profitability	Unmatched	0.401	0.403	-0.3		
Profitability	Matched	0.401	0.439	-7.8	-2359.5	-0.054
Employment						
Positive employment expectation	Unmatched	0.249	0.157	23.0		
Positive employment expectation	Matched	0.249	0.249	0.0	100.0	0.000
Employment < 10	Unmatched	0.168	0.369	-46.6		
Employment < 10	Matched	0.168	0.157	2.4	95.0	0.019
$10 \leq$ Employment < 50	Unmatched	0.310	0.369	-12.6		
$10 \leq$ Employment < 50	Matched	0.310	0.305	1.1	91.5	0.008
$50 \leq$ Employment < 250	Unmatched	0.373	0.200	39.0		
$50 \leq$ Employment < 250	Matched	0.373	0.376	-0.6	98.5	-0.004
$250 \leq$ Employment < 1000	Unmatched	0.129	0.051	27.7		
$250 \leq$ Employment < 1000	Matched	0.129	0.127	0.9	96.8	0.005
Employment ≥ 1000	Unmatched	0.020	0.011	7.3		
Employment ≥ 1000	Matched	0.020	0.036	-12.2	-68.2	-0.065
Exporter	Unmatched	0.480	0.230	53.9		
Exporter	Matched	0.480	0.485	-1.1	98.0	-0.007
Log avg. wage	Unmatched	4.663	4.423	61.1		
Log avg. wage	Matched	4.663	4.691	-7.0	88.5	-0.048
Log avg. wage squared	Unmatched	21.914	19.706	62.6		
Log avg. wage squared	Matched	21.914	22.156	-6.9	89.1	-0.046
Share of medium-skilled	Unmatched	0.739	0.817	-37.0		
Share of medium-skilled	Matched	0.739	0.741	-1.0	97.3	-0.007
Share of high-skilled	Unmatched	0.194	0.132	29.3		
Share of high-skilled	Matched	0.194	0.192	1.1	96.2	0.007
Number of hierarchical layers	Unmatched	2.850	2.114	69.0		
Number of hierarchical layers	Matched	2.850	2.850	0.0	100.0	0.000
Industries						
Agriculture, foresting, fishing	Unmatched	0.003	0.020	-16.6		
Agriculture, foresting, fishing	Matched	0.003	0.003	0.0	100.0	0.000
Manufacturing	Unmatched	0.470	0.301	35.2		
Manufacturing	Matched	0.470	0.470	0.0	100.0	0.000
Mining and construction	Unmatched	0.056	0.124	-24.0		
Mining and construction	Matched	0.056	0.056	0.0	100.0	0.000
Retail and warehousing	Unmatched	0.261	0.235	6.2		
Retail and warehousing	Matched	0.261	0.261	0.0	100.0	0.000
Finance and insurance services	Unmatched	0.165	0.141	6.7		
Finance and insurance services	Matched	0.165	0.165	0.0	100.0	0.000
Public and private services	Unmatched	0.046	0.180	-43.4		
Public and private services	Matched	0.046	0.046	0.0	100.0	0.000
Private households	Unmatched	0.000	0.000	-1.2		
Private households	Matched	0.000	0.000	0.0	100.0	0.000
Year	Unmatched	2008.8	2008.5	5.1		
Year	Matched	2008.8	2008.8	0.0	100.0	0.000
Sample				*Mean bias*	*Median bias*	
Unmatched				30.0	31.1	
Matched				1.2	0.0	

Notes: All variables are measured in pre-acquisition year $t-1$. I conduct exact matching without replacement on the number of hierarchical layers, seven industries and year.

3.8.2 Additional results

In Table 3.11 I restrict the sample of foreign-acquired and matched control plants to include the first year after ownership change only. This reduces the sample size considerably and, therefore, also results in less precise estimates. Restricting the sample in this way helps in assessing, whether foreign ownership has a direct impact effect or whether the full effect of foreign takeover on the task composition takes time to materialise. The results show that the effect for the non-routine analytical task share remains negative and is reduced by about 50% compared to Table 3.6. As expected, the reduction in the sample size also results in a statistically insignificant coefficient with a p-value of 0.22.

Table 3.11: The effect of foreign acquisition on the task composition - Restricted sample

Dependent variable:	Non-routine Analytical	Non-routine Interactive	Non-routine Manual	Routine Cognitive	Routine Manual
Average task share	(1)	(2)	(3)	(4)	(5)
Foreign acquisition	-0.001 (0.001)	0.001 (0.001)	-0.000 (0.001)	-0.000 (0.000)	0.001 (0.001)
Observations	1,576	1,576	1,576	1,576	1,576

Notes: Dependent variable is the plant-averaged share for non-routine (analytical, interactive, manual) and routine (cognitive and manual) tasks. The estimation includes year dummies and plant fixed effects. The sample is restricted to only include the year before and after acquisition. Standard errors in parentheses are clustered at the plant-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

In Table 3.12 I present additional results after restricting the sample to include all treated and matched establishments, which can be observed in the two years after ownership change. With this sample at hand, I estimate Equation (3.3), but instead of calculating a single average effect, I evaluate the effect of foreign takeover separately for both post-acquisition periods (see e.g. Hijzen et al., 2013; Egger et al., 2020). The purpose of this analysis is to investigate, whether there is some evidence that the effect of foreign takeover on the task composition takes time to develop. The results show that, still, there is no evidence for an effect of foreign acquisition on interactive, non-routine manual, cognitive or routine manual task shares. However, the estimates for the analytical task sub-category are well in line with the main results presented in Table 3.6. Two years after ownership change, I find a marginally insignificant reduction (p-value of 0.11) of 0.3 percentage points in the non-routine analytical task sub-category.

Finally, I also report results from an alternative set of matching covariates. In Table 3.13 I do not include the number of hierarchical layers as a matching covariate to avoid any relationship between matching covariates and the outcome variable task shares. This exercise, however, does not change the main conclusion that foreign acquisition decreases the non-routine analytical task share by about 0.2 percentage points.

3.8.3 The effect of foreign ownership on hierarchical organization in independent plants

The need to restructure plants after acquisition could differ depending on the type of plant targeted by a foreign owner. In case a foreign investor acquires plants belonging to multi-establishment

Table 3.12: The effect of foreign acquisition on the task composition - Effect by year

Dependent variable:	Non-routine Analytical	Non-routine Interactive	Non-routine Manual	Routine Cognitive	Routine Manual
Average task share	(1)	(2)	(3)	(4)	(5)
Foreign	-0.002	0.000	0.001	0.000	0.001
acquisition $t = 1$	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Foreign	-0.003	-0.000	0.002	0.000	0.001
acquisition $t = 2$	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1,326	1,326	1,326	1,326	1,326

Notes: Dependent variable is the plant-averaged share for non-routine (analytical, interactive, manual) and routine (cognitive and manual) tasks. The estimation includes year dummies and plant fixed effects. The sample is restricted to only include treated and matched establishments which are available in the two years after ownership change. Standard errors in parentheses are clustered at the plant-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Table 3.13: The effect of foreign acquisition on the task composition - Alternative matching

Dependent variable:	Non-routine Analytical	Non-routine Interactive	Non-routine Manual	Routine Cognitive	Routine Manual
Average task share	(1)	(2)	(3)	(4)	(5)
Foreign	-0.002*	0.001	0.001	-0.000	0.001
acquisition	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Observations	7,021	7,021	7,021	7,021	7,021

Notes: Dependent variable is the plant-averaged share for non-routine (analytical, interactive, manual) and routine (cognitive and manual) tasks. The estimation includes year dummies and plant fixed effects. Standard errors in parentheses are clustered at the plant-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

firms, communication and, therefore, the introduction of an additional hierarchical layer, could be achieved at only one plant belonging to the multinational network. In Table 3.14 I check, whether the finding of no significant reorganization after foreign acquisition is altered when confining the treatment and control group to single, independent establishments. The reason for this restriction is that a foreign investor can only restructure the hierarchical organization of acquired single plants by increasing or decreasing the number of hierarchical layers at the given plant. Using independent plants, thus, shields the estimates against the possibility that reorganization takes place in other plants belonging to the multi-establishment network in Germany.

The results using this restricted sample, however, do not alter the conclusion. I find no significant effect of foreign ownership on the number of hierarchical layers. Summing up, the single-plant sample suggests that foreign takeover also does not lead to hierarchical reorganization in independent acquired plants. Therefore, the main result of a negative effect of foreign acquisition on the non-routine analytical task share cannot be attributed to hierarchical reorganization taking place after

Table 3.14: The effect of foreign acquisition on the number of hierarchical layers in single plants

Dependent variable:	All	One layer	Two layers	Three layers	Four layers
Number of layers	(1)	(2)	(3)	(4)	(5)
Foreign acquisition	0.029 (0.064)	0.042 (0.143)	0.081 (0.196)	0.107 (0.138)	-0.022 (0.081)
Observations	3,200	518	642	859	1,181

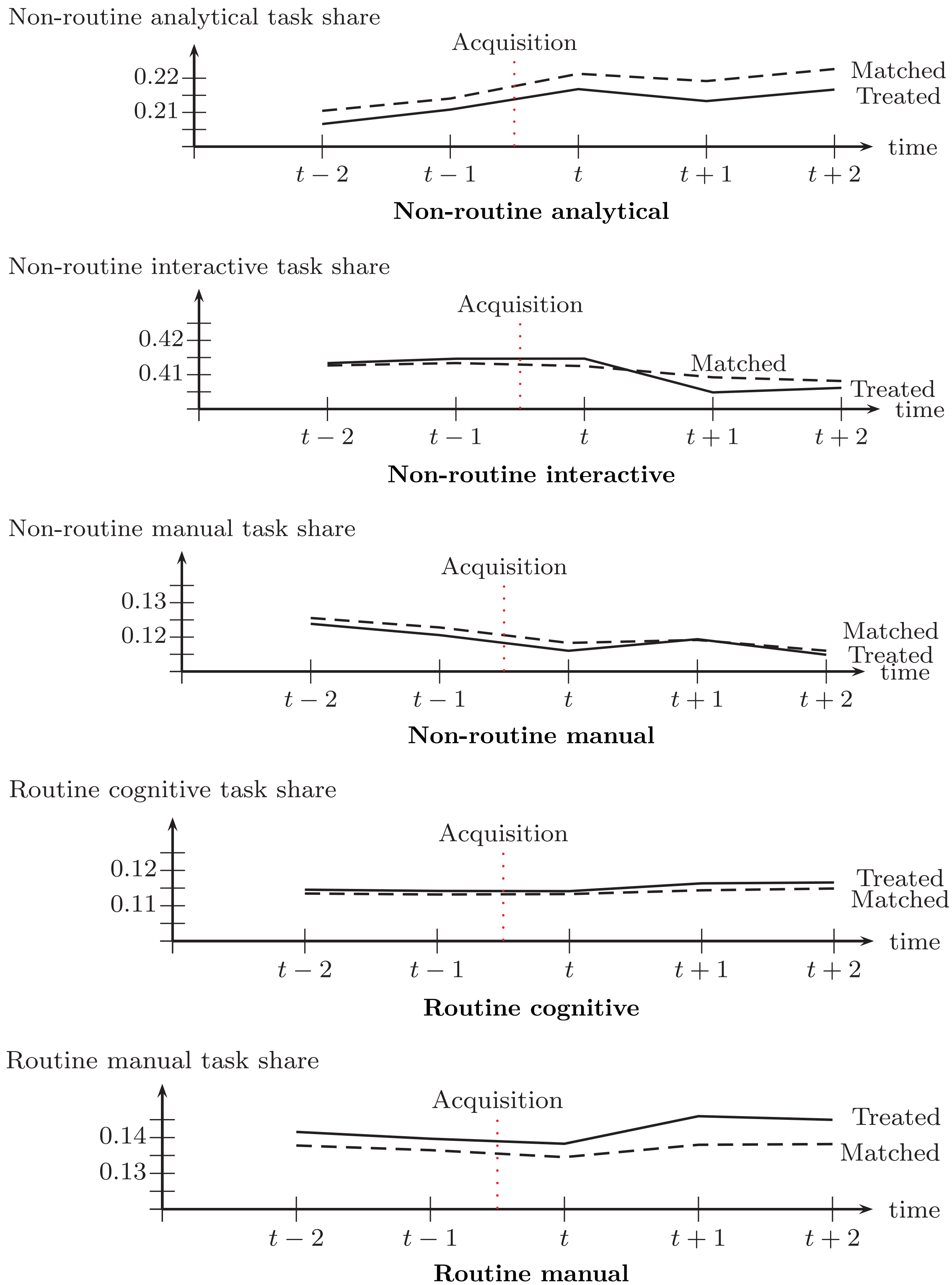
Notes: Dependent variable is the number of hierarchical layers. The estimation includes year dummies and plant fixed effects. Standard errors in parentheses are clustered at the plant-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

the takeover event.

3.8.4 The development of task shares in treated and matched control group

Figure 3.1 shows the development in the shares of each task sub-category for treated (solid line) and matched control plants (dashed line) before and after ownership change. The graph shows that task shares in every task sub-category grow similarly prior to acquisition. Consistent with my main results, a substantial widening in the gap between treated and matched control plants, however, can only be observed after foreign acquisition in the non-routine analytical task sub-category.

Figure 3.1: Task shares in treated and matched control group



Chapter 4

How Does the Position in Business Group Hierarchies Affect Workers' Wages?

4.1 Introduction

Although it is widely perceived that business groups account for a major part of economic activity (UNCTAD, 2016), as a hybrid form between firms and markets they are not well-defined objects of economic theory and have therefore so far received little attention in academic research (see Baker et al., 2002; Khanna and Yafeh, 2007; Altomonte et al., 2018). In particular, it is not understood yet, how the specific organizational form of a business group influences its economic performance and workers' wages. This is surprising given the vast empirical evidence showing that firm organization is a key determinant of productivity and wages (see Caroli and Van Reenen, 2001; Rajan and Wulf, 2006; Bloom et al., 2010, 2018). A prominent strand of the literature points to the vertical position in firm hierarchy as a crucial determinant of workers' wages (see Caliendo et al., 2015; Bastos et al., 2018; Friedrich, 2022). Due to the lack of data combining detailed information on business groups, firms, and workers, empirical research on the role of business group hierarchy for workers' wages is missing so far, despite the material role of these groups for economic activity. To fill this gap, we construct and use a new dataset that allows us to study in a systematic way how the position of the employer in a business group hierarchy affects workers' wages.[1]

For our analysis, we define business groups as ownership networks, in which the ultimate owner exercises hierarchical control over the decisions made in all affiliated firms. We extract the relevant ownership information from the Bureau van Dijk global firm database Orbis. This database provides insights on worldwide ownership linkages and thus gives detailed information on the hierarchical position of firms in their business groups. To determine how the hierarchical position impacts workers' wages, we merge Orbis with administrative data on German employees from the Institute for Employment Research (IAB) in Nuremberg. As a result, we obtain a novel dataset that provides detailed information on the business groups to which German establishments belong and that contains information on the establishments' workforce at the individual level. However, ownership linkages are not one-directional. Thus, a simple count of hierarchical layers between an

[1] Business groups play a prominent role in a sizable, mostly empirical literature on foreign ownership wage premia (see Girma et al., 2001; Girma and Görg, 2007; Balsvik and Haller, 2010; Hijzen et al., 2013; Egger et al., 2020; Egger and Jahn, 2020). This literature emphasizes the geographical location of the ultimate owner as an important determinant of wages in foreign subsidiaries.

establishment and its ultimate owner would give at best an imprecise measure of vertical distance. To capture the complex structure of ownership networks, we develop a hierarchical distance index, which is motivated by recent work on sectoral input-output relationships (cf. Antràs and Chor, 2013) and measures hierarchical distance more consistently than a pure count of ownership layers.

To explain how the position in business groups affects workers' wages, we set up a theoretical model, in which production requires consecutive performance of a continuum of stages along the value chain of the business group. The value chain is split into two segments of endogenous length which are operated by an upstream and a downstream firm (cf. Costinot et al., 2013). Crucial for our analysis, we assume that the production process is prone to a loss of control problem due to limited monitoring capacity of the downstream firm (see Calvo and Wellisz, 1979; Chen, 2017). Focussing on the problem of a single business group, we show that the optimal labor allocation and the wage profile depend on relative monitoring efficiency in the upstream and downstream firm. We assume that the value chain follows the hierarchical structure of the business group, which is common practice, for instance, in the context of vertical multinational enterprises (see Helpman, 1984; Antràs and Yeaple, 2014). That is, we associate the upstream producer with a firm in larger hierarchical distance to the owner of the business group. In this case, lower monitoring efficiency in the upstream firm than in the downstream firm leads to a positive impact of hierarchical distance on wages. In contrast, if monitoring efficiency were lower in the downstream firm, the impact of hierarchical distance on wages would be negative.[2]

In the empirical analysis, we control for observable worker and establishment characteristics to isolate the effect of hierarchical distance from other factors that are important for wage payments. Including these controls, we identify a positive effect of larger hierarchical distance to the ultimate owner of a business group on individual wages in German establishments. Estimates from a parsimonious OLS specification show that an increase in the hierarchical distance by one standard deviation amounts to a sizable increase in wages of almost two log points. Although this estimate is reduced when additionally controlling for unobserved worker, establishment, and business group heterogeneity by fixed-effects, a positive and significant effect of hierarchical distance on wages still exists.

To make sure that the hierarchical distance variable does not erroneously pick up other features of business groups, we control for the total number of subsidiaries, as suggested by rich evidence for a firm size-wage premium (see, for instance, Brown and Medoff, 1989; Idson and Oi, 1999; Winter-Ebmer and Zweimüller, 1999; Colonnelli et al., 2018). In addition, we combine information on the horizontal and the vertical dimension of business groups to an entropy index, measuring business group complexity (see Altomonte and Rungi, 2015). Adding these covariates, the impact of hierarchical distance on wages remains positive. We complement our empirical analysis by combining propensity-score matching with a difference-in-difference estimator. This two-stage procedure gives a picture that is broadly in line with our baseline results: A larger hierarchical distance to the ultimate owner of the business group increases workers' wages.

Against the background of our theoretical model, the empirical results indicate that larger hierarchical distance is associated with lower monitoring efficiency, making higher wages necessary to provide an incentive for workers to follow the profit-maximizing objectives of the ultimate owner of

[2] Our model bears close resemblance to the monitoring-based theory of firm hierarchies that has been put forward by Calvo and Wellisz (1978, 1979), Qian (1994), and Chen (2017). According to this theory, hierarchical layers can alleviate the loss of control problem inside the firm by increasing monitoring capacity and thereby reducing the incentive pay necessary to align workforce behavior with the objective of the owner. Our model is also related to the knowledge-based theory of firm hierarchies, in which hierarchical layers facilitate the information flow between workers and their superiors and thereby reduce the number of unsolved problems in the production process (see Garicano, 2000; Garicano and Rossi-Hansberg, 2006; Caliendo and Rossi-Hansberg, 2012). Chen and Suen (2019) discuss differences and similarities between monitoring-based and knowledge-based theories of firm hierarchies.

the business group. Missing information on monitoring effort does not allow us to directly test the theoretical hypothesis from our model. However, we provide supportive evidence by splitting our sample into sub-groups of workers with differing levels of skills and sub-groups of occupations with differing shares of routine tasks. We find that the hierarchical distance effect is most pronounced for workers with high skills and for workers performing non-routine tasks – whose effort is the most difficult to observe. This indicates that our monitoring-based theory of business groups provides a suitable explanation for the positive effect of larger hierarchical distance to the ultimate owner on workers' wages.

The remainder of this chapter is organized as follows. In Section 4.2, we outline a theoretical model for explaining wage payments along the business group hierarchy. In Section 4.3, we explain how we merge global firm data from Orbis with administrative data of German workers from the IAB. There, we also report summary statistics and show descriptive evidence on the relationship between hierarchical distance to the ultimate owner of the business group and workers' wages. In Section 4.4, we present the empirical analysis and report our estimation results. Section 4.5 concludes.

4.2 A monitoring-based theory of business group hierarchies

In this section, we set up a theoretical model to study the comparative-static effects of changes in a firm's hierarchical distance to the ultimate owner of the business group on its wages. For this purpose, we consider a single business group in a competitive market that can sell its output at a given price equal to one. The business group operates a continuum of consecutively performed production stages with measure one (see Costinot et al., 2013) and faces the trade-off between monitoring workers or paying higher wages to reduce shirking (cf. Calvo and Wellisz, 1979; Chen, 2017).[3] To facilitate our analysis, we assume a simple structure with two firms, which are associated with an upstream (intermediate goods) producer, $j = u$, and a downstream (final goods) producer, $j = d$, respectively.[4] To make the structure of a value chain informative about the structure of a business group hierarchy, we impose the assumption that the position of a firm in the value chain is decisive for its position in business group hierarchy, which is common practice, for instance, in the literature on vertical multinational enterprises.[5] Consequently, the upstream firm u has a larger hierarchical distance to its ultimate owner than the downstream firm d.

The value chain of the business group is split between these two firms into two disjoint segments with endogenous length. Capturing the value chain by the unit interval, we denote by $S \in (0, 1)$ the segment performed by the upstream producer and by $1 - S$ the segment performed by the downstream producer. The ultimate owner of the business group makes all relevant decisions on production, hiring, and monitoring for both firms. More specifically, the ultimate owner chooses the employment levels (and thus the value chain segments), wages, and the monitoring intensity for the two firms.

[3] Although we employ the same production technology as Costinot et al. (2013), our model differs considerably from theirs. In particular, we do not embed our model into a general equilibrium framework and do not elaborate on how Ricardian technology differences affect the position of countries in the global value chain. Instead we consider a loss of control problem and focus on the role of monitoring efficiency for the allocation of production and the wages paid along the value chain to develop a monitoring-based theory of business group hierarchies.

[4] In the theoretical extension, we discuss an extension of our model to business groups with more than just two firms and show that this leaves the main insights from our analysis unchanged.

[5] Starting with the seminal work by Helpman (1984) the theory of multinational firms associates a vertical investment with imports from foreign affiliates to the country hosting the headquarters of the multinational enterprise for final assembly of consumer goods (see Grossman and Helpman, 2003; Antràs and Helpman, 2004; Antràs and Yeaple, 2014).

Production technology

Following Costinot et al. (2013), we consider a Leontief technology that combines one unit of labor input with one unit of intermediate good from the previous stage to produce (intermediate) output. Parameter $\lambda \in (0,1)$ captures a Poisson rate at which mistakes occur and destroy output in the production of the two firms. For an infinitesimal ds, we can express the technology of producing stage $s + ds$ as

$$q(s+ds) = (1-\lambda ds)q(s), \tag{4.1}$$

where $s \in (0,1)$. In the limit of $ds \to 0$, Eq. (4.1) establishes the differential equation $q'(s) = -\lambda q(s)$, whose solution is given by $q(s) = q(0)\exp(-\lambda s)$ and determines business group output at stage s as a function of the initial input $q(0)$, which we associate with a cost-free intangible asset of the business group.

We denote the accumulated production cost for one unit of output at stage s in firm j by $c_j(s)$. Accordingly, for an infinitesimal ds the costs of producing $q(s+ds)$ in firm j can be expressed as $c_j(s)q(s) + w_j q(s)ds$, with w_j as the wage rate paid by producer j. Substituting $q(s+ds) = (1-\lambda ds)q(s)$ from Eq. (4.1) gives $c_j(s+ds) = [c_j(s) + w_j ds]/(1-\lambda ds)$, which in the limit can be expressed as the differential equation $c_j'(s) = \lambda c_j(s) + w_j$. Solving this differential equation for either firm and making use of the boundary conditions $c_u(0) = 0$ and $c_u(S) = c_d(S)$, we can compute the labor costs of producing one unit of final output of the business group at $s = 1$ according to

$$c_d(1) = -\frac{w_d}{\lambda} + \left\{\frac{w_u}{\lambda}\left[\exp(\lambda S) - 1\right] + \frac{w_d}{\lambda}\right\}\exp[\lambda(1-S)] \equiv c.$$

Due to the Leontief technology, we can determine labor demand of the upstream and the downstream firm according to $\ell_u = \int_0^S q(s)ds$ and $\ell_d = \int_S^1 q(s)ds$, respectively. Solving these two integrals gives

$$\ell_u + \ell_d = \frac{q(0)}{\lambda}\left\{1 - \exp(-\lambda)\right\}, \quad \text{and} \quad S = -\frac{1}{\lambda}\ln\left[\frac{q(0) - \lambda \ell_u}{q(0)}\right]. \tag{4.2}$$

The first expression in Eq. (4.2) determines, for a given level of initial input $q(0)$, *total* labor demand of the business group. Due to our assumption of a Leontief technology and due to a constant Poisson rate of mistake λ the labor input needed for production is proportional to the aggregate output loss along the value chain. This loss is determined by the difference between initial input $q(0)$ and final output $q(0)\exp(-\lambda)$. Facing identical Poisson rates of mistake λ, the technologies of the upstream and downstream firm are the same making labor inputs of these firms perfect substitutes in the production process. However, the allocation of labor input determines the segments of the value chain that can be produced by the upstream and the downstream firm, respectively. This is captured by the second expression in Eq. (4.2), which states that an increase in the labor input of the upstream producer, ℓ_u, relative to the initial input, $q(0)$, increases the value chain segment produced by this firm. Finally, $q(0) - \lambda \ell_u$ is the intermediate output of the upstream producer, which serves as an input in the production of final output $q(0)\exp(-\lambda)$ by the downstream firm. Making use of Eq. (4.2), the unit cost of production simplifies to

$$c = \frac{w_u \ell_u + w_d \ell_d}{q(0)\exp(-\lambda)}. \tag{4.3}$$

The tractable form of the unit production costs in Eq. (4.3) is a direct consequence of assuming that the two firms of the business group share the same production technology.

Hiring, monitoring, and incentive pay

Firms hire workers at a convex cost of ℓ_j^2.[6] Workers have a binary choice between effort of one and zero. Providing effort of one decreases workers' utility by one. In the absence of monitoring, this induces an incentive to shirk, which decreases worker effort and thus labor productivity to zero.

If detected, shirking leads to an immediate job loss and zero income. The probability of a shirker to be detected by the ultimate owner of the business group is firm specific and given by $p_j = m_j/(\ell_j a_j)$, where m_j is monitoring input while $1/a_j > 0$ captures monitoring efficiency. The incentive compatibility constraint of workers can be written as $w_j \geq 1/p_j = a_j \ell_j / m_j$ and it holds with equality if the ultimate owner chooses the profit-maximizing wage. Similar to other models featuring a loss of control problem, we assume that the monitoring capacity of the ultimate owner of the business group is limited and normalized to one: $m_u + m_d = 1$ (see Calvo and Wellisz, 1979; Chen, 2017).

The optimization problem

We can study the business group's optimization problem in two steps. In step one, we solve for cost-minimizing labor and monitoring inputs, ℓ_j, m_j, holding output $q(0)\exp(-\lambda)$ constant. In step two, we then determine the profit-maximizing level of output, $q(0)\exp(-\lambda)$, given the business group's cost function.

Making use of the binding incentive compatibility constraint $w_j = a_j \ell_j / m_j$ and the production technology in Eq. (4.2), total (production plus hiring) costs can be expressed as

$$C(m_u, \ell_u, q(0)) \equiv \zeta \left\{ \left(\frac{a_u}{m_u} + 1 \right) \ell_u^2 + \left(\frac{a_d}{1 - m_u} + 1 \right) \left[\frac{q(0)}{\lambda} \{1 - \exp(-\lambda)\} - \ell_u \right]^2 \right\},$$

where ζ is a technology parameter that captures further cost factors. For instance, $\zeta > 1$ can arise due to costs of inventory (see Blinder and Maccini, 1991; Obermaier, 2012). In contrast, $\zeta < 1$ can be justified by the usage of common assets or (size) advantages in product markets (see Khanna and Yafeh, 2007). Minimizing $C(m_u, \ell_u, q(0))$ with respect to ℓ_u and m_u establishes for a given level of $q(0)$:

$$\ell_u = \frac{a_d m_u + m_u(1 - m_u)}{a_u(1 - m_u) + a_d m_u + 2m_u(1 - m_u)} \frac{q(0)}{\lambda} \{1 - \exp(-\lambda)\} \tag{4.4}$$

and

$$m_u = \frac{\sqrt{a_u}(1 + a_d) - \sqrt{a_d} a_u}{\sqrt{a_u} + \sqrt{a_d}}. \tag{4.5}$$

An interior solution with $m_u \in (0, 1)$ requires $\sqrt{a_u a_d} < 1 + \min\{a_u, a_d\}$ and thus the difference between a_u and a_d to be not too large. Using the solution to the cost-minimization problem, we can express total profits of the business group as

$$\Pi = q(0)\exp(-\lambda) - \zeta \left(\frac{q(0)}{\lambda} \right)^2 \{1 - \exp(-\lambda)\}^2 \frac{(a_d + 1 - m_u^*)(a_u + m_u^*)}{a_u(1 - m_u^*) + a_d m_u^* + 2m_u^*(1 - m_u^*)},$$

where an asterisk is used to indicate the solution to the cost-minimization problem. Maximizing profits over $q(0)$ then gives an interior solution with $p_j < 1$ if ζ is sufficiently small (see the Appendix for derivation details).

[6] Whereas it is important for our analysis that hiring costs can differ between the upstream and downstream firm, a quadratic form is not necessary and imposed for the sake of analytical tractability.

Hierarchical wage profile

Differences in exogenous monitoring efficiency lead to differences in endogenous monitoring, according to Eq. (4.5). Moreover, it follows from Eqs. (4.2), (4.4), and (4.5) that higher monitoring efficiency is associated with higher labor input. We have $\ell_u > \ell_d$ if $a_u < a_d$, $\ell_u < \ell_d$ if $a_u > a_d$, and $\ell_u = \ell_d$ in the symmetric case of $a_u = a_d$. The effect of monitoring efficiency on labor allocation follows from its effect on wages, which can be determined when noting that the optimal allocation of monitoring input is characterized by the condition

$$\frac{\sqrt{a_u}\ell_u}{m_u} = \frac{\sqrt{a_d}\ell_d}{(1-m_u)}. \tag{4.6}$$

Making use of the binding incentive compatibility constraint, Eq. (4.6) can be reformulated to $w_u = w_d\sqrt{a_u/a_d}$.[7]

Provided that the position of a firm in the value chain is decisive for its position in business group hierarchy, we can derive the following result.

Proposition 1. *If larger hierarchical distance to the ultimate owner of the business group is associated with lower monitoring efficiency, i.e.* $a_u > a_d$*, firm-level wages decrease along the value chain, i.e.* $w_u > w_d$*.*

Proof. Follows from Eq. (4.6) and the analysis in the text. □

Proposition 1 captures our main comparative-static result for the impact of larger hierarchical distance to the ultimate owner on a firm's wages in the business group. The proposition focuses on the case in which monitoring efficiency is negatively related to the hierarchical distance between the firm and its ultimate owner. This refers to the empirically relevant case, since research on organization networks gives good reason to believe that larger (hierarchical) distance is associated with higher costs of supervision (see Gumpert, 2018) – with the cost-saving motive providing a plausible explanation for the observed flattening of firm hierarchies over recent years (see Rajan and Wulf, 2006).

4.3 Data source and descriptives

In the following two subsections we introduce and describe our dataset. In the first one, we explain how we combine information on business groups, firms, and workers from two different sources. There, we also introduce the main variables and provide summary statistics. In the second subsection, we show descriptive evidence for the link between the hierarchical distance to the ultimate owner of a business group and workers' wages.

[7] The Poisson rate of mistake λ plays an important role in our model, because it determines the employment level by firm and thus monitoring intensity and the wages paid by the two producers according to the efficiency wage mechanism. Assuming that firms have identical labor productivity may therefore appear to be a restrictive assumption, as it affects the assignment of production stages to and thus employment of the two firms in the business group. However, as long as a positive employment level is chosen for either firm, the incentive compatibility constraint, which is independent of the employment level, ensures that the fundamental condition in Eq. (4.6) would remain unchanged if productivity differences existed. Compared to the case of a uniform λ, productivity differences would lead to a production increase in the firm showing the lower Poisson rate of mistake λ and to a production decrease in the other firm.

4.3.1 Construction of the dataset

For our empirical analysis, we rely on two datasets. The first one covers the years 2013-2017 of Bureau van Dijk's commercial firm database Orbis. Orbis reports balance sheet information for several 100 million companies and their ownership linkages worldwide.[8] Orbis covers all firms that are subject to reporting obligations. For Germany, these are all corporate enterprises and cooperatives as well as large private companies with total assets or revenues above thresholds defined by law.[9] We select for each observation year German firms from Orbis that fulfill some minimum quality criteria and determine their ultimate owner, who can be German or not.[10]

To build the relevant business group, we follow Altomonte and Rungi (2013) and associate business groups with ownership networks of legally autonomous firms. We then extract the whole business group of the ultimate owner and keep firms with valid information on a unique ultimate owner. We restrict attention to *major shareholders*, which are the owners with the highest fraction of shares above a 25 percent threshold.[11]

Controlling ownership linkages are hierarchical. They must be unique and can be used to divide the business group hierarchy into different layers of ascending order, assigning the ultimate owner a layer number of zero. Within the thus determined business groups, we also observe linkages of minor shareholders. Due to their existence, ownership needs not to be one-directional. For instance, a subsidiary can hold shares of its major shareholder and thus be minor shareholder of its owner.

Figure 4.1 shows the ownership structure of a typical business group in Orbis. In this example, firm A is the ultimate owner of the business group, which directly owns firms B and C and indirectly owns firms D, E, and F through its subsidiary C. Controlling ownership linkages of major shareholders are captured by solid arrows, whereas ownership by minor shareholders is captured by dashed arrows in Figure 4.1. Firms E and F are an example, in which ownership linkages are not one-directional. Using our network definition, we identify for each year about 40,000 different business groups, which cover at least one firm in Germany and represent in total almost one million firms worldwide.

As a second dataset, we use the Integrated Employment Biographies (IEB) from the Institute for Employment Research (IAB) of the German Federal Employment Agency. This dataset contains administrative records on all employees who are subject to social security contributions and covers about 80 percent of the German workforce. The IEB provides detailed information about age, gender, nationality, occupation, education, and the daily wage of workers employed in German establishments (see Klosterhuber et al., 2016). The IEB does not contain exact information on hours worked. Moreover, since worker information comes from social security records, wages are top-coded at the social security contribution ceiling. To deal with these issues, we consider only full-time workers aged 16–65 for our analysis and impute wages above the social security contribution ceiling, using the two-step Tobit procedure suggested by Card et al. (2013).[12]

[8] Orbis data have been used previously to study business groups, e.g. by Belenzon et al. (2013), Cravino and Levchenko (2017), and Altomonte et al. (2018). Altomonte et al. (2018) validate the Orbis data by comparing for the year 2010 the numbers of parents and subsidiaries of business groups by country with the respective numbers from UNCTAD. For these two key business group determinants they report a correlation well above 0.90.

[9] A firm has extensive reporting obligations if it exceeds two of the following three criteria: (1) net turnover above 12 million EUR, (2) total assets of 6 Mio EUR, (3) annual average of more than 50 employees.

[10] Firms must be active and their legal form as well as their independence indicator have to be known. Moreover, operating revenues and the number of employees have to be available for at least one year between 2010 and 2017.

[11] Using this threshold, we follow the German regulation according to which the Federal Cartel Office (Bundeskartellamt) has to review acquisitions if an acquiring firm takes over 25 percent or more of the shares of the acquired firm. In this case, the law assumes that there is a concentration of ownership giving the acquiring firm a material influence on the business of the acquired firm (see Montag and Wilson, 2011). Barbosa and Louri (2002) show evidence that the choice of the threshold does not play a role for the structure of multinational ownership networks.

[12] This procedure has been implemented for the IEB data by Dauth and Eppelsheimer (2020).

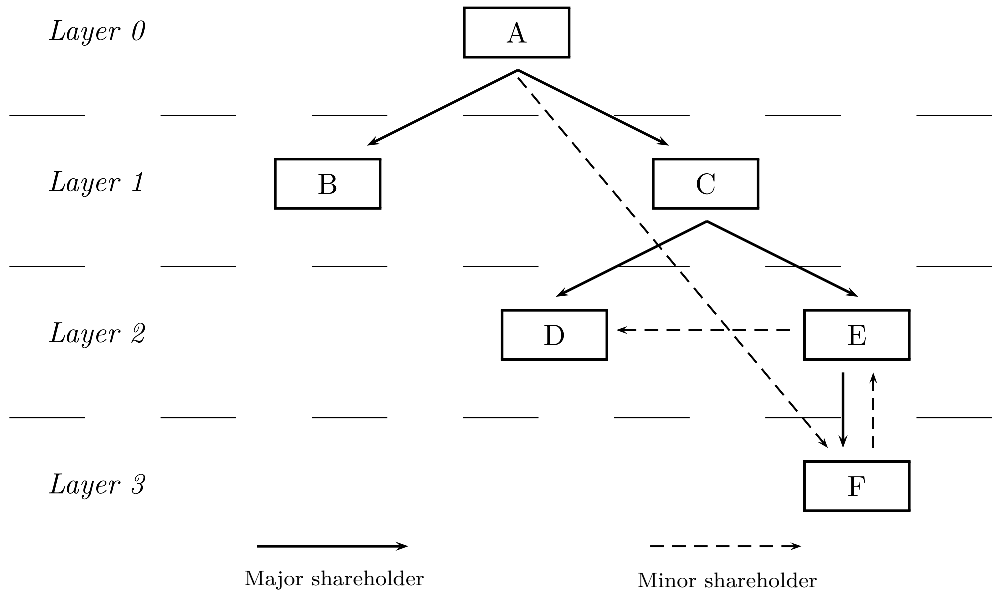


Figure 4.1: The business group as hierarchical ownership network

To merge information on administrative data of German workers from IEB with firm-level information on business groups from Orbis, we employ the procedure of the IAB, establishing linkages between observations in the two datasets relying on company names, addresses, and legal forms. Details on this procedure are provided by Antoni et al. (2018). To make sure that we correctly allocate establishments to firms over the whole sample period, we link them separately for each year between 2013 and 2017. The resulting record linkage keys allow us to merge on average 50,000 firms belonging to one of the business groups in Orbis with 86,000 establishments in the IEB per year. Finally, to ensure that each full-time worker is uniquely linked to a business group, we only keep employment spells that are valid on the 31st of December of a given year.

Firm-level variables from Orbis

Table 4.1 summarizes descriptive statistics on the main firm-level variables in our final dataset, which by construction do not vary over establishments or workers merged with the same firm. For the whole sample period, we count 250,494 firm-year observations.

The first two variables reported in Table 4.1 capture characteristics of the entire business group and are therefore identical for all firms belonging to the same group. The first variable is the total number of subsidiaries of a business group and therefore refers to *group size*. For the smallest business group, we count only one subsidiary, whereas, for the largest one, we count more than 13,000 subsidiaries. The average group size is 93 and thus fairly large.

The second variable combines information on the horizontal and vertical dimensions of business groups, that is the number of subsidiaries and the number of ownership layers, to an entropy index, which we refer to as *group complexity* (GC). It is constructed following Altomonte and Rungi (2015): $GC \equiv \sum_{l=1}^{L} l \frac{n_l}{N-1} \ln\left(\frac{N-1}{n_l}\right)$, where $N-1$ is the total number of subsidiaries, L is the total number of ownership layers, and n_l is the number of subsidiaries at ownership layer $l \in \{1, ..., L\}$. Group complexity picks up how the number of subsidiaries is spread over different ownership layers of a business group. It increases with the number of layers and places a higher weight on hierarchically more distant subsidiaries. Group complexity takes a minimum value of zero for business groups with only one layer and is unbounded from above. Its maximum level in our dataset is 28.4.

Table 4.1: Business group characteristics and hierarchical distance

	Mean	*Std. Dev.*	*Median*	*Min*	*Max*
Group size	93.272	389.587	4	1	13,434
Group complexity	1.376	2.243	0	0	28.448
Hierarchical distance	1.245	1.178	1	0	18.770

Notes: Business group characteristics are constructed for the years 2013-2017, using firm-level information on ownership linkages from Bureau van Dijk's Orbis database. Group size is given by the total count of subsidiaries of a business group. Group complexity (GC) is defined following Altomonte and Rungi (2015). Data moments are reported for 250,494 firm-year observations.

The main variable of interest in our analysis is the hierarchical distance of a firm to its ultimate owner. To construct a sensible measure of hierarchical distance, we have to acknowledge that more than nine percent of the firm-year observations in our dataset show ownership linkages that are not one-directional. For instance, in Figure 4.1 ownership linkages are circular for firms E and F. Firm E is a major shareholder of firm F, which in turn is a minor shareholder of firm E. However, circular ownership linkages can be even more complicated than that, spanning over multiple layers of hierarchy and including many different firms. We account for this complex pattern by developing an index of hierarchical distance that comprehensively captures circular network structures. To construct our index, we build on a method that has recently been applied for determining the vertical position of industries in global value chains (cf. Antràs et al., 2012; Antràs and Chor, 2013).

As a point of departure, we use the available ownership information, denote by ρ_{jk} the share of firm j that is owned by firm k, and express the chain of ownership in a business group as follows:

$$\sum_{k=1}^{N} \rho_{jk} + \sum_{k=1}^{N} \sum_{h=1}^{N} \rho_{jh} \rho_{hk} + \sum_{k=1}^{N} \sum_{h=1}^{N} \sum_{l=1}^{N} \rho_{jl} \rho_{lh} \rho_{hk} + \ldots \,, \tag{4.7}$$

where N is the total number of firms in a business group, including the ultimate owner and all its subsidiaries. Setting ρ_{jj} equal to zero, the first element of the series in (4.7) measures how the *direct* ownership of firm j is spread in the business group and therefore refers to the first level of outside control. The other elements refer to *indirect* ownership, taking into account that firms holding shares of subsidiary j can in turn be owned by other firms in the business group. Since we observe $\sum_{k=1}^{N} \rho_{jk} > 1$, the series in (4.7) can be divergent. To address this problem and to disregard all ownership linkages outside the business group, we replace ρ_{jk} by $\hat{\rho}_{jk} \equiv \rho_{jk} / \sum_{k=1}^{N} \rho_{jk}$, and define hierarchical distance of firm j to its ultimate owner according to

$$H_j = \sum_{k=1}^{N} \hat{\rho}_{jk} + \sum_{k=1}^{N} \sum_{h=1}^{N} \hat{\rho}_{jh} \hat{\rho}_{hk} + \sum_{k=1}^{N} \sum_{h=1}^{N} \sum_{l=1}^{N} \hat{\rho}_{jl} \hat{\rho}_{lh} \hat{\rho}_{hk} + \ldots \,.$$

Using matrix notation, we can then summarise the hierarchical distance of all firms in a business group to their common ultimate owner by a single vector:

$$\mathbf{H} = \mathbf{R} \cdot \mathbf{1} + \mathbf{R}^2 \cdot \mathbf{1} + \mathbf{R}^3 \cdot \mathbf{1} \ldots = [\mathbf{I} - \mathbf{R}]^{-1} \mathbf{1} - \mathbf{1}, \tag{4.8}$$

where $\mathbf{1}$ is an $N \times 1$ column vector of ones and $\mathbf{R}$ is an $N \times N$ matrix with $\hat{\rho}_{jk}$ as its (j,k)-th element.[13] The hierarchical distance of j from its ultimate owner is then given by the j-th row

[13] Note that $[\mathbf{I} - \mathbf{R}]^{-1}$ is commonly known as the Leontief inverse matrix.

of the $N \times 1$ column vector $\mathbf{H}$. Eq. (4.8) determines the hierarchical distance of a subsidiary as a value-weighted count of the number of ownership layers between j and the ultimate owner in the business group (see Johnson, 2018). Higher values of H_j refer to a longer hierarchical distance and the index is normalized to give the ultimate owner a hierarchical distance value of zero. In our dataset, the hierarchical distance has a maximum of 18.8. Relying on standardized ownership shares $\hat{\rho}_{jk}$ (instead of ρ_{jk}) ensures that ownership shares within a business group add up to 100 percent. As a consequence, index H_j would coincide with a simple layer count if all subsidiaries had just a single shareholder in the business group.

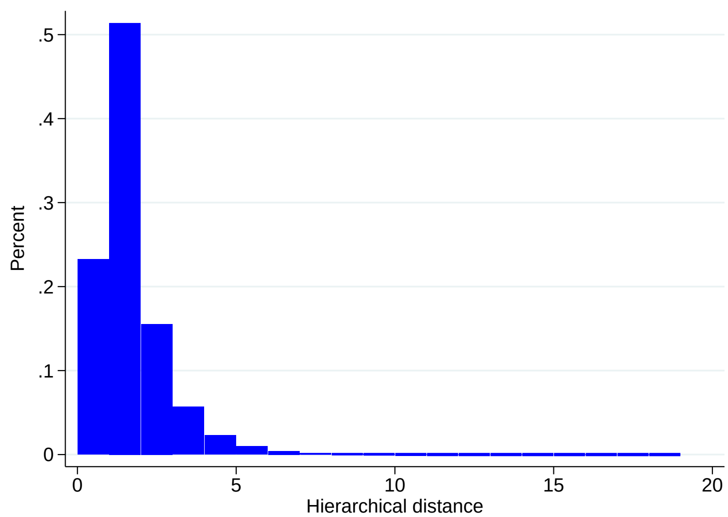


Figure 4.2: Frequency of hierarchical distances in firm-year observations

In contrast to the other two business group controls discussed above, hierarchical distance varies over firms within the same business group. Table 4.1 shows that both the mean and the standard deviation of our hierarchical distance variable are fairly small, indicating a concentration of the firm-year observations at the bottom of its domain. Figure 4.2 illustrates this pattern, showing the frequencies of hierarchical distances in our dataset. Since H_j is a continuous variable, we report its frequencies for symmetric intervals of unit length. The first bar of the histogram captures the 23.2 percent ultimate owners among our firm-year observations. The remaining bars refer to the 76.8 percent subsidiaries, for which we find a strongly right-skewed density. Thus, a significant fraction of firm-year observations shows a low hierarchical distance to their ultimate owner.

Establishment and worker variables from IEB

Table 4.2 reports key summary statistics for the establishments and workers linked from the Integrated Employment Biographies (IEB) to the Orbis data. We count 21,609,088 worker-year observations that can be aggregated to 430,699 establishment-year observations over the sample period 2013–2017. The variation in log establishment size is fairly high and a major part of establishments come from three broad sector categories, namely manufacturing, retail & repair, and finance & insurance. Moreover, we observe considerable variation in (imputed) log daily wages, sizable age differences of workers, and underrepresentation of females. Classifying workers with no vocational training and no high-school degree as low-skilled, workers with a high-school degree and/or vocational training as medium-skilled, and workers with a degree from a university or a university of applied sciences as high-skilled, we find strong differences in the coverage of skill groups, with medium-skilled workers accounting for more than 70 percent of the worker-year observations.

Table 4.2: Establishment and worker characteristics

	Mean	*Std. Dev.*	*Median*
(a) Establishment characteristics			
Log employment	2.997	1.497	2.890
Agriculture	0.008	0.087	
Manufacturing	0.161	0.368	
Mining, utilities & construction	0.080	0.271	
Retail & repair	0.444	0.497	
Finance & insurance	0.211	0.408	
Private & public services	0.096	0.295	
(b) Worker characteristics			
Log wage	4.815	0.496	4.790
Age	42.6	11.2	44.0
Female	0.265	0.442	
Low-skilled	0.048	0.046	
Medium-skilled	0.716	0.451	
High-skilled	0.236	0.425	

Notes: Establishment and worker descriptives are constructed for the years 2013-2017, using the Integrated Employment Biographies (IEB) from the Institute for Employment Research in Nuremberg. Establishment characteristics are computed for 430,699 establishment-year observations. Worker characteristics are computed for 21,609,088 worker-year observations. Low-skilled workers have no vocational training and no high-school degree. Workers with a high-school degree and/or vocational training are medium-skilled, whereas workers holding a degree from a university or a university of applied sciences are high-skilled. Median values of dummy variables are not reported.

4.3.2 Hierarchical distance and wages

Before turning to the econometric analysis, we use the linked IEB-Orbis dataset to provide descriptive evidence on how hierarchical distance to the ultimate owner affects workers' wages. To cancel out the impact of other covariates that have shown to be important wage determinants by previous empirical research, we first run a Mincer (1958)-type regression, in which we explain the log (daily) wage by worker observables on age (as a proxy for experience), age squared, and dummies for three skill groups, German nationality, female gender, and 16 federal states. We additionally control for time dummies and the six broad sector categories listed in Table 4.2.

To illustrate the correlation between the residual wage of workers and their hierarchical distance to the ultimate owner, we assign establishments to the hierarchical distance we have computed for the firm they are merged with. We then cluster establishments into deciles of hierarchical distances and compute averages of hierarchical distances and residual wages for these deciles. Finally, we plot each pair of averages as an individual data point in Figure 4.3. Since a high frequency of firms (and thus establishments) show a hierarchical distance of zero or one according to Figure 4.2, the number of distinct data points is less than ten. To capture this feature of our data, we display circles that are scaled by the number of observations they represent. Accordingly, larger circles represent more observations.

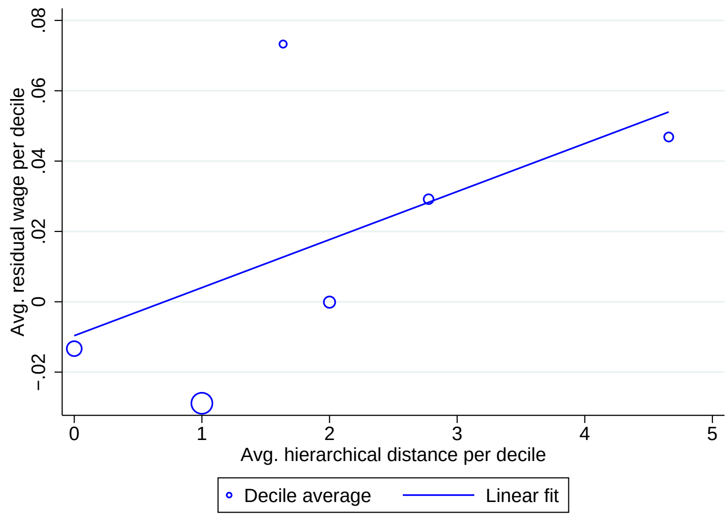


Figure 4.3: Hierarchical distance and wages in business groups

Figure 4.3 shows a positive relationship between the hierarchical distance to the ultimate owner of a business group and workers' wages. According to our theoretical model outlined in Section 4.2, monitoring efficiency decreases with a larger hierarchical distance to the ultimate owner. Consequently, more distant establishments must pay higher wages to prevent shirking by workers. However, the evidence reported in Figure 4.3 is far from being conclusive and does not allow for causal inference on how changes in hierarchical distance affect workers' wages. In the empirical analysis of Section 4.4, we analyze the relationship between hierarchical distance and wage payments in business groups in further detail.

4.4 Estimation and empirical results

To study the role of business groups for individual wages in a systematic way, we first run OLS and fixed-effects regressions, in which we control for observable and unobservable worker and establishment characteristics. In a second step, we use propensity-score matching to select a control group that is (ex-ante) comparable to our treatment group. Relying on this more homogeneous sample, we then determine the effect of changes in hierarchical distance to the ultimate owner on wages by a difference-in-difference approach.

4.4.1 Baseline estimations

In the subsequent analysis, we estimate a model of the following form:

$$w_{ijkt} = \alpha + \mathbf{X}_{it} \cdot \beta + \mathbf{C}_{jt} \cdot \gamma + \mathbf{N}_{jkt} \cdot \nu + \mu_t + \epsilon_{ijkt}, \tag{4.9}$$

where w_{ijkt} is the log daily wage of worker i in establishment j, business group k, and year t and α is a constant. $\mathbf{X}_{it}$ is a (row) vector of the (time-varying) worker covariates age, age squared, and dummies for three skill groups, German nationality, and female gender, with β as the corresponding (column) vector of coefficients. $\mathbf{C}_{jt}$ is a vector of the (time-varying) establishment covariates log employment, log employment squared, and dummies for 16 German federal states and six broad sector categories, with γ as the corresponding vector of coefficients. Moreover, $\mathbf{N}_{jkt}$ is a vector of business group determinants with ν as the vector of coefficients. Depending on the specification $\mathbf{N}_{jkt}$ includes group size, group complexity, and our main variable of interest, the hierarchical distance index. While group size and group complexity capture characteristics of the entire business group, the hierarchical distance index varies across establishments, business groups, and time. Finally, μ_t is a vector of time dummies and ϵ_{ijkt} is the error term.

Of course, the baseline specification in Eq. (4.9) is prone to omitted variable bias if our set of controls does not cover all important worker, establishment, and business group determinants of wages. We capture unobserved, time-invariant determinants by adding worker-establishment-(business-)group fixed-effects. This gives a modified regression model of the following form:

$$w_{ijkt} = \alpha + \mathbf{X}_{it} \cdot \beta + \mathbf{C}_{jt} \cdot \gamma + \mathbf{N}_{jkt} \cdot \nu + \mu_t + \phi_{ijk} + \epsilon_{ijkt}, \tag{4.9$'$}$$

where ϕ_{ijk} denotes worker-establishment-group fixed-effects. By including these fixed-effects, we time-demean each worker-establishment-group observation and identify the effects of changes in the business group covariates through their variation over time. A change in the hierarchical distance variable can then only exert an effect on wages if a worker-establishment observation changes its hierarchical position in a given business group (by adding or dropping hierarchical layers). However, the effects arising from time-invariant worker, establishment, and business group determinants as well as the effects of workers switching the establishment or of establishments switching the business group are eliminated. This allows us to isolate the effect of changes in hierarchical distance from other factors influencing workers' wages, such as firm-size or foreign-ownership wage premia. As a result, the regression model in Eq. (4.9′) gives consistent estimates of ν, but it may underestimate the overall importance of business group variables for wages in our dataset.

Table 4.3 shows our estimation results. In all regressions, we control for the full set of worker and establishment covariates reported in Table 4.2 and additionally include time and federal state dummies. In Models (1), (3), and (5) we estimate Eq. (4.9) using OLS, whereas the remaining models refer to fixed-effects regressions based on Eq. (4.9′). Model (1) captures the most parsimonious specification and only includes the hierarchical distance of establishments to their ultimate owner as a business group control. The estimated effect is positive and significant at the one percent level. Increasing the hierarchical distance by one standard deviation ($\widehat{=}$ 1.20) increases wages by 1.71 log points. Abstracting from circular ownership linkages, one can interpret the size of this effect more intuitively as follows. Moving down one layer in a business group hierarchy would increase worker's wages by almost two percent. This effect is of similar magnitude as the foreign ownership premium typically found in the literature (see Girma and Görg, 2007; Egger et al., 2020). Model (2) shows that the size of this effect decreases when controlling for worker-establishment-group fixed-effects.

In Models (3) to (6) we add further business group covariates. In Models (3) and (4) these are group size as well as its interaction with hierarchical distance. Adding these controls has rather small effects on our hierarchical distance estimate. Moreover, the positive direct effect of group size is well in line with evidence on size-wage premia at the firm level (cf. Colonnelli et al., 2018). The negative sign of the interaction term indicates that hierarchical distance is less important for wages in larger business groups. In Models (5) and (6) we investigate the role of group complexity and its interaction with hierarchical distance. In the OLS regression, we find that the impact of hierarchical distance, while staying positive, becomes considerably smaller than in the parsimonious specification of Model (1) and loses its statistical significance. In contrast, the direct effect of higher group complexity on wages is positive, sizable, and significant. This result changes considerably in the fixed-effects regression. Controlling for time-invariant unobserved heterogeneity of workers, establishments, and business groups, we find a positive and significant impact of larger hierarchical distance to the ultimate owner on workers' wages, while the impact of group complexity falls substantially. The

Table 4.3: Business groups, ownership hierarchy, and wages

Dependent variable: log daily wage	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
Hierarchical distance	0.0145***	0.0013*	0.0130***	0.0028***	0.0025	0.0040***
	(0.0014)	(0.0007)	(0.0015)	(0.0008)	(0.0026)	(0.0014)
Group size			0.0103***	0.0013***		
			(0.0007)	(0.0003)		
Hierarchical distance ×Group size			-0.0012***	-0.0002***		
			(0.0002)	(0.0001)		
Group complexity					0.0269***	0.0015*
					(0.0013)	(0.0008)
Hierarchical distance ×Group complexity					-0.0030***	-0.0005***
					(0.0003)	(0.0002)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Worker Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Establishment Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Worker-establ.-group FE	No	Yes	No	Yes	No	Yes
R-sq. (within)	0.4440	0.0740	0.4504	0.0740	0.4500	0.0740
Observations	21,609,088	21,609,088	21,609,088	21,609,088	21,609,088	21,609,088

Notes: Worker covariates include age, age squared, dummies for three skill groups, German nationality, and gender. Establishment covariates include log employment, log employment squared, dummies for 16 German federal states, and six broad sector categories. In all models, we estimate a constant as well as a full set of time dummies. Hierarchical distance and the group index of complexity are constructed as outlined in Section 4.3. Group size is given by the total count of subsidiaries within a business group (in hundreds). Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

negative and significant interaction term indicates that hierarchical distance plays a less important role for wages in more complex business groups.

Summing up, the results from Table 4.3 show that the omitted variable bias in estimating the link between hierarchical distance to the ultimate owner of a business group and workers' wages with simple OLS can be severe so that controlling for unobserved heterogeneity appears important. Moreover, the results from fixed-effects regressions are broadly in line with the descriptive evidence and support the conclusion that larger hierarchical distance reduces monitoring efficiency so that higher wages are needed to prevent shirking by workers in establishments at low hierarchical layers of the business group.

In the next subsection, we go one step further and exploit a two-stage regression procedure, combining propensity-score matching with a difference-in-difference approach. This procedure has two advantages over our fixed-effects regressions. First, we make the sample more homogeneous. Workers experiencing an increase in the hierarchical distance and workers who do not experience such an increase become more similar. Second, we address potential bias from time-variant omitted variables that jointly influence hierarchical distance between a plant and its ultimate owner as well as workers' wages. One example for this could be a technology shock in the form of automation or computerization. Such a shock can increase wages of workers with programming skills and at the same time lead to higher hierarchical distance of plants with a workforce that is intensive in these skills. For instance, according to our theoretical model a larger hierarchical distance to the ultimate owner would be observed if the technology shock makes monitoring workers with programming skills easier. By making the treatment and control group of workers more similar through propensity-score matching and by considering a short post-treatment period, we hope to eliminate biases of this form.

4.4.2 Selection into business groups

In line with our analysis in Section 4.4.1, we specify the treatment as an increase in the hierarchical distance (HD) between the ultimate owner and a worker-establishment pair. To isolate the hierarchical distance effect from other wage determinants associated with employer effects, we focus on workers who stay within the same establishment and business group around the treatment event. Therefore, we define the treatment as an increase in hierarchical distance between a worker-establishment pair and its ultimate owner within a given business group. Accordingly, we classify worker-establishment pairs as untreated if they show no change of hierarchical distance to their ultimate owner within a given business group.

Following the matching literature, we collapse the observation period 2013 to 2017 into two-year windows around the treatment period. We then eliminate all observations that are not classified as treated or untreated, that is workers switching their employer or establishments switching their business group between two time periods. Moreover, to avoid an influence on our estimate from worker heterogeneity, we specify the treatment at the worker level and capture this treatment by a binary indicator

$$D_{ijk} = \begin{cases} 1 & HD_{ijk,t=0} < HD_{ijk,t=1} \\ 0 & HD_{ijk,t=0} = HD_{ijk,t=1}, \end{cases}, \tag{4.10}$$

which takes a value of one, if the hierarchical distance to the ultimate owner of worker i from establishment j and business group k increases between periods $t = 0$ and $t = 1$. In contrast, the indicator takes a value of zero if the hierarchical distance to the ultimate owner of worker i from establishment j and business group k does not change.

To select for each treated observation a suitable control from the pool of untreated worker-establishment pairs, we rely on nearest-neighbor propensity-score matching (Rosenbaum and Rubin, 1983). For this purpose, we determine the probability in $t = 0$ that an observation is subject to treatment between periods 0 and 1 and estimate the following probit model:

$$P(D_{ijk} = 1) = \Phi(\nu \cdot \mathbf{N}_{jk,0} + \gamma \cdot \mathbf{C}_{j,0} + \beta \cdot \mathbf{X}_{i,0}), \tag{4.11}$$

where $\mathbf{N}_{jk,0}$, $\mathbf{C}_{j,0}$, $\mathbf{X}_{i,0}$ are vectors of business group, establishment, and worker covariates in period $t = 0$, with ν, γ and β being the corresponding vectors of coefficients. Business group covariates are hierarchical distance and group complexity. Establishment covariates include the log of employment to control for establishment size, sector dummies indicating the establishments' industry affiliation, and federal-state dummies to control for establishment location. Finally, worker covariates are dummies for females and three skill levels, workers' age, and their log daily wages. To exclude time effects, we estimate the probit model in Eq. (4.11) within treatment cohorts, i.e. we match observations from the same year.[14] Since 206 observations are off support, we eliminate them from the treatment group after the probit estimation.

[14]As a robustness check, we account for the change in log employment before treatment as an additional control in the probit model. We include this variable to take employment dynamics before the treatment into account and report the results along with those from four further robustness checks in the Appendix.

Using the estimates from our probit model, we then assign to each worker-establishment-group triple from the treatment group the worker-establishment-group triple from the pool of untreated observations with the smallest absolute difference in the propensity-score. This forms our control group, which contains fewer unique observations than the treatment group because we match with replacement (see Caliendo and Kopeinig, 2008). Moreover, since we match individuals, workers from a single establishment of the treatment group can be assigned to workers from different establishments belonging to different ownership networks in the control group. Overall, our matching procedure gives us a sample of 597,432 unique worker-establishment observations in the treatment group and 448,780 unique worker-establishment observations in the control group.

To evaluate the success of our matching procedure, we compare averages of all covariates used in the probit estimation before and after matching and report the results in the Appendix. There, we show two diagnostics that are commonly used to assess the matching quality. The first one is the standardized percentage bias introduced by Rosenbaum and Rubin (1985). Matching reduces the mean bias considerably from 12.6 percent to 1.9 percent. We also report the normalized difference between individual covariates from the treatment and control group, as put forward by Imbens and Wooldridge (2009) and Imbens and Rubin (2015). Imbens and Rubin (2015) suggest an upper limit of one quarter of the normalized difference to consider a variable as balanced. This critical threshold is not surpassed by any of our covariates after matching. The two diagnostics, therefore, indicate that we were successful in matching observations from the treatment group to similar untreated observations.

With the matched sample at hand, we can quantify the causal effect of a larger hierarchical distance to the ultimate owner on wages using a difference-in-difference approach. In doing so, we contrast wages before and after treatment and compare the change in wages between workers from the treatment and the control group by estimating the following equation:

$$w_{ijkt} = \alpha_i + \mu + \eta \cdot D_{ijk} \cdot \mu + \epsilon_{ijkt}, \tag{4.12}$$

where w_{ijkt} is the log daily wage of worker i in establishment j, business group k, and year t, α_i is a worker fixed-effect to control for any remaining, time-invariant unobserved heterogeneity of workers, and μ is a time dummy that takes a value equal to one in the post-treatment period $t = 1$. D_{ijk} is the treatment indicator equal to one for each stayer i, whose establishment j has been subject to treatment between $t = 0$ and $t = 1$, and zero otherwise. Coefficient η captures the wage effect for workers, whose establishment increases its hierarchical distance to the ultimate owner within a given business group. Finally, ϵ_{ijkt} is the error term.

Table 4.4: Wage effect of larger distance in business group hierarchy

Dependent variable: Log daily wage	*All workers*	*Low-skilled*	*High-skilled*
Higher *HD* in $t = 1$	0.0134***	0.0138***	0.0201***
	(0.0013)	(0.0025)	(0.0017)
Observations	2,389,728	120,260	589,120

Notes: The treatment is defined as an increase in the hierarchical distance within a given business group. The estimation includes a time dummy and worker fixed-effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

The first column of Table 4.4 summarizes the results for the pooled sample of all workers. In line with the results of Section 4.4.1, we find that a larger hierarchical distance to the ultimate owner of the business group increases workers' wages by 1.3 percent. According to our theoretical model, this result indicates that monitoring efficiency decreases with higher hierarchical distance. Consequently, ultimate owners have to increase incentive payments for workers employed by establishments at comparably low layers in the business group hierarchy.

Lack of information on monitoring effort prevents a direct test of the specific mechanism for explaining the positive link between larger hierarchical distance and workers' wages put forward by our theoretical model. However, we can use the observation of Jones (1984, p. 689) that "[i]n general, the more unstructured or ambiguous the task and the more specialized the skills of the job incumbent, the greater will be the difficulty of measuring performance" as an argument that the positive effect of hierarchical distance on wages should be strongest for workers with high skills and workers performing non-routine tasks since their performance is most difficult to observe. Accordingly, we interpret evidence for this argument as indirect support for the monitoring-based mechanism in our model.

To show evidence for the first part of this argument, we split our sample and estimate the effect of hierarchical distance to the ultimate owner of the business group on workers' wages separately for the sub-groups of high- and low-skilled workers. For these workers, Jones (1984) provides a clear prediction regarding the costs to monitor their workplace performance, while the prediction is less clear for medium-skilled workers for whom specialization might vary considerably across vocational degrees. Columns 2 and 3 of Table 4.4 report the results. There, we see that the effect of larger hierarchical distance on workers' wages is 50 percent higher for high-skilled than for low-skilled workers, with the difference being highly statistically significant. This result lends support to the monitoring-based theory of business group hierarchies outlined in Section 4.2. Showing evidence for (or against) the second part of the argument requires information on the task content of occupations, which we do not directly observe in our dataset. Hence, we have to rely on task data from a different source.

For Germany, the task content of occupations can be constructed from employment surveys conducted by the Federal Institute for Vocational Education and Training (BIBB) and the Federal Institute for Occupational Safety and Health (BAuA) every six to seven years since 1979. These surveys cover about 20,000 – 30,000 individuals in each wave and they provide detailed information on the tasks performed by the respondents in their workplaces. Since it is shown by Becker and Muendler (2015) that the task content of occupations varies considerably over time, we only use the survey information from 2012 and thus the year prior to the first observation period in the dataset. Based on this survey, we distinguish 10 broad task categories, such as *manufacture and produce goods*; *repair and maintain*; or *purchase, procure, and sell*. Following Spitz-Oener (2006), Gathmann and Schönberg (2010), and Becker et al. (2013), we then classify tasks as either routine or non-routine. In the Appendix, we provide a list of all tasks and their classification as either routine (three tasks) or non-routine (seven tasks).[15]

Based on our classification, we compute for each respondent in the survey the fraction of routine and non-routine tasks conducted. We then determine for the 136 occupations observed in our dataset a routineness and non-routineness index, by averaging the previously computed task fractions over all individuals reporting to be employed in that occupation. We finally label the 33 occupations as routine for which the share of routine tasks is above while the share of non-routine tasks is below the median of all occupations. Conversely, we label the 33 occupations as non-routine for which

[15]The category of routine tasks comprises the three activities *manufacture and produce goods*; *measure, inspect, and control quality*; and *oversee and control machinery and technical processes*. These tasks are easily codifiable and their usage has thus been negatively affected by the diffusion of computers and recent trends of automation (see Spitz-Oener, 2006; Becker and Muendler, 2015; de Vries et al., 2020).

the share of routine tasks is below while the share of non-routine tasks is above the median of all occupations. The remaining 70 occupations cannot be classified as being predominantly routine or non-routine, which is the reason we exclude these occupations from our estimations. We finally link this classification to our dataset, relying on occupation codes.

Table 4.5: Distance effect by predominant task

Dependent variable:	*All workers*	*Predominant tasks*	
Log daily wage		*routine*	*non-routine*
Higher *HD* in $t = 1$	0.0134***	0.0089***	0.0170***
	(0.0013)	(0.0016)	(0.0019)
Observations	2,389,728	777,200	211,548

Notes: The treatment is defined as an increase in the hierarchical distance within a given business group. The estimation includes a time dummy and worker fixed-effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Table 4.5 shows the treatment effects for all workers as well as the two sub-groups of workers employed in routine and non-routine occupations. Contrasting Columns 2 and 3, we find a sizable difference in the distance effect between occupations with a predominant share of routine tasks and a predominant share of non-routine tasks, respectively. The hierarchical distance effect for workers employed in non-routine occupations is 1.7 percent and almost twice as high as for workers performing routine tasks who nevertheless receive a distance premium of 0.9 percent. These results further support the hypothesis of our monitoring-based theory of business groups that a larger hierarchical distance to the ultimate owner increases workers' wages.

4.4.3 Robustness checks

To complete our empirical analysis, we investigate in a final step whether our main results from Section 4.4.2 are robust to changes in the treatment and sample definitions. In Table 4.6, Model (1), we set a threshold for the hierarchical distance of 0.25 and drop observations with changes in the hierarchical distance smaller than this threshold from the treatment group. With this refinement, we eliminate small changes in ownership shares that could be the results of mismeasurement. Table 4.6 shows that introducing a lower threshold for the hierarchical distance variable lowers the sample size considerably and reduces the treatment effect. However, it does not change our results qualitatively.[16] In Model (2), we drop all observations showing an increase in hierarchical distance larger than two. This makes the treatment group more homogeneous and ensures that our results are not driven by a small number of outliers. Introducing the upper bound does not affect the estimation result.

In two further exercises, we no longer restrict the analysis to worker-establishment observations that stay in the same business group around the treatment event. In Model (3), the treatment is defined as a change in the hierarchical distance of an establishment to its ultimate owner *when* changing the business group. This lowers the treatment effect by more than 50 percent. In Model (4), we use all worker-establishment observations. In this case, the treatment is defined by a change in the hierarchical distance to the ultimate owner, irrespective of whether the establishment changes its business group or not. Similar to Model (3), changing the definition of treated and untreated observations lowers the treatment effect considerably.

[16] Increasing the threshold to 0.5 or 0.75 would further reduce sample size but not substantively change our results.

Table 4.6: Hierarchical distance and wages: alternative specifications

Dependent variable:			*All workers*		
Log daily wage	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Higher *HD* in $t = 1$	0.0115***	0.0133***	0.0029**	0.0063***	0.0158***
	(0.0015)	(0.0012)	(0.0015)	(0.0007)	(0.0016)
Observations	1,868,148	2,342,520	3,005,852	4,875,328	1,964,816

Notes: In Model (1), we confine the treatment to increases in the hierarchical distance by at least 0.25. In Model (2), we confine the treatment to increases in the hierarchical distance by at most two. In Model (3), we consider worker-establishment pairs that change their business group around the treatment period. In Model (4), we broaden the definition of treatment and control group, including worker-establishment pairs that stay in their business group as well as worker-establishment pairs that change their business group. In Model (5), we restrict the definition of controlling ownership to the case of majority-owned subsidiaries. All estimations include a time dummy and worker fixed-effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

However, one should be cautious when contrasting the estimates from Model (3) and (4) in Table 4.6 with those from Table 4.4. First, by changing the definition of the treatment group, we have also changed the sample of untreated observations in the control group, hampering the comparison of parameter estimates. Second, we cannot rule out that the treatment effects in Models (3) and (4) of Table 4.6 capture at least partially the impact of changing the business group, which has been put forward to exert sizable wage effects in the context of multinational enterprises. Of course, changing the business group is not confined to foreign takeover in our analysis, so that the observed drop of the treatment effect does not contradict the existence of a foreign ownership wage premium.[17]

In Model (5), we restrict the definition of controlling ownership to the case of majority-owned subsidiaries, i.e. to linkages in Figure 4.1 in which the major shareholder of a subsidiary owns at least 50 percent of its shares. This lowers the sample size considerably and slightly increases the estimated hierarchical distance effect. However, confining the definition of controlling ownership to shareholders of more than 50 percent does not change the main insights from our analysis in a substantive way.

In a further robustness check we consider the role of trade unions, which still play a prominent role for the wage setting of German establishments. For this purpose, we use data from the Federal Statistical Office on the share of establishments within an industry applying a collective bargaining agreement in 2014. In the median industry, 25 percent of the establishments are covered by collective bargaining agreements. We use this information to split our sample into subsamples of workers employed in industries above or below the median union coverage of 25 percent.

Table 4.7 reports the results. The first column presents the results for the full sample of all workers. The second and third columns report the results for industries with union coverage rates above and below the median industry. We expect wage flexibility to be larger and thus the positive effect of larger hierarchical distance on wages to be stronger in industries with lower union coverage. This conjecture is supported by our empirical results. However, we also find evidence for a significant positive effect of higher hierarchical distance on wages in industries with relatively high union coverage.

In a final robustness check, we perform both the propensity-score matching and the difference-in-difference estimation at the establishment instead of the worker level. This reduces the number

[17]In two extensions to Models (3) and (4), we have added a dummy for foreign takeover and its interaction term with the treatment indicator. In these extensions, which are available upon request, we find evidence for both a positive wage effect of a larger hierarchical distance to the ultimate owner and a positive wage effect of a foreign takeover.

Table 4.7: Distance effect by likelihood of bargaining coverage

Dependent variable: Log daily wage	*All workers*	*Union coverage* below median	*Union coverage* above median
Higher *HD* in $t = 1$	0.0134***	0.0183***	0.0122***
	(0.0013)	(0.0019)	(0.0015)
Observations	2,389,728	463,040	1,926,684

Notes: The treatment is defined as an increase in the hierarchical distance within a given business group. The estimation includes a time dummy and establishment fixed-effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

of observations considerably, lowers matching quality and leads to less precise estimates.[18] We report the results from this exercise in Table 4.8. The first column shows the results for the baseline specification covering all establishments. Compared to the worker-level evidence in Table 4.4, the estimated coefficient for the impact of an increase in hierarchical distance on wages is lower, but still significant. Whereas choosing establishments as our main observational units prohibits distinguishing wage effects for workers with differing skills, we can still analyze the results separately for establishments that are intensive in occupations which are classified as routine or non-routine, respectively.

Table 4.8: Hierarchical distance and wages at the establishment level

Dependent variable: Log daily wage	*All workers*	*Predominant tasks* routine	*Predominant tasks* non-routine
Higher *HD* in $t = 1$	0.0042**	-0.0057	0.0072
	(0.0020)	(0.0040)	(0.0044)
Observations	35,048	6,140	6,840

Notes: The treatment is defined as an increase in the hierarchical distance within a given business group. The estimation includes a time dummy and establishment fixed-effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Starting from the classification of occupations in Section 4.4.2, we compute averages of routineness and non-routineness over all occupations at the establishment level and classify establishments as (predominantly) routine for which the share of routine occupations is above while the share of non-routine occupations is below the median of all establishments. Conversely, we label establishments as non-routine for which the share of routine occupations is below while the share of non-routine occupations is above the median of all establishments. Table 4.8 shows a positive hierarchical distance effect on wages in establishments that are intensive in non-routine occupations. Although the estimate itself is marginally insignificant, the difference to the negative hierarchical distance effect on wages in establishments that are intensive in routine occupations is significant at the five percent level.

[18]When matching at the establishment level, we rely on the same covariates as in the worker level analysis, but use establishment-level averages where necessary.

4.5 Conclusion

Although the largest companies covered by the Fortune 500 list are all organized as business groups (see Altomonte et al., 2018) and some of these groups generate yearly revenues higher than the GDP of entire economies, business groups and their effects on workers' wages have received surprisingly little attention in economic research so far. The main reason for the lack of research is that existing datasets do not provide the detailed information needed for such an analysis. This chapter contributes to the literature by merging firm-level data on ownership linkages in business groups with administrative worker and establishment data for Germany. This gives a unique dataset that allows analysing in a systematic way how the position in business group hierarchy affects workers' wages. Since the ownership linkages are not one-directional, we propose a measure of hierarchical distance that acknowledges the complex structure of business groups in our data. In the pooled sample of all workers, we find clear evidence for a positive impact of larger hierarchical distance on wages.

We complement our empirical analysis by a two-stage estimation procedure, in which we first select a treatment and control group based on propensity-score matching and then estimate the effect of an increase in the hierarchical distance to the ultimate owner on workers' wages using a difference-in-difference estimator. The results from this more elaborate empirical approach are similar to those from OLS and fixed-effects regressions. Larger hierarchical distance exerts a positive effect on workers' wages, with the effect being remarkably robust to changes in the composition of the treatment group.

Overall, our results speak for a sizable impact of larger hierarchical distance to the ultimate owner of a business group on workers' wages. In a parsimonious specification, we show that increasing hierarchical distance by one standard deviation or approximately one layer increases wages by almost two log points. This effect remains fairly stable when matching similar worker-establishment pairs.

To explain the positive link between the hierarchical distance to the ultimate owner of the business group and workers' wages, we propose a monitoring-based theory of business group hierarchies. Lack of information on monitoring effort prohibits a direct test of the theoretical hypotheses derived from our model. However, the finding that the hierarchical distance effect is most pronounced for workers with high skills and workers performing non-routine tasks – whose performance is difficult to observe – indicates that monitoring inefficiency indeed provides a reasonable explanation for the positive effect of a larger hierarchical distance on workers' wages.

4.6 Theory appendix

4.6.1 Cost minimization and profit maximization

Minimizing costs $C(m_u, \ell_u, q(0))$ with respect to ℓ_u and m_u, keeping $q(0)$ constant, gives the two first-order conditions

$$\frac{\partial C}{\partial \ell_u} = 2\zeta \left\{ \left(\frac{a_u}{m_u} + 1 \right) \ell_u - \left(\frac{a_d}{1 - m_u} + 1 \right) \left[\frac{q(0)}{\lambda} \{1 - \exp(-\lambda)\} - \ell_u \right] \right\} = 0, \tag{4.13}$$

$$\frac{\partial C}{\partial m_u} = \zeta \left\{ -\frac{a_u}{m_u^2} \ell_u^2 + \frac{a_d}{(1 - m_u)^2} \left[\frac{q(0)}{\lambda} \{1 - \exp(-\lambda)\} - \ell_u \right] \right\}^2 = 0. \tag{4.14}$$

Since the first-order condition in Eq. (4.13) is linear in ℓ_u, it is straightforward to derive the interior solution in Eq. (4.4). Using this solution in first-order condition (4.14), we find that an interior solution for m_u is characterized by

$$\frac{\sqrt{a_u}}{m_u} = \frac{\sqrt{a_d}}{1 - m_u} \frac{a_u + m_u}{a_d + 1 - m_u},$$

which gives the explicit solution for m_u in Eq. (4.5). To ensure that the solutions in Eqs. (4.4) and (4.5) characterize a cost minimum, the second-order condition requires that the Hesse matrix

$$\mathbf{H} = \begin{pmatrix} \frac{\partial^2 C}{\partial \ell_u^2} & \frac{\partial^2 C}{\partial \ell_u \partial m_u} \\ \frac{\partial^2 C}{\partial m_u \partial \ell_u} & \frac{\partial^2 C}{\partial m_u^2} \end{pmatrix} \tag{4.15}$$

is positive semi-definite. This is the case for instance, if the two principal minors, $\partial^2 C / \partial \ell_u^2$ and $|\mathbf{H}|$, are positive. Making use of

$$\frac{\partial^2 C}{\partial \ell_u^2} = 2\zeta \left\{ \frac{a_u + m_u}{m_u} + \frac{a_d + 1 - m_u}{1 - m_u} \right\}$$

$$\frac{\partial^2 C}{\partial m_u^2} = 2\zeta \left(\frac{\ell_u}{m_u} \right)^2 \left\{ \frac{a_u}{m_u} + \frac{a_d}{1 - m_u} \left(\frac{a_u + m_u}{a_d + 1 - m_u} \right)^2 \right\},$$

$$\frac{\partial^2 C}{\partial \ell_u \partial m_u} = \frac{\partial^2 C}{\partial m_u \partial \ell_u} = -2\zeta \frac{\ell_u}{m_u} \left\{ \frac{a_u}{m_u} + \frac{a_d}{1 - m_u} \left(\frac{a_u + m_u}{a_d + 1 - m_u} \right) \right\}$$

it can be shown in a straightforward way that the two principal minors of $\mathbf{H}$ are positive, confirming that the solutions in (4.4) and (4.5) characterize a cost minimum.

Maximizing profits Π with respect to $q(0)$ gives the first-order condition

$$\frac{\partial \Pi}{\partial q(0)} = \exp(-\lambda) - 2\zeta \frac{q(0)}{\lambda^2} [1 - \exp(-\lambda)]^2 \frac{(a_d + 1 - m_u)(a_u + m_u)}{a_u(1 - m_u + a_d m_u + 2m_u(1 - m_u))} = 0. \tag{4.16}$$

The first-order condition in Eq. (4.16) has a unique solution in $q(0) > 0$ and $\partial^2 \Pi / \partial q(0)^2 < 0$ confirms that this solution determines a maximum. Moreover, substituting Eq. (4.4) and making use of $p_j = m_j/(a_j l_j)$, we can rewrite the first-order condition to get explicit solutions for p_u and p_d:

$$p_u = 2\zeta \left(1 + \frac{m_u}{a_u} \right) \frac{\exp(\lambda) - 1}{\lambda}, \quad p_d = 2\zeta \left(1 + \frac{1 - m_u}{a_d} \right) \frac{\exp(\lambda) - 1}{\lambda}, \tag{4.17}$$

where the second expression makes use of $\ell_d = [q(0)/\lambda]\{1 - \exp(-\lambda)\} - \ell_u$. From Eqs. (4.5) and (4.17) it follows that $p_u, p_d < 1$ requires a sufficiently small level of ζ. This completes the proof.

4.7 Empirical appendix

4.7.1 Balancing test for the matching procedure

Table 4.9: Balancing test for the matching procedure with replacement

Variable	*Sample*	*Mean*		*Stand.*	*Bias*	*Normal.*
		Treated	*Control*	*bias %*	*reduction*	*diff.*
(a) Group characteristics						
Hierarchical distance	Unmatched	2.313	1.028	113.6		
Hierarchical distance	Matched	2.313	2.306	0.6	99.5	0.002
Group complexity	Unmatched	4.173	2.063	78.3		
Group complexity	Matched	4.173	4.043	4.8	93.8	0.029
(b) Establishment characteristics						
Log employment	Unmatched	6.010	6.003	0.3		
Log employment	Matched	6.010	5.904	5.8	-1583.4	0.042
Agriculture	Unmatched	0.000	0.003	-7.2		
Agriculture	Matched	0.000	0.000	0.1	98.2	0.003
Manufacturing	Unmatched	0.538	0.453	17.0		
Manufacturing	Matched	0.538	0.531	1.4	91.8	0.010
Mining, util. & constr.	Unmatched	0.059	0.082	-9.0		
Mining, util. & constr.	Matched	0.059	0.055	1.3	85.0	0.011
Retail & repair	Unmatched	0.211	0.236	-6.0		
Retail & repair	Matched	0.211	0.217	-1.3	77.8	-0.010
Finance & insurance	Unmatched	0.164	0.121	12.4		
Finance & insurance	Matched	0.164	0.183	-5.4	56.1	-0.036
Priv. & publ. services	Unmatched	0.028	0.105	-31.2		
Priv. & publ. services	Matched	0.028	0.014	5.7	81.7	0.070
Schleswig-Holstein	Unmatched	0.023	0.021	1.3		
Schleswig-Holstein	Matched	0.023	0.023	0.2	82.7	0.002
Hamburg	Unmatched	0.053	0.029	11.9		
Hamburg	Matched	0.053	0.046	3.3	72.0	0.022
Lower Saxony	Unmatched	0.080	0.087	-2.4		
Lower Saxony	Matched	0.080	0.073	2.5	-6.3	0.019
Bremen	Unmatched	0.015	0.012	2.0		
Bremen	Matched	0.015	0.012	2.2	-8.9	0.015
North Rhine-Westphalia	Unmatched	0.200	0.201	-0.2		
North Rhine-Westphalia	Matched	0.200	0.205	-1.2	-481.5	-0.009
Hesse	Unmatched	0.123	0.081	13.8		
Hesse	Matched	0.123	0.131	-2.6	81.4	-0.016
Rhineland-Palatinate	Unmatched	0.035	0.044	-4.7		
Rhineland-Palatinate	Matched	0.035	0.033	0.6	86.4	0.005
Baden-Württemberg	Unmatched	0.138	0.168	-8.4		
Baden-Württemberg	Matched	0.138	0.138	0.1	98.3	0.001
Bavaria	Unmatched	0.170	0.175	-1.4		
Bavaria	Matched	0.170	0.177	-1.9	-35.1	-0.013
Saarland	Unmatched	0.006	0.014	-7.8		
Saarland	Matched	0.006	0.010	-3.5	54.7	-0.028
Berlin	Unmatched	0.031	0.035	-2.4		
Berlin	Matched	0.031	0.032	-0.5	78.7	-0.004
Brandenburg	Unmatched	0.028	0.023	3.6		
Brandenburg	Matched	0.028	0.029	-0.5	87.3	-0.003
Mecklenburg West-Pomerania	Unmatched	0.012	0.013	-0.9		
Mecklenburg West-Pomerania	Matched	0.012	0.010	1.5	-66.4	0.011
Saxony	Unmatched	0.044	0.049	-2.6		
Saxony	Matched	0.044	0.041	1.4	48.0	0.010
Saxony-Anhalt	Unmatched	0.026	0.022	2.5		
Saxony-Anhalt	Matched	0.026	0.024	1.2	49.5	0.009
Thuringia	Unmatched	0.016	0.024	-5.7		
Thuringia	Matched	0.016	0.016	0.4	93.5	0.003
(c) Worker characteristics						
Female	Unmatched	0.229	0.253	-5.4		
Female	Matched	0.229	0.226	0.8	85.3	0.006

Table 4.9 – *continued from previous page*

Variable	*Sample*	*Mean*		*Stand.*	*Bias*	*Normal.*
		Treated	*Control*	*bias %*	*reduction*	*diff.*
Age	Unmatched	42.9	42.9	0.3		
Age	Matched	42.9	42.8	0.5	-81.5	0.004
Low skilled	Unmatched	0.051	0.045	2.6		
Low skilled	Matched	0.051	0.051	0.0	98.9	0.000
Medium skilled	Unmatched	0.703	0.740	-8.3		
Medium skilled	Matched	0.703	0.692	2.6	68.9	0.018
High skilled	Unmatched	0.246	0.215	7.5		
High skilled	Matched	0.246	0.258	-2.8	63.3	-0.019
Log wage	Unmatched	4.915	4.819	20.5		
Log wage	Matched	4.915	4.929	-2.9	85.6	-0.021
Sample				*Mean bias*	*Median bias*	
Unmatched				12.6	5.7	
Matched				1.9	1.4	

Notes: All variables are measured in $t = 0$ and averaged at the worker-level in the treated and control group respectively.

4.7.2 Further robustness checks

To make sure that the positive effect of larger hierarchical distance on wages reported in Section 4.4.2 is robust to different specifications of the propensity-score matching, we report in Table 4.10 the results for the pooled sample of all workers, relying on five alternatives to our main matching procedure. In Model (1), we match without replacement and find that this has a comparably small impact on the treatment effect. In Model (2), we add the difference in log establishment employment between period $t = -1$ and $t = 0$ as a further covariate in the probit model. This allows us to control for differences in the employment dynamics prior to the treatment. Adding this covariate somewhat reduces sample size and slightly lowers the treatment effect, while leaving unchanged the main insight from our baseline specification in Table 4.4. In Model (3), we replace the continuous log employment variable in the probit model by dummies for five establishment size categories. We distinguish establishments with less than ten, between ten and 49, between 50 and 249, between 250 and 999, and with more than 1000 employees. Additionally, we control for employment dynamics prior to treatment by introducing two dummies equal to one if the establishment has either increased or decreased its workforce by at least three percent between $t = -1$ and $t = 0$ (with the omitted category referring to establishments with an absolute change in workforce size by less than three percent). This modification increases the estimated treatment effect.

In the robustness check of Model (4), we define the treatment at the establishment and not the worker level, imposing the constraint that all workers from a given establishment in the treatment group are matched with workers from a single establishment of the control group. However, in contrast to the results reported in Table 4.8, we conduct the difference-in-difference estimation at the worker level. As expected, imposing the additional constraint lowers matching quality. Moreover, it reduces the estimated treatment effect by about 50 percent, while leaving the main insight from our empirical analysis that larger hierarchical distance increases wages intact. In the final robustness check of Model (5), we do not drop firms experiencing a decline in hierarchical distance from our analysis. This increases the group of untreated observations and reduces the number of treated workers, for which we do not find a valid match. As a consequence the observation number increases. However, the estimated distance effect remains almost unaffected by this change.

4.7.3 Tasks and their classification as routine or non-routine

Table 4.11 shows the classification of tasks into the routine or non-routine category.

Table 4.10: The effect of an increase in hierarchical distance on wages

Dependent variable:			*All workers*		
Log daily wage	Model (1)	Model (2)	Model (3)	Model (4)	Model(5)
Higher *HD* in $t = 1$	0.141***	0.0127***	0.0146***	0.0064*	0.0130***
	(0.0012)	(0.0013)	(0.0014)	(0.0034)	(0.0013)
Observations	2,389,728	2,372,852	2,389,800	2,615,608	2,390,528

Notes: In Model (1), we match without replacement. In Model (2) we take into account employment dynamics prior to treatment by additionally matching on the difference in log (establishment) employment between $t = -1$ and $t = 0$. In Model (3), we match on five establishment size categories and two dummy variables indicating an absolute change in log (establishment) employment between $t = -1$ and $t = 0$ of at least three percent. In Model (4), we define the treatment at the establishment level and match accordingly. In Model (5) we consider workers experiencing a decline in hierarchical distance as part of the control group. All estimations include a time dummy and worker fixed-effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Table 4.11: Routine and non-routine tasks

Tasks	Routine	Non-routine
Manufacture and produce goods	yes	
Measure, inspect, and control quality	yes	
Oversee and control machinery and technical processes	yes	
Repair and maintain; or entertain, accommodate, and prepare food		yes
Purchase, procure, and sell		yes
Organize, plan, and prepare (others' work)		yes
Train, teach, instruct, and educate		yes
Consult and inform		yes
Gather information, develop, research, and construct		yes
Apply legal knowledge		yes

Notes: BIBB-BAuA Employment Survey 2012. Classification of tasks as routine and non-routine according to Spitz-Oener (2006) and Becker et al. (2013).

4.8 Theoretical extension

The purpose of this extension is twofold. In Part 4.8.1, we extend the monitoring-based theory of business group hierarchies outlined in the main text to the case of a business group with three firms. In Part 4.8.2, we provide further empirical evidence for the link between hierarchical distance and wages.

4.8.1 A monitoring based-theory of business group hierarchies for more than two firms

In contrast to the baseline model outlined in Section 4.2, we now consider a business group that operates three firms along the value chain. In all other respects, we keep the assumptions of the baseline model, while relying on a numeric index $j = 1, 2, 3$ to distinguish firms by their position in the value chain. This implies that the firm with index $j = 1$ is the first (or most upstream) producer in the value chain, while the firm with index $j = 3$ is the last (or most downstream) producer in the value chain. Since we follow the analysis from the main text step by step, we only present the formal analysis necessary to show our results, but do not repeat the intuition behind these results. The variables used below have the same interpretation as in the main text and are not separately discussed.

Starting from the differential equation for the evolution of production costs $c_j'(s) = \lambda c_j(s) + w_j$, we compute the following general solution for the cost function:

$$c_j(s) = B_j \exp(\lambda s) - \frac{w_k}{\lambda}. \tag{4.18}$$

Denoting by S_j, the upper bounds of the stages produced by firms j – with $S_3 = 1$ by assumption – and noting that S_{j-1} refers to the lower bound of production stages produced by firm j – with $S_0 = 0$ by assumption – we can determine the specific solution for the differential equations by making use of the boundary conditions $c_j(0) = 0$ and $c_j(S_{j-1}) = c_{j-1}(S_j)$ for $j = 2, 3$. This allows us to determine

$$B_1 = \frac{w_1}{\lambda_1}, \qquad B_2 = \frac{w_1}{\lambda}\{1 - \exp(-\lambda S_1)\} + \frac{w_2}{\lambda}\exp(-\lambda S_1),$$

and

$$B_3 = \frac{w_1}{\lambda}\{1 - \exp(-\lambda S_1)\} + \frac{w_2}{\lambda}\{\exp(-\lambda S_1) - \exp(-\lambda S_2)\} + + \frac{w_3}{\lambda}\exp(-\lambda S_2).$$

Substituting B_3 into $c_3(s)$ and evaluating the resulting expression at $s = 1$ gives the unit production cost:

$$\begin{aligned} c_3(1) = \frac{w_1}{\lambda}\exp[\lambda(1 - S_1)]\{\exp(\lambda S_1) - 1\} + \frac{w_2}{\lambda}\exp[\lambda(1 - S_2)]\{\exp[\lambda(S_2 - S_1] - 1\} \\ + \frac{w_3}{\lambda}\{\exp[\lambda(1 - S_2)] - 1\} \equiv c. \end{aligned}$$

We continue our analysis by making use of the firm-level demand function $\ell_j = \int_{S_{j-1}}^{S_j} q(s)ds$. Substituting $q(s) = q(0)\exp(-\lambda s)$ from Section 4.2 and solving the integral gives

$$S_1 = -\frac{1}{\lambda}\ln\left[\frac{q(0) - \lambda\ell_1}{q(0)}\right], \quad S_2 = -\frac{1}{\lambda}\ln\left[\frac{q(0) - \lambda\ell_1 - \lambda\ell_2}{q(0) - \lambda\ell_1}\right]$$

and, setting $S_3 = 1$, the output equation $q(0)\exp(-\lambda) = q(0) - \lambda\sum_{j=1}^{3}\ell_j$. Substituting into $c_3(1)$, we then obtain the unit cost function

$$c = \frac{w_1\ell_1 + w_2\ell_2 + w_3\ell_3}{q(0)\exp(-\lambda)}, \tag{4.19}$$

in accordance with Eq. (4.3).

Making use of the two constraints $\sum_{j=1}^{3} m_j = 1$ and $\sum_{j=1}^{3}\ell_j = [q(0)/\lambda]\{1 - \exp(-\lambda)\}$, we can write $m_3 = 1 - m_1 - m_2$, $\ell_3 = [q(0)/\lambda]\{1 - \exp(-\lambda)\} - \ell_1 - \ell_2$ and can express total hiring plus production costs as follows:

$$\begin{aligned} C(m_1, m_2, \ell_1, \ell_2, q(0)) = \zeta\left\{\left(\frac{a_1}{m_1} + 1\right)\ell_1^2 + \left(\frac{a_1}{m_2} + 1\right)\ell_2^2\right. \\ \left. + \left(\frac{a_3}{1 - m_1 - m_2} + 1\right)\left[\frac{q(0)}{\lambda}\{1 - \exp(-\lambda)\} - \ell_1 - \ell_2\right]^2\right\}. \end{aligned}$$

Minimizing total costs for a given level of $q(0)$ gives the solutions for ℓ_1, ℓ_2 and m_1, m_2. We compute

$$\ell_1 = \frac{q(0)}{\lambda}\{1-\exp(-\lambda)\}$$
$$\times \frac{m_1(a_2+m_2)(a_3+1-m_1-m_2)}{(a_1+m_1)(a_2+m_2)(1-m_1-m_2)+[m_1(a_2+m_2)+m_2(a_1+m_1)](a_3+1-m_1-m_2)},$$
$$\ell_2 = \frac{q(0)}{\lambda}\{1-\exp(-\lambda)\}$$
$$\times \frac{m_2(a_1+m_1)(a_3+1-m_1-m_2)}{(a_1+m_1)(a_2+m_2)(1-m_1-m_2)+[m_1(a_2+m_2)+m_2(a_1+m_1)](a_3+1-m_1-m_2)},$$

and

$$m_1 = \frac{\sqrt{a_1}(a_2+a_3+1)-a_1(\sqrt{a_2}+\sqrt{a_3})}{\sqrt{a_1}+\sqrt{a_2}+\sqrt{a_3}},$$
$$m_2 = \frac{\sqrt{a_2}(a_1+a_3+1)-a_2(\sqrt{a_1}+\sqrt{a_3})}{\sqrt{a_1}+\sqrt{a_2}+\sqrt{a_3}}.$$

An interior solution with $m_j \in (0,1)$ for all $j = 1,2,3$ requires that the three (mutually non-excluding) parameter constraints $1+a_2+a_3 > \sqrt{a_1}(\sqrt{a_2}+\sqrt{a_3})$, $1+a_1+a_3 > \sqrt{a_2}(\sqrt{a_1}+\sqrt{a_3})$, and $1+a_1+a_2 > \sqrt{a_3}(\sqrt{a_1}+\sqrt{a_2})$ hold simultaneously.

Setting the output price equal to one, joint profits of the business group can then be expressed as

$$\Pi = q(0)\exp(-\lambda) - \zeta\left(\frac{q(0)}{\lambda}\right)^2\{1-\exp(-\lambda)\}^2$$
$$\times \frac{(a_1+1-m_1^*)(a_1+m_2^*)(a_3+1-m_1^*-m_2^*)}{(a_1+m_1)(a_2+m_2)(1-m_1-m_2)+[m_1(a_2+m_2)+m_2(a_1+m_1)](a_3+1-m_1-m_2)}.$$

For a sufficiently low level of ζ maximizing these profits establishes a solution with $p_j < 1$ for $j = 1,2,3$.

The first-order conditions for the cost-minimizing choices of m_1, m_2 establish for any two firms j and $-j$ an optimality condition similar to Eq. (4.6):

$$\frac{\sqrt{a_j}\ell_j}{m_j} = \frac{\sqrt{a_{-j}}\ell_{-j}}{m_{-j}}. \tag{4.20}$$

Making use of the incentive compatibility constraint $w_j = a_j\ell_j/m_j$, we finally obtain $w_j = w_{-j}\sqrt{a_j/a_{-j}}$. This shows that the comparative-static result for the impact of larger hierarchical distance to the ultimate owner on a firm's wages extend to business groups with three subsidiary firms.

4.8.2 Further supportive evidence for a positive link between hierarchical distance and wages

In this section, we provide further supportive evidence for a positive link between hierarchical distance to the ultimate owner in a business group and workers' wages. In a first step, we drop all group-establishment-worker-triple for which we do not observe a change in the hierarchical distance over time. We then repeat the regressions from Section 4.4.1 for the new sample and report the results in Table 4.12. There, we see that eliminating observations for which we do not observe a change in the hierarchical distance over time lowers the sample size considerably, while it does not

Table 4.12: Business groups, ownership hierarchy, and wages when excluding observations without changes in hierarchical distance over time

Dependent variable: log daily wage	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
Hierarchical distance	0.0121***	0.0016**	0.0167***	0.0023***	0.0198***	0.0026**
	(0.0020)	(0.0007)	(0.0022)	(0.0007)	(0.0047)	(0.0012)
Group size			0.0060***	0.0005***		
			(0.0009)	(0.0001)		
Hierarchical distance			-0.0010***	-0.0001**		
×Group size			(0.0001)	(0.0000)		
Group complexity					0.0157***	-0.0002
					(0.0030)	(0.0005)
Hierarchical distance					-0.0028***	-0.0001
×Group complexity					(0.0008)	(0.0001)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Worker Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Establishment Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Worker-establ.-group FE	No	Yes	No	Yes	No	Yes
R-sq. (within)	0.4203	0.0708	0.4228	0.0709	0.4227	0.0708
Observations	3,041,750	3,041,750	3,041,750	3,041,750	3,041,750	3,041,750

Notes: Worker covariates include age, age squared, dummies for three skill groups, German nationality, and gender. Establishment covariates include log employment, log employment squared, dummies for 16 German federal states, and six broad sector categories. In all models, we estimate a constant as well as a full set of time dummies. Hierarchical distance and the group index of complexity are constructed as outlined in Section 4.3. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

change the main insights regarding the link between hierarchical distance and wages in a substantive way.

In a further extension, we complement the analysis from Section 4.4.2 by confining the treatment to workers changing establishments within the same business group. To be more specific, the treatment group consists of workers moving to an establishment with higher hierarchical distance within the same business group. In contrast, the control group comprises workers moving to a new establishment within the same business group without changing the hierarchical distance to the ultimate owner. These alternative definitions of the treatment and the control group drastically lower the number of observations in the difference-in-difference estimation. Whereas the matching is still successful, the strong reduction in observations leads to less precise estimates. These estimates are summarized in Table 4.13 and 4.14. There, we see that we still find positive and significant estimates for those sub-groups of workers, for which we expect the impact of hierarchical distance on wages to be strongest. These are workers with high skills and workers performing non-routine tasks.

Table 4.13: Wage effect of larger distance in business group hierarchy: Movers between establishments within business groups

Dependent variable: Log daily wage	*All workers*	*Low-skilled*	*High-skilled*
Higher *HD* in $t = 1$	0.0024	0.0181	0.0134**
	(0.0044)	(0.0117)	(0.0064)
Observations	116,808	4,308	37,324

Notes: The treatment is defined as an increase in the hierarchical distance within a given business group. The estimation includes a time dummy and worker fixed-effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Table 4.14: Distance effect by predominant task: Movers between establishments within business groups

Dependent variable:	*All workers*	*Predominant tasks*	
Log daily wage		*routine*	*non-routine*
Higher *HD* in $t = 1$	0.0024	-0.0139	0.0152*
	(0.0044)	(0.0086)	(0.0092)
Observations	116,808	26,976	10,612

Notes: The treatment is defined as an increase in the hierarchical distance within a given business group. The estimation includes a time dummy and worker fixed-effects. Standard errors in parentheses are clustered at the establishment-level. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

Chapter 5

Conclusion

The purpose of this thesis was to analyse the effects of multinational firm activity by shedding light on three separate, albeit related research questions. Chapter 2 has presented an empirical analysis of the effect of foreign takeover on wages of workers in German establishments in the period from 2003 to 2014. Making use of propensity-score matching with a difference-in-difference estimator, this chapter has shown that a takeover by a foreign investor leads to a wage premium of 4.0 log points in the year after ownership change, which further increases to 6.3 log points three years after acquisition. The wage premium is largest for high-skilled workers, which is consistent with three theoretical arguments, namely rent appropriation by managers, technology protection, and training on new technology. The analysis also shows that the wage premium does not pick up an exporter effect due to a platform investment of the foreign owner, that the wage premium takes about four years before it fully develops, that the wage premium does not vanish after foreign divestment, and that the wage increase is specific to foreign acquisition instead of ownership change per se.

Chapter 3 has investigated the effect of foreign takeover on the task composition in German plants in the period from 2000 to 2019. The analysis has provided two main insights. First, descriptive evidence illustrates that foreign-owned establishments in Germany are more intensive in routine tasks. And second, combining propensity-score matching with a difference-in-difference estimator, this chapter shows that foreign takeover leads to a reduction in the non-routine analytical task share of 0.2 percentage points. This result is consistent with the theoretical argument that in multinational firms non-routine tasks are less easily performed abroad. This finding also cannot be attributed to foreign owners changing the hierarchical organization of plants by adding or dropping layers.

In Chapter 4, firm-level data on ownership linkages have been merged with administrative data on German workers to analyse how the position in a multinational business group hierarchy affects the wages paid to workers. To acknowledge that ownership linkages are not one-directional, an index accounting for the complex network structure of business groups to measure hierarchical distance of firms to their ultimate owner was proposed. The analysis documents a positive effect of larger hierarchical distance to the ultimate owner of a business group on workers' wages. To explain this finding, a monitoring-based theory of business groups was developed. This model predicts higher wages to prevent shirking by workers if a larger hierarchical distance to the ultimate owner is associated with lower monitoring efficiency.

This thesis was motivated by the growing importance of multinational firm activity in a world characterized by a substantial increase in international trade and collaboration as a result of globalisation over the last decades. Today, it is a well-known stylised fact that the biggest multinational firms account for a major part of economic activity around the globe. Unsurprisingly, the question about the impacts of multinational firms and foreign ownership have not only been at the forefront of research, but also pervaded the public discussion in many advanced economies. Against this background, I hope that the research presented in this thesis can broaden our understanding of the effects of multinational firm activity. Building on global firm data that has become available over the last years, the findings presented in this thesis will hopefully also encourage further empirical and theoretical research to advance our knowledge.

Bibliography

Acemoglu, D. and D. Autor (2011): "Skills, Tasks and Technologies: Implications for Employment and Earnings," *Handbook of Labor Economics*, 4, 1043–1171.

Aitken, B., A. Harrison, and R. E. Lipsey (1996): "Wages and Foreign Ownership: A comparative study of Mexico, Venezuela and the United States," *Journal of International Economics*, 40, 345–371.

Alda, H., S. Bender, and H. Gartner (2005): "The Linked Employer-employee Dataset Created from the IAB Establishment Panel and the Process-produced Data of the IAB (LIAB)," *Schmollers Jahrbuch*, 125, 327–336.

Almeida, R. (2007): "The labor market effects of foreign owned firms," *Journal of International Economics*, 72, 75–96.

Altomonte, C., G. Ottaviano, and A. Rungi (2018): "Business Groups as Knowledge-Based Hierarchies of Firms," *Working Paper*.

Altomonte, C. and A. Rungi (2013): "Business groups as hierarchies of firms: determinants of vertical integration and performance," *ECB Working Paper 1554*.

——— (2015): "Firm Performance and the Optimal Organization of Business Groups," *Working Paper*.

Andrews, M. J., L. Bellmann, T. Schank, and R. Upward (2009): "The takeover and selection effects of foreign-owned establishments: an analysis using linked employer-employee data," *Review of World Economics*, 145, 293–317.

Antonczyk, D., B. Fitzenberger, and U. Leuschner (2009): "Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure?" *Jahrbücher für Nationalökonomie und Statistik*, 229, 214–238.

Antoni, M., K. Koller, M.-C. Laible, and F. Zimmermann (2018): "Orbis-ADIAB: From record linkage key to research dataset," *FDZ Methodenreport 04/2018*.

Antràs, P. and D. Chor (2013): "Organizing the Global Value Chain," *Econometrica*, 81, 2127–2204.

Antràs, P., D. Chor, T. Fally, and R. Hillberry (2012): "Measuring the Upstreamness of Production and Trade Flows," *American Economic Review: Papers and Proceedings*, 102, 412–16.

Antràs, P., L. Garicano, and E. Rossi-Hansberg (2006): "Offshoring In A Knowledge Economy," *Quarterly Journal of Economics*, 121, 1375–1418.

Antràs, P. and E. Helpman (2004): "Global Sourcing," *Journal of Political Economy*, 112, 552–.

Antràs, P. and S. Yeaple (2014): "Multinational Firms and the Structure of International Trade," in *Handbook of International Economics*, ed. by G. Gopinath, E. Helpman, and K. Rogoff, Elsevier, vol. 4, chap. 2, 55–130.

Autor, D. H., F. Levy, and R. J. Murnane (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 118, 1279–1333.

Baker, G., R. Gibbons, and K. J. Murphy (2002): "Relational Contracts and the Theory of the Firm," *The Quarterly Journal of Economics*, 117, 39–84.

Balsvik, R. (2011): "Is Labor Mobility a Channel for Spillovers From Multinationals? Evidence From Norwegian Manufacturing," *Review of Economics and Statistics*, 93, 285–297.

Balsvik, R. and S. A. Haller (2010): "Picking Lemons or Picking Cherries? Domestic and Foreign Acquisitions in Norwegian Manufacturing," *The Scandinavian Journal of Economics*, 112, 361–387.

Balsvik, R. and M. Saethre (2016): "Rent Sharing with Footloose Production. Foreign Ownership, Union and Wages." Unpublished Manuscript, NHH Bergen.

Bandick, R. (2011): "Foreign Acquisition, Wages and Productivity," *The World Economy*, 34, 931–951.

Bandick, R. and H. Görg (2010): "Foreign acquisition, plant survival, and employment growth," *Canadian Journal of Economics*, 43, 547–573.

Barba Navaretti, G. and A. J. Venables (2004): *Multinationals Firms in the World Economy*, Princeton University Press, Princeton, NJ.

Barbosa, N. and H. Louri (2002): "On the Determinants of Multinationals' Ownership Preferences: Evidence from Greece and Portugal," *International Journal of Industrial Organization*, 20, 493–515.

Bastos, P., N. Monteiro, and O. R. Straume (2018): "Foreign Acquisition and Internal Organization," *Journal of International Economics*, 114, 143–163.

Baumgarten, D. (2013): "Exporters and the rise in wage inequality: Evidence from German linked employer-employee data," *Journal of International Economics*, 90, 201–217.

Bayard, K. and K. R. Troske (1999): "Examining the Employer-Size Wage Premium in the Manufacturing, Retail Trade, and Service Industries Using Employer-Employee Matched Data," *The American Economic Review*, 89, 99–103.

Becker, S. O., K. Ekholm, and M.-A. Muendler (2013): "Offshoring and the Onshore Composition of Tasks and Skills," *Journal of International Economics*, 90, 91–106.

Becker, S. O. and M.-A. Muendler (2015): "Trade and Tasks: An Exploration over Three Decades in Germany," *Economic Policy*, 30, 589–641.

Belenzon, S., T. Berkovitz, and L. A. Rios (2013): "Capital Markets and Firm Organization: How Financial Development Shapes European Corporate Groups," *Management Science*, 59, 1326–1343.

Bernard, A. B. and J. B. Jensen (1995): "Exporters, Jobs, and Wages in U.S. Manufacturing: 1976-1987," *Brookings Papers*, 67–119.

——— (1999): "Exceptional exporter performance: cause, effect or both?" *Journal of International Economics*, 47, 1–25.

Bernard, A. B. and F. Sjöholm (2003): "Foreign Owners and Plant Survival," *NBER Working Paper No. 10039.*

Bircan, Ç. (2019): "Ownership Structure and Productivity of Multinationals," *Journal of International Economics*, 116, 125–143.

Blinder, A. S. (2006): "Offshoring: The Next Industrial Revolution?" *Foreign Affairs*, 85, 113–128.

Blinder, A. S. and L. J. Maccini (1991): "Taking Stock: A Critical Assessment of Recent Research on Inventories," *Journal of Economic Perspectives*, 5, 73–96.

Bloom, N., C. Genakos, R. Sadun, and J. Van Reenen (2012a): "Management Practices Across Firms and Countries," *Academy of Management Perspectives*, 26, 12–33.

Bloom, N., F. Guvenen, B. S. Smith, J. Song, and T. von Wachter (2018): "The Disappearing Large-Firm Wage Premium," *AEA Papers and Proceedings*, 108, 317–22.

Bloom, N., R. Sadun, and J. Van Reenen (2010): "Recent Advances in the Empirics of Organizational Economics," *Annual Review of Economics*, 2, 105–137.

——— (2012b): "Americans Do IT Better: US Multinationals and the Productivity Miracle," *American Economic Review*, 102, 167–201.

Bloom, N. and J. Van Reenen (2010): "Why Do Management Practices Differ across Firms and Countries," *Journal of Economic Perspectives*, 24, 203–224.

Brown, C. and J. Medoff (1989): "The Employer Size-Wage Effect," *Journal of Political Economy*, 97, 1027–1059.

Budd, J. W., J. Konings, and M. J. Slaughter (2005): "Wages And International Rent Sharing In Multinational Firms," *The Review of Economics and Statistics*, 87, 73–84.

Caliendo, L., F. Monte, and E. Rossi-Hansberg (2015): "The Anatomy of French Production Hierarchies," *Journal of Political Economy*, 123, 809–852.

Caliendo, L. and E. Rossi-Hansberg (2012): "The Impact of Trade on Organization and Productivity," *The Quarterly Journal of Economics*, 127, 1393–1467.

Caliendo, M. and S. Kopeinig (2008): "Some Practical Guidance For The Implementation Of Propensity Score Matching," *Journal of Economic Surveys*, 22, 31–72.

Calvo, G. A. and S. Wellisz (1978): "Supervision, Loss of Control, and the Optimum Size of the Firm," *Journal of Political Economy*, 86, 943–952.

——— (1979): "Hierarchy, Ability, and Income Distribution," *Journal of Political Economy*, 87, 991–1010.

Card, D., J. Heining, and P. Kline (2013): "Workplace Heterogeneity and the Rise of West German Wage Inequality," *The Quarterly Journal of Economics*, 128, 967–1015.

Caroli, E. and J. Van Reenen (2001): "Skill-biased Organizational Change? Evidence from a Panel of British and French Establishments," *The Quarterly Journal of Economics*, 116, 1449–1492.

Chen, C. (2017): "Management Quality and Firm Hierarchy in Industry Equilibrium," *American Economic Journal: Microeconomics*, 9, 203–244.

Chen, C. and W. Suen (2019): "The Comparative Statics of Optimal Hierarchies," *American Economic Journal: Microeconomics*, 11, 1–25.

Colonnelli, E., J. Tåg, M. Webb, and S. Wolter (2018): "A Cross-Country Comparison of Dynamics in the Large Firm Wage Premium," *American Economic Review: Papers and Proceedings*, 108, 323–327.

Conyon, M., S. Girma, S. Thompson, and P. Wright (2004): "Do Wages Rise or Fall Following Merger?" *Oxford Bulletin of Economics and Statistics*, 66, 847–862.

Costinot, A., J. Vogel, and S. Wang (2013): "An Elementary Theory of Global Supply Chains," *The Review of Economic Studies*, 80, 109–144.

Cravino, J. and A. A. Levchenko (2017): "Multinational Firms and International Business Cycle Transmission," *The Quarterly Journal of Economics*, 132, 921–962.

Datta, S., M. Iskandar-Datta, and K. Raman (2002): "Executive Compensation and Corporate Acquisition Decisions," *Journal of Finance*, 56, 2299–2336.

Dauth, W. and J. Eppelsheimer (2020): "Preparing the Sample of Integrated Labour Market Biographies (SIAB) for Scientific Analysis: A Guide," *Journal for Labor Market Research*, 54.

Dauth, W., S. Findeisen, and J. Suedekum (2014): "The Rise of the East and the Far East: German Labor Markets and Trade Integration," *Journal of the European Economic Association*, 12, 1643–1675.

de Vries, G. J., E. Gentile, S. Miroudot, and K. M. Wacker (2020): "The Rise of Robots and the Fall of Routine Jobs," *Labour Economics*, 66, 101885.

Dengler, K., B. Matthes, and W. Paulus (2014): "Occupational Tasks in the German Labour Market," *FDZ-Methodenreport 12/2014*.

Dustmann, C., B. Fitzenberger, U. Schönberg, and A. Spitz-Oener (2014): "From Sick Man of Europe to Economic Superstar: Germany's Resurgent Economy," *Journal of Economic Perspectives*, 28, 167–188.

Egger, H., P. Egger, and D. Greenaway (2008): "The Trade Structure Effects of Endogenous Regional Trade Agreements," *Journal of International Economics*, 74, 278–298.

Egger, H. and E. Jahn (2020): "Ownership and the multinational wage premium," *Applied Economics Letters*, 27.

Egger, H., E. Jahn, and S. Kornitzky (2020): "Reassessing the foreign ownership wage premium in Germany," *The World Economy*, 43, 302–325.

——— (2022): "How does the position in business group hierarchies affect workers' wages?" *Journal of Economic Behavior and Organization*, 194, 244–263.

Egger, H. and U. Kreickemeier (2013): "Why Foreign Ownership May Be Good For You," *International Economic Review*, 54, 693–716.

Egger, H., U. Kreickemeier, C. Moser, and J. Wrona (2019): "Exporting and Offshoring with Monopsonistic Competition," CESifo working Paper No. 7774.

Ekholm, K., R. Forslid, and J. R. Markusen (2007): "Export-Platform Foreign Direct Investment," *Journal of the European Economic Association*, 5, 776–795.

Fosfuri, A., M. Motta, and T. Rønde (2001): "Foreign Direct Investment and Spillovers Through Workers' Mobility," *Journal of International Economics*, 53, 205–222.

Friedrich, B. U. (2022): "Trade Shocks, Firm Hierarchies, and Wage Inequality," *Review of Economics and Statistics*, 104, 621–635.

Garicano, L. (2000): "Hierarchies and the Organization of Knowledge in Production," *Journal of Political Economy*, 108, 874–904.

Garicano, L. and E. Rossi-Hansberg (2006): "Organization and Inequality in a Knowledge Economy," *The Quarterly Journal of Economics*, 121, 1383–1435.

——— (2015): "Knowledge-Based Hierarchies: Using Organizations to Understand the Economy," *Annual Review of Economics*, 7, 1–30.

Gartner, H. (2004): "Die Imputation von Löhnen oberhalb der Beitragsbemessungsgrenze in der IAB-Beschäftigten-Stichprobe," *IAB Methodenreport*.

Gathmann, C. and U. Schönberg (2010): "How General Is Human Capital? A Task-Based Approach," *Journal of Labor Economics*, 28, 1–49.

Gelübcke, J. P. W. (2013): "Foreign and Domestic Takeovers in Germany: Cherry-picking and Lemon-grabbing," *Applied Economics Quarterly*, 59, 275–294.

Girma, S. and H. Görg (2004): "Blessing or Curse? Domestic Plants' Survival and Employment Prospects after Foreign Acquisition," *Applied Economics Quarterly*, 50, 89–110.

——— (2007): "Evaluating The Foreign Ownership Wage Premium Using a Difference-in-Differences Matching Approach," *Journal of International Economics*, 72, 97–112.

Girma, S., D. Greenaway, and K. Wakelin (2001): "Who Benefits from Foreign Direct Investment in the UK?" *Scottish Journal of Political Economy*, 48, 119–133.

Girma, S., S. Thompson, and P. W. Wright (2006): "The Impact of Merger Activity on Executive Pay in the United Kingdom," *Economica*, 73, 321–339.

Glass, A. J. and K. Saggi (2002): "Multinational Firms and Technology Transfer," *The Scandinavian Journal of Economics*, 104, 495–513.

Görg, H., E. Strobl, and F. Walsh (2007): "Why Do Foreign-Owned Firms Pay More? The Role of On-the-Job Training," *Review of World Economics*, 143, 464–482.

Greaney, T. M. and Y. Li (2017): "Examining Determinants of Foreign Wage Premiums in China," *The World Economy*, 40, 2056–2077.

Grossman, G. M. and E. Helpman (2003): "Outsourcing versus FDI in Industry Equilibrium," *Journal of the European Economic Association*, 1, 317–327.

Guest, P. M. (2009): "The Impact of Mergers and Acquisitions on Executive Pay in the United Kingdom," *Economica*, 76, 149–175.

Gumpert, A. (2018): "The organization of knowledge in multinational firms," *Journal of the European Economic Association*, 16, 1929–1976.

Gumpert, A., H. Steimer, and M. Antoni (2022): "Firm Organization with Multiple Establishments," *Quarterly Journal of Economics*, 137, 1091–1138.

Hakkala, K. N., F. Heyman, and F. Sjöholm (2014): "Multinational firms, acquisitons and job tasks," *European Economic Review*, 66, 248–265.

Helpman, E. (1984): "A Simple Theory of International Trade with Multinational Corporations," *Journal of Political Economy*, 92, 451–471.

Heyman, F., F. Sjöholm, and P. G. Tingvall (2007): "Is there really a foreign ownership wage premium? Evidence from matched employer-employee data," *Journal of International Economics*, 73, 355–376.

Heyman, F., F. Sjöholm, and P. G. Tingvall (2011): "Multinationals, Cross-Border Acquisitions and Wage Dispersion," *Canadian Journal of Economics*, 44, 627–650.

Hijzen, A., P. S. Martins, T. Schank, and R. Upward (2013): "Foreign owned firms around the world: A comparative analysis of wages and employment at the micro-level," *European Economic Review*, 60, 170–188.

Hummels, D., R. Jørgensen, J. Munch, and C. Xiang (2014): "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data," *American Economic Review*, 104, 1597 – 1629.

Huttunen, K. (2007): "The Effect Of Foreign Acquisition On Employment And Wages: Evidence From Finnish Establishments," *The Review of Economics and Statistics*, 89, 497–509.

Idson, T. L. and W. Y. Oi (1999): "Firm Size and Wages," in *Handbook of Labor Economics*, ed. by O. C. Ashenfelter and D. Card, Elsevier, vol. 3, Part B, chap. 33, 2165–2214.

Imbens, G. W. and D. W. Rubin (2015): *Causal Inference for Statistics, Social and Biomedical Sciences*, Cambridge University Press.

Imbens, G. W. and J. M. Wooldridge (2009): "Recent developments in the econometrics of program evaluation," *Journal of Economic Literature*, 47, 5–86.

Javorcik, B. and S. Poelhekke (2017): "Former Foreign Affiliates: Cast Out And Outperformed?" *Journal of the European Economic Association*, 15, 501–539.

Johnson, R. C. (2018): "Measuring Global Value Chains," *Annual Review of Economics*, 10, 207–236.

Jones, G. R. (1984): "Task Visibility, Free Riding, and Shirking: Explaining the Effect of Structure and Technology on Employee Behavior," *The Academy of Management Review*, 9, 684–695.

Kemeny, T. and D. Rigby (2012): "Trading away what kind of jobs? Globalization, trade and tasks in the US economy," *Review of World Economics*, 148, 1–16.

Khanna, T. and Y. Yafeh (2007): "Business Groups in Emerging Markets: Paragons or Parasites?" *Journal of Economic Literature*, 45, 331–372.

Kim, J. W. (2011): "The Economic Growth Effect of R&D Activity in Korea," *Korea and the World Economy*, 12, 25–44.

Klosterhuber, W., P. Lehnert, and S. Seth (2016): "Linked-Employer-Employee-Daten des IAB: LIAB-Querschnittsmodell 2 1993-2014 (LIAB QM2 9314)," *FDZ Datenreport 05/2016*.

Kong, D., G. Kong, L. Panga, and J. Zhang (2018): "Who Gets the Wage Premium from Export: Top Managers or Employees?" *International Review of Economics and Finance*, 58, 356–370.

Lipsey, R. E. and F. Sjöholm (2004): "Foreign direct investment, education and wages in Indonesian manufacturing," *Journal of Development Economics*, 73, 415–422.

Manasse, P. and A. Turrini (2001): "Trade, Wages, and 'Superstars'," *Journal of International Economics*, 54, 97–117.

Martins, P. S. (2004): "Do Foreign Firms Really Pay Higher Wages? Evidence from Different Estimators," *IZA Discussion Paper No. 1388*.

Mincer, J. (1958): "Investment in Human Capital and Personal Income Distribution," *Journal of Political Economy*, 66, 281–302.

Montag, F. and T. Wilson (2011): "Differences in German and EU Merger Control Law – Should a Common EU Rulebook for Mergers Follow the German or European Model?" 18th St. Gallen International Competition Law Forum ICF.

Mora, R. and I. Reggio (2012): "Treatment Effect Identification Using Alternative Parallel Assumptions," *Universidad Carlos III De Madrid Working Paper 12-33*.

Motta, M. and G. Norman (1996): "Does Economic Integration Cause Foreign Direct Investment?" *International Economic Review*, 37, 757–783.

Nadiri, M. I. (1993): "Innovations And Technological Spillovers," *NBER Working Paper*.

Neary, J. P. (2009): "Trade Costs and Foreign Direct Investment," *International Review of Economics and Finance*, 18, 207–218.

Obermaier, R. (2012): "German Inventory to Sales Ratios 1971–2005 — An Empirical Analysis of Business Practice," *International Journal of Production Economics*, 135, 964–976.

Oldenski, L. (2012): "The Task Composition Of Offshoring By U.S. Multinationals," *International Economics*, 131, 5–21.

Pischke, J.-S. (2005): "Empirical Methods in Applied Economics," *LSE Lecture Notes*.

Qian, Y. (1994): "Incentives and Loss of Control in an Optimal Hierarchy," *Review of Economic Studies*, 61, 527–544.

Rajan, R. G. and J. Wulf (2006): "The Flattening Firm: Evidence from Panel Data on the Changing Nature of Corporate Hierarchies," *The Review of Economics and Statistics*, 88, 759–773.

Rosenbaum, P. R. and D. B. Rubin (1983): "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika*, 70, 41–55.

——— (1985): "Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score," *The American Statistician*, 39, 33–38.

Schafer, J. (1997): *Analysis of Incomplete Multivariate Data*, Chapman and Hall/CRC.

Schank, T., C. Schnabel, and J. Wagner (2007): "Do exporters really pay higher wages? First evidence from German linked employer-employee data," *Journal of International Economics*, 72, 52–74.

Schmidt, D. R. and K. L. Fowler (1990): "Post-Acquisition Financial Performance and Executive Compensation," *Strategic Management Journal*, 11, 559–569.

Spitz-Oener, A. (2006): "Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure," *Journal of Labor Economics*, 24, 235–270.

UNCTAD (2016): *World Investment Report 2016: Investor Nationality: Policy Challenges*, UNCTAD, Geneva.

Vahter, P. and J. Masso (2018): "The contribution of multinationals to wage inequality: foreign ownership and the gender pay gap," *Review of World Economics*, 155, 105–148.

Velde, D. W. t. and O. Morrissey (2003): "Do Workers in Africa Get a Wage Premium if Employed in Firms Owned by Foreigners?" *Journal of African Economies*, 12, 41–73.

Wagner, J. (2007): "Exports and Productivity: A Survey of the Evidence from Firm-level Data," *The World Economy*, 30, 60–82.

Winter-Ebmer, R. and J. Zweimüller (1999): "Firm-Size Wage Differentials in Switzerland: Evidence from Job-Changers," *The American Economic Review*, 89, 89–93.

Yeaple, S. (2003): "The Complex Integration Strategies of Multinationals and Cross-Country Dependencies in the Structure of Foreign Direct Investment," *Journal of International Economics*, 60, 293–314.