Human Capital in Labor Economics
Novel Perspectives and Research Strategies

Dissertation

zur

Erlangung des Grades eines Doktors der Wirtschaftswissenschaft

eingereicht an der

Fakultät für Wirtschaftswissenschaften der Universität Regensburg

von

Johann Eppelsheimer

Tag der Einreichung: 16.07.2019
Tag der Disputation: 30.10.2019

Berichterstatter:
Prof. Dr. Dr. h.c. Joachim Möller
Prof. Dr. Uwe Blien

Acknowledgments

I gratefully acknowledge support from the graduate program of the Institute for Employment Research (IAB) and the University of Erlangen-Nuremberg (GradAB). I would also like to thank my supervisors, Joachim Möller and Uwe Blien, for their guidance and encouragement. My research benefited substantially from their immense knowledge. Besides my advisors, I am also profoundly grateful to Florian Lehmer for mentoring me. In numerous discussions, many scholars gave me invaluable feedback. To name a few, I would like to thank Annette Bergemann, Gerard van den Berg, Uta Schönberg, Heiko Stüber, Erwin Winkler, Jeffrey Wooldridge and Anthony Yezer for their insightful comments. My heartfelt thanks goes to all my colleagues and fellow Ph.D. students at the IAB and the University of Regensburg. I deeply appreciated working together with Linda Borrs, Peter Haller, Markus Janser and Christoph Rust. They were a great source of motivation for me. Finally, I would like to thank Marie and my family for their constant support.

Nürnberg, July 16, 2019 *Johann Eppelsheimer*

Contents

List of Figures

List of Tables

Introduction

The level of education grows steadily. Between 1980 and 2014, the percentage of male regular full-time workers in West Germany with a degree from a university or university of applied science rose from six to twenty percent. In other words, the share of workers with tertiary education increased by 0.4 percentage points every year. However, human capital is not equally distributed in Germany.[1] On the one hand, there are regions where over 30 percent of the workforce went to university or university of applied science. On the other hand, there are regions in which less than five percent of the workforce studied at a university (source: IAB-SIAB, own calculations).

At least since Smith (1776), von Thünen (1826) and Marshall (1890) scholars argue that human capital raises the productivity of workers and societies. Analogously to investments in physical capital, investments in human capital increase production capabilities and efficiency. Economists, therefore, believe that human capital is crucial for economic development and explain income differences between countries by differences in their human capital endowments (Lucas, 1988; Mankiw *et al.* , 1992). Specifically, the economic literature highlights the role of human capital in implementing new technologies (Nelson & Phelps, 1966), the generation of new ideas (Romer, 1990) and demonstrates how human capital creates incentives for firms to invest in physical capital (Acemoglu, 1996).

The literature also postulates that individuals themselves benefit from investments in their human capital. Prominently, Mincer (1958) shows that schooling and work experience raise earnings. Importantly, workers not only benefit from general investments in human capital, like schooling, they also gain from training on the job (Blundell *et al.* ,

[1] Human capital refers to the skills and knowledge people possess and encompasses a variety of dimensions (Fisher, 1897; Mincer, 1958; Schultz, 1961; Becker, 1962). Students acquire very general abilities in schools, craftsmen learn their trade in formal training programs and by adopting the technical aptitude of their colleagues, and engineers earn their qualification through university lectures and practical experience on the job. Social competences, like management skills and the ability to work in teams, are also part of the human capital stock of individuals. Commonly, empiricists measure human capital by the level of formal education of individuals or by the complexity of their jobs.

1996). Furthermore, when switching jobs, workers can transfer their task-specific human capital to their new occupations (Gathmann & Schönberg, 2010). In addition to the individual returns to human capital, human capital might create positive spillover effects and raise the productivity of peers (Schultz, 1988).

This thesis contributes to two research areas on human capital in labor economics. First, I add to the literature on human capital externalities, which investigates spillover effects from individual human capital on peers. In particular, I aim to add new perspectives on the dynamics and the spatial scope of human capital externalities to the existing literature. Second, I contribute to the literature on the labor market consequences of globalization. Here, I highlight the importance of firm-internal restructuring of the workforce as an understudied adjustment channel to foreign direct investment. While the former research area focuses on the external effects of human capital *on* workers, the latter addresses the development of human capital *of* workers after an exogenous shock. In the following paragraphs, I provide brief overviews of the literature on human capital externalities and the literature on the labor market effects of globalization. Furthermore, I highlight research gaps and explain how this thesis aims to fill them.

Human capital externalities

Whenever people interact, they potentially learn from each other. Therefore, investments in individual human capital may cause positive externalities.[2] A vast body of the literature empirically supports this hypothesis. Rauch (1993) provides first empirical evidence that the regional level of schooling raises wages beyond individual returns to education. Furthermore, Moretti (2004) shows that an increase in the local share of college-educated workers raises the wages of locals. He uses panel data to compute knowledge spillovers and therefore is able to abstract from ability driven regional sorting of individuals. Furthermore, he exploits exogenous variation in the share of college-educated workers from the lagged regional demographic structure and the presence of land-grant colleges (established by the Morrill Act over a century ago).

Moretti (2004) investigates externalities from expansions at the upper part of the skill distribution. Plausibly, raising the education of low- and high-skilled individuals may create different kinds of externalities. Krueger & Lindahl (2001) suggest that increases of human capital at the upper part of the skill distribution induce technological development, whereas expansions at the lower end of the distribution lead to reductions in crimes and

[2] Intuitive examples of knowledge spillovers are when people share their knowledge or when they adopt novel technologies or production procedures from their peers. Naturally, knowledge spillovers transmit through social networks and are thus likely to be regionally limited.

welfare participation. Consequently, there is almost no empirical evidence for productive externalities from expansions at the lower part of the skill distribution. For example, Acemoglu & Angrist (2000) use variation in the regional level of human capital that comes from changes in compulsory schooling laws and child labor laws. According to Moretti (2004), their approach therefore primarily captures changes in the lower part of the skill distribution. Acemoglu & Angrist (2000) find almost no evidence for wage gains due to human capital externalities. Thus, increases in human capital at the lower part of the skill distribution may not create externalities that significantly raise the productivity of peers.

Rauch (1993), Acemoglu & Angrist (2000) and Moretti (2004) motivated a series of follow-up studies in various countries. For instance, Dalmazzo & de Blasio (2007) investigate externalities from the regional level of schooling on wages and rents in Italy. Muravyev (2008) uses exogenous variation from the economic transition at the end of communism in Russia to estimate wage externalities. Heuermann (2011) explores German social security data to measure knowledge spillovers from high-skilled workers on individual earnings. Additionally, he examines heterogeneous effects across industries. With Chinese data, Liu (2014) finds that human capital externalities are stronger in non-state-owned firms than in state-owned firms. Broersma *et al.* (2016) use data from the Netherlands to distinguish between consumption and production externalities and provide evidence for both. Analyzing Swedish data, Mellander *et al.* (2016) suggest that both, high-skilled individuals around the workplace and high-skilled individuals around the place of residence, increase wages of workers. Overall, a large number of studies empirically underpin that human capital generates positive externalities.

So far, the literature on human capital externalities focuses on spillover effects from the stock of high-skilled workers within predefined geographical boundaries. This thesis aims to add two novel perspectives to the literature. In the first chapter, I analyze external effects of intra-country migration flows of high-skilled workers. Specifically, I decompose the regional stock of high-skilled workers into immigration and emigration of high-skilled workers, as well as labor market entries and exits of high-skilled workers. The decomposition contributes to the understanding of knowledge spillovers and enables me to assess how knowledge spillovers accrue over time. In the second chapter, I investigate the spatial decay of knowledge spillovers. For the first time, I apply functional data analysis (FDA) to geocoded register data to estimate a functional representation of knowledge spillovers that depends on distance. This approach allows me to determine the spatial scope of knowledge spillovers and to assess how fast spillovers attenuate with distance. Furthermore, both chapters use a novel estimation procedure that potentially allows disentangling human capital externalities from labor market demand and supply effects.

The first chapter of this dissertation is joint work with Joachim Möller and studies human capital externalities from regional in- and outflows of high-skilled workers with German social security data. Analyzing flows of high-skilled workers as a source of knowledge spillovers allows assessing the dynamic evolution of spillover effects after individuals have moved. Additionally, investigating in- and outflows contributes to understanding the importance of personal networks in the transmission of knowledge spillovers. While local personal networks from incoming workers plausibly start small and develop over time, workers leaving the region generally abandon already well-established networks. Thus, if human capital externalities were mainly transmitted through personal networks, we would expect gradually increasing positive effects from inflows but abrupt negative effects from outflows. Additionally, workers who accumulated knowledge in other labor markets than the current one might increase the diversity of the local knowledge pool and thus generate particularly large spillover effects (compare Ottaviano & Peri, 2005; Timmermans & Boschma, 2014). Consequently, in- and outflows of high-skilled workers might create asymmetric spillover effects.

So far evidence on asymmetric spillover effects from in- and outflows of high-skilled workers is limited to the study of Docquier *et al.* (2014), who examine labor market effects from international migration. In an earlier version of the paper, the authors present the first evidence that externalities from in- and outflows are equal in the short run but different in the long run (Docquier *et al.* , 2010). In the long run, the positive effects of immigration are larger than the negative effects of emigration.

There are two major threats when identifying human capital externalities. First, as Moretti (2004) shows in his theoretical framework, in addition to spillovers, changes in the local concentration of high-skilled workers induce neoclassical demand and supply effects. Specifically, demand and supply effects raise the wages of low-skilled workers and depress wages of high-skilled workers. Acemoglu & Angrist (1999) suggest similar demand and supply effects in the working paper version of their article. Consequently, knowledge spillovers are inherently entangled with labor market demand and supply effects. To the best of my knowledge only Ciccone & Peri (2006) explicitly address this problem in their empirical strategy. Ciccone & Peri (2006) demonstrate that human capital externalities correspond to the effect of local human capital on average wages when holding the skill composition in the local labor market constant and estimate effects accordingly.[3] To disentangle knowledge spillovers from labor market demand and supply

[3] Note that the empirical estimates of Ciccone & Peri (2006) provide no evidence for external effects

effects we suggest an alternative approach. Our approach exploits the different spatial scopes of human capital externalities and demand and supply effects. While externalities attenuate sharply with distance and are thus strongly localized (Rosenthal & Strange, 2008; Fu, 2007), demand and supply effects are plausibly common within larger areas. We, therefore, assign regions to functional areas with common labor markets. Our large panel data set then allows us to eliminate all variation that is common within these labor market areas, including supply and demand effects, without removing localized knowledge spillovers.

The second major threat to the identification of human capital externalities is the endogenous sorting of individuals into regions (Acemoglu & Angrist, 2000). We address the spatial sorting of individuals with an extensive set of fixed effects. For instance, in our estimates, we use specific intercepts for every labor market area in every year. These fixed effects nullify unobserved regional heterogeneity that might attract high-skilled workers, such as average wages, general labor-market conditions or amenities. Because we allow fixed effects to vary over time, our procedure also eliminates temporal labor market shocks.

Our results suggest that regional immigration and labor market entries of high-skilled workers significantly raise the wages of locals, whereas emigration and labor market exits of high-skilled workers depress wages. Analyzing the evolution of effects reveals that positive externalities from immigration and entries grow over time, whereas negative externalities from emigration and exits remain stable. While in the short run negative externalities from outflows outweigh positive externalities from inflows, in the long run, positive externalities from inflows even overcompensate negative externalities from outflows. These findings are in line with our considerations that knowledge spillovers transmit through personal networks, that develop over time and that diverse human capital amplifies externalities.

Plausibly, human capital externalities are regionally limited. However, from a theoretical point of view it is unclear how far knowledge spillovers reach. While most empirical studies assess knowledge spillovers in predefined regions, Rosenthal & Strange (2008) are the first to abstract from fixed boundaries and try to estimate the spatial scope of knowl-

from schooling on wages. There are two possible explanations for the insignificant results. First, there are no positive externalities from schooling and other studies confound spillover effects with labor market demand and supply effects. Second, insignificant estimates are due to the choice of instruments. Identical to Acemoglu & Angrist (2000), Ciccone & Peri (2006) use changes in compulsory schooling laws and child labor laws to instrument average schooling. As argued before, changes in the lower part of the skill distribution might not create productive externalities (Krueger & Lindahl, 2001; Moretti, 2004). Therefore, the choice of instruments might explain why Ciccone & Peri (2006) find no evidence for schooling externalities.

edge spillovers. The authors construct concentric rings around workplaces that quantify the concentration of human capital within 5 miles, and between 5 to 25 miles and regress individual wages on the concentration of human capital within these rings. They show that externalities from the first ring are larger than spillovers from the second ring and conclude that spillover effects attenuate with distance. Fu (2007) and Verstraten (2018) adopt the strategy of Rosenthal & Strange (2008) and come to similar conclusions. Although these papers suggest that knowledge spillovers decrease with distance, the exact scope of effects remains unclear. The second chapter of the thesis is joint work with Christoph Rust and aims to fill this research gap.

We analyze a large and novel administrative micro panel dataset that has the exact coordinates of nearly all German establishments and rich information on individual workers. To process the detailed geographic information, we employ a novel estimation approach and measure the strength of knowledge spillovers with respect to distance in a continuous manner. Specifically, we use methods from functional data analysis (FDA). FDA is a branch in statistics that extends classical econometric methods to variables with a functional nature, such as curves. Typical examples of such data are temperature curves and stock prices over time. Continuity of curves entails that adjacent values are related. In many applications, exploiting this information makes FDA more efficient than classical multivariate methods. Specifically, we use the estimator of Crambes *et al.* (2009), which allows estimating the impact of a functional object (share of high-skilled workers with respect to distance) on a scalar variable (log wages). Our identification strategy is similar to that in the first chapter and bases on an extensive set of fixed effects.

We find that high-skilled workers increase the wages of others in their neighborhood. Moreover, our estimates show that spillover effects decay with distance. Specifically, knowledge spillovers from the close neighborhood are twice as large as spillovers from ten kilometers away. After fifteen kilometers, the effects vanish. Our findings imply that human capital externalities cover entire cities. However, a majority of the effects are bounded to the closer neighborhood. Individuals in very remote regions do not gain from knowledge spillovers.

Overall, the first two chapters of this thesis view human capital externalities from two new perspectives. The first chapter introduces dynamics that allow assessing the evolution of spillover effects after workers have moved. The second chapter explores the spatial scope of externalities with novel data and methodologies.

FDI and job stability

In addition to formal training, individuals invest in their human capital by learning on the job (Mincer, 1958; Blundell *et al.* , 1996; Gathmann & Schönberg, 2010). Thus, employment biographies shape the human capital stock of workers. While employment disruptions lead to the deterioration of human capital (Ben-Porath, 1967; Phelps, 1972; Heap, 1980; Möller, 1990), employment in more complex occupations potentially raises human capital (Mincer, 1958). The third chapter of this thesis, therefore, analyzes the employment stability of workers after an exogenous shock. Specifically, I investigate the impact of foreign direct investment (FDI) of firms on the likelihood of separations of workers and firms, and the probability to up- or downgrade to more or less complex jobs.

There is an ongoing public debate about the employment effects of globalization. While firms highlight benefits from internationalization through access to greater markets and the possibility to raise efficiency, politicians and workers are concerned with negative consequences for the domestic labor market. Scholars argue that globalization leads to a fragmentation of tasks, which might increase labor demand for some tasks, but decreases demand for others (Feenstra & Hanson, 1996a,b). Additionally, researchers emphasize that international trade raises productivity and thus might be beneficial for all workers (Grossman & Rossi-Hansberg, 2008). Determining the overall effects remains an empirical question.

The empirical literature on labor market effects of globalization almost exclusively focuses on effects on earnings and job separations (Hummels *et al.* , 2018). Overall, results suggest heterogeneous effects on different groups of workers. On the one hand, there is evidence that offshoring raises the wages of skilled workers (Feenstra & Hanson, 1997, 1999; Baumgarten *et al.* , 2013; Hummels *et al.* , 2014) and workers in non-routine and interactive tasks (Ebenstein *et al.* , 2014). On the other hand, offshoring depresses the wages of low-skilled workers (Hummels *et al.* , 2014; Baumgarten *et al.* , 2013) and of workers in occupations with very routine tasks (Ebenstein *et al.* , 2014). Findings on displacement effects of offshoring are mixed. For instance, Egger *et al.* (2007) find no evidence for negative employment effects from offshoring, whereas Geishecker (2008) present evidence that offshoring increases the risk of unemployment. Additionally, Munch (2010) illustrates that offshoring raises the hazard of being unemployed only for low-skilled workers. Furthermore, there is initial evidence that workers who lose their job due to offshoring take up training courses more often than other unemployed individuals (Hummels *et al.* , 2012).

Globalization changes the labor demand of firms. Although wages and displacements are important channels to adjust the labor force, the literature has overlooked that globalization might also incentivize firms to restructure their workforce internally. For several reasons, firms might benefit from restructuring their workforce internally instead of hiring and firing workers. First, incumbent workers have firm-specific human capital (Becker, 1962) and are thus *ceteris paribus* more valuable than outsiders. Second, asymmetric information about worker skills is less problematic when hiring internally (Waldman, 1984; Greenwald, 1986). Third, hiring internally might be cheaper than hiring externally (Demougin & Siow, 1994). Fourth, especially in regulated labor markets, it might be cheaper for firms to demote workers than to dismiss them. Together with Linda Borrs, I study how FDI influences internal restructuring. In particular, we assess the impact of FDI on internal up- and downgrades of workers to more or less complex jobs.

To the best of our knowledge, only Liu & Trefler (2011) and Baumgarten (2015) examine the effect of offshoring on job changes. Both papers present evidence that offshoring causes workers to switch occupations. However, compared to our contribution, the articles differ in two important aspects. While Liu & Trefler (2011) and Baumgarten (2015) analyze effects from industry-level offshoring, we study actual foreign direct investment of firms. Thus, we focus on a more specific treatment. Moreover, Liu & Trefler (2011) and Baumgarten (2015) consider very general occupational switches within and across firms, whereas we intentionally investigate firm-internal switches. As argued before, firm-internal restructuring itself represents a potential adjustment channel to changes in labor demand.

To analyze the effect of FDI on occupational up- and downgrades, and separations of workers and firms, we use a unique administrative linked employer-employee dataset. The data comprise the entire universe of German firms with Czech affiliates as of 2010 and a huge set of control firms that never invested abroad. We follow workers for twenty quarters after the investment abroad.

To identify effects, we pursue a three-step procedure. Because only the most productive firms conduct FDI (Helpman *et al.* , 2004), we first construct a balanced sample of treatment and control firms with equal probabilities to invest. To achieve this, we propose a new iterative matching procedure based on propensity score matching. Our iterative matching procedure achieves a distinct one-to-one matching of treatment and control firms over the entire observation period. In contrast to standard propensity score matching, our procedure additionally ensures that we match firms exactly in the same year. Importantly, our matching approach enables us to assign the investment dates of matched treatment firms as *pseudo* investment dates to control firms.

We match firms two years before investment. Because of the equal investment probabilities and the significant time lag between the matching and the (pseudo) investment, workers should be unable to distinguish between treatment and control firms at the time of matching. Second, to address unobserved sorting of workers into treatment firms (Abowd *et al.* , 1999; Card *et al.* , 2013), we restrict our data to individuals who already worked in the firm in the year of matching. Third, we use Cox (1972) proportional hazard models to compare the likelihood of job upgrades and downgrades and separations between treatment and control firms at the worker level. We define occupational upgrades (downgrades) as job switches within the firm to occupations with a higher (lower) share of analytical and interactive tasks.

We present first evidence that firms internally restructure their workforce after FDI. When firms invest abroad, the likelihood that workers will upgrade internally to more-complex jobs increases by 24 percent. The hazard to downgrade to less-complex jobs increases by 34 percent. Both effects grow over time and become traceable two years after the investment. Furthermore, we find that only workers performing non-routine and interactive jobs receive the opportunity to switch occupations internally after FDI. The same group of workers faces lower risks of employment separations. On average, we find only weak effects of FDI on separations of workers and firms.

In summary, chapter three shows that FDI raises the chance for workers to upgrade to jobs that are more complex. Plausibly, upgrades to more complex jobs are an opportunity for workers to raise their human capital over time. However, FDI also increases the risk of a downgrade to less complex jobs. Occupational downgrades are likely not beneficial for the human capital endowment of individuals. It might even be the case that downgrades deteriorate human capital.

Chapter 1

Human Capital Spillovers and the Churning Phenomenon: Analyzing Wage Externalities from Gross In- and Outflows of High-Skilled Workers

Abstract[*]

The article estimates human capital externalities on wages originating from internal gross migration flows of high-skilled workers. We draw on rich administrative micro panel data that allow us to disentangle externalities from sorting and labour market supply and demand effects through an extensive set of time-varying fixed effects. We show that regional inflows and outflows of high-skilled workers occur simultaneously and that both are positively correlated. Given the existence of such a churning phenomenon, looking only at net migration flows might be misleading. Our econometric analysis indicates that inflows of high-skilled workers increase the wages of locals, whereas outflows decrease those wages. Although externalities from outflows outweigh those from inflows in the short run, the opposite holds in the long run. Our results suggest that human capital externalities are transmitted through the productivity effects of local personal networks, which, for newcomers, develop over time.

Keywords: high-skilled workers, churning, brain gain, brain drain, human capital externalities, internal migration, wages

---

* This part is joint work with Joachim Möller. A revised version of the chapter is published in Regional Science and Urban Economics (Eppelsheimer & Möller, 2019)

JEL Codes: D62, J24, J31, O15, R10, R23

1.1 Introduction

There is a broad consensus among economists that the amount of human capital in a location plays a key role in its economic development. Hence, an increase in the share of high-skilled workers in the total workforce tends to spur economic performance in that location, whereas a decrease hinders it. Labour market entries and exits as well as migration of high-skilled workers lead to changes in the human capital endowment of an area. Migration streams can be regarded as merely an equilibrating force: excess demand for human capital attracts high-skilled workers, whereas excess supply deters them. Thus, areas with a high inflow of high-skilled workers should tend to have a low outflow and *vice versa*. As figure 1.1.1 shows, however, inter-regional inflow and outflow rates are even *positively* correlated in our data. This churning phenomenon corresponds to the well-established fact in labour economics that job turnover exceeds the minimal amount of turnover needed for job reallocation (e.g., Burgess *et al.* , 2000).

Thus far, the literature on the mobility of high-skilled workers almost exclusively focuses on net flows (Docquier & Rapoport, 2012). Analysing pure net flows neglects the churning phenomenon and could hide an important part of the story. In particular, net flow analysis would be inadequate if externalities from gains and losses of human capital were asymmetric. Consider, for instance, two regions that both have a zero net flow. Assume that region A has no inflow of high-skilled workers and that its incumbent workers are immobile, whereas region B has large outflows that are exactly matched by the number of inflows. If positive externalities from an incoming person do not compensate the negative externalities from an outgoing person, the effects of aggregate human capital in the two regions would clearly differ. As a consequence, net flow analysis could be misleading.

On the international level, empirical evidence already supports the existence of asymmetric effects. Docquier *et al.* (2014) analyse immigration and emigration streams in OECD countries to calculate wage and employment effects. Using a structural model, their study indeed highlights differences in the absolute size of wage effects from in- and outflows of human capital.[1] As the mechanisms of international migration probably work through different channels than do the changes in the human capital endowment of regions, an investigation of intra-country gross migration flows of high-skilled workers is required. To the best of our knowledge, our study is the first to fill this gap.

Generally, the existence of spillovers from high-skilled workers to other workers is

[1] In an earlier version of the paper (Docquier *et al.* , 2010), the authors find that in absolute values, the negative effects from emigration are roughly equal to the positive effects from immigration in the short run. In the long run, however, positive effects from immigration outweigh negative effects from emigration.

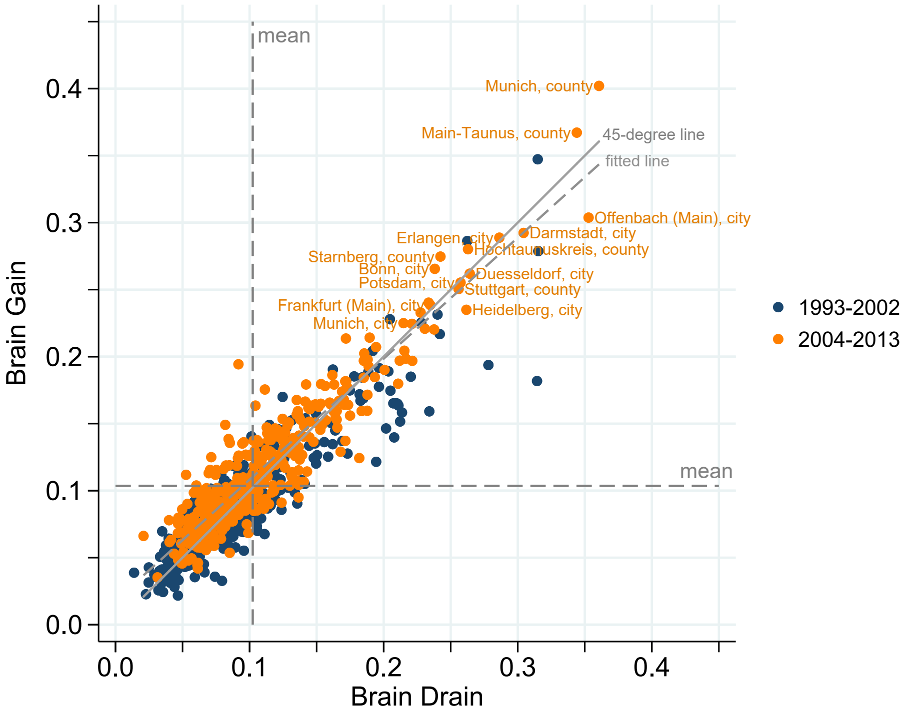
well documented in the literature (e.g., Che & Zhang, 2017; Cornelissen *et al.* , 2017; Ciccone & Peri, 2006; Moretti, 2004; Rauch, 1993). Less is known, however, about the underlying mechanisms of these spillovers. Theoretically, two traditional approaches address the positive externalities of aggregate human capital in a location. The first (Marshall, 1890; Lucas, 1988) stresses knowledge diffusion, whereas the second points to the productivity effects of implementing new technologies through high-skilled workers (Nelson & Phelps, 1966; Acemoglu, 1998). Empirical studies (Rosenthal & Strange (2008) and Fu (2007)) find that human capital externalities sharply decay with distance. The results point to the importance of inter-personal knowledge exchange, for instance, through face-to-face contacts and local personal networks. A simultaneous analysis of regional in- and outflows of high-skilled workers, as in our empirical approach, can shed more light on the importance of personal networks for knowledge spillovers. While local personal networks from incoming workers plausibly start small and develop over time, workers leaving the region generally abandon already well-established networks. Thus, if human capital externalities were mainly transmitted through personal networks, we would expect gradually increasing positive effects from high-skilled inflows but more or less abrupt negative effects from corresponding outflows.

An additional effect is related to the diversity literature (see Ottaviano & Peri, 2005; Timmermans & Boschma, 2014). An inflow of workers who accumulated knowledge in labour markets other than the current one might generate particularly large spillover effects. Other things being equal, a region with higher fluctuations in high-skilled workers should then be better off compared to a region with low mobility. Again, however, if the benefits of diversity work through personal networks, such a positive effect of diversity through brain gain should accrue over time.

Our paper scrutinizes inter-regional migration flows of high-skilled workers over two decades and uses detailed micro panel data on workers. The analysis builds on extensive research on human capital externalities within the urban economics literature (e.g., Rauch, 1993; Acemoglu & Angrist, 2000; Ciccone & Peri, 2006; Shapiro, 2006) and particularly on Moretti (2004), who theoretically derives and empirically investigates a relationship between individual earnings and aggregate levels of regional human capital. Using a Mincerian approach, Moretti (2004) finds a causal effect of the share of college-educated workers in an urban region on individual earnings.

We extend Moretti's approach to incorporate gross flows of high-skilled workers. In particular, we decompose the regional share of high-skilled workers in period t into the k-period's lagged share and inter-regional inflows and outflows of high-skilled workers between t and $t-k$. Additionally, we identify labour market entries of young high-skilled

Figure 1.1.1: Correlation between inter-regional inflows and outflows of high-skilled workers in 402 German counties



Notes: The figure shows the correlation between inter-regional gains and losses of human capital. We measure the human capital gain as the sum of incoming high-skilled workers over a period of ten years relative to the size of the workforce in the focal year. Accordingly, human capital losses are measured as the sum of emigrating high-skilled workers relative to the regional workforce in the focal year. The mean human capital gain is 0.1. Hence, within ten years, regions receive, on average, 10 high-skilled workers per 100 local workers through inter-regional migration.

workers and exits of retiring workers and extend the decomposition accordingly. In the spirit of Moretti, we employ Mincerian wage equations to estimate externalities from the separate components of regional human capital.

Moretti (2004) raises the concern that spillovers from high-skilled workers are inherently entangled with conventional labour market supply and demand effects that arise when the skill composition of the local labour market changes. To the best of our knowledge, only Ciccone & Peri (2006) explicitly address this problem in their identification strategy. The authors theoretically show that the size of human capital externalities is identical to the effect of human capital on the average regional wage when holding the skill composition constant, and they estimate spillover effects accordingly. We propose an alternative approach to disentangle spillover effects from conventional supply and demand effects. Our approach exploits the different spatial scopes of human capital externalities on the one hand and supply and demand effects on the other. Externalities attenuate sharply with distance and are thus strongly localized (Rosenthal & Strange, 2008; Fu, 2007). Therefore, the spatial scope of externalities should typically not exceed our basic spatial unit of observation, the county level. By contrast, supply and demand effects are plausibly common within larger areas. We therefore assign counties to functional areas with common labour markets. Our large panel data set allows us to eliminate all variation that is common within these labour market areas, including supply and demand effects. Technically, we achieve this by introducing time-varying fixed effects on the labour-market-area level in our econometric model.

When estimating human capital externalities, another major concern is endogenous sorting of highly productive workers into prosperous regions (Acemoglu & Angrist, 2000; Moretti, 2004). To address this problem, we adopt the strategy of Cornelissen *et al.* (2017), who deal with worker sorting on the firm level to estimate knowledge spillovers within establishments, and we control for an extensive set of (time-varying) fixed effects. First, the panel structure allows us to control for time-constant unobserved individual and regional heterogeneity and thus nullify general push and pull factors that might draw high-wage workers into regions with high wages and high levels of human capital. Second, we account for labour market shocks that could create temporal push and pull factors (see Moretti, 2004). These shocks might originate from global and local sources. To address shocks stemming from global sources, we purge the data for unobserved yearly variation on the industry and occupational levels. To eliminate shocks on the local level, we cluster administrative regions into functional labour market areas and add corresponding time-varying fixed effects to our econometric model. Furthermore, we control for time-varying observable characteristics of workers and regions. Overall, we assess how changes in the local concentration of high-skilled workers affect the wages of individuals with identical observable labour market characteristics, time-constant unobservable traits, who work in similar labour markets and identical industries and occupations.

We find that regional inflows and labour market entries of high-skilled workers significantly raise wages in the respective region, whereas the opposite is the case for outflows and labour market exits of high-skilled workers. As an important result, we show that in the short run, negative externalities from the emigration of high-skilled workers outweigh the positive externalities from immigration. Moreover, our econometric analysis supports the view that externalities from inflows of high-skilled workers grow over time, whereas externalities from outflows remain constant. Therefore, gains in human capital can eventually overcompensate equally sized losses in the long run. The former observation is in line with our conceptual considerations that externalities are transmitted through personal networks that develop over time. Moreover, our findings corroborate the hypothesis that enhancing diversity by importing the knowledge of high-skilled workers from other regions amplifies human capital externalities. Finally, our study shows that the effects of the intra-country mobility of high-skilled workers are qualitatively remarkably similar to what Docquier *et al.* (2014) find using a fundamentally different empirical approach to the international migration of human capital.

The remainder of the paper is organized as follows. In section 1.2, we extend the theoretical framework of Moretti (2004) and link individual wages in a specific county to regional gross flows of high-skilled workers. In the same section, we also outline our estimation strategy. Section 1.3 summarizes the data. In section 1.4, we sequentially report our findings. First, we present results from our baseline model, which relates individual wages to the regional stock of high-skilled workers. Second, we introduce some flexibility and allow idiosyncratic externalities from gross flows of high-skilled workers. Third, we illustrate the evolution of externalities over time. Section 1.5 summarizes the results and discusses some policy implications.

1.2 Theoretical framework and estimation strategy

1.2.1 Theoretical framework

The theoretical framework behind our empirical investigation is a modification of Moretti's model (Moretti, 2004). We begin by analysing a baseline model with human capital externalities and examine how changes in the regional share of high-skilled workers generate externalities that affect individual wages. We then extend this model and replace the regional share of high-skilled workers at time t by its lagged value in $t-k$ and various gross flows of high-skilled workers between $t-k$ and t (i.e., inter-regional inflows and outflows as well as labour market entries and exits of high-skilled workers).

Baseline model

Moretti (2004) illustrates externalities from the regional share of high-skilled workers on wages in a Cobb-Douglas-type production framework. Although this approach is well suited to analyse fundamental mechanics, we utilize the more general constant elasticity of substitution (CES) model (Arrow *et al.* , 1961) instead. The benefit of the CES specification is that it is capable of distinguishing idiosyncratic external effects from human capital spillovers for different types of workers. Bratti & Leombruni (2014) were the first to allude to this in the given context.

In our setting, output at time t, Y_t, is produced by using low-skilled and high-skilled workers, L_t and H_t, as the only inputs:

$$Y_t = \left[\gamma(A_{H,t}H_t)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_{L,t}L_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{1.1}$$

where σ is the elasticity of substitution and γ denotes a distributional parameter.

For both types of labour $s \in \{H, L\}$, the factor productivity $A_{s,t}$ depends on productivity-enhancing externalities generated by the regional share of high-skilled workers $h_t := H_t/N_t$ with $N_t = H_t + L_t$. We allow specific spillovers on low-skilled and high-skilled workers because empirical evidence suggests that these spillovers vary by worker type (Rosenthal & Strange, 2008; Heuermann, 2011; Bratti & Leombruni, 2014). For simplicity, let us assume that factor productivity is proportional to the regional share of high-skilled workers with the corresponding parameter λ_s:

$$\ln A_{s,t} = \lambda_s h_t, \quad s \in \{H, L\}, \qquad \lambda_H \geq \lambda_L \geq 0. \tag{1.2}$$

Under profit maximization and perfect competition, wages are equal to marginal productivity:

$$\ln(w_{L,t}) = \ln(1-\gamma) + \frac{\sigma-1}{\sigma}\ln A_{L,t} + \frac{1}{\sigma}\ln\left(\frac{Y_t}{L_t}\right) \quad \text{and} \tag{1.3}$$

$$\ln(w_{H,t}) = \ln\gamma + \frac{\sigma-1}{\sigma}\ln A_{H,t} + \frac{1}{\sigma}\ln\left(\frac{Y_t}{H_t}\right). \tag{1.4}$$

Next, we make use of the fact that the Cobb-Douglas production function is a special case of the CES function. By drawing on a suggestion by Kmenta (1967), we linearize the terms $\ln(Y_t/L_t)$ and $\ln(Y_t/H_t)$ around the Cobb-Douglas case ($\sigma = 1$) using Taylor's formula.[2] Neglecting terms with higher orders than two, the log wages for both types of workers are:

$$\ln w_{L,t} = \ln(1-\gamma) + \ln A_{L,t} + \frac{\gamma}{\sigma}z_t + \frac{\sigma-1}{\sigma}c_t, \tag{1.5}$$

$$\ln w_{H,t} = \ln\gamma + \ln A_{H,t} - \frac{1-\gamma}{\sigma}z_t + \frac{\sigma-1}{\sigma}c_t \tag{1.6}$$

2 The Taylor series approximation keeps things tractable. Note, however, that the approximation limits the analysis to solutions near the Cobb-Douglas case (see Thursby & Lovell 1978; Henningsen & Henningsen 2012).

with

$$z_t := \ln\left(\frac{A_{H,t}}{A_{L,t}}\right) + \ln\left(\frac{h_t}{1-h_t}\right) \qquad \text{and} \qquad c_t := \frac{(1-\gamma)\gamma}{2}\, z_t^2.$$

Substituting equation (1.2) for factor productivities and taking derivatives yields the response of wages to an increasing regional share of high-skilled workers:

$$\frac{\partial \ln w_{L,t}}{dh_t} = \lambda_L + \frac{\gamma}{\sigma}\, z_t' + \frac{\sigma-1}{\sigma}\, c_t', \tag{1.7}$$

$$\frac{\partial \ln w_{H,t}}{dh_t} = \lambda_H - \frac{1-\gamma}{\sigma}\, z_t' + \frac{\sigma-1}{\sigma}\, c_t' \tag{1.8}$$

with

$$z_t' := \lambda_H - \lambda_L + \frac{1}{(1-h_t)h_t} \qquad \text{and} \qquad c_t' := (1-\gamma)\gamma z_t' \left[(\lambda_H - \lambda_L)h_t + \ln\left(\frac{h_t}{1-h_t}\right)\right].$$

In the Cobb-Douglas case ($\sigma = 1$), both types of workers benefit from identical spillover effects, $\gamma\lambda_H + (1-\gamma)\lambda_L > 0$. Low-skilled workers additionally gain from a neoclassical relative supply effect, $\gamma/((1-h_t)h_t) > 0$, whereas this effect reduces the wages of high-skilled workers, $-(1-\gamma)/((1-h_t)h_t) < 0$. However, research on labour demand has established that low-skilled and high-skilled workers are gross substitutes, i.e., $\sigma > 1$ (see, for instance, Autor *et al.* (2008); Ciccone & Peri (2005); Card & Lemieux (2001); Krusell *et al.* (2000)). Wage effects are then the sum of group-specific effects ($\lambda_L + (\gamma/\sigma)z_t'$ and $\lambda_H - ((1-\gamma)/\sigma)z_t'$, respectively) and a general correction term due to deviation from the Cobb-Douglas form ($((\sigma-1)/\sigma)c_t'$). Note that for $\sigma > 1$, specific spillover effects on high-skilled workers exceed those on low-skilled workers: $\lambda_H - [(1-\gamma)/\sigma](\lambda_H - \lambda_L) > \lambda_L + (\gamma/\sigma)(\lambda_H - \lambda_L) > 0$. Again, low-skilled workers gain from relative supply effects, whereas the wages of high-skilled workers are reduced: $(\gamma/\sigma) \times ((1-h_t)h_t)^{-1} > 0$, $-(1-\gamma)/\sigma \times ((1-h_t)h_t)^{-1} < 0$. In absolute values, these relative supply effects are smaller than in the Cobb-Douglas case. The reason is that – given that the two types of labour are gross substitutes – the factors are more easily exchangeable, and thus, firms can react more flexibly to a changing supply of high-skilled workers.

Additionally, a general correction term, c_t', appears in equations (1.7) and (1.8) for both types of workers. This correction includes a spillover and a relative supply effect as well as an interaction of the two. Both the spillover and the interaction effect of the general correction increase the wage, whereas the relative supply effect decreases it.[3]

[3] Actually, the relative supply effect only decreases wages if the regional share of high-skilled workers is below 50 percent. Because the regional share of high-skilled workers is, in fact, always well below 50 percent in our data, we only consider this scenario. To prevent the model from generating extreme relative supply effects, we also exclude the possibility of shares of high-skilled workers being close to

Typically, worker-specific effects dominate the general correction. Hence, if the regional share of high-skilled workers increases, low-skilled workers will benefit from spillover and relative supply effects. High-skilled workers gain more from spillover effects, but the relative supply effect reduces their wages. Hence, the total effect on high-skilled workers is theoretically indeterminate in sign. Note, however, that in the case of strong spillover effects for the high-skilled workers and low relative supply effects, it might well be that the total wage effect of human capital spillovers for the high-skilled workers exceeds the effect for the low-skilled workers.

Average wage effects are a weighted sum of worker-type wage effects:

$$(1-h_t)\frac{\partial \ln w_{L,t}}{\partial h_t} + h_t\frac{\partial \ln w_{H,t}}{\partial h_t} = \frac{\partial \ln w_{L,t}}{\partial h_t} + \frac{h_t}{\sigma}\left[(\sigma-1)(\lambda_H-\lambda_L) - \frac{1}{(1-h_t)h_t}\right]. \tag{1.9}$$

Clearly, human capital spillovers increase average wages, whereas the sign of the supply effect depends on the relative number of low-skilled to high-skilled workers. Only for very large spillover differences ($\lambda_H - \lambda_L \gg 0$) does the general correction exceed the worker-specific effects. In this special case, the overall correction is positive because the negative supply effect is compensated by the interaction of spillover and supply effects, which also grows with ($\lambda_H - \lambda_L$). Thus, in total, both types of workers would unambiguously benefit from an increasing regional share of high-skilled workers.

Gross flow model

To incorporate the reaction of wages to specific changes in the regional share of high-skilled workers, we now extend the baseline model. We first decompose the current number of high-skilled workers, H_t, into the k-period lagged number, H_{t-k}, and various gross flows of high-skilled workers between period $t-k$ and t. Let $D_{t-k,t}$ describe the emigration of high-skilled workers and $G_{t-k,t}$ the immigration of high-skilled workers between periods $t-k$ and t. Correspondingly, $R_{t-k,t}$ and $E_{t-k,t}$ stand for exits of high-skilled workers through retirement and new entries into the labour market, respectively. Finally, $U_{t-k,t}$ captures all other flows of high-skilled workers that are not explicitly addressed so

zero.

far.[4] Hence, one can write

$$H_t = H_{t-k} - D_{t-k,t} + G_{t-k,t} - R_{t-k,t} + E_{t-k,t} - U_{t-k,t}. \tag{1.10}$$

Let $\hat{n}_{t-k,t}$ be the growth rate of the total workforce in the region between period $t-k$ and t and define brain drain and brain gain as the accumulated outflows and inflows between $t-k$ and t divided by the workforce in period t.[5] Using a corresponding definition for labour market entries and exits, one can re-write equation (1.10) in relative terms

$$\begin{aligned} h_t &= \frac{h_{t-k}}{1+\hat{n}_{t,k}} - \underbrace{\frac{D_{t-k,t}}{N_t}}_{\text{brain drain}} + \underbrace{\frac{G_{t-k,t}}{N_t}}_{\text{brain gain}} - \underbrace{\frac{R_{t-k,t}}{N_t}}_{\text{exits}} + \underbrace{\frac{E_{t-k,t}}{N_t}}_{\text{entries}} - \underbrace{\frac{U_{t-k,t}}{N_t}}_{\text{others}} \\ &= \tilde{h}_{t-k} + \sum_{f=1}^{5} (-1)^f \dot{h}_{f,t-k,t}, \qquad \text{for } f = 1, \cdots, 5\ , \end{aligned} \tag{1.11}$$

where $\tilde{h}_{t-k} := h_{t-k}/(1+\hat{n}_{t-k,t})$, $\dot{h}_{1,t-k,t} := D_{t-k,t}/N_t$, and the rates $\dot{h}_{f,t-k,t}, f = \{2, \cdots, 4\}$ are defined accordingly. Outflows lower the current share of high-skilled workers ($f \in \{1,3,5\}$), and inflows raise the share ($f \in \{2,4\}$). Adjusting the productivity shifter in equation (1.2) accordingly yields

$$\ln A_s = \lambda_{0,s}\tilde{h}_{t-k} + \sum_{f=1}^{5} (-1)^f \lambda_{f,s}\dot{h}_{f,t-k,t}, \quad \text{with } s \in \{L, H\} \text{ and } \lambda_{f,H} \geq \lambda_{f,L} \geq 0. \tag{1.12}$$

The adjusted productivity shifter allows each gross flow to generate a specific spillover effect. Plugging equations (1.11) and (1.12) into equations (1.5) and (1.6) and taking first

---

4 The rest term contains temporal transitions into and out of unemployment if the regions where workers become unemployed and employed are identical within the observation period. The emigration of middle-aged high-skilled workers out of the economy and immigration from other countries into the economy are also captured in $U_{t-k,t}$. To simplify the following equations, we assign here a negative sign to flows into $U_{t-k,t}$ and a positive sign to flows out of $U_{t-k,t}$.

5 In the public debate, the terms brain drain and brain gain are often confounded with one-sided value judgments. The recent literature stresses that brain drain (gain) must not necessarily be negative (positive) (Clemens, 2016; Docquier & Rapoport, 2012). In the context here, brain drain and brain gain are understood to be neutral and are only used as shortcuts for emigration and immigration of high-skilled workers.

derivatives gives the wage effects of a particular gross flow, $\dot{h}_{f,t-k,t}$:

$$\frac{\partial \ln w_{L,t}}{\partial \dot{h}_{f,t-k,t}} = (-1)^f \left\{ \lambda_{f,L} + \frac{\gamma}{\sigma}\, z'_{f,t} + \frac{\sigma-1}{\sigma}\, c'_{f,t} \right\} \quad \text{and} \tag{1.13}$$

$$\frac{\partial \ln w_{H,t}}{\partial \dot{h}_{f,t-k,t}} = (-1)^f \left\{ \lambda_{f,H} - \frac{1-\gamma}{\sigma}\, z'_{f,t} + \frac{\sigma-1}{\sigma}\, c'_{f,t} \right\} \tag{1.14}$$

with

$$z'_{f,t} := \lambda_{f,H} - \lambda_{f,L} + \frac{1}{(1-h_t)h_t} \quad \text{and} \quad c'_{f,t} := (1-\gamma)\gamma z'_{f,t} \left[\ln A_H - \ln A_L + \ln\left(\frac{h_t}{1-h_t}\right)\right].$$

In contrast to the baseline model, there are now distinct spillover effects corresponding to each gross flow. Inflows of high-skilled workers (brain gain and entries) entail positive spillover effects on both types of workers, whereas outflows (brain drain and exits) entail negative ones. More precisely, the negative spillover effects of outflows are the forgone effects that the outflows would have generated had they stayed.

Similar to the baseline model, the supply effects are different for low-skilled and high-skilled workers. Because their relative scarcity rises, low-skilled workers gain from the supply effects of an inflow of high-skilled workers and *vice versa*. In contrast, for high-skilled workers, spillover and relative supply effects work in the opposite direction. Therefore, the total impact of an increasing concentration of regional human capital on high-skilled workers' wages is theoretically ambiguous. If spillover effects are much larger for the high-skilled workers, $\lambda_{f,H} - \lambda_{f,L} \gg 0$, the general correction dominates the worker-specific effects. In this special case, both types of workers will unambiguously gain from inflows, while outflows will decrease wages. Moreover, the absolute value of the spillover effect of a particular gross flow is larger for high-skilled workers than for low-skilled workers.

1.2.2 Estimation strategy

Based on our theoretical considerations, we aim to empirically investigate the existence and strength of human capital externalities. We carefully take into account two major concerns in the related literature, i.e., spatial sorting of workers and the entanglement of spillover and conventional supply and demand effects (Acemoglu & Angrist, 2000; Moretti, 2004; Ciccone & Peri, 2006). Our empirical strategy is to include various constant and time-varying fixed effects along with a comprehensive set of covariates to isolate regional human capital externalities from other influences.

For the empirical analysis, we employ three estimation equations. The first equation corresponds to our theoretical baseline model and builds on an augmented skill-specific Mincerian wage equation for an individual i living in region r observed at time t:

$$\begin{aligned}\ln w^s_{i,r,t,b,o,l,n} = \eta^s h_{r,t} + \mathbf{X}_{i,t}\alpha^s + \mathbf{Z}_{r,t}\beta^s + \mu_i + \rho_r + \tau_t + \iota_b + \omega_o \\ + \tilde{\iota}_{bt} + \tilde{\omega}_{ot} + \phi_{\ell t} + \epsilon^s_{i,r,t,b,o,l,n}, \quad s \in \{H, L\}. \quad (1.15)\end{aligned}$$

In our theoretical model, the individual log wage of a worker of skill group s responds to the regional share of high-skilled workers $h_{r,t}$; hence, the corresponding parameters η^H and η^L are of particular interest. $\mathbf{X_{i,t}}$ is a row vector of relevant labour market characteristics of the individual worker and his or her workplace, and α^s is the corresponding parameter vector. The row vector $\mathbf{Z_{r,t}}$ is related to the parameter vector β^s and contains regional characteristics such as population density or the number of hotel beds as a proxy for amenities. Confounding variation from local labour market conditions is proxied by including the regional unemployment rate as control. To capture the effects of changes in the regional composition of firms, we add separate indicators for openings and closures of small and large firms to the model.[6]

To control for unobserved heterogeneity and the sorting of high-skilled workers into high-wage regions, we include a set of fixed effects for worker (μ_i), region (ρ_r), time (τ_t), industry (ι_b) and occupation (ω_o). In particular, the inclusion of worker and region fixed effects captures general push and pull factors that draw high-skilled workers into thriving regions. To address temporal shocks stemming from global sources, we expand equation (1.15) with time-varying fixed effects. These fixed effects should absorb all industry ($\tilde{\iota}_{bt}$) or occupation ($\tilde{\omega}_{ot}$) specific shocks and thereby substantially reduce the sorting problem. To further lessen any concern about biased estimates, we additionally cluster administrative regions into functional labour market areas and include time-varying labour-market-area fixed effects $\phi_{\ell t}$ in the model. In the estimation, we therefore only exploit variation stemming from administrative regions that deviate from the time trend of their respective labour market areas, and hence, we eliminate all shocks that are related to the labour market area.[7]

6 As indicators for openings and closures of small and large firms, we aggregate the number of regional openings and closures of firms with fewer and more than 300 employees, respectively.

7 A common strategy to address regional sorting in the urban economics literature is the use of instrumental variable estimates. For instance, Moretti (2004) uses the lagged demographic structure and land grant colleges as sources of exogenous variation. However, an estimation strategy based on instrumental variables is (almost) infeasible in our application. The reason is that we would need five independent instruments in the gross flow model below – one for brain gain, one for brain drain, one for entries, one for exits and one for the lagged share of high-skilled workers.

However, our theoretical model also highlights a second concern expressed in the literature on human capital externalities, namely, the entanglement of spillovers and conventional supply and demand effects (e.g., Ciccone & Peri 2006). We address this problem by exploiting the different natures of spillover and supply effects. While spillovers attenuate sharply with distance and are hence very localized (Rosenthal & Strange, 2008; Fu, 2007), we argue that supply effects operate within larger areas. Therefore, assigning counties to functional areas with common labour markets enables us to disentangle spillover from supply effects. By including time-varying labour-market-area fixed effects in equation (1.15), we eliminate all variation that is common within functional labour markets, e.g., supply effects; however, variation that deviates from the common time trend of the local labour market area remains in the model, e.g., spillover effects.

To define functional labour market areas, we resort to Kosfeld & Werner (2012), who use a factor analysis to cluster German counties into functional labour markets based on commuter flows. These labour market areas are designed to represent common seclusive labour markets. There are 141 such labour market areas in Germany, which integrate 402 counties. The number of counties within a labour market area ranges from one to eleven and has a mean of four. The majority of labour market areas include three or four counties.[8] [9]

Overall, our estimation framework measures external effects from changes in the concentration of high-skilled workers within counties that are unrelated to changes in the wider local labour market area. Within counties, changes are also unrelated to industry or occupation trends. Furthermore, changes in the local share of high-skilled workers are orthogonal to time-variant observable characteristics of workers and counties as well as to time-constant unobservable characteristics. In other words, we assess how changes in the local concentration of high-skilled workers affect the wages of individuals with the same observable labour market characteristics and equivalent time-constant unobservable traits who work in similar labour markets and identical industries and occupations. Under the condition that our extensive set of fixed effects and control variables suffice to address the sorting and the entanglement of spillover as well as supply and demand effects, our estimation framework therefore identifies the impact of human capital externalities on individual wages.

Our second econometric model corresponds to the gross flow model of subsection 1.2.1

[8] Figure 1.A.1 in Appendix 1.A.3 shows a histogram of the number of counties within labour market ares.

[9] If a labour market area consists of only one county, time-varying labour-market-area fixed effects absorb all regional variation. Thus, affected observations do not contribute to the estimation of spillover effects. However, as we will see in section 1.4, this does not change the results.

and includes the same control variables and fixed effects as equation (1.15). However, because it allows various flows of high-skilled workers to have an idiosyncratic effect on wages, it is more general. First, we consider gross flows within the past ten years relative to the current year t:

$$\ln w^s_{i,r,t,b,o,\ell,n} = \eta^s \tilde{h}_{r,t-10} + \mathbf{F_{r,t-10,t}}\theta^{\mathbf{s}} + \mathbf{X_{i,t}}\alpha^{\mathbf{s}} + \mathbf{Z_{r,t}}\beta^{\mathbf{s}} + \mu_{\mathbf{i}} + \rho_{\mathbf{r}} + \tau_{\mathbf{t}} + \iota_{\mathbf{b}} + \omega_{\mathbf{o}} + \tilde{\iota}_{bt} + \tilde{\omega}_{ot} + \phi_{\ell t} + \epsilon^s_{i,r,t,b,o,\ell,n}, \quad s \in \{H, L\}. \quad (1.16)$$

$\mathbf{F}_{r,t-10,t}$ represents a row vector that contains the gross flow rates of human capital over a time period of ten years, and θ^s is the corresponding parameter vector. More specifically, $\mathbf{F}_{r,t-10,t}$ includes gains and losses of human capital through inter-regional mobility, entries of young high-skilled workers into the labour market, retirement of elderly high-skilled workers and other unspecified changes in the regional concentration of human capital that are not explicitly modeled:[10]

$$\mathbf{F}_{r,t-10,t} := \left(\frac{D_{r,t-10,t}}{N_{r,t}}, \frac{G_{r,t-10,t}}{N_{r,t}}, \frac{E_{r,t-10,t}}{N_{r,t}}, \frac{R_{r,t-10,t}}{N_{r,t}}, \frac{U_{r,t-10,t}}{N_{r,t}} \right). \quad (1.17)$$

All gross flows are relative to the number of workers N in region r at time t. To consistently replace the regional share of high-skilled workers by gross flows, it is necessary to add the lagged share of high-skilled workers divided by the growth rate of the regional workforce, $\tilde{h}_{r,t-10}$, to equation (1.16).[11] The remaining control variables in equation (1.16) are identical to those in the baseline model of equation (1.15).

As illustrated in the introduction (Figure 1.1.1), regional in- and outflows of high-skilled workers are highly positively correlated. Primarily, strong multicollinearity among regressors reduces the efficiency of the model. However, as we will see in section 1.4.2, there is enough variation in the data to precisely estimate spillovers from in- and outflows of high-skilled workers. Thus, efficiency is not an issue in our application. Furthermore,

---

[10] To implement these flow measures, we impose the condition that entrants must be younger than 30 years and permanent leavers older than 58 years.

[11] Including the lagged share of high-skilled workers in equation (1.16) is in accordance with the theoretical considerations made in the previous section. Moreover, it accounts for empirical findings suggesting a relationship between the local share of high-skilled workers and its growth. In the US, the skill composition of regions seems to follow a divergence process, which means that the gap between locations with high and low concentrations of human capital increases over time (Berry & Glaeser 2005, Glaeser *et al.* 2014). Waldorf (2009) finds that, on average, regions with a well-educated labour force attract better-educated migrants than regions with a less-educated labour force. Contrary to the findings for the US, Südekum (2008) identifies a convergence process of the skill distribution across German counties. In any case, the regional share of high-skilled workers seems to exert an influence on its future growth.

estimating various gross flows within one model isolates each gross flow from the influences of the others. Thus, point estimates should be valid. Another concern might be that strong multicollinearity leads to unstable estimates. However, our results clearly rebut these concerns. We further discuss these topics in section 1.4.5.

Additionally, we investigate how spillovers from in- and outflows of high-skilled workers evolve over time. To do so, we estimate a third model, in which we split up the vector of total gross flows between $t - 10$ and t into five separate two-year gross flows $\tilde{\mathbf{F}}_{r,t-\tau,t-\tau+2}$, where $\tau = 10, 8, \cdots, 2$. Estimating equation (1.16) with these two-year flows allows us to study the evolution of wage effects over time and to distinguish between short-term and long-term effects.

Clearly, splitting each gross flow into several two-year flows further impairs the efficiency of our model. However, as we will see in section 1.4.4, there is still enough variation in the data to precisely estimate the model. Moreover, the smooth connection between the calculated point estimates underpins the identification of isolated effects.

Due to the fixed effects in our specifications, variation in the regional concentration of high-skilled workers comes from two sources. First, for individuals who do not change their workplace location (‘*stayers*’), variation stems from changes in the regional concentration of high-skilled workers over time. Second, for individuals who change their location (*‘movers’*), variation stems from the difference between their new and old locations. Because most policy implications are particularly relevant for stayers, we restrict the data to stayers in our main estimates. Focusing on stayers also eases the interpretation of the results. We define stayers as workers who have not changed the county of their workplace within a period of at least ten years or since labour market entry. The robustness section shows that the effects on stayers only and stayers and movers together are very similar.

1.3 Data and descriptive statistics

1.3.1 Data

Our main database is the ‘Sample of Integrated labour Market Biographies’ (SIAB), provided by the Institute of Employment Research, Nuremberg (IAB). The SIAB is a random register data sample of all employees subject to social security in Germany. Self-employed workers and public servants are excluded. The data set gives information on wage, age, education and further personal characteristics. Note that information on wages is highly reliable because employers will face legal sanctions in the event of misreporting.

We restrict the data to regular full-time workers and thus exclude part-time workers and marginally employed workers. Furthermore, we only consider workers between the ages of 18 and 64 who have completed their educational training. We transfer the spell data into a yearly panel with June 30 as the reference date.

The wage data are top-coded because of the contribution assessment ceiling in the German social security system. However, this affects no more than 9 percent of our observations. As a correction method, we use an imputation procedure similar to that employed by Dustmann *et al.* (2009) and Card *et al.* (2013) (see Appendix 2.A.1). Wages in the data source are given per calendar day of the corresponding employment spell. We deflate these daily wages by a general price index with 2010 as the base year. As suggested by Fitzenberger *et al.* (2005), we improve the education variable in the data set. Occupations are classified based on Schimpl-Neimanns (2003). The IAB also provides information on the size, industry and location of employers (BHP)[12]. We use a 3-digit industry classification that is consistent over our observation period (Eberle *et al.* , 2014). Regional information refers to the workplace of individuals, not their place of residence.

Additionally, we add regional characteristics of the 402 German counties ("*Landkreise und kreisfreie Städte*")[13] to the data set. The Federal Institute for Research on Building, Urban Affairs and Spatial Development supplies information on population density, number of hotel beds (our proxy for amenities) and the local unemployment rate.

We define the high-skilled as workers with a degree from a university or university of applied science.[14] For simplicity, we refer to all non-high-skilled workers as low-skilled. Because the years shortly after the German reunification might distort our estimates, gross flows of high-skilled workers are calculated for the years 1993 and later. Because we consider flows of high-skilled workers in time frames up to $k = 10$ years, the multivariate analysis is restricted to the period 2002-2013. As explained in the previous section, we restrict our main analysis to *stayers* (i.e., workers who do not move between regions). As a result of the selection process, 3,030,957 observations of 469,668 individuals remain in the sample.

12 For further information on the data provided by the IAB, see Antoni *et al.* (2016) and Schmucker *et al.* (2016).

13 German counties are identical to the NUTS-3 level.

14 Universities of applied science are in general very similar to classical universities. However, universities of applied science focus more on applied topics and tend to have closer connections to the private sector than do classical universities.

1.3.2 Descriptive statistics

Table 1.3.1 gives an overview of key variables at the regional level. The average wage of full-time workers in Germany is 108 euros per calendar day. The average regional share of high-skilled full-time workers is 13.1 percent, ranging from a minimum of 3 percent in some peripheral rural regions to a maximum of 42 percent in the city of Erlangen, which hosts a technical university and the headquarters of large companies such as Siemens.

Although German re-unification occurred more than 25 years ago, there are still apparent differences between the western and eastern parts of the country. Although the share of high-skilled workers grew steadily in West Germany and more or less stagnated in East Germany during our observation period, the average share of high-skilled workers in East Germany is still larger than that in West Germany. The explanation is the historically high share of (formally) high-skilled workers in East Germany.[15] However, part of the human capital acquired in the socialist system might have become obsolete. Furthermore, Blien *et al.* 2016 stress the fact that there are almost no headquarters of large firms located in the *new laender*. Hence, research and development departments are less common there. Note that despite the higher shares of high-skilled workers in the east, average West German wages exceed East German wages by 36 Euros in our observation period.

Table 1.3.1 also shows gross flows of high-skilled workers for a time frame of $k = 10$ years. For the complete sample, the average rate of brain gain is 10.4 percent. This means that an average region experiences the immigration of 10.4 high-skilled workers per 100 local workers in all skill categories within ten years. The average brain drain is 10.2 percent and is thus slightly lower than the average brain gain. Both rates vary considerably across regions. Most of the mobility of high-skilled workers is either within East or within West Germany. This is especially true for the *old laender*. For instance, the average brain drain from a West German county to an East German county is only 0.4 percent and makes up no more than 4 percent of the overall brain drain. Although the brain drain from East Germany towards West Germany is notably higher, it does not exceed 16 percent of the overall brain drain.

In contrast to most datasets on international migration, our data include all sending and receiving regions. Hence, by definition, an emigrant from one region is an immigrant in another region. Consequently, the absolute number of immigrations and emigrations are equal. However, because we measure brain gain and brain drain in relative

[15] Until the early 1970s, East Germany had notably more first-year university students per capita than West Germany did (Baumert *et al.* 1994).

Table 1.3.1: Descriptive statistics of key variables at the county level (2002-2014)

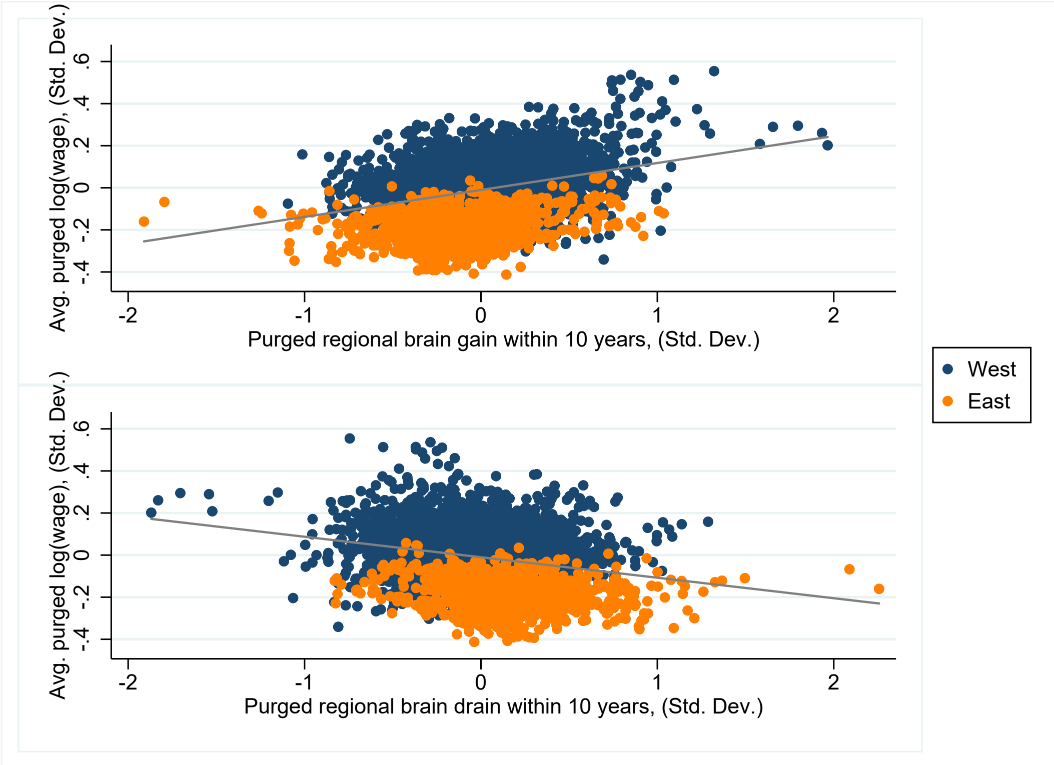
	Mean	**Std. Dev.**	**25th Perc.**	**Median**	**75th Perc.**
			All (402 counties, 12 years)		
Daily wage	108.05	30.09	89.35	103.08	120.00
Share of high-skilled	0.131	0.059	0.092	0.119	0.154
Brain Gain	0.104	0.050	0.070	0.093	0.124
Brain Drain	0.102	0.052	0.066	0.091	0.123
Entries	0.041	0.022	0.026	0.035	0.049
Exits	0.016	0.013	0.007	0.012	0.021
			West Germany (325 counties, 12 years)		
Daily wage	114.84	29.04	96.16	108.51	124.44
Share of high-skilled	0.126	0.058	0.087	0.113	0.150
Brain Gain	0.102	0.051	0.069	0.091	0.121
Brain Drain	0.098	0.052	0.063	0.087	0.117
(within West)	0.094	0.051	0.060	0.083	0.112
(from W. to E.)	0.004	0.003	0.002	0.004	0.006
Entries	0.042	0.022	0.027	0.036	0.050
Exits	0.012	0.007	0.006	0.010	0.016
			East Germany (76 counties, 12 years)		
Daily wage	78.86	11.39	70.57	75.42	84.50
Share of high-skilled	0.151	0.055	0.115	0.137	0.165
Brain Gain	0.110	0.043	0.076	0.100	0.140
Brain Drain	0.119	0.051	0.081	0.108	0.144
(within East)	0.100	0.043	0.068	0.090	0.122
(from E. to W.)	0.019	0.010	0.012	0.018	0.024
Entries	0.036	0.020	0.024	0.031	0.042
Exits	0.036	0.014	0.027	0.034	0.044

Notes: Brain gain and brain drain are measured as in- and out-migrations of high-skilled workers within the past ten years relative to the total regional workforce in the focal period. Berlin is only included in the overall sample. Daily wages represent gross earnings per calendar day.

terms (i.e., relative to the number of workers in sending or receiving regions), the average brain gain and brain drain would only be identical if all counties had the same number of workers. Because we simultaneously observe migrants as immigrants and emigrants, the pre-migration characteristics of workers are identical. Additionally, the data also show that pre-migration wages relative to wages in sending or receiving regions are almost the same. Specifically, high-skilled immigrants earn 10 percent less than incumbent high-skilled workers, and high-skilled emigrants earn 11 percent less than workers who stay in the region.

Figure 1.4.1 gives a first impression of the relationship between wages of incumbent workers and the immigration and emigration of high-skilled workers. After purging all three variables of basic individual, firm and regional characteristics, we see a positive correlation between wages and brain gain and a negative correlation between wages and

Figure 1.3.1: Correlation between aggregated individual wages and brain gain / brain drain (325 West German counties and 76 East German counties)



Notes: The figure shows the correlation between brain gain / brain drain and wages, purged from basic individual and regional influences. The control variables used to generate the graphs are age, experience, tenure, education, gender, nationality, firm size, population density and year dummies. Both axes are measured in standard deviations. Each dot represents a county-year. Wages are averaged on the county-year level.

brain drain.

1.4 Empirical results

1.4.1 Baseline model

Before we proceed to examine the gross flow model, we first present estimates of our baseline model, which explains individual wages by the regional share of high-skilled workers. With respect to theory and the described differences between the two parts of the country, separate results are shown for different skill groups for the whole sample and for West and East Germany separately.

Table 1.4.1 summarizes the findings. The first column shows results without controls for regional labour market shocks. In column (2), we include the local unemployment rate and industry-year dummies. In column (3), we add regional openings and closures of small and large firms and occupation-year dummies. The most comprehensive specification in column (4) also contains yearly labour market area fixed effects. Overall, the results confirm the conceptual implications. In all estimates for the whole sample, the regional share of high-skilled workers is positively related to wages. Adding more controls in columns (2) to (4) lowers the estimated coefficient, but it remains statistically and economically significant. According to the most comprehensive specification in column (4), a one standard deviation increase in the regional share of high-skilled workers raises wages by 1.3 percent ($100 \times 0.213 \times 0.059$). Compared to the papers by Moretti (2004) for the U.S. or Heuermann (2011) for Germany, this point estimate is approximately three-fourths lower. The difference is likely due to the tight set of controls used in our most comprehensive specification. Note that here, we only exploit variation in the regional share of high-skilled workers that deviates from the time trend of the labour market area, which, from a worker's perspective, does not stem from shocks or trends in his or her industry or occupation. Interestingly, our results are similar to those of Cornelissen *et al.* (2017), who measure peer effects within establishments and apply a comparable comprehensive identification strategy.

The inclusion of yearly labour market area fixed effects in columns (4) to (8) potentially allows us to interpret the estimated effects as pure spillovers that are not confounded by supply effects. Note that the estimated coefficients in columns (3) and (4) are nearly identical, indicating that the specification of column (3) already absorbs major supply effects. What also stands out in Table 1.4.1 is that the wage effect of the regional share of high-skilled workers is considerably smaller and only weakly significant in the East German sample - a result we will also see in the gross flow model. A possible explanation for this might be the differences between formal university degrees attained in the Federal Republic of Germany and West Germany.

In columns (7) and (8), we differentiate between low-skilled and high-skilled workers. As mentioned in the data description, wages are top-coded. Although this is the case for only a small fraction of the whole sample, a considerable proportion of the high-skilled sample is affected. To compare estimates of low-skilled and high-skilled workers, we therefore restrict the sample to workers younger than 35 in columns (7) and (8). In this age group, even in the high-skilled group, only 14 percent of wages are top coded.

As modeled in section 1.2, Table 1.4.1 shows that (young) high-skilled workers gain more from human capital externalities than do low-skilled workers. Through spillovers, a one-standard-deviation increase in the regional share of high-skilled workers even raises the wages of the high-skilled by 4.0 percent. However, our conceptual framework also

Table 1.4.1: Regression results for the baseline model

	Dependent variable: individual log wage							
					Region		Skill level	
	All	All	All	All	West	East	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share high-skilled	0.442***	0.283***	0.218***	0.213***	0.224***	0.108	0.258***	0.686**
	(0.063)	(0.040)	(0.036)	(0.037)	(0.042)	(0.060)	(0.047)	(0.211)
	Further controls							
Unemployment	–	Y	Y	Y	Y	Y	Y	Y
Firm composition	–	–	Y	Y	Y	Y	Y	Y
	Interaction dummies							
Industry × year	–	Y	Y	Y	Y	Y	Y	Y
Occup. × year	–	–	Y	Y	Y	Y	Y	Y
Lab. area × year	–	–	–	Y	Y	Y	Y	Y
N	3,011,957	3,011,943	3,011,942	3,011,942	2,416,931	464,456	676,122	107,628
Counties	402	402	402	365	299	59	365	365
$\bar{R}^2$	0.879	0.880	0.881	0.881	0.872	0.906	0.883	0.772

Notes: All regressions include worker, occupation, industry, region and year fixed effects. Estimates also include a constant, worker controls (age, age^2, experience, experience^2, tenure, tenure^2 and education dummies), firm size and regional controls (population density and number of hotel beds as a proxy for amenities). The estimation period is from 2002 to 2013. Column 7 and 8 include workers younger than 35 only. Two-way robust clustered standard errors with clustering at the individual and region level in parentheses. ***, ** and * indicate significance at the 0.1%, 1% and 5% level, respectively.

predicts that a rising share of high-skilled workers puts downward pressure on high-skilled wages due to supply effects. Additional results for specifications in which spillover and supply effects are entangled show that even in the presence of supply effects, high-skilled workers profit from a higher concentration of other high-skilled workers in the same region. Hence, we find a clear indication that spillover effects dominate supply effects. The corresponding regression coefficients are even larger than in the sample of low-skilled workers. According to the theoretical framework, the overall wage effect for high-skilled workers can surpass the effect on low-skilled workers only if the elasticity of substitution between low- and high-skilled workers σ is greater than one. Thus, these additional findings support the consensus in the literature that low-skilled and high-skilled workers are gross substitutes (Autor *et al.* , 2008; Ciccone & Peri, 2005; Card & Lemieux, 2001; Krusell *et al.* , 2000). See Appendix 1.A.2 for details.

1.4.2 Gross flow model

We now turn to the gross flow model that explicitly models externalities from internal immigration of high-skilled workers (brain gain), internal emigration of high-skilled workers (brain drain), entries of young high-skilled workers into the labour market and exits of retiring high-skilled workers from the labour market. Before examining the dynamics, we analyse the wage effects of gross flows within a fixed time span of ten years. The subsamples and covariates are identical to the baseline model.

Table 1.4.2 provides an overview of the regression results. Again, the empirical results support our conceptual expectations. Column (1) presents results without controls for regional labour market shocks. Adding such controls in columns (2) to (4) lowers the estimated coefficient of gross flows of high-skilled workers. As before, we subsequently add the local unemployment rate and industry-year dummies in column (2), regional openings and closures of small and large firms and occupation-year dummies in column (3) and yearly labour-market-area fixed effects in column (4).

With few exceptions, the estimated coefficients are statistically and economically significant, and the sign pattern corresponds to our theoretical expectations. Typically, inflows of high-skilled workers increase wages, while outflows decrease wages. However, the result does not hold for East Germany. In the corresponding subsample, almost all the effects are statistically insignificant.

Columns (4) to (8) show pure spillover effects of various gross flows. For instance, in the results for the overall sample presented in column (4), a one-standard-deviation increase in brain gain leads to 1.0 percent higher wages, whereas a brain drain of the same size lowers wages by the same order of magnitude (0.9 percent). The difference is not statistically significant. Hence, over a time span of ten years, a brain gain can compensate for an equal-sized brain drain. However, as we will see in the following section, this is not the case in the short run.

The coefficients for entries of young high-skilled workers into the labour market and exits of elderly high-skilled workers from the labour market are even larger than those for gains and losses of human capital through inter-regional mobility. Hence, these two groups would exert larger spillover effects on local workers if they had the same magnitude as brain gain and brain drain. A possible explanation might be that young high-skilled workers are especially valuable because of their innovativeness, and elderly high-skilled workers are valuable because of their work experience (see Frosch 2011 for a literature survey of age effects on innovative performance). Moreover, exits are related to residents of the region who are typically well embedded in regional networks. Note,

Table 1.4.2: Regression results for the gross flow model

	Dependent variable: individual log wage							
					Region		Skill level	
	All	All	All	All	West	East	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\tilde{h}_{r,t-10}$	0.471***	0.294***	0.221***	0.236***	0.287***	−0.012	0.217***	0.636*
	(0.073)	(0.046)	(0.041)	(0.043)	(0.051)	(0.064)	(0.061)	(0.290)
	Gross flows (time frame: 10 years)							
Brain Gain	0.413***	0.268***	0.214***	0.193***	0.210***	0.046	0.278***	0.458
	(0.060)	(0.043)	(0.041)	(0.046)	(0.050)	(0.068)	(0.065)	(0.270)
Brain Drain	−0.269***	−0.187***	−0.138**	−0.178**	−0.176**	−0.077	−0.224***	−0.792**
	(0.072)	(0.052)	(0.050)	(0.054)	(0.062)	(0.069)	(0.067)	(0.283)
Entries	0.507***	0.352***	0.252***	0.267***	0.255**	0.413***	0.287***	1.014*
	(0.113)	(0.077)	(0.071)	(0.073)	(0.082)	(0.096)	(0.081)	(0.399)
Exits	−1.063***	−0.618***	−0.514***	−0.516***	−0.829***	0.143	−0.265	−0.446
	(0.285)	(0.143)	(0.134)	(0.136)	(0.177)	(0.116)	(0.180)	(0.936)
Others	0.306**	0.217***	0.174**	0.162***	0.204***	0.017	0.236***	0.699*
	(0.094)	(0.058)	(0.054)	(0.044)	(0.052)			
	Further controls							
Unemployment	–	Y	Y	Y	Y	Y	Y	Y
Firm composition	–	–	Y	Y	Y	Y	Y	Y
	Interaction dummies							
Industry × year	–	Y	Y	Y	Y	Y	Y	Y
Occup. × year	–	–	Y	Y	Y	Y	Y	Y
Lab. area × year	–	–	–	Y	Y	Y	Y	Y
N	3,011,957	3,011,943	3,011,942	3,011,942	2,416,931	464,456	676,122	107,628
Counties	402	402	402	365	299	59	365	365
$\bar{R}^2$	0.879	0.880	0.881	0.881	0.872	0.906	0.883	0.772

Notes: All regressions include worker, occupation, industry, region and year fixed effects. Estimates also include a constant, worker controls (age, age^2, experience, experience^2, tenure, tenure^2 and education dummies), firm size and regional controls (population density and number of hotel beds as a proxy for amenities). To fully decompose the regional share of high-skilled workers into gross flows estimates also include the lagged share of high-skilled workes divided by total employment growth ($\tilde{h}_{r,t-10}$). The estimation period is from 2002 to 2013. Column 7 and 8 include workers younger than 35 only. Two-way robust clustered standard errors with clustering at the individual and region level in parentheses. ***, ** and * indicate significance at the 0.1%, 1% and 5% level, respectively.

however, that the variations of flows from entries and exits are smaller than those from inter-regional mobility. Hence, their actual effects are also lower. For instance, a one standard deviation increase in entries only leads to 0.6 percent higher wages. Additionally, the coefficient on the lagged share of high-skilled workers ($\tilde{h}_{r,t-10}$) is positive and significant. Hence, incumbent high-skilled workers also generate positive human capital externalities.

Similar to the baseline model, we find strong effects in West Germany but almost no partial correlations between gross flows of high-skilled workers and wages in East Germany. Interestingly, the model shows that only entries of young high-skilled workers raise wages in the East German sample. A possible explanation for these results might be that formal degrees attained in the Federal Republic of Germany and West Germany differ in their current relevance.

Also analogous to the results from the baseline model, the point estimates in the high-skilled sample are larger than in the low-skilled sample, indicating that high-skilled workers benefit more from spillover effects than do low-skilled workers. However, due to the low number of observations in the high-skilled sample, the effects are less precisely estimated. In this sub-population, we do not detect statistically significant wage effects from brain gain and exits, although we do find spillover effects from brain drain, entries of young high-skilled workers and incumbent high-skilled workers. Additionally, in the sample of low-skilled workers, exits of elderly high-skilled workers seem not to affect wages via spillovers. Because we restrict the samples to workers younger than 35 in columns (7) and (8), a possible explanation might be that there is an age barrier between young and old workers. Indeed, additional estimates with the mixed sample of low- and high-skilled workers younger than 35 also show no effect of exits of elderly high-skilled workers from the labour market on individual wages.

In addition to the presented regressions, we estimated various alternative specifications of equation (1.16). In these alterations, we subsequently left out individual, firm, industry and regional control and dummy variables. Qualitatively, these exercises do not change the main findings.

1.4.3 Comparing the gross flow model to the baseline model

The empirical results of the gross flow model can be compared to the findings of the baseline model. To this end, we compute wage effects for each West German county based on the two models. For the baseline model, we use the estimated coefficient on the variable 'share of high-skilled' in Table 1.4.1 column (5) and calculate the associated wage effects by multiplying the actual share of high-skilled workers of every region-year combination with the regression coefficient. To derive wage effects in the gross flow model, we use the coefficients of Table 1.4.2 column (5) and separately calculate wage effects for each gross flow and $\tilde{h}_{r,t-10}$. Finally, we add up these partial effects for each region in every year.

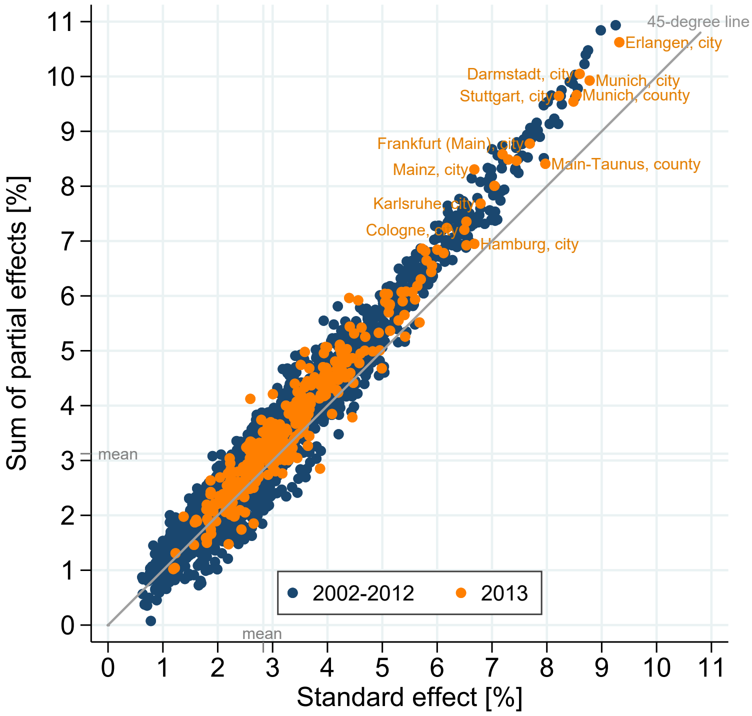
In the baseline model, the average regional share of high-skilled workers is associated with wage gains of 2.8 percent. In the gross flow model, the corresponding average effect is 3.1 percent and is thus only marginally larger. Figure 1.4.2 provides a detailed visualization of the comparison. Both models predict similar spillover effects, especially around the mean. Only in counties with large effects does the baseline model predict wage effects that are lower than the more general gross flow model. For instance, due to human capital externalities, the gross flow model suggests that a worker in the city of Munich earns 9.9 percent more than an otherwise observationally equivalent worker from a region where there are no other high-skilled workers. The baseline model would predict a wage difference of 8.8 percent. Hence, studies that do not decompose the regional share of high-skilled workers seem to produce only moderately biased estimates of human capital externalities.

1.4.4 Dynamics

Having thoroughly discussed the wage effects of gross flows of high-skilled workers within a time frame of ten years, we now explore the dynamic evolution of these effects. Based on our full specification and the West German sample, we re-estimate the gross flow model using five two-year flows of each explanatory variable (equation (1.16)). Figure 1.4.3 illustrates the results. The four panels of the graph show separate coefficient estimates on brain gain, brain drain, entries and exits. Each point within a panel represents an estimated coefficient. For instance, the rightmost point in the first panel corresponds to the gross inflow of high-skilled workers between $t-10$ and $t-8$. To make the visual comparison easier, the figure shows coefficients in absolute values in the panel on brain drain and exits. All estimated coefficients exhibit the theoretically expected signs. Dashed lines indicate 95 percent confidence intervals.

The first panel of Figure 1.4.3 illustrates an increase in spillover effects from brain gain over time. Assume that there is an inflow of high-skilled workers of one percent within a two-year period. While the effect is minor and statistically not significant in the first two years, it grows in the years after and becomes statistically significant. After ten years, an initial brain gain of the given size happens to have raised wages by 0.45 percent. At the 5 percent significance level, this effect is larger than short- or medium-run effects. The panel on entries of young high-skilled workers into the labour market portrays a very similar pattern. The estimated effect of human capital externalities on wages is approximately 0.3 percent in the first two years and grows to 0.6 percent after eight to ten years. Again, long-run effects are statistically larger than short- or medium-

Figure 1.4.1: Estimated wage effects: baseline model and gross flow model

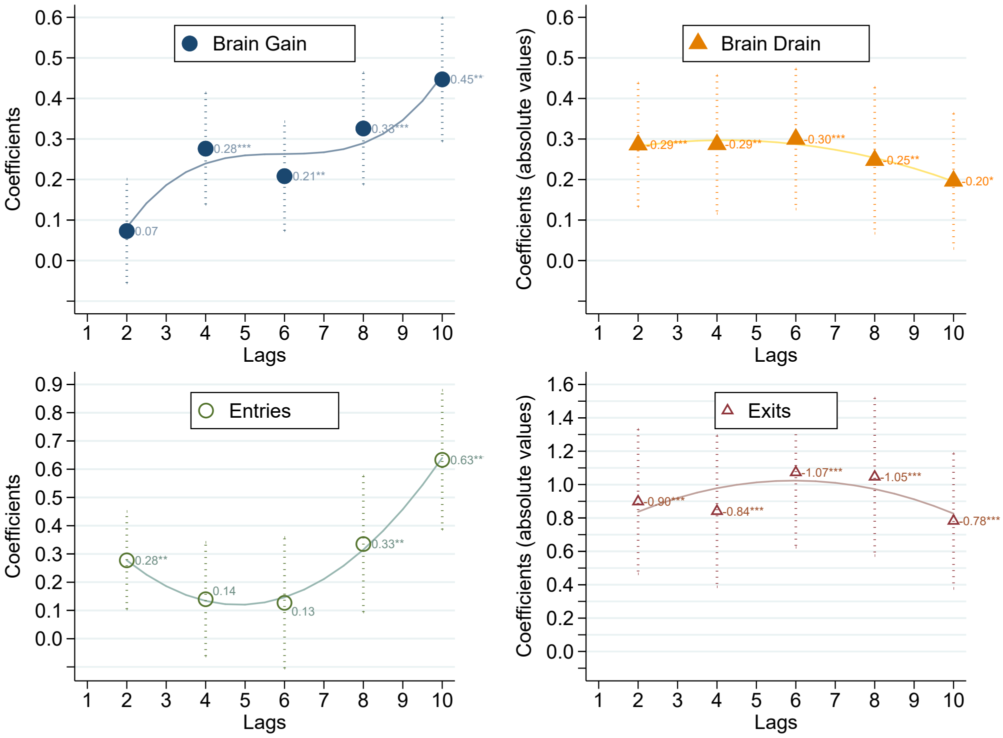


Notes: The figure compares predicted wage premia due to regional spillover effects from high-skilled workers based on the baseline and the gross flow model. Predictions from the baseline model are based on Table 1.4.1 column (5). Predictions from the gross flow model are based on Table 1.4.2 column (5). The magnitudes of the effects are in comparison to regions without any high-skilled workers. The graph shows West German counties only. The orange dots highlight effects in 2013.

run effects. Both patterns are similar to the wage growth effects on rural-to-urban movers found in the agglomeration literature (De la Roca & Puga, 2017; Lehmer & Möller, 2009; Maré & Glaeser, 2001). Both the agglomeration literature and our findings suggest that the transfer of knowledge and other possible externalities of human capital accrue over time.

There are several possible explanations for growing spillover effects from inflows over time. First, there should be a certain delay until wages reflect productivity gains. Second, spillover effects spread through social networks. It appears likely that regional social networks of newcomers are relatively small in the beginning but grow over time. Similarly, the reach and average strength of spillovers should be small in the beginning and increase over time. Third, especially in the case of entries of young workers, learning on the job should also play a role. If workers increase their knowledge and skills over time, their ability to generate spillovers should grow over time as well. In contrast, the negative effect of forgone spillovers from brain drain remains constant over time. Statistically, the accord-

Figure 1.4.2: Coefficient estimates for two-year gross flows



Notes: The figure shows coefficient estimates for two-year gross flows from the West German sample and our strictest specification (equation (1.16), with $\tilde{\mathbf{F}}_{r,t-\tau,t-\tau+2}$, where $\tau = 10, 8, \cdots, 2$). Estimates are based on 3,011,942 observations in the period 2002-2013. The model includes worker, occupation, industry, region and year fixed effects. Furthermore, we control for time-varying industry, occupation, and labour-market-area fixed effects. Estimates also include constant, worker controls (age, age^2, experience, experience^2, tenure, tenure^2 and education dummies), firm size and regional controls (unemployment rate, population density and number of hotel beds as a proxy for amenities). We use two-way robust clustered standard errors with clustering at the individual and region levels. ***, ** and * indicate significance at the 0.1%, 1% and 5% levels, respectively. Vertical lines show 95% confidence intervals. Fitted curves are obtained from simple quadratic and cubic models and suggest the evolution of spillover effects.

ing coefficients are all of the same size. It seems plausible that the mechanisms through which regional social networks generate productive effects are immediately weakened after active members of the network have left the region. For instance, it can be expected that the probability of face-to-face contacts is instantaneously reduced. Hence, negative effects from forgone spillovers should appear without a time lag.

When looking at exits of retiring high-skilled workers, we see almost the same picture as for workers leaving the region, albeit the effects are less precisely estimated. This result supports the view that social network effects predominately work through contacts between persons who are still active in the labour force. Externalities of human capital probably arise mainly through joint project work and cooperation within or between firms and research and development institutions. Given the fact that innovations are frequently made through new ways of combining existing knowledge (Taylor & Greve, 2006), it can be assumed that there are scale effects of the pool of knowledge, and those effects are mainly incorporated by economically active high-skilled persons in a region.

Of special interest is the relative size of externalities from brain gain and brain drain at different points in time. Within two years, the negative effects from the outflow of high-skilled workers outweigh the positive spillover effects from a corresponding inflow at the 5 percent level of significance. In the medium run, the effects do not statistically differ from each other ($t-3$ to $t-8$). In the long run ($t-9$ to $t-10$), spillovers from brain gain surpass negative externalities from brain drain at the 1 percent level. These results imply that it takes at least three years until a brain gain can compensate for an equal-sized brain drain. In the medium run, effects counterbalance each other, and in the long run, a brain gain even overcompensates a brain drain. An explanation of this result is that immigrating workers increase the local diversity pool and thus cause particularly large spillover effects (compare to Ottaviano & Peri, 2005; Südekum *et al.* , 2014, who find positive labour market effects of cultural diversity).

1.4.5 Net flows and further robustness checks

To check the validity of our results, we carry out several robustness checks. First, we estimate models examining the effects of net flows instead of gross flows. Second, we evaluate the gross flow model with various subsamples of the population.

Net flows

As illustrated in the introduction (Figure 1.1.1), regional in- and outflows of high-skilled workers are highly correlated. Obviously, the collinearity between in- and outflows impairs the efficiency of the gross flow model (equation 1.16). However, as shown in section 1.4.2, there is enough variation in the data to simultaneously estimate effects from in- and outflows. In principle, estimating gross flows within one model isolates each gross flow from the influences of the other gross flows. Hence, point estimates should be valid. To buttress these conceptual considerations, we compare the gross flow model to a less demanding net flow model. We define the net flow model as follows:

$$\ln w^s_{i,r,t,b,o,\ell,n} = \eta^s h_{r,t-10} + \theta^s f_{r,t-10,t} + \mathbf{X}_{i,t}\alpha^s + \mathbf{Z}_{r,t}\beta^s + \mu_i + \rho_r + \tau_t + \iota_b + \omega_o + \tilde{\iota}_{bt} + \tilde{\omega}_{ot} + \pi_{nt} + \phi_{\ell t} + \epsilon^s_{i,r,t,b,o,\ell,n}, \quad s \in \{H, L\}., \quad (1.18)$$

where $h_{r,t-10}$ represents the ten-year-lagged regional share of high-skilled workers and $f_{r,t-10,t}$ is the net flow of high-skilled workers within ten years. The net flow is equal to the sum of gross flows and can also be interpreted as the difference between $h_{r,t}$ and $h_{r,t-10}$. The remainder of equation 1.18 is identical to the control variables of the gross flow model (equation 1.16). In terms of flexibility, the net flow model lies between the baseline and the gross flow model. The net flow model is more flexible than the baseline model because it allows different spillover effects from incumbent high-skilled workers and flows of high-skilled workers. However, it is less flexible than the gross flow model because it assumes symmetric effects from in- and outflows, whereas the gross flow model relaxes this assumption.

Table 1.4.3 summarizes the results from the net flow model. In line with Tables 1.4.1 and 1.4.2, column (1) of Table 1.4.3 presents results without controls for regional labour market shocks. We add such controls in columns (2) to (4). Furthermore, we subsequently add the local unemployment rate and industry-year dummies in column (2), regional openings and closures of small and large firms and occupation-year dummies in column (3), and yearly labour market area fixed effects in column (4). The remaining columns show results for selected subsamples.

All coefficients are of reasonable size and, with the exception of East Germany, are also highly significant. In line with the gross flow model, the lagged share of high-skilled workers and inflows of high-skilled workers raise wages. Effects from incumbent workers are larger than from inflows. For instance, a one-percentage-point increase in the ten-year-lagged share of high-skilled workers raises wages by 0.3 percent, whereas the same increase in inflows raises wages by only 0.2 percent (column 4). Additionally, in line with our main findings, the effects on high-skilled workers are larger than on low-skilled workers.

Brain gain and brain drain have a dominant weight within all types of net flows (see Table 1.3.1), and the corresponding coefficients in the gross flow model (Table 1.4.2) are of equal size. Hence, there is no asymmetry between the effects of an equally sized inflow and outflow of high-skilled workers in the 10-year model. Consequently, the coefficient on net flows (Table 1.4.3) should also be of comparable size if both specifications (equation 1.16 and equation 1.18) are correct. Indeed, this is the case. Absolute values

Table 1.4.3: Regression results for the net flow model

	Dependent variable: individual log wage							
					Region		Skill level	
	All	All	All	All	West	East	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$h_{r,t-10}$	0.707***	0.445***	0.325***	0.346***	0.362***	0.178*	0.409***	1.059***
	(0.070)	(0.048)	(0.042)	(0.046)	(0.052)	(0.073)	(0.065)	(0.292)
Net flows	0.371***	0.244***	0.192***	0.179***	0.188***	0.096	0.226***	0.620**
	(0.062)	(0.040)	(0.038)	(0.038)	(0.044)	(0.060)	(0.047)	(0.207)
	Further controls							
Unemployment	–	Y	Y	Y	Y	Y	Y	Y
Firm composition	–	–	Y	Y	Y	Y	Y	Y
	Interaction dummies							
Industry $\times$ year	–	Y	Y	Y	Y	Y	Y	Y
Occup. $\times$ year	–	–	Y	Y	Y	Y	Y	Y
Lab. area $\times$ year	–	–	–	Y	Y	Y	Y	Y
N	3,011,957	3,011,943	3,011,942	3,011,942	2,416,931	464,456	676,122	107,628
Counties	402	402	402	365	299	59	365	365
$\bar{R}^2$	0.879	0.880	0.881	0.881	0.872	0.906	0.883	0.772

Notes: All regressions include worker, occupation, industry, region and year fixed effects. Estimates also include a constant, worker controls (age, age^2, experience, experience^2, tenure, tenure^2 and education dummies), firm size and regional controls (population density and number of hotel beds as a proxy for amenities). Estimates further include the 10-year lagged share of high-skilled workers $h_{r,t-10}$. The estimation period is from 2002 to 2013. Column 7 and 8 include workers younger than 35 only. Two-way robust clustered standard errors with clustering at the individual and region level in parentheses. ***, ** and * indicate significance at the 0.1%, 1% and 5% level, respectively.

of coefficients on brain gain and brain drain (Table 1.4.2) and coefficients on net flows (Table 1.4.3) are very similar in all estimates.

For the same reason, predicted effects from the net flow model and the gross flow model should be of comparable size. According to the net flow model with the full set of control variables, increasing the lagged share of high-skilled workers ($h_{r,t-10}$) and the net flow of high-skilled workers by one standard deviation raises wages by 2.5 percent. According to the gross flow model, increasing $\tilde{h}_{r,t-10}$, as well as all gross flows by one standard deviation, leads to 2.1 percent higher wages. The small difference further corroborates the validity of our main specification.

Stayers and movers

For individuals who do not move between regions (‘*stayers*’), variation in the regional concentration of high-skilled workers comes from regional changes over time. In contrast, for individuals who change their location (‘*movers*’), variation stems from the difference between their new and their old locations. To ease the interpretation of our main findings, we restrict the sample to stayers and therefore allow only one source of variation. In the following, we relax this restriction and allow variation from stayers and movers.

Estimating equation 1.16 with stayers and movers yields Table 1.4.4. Overall, the results are similar to our main findings, and the estimated coefficients are only slightly larger. For instance, while a one standard deviation increase in brain gain raises wages of stayers by 1.0 percent (Table 1.4.2, Column 4), the mixed effect on stayers and movers is 1.1 percent (Table 1.4.4, Column 4). We conclude that the effects on movers and stayers are of comparable magnitude and that our main findings are not affected by the restriction on stayers.

Rural and urban

Theoretically, human capital externalities could vary in different types of regions. It might well be that information flows more easily in densely populated cities than in rural areas. Table 1.4.5 therefore replicates results from the gross flow model in the 15 largest German cities (*metropolises*), other cities and rural areas. To compute effects, we estimate our main model (Equation (1.16)) with interactions of gross flows of high-skilled workers and the region type.[16] As before, we include controls for local labour market shocks. The table reports joint coefficients of interaction terms and F-statistics on the joint significance of effects. Hence, the results can be interpreted directly.

Table 1.4.5 indicates that estimated effects in cities are similar to effects in the full sample. For instance, externalities from a one-percentage-point increase in brain gain are only 0.3 percentage points smaller in cities than in all regions (compare Table 1.4.5, Column 2 to Table 1.4.2, Column 4). Differences from the effects of brain drain are even smaller. Although point estimates for metropolises are of identical magnitude, they are less precisely estimated and thus statistically insignificant. This is very likely due to

[16] Note that it is impossible to estimate Equation 1.16 with separate samples of metropolises and (most) cities. The reason is that in such samples, time-varying labour-market-area fixed effects would be identical to yearly region fixed effects. Hence, all (yearly) regional variation, including flows of high-skilled workers, would be nullified. In contrast, joint estimates with interactions only wipe out variation on the labour-market-area year level, and therefore variation from within labour market areas remains in the data.

Table 1.4.4: Regression results for the gross flow model (effects on stayers and movers)

	Dependent variable: individual log wage							
					Region		Skill level	
	All	All	All	All	West	East	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\tilde{h}_{r,t-10}$	0.628***	0.409***	0.315***	0.339***	0.394***	–0.040	0.222***	0.954***
	(0.068)	(0.042)	(0.037)	(0.041)	(0.046)	(0.064)	(0.057)	(0.211)
	Gross flows (time frame: 10 years)							
Brain Gain	0.500***	0.319***	0.243***	0.224***	0.228***	0.041	0.224***	0.690**
	(0.057)	(0.040)	(0.037)	(0.044)	(0.049)	(0.058)	(0.065)	(0.219)
Brain Drain	–0.346***	–0.232***	–0.173***	–0.228***	–0.242***	0.033	–0.208***	–0.795***
	(0.065)	(0.047)	(0.044)	(0.049)	(0.054)	(0.070)	(0.062)	(0.202)
Entries	0.644***	0.430***	0.318***	0.349***	0.356***	0.300***	0.331***	0.753*
	(0.107)	(0.071)	(0.064)	(0.060)	(0.066)	(0.082)	(0.075)	(0.313)
Exits	–1.043***	–0.645***	–0.533***	–0.506***	–0.697***	0.087	0.036	–1.159
	(0.226)	(0.118)	(0.110)	(0.126)	(0.160)	(0.102)	(0.152)	(0.768)
Others	0.397***	0.279***	0.227***	0.216***	0.252***	0.051	0.203***	0.783***
	(0.086)	(0.054)	(0.052)	(0.043)	(0.051)	(0.055)	(0.054)	(0.235)
	Further controls							
Unemployment	–	Y	Y	Y	Y	Y	Y	Y
Firm composition	–	–	Y	Y	Y	Y	Y	Y
	Interaction dummies							
Industry × year	–	Y	Y	Y	Y	Y	Y	Y
Occup. × year	–	–	Y	Y	Y	Y	Y	Y
Lab. area × year	–	–	–	Y	Y	Y	Y	Y
N	3,111,179	3,111,165	3,111,164	3,111,164	2,498,202	476,884	713,542	107,628
Counties	402	402	402	365	299	59	365	365
$\bar{R}^2$	0.877	0.878	0.879	0.879	0.871	0.904	0.876	0.773

Notes: All regressions include worker, occupation, industry, region and year fixed effects. Estimates also include a constant, worker controls (age, age^2, experience, experience^2, tenure, tenure^2 and education dummies), firm size and regional controls (population density and number of hotel beds as a proxy for amenities). To fully decompose the regional share of high-skilled workers into gross flows estimates also include the lagged share of high-skilled workes divided by total employment growth ($\tilde{h}_{r,t-10}$). The estimation period is from 2002 to 2013. Column 7 and 8 include workers younger than 35 only. Two-way robust clustered standard errors with clustering at the individual and region level in parentheses. ***, ** and * indicate significance at the 0.1%, 1% and 5% level, respectively.

the low number of regions that provide variation (only 15) and thus should not be over-interpreted. In rural areas, all effects are close to and statistically not different from zero. These results imply that rural areas benefit much less, if they benefit at all, from human capital externalities. This result would corroborate the idea that information spread is less effective in sparsely populated regions. However, these estimates should not be over-

Table 1.4.5: Regression results for the gross flow model (region types)

	Dependent variable: individual log wage		
	Metropolises (1)	Cities (2)	Rural areas (3)
$\tilde{h}_{r,t-10}$	0.445***	0.224***	−0.070
	(15.88)	(17.79)	(1.36)
	Gross flows (time frame: 10 years)		
Brain Gain	0.282	0.226***	−0.076
	(2.08)	(18.81)	(1.11)
Brain Drain	−0.180	−0.184***	−0.010
	(1.01)	(9.40)	(0.02)
Entries	0.189	0.212*	0.014
	(0.99)	(6.12)	(0.02)
Exits	−0.709*	−0.832***	0.163
	(5.44)	(17.72)	(1.92)
Others	0.222	0.209***	−0.046
	(2.09)	(14.87)	(0.95)
Counties	15	188	199
N per group	675,675	1,479,292	856,975
$\bar{R}^2$	0.88		

Notes: The table shows estimation results from our full model (Equation (1.16)) with additional interaction effects of all gross flows of high-skilled workers and indicators for metropolises, cities and rural regions. Estimates come from one model. Columns indicate *joint* coefficients (sum of interaction effects). Accordingly, ***, ** and * indicate joint significance at the 0.1%, 1% and 5% level, respectively and values in parentheses are F-statistics based on two-way robust clustered standard errors with clustering at the individual and region level. We assign the 15 largest cities, with more than 400,000 inhabitants, to *Metropolises*. Control variables and fixed effects are identical to those in Table 1.4.2, Column 4. Estimates include worker, occupation, industry, region, year, labor market area year, occupation year, and industry year fixed effects. Estimates also include a constant, worker controls (age, age^2, experience, experience^2, tenure, tenure^2 and education dummies), firm size and regional controls (population density and number of hotel beds as a proxy for amenities). To fully decompose the regional share of high-skilled workers into gross flows estimates also include the lagged share of high-skilled workes divided by total employment growth ($\tilde{h}_{r,t-10}$).

interpreted, as the number of observations is relatively low.

Further robustness checks

Our findings could also be distorted by labour market areas that consist of only one or very few counties. Therefore, we additionally compute effects for a subsample that only includes labour market areas with at least three counties. The results are summarized in Appendix 1.A.3 (Table 1.A.2). The robustness exercise produces very similar results and supports our main findings.

To corroborate our results regarding the dynamic evolution of effects, we also estimated an alternative version of our third specification, in which we split up gross flows of high-skilled workers into ten separate yearly flows. Figure 1.A.2 in the Appendix illustrates the results. Compared to our main model based on two-year flows (Section 1.4.4), the results barely change. Two-year flows and yearly flows indicate the same evolution of externalities over time, and point estimates are of the same magnitude.

In summary, our results are remarkably robust across varying specifications and samples. Furthermore, consistent estimates across different subsamples also clearly indicate that multicollinearity among gross flows does not influence the results.

1.5 Conclusions

Descriptive evidence suggests that inter-regional mobility of high-skilled workers is characterized by a churning phenomenon: regional in- and outflows of high-skilled workers are positively correlated. This phenomenon motivates us to analyse human capital externalities from gross flows instead of net flows. Changes in the stock of regional human capital result not only from labour market entries and exits but also from internal migration of the high-skilled. Based on these flows, we estimate human capital externalities from various sources. Our analyses are based on a rich administrative micro panel data set and thoroughly take into account the sorting of workers as well as the entanglement of externalities and conventional labour market supply and demand effects with an extensive set of time-varying fixed effects.

We find that a gain of human capital through inter-regional migration and labour market entries of high-skilled workers significantly raises the wages of all workers in that area, whereas the opposite is the case for emigration and labour market exits of high-skilled workers. For instance, a one-standard-deviation increase in the high-skilled immigration rate, pooled over a period of ten years, increases individual wages of incumbent workers in the region by one percent. In absolute terms, negative externalities from the loss of human capital are of similar size. However, a closer investigation of dynamic effects shows that positive externalities from inflows increase over time, whereas negative externalities from outflows remain stable. A suitable explanation for this pattern might be that externalities transmit through personal networks that develop over time. In the short run, the negative externalities from an outflow of high-skilled workers outweigh the positive externalities from a corresponding inflow. However, after approximately three years, a regional inflow of high-skilled workers compensates for an equal-sized outflow. In the medium run, effects counterbalance each other, and in the long run, externalities from inflows eventually overcompensate negative effects from outflows of the same size. This observation supports the hypothesis that the size diversity in the regional pool of knowledge, i.e., the knowledge that workers accumulate in other regions, might amplify human capital externalities.

Our results also indicate that high-skilled workers benefit more from human capital externalities than do low-skilled workers. Theoretically, this result is consistent with an elasticity of substitution between the two types of workers exceeding unity. Differentiating geographically, we find highly robust effects for West Germany but only weak effects, if any, for East Germany. A possible explanation could be that some of the formal skills acquired in the East before 1990 became obsolete after unification.

Our findings support the common view that attracting skilled individuals is beneficial for regions. However, to fully reap the benefits of immigration of high-skilled workers, regions should also aim to retain their human capital. Of course, the inflow of one region corresponds to the outflow of other regions for a given total number of high-skilled workers. Our results suggest, however, that on the national level, internal migration is, in sum, beneficial for the economy if the frequency of relocation is not too high. Otherwise, the frictional costs of building new local personal networks vitiate potential human capital externalities.

1.A Appendix

1.A.1 Imputation of wages

To impute top-coded wages, we follow a two-step procedure similar to that in Dustmann *et al.* (2009) and Card *et al.* (2013). First, we cluster observations by year, by East and West Germany and by three education groups. For each of these clusters, we estimate Tobit wage equations, controlling for typical transformations of the variables gender, age, work experience, tenure, firm size and regional population density. Next, we impute censored wages by $X\hat{\beta}+\hat{\sigma}\Phi^{-1}\left[k+u(1-k)\right]$, where $\hat{\beta}$ are coefficient estimates, $\hat{\sigma}$ is the estimated standard deviation, Φ is the standard normal density, u is a random draw from a uniform distribution between zero and one, $k=\Phi\left[(c-X\hat{\beta})/\hat{\sigma}\right]$ and c is the censoring point.

Second, we calculate average worker and firm wages over time, excluding the current period. If a worker or firm is only observed once, we instead use the sample mean. Next, we re-estimate the Tobit wage equations from step one, but we include worker and firm mean wages as well as a dummy that indicates whether the sample mean was used or not. Again, we impute censored wages by $X\hat{\beta}+\hat{\sigma}\Phi^{-1}\left[k+u(1-k)\right]$.

1.A.2 Detailed effects on low-skilled and high-skilled workers

Table 1.A.1 gives a detailed description of wage effects on low- and high-skilled workers. In all estimates, the regional share of high-skilled workers increases wages. The first and fifth columns show results without controls for regional labour market shocks. Subsequently, adding such controls in columns (2) to (4) and (6) to (8) lowers the estimated relationship between the share of high-skilled workers and wages in both subsamples. According to the strictest estimates, a one-standard-deviation increase in the regional share of high-skilled workers raises the wages of low-skilled workers by 1.5 percent; see column (4). The associated effect on high-skilled workers is 4.1 percent and is thus considerably larger.

Let us now turn to the results where we jointly measure spillover and supply effects (columns 1-3 and 6-8). Our conceptual framework predicts that a rising share of high-skilled workers increases the wages of low-skilled workers, while the wages of high-skilled workers will only increase if spillover effects dominate supply effects. Indeed, the regression results show that low-skilled workers profit from a higher concentration of high-skilled workers in the same region. The same applies to high-skilled workers, even in the presence of supply effects. Hence, spillover effects dominate supply effects, and

Table 1.A.1: Regression results for the baseline model (detailed effects on low- and high-skilled workers)

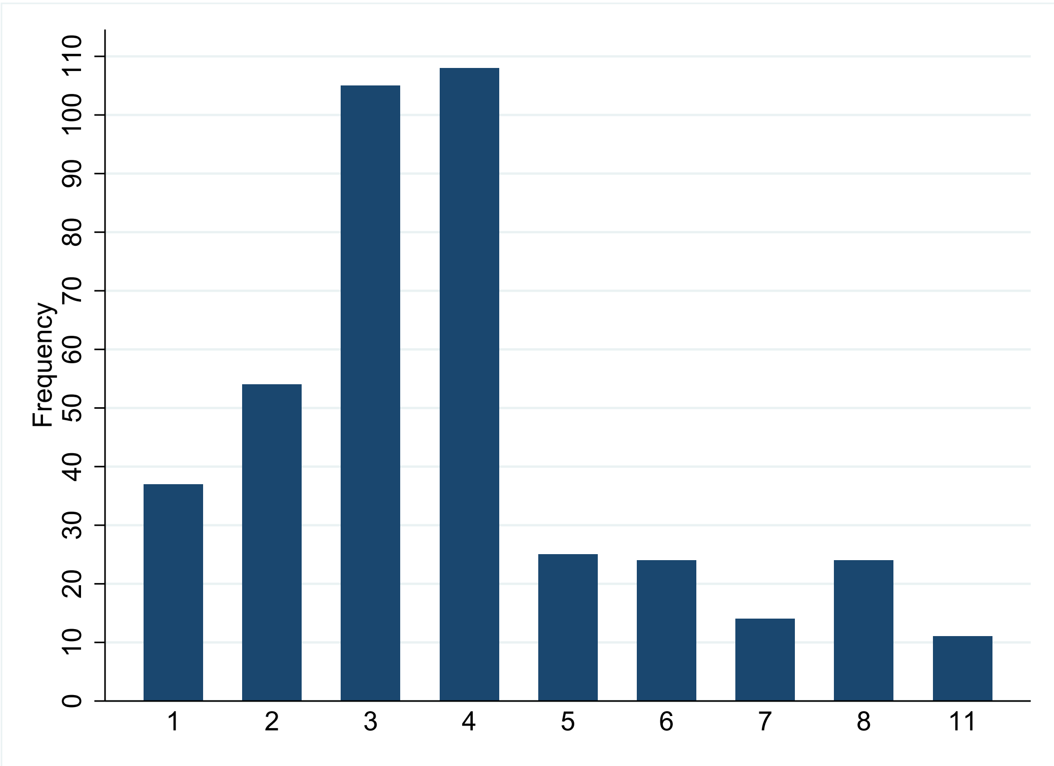
	Dependent variable: individual log wage							
	low-skilled				high-skilled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share high-skilled	0.430***	0.295***	0.273***	0.258***	1.180***	0.967***	0.874***	0.686**
	(0.055)	(0.050)	(0.049)	(0.047)	(0.242)	(0.231)	(0.222)	(0.211)
	Further controls							
Unemployment	–	Y	Y	Y	–	Y	Y	Y
Firm composition	–	–	Y	Y	–	–	Y	Y
	Interaction dummies							
Industry × year	–	Y	Y	Y	–	Y	Y	Y
Occup. × year	–	–	Y	Y	–	–	Y	Y
Lab. area × year	–	–	–	Y	–	–	–	Y
N	676,140	676,122	676,122	676,122	107,890	107,641	107,641	107,628
Counties	402	402	402	365	402	402	402	365
$\bar{R}^2$	0.879	0.882	0.883	0.883	0.763	0.770	0.772	0.772

Notes: All regressions include worker, occupation, industry, region and year fixed effects. Estimates also include a constant, worker controls (age, age^2, experience, experience^2, tenure, tenure^2 and education dummies), firm size and regional controls (population density and number of hotel beds as a proxy for amenities). To fully decompose the regional share of high-skilled workers into gross flows estimates also include the lagged share of high-skilled workes divided by total employment growth ($\tilde{h}_{r,t-10}$). The estimation period is from 2002 to 2013. Only workers younger than 35 included. Two-way robust clustered standard errors with clustering at the individual and region level in parentheses. ***, ** and * indicate significance at the 0.1%, 1% and 5% level, respectively.

the net effects on high-skilled workers are positive.

1.A.3 Tables and graphs

Figure 1.A.1: Number of counties within labour market areas



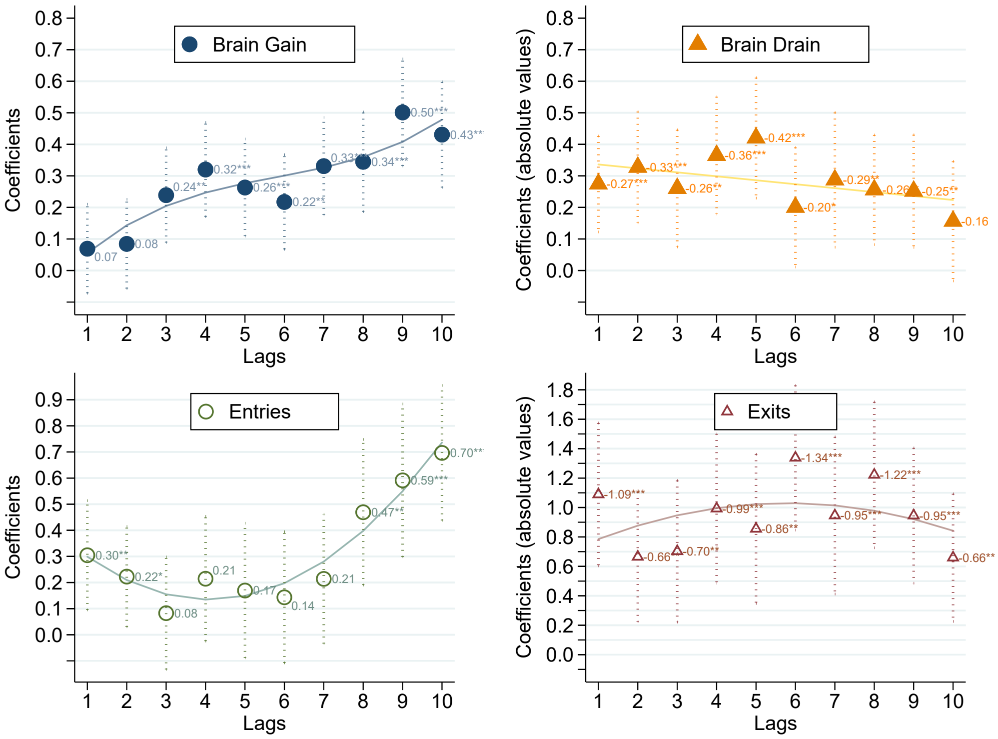
Notes: Frequencies based on counties; N = 402; Mean = 3.9; Median = 4; Number of labour market areas = 141

Table 1.A.2: Regression results for the gross flow model (only labor market areas with at least three counties)

	Dependent variable: individual log wage							
					Region		Skill level	
	All	All	All	All	West	East	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\tilde{h}_{r,t-10}$	0.481***	0.316***	0.239***	0.235***	0.292***	–0.092	0.231***	0.711*
	(0.082)	(0.052)	(0.047)	(0.046)	(0.052)	(0.067)	(0.065)	(0.306)
	Gross flows (time frame: 10 years)							
Brain Gain	0.374***	0.270***	0.222***	0.203***	0.217***	0.001	0.267***	0.413
	(0.064)	(0.046)	(0.044)	(0.048)	(0.051)	(0.076)	(0.068)	(0.282)
Brain Drain	–0.231**	–0.179**	–0.134*	–0.181**	–0.181**	–0.027	–0.215**	–0.774**
	(0.080)	(0.057)	(0.056)	(0.058)	(0.064)	(0.078)	(0.071)	(0.292)
Entries	0.485***	0.345***	0.243**	0.265***	0.266**	0.372**	0.266**	1.302**
	(0.126)	(0.084)	(0.078)	(0.078)	(0.085)	(0.120)	(0.087)	(0.403)
Exits	–1.262***	–0.750***	–0.637***	–0.566***	–0.894***	0.176	–0.261	–1.178
	(0.373)	(0.177)	(0.166)	(0.146)	(0.176)	(0.135)	(0.193)	(0.987)
Others	0.298**	0.226***	0.182**	0.172***	0.222***	–0.042	0.240***	0.807*
	(0.114)	(0.068)	(0.064)	(0.047)	(0.053)	(0.066)	(0.064)	(0.320)
	Further controls							
Unemployment	–	Y	Y	Y	Y	Y	Y	Y
Firm composition	–	–	Y	Y	Y	Y	Y	Y
	Interaction dummies							
Industry × year	–	Y	Y	Y	Y	Y	Y	Y
Occup. × year	–	–	Y	Y	Y	Y	Y	Y
Lab. area × year	–	–	–	Y	Y	Y	Y	Y
N	2,501,314	2,501,292	2,501,291	2,501,291	2,074,971	296,124	552,463	96,065
Counties	311	311	311	311	267	43	311	311
$\bar{R}^2$	0.874	0.876	0.876	0.877	0.870	0.904	0.882	0.768

Notes: All regressions include worker, occupation, industry, region and year fixed effects. Estimates also include a constant, worker controls (age, age^2, experience, experience^2, tenure, tenure^2 and education dummies), firm size and regional controls (population density and number of hotel beds as a proxy for amenities). To fully decompose the regional share of high-skilled workers into gross flows estimates also include the lagged share of high-skilled workes divided by total employment growth ($\tilde{h}_{r,t-10}$). The estimation period is from 2002 to 2013. Column 7 and 8 include workers younger than 35 only. Two-way robust clustered standard errors with clustering at the individual and region level in parentheses. ***, ** and * indicate significance at the 0.1%, 1% and 5% level, respectively.

Figure 1.A.2: Coefficient estimates for yearly gross flows



Notes: The figure shows coefficient estimates for yearly gross flows from the West German sample and our strictest specification (equation (1.16), with $\tilde{\mathbf{F}}_{r,t-\tau,t-\tau+2}$, where $\tau = 10, 8, \cdots, 2$). Estimates are based on 3,011,942 observations in the period 2002-2013. The model includes worker, occupation, industry, region and year fixed effects. Furthermore, we control for time-varying industry, occupation, and labour-market-area fixed effects. Estimates also include constant, worker controls (age, age^2, experience, experience^2, tenure, tenure^2 and education dummies), firm size and regional controls (unemployment rate, population density and number of hotel beds as a proxy for amenities). We use two-way robust clustered standard errors with clustering at the individual and region levels. ***, ** and * indicate significance at the 0.1%, 1% and 5% levels, respectively. Vertical lines show 95% confidence intervals. Fitted curves are obtained from simple quadratic and cubic models, respectively, and suggest the evolution of spillover effects.

Chapter 2

The Spatial Decay of Knowledge Spillovers: A Functional Regression Approach with Precise Geo-Referenced Data

Abstract[*]

This paper analyzes knowledge spillovers from high-skilled workers by applying functional regression to precise geocoded register data. Functional regression enables us to describe the concentration of high-skilled workers around workplaces as continuous curves and to estimate a spillover function that depends on distance. Furthermore, our rich panel data allow us to address the sorting of workers and to disentangle spillover from supply effects by using an extensive set of time-varying fixed effects. Our estimates reveal that knowledge spillovers attenuate with distance and disappear after 15 kilometers. Spillovers from the immediate neighborhood are twice as large as spillovers from surroundings ten kilometers away.

Keywords: knowledge spillovers, functional regression, geodata, wages
JEL Codes: C13, D62, J24, J31, R10, R12

[*] This part is joint work with Christoph Rust.

2.1 Introduction

Workers interact with colleagues within and across firms. They share knowledge, discuss ideas and adopt novel technologies. These interactions potentially increase the productivity of workers and are a major source of agglomeration economies (Davis & Dingel, 2019; Acemoglu, 1996; Lucas, 1988; Marshall, 1890). Empirical research supports the existence of such 'knowledge spillovers' within predefined geographical boundaries (Cornelissen *et al.* , 2017; Ciccone & Peri, 2006; Moretti, 2004; Rauch, 1993). However, little is known about the exact spatial extent of knowledge spillovers. For several reasons, knowledge spillovers should decline with distance. For instance, distance raises the costs of planed social interactions, such as meetings. Similarly, distance reduces the likelihood of encounters that lead to the exchange of knowledge. Moreover, distance depresses information flows within social networks. The reason is that distance generally raises the number of intermediaries between individuals, and a higher number of intermediaries hinders information transfers.

Previous empirical studies provide initial evidence for spatially decreasing knowledge spillovers. Using cross-sectional data from the US, Rosenthal & Strange (2008) construct concentric rings around workers that measure the concentration of human capital within 5 miles and between 5 to 25 miles. To explore how knowledge spillovers attenuate with distance, they regress individual wages on the concentration of human capital within these rings. They find that knowledge spillovers from the inner ring are notably larger than spillovers from the outer ring. A closely related study by Fu (2007) adopts the strategy of Rosenthal & Strange (2008) to analyze cross-sectional data from the Boston metropolitan area. Using more precise geocoded data, Fu (2007) measures the concentration of human capital within finer rings (i.e., 0-1.5, 1.5-3, 3-6 and 6-9 miles). Fu (2007) finds evidence that knowledge spillovers may vanish after only three miles. Recent findings from the Netherlands in a setting with panel data and concentric rings of 0-10, 10-40, and 40-80 kilometers' distance suggest that knowledge spillovers reach 10 kilometers (Verstraten, 2018). Although these studies provide evidence for the spatial attenuation of knowledge spillovers, the exact decay of the effects remains unclear because the literature is constrained either by relatively imprecise geo-information or by specific data from a single area. Furthermore, most empirical evidence is restricted to cross-sectional data, which complicates causal inference. Additionally, the described studies overlook that spillover effects from high-skilled workers are entangled with labor market supply and demand effects (Katz & Murphy, 1992; Card & Lemieux, 2001; Borjas, 2003; Moretti, 2004; Ciccone & Peri, 2006). Scholars also investigate spatial patterns in other agglomeration effects. For instance, Arzaghi & Henderson (2008) study networking effects within the advertising agency industry in Manhattan, Ahlfeldt *et al.* (2015) examine productivity externalities in Berlin, and Andersson *et al.* (2019) evaluate productivity effects from industry specialization and diversity in Swedish cities.

In this paper, we analyze the spatial decay of knowledge spillovers from high-skilled workers. To this end, we draw on a large and novel administrative micro panel dataset that features the exact coordinates of nearly all German establishments and rich information on individual workers over one and a half decades. Since productivity is not available on the individual level, we follow the existing literature and take individual wages as a proxy for productivity. This also is in line with standard economic theory, where wages equal marginal productivity.

To fully exploit the information from exact geocodes of workplaces, we adopt a methodologically fresh approach and measure the magnitude of knowledge spillovers with respect to distance in a continuous manner. Recent developments in functional data analysis (FDA) provide particularly suitable frameworks. FDA is a branch of statistics that extends classical statistical methods to random variables with a functional nature, such as curves or surfaces over a continuous domain. Typical examples of such data are temperature curves, growth curves or the continuous evolution of stock prices over time. The continuity of curves entails that adjacent values are somehow related. In many applications, exploiting this information makes FDA more efficient than classical multivariate methods on discretized data.

While statisticians employ FDA in a wide range of applications (see Ullah & Finch, 2013 for a systematic overview), FDA is applied quite rarely in economics (examples include Ramsay & Ramsey, 2002, Wang *et al.* , 2008 and Caldeira & Torrent, 2017).[1] This paper, therefore, illustrates the potential of FDA in economic research with high-dimensional variables. Our approach relies on a functional linear regression model in which a scalar outcome variable (log wage) is regressed on observations of a functional random variable (share of high-skilled workers as a function of distance to a worker's workplace). For this purpose, we augment the classical scalar-on-function regression model to incorporate further scalar-valued explanatory variables and use an estimation procedure, suggested by Crambes *et al.* (2009), that is based on smoothing splines and makes it possible to very flexibly model the function-valued spillover parameter. The estimated spatial spillover function relates wages to the share of high-skilled workers as a function of distance, which is evaluated at 500 meter intervals up to 50 kilometers.

[1] Readers with a general interest in FDA are referred to the textbooks of Ramsay & Silverman (2005); Ferraty & Vieu (2006); Horváth & Kokoszka (2012) and Hsing & Eubank (2015).

There are two major challenges in identifying regional knowledge spillovers, namely, confounding labor market supply and demand effects and the sorting of high-skilled workers into high-wage regions. We address both problems with an extensive set of time-varying fixed effects. If high- and low-skilled workers are imperfect substitutes, standard supply and demand models indicate that an increase in the share of high-skilled workers raises (lowers) the wages of low-skilled (high-skilled) workers (see Ciccone & Peri, 2006 and Moretti, 2004 for detailed explanations in our context). Thus, spillovers are potentially entangled with labor market supply and demand effects. We disentangle spillover from supply and demand effects by exploiting the different spatial natures of the two effects. While supply and demand effects are plausibly common within local labor markets (i.e., supply and demand effects originating in one part of the city uniformly affect wages throughout the city), the intensity of spillover effects truly depends on distance (i.e., spillovers affect close neighbors more than distant neighbors). Thus, in the data, we are able to purge spillover effects from supply and demand effects by eliminating variation that is common within regional labor markets. To do so, we include time-varying labor-market-area fixed effects in the econometric specification (i.e., a specific intercept for every labor market area in each year). Because supply and demand effects may have different impacts on high- and low-skilled workers, we further interact these labor-market-area-year fixed effects with a skill dummy.

Following Cornelissen *et al.* (2017), who, in a related context, address worker sorting at the firm level (Abowd *et al.* , 1999; Card *et al.* , 2013), we address sorting of high-skilled workers into high-wage regions (Acemoglu & Angrist, 2000) by including a comprehensive set of fixed effects. In particular, the above-introduced labor-market-area-year fixed effects nullify unobserved regional heterogeneity that might attract high-skilled workers, such as (changes in) average wages, general labor market conditions and amenities. Importantly, labor-market-area-year fixed effects also cover temporal labor market shocks that might pull or push skilled workers into or out of regions—a concern raised by Moretti (2004). Additionally, we account for locational advantages within regions (e.g., proximity to infrastructure and facilities) and unobserved individual heterogeneity with worker-firm match fixed effects.

We find significant spillover effects from the local concentration of high-skilled workers. Moreover, our estimates reveal that spillover effects decay with distance. Knowledge spillovers from direct neighbors (i.e., high-skilled workers who are located within a 0.5 kilometer radius) are roughly twice as large as spillovers from high-skilled workers that are located 10 kilometers apart. After 15 kilometers, spillover effects vanish completely. Overall, an evenly distributed, one-standard-deviation increase in the local share of high-skilled workers leads to wage gains of 2%. The magnitude of this effect is comparable to *classical* estimates at the aggregate level. In general, our findings are in line with the urban economic literature and support the existence of knowledge spillovers. Additionally, our results imply that knowledge spillovers cover entire cities. However, the majority of their effect is bounded within the near neighborhood of high-skilled workers. Workers at firms located in, or very close to, a skilled neighborhood, therefore, benefit most from spillovers. Those who work farther away from skilled neighbors gain less, and workers in very remote regions do not profit from knowledge spillovers at all.

The remainder of the paper is organized as follows. The next section explains the estimator and our identification strategy. Section 2.3 summarizes the data. Section 2.4 presents our main findings, illustrates the statistical properties of the estimator in a simulation study and provides an overview of several robustness checks. Section 2.5 concludes the paper.

2.2 Estimation strategy

This paper seeks to measure the spatial attenuation and reach of knowledge spillovers. Therefore, our aim is to describe the share of high-skilled workers around establishments as continuous curves and model a spillover function that depends on distance. In the following, we explain the estimator, discuss statistical inference and describe our representation of the share of high-skilled workers as curves. Finally, we specify the identification strategy that addresses endogenous sorting of workers and confounding labor market supply and demand effects.

2.2.1 The estimator

The spatial allocation of human capital varies considerably across and within administrative boundaries. For a given location (say worker i's workplace), the concentration of high-skilled workers in the immediate neighborhood, therefore, may differ from the concentration in the greater neighborhood. Moreover, one can measure the concentration of high-skilled workers at any distance to worker i's workplace. It is thus natural to regard the concentration of high-skilled workers with respect to the distance to worker i's workplace as a curve. We use curves to assess how the concentration of human capital influences productivity in space.

The functional linear regression model with a scalar response variable is a suitable framework to measure such a relationship. With Y_i being the scalar dependent variable, the model is defined as

$$Y_i = \int_0^1 \beta(z) X_i(z)\,\mathrm{d}z + \varepsilon_i, \tag{2.1}$$

where $X_i \in L^2([a,b])$ are independent and identically distributed (iid) random functions defined on a common domain, which we set to $[0,1]$ without loss of generality. The function-valued coefficient parameter $\beta \in L^2([0,1])$ describes the influence of X_i on Y_i and varies over distance z. The error term ε_i is independently distributed and has a mean of zero and homoscedastic variance (we will later consider heteroscedastic and autocorrelated errors).

Model (2.1) has received considerable attention in the FDA literature (see Morris, 2015, for an overview). Classically, the estimation of β is based on the Karhunen-Loève decomposition of the empirical covariance operator of the observed curves X_i. Therefore, the expansion of the so-called functional principal component (FPC) estimator depends heavily on the random curves' correlation structure. In this paper, we instead build on the smoothing spline estimator proposed by Crambes *et al.* (2009). This approach has the advantage that the basis functions are independent of the curves X_i, which results in a more flexible function space for $\widehat{\beta}$. From an asymptotic perspective, both estimators have minimax-optimal convergence rates (Hall & Horowitz, 2007; Crambes *et al.* , 2009).

In the following, $\mathbf{X}$ denotes the $n \times p$ matrix holding all n curves $X_i(z)$ observed at p grid values $z_1, \ldots, z_p$, and $\mathbf{Y}$ denotes the n-vector with observations of the dependent variable. To estimate β, the approach of Crambes *et al.* (2009) minimizes the penalized sum of squared residuals

$$\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \frac{1}{p}\sum_{j=1}^{p}\beta(z_j)X_i(z_j)\right)^2 + \rho\left(\frac{1}{p}\sum_{j=1}^{p}\pi_\beta^2(z_j) + \int_0^1 (\beta^{(m)}(z))^2\,\mathrm{d}z\right). \tag{2.2}$$

Here, $\pi_\beta(z)$ is the best approximation of $\beta(z)$ by a polynomial of degree $m-1$ and ensures uniqueness without imposing further assumptions on the random functions X_i. The penalty parameter $\rho \geq 0$ controls the flexibility of the estimated parameter function $\widehat{\beta}$. With $\rho = 0$, for instance, equation (2.2) coincides with the least-squares criterion. The minimizer of equation (2.2) is

$$\left(\widehat{\beta}(z_1), \ldots, \widehat{\beta}(z_p)\right) = \frac{1}{n}\left(\frac{1}{np}\mathbf{X}'\mathbf{X} + \rho\mathbf{A}\right)^{-1}\mathbf{X}'\mathbf{Y}, \tag{2.3}$$

where $\mathbf{A} = \mathbf{P} + p\mathbf{A}^*$ is a penalty matrix introduced by Crambes *et al.* (2009). This matrix is a combination of a classical regularization matrix $\mathbf{A}^* \in \mathbb{R}^{p\times p}$ and a nonstandard projection matrix $\mathbf{P} \in \mathbb{R}^{p \times p}$ projecting into the space spanned by polynomial functions of degree $m-1$. The latter ensures the invertibility of $\mathbf{X}'\mathbf{X} + \rho\mathbf{A}$ and is defined by $\mathbf{P} = \mathbf{W}(\mathbf{W}'\mathbf{W})^{-1}\mathbf{W}'$, where $\mathbf{W} = (z_j^q)_{j,q} \in \mathbb{R}^{p \times m}$, $q = 0, \ldots, m-1$. Traditional smoothing splines penalize second derivatives. Thus, we set $m = 2$, which results in an expansion of cubic natural splines with knots at $z_1, \ldots, z_p$. The regularization matrix $\mathbf{A}^*$ is defined as usual by

$$\mathbf{A}^* = \mathbf{B}(\mathbf{B}'\mathbf{B})^{-1} \left(\int_0^1 \mathbf{b}^{(2)}(z)\mathbf{b}^{(2)}(z)' \, \mathrm{d}z \right) (\mathbf{B}'\mathbf{B})^{-1}\mathbf{B},$$

where $\mathbf{B}$ denotes the $p \times p$ matrix of the p basis functions, evaluated at the p grid values, and $\mathbf{b}^{(2)}(z)$ is, for given value of $z \in [0, 1]$, a p-vector of second derivatives for each of the p basis functions.

To account for the influence of further explanatory variables, we expand model (2.1) with a k-vector of scalar-valued explanatory variables Z_i and a corresponding parameter vector γ:

$$Y_i = \int_0^1 \beta(z)X_i(z) \, \mathrm{d}z + Z_i'\gamma + \varepsilon_i. \tag{2.4}$$

Accordingly, we augment the smoothing spline estimator of Crambes *et al.* (2009) to incorporate scalar-valued explanatory variables. Let $\mathbf{X_Z}$ denote the compound data matrix $(\mathbf{X}, p\mathbf{Z})$, where the matrix $\mathbf{Z}$ holds the sample values of the k additional scalar explanatory variables. The compound estimator of (discretized) β and γ then is:

$$\widehat{\boldsymbol{\beta}} = \left(\widehat{\beta}(z_1), \ldots, \widehat{\beta}(z_p), \widehat{\gamma}_1, \ldots, \widehat{\gamma}_k\right) = \frac{1}{n} \left(\frac{1}{np} \mathbf{X}_\mathbf{Z}'\mathbf{X}_\mathbf{Z} + \rho\mathbf{A}_\mathbf{Z} \right)^{-1} \mathbf{X}_\mathbf{Z}'\mathbf{Y}. \tag{2.5}$$

Because the scalar-valued explanatory variables do not load into the roughness penalty, we extend the penalty matrix $\mathbf{A}$ by appending k zero columns and k zero rows:

$$\mathbf{A_Z} = \begin{pmatrix} \mathbf{A} & 0 \\ 0 & 0 \end{pmatrix} \in \mathbb{R}^{(p+k)\times(p+k)}.$$

The estimator (2.5) depends on the smoothing parameter ρ that controls the complexity of the estimate of the function-valued slope parameter β. The smoothing parameter ρ itself has no meaningful interpretation. Instead, a well-established measure for the complexity of the estimate $\widehat{\beta}$ is the *effective number of degrees of freedom* (edf):

$$\mathrm{edf}(\rho) = \mathrm{trace}\big(\mathbf{H}_\mathbf{Z}^\rho\big), \tag{2.6}$$

where $\mathbf{H}_{\mathbf{Z}}^{\rho} = (np)^{-1}\mathbf{X}_{\mathbf{Z}}\left((np)^{-1}\mathbf{X}_{\mathbf{Z}}'\mathbf{X}_{\mathbf{Z}} + \rho\mathbf{A}_{\mathbf{Z}}\right)^{-1}\mathbf{X}_{\mathbf{Z}}'$ is the *hat* matrix of model (2.4). Given a predefined number of degrees of freedom, equation (2.6) allows us to determine ρ. In our preferred specification, we set $\mathrm{edf}(\rho) = 2.5$; the resulting estimate can thus be substantially more complex than a straight line. We experiment with different penalties in appendix 2.A.5. Qualitatively, our results do not depend on the exact choice of the penalty term ρ.

2.2.2 Inference

From a theoretical perspective, drawing local inference about the slope parameter β in the functional linear regression model is a difficult issue. When $X_i(z)$ are elements of the infinite-dimensional Hilbert space L^2, the estimator $\widehat{\beta}$ is not asymptotically normal (w.r.t. the strong topology on L^2). The reason is that such models belong to the class of ill-posed inversion problems, that is, the (compact) covariance operator of the random curves $X_i(z)$ has no bounded inverse (see Cardot *et al.* , 2007, for details).

To quantify the estimation uncertainty, we proceed as in the classical linear regression framework. In classical linear regression, inference about the model parameters builds on the variance of the parameter estimates conditional on the observed regressors. Similarly, the (pointwise) variance of the compound parameter vector $\widehat{\boldsymbol{\beta}}$ for given observations of curves and covariates, $\mathbf{X}_{\mathbf{Z}}$, and the regularization parameter, ρ, can be computed by (see also Ramsay & Silverman, 2005, equation 15.16)

$$\mathrm{Var}\big(\widehat{\boldsymbol{\beta}}|\mathbf{X}_{\mathbf{Z}}, \rho\big) = \frac{1}{n^2}\left(\frac{1}{np}\mathbf{X}_{\mathbf{Z}}'\mathbf{X}_{\mathbf{Z}} + \rho\mathbf{A}_{\mathbf{Z}}\right)^{-1}\mathbf{X}_{\mathbf{Z}}'\boldsymbol{\Omega}\mathbf{X}_{\mathbf{Z}}\left(\frac{1}{np}\mathbf{X}_{\mathbf{Z}}'\mathbf{X}_{\mathbf{Z}} + \rho\mathbf{A}_{\mathbf{Z}}\right)^{-1}. \quad (2.7)$$

Here, $\boldsymbol{\Omega}$ is the covariance matrix of the error term, which does not necessarily have to be diagonal. By replacing this matrix with an appropriate estimate $\widehat{\boldsymbol{\Omega}}$, we obtain an estimate for the variance of the parameter vector $\widehat{\boldsymbol{\beta}}$. Furthermore, we estimate the 'meat', $\mathbf{X}_{\mathbf{Z}}'\boldsymbol{\Omega}\mathbf{X}_{\mathbf{Z}}$, based on clustered standard errors at the firm level (see, for instance, Abadie *et al.* , 2017, equation 2.3).

We use the variance (2.7) to visualize the pointwise variability of the estimate $\widehat{\boldsymbol{\beta}}$ with confidence bands. We obtain confidence bands by multiplying the square-root of the corresponding diagonal entry of $\mathrm{Var}\big(\widehat{\boldsymbol{\beta}}|\mathbf{X}_{\mathbf{Z}}, \rho\big)$ by appropriate quantiles of the normal distribution. To account for the family-wise error rate, we divide the significance level by the effective degrees of freedom. The simulation exercise (section 2.4.2) supports such a procedure and shows that it indeed controls size when the (global) null is a linear function. Even if the true parameter β_0 is more complex, the estimator is able to resemble

β_0 quite well, although a local bias leads to a pointwise violation of the nominal coverage probability of the confidence bands.

2.2.3 Calculation of curves

A key feature of our analysis is the representation of the spatial density of high-skilled workers around workplaces as curves. To calculate these curves from geocoded data, we compute the values of the functions $X_i(z)$ for each worker i on an equidistant grid $z_1, \dots, z_p$:

$$X_i(z_j) = \frac{n^{hs}_{[z_j \, - \, h; \, z_j)}}{n_{[z_j \, - \, h; \, z_j)}}. \tag{2.8}$$

Here, $n^{hs}_{[z_j \, - \, h; \, z_j)}$ refers to the number of high-skilled individuals for which the spheric distance between their working location and the workplace of worker i is at least as large as $z_j - h$ and smaller than z_j. Similarly, $n_{[z_j \, - \, h; \, z_j)}$ is the number of all workers (high-skilled and low-skilled) within the distance window. In other words, the value of the curve X_i at distance z_j indicates the share of high-skilled workers in all workers within the distance window $[z_j - h, z_j)$, where h is a fixed bandwidth. To ensure that a firm's own skill structure does not affect measurements of its neighborhood, we compute $X_i(z_1)$ without its own number of workers. To balance analytical precision and computational costs, we choose a bandwidth of $h = 500$ meters and compute $X_i(z_j)$ on the grid $z_j = 500m, 1000m, \dots, 50000m$.

There are several options for the actual measure of the concentration of high-skilled workers. We, decide to measure density as shares instead of, for instance, in absolute numbers or high-skilled workers per square meter for several reasons. First, just as the geographic area covered by $[z_j - h, z_j)$ increases with distance z_j, the absolute number of high-skilled workers that could potentially populate that area also increases with distance. Thus, when using absolute numbers, the intensity of high-skilled workers would increase with distance by definition and would therefore not provide comparable values of $X_i(z)$ across space. Second, as the data show, the proportion of inhabited land decreases with z. As knowledge transfers appear only in inhabited areas, using high-skilled workers per square meter would therefore decrease the intensity of human capital with distance by construction. Thus, high-skilled workers per square meter would also not suffice to compare the concentration of high-skilled workers at varying distances. By contrast, the number of workers within the distance window $[z_j - h, z_j)$ is a reasonable unit of measurement of the *de facto* populated area, which, thinking of skyscrapers, not only covers actual land use but also the intensity of land use. Therefore, we measure the intensity of human capital as high-skilled workers relative to the total number of workers (i.e., we take the share of high-skilled workers). Using shares is also in line with the recent literature on regional knowledge spillovers following Moretti (2004).

2.2.4 Identification

Having explained the estimator, we will now address confounding labor market demand and supply effects and endogenous sorting of individuals. The empirical literature has established that high- and low-skilled labor are imperfect substitutes (e.g., Autor *et al.* , 2008; Ciccone & Peri, 2005; Card & Lemieux, 2001; Krusell *et al.* , 2000). As Acemoglu & Angrist (1999), Moretti (2004) and Ciccone & Peri (2006) illustrate, changes in the supply of high-skilled labor entail a market mechanism that affects wages. Due to labor market demand and supply effects, an increase in the share of high-skilled workers in the labor market depresses the wages of high-skilled workers and raises the wages of low-skilled workers.

If, for instance, a firm hires additional high-skilled workers, the functional variable X_i has a higher value at z for those individuals who work between $z - 500m$ and z away from that firm (for $z = 500m, 1000m, \ldots, 50000m$). The firm's decision also leads to an increase in the share of high-skilled workers within the local labor market and, therefore, entails a change in the local labor market situation. The corresponding wage effects of this market mechanism depend on whether the firm's decision is demand-driven (i.e., the firm needs more high-skilled workers) or is a result of a larger supply of high-skilled workers (maybe the firm's location offers amenities that attract such workers). However, it is not possible to infer from the data which side of the market was responsible for the firm's decision, but ignoring this mechanism in equation (2.4) likely yields a biased estimate of $\beta(z)$. The magnitude of the bias depends on the relative number of high- and low-skilled workers in the local labor market and the elasticity of substitution between the two groups (see Moretti, 2004).

To disentangle knowledge spillover from labor market supply and demand effects, we exploit the different spatial nature of the two effects. On the one hand, the intensity of knowledge spillovers should decay with distance. We therefore expect larger spillovers from close neighbors than from distant neighbors. On the other hand, labor market supply and demand effects plausibly uniformly affect the local labor market. Thus, independent of the exact location, a shift in the supply of high-skilled labor homogeneously affects wages within a local labor market. We are thus able to nullify labor market supply and demand effects by eliminating all variation that is common within local labor markets without removing intra-regional variation from knowledge spillovers.

As labor market supply and demand shifts vary over time and the direction of such shifts idiosyncratically affects high- and low-skilled individuals, we expand equation (2.4) to include time-varying labor-market-area fixed effects for each skill group π_{rst} (i.e., an intercept for each labor market area and skill group in every year). Our full estimation equation is:

$$Y_{it} = \int_0^1 \beta(z) X_{it}(z)\,\mathrm{d}z + Z_{it}'\gamma + \theta_{if} + \tau_t + \omega_o + \pi_{rst} + u_{it}. \tag{2.9}$$

Here, Y_{it} is the individual log wage of worker i in year t, and $X_{it}(z)$ is the share of high-skilled workers, described as a continuous curve around the workplace of individual i that depends on distance z. Note that all workers of firm i in year t share the same locational characteristics, specifically they all have the same curve $X_{it}(z)$. $\beta(z)$ is the associated spillover function that we seek to retrieve from the data. The model controls for time-varying observable individual, establishment and regional characteristics Z_{it} and a series of fixed effects. θ_{if} is a worker-firm match fixed effect, τ_t is a year fixed effect and ω_o is an occupation fixed effect.

Endogenous sorting of workers (Acemoglu & Angrist, 2000) constitutes another challenge in identifying regional knowledge spillovers. In our application, sorting threatens identification on two levels: first on the level of treated individuals (i.e., individuals whose wages we observe) and second on the treatment level itself (i.e., the spatial density of high-skilled workers). Regarding treated individuals, the most able workers might sort into high-skilled neighborhoods. Sorting would thus create a spurious relationship between wages and the local concentration of human capital. Regarding the treatment level, high-wage areas might attract high-skilled workers. Sorting would thus lead to reverse causality. Inspired by Cornelissen *et al.* (2017), we address sorting with an extensive set of fixed effects.

Although the empirical literature finds that workers do not sort into cities based on their (unobserved) abilities (De la Roca & Puga, 2017; Glaeser & Mare, 2001), there is evidence of ability-driven sorting of workers into firms (Card *et al.* , 2013; Abowd *et al.* , 1999). If more-productive firms locate in neighborhoods with high concentrations of human capital, sorting of workers would create a spurious relationship between wages and the local share of high-skilled workers. Thus, to ensure that neither sorting of workers nor sorting of firms biases the estimates, we include worker-firm match fixed effects (θ_{if}) in our model. Worker-firm match fixed effects additionally eliminate other unobservable characteristics of workers and firms, such as personal traits and locational advantages (e.g., proximity to infrastructure).

Regarding sorting at the treatment level, high-wage areas might attract high-skilled workers, which would reverse the direction of causality in equation (2.9). However, as worker-firm match fixed effects (θ_{if}) nullify permanent locational advantages, they also eliminate general push and pull factors that might draw high-skilled workers into high-wage regions. Moretti (2004) additionally raises the concern that temporal shocks in the local labor market might affect the concentration of high-skilled workers. We address this issue with time-varying labor-market-area fixed effects (π_{rst}). Because time-varying labor-market-area fixed effects remove temporal variation in the supply of high-skilled labor, they also remove supply changes due to temporal shocks.

In summary, equation (2.9) allows us to estimate knowledge spillovers that are unrelated to labor market demand and supply effects and endogenous sorting of individuals. The remaining variation of $X_{it}(z)$ in equation (2.9) stems from temporal intra-regional changes in the concentration of high-skilled workers.

2.3 Data and descriptive statistics

2.3.1 Data

In the empirical analysis, we combine administrative data on almost all German firms and rich data from a representative sample of workers over a period of 15 years. Our panel data include exact geo-coordinates of establishments and therefore allow us to describe the distribution of high-skilled workers as spatial functions around workers. We evaluate the share of high-skilled workers at 500-meter intervals up to a distance of 50 kilometers.

Our main meso-level data sources are the *Establishment History Panel* (BHP 7516) and *IEB GEO* from the Institute for Employment Research (IAB).[2] The *Establishment History Panel* comprises all German establishments with at least one employee on June 30 of each year. The dataset provides establishment-level information on, among other metrics, the number of employees and the number of employees with tertiary education. To measure the distribution of high-skilled workers, we classify employees holding a degree from a university or a university of applied sciences as high skilled.[3]

2 For a detailed description of the Establishment History Panel, see Schmucker *et al.* (2016)

3 There are two types of universities in the German tertiary education system: traditional universities and universities of applied sciences (*Fachhochschulen*). Compared to traditional universities, universities of applied sciences focus more on practical topics. Universities of applied science usually also have a stronger focus on engineering and technology. Both kinds of universities award bachelor's and master's degrees.

We expand the dataset with exact geo-coordinates from IEB GEO. IEB GEO is a novel data source that includes addresses of establishments in the *Establishment History Panel* between 2000 and 2014 as geo-coordinates. In Germany, firms are obliged to register at least one of their establishments per municipality and industry. In general, the registration of one establishment per municipality provides a detailed description of the geographic landscape of workplaces. In some cases, however, firms might actually have multiple establishments within the same industry in a single municipality, which they do not report. In these cases, we cannot confirm that individuals work where they are registered. We therefore exclude the following chain-store industries from our data: construction, financial intermediation, public service, retail trade, temporary agency work and transportation. With the remaining set of establishments, we compute the density of high-skilled workers as spatial functions around establishments as described in section 2.2.3.

In the econometric analysis of knowledge spillovers, we merge the constructed spatial functions of high-skilled workers with micro-level data from the *Sample of Integrated Labour Market Biographies* (SIAB 7514).[4] The Sample of Integrated Labour Market Biographies is a 2% random sample of social security records. The dataset contains information on wages, age, work experience and education, among other data, with daily precision. To join the individual-level data to the establishment-level data we transform the spell dataset into a yearly panel with June 30 as the reference date.

Because employers face legal sanctions for misreporting, information on wages in German social security data is generally highly reliable. However, one limitation is that roughly 10% of earnings are right-censored at the social security maximum. Therefore, we impute top-coded wages following Dustmann *et al.* (2009) and Card *et al.* (2013) (see appendix 2.A.1 for details). Further, we improve information on education following Fitzenberger *et al.* (2005) and restrict the sample to full-time workers aged between 18 and 64. As we are only interested in the effects on individuals in regular employment, we exclude apprentices, interns, marginally employed workers and trainees. The final dataset consists of 3,498,536 observations from 539,179 individuals between 2000 and 2014.

To assign workplaces to local labor markets, we use the *de facto* standard definition of local labor market areas in Germany from the Federal Ministry for Economic Affairs and Energy (BMWi). The goal in designating these local labor market areas is to design regions with strong internal commuter links but clear detachment from other areas. The construction is based on Kosfeld & Werner (2012), who use factor analysis on commuter flows to identify local labor market areas in Germany. The BMWi partitions Germany

4 For a detailed description of the Sample of Integrated Labour Market Biographies, see Antoni *et al.* (2016)

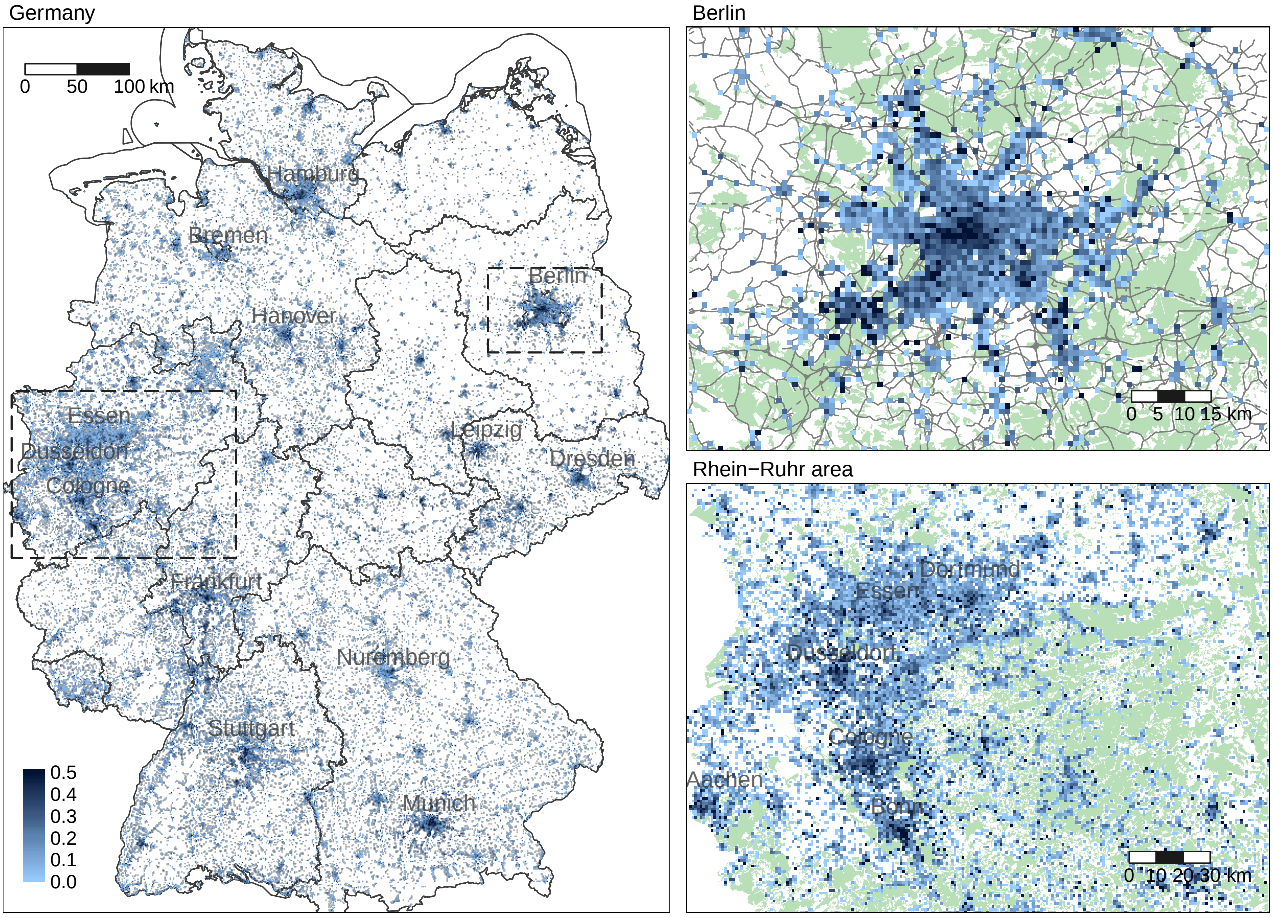
into 258 local labor market areas with an average radius of 21 kilometers. The size of these local labor market areas corresponds well to the findings of Manning & Petrongolo (2017), implying that 80% of the effects of local labor demand shocks are measurable within 20 kilometers. As a rule of thumb, the authors further suggest that treatment areas for labor demand shocks should be 2.5 times the median commute. In our case the rule of thumb would suggest 24 kilometers and is therefore close to the actual size of the labor market areas from the BMWi (Dauth & Haller, 2018, own calculations). Because labor market areas consist of multiple counties (*Stadt- und Landkreise*, NUTS-3), we complete our dataset with county-level indicators on population density, unemployment and number of hotel beds (as a proxy for amenities) from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR).

2.3.2 Descriptive statistics

Figure 2.3.1 provides an overview of the distribution of high-skilled workers in Germany. For data protection reasons, the map shows the share of high-skilled workers in 1×1 kilometer grid cells. Note that the data used in the econometric analysis are more precise and offer exact coordinates. The map illustrates the considerable diversity in the distribution of high-skilled workers in Germany. For instance, among the largest cities, there is a massive concentration of high-skilled workers in Munich, Hamburg and Berlin. By contrast, Nuremberg and Bremen exhibit significantly lower shares of high-skilled workers. Moreover, apart from metropolitan areas, there are several hot spots for skilled labor. For example, in Erlangen (15 kilometers north of Nuremberg), Darmstadt (25 kilometers south of Frankfurt) and Jena (70 kilometers south east of Leipzig) over 30% of full-time workers hold a degree from a university or university of applied sciences. Moreover, the distribution of high-skilled workers also varies considerably within administrative regions. The upper-right panel of figure 2.3.1 shows a substantial cluster of high-skilled workers in the city center of Berlin. Additionally, there are several smaller clusters along the main traffic connections. The bottom-left panel focuses on the Rhein-Ruhr area. While high-skilled workers are evenly distributed in Essen and Dortmund, they appear to be very concentrated in the city centers of Düsseldorf, Cologne and Bonn. There are numerous small hot spots between the cities.

To capture the heterogeneous distribution of high-skilled workers, we compute a spatial function that relates the share of high-skilled workers to distance for each workplace in our data. Figure 2.3.2 illustrates the resulting curves. The light gray curves are 100 random examples and provide an impression of the variability in the data. The solid line

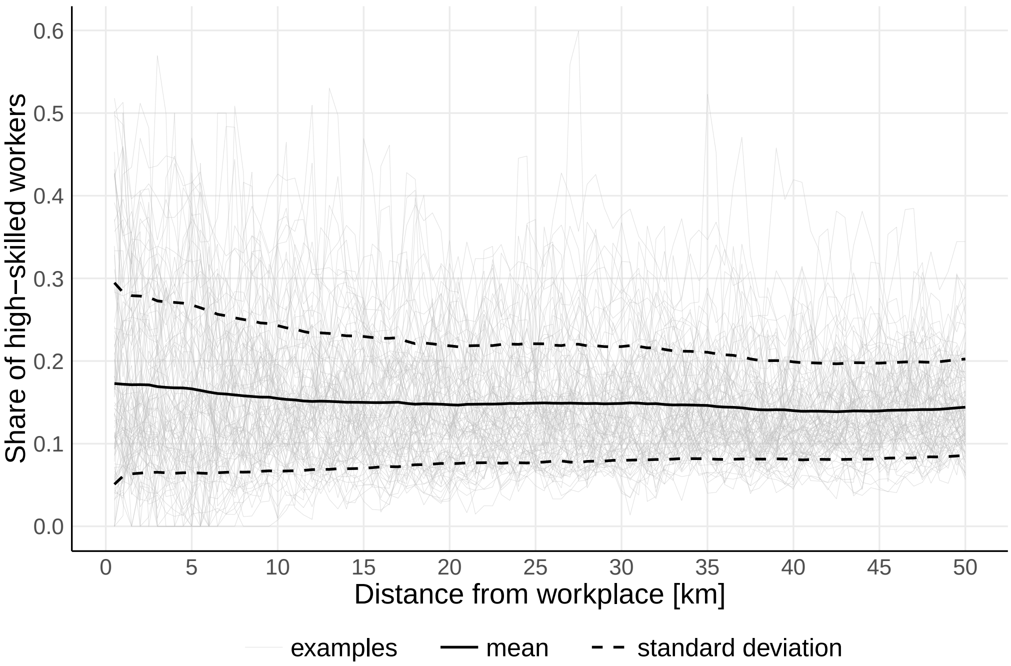
Figure 2.3.1: Distribution of high-skilled workers in Germany



Notes: The figure depicts the share of high-skilled workers in 1×1 kilometer grid cells in Germany (left panel), Berlin (upper-right panel), and the Rhein-Ruhr area (bottom-right panel) in 2014. For data protection reasons, the maps depict aggregated data in grid cells. For the same reason, we removed cells with fewer than four establishments from the graphs. Note that the data for our statistical analysis are more precise and provide the exact coordinates of workplaces. Light blue cells indicate low shares of high-skilled workers, and dark cells signal high shares (see the scale at the bottom left). For the sake of clarity, values are capped at 50%. In the left panel, black lines depict the boundaries of federal states. In the right panels, green areas depict forests, and in the upper-right panel, gray lines and dashed gray lines illustrate streets and railways, respectively.

shows the average share of high-skilled workers around establishments, and the dashed lines indicate the pointwise standard deviation around the mean. Although individual curves have strong variation, the average share of high-skilled workers around workplaces is stable in space. On average, the share of high-skilled workers is 17% in the direct neighborhood of establishments and gradually declines to 14.5% 50 kilometers away. The graph shows that there is no inherent distance at which the share of high-skilled workers suddenly falls. Instead, irregular city sizes and distances between settlements lead to a stable mean of the intensity of human capital over the whole domain. Note that the

Figure 2.3.2: Spatial functions of the share of high-skilled workers



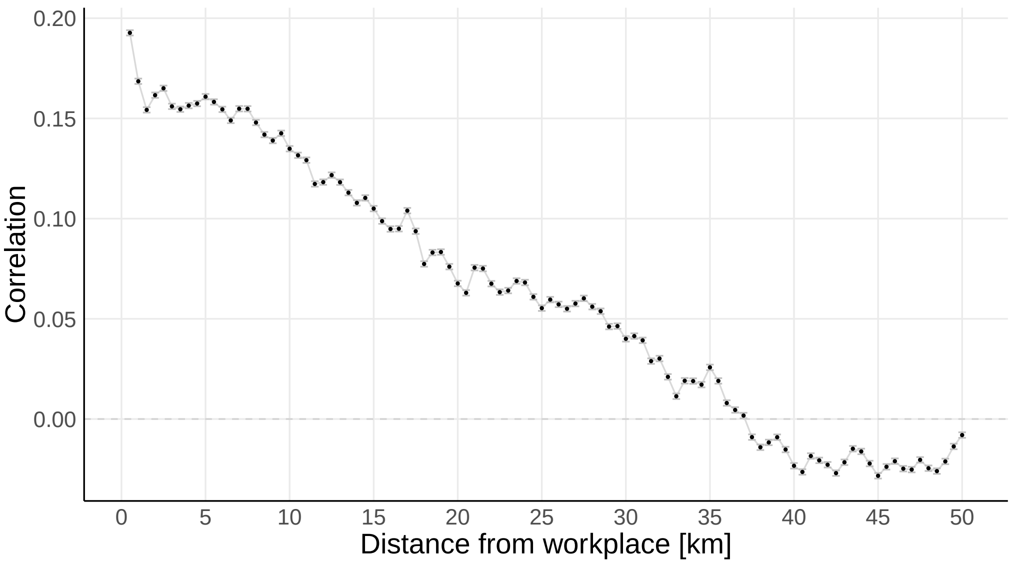
Notes: The figure shows the pointwise mean (solid line) and standard deviation (dashed lines) of the share of high-skilled workers around workplaces. Throughout the paper, we describe the share of high-skilled workers with spatial functions that map the share of high-skilled workers to the distance from a workplace. The graph also illustrates the variability of the spatial functions with 100 randomly selected curves (light gray lines). Each gray line depicts the spatial distribution of high-skilled workers around an establishment.

slight decline in the standard deviation is an artifact: The share of high-skilled workers within a distance window $[z_j - 500m, z_j)$ is the average of a binary variable, and since the absolute number of workers in $[z_j - 500m, z_j)$ increases with z, the variance of the average decreases. Refer to appendix 2.A.2 for illustrative examples on the distribution of high-skilled workers around workplaces.

To obtain a first impression of the relationship between individual earnings and the spatial concentration of human capital, figure 2.3.3 shows the correlation between log wages and the share of high-skilled workers within distance windows $[z_j - 500m, z_j), z_j = 500m, 1000m, ..., 50000m$. While the magnitude of the *ordinary* correlation has no direct interpretation, the declining trend signals that the relationship between income and the spatial concentration of high-skilled labor decays with distance.[5]

[5] The magnitude of the correlation between wages and the share of high-skilled workers in some distance window has no direct interpretation for two reasons. First, the bandwidth of the distance window determines the strength of the correlation. We could, for instance, shrink the correlation coefficient to arbitrarily small values by decreasing the bandwidth of the distance window. Second, the *ordinary* correlation does not partial out the relationship between wages and other distance windows than the focal one. Naturally, neighboring distance windows are (spatially auto-) correlated.

Figure 2.3.3: Correlation of individual wages and the regional share of high-skilled workers

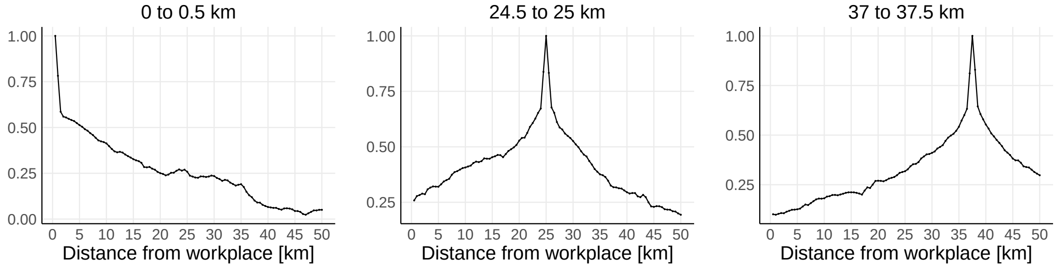


Notes: The figure illustrates the correlation between log wages and the share of high-skilled workers within distance windows $[z_j - 500m, z_j], z_j = 500m, 1000m, ..., 50000m$. The graph suggests that the correlation between individual earnings and the intensity of human capital attenuates with distance. Note that the magnitude of the correlation coefficients cannot be interpreted directly.

One reason that the magnitude of the correlation coefficients has no direct interpretation is that the functions for the share of high-skilled workers are spatially autocorrelated. Figure 2.3.4 illustrates this issue. The graph depicts the correlation between the share of high-skilled workers in three selected distance windows with the remaining 99 measurement points. For instance, the first panel presents the correlation of the share of high-skilled workers between measurement point t_1 and the random curve's value at $t_2, \ldots, t_{100}$. As the figure shows, adjacent values have a very high correlation compared to more distant measurement points.

While ordinary correlations (figure 2.3.3) ignore spatial autocorrelation, standard OLS regression is in principle able to orthogonalize covariates. However, as discussed in the next section, given the strong correlation between adjacent measurements, an unpenalized OLS regression does not reveal any relationship at all. For further summary statistics on individual wages and other covariates in our dataset, we refer to appendix 2.A.3.

Figure 2.3.4: Spatial autocorrelation at selected measurement points



Notes: The graphs shows the spatial autocorrelation of the spatial functions of high-skilled workers at different measurement points. For instance, the panel in the middle shows the correlation of the share of high-skilled workers 24.5 to 25 kilometers away from workplaces with the share of high-skilled workers at the other 99 measurement points. The focal points in the remaining two panels are 0 to 0.5 and 37 to 37.5 kilometers, respectively. As is typical with functional data, values close to the focal point have high correlation. The correlation declines with distance from the focal point. Note that the three selected focal points well illustrate the general pattern of the underlying three-dimensional correlation function.

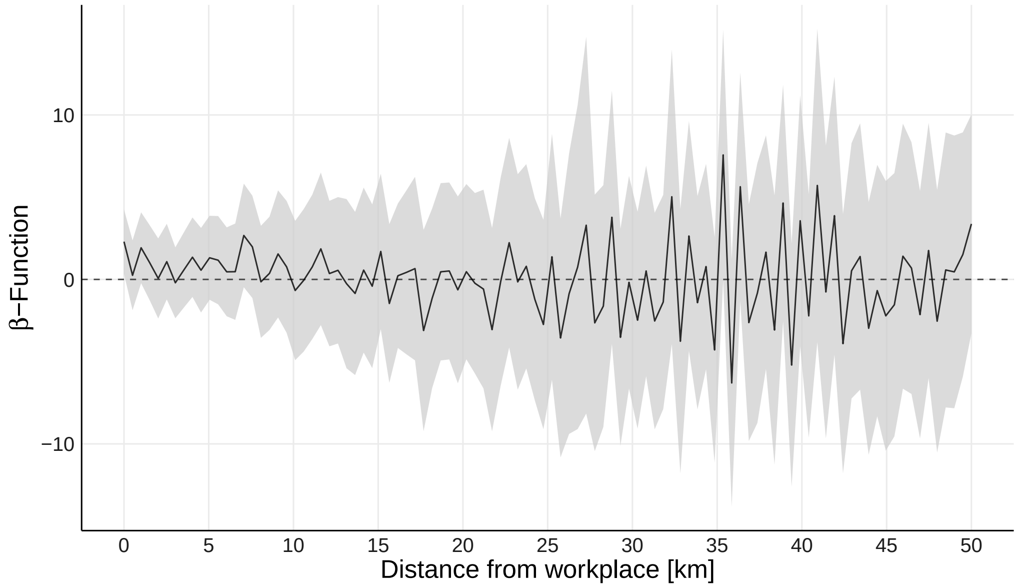
2.4 Results

Our main results show that spillover effects from the local concentration of high-skilled workers significantly increase individual wages. The spillover effects decay with distance, and the point estimates suggest that after 10 kilometers, the effects are reduced by half. Beyond 15 kilometers, the effects are no longer distinguishable from zero. In the following, we present the estimation results and discuss our findings. Next, we corroborate the robustness of our estimates with a simulation study and a placebo test. Finally, we summarize several additional robustness checks.

2.4.1 Main findings

We illustrate estimates of the spatial intensity of knowledge spillovers from high-skilled workers in figures 2.4.1 and 2.4.2. Figure 2.4.1 depicts an unrestricted estimate of equation (2.9) (i.e., $\rho = 0$ in equation (2.5)), which coincides with standard OLS regression. Figure 2.4.2 presents penalized estimates of equation 2.9 (i.e., $\rho > 0$). Both estimates control for labor market demand and supply effects and endogenous sorting of individuals with an extensive set of fixed effects. In addition to standard controls form the labor literature, our models include worker-firm match fixed effects and skill-specific yearly labor-market-area fixed effects. In the graphs, black lines display the estimated spillover functions. The gray area indicates the associated 99% confidence band. Note that OLS estimates of equation (2.9) would be mis-scaled by the number of discretization points of $X_{it}(z)$. By contrast, our estimates provide an approximation via a Riemann sum and are

Figure 2.4.1: Unrestricted estimates of spatial knowledge spillovers from high-skilled workers



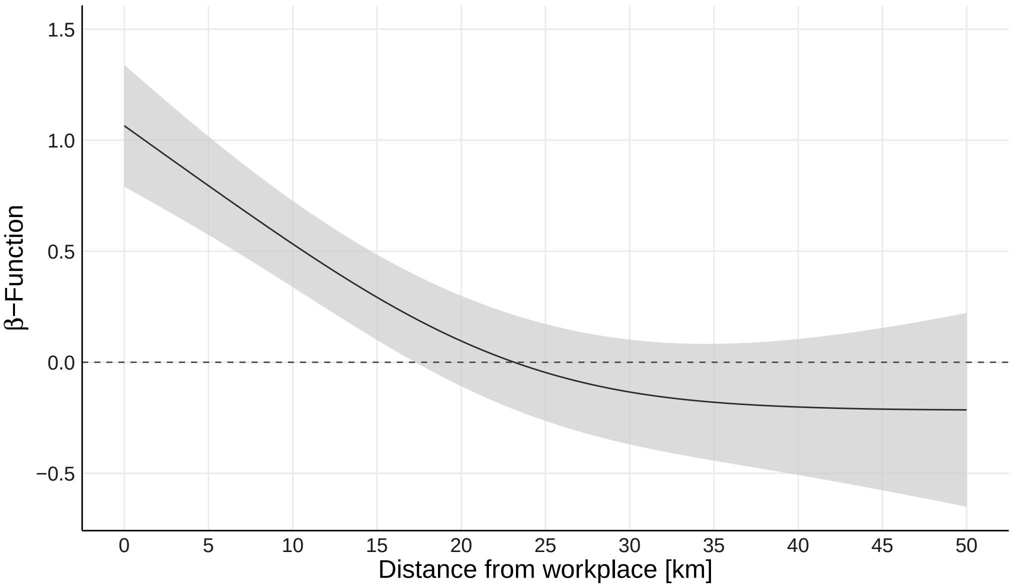
Notes: The figure presents an unrestricted estimation of spatial knowledge spillovers from high-skilled workers into individual log wages (equation (2.9)). We measure the concentration of high-skilled workers as the share of high-skilled workers within distance z. The black line illustrates the estimated spillover function ($\beta(z)$), and the gray area indicates the 99% confidence band. The unrestricted estimator (equation (2.5), with $\rho = 0$) coincides with the standard OLS estimator. Due to multicollinearity and overfitting, the estimator cannot retrieve valid estimates of $\beta(z)$ from the data. The underlying model controls for worker-firm match fixed effects, skill-specific yearly labor-market-area fixed effects, occupation and time fixed effects and worker characteristics (age, work experience, tenure and the respective second-order polynomials), log establishment size and county characteristics (unemployment rate, log population density and the log number of hotel beds as a proxy for amenities). $N = 3,498,536$

thus correctly scaled.

As figure 2.4.1 shows, the unpenalized estimate of equation (2.9) identifies no significant link between the spatial concentration of high-skilled workers and individual earnings. The point estimates are very unstable, and the confidence bands include the null over the whole domain. There are two reasons for the unstable behavior of the curve. First, as described in the previous section, the measurement points of the share of high-skilled workers are highly correlated. Because the unrestricted estimator is (up to a scale) identical to the standard OLS estimator, high correlation among a large set of regressors poses multicollinearity problems. Consequently, the estimates exhibit high variance. Second, an unrestricted estimator allows one to compute unnecessarily complex functions and is therefore potentially prone to overfitting the data by modeling noise.

By contrast, the penalized estimates in figure 2.4.2 reveal a clear influence of the spatial concentration of high-skilled workers on individual wages. The spatial spillover

Figure 2.4.2: Spatial knowledge spillover from high-skilled workers



Notes: The figure shows spatial knowledge spillover from high-skilled workers into individual log wages. We measure the concentration of high-skilled workers as the share of high-skilled workers within distance z. To compute the spatial spillover function ($\beta(z)$) we estimate equation (2.9) with the estimator (2.5). We restrict the capacity of the β curve to a parabola-like function that may remain flat over some interval, and we set the penalty parameter ρ accordingly. The black line illustrates the estimated spillover function ($\beta(z)$), and the gray area indicates the 99% confidence band. The graph shows significant spillover effects that decay with distance. The effect of a p-percentage-point increase in the share of high-skilled workers within distance z_0 and z_1 (in a 0 to 1 range) is p times the area bellow the estimated spillover function from z_0 to z_1. For instance, a 20-percentage-point increase in the concentration of high-skilled workers within 5 kilometers ($z_0 = 0, z_1 = \frac{5}{50}$) leads to wage gains of 1.75%. The underlying model controls for worker-firm match fixed effects, skill-specific yearly labor-market-area fixed effects, occupation and time fixed effects and worker characteristics (age, work experience, tenure and the respective second-order polynomials), log establishment size and county characteristics (unemployment rate, log population density and the log number of hotel beds as a proxy for amenities). Refer to table 2.A.2 in the appendix for a complete list of parameter estimates. $N = 3,498,536$

function depicted in the figure was obtained with 2.5 effective degrees of freedom. With such a specification, the estimate can be substantially more complex than a straight line. Estimates with more (fewer) effective degrees of freedom are qualitatively similar but are of course more (less) flexible (see appendix 2.A.5).

Our estimates in figure 2.4.2 reveal economically significant spillover effects from the local concentration of high-skilled workers. The spillover effects decay with distance and vanish after approximately 15 kilometers. The magnitude of the effects from direct neighbors is roughly twice as large the size of effects from high-skilled workers located ten kilometers away. In the graph, the effect of a p-percentage-point increase in the share of high-skilled workers within distance z_j and $z_{j'}$ (in a 0 to 1 range), is p times the area bellow the estimated spillover function from z_j to $z_{j'}$. For instance, a 20-percentage-point increase in the concentration of high-skilled workers within 5 kilometers leads to wage gains of 1.75% ($\approx 20 \times \{0.75 \times \frac{5}{50} + \frac{1}{2}\left[(1-0.75) \times \frac{5}{50}\right]\}$). An evenly distributed ten-percentage-point (one standard deviation) increase in the share of high-skilled workers over the whole domain raises individual wages by 2% ($\approx 10 \times \frac{1}{2}\left(1 \times \frac{20}{50}\right)$). Reassuringly, *classical* estimates at an aggregate level, where we use OLS to model the wage effect of the share of high-skilled workers within counties and identical covariates as in equation (2.9), suggest effects of the same magnitude (see appendix 2.A.6).

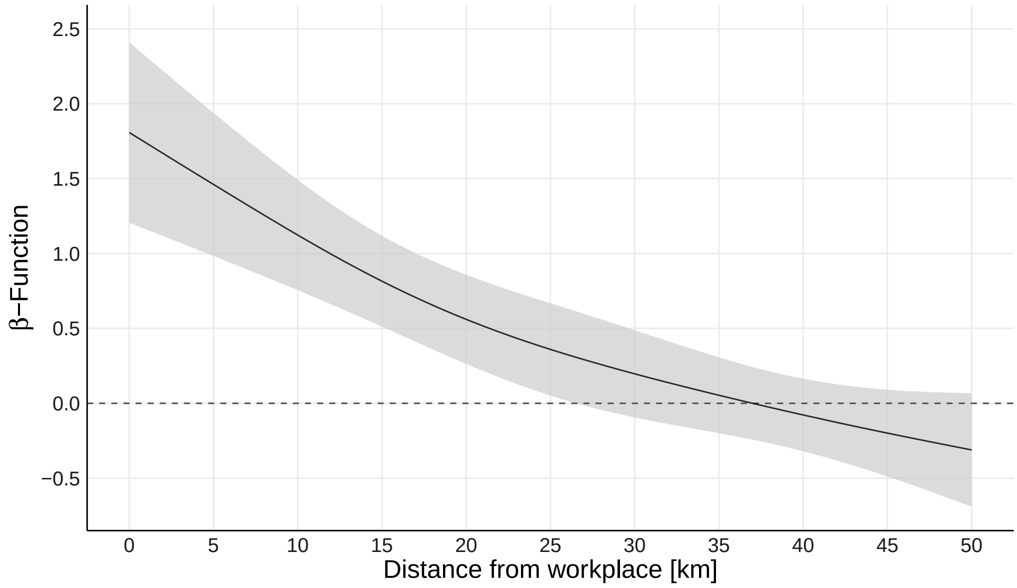
Our results are also similar to the findings of Rosenthal & Strange (2008) for the US. The authors regress wages on the number of workers with a college degree or higher education within 5 miles' distance and within 5 to 25 miles' distance. They report that spillovers from high-skilled workers within 5 miles' distance are up to 3.5 times larger than spillovers from high-skilled workers 5 to 25 miles away. Averaging our estimates within the same distance windows yields a ratio of 6. Although we follow a different estimation approach with different data, our findings seem to be consistent with those of Rosenthal & Strange (2008).

Let us now briefly discuss the importance of removing demand and supply effects when estimating knowledge spillovers. Figure 2.4.3 reports estimates of our model (equation (2.9)) without skill-specific yearly labor-market-area fixed effects (π_{rst}) and thus includes labor market demand and supply effects that stem from imperfect substitution of high- and low-skilled labor (see Moretti, 2004; Ciccone & Peri, 2006). Compared to our main findings, the estimated relationship between individual wages and the concentration of high-skilled workers appears stronger in these estimates. Specifically, there is a global upward shift of the estimated $\beta(z)$ by, roughly, a factor of two. Although π_{rst} also nullifies other confounders (e.g., temporal effects from sorting of high-skilled workers), the uniform upward shift of $\beta(z)$ corresponds well to Ciccone & Peri (2006). They find that the bias from demand and supply effects in Mincerian estimates of knowledge spillovers amounts to 60-70% of the individual returns to schooling.

2.4.2 Simulation study

As outlined in section 2.2.2, drawing local inference about the function-valued parameter β is difficult. The following simulation exercise, therefore, is intended to evaluate the statistical properties of our estimation framework. The results show that our estimation framework, although yielding locally biased estimates, is reliable in the sense that it is able to reproduce the structure of the true curve well. We also show that the inference

Figure 2.4.3: Spurious estimates of spatial knowledge spillovers from high-skilled workers



Notes: The figure presents estimates of the spatial knowledge spillover from high-skilled workers into individual log wages without nullifying labor market demand and supply effects that stem from imperfect substitution of high- and low-skilled workers. Specifically, the graph depicts estimates of the spatial spillover function ($\beta(z)$) from equation (2.9) without skill-specific yearly labor-market-area fixed effects (π_{rst}). We measure the concentration of high-skilled workers as the share of high-skilled workers within distance z and compute the model with the estimator (2.5). We restrict the capacity of the β curve to a parabola-like function that may remain flat over some interval, and we set the penalty parameter ρ accordingly. The black line illustrates the estimated spillover function ($\beta(z)$), and the light gray area indicates the 99% confidence band. The graph shows a significant relationship between the spatial concentration of high-skilled workers and wages. However, approximately half of the relationship is attributable to labor market supply and demand effects and other confounders. The underlying model controls for worker-firm match fixed effects, occupation and time fixed effects and worker characteristics (age, work experience, tenure and the respective second-order polynomials), log establishment size and county characteristics (unemployment rate, log population density and the log number of hotel beds as a proxy for amenities). $N = 3,498,536$

procedure controls for size when the null is a linear function.

In the simulation study, we consider four scenarios. First, we evaluate the estimator's properties in a situation where the data generating process (DGP) resembles the particular real-world problem. Therefore, we take the DGP from the preferred estimate (figure 2.4.2). We also incorporate parameter estimates from all covariates and generate artificial observations of the dependent variable based on iid errors that are drawn from $N(0, \widehat{\sigma}_u^2)$. Here, $\widehat{\sigma}_u$ denotes the standard error of the residuals of the estimated model. The structure of the simulated dataset (e.g., sample size, number of firms, number of workers per firm), therefore, is the same as in the original sample. The remaining three scenarios assess the statistical properties of the estimator in different extreme situations. Here, we simulate data that have a similar structure as the real dataset. In particular, we replicate the first two moments of the original data.[6] The second and third scenarios evaluate the accuracy of the inference procedure when the null is the zero function or a linear function. The fourth and most extreme setting analyzes the performance of the estimator when the true parameter is a non-smooth step function. To asses the statistical properties of the estimator, we simulate 1000 replications in each scenario.

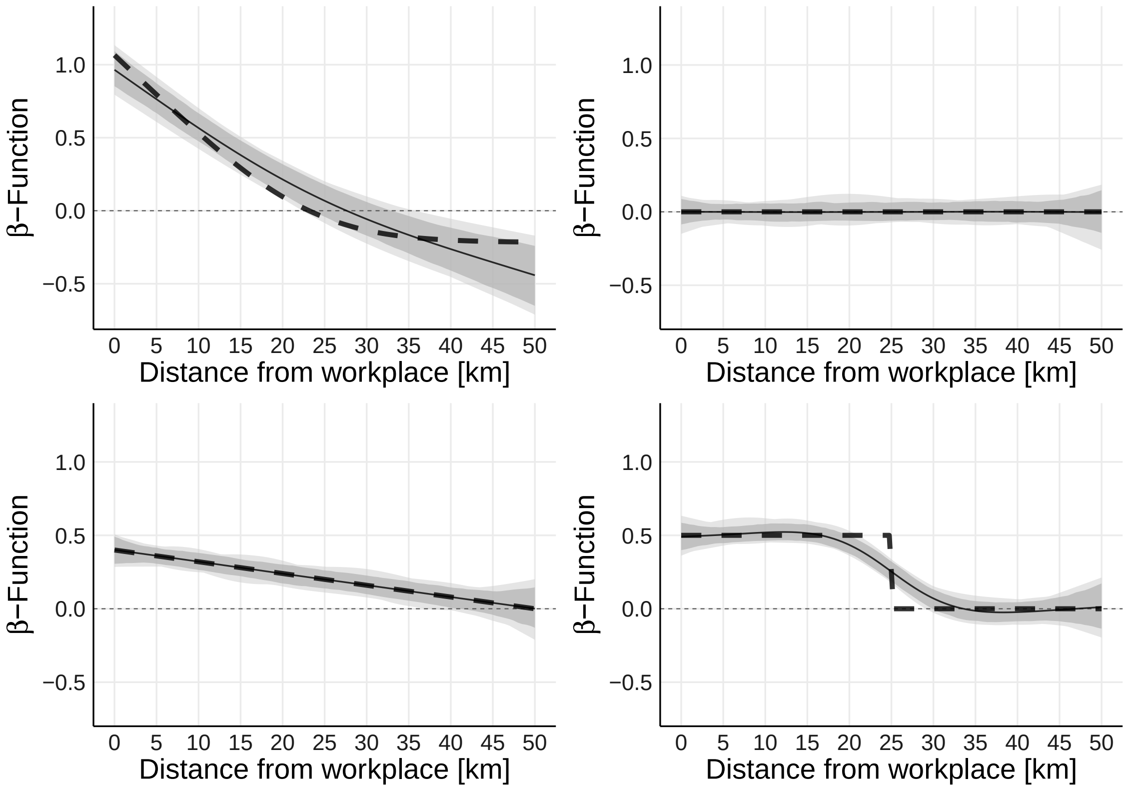
Figure 2.4.4 summarizes the results of the four simulations. In each panel, the bold dashed line depicts the true parameter function $\beta_0(z)$ of the DGP, the light gray areas show pointwise minimum and maximum of all estimates, and the dark gray areas show the first and the 99$^{\text{th}}$ percentiles of all estimates of the parameter function. The solid line represents the pointwise mean over all replications. In general, the estimates follow the true parameter function well, and no replication deviates substantially from the DGP. However, as is typical for penalized (or nonparametric) models, the estimates deviate from the true curve in regions with complex structure (i.e., in regions with strong nonlinearities). In such regions, the estimator possesses a local bias. As one might expect, this behavior is especially pronounced at the jump discontinuity of the step function in the bottom-right panel of figure 2.4.4. By construction, however, the smoothing splines estimator never produces estimates different from zero in regions where the true curve is zero in a larger neighborhood. Therefore, if the underlying functional shape of the spatial decay of knowledge spillovers is monotonically decreasing and zero beyond a certain distance, the regularized estimation captures the true curve well. This appears to be a reasonable assumption in our application.

Table 2.4.1 provides the integrated squared bias, integrated variance, and the coverage probability of the confidence bands for each scenario. The integrated (squared) bias is largest for the setup in which the function-valued parameter is taken from the real-data application because the true parameter is curved over the whole domain (column 1). Similarly, the variance is the largest in this setup. The two scenarios with linear parameter functions, by the construction of the estimator, show favorable properties and exhibit the lowest variance and no bias (columns 2 and 3). In this situation, confidence bands based on equation (2.7) have proper coverage probability that, however, no longer holds with more complex parameter functions. In the most extreme case (discontinuous β_0), the bias at the jump discontinuity is so large that the confidence bands are unable to cover the true parameter over the whole domain (column 4).

The implications from the simulation study for our main findings are as follows. If the true spatial decay of knowledge spillovers is not too complex, our estimates and con-

[6] To replicate this part of the simulation study, refer to the code in the online supplement of this article.

Figure 2.4.4: Performance of the estimator in different simulations



Notes: The figure shows four Monte-Carlo simulations. The bold dashed line depicts the true parameter function $\beta_0(z)$, the light gray areas show pointwise minimum and maximum of all estimates, and the dark gray areas show the first and 99th percentile of all estimates of the parameter function. The solid line represents the pointwise mean over all replications. Simulated replications of the estimator were obtained by estimating model (2.9) based on simulated data. The setup corresponding to the top-left panel uses the predictors from the real-data application, and observations of the dependent variable are simulated based on estimated coefficients and iid normally distributed errors. All other setups are based solely on simulated data that mimic the original sample but use different specifications for the functional parameter $\beta(z)$. In the top-right panel $\beta(z) = 0$, bottom-left: $\beta(z) = 0.4(1 - z)$ and bottom-right $\beta(z) = 0.5 \cdot \mathbb{1}(z < 0.5)$.

fidence bands are generally reliable. However, because the estimator is locally biased in regions with a more complex β_0, identifying the exact distance at which knowledge spillovers cease is difficult. A conservative strategy would be to choose a threshold somewhat lower than indicated by the confidence bands. Regarding our main findings, such a strategy suggests that knowledge spillovers might already be statistically insignificant after 15 kilometers.

2.4.3 Placebo test: future concentration of high-skilled workers

Following Cornelissen *et al.* (2017), who identify knowledge spillovers in the workplace, we corroborate our findings with a placebo test, in which we expand our model with a

Table 2.4.1: Performance measurements in different simulations

	Specification for β_0			
	I	II	III	IV
Integrated squared bias	0.0096	0.0000	0.0000	0.0055
Integrated variance	0.0030	0.0009	0.0009	0.0010
Coverage probability of 99%-CIs	0.7290	0.9920	0.9930	0.0000

Notes: The table contains integrated variance, integrated squared bias and the coverage probability of confidence bands of the parameter estimate for the functional coefficient for all four setups considered in the simulation exercise. In the first setup, the data were generated based on the regressors and functional predictors with corresponding coefficients taken from the original estimate. The other setups are based solely on simulated data but with similar characteristics. In setup II, the functional coefficient of the DGP is zero; in setup III it is a linear function. The coefficient in the last setup (column IV) is discontinuous and possesses a discrete jump in the interior of its domain. We compute integrated variance as $1000^{-1} \int \sum_{r=1}^{1000} \left(\widehat{\beta}_r(z) - \overline{\beta}(z)\right)^2 \mathrm{d}z$ and integrated squared bias as $\int \left(\overline{\beta}_r(z) - \beta_0(z)\right)^2 \mathrm{d}z$, where $\overline{\beta}(z) = 1000^{-1} \sum_{r=1}^{1000} \widehat{\beta}_r(z)$.

one-year lead of the spatial distribution of high-skilled workers. Because workers cannot receive spillovers from neighbors who have not yet moved in, the future concentration of high-skilled workers serves as a placebo. As figure 2.4.5 indicates, the future concentration of high-skilled workers is almost unrelated to wages (bottom curve). Only after 17 kilometers' distance from the workplace does the model detect a small and economically negligible negative relationship between wages and the future concentration of high-skilled workers. Moreover, estimates of the knowledge spillover from the current share of high-skilled workers change only slightly relative to the baseline specification (top curve). Overall, the placebo test buttresses our main findings.

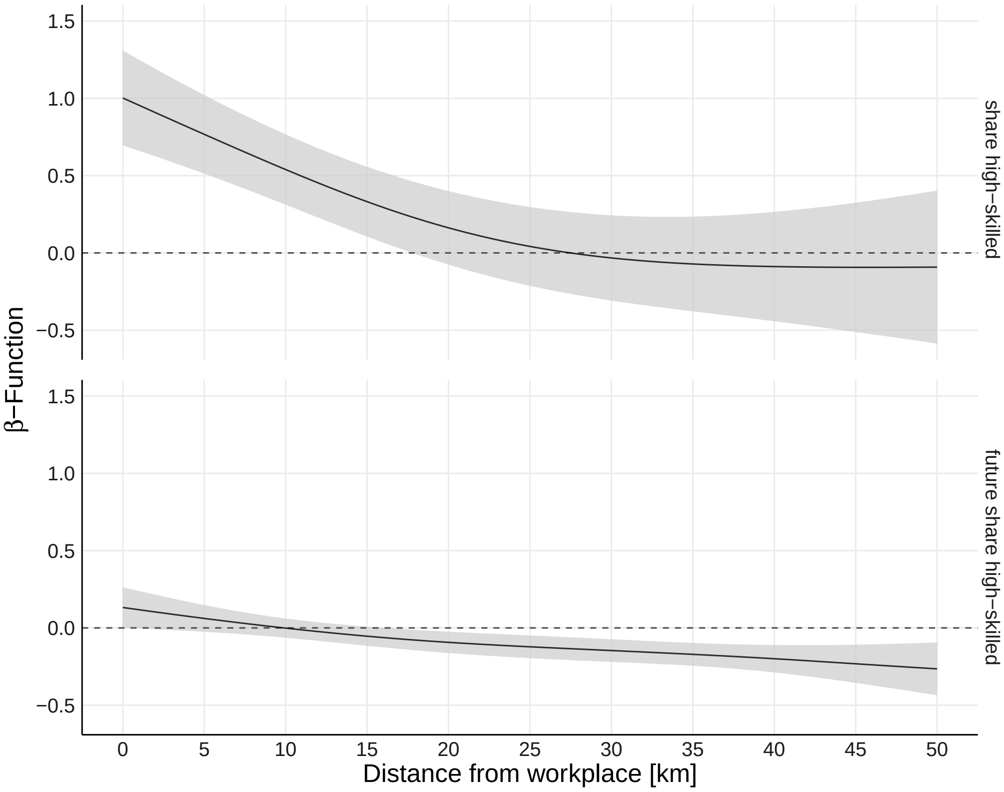
2.4.4 Further robustness checks

Appendix 2.A.7 provides details on further robustness checks. In this section, we briefly summarize the results of these exercises.

As the data source is based on register data from the German social security system, information on high-skilled workers outside of Germany is not available. Consequently, in border regions, we construct our measure of the spatial concentration of human capital with partly truncated information. However, excluding border regions from our model yields similar results to our main findings. We conclude that truncated information from border regions does not affect our results.

Another concern may be that global labor market shocks influence our findings through

Figure 2.4.5: Estimates of knowledge spillovers from the current and the future distribution of high-skilled workers



Notes: The figure depicts estimates of the knowledge spillover from the current and future distributions of high-skilled workers on individual log wages. We measure the concentration of high-skilled workers as the share of high-skilled workers within distance z and define the future concentration of high-skilled workers as the one-year lead of the share of high-skilled workers within distance z. We estimate equation (2.9), expanded with the lead of $X_{it}(z)$, with the estimator (2.5). The top panel presents estimates of the contemporaneous spillover function. The bottom panel depicts estimates of the link between log wages and the future concentration of high-skilled workers, which serves as the placebo. Black lines illustrate computed β functions, and gray areas indicate 99% confidence bands. The underlying model controls for worker-firm match fixed effects, skill-specific yearly labor-market-area fixed effects, occupation and time fixed effects and worker characteristics (age, work experience, tenure and the respective second-order polynomials), log establishment size and county characteristics (unemployment rate, log population density and the log number of hotel beds as a proxy for amenities). $N = 2,959,357$

local industry or occupation clusters. If, for instance, wages and the demand for skilled labor temporarily rise within a sector and firms in this sector tend to cluster locally, our estimates would capture a spurious relation between wages and the local concentration of high-skilled workers. To rebut these concerns, we augment our model with year-specific industry and occupation fixed effects. Reassuringly, absorbing industry and occupation trends does not affect our results.

To ensure that our results are not driven solely by urban or rural regions, we separately estimate our model in urban and rural areas. Generally, the results in both subgroups are very similar to our main findings. However, estimates in urban areas are comparably imprecise and do not allow us to infer the exact spatial reach of knowledge spillovers within cities. The robustness exercise provides initial evidence that knowledge spillovers are more widespread (in terms of distance) in rural areas.

Appendix 2.A.5 shows that our results are robust to alternative choices of the penalty parameter ρ. Finally, appendix 2.A.6 outlines that the magnitude of the effects from our functional model is close to comparable estimates at the county level.

2.5 Conclusions

This paper studies the impact of knowledge spillovers from the regional concentration of high-skilled workers into the individual wages of neighboring workers. We use, for the first time, precise geocoded register data of an entire economy and a novel estimation method from the field of functional data analysis (FDA) to compute the spatial decay of knowledge spillovers. We find significant spillover effects from the local concentration of high-skilled workers that attenuate with distance. Knowledge spillovers from the direct neighborhood of firms are roughly twice as large as those from high-skilled workers that are located 10 kilometers away. After 15 kilometers, the effects vanish. Overall, an evenly distributed one-standard-deviation increase in the local share of high-skilled workers leads to wage gains of 2%.

Two developments in modern social science are primarily responsible for our ability to derive a precise functional relationship between the concentration of high-skilled workers and individual earnings. First, the availability of exact geospatial data enables us to describe the distribution of high-skilled workers around workplaces as functional objects with high resolution. Specifically, we evaluate the concentration of high-skilled workers every 500 meters within a radius of 50 kilometers around almost all establishments in Germany. Second, FDA provides tools to fully exploit such detailed data. We employ the estimator of Crambes *et al.* (2009) to regress a scalar outcome (log wage) on a continuous functional variable (the concentration of high-skilled workers depending on distance). Our application illustrates the potential of FDA in economic research. FDA is particularly beneficial when the variable of interest can be regarded as a function over some continuum.

Generally, our findings imply that education creates positive externalities in local labor markets. Thus, regions benefit from attracting and training skilled workers. Moreover, to maximize these external effects, firms should settle close to one another. Although spillover effects cover entire cities, workers and firms benefit most from the skill distribution in their near neighborhood. Because the effects vanish after 15 kilometers, firms in remote regions do not gain from knowledge spillovers. Overall, our findings support Rosenthal & Strange (2008), who argue that the physical concentration of human capital remains important for economic development. Among other agglomeration effects, knowledge spillovers help to explain differences in productivity between densely populated cities and rural areas.

2.A Appendix

2.A.1 Imputation of wages

A common limitation of social security data is the right-censoring of earnings. To address this issue, we follow Dustmann *et al.* (2009) and Card *et al.* (2013) and impute censored wages with a two-step procedure.

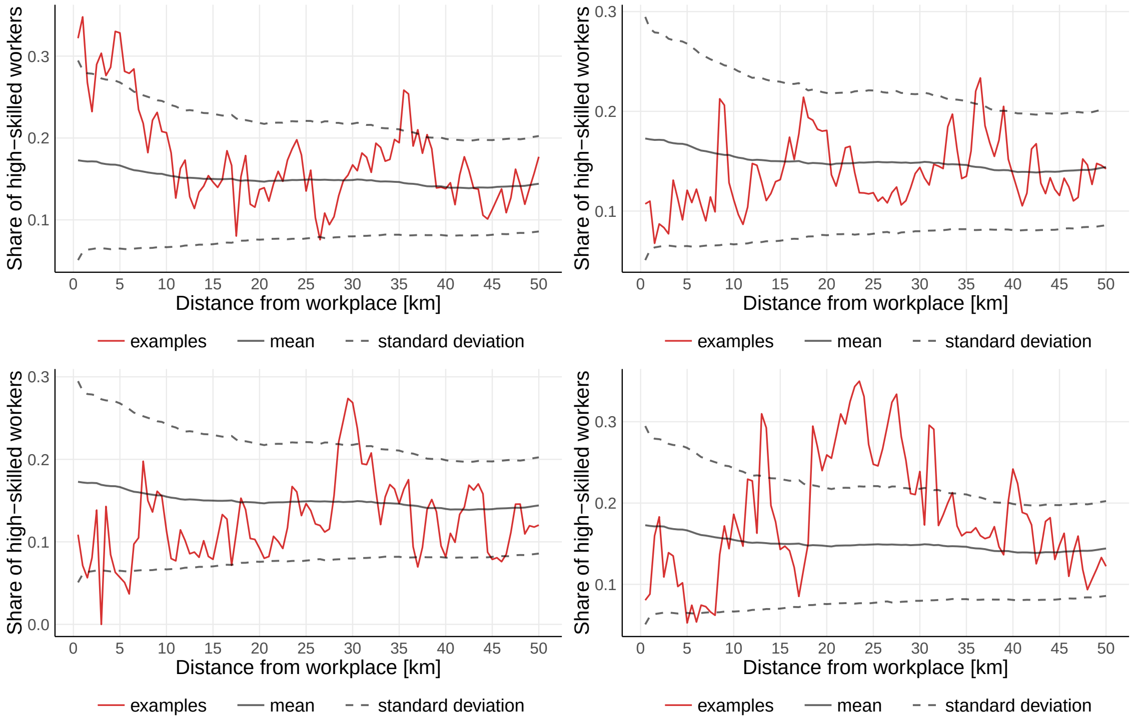
In the first step, we group observations by year, East and West Germany, and three levels of education (i.e., no vocational training, vocational training and degree from a university or university of applied science). Within each group, we fit a Tobit model with the following list of explanatory variables: age, age^2, tenure, tenure^2, work experience, (work experience)^2, firm size, and indicators for gender, being older than 40 years and being foreign born. Additionally, we include interaction terms of age and age^2 with the indicator variable *older than 40*. At the county level, we further include the predictors population density, the unemployment rate, the number of hotel beds and the share of high-skilled workers. With the parameters from the Tobit estimates ($\hat{\zeta}$), we impute wages by $X\hat{\zeta} + \hat{\sigma}\Phi^{-1}\left[k + u(1-k)\right]$, where $\hat{\sigma}$ is the estimated standard error of the regression, Φ is the standard normal density, u is a random value from a uniform distribution between zero and one, $k = \Phi\left[(c - X\hat{\zeta})/\hat{\sigma}\right]$ and c is the censoring point.

In the second step, we compute the lifetime average wages of each worker and firm, excluding the focal period. For workers and firms with only one observation, we assign the sample mean. With the period-specific lifetime average wages as additional predictors, we repeat the Tobit estimates. Finally, we impute censored wages by $X\hat{\zeta} + \hat{\sigma}\Phi^{-1}\left[k + u(1-k)\right]$.

2.A.2 Examples of spatial functions of high-skilled workers

In the paper, we describe the distribution of high-skilled workers as continuous curves. More precisely, we define spatial functions that map the share of high-skilled workers to the distance from the workplace. To illustrate these functional objects, figure 2.A.1 provides four randomly drawn examples. In each of the four graphs, red lines represent the share of high-skilled workers around an establishment. The light gray lines in the background indicate the pointwise mean and standard deviation in our dataset. For instance, in the first panel, we observe a high concentration of skilled labor of 30% in the near neighborhood of the workplace. Between 5 and 15 kilometers' distance, the share of high-skilled workers declines to 15%. After a decline around 25 kilometers away from the workplace, the share of high-skilled workers increases again. At the end of the do-

Figure 2.A.1: Examples of spatial functions of the share of high-skilled workers



Notes: The figure shows the distribution of high-skilled workers around four randomly drawn workplaces (red lines). The light gray lines indicate the pointwise mean and standard deviation of the share of high-skilled workers in the dataset. Throughout the paper, we describe the share of high-skilled workers as spatial functions that map the share of high-skilled workers to the distance from a workplace.

main,the share of high-skilled workers is approximately 15%. The remaining three panels illustrate different patterns.

2.A.3 Summary statistics

The dataset used in our econometric analysis covers 15 years and consists of 3.5 million records of 540,000 workers. Table 2.A.1 summarizes the dependent variable (log wage) and numerical control variables. In the data, the mean daily wage is 111 euros, and the first and second quartile range from 68 to 129 euros. The average individual in the dataset is 41 years old and has 15 years of work experience. The median population density in the dataset is 119 inhabitants per square kilometer ($\exp(4.78)$). Furthermore, 36% of the observations are from females and 7% are from workers with foreign nationality. The proportions of low-, medium- and high-skilled workers are 8%, 73% and 19%, respectively.

Table 2.A.1: Summary statistics

	Mean	**Std. Dev.**	25^{th} **Perc.**	**Median**	75^{th} **Perc.**
daily wage	111.37	78.05	68.17	94.64	129.02
daily log wage	4.55	0.56	4.22	4.55	4.86
age	41.14	10.65	33.00	41.00	49.00
work experience (days)	5528.31	3305.44	2860.00	5105.00	7974.00
tenure (days)	3059.98	2796.97	883.00	2160.00	4398.00
log firm size	4.68	2.10	3.14	4.63	6.10
log population density	3.71	2.38	0.97	4.78	5.66
log hotel beds	3.16	0.70	2.68	3.14	3.53
unemployment rate	8.74	4.11	5.60	7.90	11.00

Notes: The table presents summary statistics of wages and (numerical) control variables. The underlying dataset contains 3,498,536 observations of 539,179 individuals over a period of 15 years. Regional characteristics come from 402 counties.

2.A.4 Estimates of spatial knowledge spillovers: full table

Table 2.A.2 presents parameter estimates from our preferred specification and accompanies figure 2.4.2. In accordance with figure 2.4.2, the table shows strong knowledge spillovers from high-skilled workers from nearby areas. The effects decay with distance and become statistically insignificant after 17 to 18 kilometers. The parameter estimates of worker characteristics are in line with the labor literature. Due to the extensive set of fixed effects in the model (equation (2.9)), the parameter estimates for county-level variables are statistically insignificant.

2.A.5 Estimates with different penalties

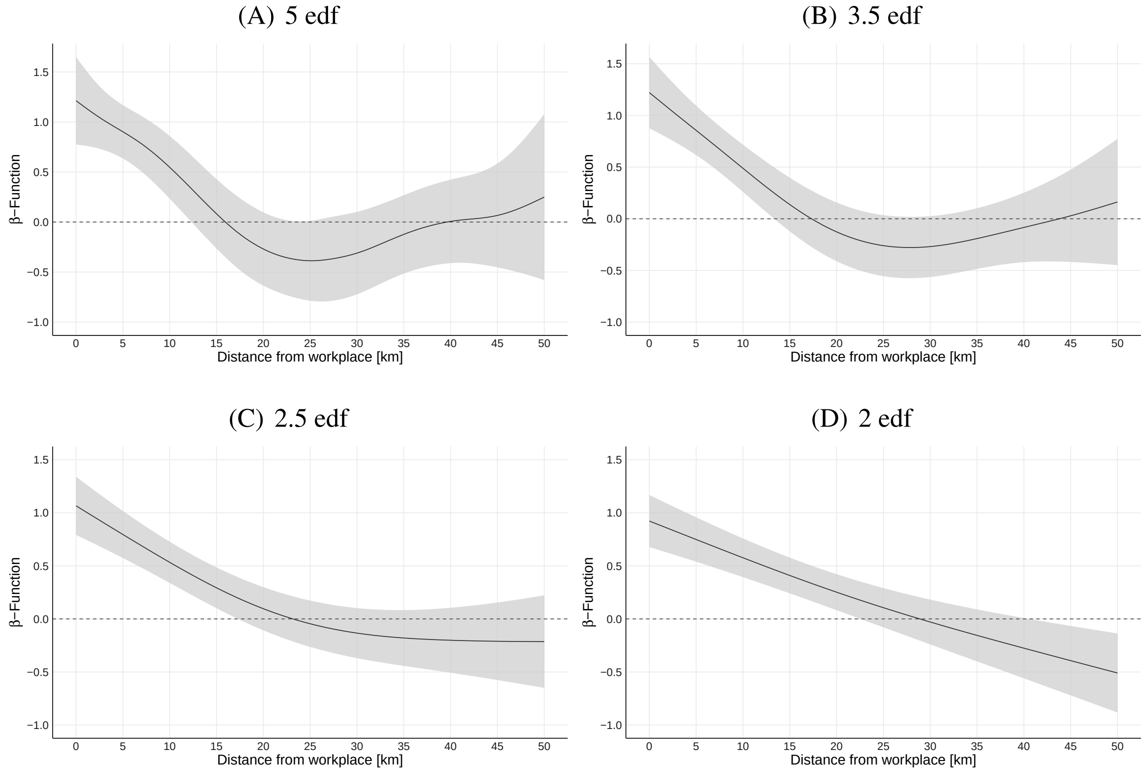
In our preferred specification, we estimate equation (2.9) with the estimator (2.5) and a penalty ρ that corresponds to 2.5 degrees of freedom, which restricts estimates of the spillover curve $\beta(z)$ to smooth parabola-like functions that may remain flat over some interval. To demonstrate the behavior of the estimator with different penalties, figure 2.A.2 reports estimates with alternative values of ρ. Panels A and B allow for more flexible curves than our preferred specification, panel C repeats our preferred specification, and panel D restricts $\beta(z)$ to a linear function. Qualitatively, all models lead to similar results. The response of individual wages to an increase in the share of high-skilled workers in the direct neighborhood is close to unity. When we reach 10 kilometers from the workplace, the effects are only approximately half the size. In all models, the spillovers become statistically insignificant after 13 to 23 kilometers. The confidence bands of the four estimates overlap over the whole domain.

Table 2.A.2: Spatial knowledge spillover from high-skilled workers (full table)

Distance	**Value**	**Sig.**	**SE**	**Distance**	**Value**	**Sig.**	**SE**	**Distance**	**Value**	**Sig.**	**SE**
0.5	1.0654	***	0.1178	20.5	0.0890		0.0876	40.5	-0.2024		0.1332
1.0	1.0380	***	0.1151	21.0	0.0723		0.0882	41.0	-0.2037		0.1355
1.5	1.0106	***	0.1125	21.5	0.0562		0.0888	41.5	-0.2049		0.1379
2.0	0.9831	***	0.1100	22.0	0.0407		0.0894	42.0	-0.2060		0.1404
2.5	0.9558	***	0.1076	22.5	0.0258		0.0900	42.5	-0.2070		0.1430
3.0	0.9284	***	0.1052	23.0	0.0115		0.0907	43.0	-0.2080		0.1456
3.5	0.9011	***	0.1029	23.5	-0.0023		0.0913	43.5	-0.2088		0.1482
4.0	0.8739	***	0.1008	24.0	-0.0155		0.0920	44.0	-0.2096		0.1509
4.5	0.8467	***	0.0987	24.5	-0.0281		0.0926	44.5	-0.2103		0.1537
5.0	0.8196	***	0.0968	25.0	-0.0401		0.0933	45.0	-0.2109		0.1566
5.5	0.7926	***	0.0949	25.5	-0.0516		0.0940	45.5	-0.2115		0.1594
6.0	0.7656	***	0.0932	26.0	-0.0625		0.0946	46.0	-0.2120		0.1624
6.5	0.7387	***	0.0916	26.5	-0.0729		0.0953	46.5	-0.2124		0.1653
7.0	0.7119	***	0.0901	27.0	-0.0828		0.0961	47.0	-0.2128		0.1683
7.5	0.6852	***	0.0887	27.5	-0.0921		0.0968	47.5	-0.2131		0.1714
8.0	0.6585	***	0.0875	28.0	-0.1009		0.0976	48.0	-0.2134		0.1745
8.5	0.6320	***	0.0864	28.5	-0.1093		0.0983	48.5	-0.2137		0.1776
9.0	0.6057	***	0.0854	29.0	-0.1171		0.0991	49.0	-0.2139		0.1808
9.5	0.5795	***	0.0846	29.5	-0.1245		0.1000	49.5	-0.2142		0.1839
10.0	0.5535	***	0.0838	30.0	-0.1314		0.1008	50.0	-0.2144		0.1872
10.5	0.5277	***	0.0832	30.5	-0.1379		0.1018	**Controls**			
11.0	0.5021	***	0.0827	31.0	-0.1440		0.1027	Age	-0.6766		1178.6
11.5	0.4768	***	0.0824	31.5	-0.1496		0.1037	Age^2	-0.0003	***	0.0000
12.0	0.4518	***	0.0821	32.0	-0.1548		0.1048	Exper.	0.0814	***	0.0016
12.5	0.4270	***	0.0819	32.5	-0.1597		0.1059	Exper.^{2}	-0.0001	***	0.0000
13.0	0.4026	***	0.0818	33.0	-0.1642		0.1071	Tenure	0.0042	***	0.0009
13.5	0.3785	***	0.0818	33.5	-0.1684		0.1083	Tenure^2	-0.0001	***	0.0000
14.0	0.3548	***	0.0819	34.0	-0.1723		0.1096	l. firm size	0.0258	***	0.0009
14.5	0.3315	***	0.0821	34.5	-0.1758		0.1109	l. p. dens.	0.0011		0.0006
15.0	0.3086	***	0.0823	35.0	-0.1792		0.1124	l. hotel b.	0.0059		0.0034
15.5	0.2861	***	0.0826	35.5	-0.1822		0.1139	Unemp.	0.0009		0.0006
16.0	0.2641	***	0.0829	36.0	-0.1851		0.1155				
16.5	0.2425	***	0.0833	36.5	-0.1877		0.1171				
17.0	0.2214	**	0.0838	37.0	-0.1901		0.1189				
17.5	0.2009	**	0.0842	37.5	-0.1923		0.1207				
18.0	0.1809	*	0.0847	38.0	-0.1943		0.1226				
18.5	0.1614		0.0853	38.5	-0.1962		0.1245				
19.0	0.1424		0.0858	39.0	-0.1980		0.1266				
19.5	0.1241		0.0864	39.5	-0.1996		0.1287				
20.0	0.1063		0.0870	40.0	-0.2011		0.1309				

Notes: The table accompanies figure 2.4.2 and shows the strength of spatial knowledge spillovers from high-skilled workers at numerous distances on individual log wages. To compute the spatial spillover function ($\beta(z)$), we estimate equation (2.9) with the estimator (2.5). We restrict the capacity of the β curve to a parabola-like function that may remain flat over some interval, and we set the penalty parameter ρ accordingly. The table also reports coefficient estimates for the control variables. The underlying model further controls for worker-firm match fixed effects, skill-specific yearly labor-market-area fixed effects, occupation fixed effects and time fixed effects. Standard errors are clustered. ***, ** and * indicate significance at the 1%-, 5%- and 10%-level, respectively. $N = 3,498,536$

Figure 2.A.2: Estimates of spatial knowledge spillovers with different penalties



Notes: The figure shows estimates of the spatial knowledge spillover from high-skilled workers into individual log wages based on four different penalty parameters. To compute the spatial spillover function ($\beta(z)$), we estimate equation (2.9) with the estimator (2.5). Each panel summarizes estimates with a different penalty ρ. The different penalty terms correspond to 5 (top left panel), 3.5 (top right panel), 2.5 (bottom left panel) and 2 (bottom right panel) effective degrees of freedom. The black line illustrates the estimated spillover function ($\beta(z)$), and the gray area indicates the 99% confidence band. The underlying model controls for worker-firm match fixed effects, skill-specific yearly labor-market-area fixed effects, occupation and time fixed effects and worker characteristics (age, work experience, tenure and the respective second-order polynomials), log establishment size and county characteristics (unemployment rate, log population density and the log number of hotel beds as a proxy for amenities). $N = 3,498,536$

However, depending on the hyperparameter ρ, the estimates of the spillover function are of course more or less flexible. Up to 20 kilometers' distance, the more volatile models in panels A and B are similar to our preferred specification and suggest that knowledge spillovers decline with distance. After 20 kilometers, however, the point estimates increase. Statistically, the rise at the end of the domain is accompanied by broad confidence bands. Thus, these estimates are imprecise. Moreover, it seems economically implausible that the intensity of knowledge spillovers follows a U-shaped pattern. Therefore, we regard the estimates from panels A and B as overly flexible. By contrast, the curve in panel D is forced to be linear. Again, up to 20 kilometers away from the workplace, the estimates are similar to our preferred model. Farther away, the point estimates diverge from our preferred specification and proceed to decline even after intersecting the abscissa. Similar to panels A and B, these estimates are less precise at the end of the domain. Moreover, theoretically, it seems implausible that knowledge spillovers follow a linear function. Thus, we regard the estimated spillover function from panel D as overly inflexible.

2.A.6 County-level effects

In our paper, we model the distribution of high-skilled workers as continuous curves around workplaces and estimate knowledge spillovers with a functional regression model based on Crambes *et al.* (2009). To evaluate the magnitude of our results, let us now estimate a *classical* OLS model, in which we estimate spillovers from high-skilled workers at an aggregate level. Specifically, we calculate spillovers from the share of high-skilled workers within counties (NUTS-3, *Landkreise* and *kreisfreie Städte*). Apart from this, our estimation equation is identical to our main model (equation (2.9)):

$$Y_{it} = \alpha x_{it} + Z'_{it}\gamma + \theta_{if} + \tau_t + \omega_o + \pi_{rst} + u_{it}. \tag{2.10}$$

Y_{it} is the individual log wage of worker i in year t, and x_{it} is the share of high-skilled workers within the county of i's workplace. Accordingly, α is the spillover coefficient we seek to measure. Identical to our main specification, the model controls for time-varying observable characteristics of individuals, establishments and regions (Z_{it}) and a series of fixed effects. θ_{if} is a worker-firm match fixed effect, π_{rst} is a skill-specific yearly labor-market-area fixed effect, τ_t is a year fixed effect, and ω_o is an occupation fixed effect.

To estimate equation (2.10), we use the same dataset as in the paper and cluster standard errors at the county-level. Table 2.A.3, column 1 summarizes the results. Our model suggests significant positive spillovers from high-skilled workers into individual wages. The coefficient of 0.323 indicates that a one-standard-deviation increase in the regional share of high-skilled workers (7.2 percentage points) raises the wages of incumbent workers by 2.3%. The magnitude of this effect is close to our main findings, which imply that an evenly distributed one-standard-deviation increase in the share of high-skilled workers increases wages by 2%. Moreover, and similar to our main findings, neglecting skill-specific labor-market-area-year fixed effects significantly increases the computed coefficient (column 2). In summary, the predicted magnitude of spillover effects from an overall increase in the share of high-skilled workers is almost identical in county-level estimates and estimates based on the exact spatial distribution of workers.

Table 2.A.3: Knowledge spillovers at the county-level

	(1)	**(2)**
Share of high-shilled workers	0.323^{***}	0.409^{***}
	(0.045)	(0.095)
Worker-firm match fixed effects	Yes	Yes
Labor-market-area $\times$ year $\times$ skill fixed effects	Yes	No

Notes: The table summarizes estimates of the knowledge spillover from high-skilled workers into individual log wages at the county level. The estimates replicate our main model at an aggregate level and serve as a comparison of the magnitude of the effects. The underlying models further control for occupation fixed effects, time fixed effects and worker characteristics (age, work experience, tenure and the respective second-order polynomials), log establishment size and county characteristics (unemployment rate, log population density and the log number of hotel beds as a proxy for amenities). Cluster-robust standard errors are in parentheses.*** indicates significance at the 0.1%-level. $N = 3,498,536$

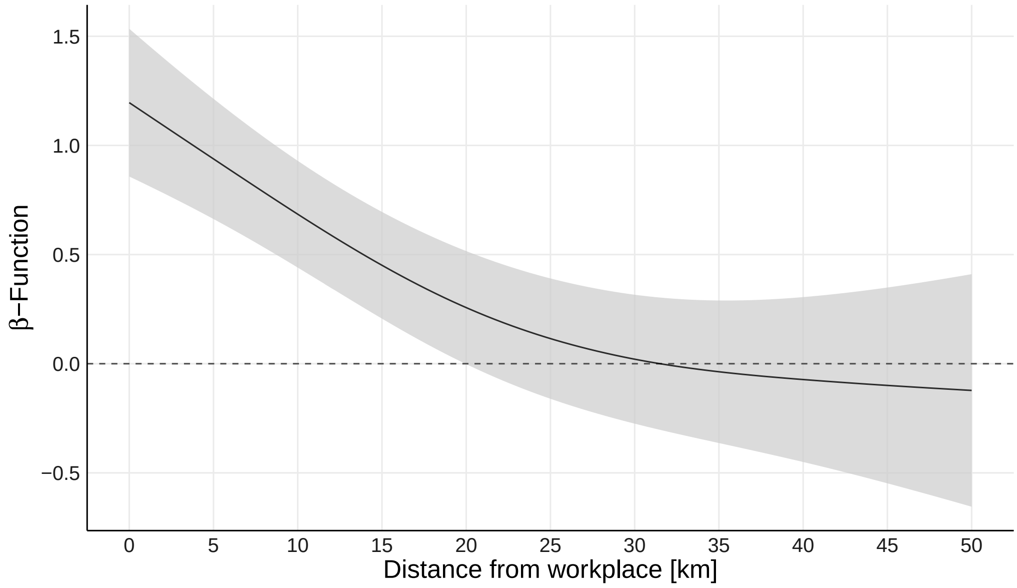
2.A.7 Robustness

Non-border regions

Because we have no data on workers outside of Germany, measurements of the distribution of high-skilled workers in border regions are partly truncated. For instance, establishments in the city center of Passau are only two kilometers from the Austrian border. Therefore, past two kilometers' distance, we observe the concentration of high-skilled workers only in southwest to northeast directions. Consequently, information on the distribution of high-skilled workers comes solely from these data points. Ignoring the partial truncation, we implicitly assume that the distribution on the Austrian side of the border is the same as on the German side of the border and that there are no costs from frictions in information flows across the border. To assess whether these assumptions influence our estimates, we now remove border regions from our dataset and re-estimate our main model with establishments that are at least 50 kilometers from the German border.

Figure 2.A.3 summarizes the results. Generally, the estimated curve resembles the spillover function from the full sample. Identically to our main findings, the function value is slightly above unity in the direct neighborhood of establishments. However, the graph implies that spillovers in non-border regions are slightly higher, and the point estimates reach seven kilometers farther than in the full sample. There are several explanations for the stronger effects in non-border regions. First, due to labor market barriers, spillovers in border regions might generally be lower, which would reduce measurements of the overall effect. Second, the concentration of high-skilled labor behind the German border might be lower than on the German side of the border, which would oppose our assumption of similar skill distributions on both sides of the border. Third, there are

Figure 2.A.3: Spatial knowledge spillover from high-skilled workers (without border regions)



Notes: The figure shows spatial knowledge spillover from high-skilled workers into individual log wages in regions that are at least 50 kilometers from the German border. We measure the concentration of high-skilled workers as the share of high-skilled workers within distance z. To compute the spatial spillover function ($\beta(z)$), we estimate equation (2.9) with the estimator (2.5). We restrict the capacity of the β curve to a parabola-like function that may remain flat over some interval, and we set the penalty parameter ρ accordingly. The black line illustrates the estimated spillover function ($\beta(z)$), and the gray area indicates the 99% confidence band. The effect of a p-percentage-point increase in the share of high-skilled workers within distance z_0 and z_1 (in a 0 to 1 range) is p times the area bellow the estimated spillover function from z_0 to z_1. The underlying model controls for worker-firm match fixed effects, skill-specific yearly labor-market-area fixed effects, occupation and time fixed effects and worker characteristics (age, work experience, tenure and the respective second-order polynomials), log establishment size and county characteristics (unemployment rate, log population density and the log number of hotel beds as a proxy for amenities). $N = 2,489,083$

institutional differences between border and non-border regions that depress knowledge spillovers in border regions. Fourth, by chance, cities in border regions benefit less from knowledge spillovers than other cities do. Given the multitude of possible explanations, it seems plausible that estimates in non-border regions differ slightly from those in the full sample. Reassuringly, the point estimates of the spillover function are nonetheless similar in both samples, and the confidence bands overlap over the whole domain. Overall, the robustness exercise therefore confirms our main findings.

Labor market trends and industry clusters

Another concern may be that industry- or occupation-specific trends in the labor market influence our results through local clusters. To illustrate this issue, consider the following scenario. Industry b experiences an economic upswing that raises wages and the demand for skilled labor. If firms in industry b tend to cluster geographically, wages and the concentration of high-skilled labor would simultaneously rise in these areas. In our estimates, a global labor market shock at the industry level would therefore create a spurious relationship between wages and the regional concentration of high-skilled workers. The same applies to labor market shocks to occupations.

To assess whether industry or occupation trends in the global labor market affect our results, we augment our estimation equation (equation (2.9)) with year-specific industry and occupation fixed effects. These fixed effects absorb changes in wages and the concentration of high-skilled workers that stem from industry- or occupation-wide shifts in the labor market. Figure 2.A.4 shows the resulting spillover function. The curve is almost identical to that from our main specification (figure 2.4.1). We therefore conclude that trends at the industry or occupational level do not influence our results.

Effects in urban and rural areas

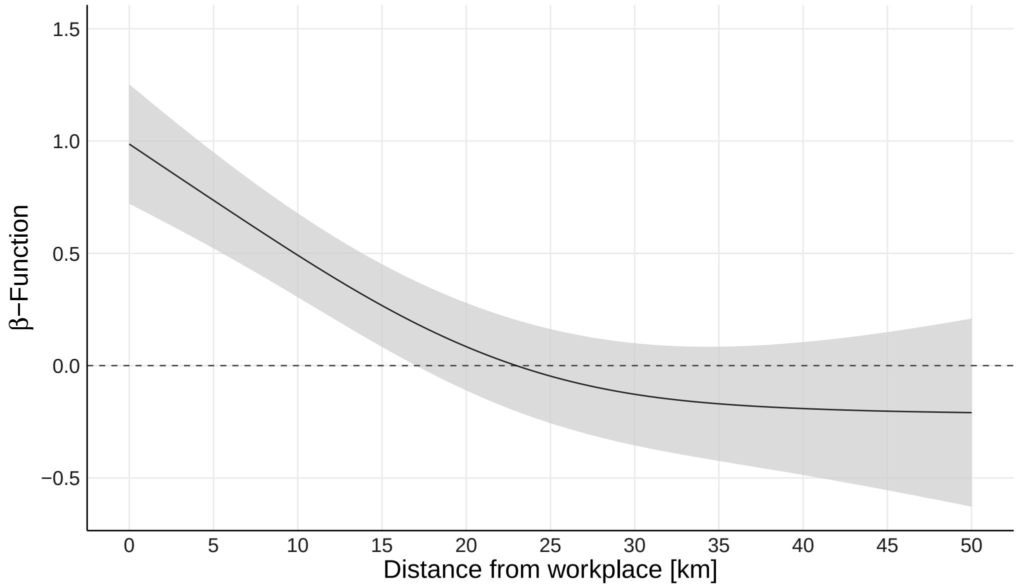
Plausibly, marginal travel costs for physical distance differ in cities and rural areas. Additionally, social interactions in sparsely populated regions might be more costly than those in dense urban areas. Thus, the intensity and spatial reach of knowledge spillovers in cities and rural areas might differ. To assess these considerations, we separately estimate knowledge spillovers in rural and urban areas. In the paper, we measure knowledge spillovers within a distance of 50 kilometers. To thoroughly separate knowledge spillovers in rural areas from spillovers in urban regions, we therefore define urban areas as regions within 50 kilometers' distance of a metropolitan city center.[7] Accordingly, rural areas are 50 kilometers from metropolitan cities.

Figure 2.A.5 and figure 2.A.6 illustrate the estimates of knowledge spillovers within rural and urban areas. Generally, the results are in line with our main findings. The point estimates for both samples indicate that spillovers decay with distance, and the effects are of reasonable size. Furthermore, the point estimates support the hypothesis that knowledge spillovers reach farther in rural areas than in cities. However, as the

---

[7] We regard the largest German cities as metropolises: Berlin, Hamburg, Munich, Cologne, Frankfurt on the Main, Stuttgart, Düsseldorf, Dortmund, Essen, Leipzig, Bremen, Dresden, Hanover, the regional cluster Nuremberg (including Erlangen and Fürth) and Duisburg.

Figure 2.A.4: Spatial knowledge spillover from high-skilled workers (removing industry and occupation trends)

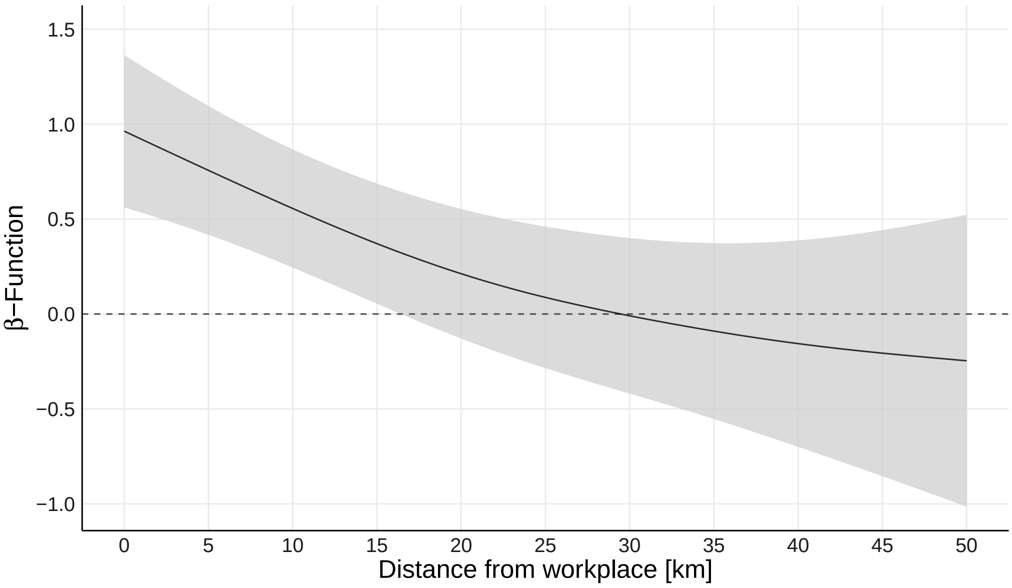


Notes: The figure shows spatial knowledge spillovers from high-skilled workers into individual log wages. We measure the concentration of high-skilled workers as the share of high-skilled workers within distance z. To compute the spatial spillover function ($\beta(z)$), we estimate equation (2.9) with the estimator (2.5). To control for industry- and occupation-specific trends in the labor market, we additionally control for time-varying industry and occupation fixed effects. We restrict the capacity of the β curve to a parabola-like function that may remain flat over some interval, and we set the penalty parameter ρ accordingly. The black line illustrates the estimated spillover function ($\beta(z)$), and the gray area indicates the 99% confidence band. The graph shows significant spillover effects that decay with distance. The effect of a p-percentage-point increase in the share of high-skilled workers within distance z_0 and z_1 (in a 0 to 1 range) is p times the area bellow the estimated spillover function from z_0 to z_1. The underlying model further controls for worker-firm match fixed effects, skill-specific yearly labor-market-area fixed effects, occupation and time fixed effects and worker characteristics (age, work experience, tenure and the respective second-order polynomials), log establishment size and county characteristics (unemployment rate, log population density and the log number of hotel beds as a proxy for amenities). $N = 3,498,536$

99% confidence bands in figure 2.A.6 indicate, the estimates of spillover effects in cities are relatively imprecise. Thus, we are unable to determine the exact spatial coverage of knowledge spillovers in cities.

Two reasons for the broader confidence bands in the split samples are the smaller sample size and tighter definitions of skill-specific yearly labor-market-area fixed effects (π_{rys} in equation (2.9)). As we explain in section 2.2.4, we address labor market demand and supply effects and the spatial sorting of workers with skill-specific yearly labor-market-area fixed effects. These fixed effects absorb variation that is contemporaneously common within regional labor markets. Splitting the sample into rural and urban areas also halves many labor market areas. Therefore, skill-specific yearly labor-market-area fixed effects

Figure 2.A.5: Spatial knowledge spillover from high-skilled workers (rural areas)

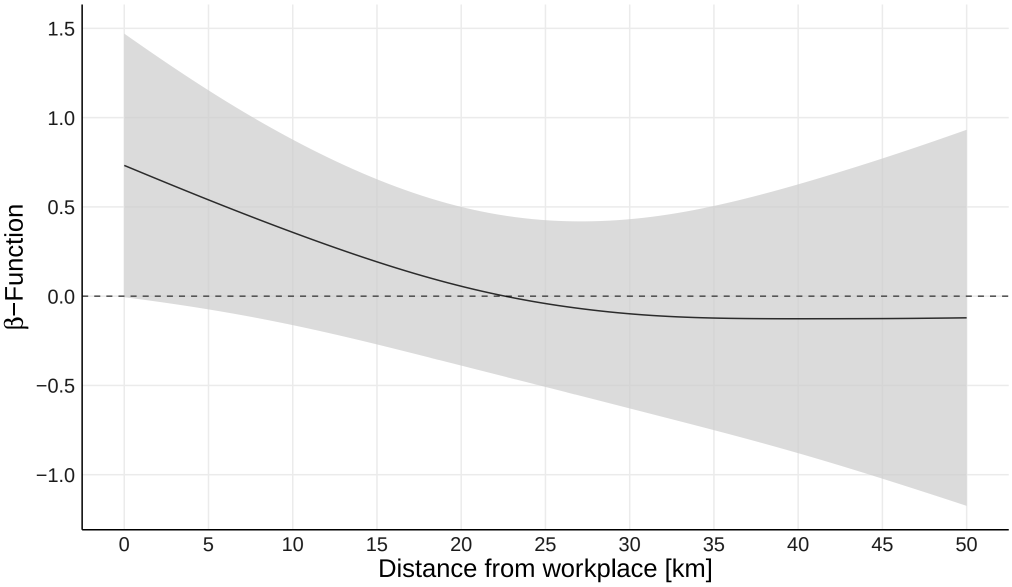


Notes: The figure shows the spatial knowledge spillover from high-skilled workers into individual log wages in rural areas. We measure the concentration of high-skilled workers as the share of high-skilled workers within distance z. To compute the spatial spillover function ($\beta(z)$), we estimate equation (2.9) with the estimator (2.5). We restrict the capacity of the β curve to a parabola-like function that may remain flat over some interval, and we set the penalty parameter ρ accordingly. The black line illustrates the estimated spillover function ($\beta(z)$), and the gray area indicates the 99% confidence band. The underlying model controls for worker-firm match fixed effects, skill-specific yearly labor-market-area fixed effects, occupation and time fixed effects and worker characteristics (age, work experience, tenure and the respective second-order polynomials), log establishment size and county characteristics (unemployment rate, log population density and the log number of hotel beds as a proxy for amenities). $N = 1.477.584$

in separate samples eliminate even more variation from the data than in the full dataset. Consequently, spatial variation declines, and confidence bands expand. As figure 2.A.7 shows, estimating knowledge spillovers in urban areas without skill-specific yearly labor-market-area fixed effects increases precision. The graph suggests a statistically significant relationship between the share of high-skilled workers within 15 kilometers' distance of the workplace and individual wages. However, without skill-specific yearly labor-market-area fixed effects, the estimates are partly due to a spurious relationship between the concentration of human capital and wages.

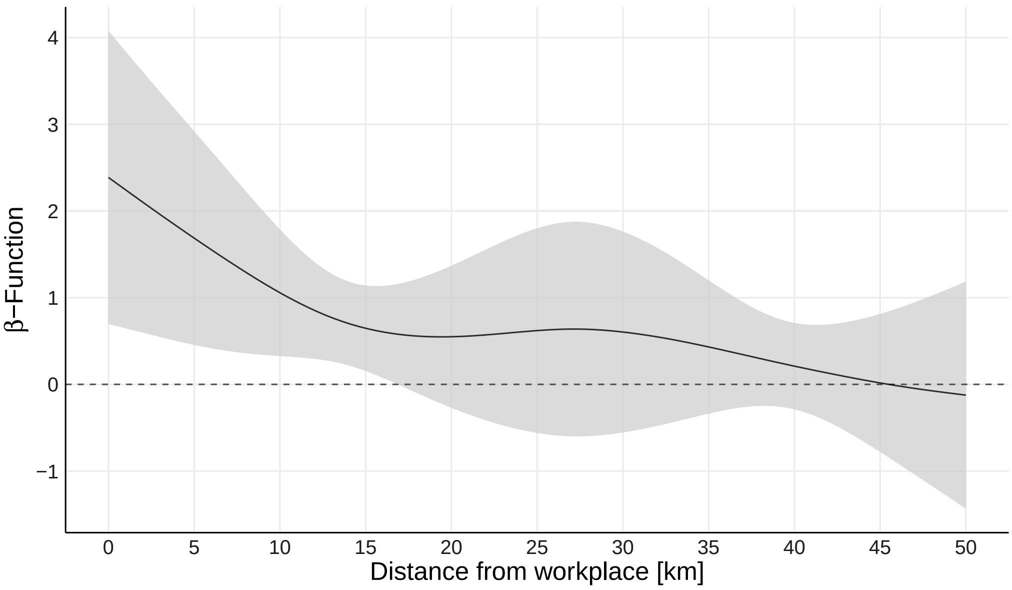
Overall, the separate point estimates for knowledge spillovers in urban and rural sample support our main findings. Due to the imprecise estimates of spillover effects in cities, this section provides only weak evidence that the spatial reach of knowledge spillovers is larger in rural than in urban areas.

Figure 2.A.6: Spatial knowledge spillover from high-skilled workers (urban areas)



Notes: The figure shows the spatial knowledge spillover from high-skilled workers into individual log wages in rural areas. We measure the concentration of high-skilled workers as the share of high-skilled workers within distance z. To compute the spatial spillover function ($\beta(z)$), we estimate equation (2.9) with the estimator (2.5). We restrict the capacity of the β curve to a parabola-like function that may remain flat over some interval, and we set the penalty parameter ρ accordingly. The black line illustrates the estimated spillover function ($\beta(z)$), and the gray area indicates the 99% confidence band. The underlying model controls for worker-firm match fixed effects, skill-specific yearly labor-market-area fixed effects, occupation and time fixed effects and worker characteristics (age, work experience, tenure and the respective second-order polynomials), log establishment size and county characteristics (unemployment rate, log population density and the log number of hotel beds as a proxy for amenities). $N = 1.331.693$

Figure 2.A.7: Estimates of the spatial knowledge spillover from high-skilled workers (urban areas, no yearly labor-market-area fixed effects)



Notes: The figure shows estimates of the spatial knowledge spillover from high-skilled workers into individual log wages in urban areas without nullifying labor market demand and supply effects and the spatial sorting of workers. Specifically, the graph shows estimates of the spatial spillover function ($\beta(z)$) from equation (2.9) without skill-specific yearly labor-market-area fixed effects (π_{rst}). We measure the concentration of high-skilled workers as the share of high-skilled workers within distance z. To compute the spatial spillover function ($\beta(z)$), we estimate equation (2.9) with the estimator (2.5). We restrict the capacity of the β curve to a parabola-like function that may remain flat over some interval, and we set the penalty parameter ρ accordingly. The black line illustrates the estimated spillover function ($\beta(z)$), and the gray area indicates the 99% confidence band. The underlying model controls for worker-firm match fixed effects, skill-specific yearly labor-market-area fixed effects, occupation and time fixed effects and worker characteristics (age, work experience, tenure and the respective second-order polynomials), log establishment size and county characteristics (unemployment rate, log population density and the log number of hotel beds as a proxy for amenities). $N = 1.331.693$

Chapter 3

The Effects of Foreign Direct Investment on Job Stability: Upgrades, Downgrades, and Separations

Abstract[*]

We use linked employer-employee data to estimate the effect of foreign direct investment (FDI) on workers' job stability. We are the first to consider firm-internal job transitions. Specifically, we examine the impact of FDI on the individual likelihood to up- or downgrade to occupations with more or less analytical and interactive tasks. To do so, we propose an iterative matching procedure that generates a homogeneous sample of firms with equal probabilities of investing. Based on this sample, we use proportional hazard models to retrieve dynamic effects on workers. We find that FDI increases the likelihood of up- and downgrades by 24% and 34%, respectively. These effects increase with the share of non-routine and interactive tasks and become measurable two years after the investment. FDI does not increase the hazard of separation of workers and firms. Instead, there is a temporal lock-in effect after the investment. Our results highlight the importance of firm-internal restructuring as a channel for adjusting to altered labor demand in response to FDI.

Keywords: FDI, multinational firms, job stability
JEL Codes: F16, F23, F66, J23, J62

---

* This part is joint work with Linda Borrs.

3.1 Introduction

Multinational enterprises (MNEs) are one of the most controversial aspects of globalization. While firms benefit from foreign direct investment (FDI) by saving production costs or by exploiting new markets, MNEs are often criticized for replacing domestic with foreign labor. Empirical results on the employment and wage effects of FDI are ambiguous and can neither support nor fully reject these fears (see Crinò, 2009 and Hummels *et al.* , 2016 for recent surveys). We argue that the literature has overlooked another important channel by which firms adjust their workforce following FDI—namely, firm-internal restructuring. Our data imply that the rate of job transitions within MNEs is 1.5 times higher than that in domestic firms. In this paper, we therefore investigate whether internal transitions increase when firms turn multinational. Moreover, we distinguish between up- and downgrading of workers to more- or less-complex jobs.

The question how FDI affects job transitions is closely related to that of how FDI affects labor demand. Managing foreign affiliates plausibly requires coordination and administration. Thus, the demand for interactive and analytical tasks should increase when firms turn multinational, as shown by previous studies (e.g., Becker *et al.* , 2013; Hakkala *et al.* , 2014; Laffineur & Mouhoud, 2015). Moreover, if FDI is accompanied by global fragmentation of production chains, MNEs can specialize their domestic workers in fewer tasks. Such fragmentation might lead to simpler task sets for some workers, while others might specialize in more-complex tasks. To adjust to these changes in labor demand, MNEs can rely on internal labor markets. Incumbent workers possess firm-specific human capital (Becker, 1962), which represents a productivity advantage over outsiders. Further, hiring internally reduces asymmetric information on the skills and abilities of workers (e.g., Waldman, 1984; Greenwald, 1986) and might cost less (Demougin & Siow, 1994) compared to hiring outside the firm. Moreover, it can be cheaper for MNEs to demote workers whose tasks become redundant over the course of FDI than to dismiss them. This might especially apply to labor markets with strict dismissal protection laws, strong works councils and unions. Thus, in addition to the extensive margin of hires and layoffs, MNEs have incentives to restructure their workforce internally after investing abroad.

No extant study has investigated the impact of FDI on internal job transitions. The two papers most closely related to the topic are Liu & Trefler (2011) and Baumgarten (2015). Both consider the effect of offshoring on occupational switches. Liu & Trefler (2011) find a positive effect on switches to occupations with higher and lower average wages for US service offshoring. For Germany, Baumgarten (2015) finds that offshoring is not associated with greater occupational instability on average. However, he shows that workers with more non-routine tasks face less occupational uncertainty through offshoring. In contrast to our paper, both studies examine the impact of offshoring in general, not FDI in particular. Moreover, they do not separately consider firm-internal occupational switches. We believe that firm-internal restructuring processes play a crucial role over the course of FDI because establishing or acquiring foreign firms entails deep organizational changes. Conversely, offshoring does not require comparably extensive organizational changes, as it mainly covers trade with unaffiliated firms. Moreover, industry-level offshoring data only permit indirect conclusions for individual workers within industries. By contrast, we can draw direct conclusions on how a firm's decision to invest abroad affects the job stability of its workers.

To investigate the impact of FDI on job stability, we exploit a unique administrative micro-panel dataset. By using these data, we can follow MNEs, domestic firms and their workers for two decades with quarterly precision. Specifically, our data comprise the entire universe of German firms with Czech affiliates as of 2010 and a large pool of domestic control firms that never conducted FDI in any country. German FDI in the Czech Republic represents a compelling case of FDI flows, as Germany is the largest economy in Europe, and the Czech Republic is one of its main recipients of investment among the Central and Eastern European Countries (CEEC).[1] In contrast to previous studies, our data also cover small firms with low investment volumes.[2] This is an advantage, as the geographic proximity and low labor costs of the Czech Republic allow small firms to also invest beyond the border. Our data further include the complete administrative employment biographies of all workers in the investing and domestic firms.

To identify the effects of FDI on the occurrence of job upgrades and downgrades and separations of workers and firms, we pursue a three-step procedure. As Helpman *et al.* (2004) show, only the most productive firms conduct FDI. We therefore first construct a balanced sample of MNEs and domestic firms with equal probabilities of investing. We propose an iterative matching procedure that allows us to achieve a distinct one-to-one matching of MNEs and domestic firms over the entire observation period. Additionally, our matching approach ensures that we match firms exactly in the same year. Standard propensity score matching cannot meet both requirements. Further, our matching approach allows us to assign the investment dates of matched MNEs as *pseudo* investment

[1] In 2010, approximately 24% of the workers employed by German firms in the CEEC worked in the Czech Republic (Deutsche Bundesbank, 2014).

[2] In the majority of datasets on FDI, small firms with low investment volumes are under-represented because only investments above a certain threshold need to be registered officially (see Pflüger *et al.* , 2013) With regard to our analysis, Schäffler (2016) shows that only one-fourth of Czech affiliates with a German owner appear in the Microdatabase Direct Investment (MiDi) provided by the Federal Bank of Germany, which is commonly used to study the FDI of German firms.

dates to domestic firms. We match firms two years before investment. Because of the equal probabilities of conducting FDI and the significant time lag between the matching and the (pseudo) investment, it should be impossible for workers to distinguish between future MNEs and domestic firms at the time of matching. Second, to overcome ability-driven sorting of workers into MNEs (e.g., Abowd *et al.* , 1999; Card *et al.* , 2013), we restrict our data to individuals who already worked in the firm in the year of matching. Third, we compare the likelihood of job upgrades and downgrades and separations between MNEs and domestic firms at the worker level. To reap the benefits of the event history design of our data, we use Cox (1972) proportional hazard models to estimate the effects. We define job upgrades (downgrades) as job switches within the firm to occupations with a higher (lower) share of analytical and interactive tasks, which we refer to as *complex tasks*.

This article is the first to show that firms meet altered labor demand due to FDI by internally restructuring their workforce. More precisely, when firms invest abroad, the likelihood that workers will upgrade internally to more-complex jobs increases by 24%. Simultaneously, the hazard to downgrade to less-complex jobs increases by 34%. Both effects increase over time and become traceable two years after investment. However, we find that only workers in relatively non-routine and interactive jobs receive the opportunity to internally switch occupations. In line with these results, the same group of workers faces lower hazards of employment separations in MNEs. Altogether, we find only weak effects of FDI on separations. The average worker has a higher chance of remaining shortly after the investment, but this lock-in effect disappears after several quarters. We further investigate whether worker productivity influences their job stability in the investing firms. Although workers in MNEs are considerably more likely to switch occupations, MNEs follow the same pattern as domestic firms do when choosing who to upgrade, downgrade or dismiss. Independent of FDI, firms promote more productive workers and dismiss or demote less productive workers.

This paper relates to several strands of the theoretical and empirical literature on the employment effects of FDI in the source country. Theory predicts both positive (e.g., Grossman & Rossi-Hansberg, 2008) and negative (e.g., Feenstra & Hanson, 1996a) effects of FDI on the employment and wages of domestic workers. Thus, determining the net effects remains an empirical question. Within the empirical literature, our paper is related to studies on the employment effects of FDI, especially those differentiating between tasks (e.g., Becker *et al.* , 2013; Laffineur & Mouhoud, 2015). Specifically, our paper relates to the empirical literature considering the effects of FDI on employment stability. Becker & Muendler (2008) were the first to consider job-separation rates of German MNEs. They find them to be four percentage points lower than those of domestic firms—half of this difference can be explained by foreign employment expansions of MNEs. Bachmann *et al.* (2014) estimate the effects of both inward and outward FDI on employment security in Germany. They find that FDI, particularity to CEEC, reduces employment security for low-skilled and older workers. In contrast to our paper and to Becker & Muendler (2008), Bachmann *et al.* (2014) use industry-level data on FDI and cannot analyze the direct effects of firm-level decisions on FDI.

A larger body of literature considers the job security effects of offshoring, which, in contrast to FDI, also includes trade with unaffiliated foreign firms. These papers yield ambiguous results (see, e.g., Liu & Trefler, 2011, Ebenstein *et al.* , 2014 for the US; Munch, 2010 for Denmark; Egger *et al.* , 2007 for Austria; and Geishecker, 2008, Bachmann & Braun, 2011, Baumgarten, 2015 and Görg & Görlich, 2015 for Germany). Within this strand of literature, some studies also consider occupational switches, although not exclusively within the borders of the firm. Baumgarten (2015) finds that offshoring—measured by an occupation-specific exposure to imported intermediates—decreases the risk of occupational switches for highly non-routine jobs. However, these effects are strongest for transitions to non-employment. He does not distinguish between occupational up- and downgrades. The only other paper that considers up- and downgrades is by Liu & Trefler (2011). They are the first to show theoretically and empirically that promotions and demotions are a common reaction to offshoring in general. They find that US offshoring to China and India increases job downgrades by 17% and job upgrades by 4%.

The remainder of the paper is structured as follows. The next section explains our identification strategy. Section 3.3 describes the data. Section 3.4 reports our results and discusses implications. Section 3.5 summarizes several robustness exercises, and Section 3.6 concludes.

3.2 Empirical strategy

Our aim in the empirical analysis is to measure the effect of FDI on job stability. Our approach consists of three steps. First, we construct a panel dataset of MNEs and domestic firms by using an iterative matching approach. Second, we address endogenous sorting of workers into firms. Third, we use proportional hazard models to estimate the influence of FDI on the probability of employment separations and occupational up- and downgrades.

As Helpman *et al.* (2004) show, only certain types of firms are likely to invest abroad. Thus, in a first step, we use a broad database of firm characteristics to estimate firm-specific investment probabilities for each MNE and control firm. We begin with propensity score matching to create a homogeneous dataset of MNEs and domestic firms with equal probabilities to invest.[3] The resulting dataset consists of comparable MNEs and domestic firms with a balanced distribution of firm characteristics across the two groups. One benefit of a matched sample is that it increases the robustness of statistical inference (Imbens & Rubin, 2015). Furthermore, matching allows us to assign pseudo investment dates to domestic firms. For workers in MNEs, the onset of the risk of switching occupations or leaving the firm begins with the investment. For workers in domestic firms, there is no investment date and thus no inherent interval to observe their risk of each event. We therefore assign the investment date of the best matched MNE to the domestic firm.

To assign appropriate investment dates, we match firms exactly in the same year. Further, we require a one-to-one matching of firms over the whole observation period. Because standard matching procedures cannot satisfy both requirements, we proceed as follows.[4] We assign MNEs two years prior to investment and domestic firms in every observation year to our pool of firms for the matching. We select a lag of two years for MNEs to avoid that their investment decision may already affect firm characteristics (see also Hijzen *et al.* , 2011). For every MNE, we use propensity score matching to find the three best matched domestic firms exactly in the same year (e.g., matches MNE A: a_{2004}, b_{2004}, c_{2004}; matches MNE B: a_{2006}, d_{2006}, e_{2006}). After this first step, domestic firms can appear multiple times as matches for different MNEs (e.g., a_{2004} and a_{2006}). In the second step of the matching approach, we thus find the single best match of treatment and control firms over the whole observation period by an iterative procedure (see Algorithm 1 in Appendix 3.A.1 for details). Initially, we select the best match out of the three potential matches for each *MNE* (e.g., matches MNE A: $\mathbf{a_{2004}}$, b_{2004}, c_{2004}; matches MNE B: $\mathbf{a_{2006}}$, b_{2006}, c_{2006}).[5] From the resulting list of potentially best matches, we retain only the best match for a *domestic firm* over the whole observation period (matches MNE A: $\cancel{\mathbf{a_{2004}}}$; matches MNE B: $\mathbf{a_{2006}}$). Then, we update the list of potential matches for *MNEs* and move up second-ranked matches if necessary (matches MNE A: $\mathbf{b_{2004}}$, c_{2004}; matches

3 Propensity score matching has previously been used in the FDI context by a wide range of studies, e.g., Bronzini (2015), Crinò (2010) and Barba Navaretti & Castellani (2004) for Italy, Hijzen *et al.* (2011) for France, Debaere *et al.* (2010) for Korea, Barba Navaretti *et al.* (2010) for France and Italy, Becker & Muendler (2008) and Kleinert & Toubal (2007) for Germany, Hijzen *et al.* (2007) for Japan, and Egger & Pfaffermayr (2003) for Austria. However, the majority of these studies consider FDI effects at the firm, not the individual, level.

4 Although matching without replacement ensures that observations—firm-years in our case—are matched only once, it does not guarantee that associated observations—firms in our case—are matched only once. Thus, control firms could be matched to multiple treatment firms in different years.

5 The goodness of a match is defined by the smallest differences in the estimated propensity scores, which we obtain from first step of our matching procedure. For a detailed description, see Appendix 3.A.2.

MNE B: a_{2006}, d_{2006}, e_{2006}). Finally, we repeat the procedure two times, which results in a one-to-one matching of firms exactly in the same year without using any domestic control firm multiple times (e.g., final best match MNE A: b_{2004}; final best match MNE B: a_{2006}). This matching procedure results in a balanced dataset of MNEs and domestic firms with equal probabilities to invest (for details, see Appendix 3.A.2).

In the second step of our empirical analysis, we link the full employment histories of workers to the matched firm data. To ensure that workers do not self-select into MNEs, we restrict our data to individuals who already worked in the firm at the time of the matching (i.e., two years prior to the (pseudo) investment). It should be impossible for workers to distinguish between future MNEs and domestic firms at the time of the matching because of the firms' equal probabilities of conducting FDI and the significant time lag between the matching and the (pseudo) investment.

In the final step of our empirical analysis, we estimate the effects of FDI on the individual likelihood to switch jobs within the firm and to separate from the firm. To reap the benefits of the event history design of our data, we use Cox (1972) proportional hazard models to measure the effects of FDI on job stability.[6] We estimate the hazard ratios of employment separations and occupational up- and downgrades in separate models and treat competing events as censoring:

$$\log h_e(t|x_{ijtyro}) = h_0(t) + \gamma I(\text{FDI}_j) + x_{ijt}\beta_1 + x_{ijt}t\beta_2 + \tau_y + \omega_r + \theta_o + u_{ijtyro}. \quad (3.1)$$

Here, $h_e(t|x_{ijtyro})$ is the hazard rate of event $e \in \{\text{separation, upgrade, downgrade}\}$, $h_0(t)$ is the baseline hazard rate, $I(\text{FDI})$ is an indicator variable for the investment, and γ measures the according treatment effect. Further, x_{ijt} is a vector of time-varying worker (i) and firm (j) characteristics, and $x_{ijt}t$ is an interaction of these characteristics and time since the (pseudo) investment. Our model further purges investment effects from year (τ_y), region (ω_r) and occupation (θ_o) fixed effects.

We measure the events e with quarterly precision. In our setting, workers become at risk of separation or up- or downgrade at the quarter of the (pseudo) investment, and we then follow them for 20 quarters. We define occupational switches within the firm as upgrades if the intensity of analytical and interactive tasks is higher in the new job than in the old one and as downgrades if the intensity of analytical and interactive tasks decreases. We summarize analytical and interactive tasks by the term *complex tasks*. Because task compositions also vary within occupations, we compare old and new jobs at the same

[6] Compared to linear probability models and logit or probit models, proportional hazard models offer several advantages. For instance, they are robust to deviations from the normality assumption and censored events, and they allow us to include time-varying covariates.

point in time (i.e., immediately after the job switch). Employment separations occur if workers leave the firm.

As indicated previously, we treat competing events as censoring. This means that after the occurrence of an event (e.g., an occupational upgrade), we remove workers from the risk set of the other two events (e.g., occupational downgrades and job separations). The underlying rationale is that each possible event is the outcome of a distinct causal mechanism. In essence, the likelihood of an event e depends on worker performance and the objective of a firm ($P(e) = f(\text{worker performance}, \text{firm objective})$). Clearly, worker performance increases the likelihood of occupational upgrades and reduces the probability of downgrades or separations. In essence, the objective of a firm consists of two dimensions: (1) firm size and (2) internal task structure. A firm might want to shrink or grow its domestic plant after FDI and simultaneously might plan to perform more- or less-complex tasks. Importantly, the objective of the firm distinctly alters the likelihood of each event for each individual.

For instance, if a firm follows the classical factor-seeking motive of FDI (see, e.g., Helpman, 1984; Markusen, 2002) and seeks to reduce labor costs by relocating offshorable tasks to a foreign plant, it attempts to (1) shrink, which raises the hazard of separations, and (2) perform more complex supervisory and management tasks, which increases the likelihood of upgrades. Since neither of the two objectives facilitates downgrades, the according probability remains constant. However, fragmentation is often not as simple as described above because modern production processes are interwoven. Therefore, offshoring certain production stages also affects tasks in the up- and downstream processes of the firm. These changes in the task structure might lead some incumbent workers to take over new tasks, which results in (2) up- and downgrades in all areas of the firm. Another motive is market-seeking FDI (see, e.g., Markusen, 1984, 2002), where a firm intends to serve the foreign market by production on site. Thus, (1) firm size remains unchanged or even increases, which reduces the hazard of separations and (2) the firm requires more complex supervisory and management tasks, which increases the likelihood of upgrades. Downgrades are not affected. In summary, the complex interplay of worker performance and firm objectives portrays parallel causal mechanisms that idiosyncratically influence the probabilities of separations and up- and downgrades. Thus, we regard competing events as censoring. However, as we show in the robustness section, alternative strategies that do not treat events as mutually exclusive do not affect the results.

The baseline model (Equation (3.1)) captures time-constant effects of FDI on job stability, i.e., the average effect over the five-year interval after the investment. However, it is possible that the effect of FDI varies over time. If, e.g., workers need further training to switch occupations within the firm, we will not observe an effect of FDI immediately after the investment. Thus, we estimate the influence of FDI on job stability over time by:

$$\log h_e(t|x_{ijtyro}) = h_0(t)+\gamma_0 I(\text{FDI}_j)+\gamma_1 I(\text{FDI}_j)t+x_{ijt}\beta_1+x_{ijt}t\beta_2+\tau_y+\omega_r+\theta_o+u_{ijtyro}, \tag{3.2}$$

where $I(\text{FDI}_j)t$ is the interaction of the investment dummy and time since the investment. The remainder of Equation (3.2) is identical to Equation (3.1). Because treatment is assigned to firms (not workers), we cluster standard errors at the firm level in both models (see Abadie *et al.* , 2017).

3.3 Data and descriptive statistics

Data

To analyze the effects of FDI on workers' job stability, we synthesize four data sources. We retrieve information on German FDI in the Czech Republic from the *Research on Locational and Organisational Change* database (*ReLOC*).[7] The ReLOC data identify the entire universe of German firms with affiliates in the Czech Republic in the Czech commercial register 2010. ReLOC covers 3,406 German investors and the exact date of their investment.[8] To compare developments in investing firms to those in domestic firms, a control group of 9,700 German firms without any foreign affiliate (in any country) completes the ReLOC data.

We link the ReLOC data to two administrative micro-datasets from the Institute for Employment Research (IAB). We receive the establishment-level information from the *Establishment History Panel (BHP 7514v1)* and individual-level data from the *Integrated Employment Biographies (IEB V10.00)*. The BHP contains information on the employment and wage structure of all German establishments with at least one employee subject to social security contributions as of June 30 between 1975 and 2014.[9] The IEB includes the complete employment biographies of all individuals in the German social security system after 1975. In particular, the data offer information on occupations and employment spells with daily precision. Because both the BHP and the IEB use mandatory social security notifications for all German employers, they are highly reliable. Applying record

7 Refer to Hecht *et al.* (2013b) for details on the ReLOC dataset.

8 Hecht *et al.* (2013a) show in their survey of 459 firms of the ReLOC dataset that almost 70% of the firms with FDI in the Czech Republic have not invested anywhere else before.

9 Refer to Eberle & Schmucker (2017) for details on the BHP.

linkage, Schäffler (2014) joins the ReLOC data and the BHP. The resulting dataset groups establishments into firms and provides investment information at the firm level. We attribute to the firm the region or industry of the largest establishment. Further, we merge the IEB with the BHP by using their readily available shared identifiers. Our observation period begins after the fall of the *iron curtain*, 1990, and ends with the most recent registered investments in the ReLOC data, 2010.

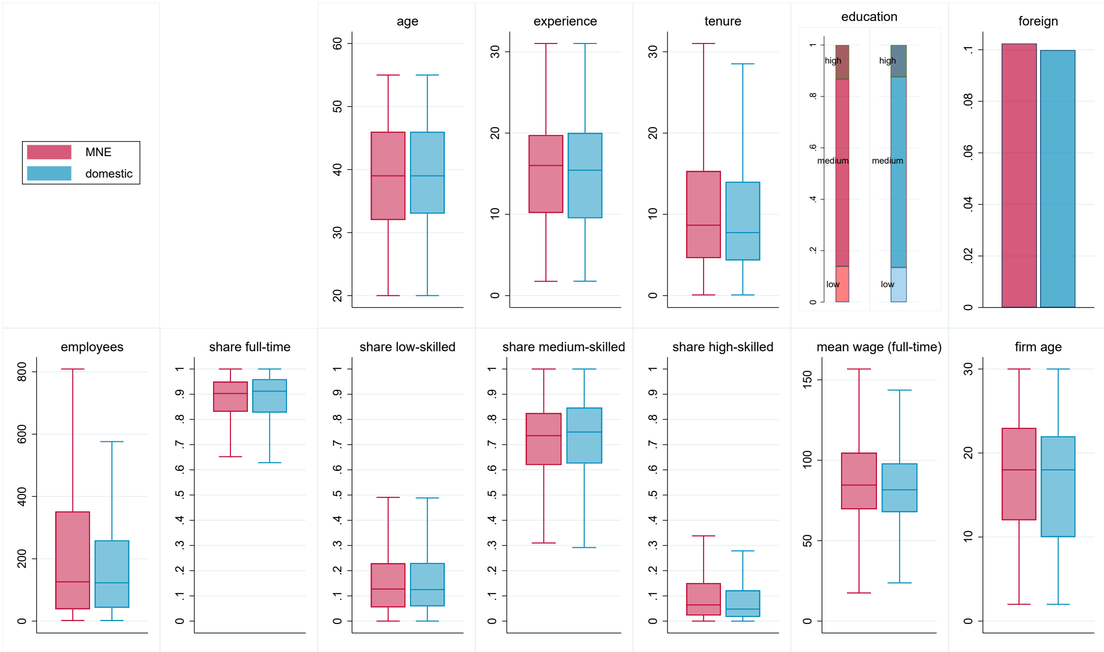
To identify occupational up- and downgrades, we extend our data with the task structures of occupations. Therefore, we use data from the *BIBB-IAB Employment Surveys* 1991, 1999 and the *BIBB/BAuA Employment Survey* 2006 (see Hall & Tiemann, 2006). For each occupation and survey year, we receive the share of each of the five task categories—i.e., routine-manual, routine-cognitive, non-routine-manual, analytical, and interactive activities—by using an algorithm described in Matthes (forthcoming).

From the spell data, we construct a quarterly panel with March 31, June 30, September 30, and December 31 as reference dates. If an employee has more than one job notification per reference date, we only use the one with the highest earnings. To ensure that we do not mistake maternity leave or retirement for job separations, we restrict the sample to male workers between 20 and 55 at the time of the investment. Further, we only consider regular full-time workers for two reasons. First, we are only interested in *regular* job changes and not in, e.g., switches from part- to full-time or from marginal to regular employment. Second, workers in marginal employment might intrinsically aim to improve their labor market positions and thus might distort our findings. To strengthen our identification strategy, we restrict the sample used for our baseline estimates to workers who, at the time of the (pseudo) investment, worked for at least for two years in their firm. We correct inconsistent information on individual education following Fitzenberger *et al.* (2005). Furthermore, the wages of approximately 10% of the spells are right-censored due to the contribution assessment ceiling in Germany. We impute these records using an imputation procedure that follows Dustmann *et al.* (2009) and Card *et al.* (2013).

Descriptive statistics

Figure 3.3.1 presents an overview of individual (first row) and firm (second row) characteristics after applying our matching algorithm. The box plots and bar charts illustrate that the worker and firm characteristics of MNEs and domestic firms are well balanced in the quarter of the (pseudo) investment, i.e., two years after matching. Although they were not part of the matching, worker characteristics are also well balanced. In both samples, the distributions of employees' age, experience and tenure are almost identical. Addition-

Figure 3.3.1: Worker and firm characteristics after matching

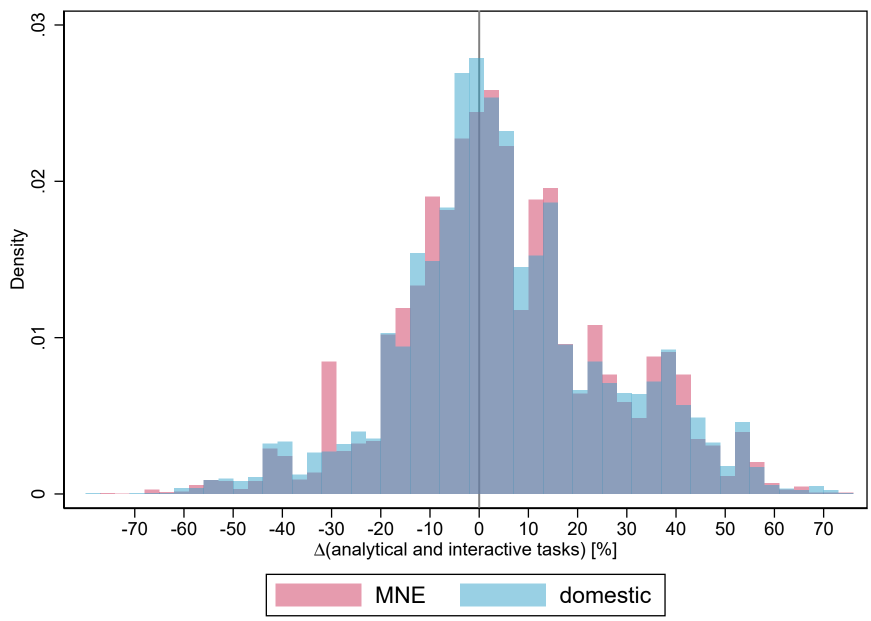


Notes: The figure shows box plots and bar charts of various worker (first row) and firm (second row) variables. The horizontal line in the middle of a box represents the median. The edges of a box indicate the first and the third quartiles. The range of the whiskers illustrates minima and maxima, limited to $\frac{3}{2}$ of the first or third quartile, respectively. For the education and foreign variables, the figure presents bar charts, which depict the shares of individuals in the corresponding group.
Source: ReLOC, IEB and BHP, own calculations.

ally, the composition of the workforce with respect to education and nationality are highly comparable. Moreover, the firm-level characteristics of the treatment and control firms are almost equivalent in their medians and first and third quartiles. The figure shows that both firm groups are similar in size, age, average wages, and shares of different worker groups. Only the firm size of MNEs has a larger variation in the upper part of the distribution.

The focus of this article is on occupational up- and downgrades. Figure 3.3.2 therefore visualizes changes in analytical and interactive tasks for workers that switch occupations within the firm. Based on these changes, we define occupational upgrades as job switches accompanied by an increase in analytical and interactive tasks (bins to the right of zero) and downgrades as job switches accompanied by a decrease in analytical and interactive tasks (bins to the left of zero). Common upgrades in our data include, e.g., promotions from instrument mechanics to technicians or line workers to stock managers. The former example leads to a broader, less routine set of tasks; the latter example enhances supervisory responsibilities. Frequent downgrades include, e.g., electricians to metal workers or metal workers to welders. Both examples lead to a less-complex task set. The graph

Figure 3.3.2: Histograms of up- and downgrades in MNEs and domestic firms

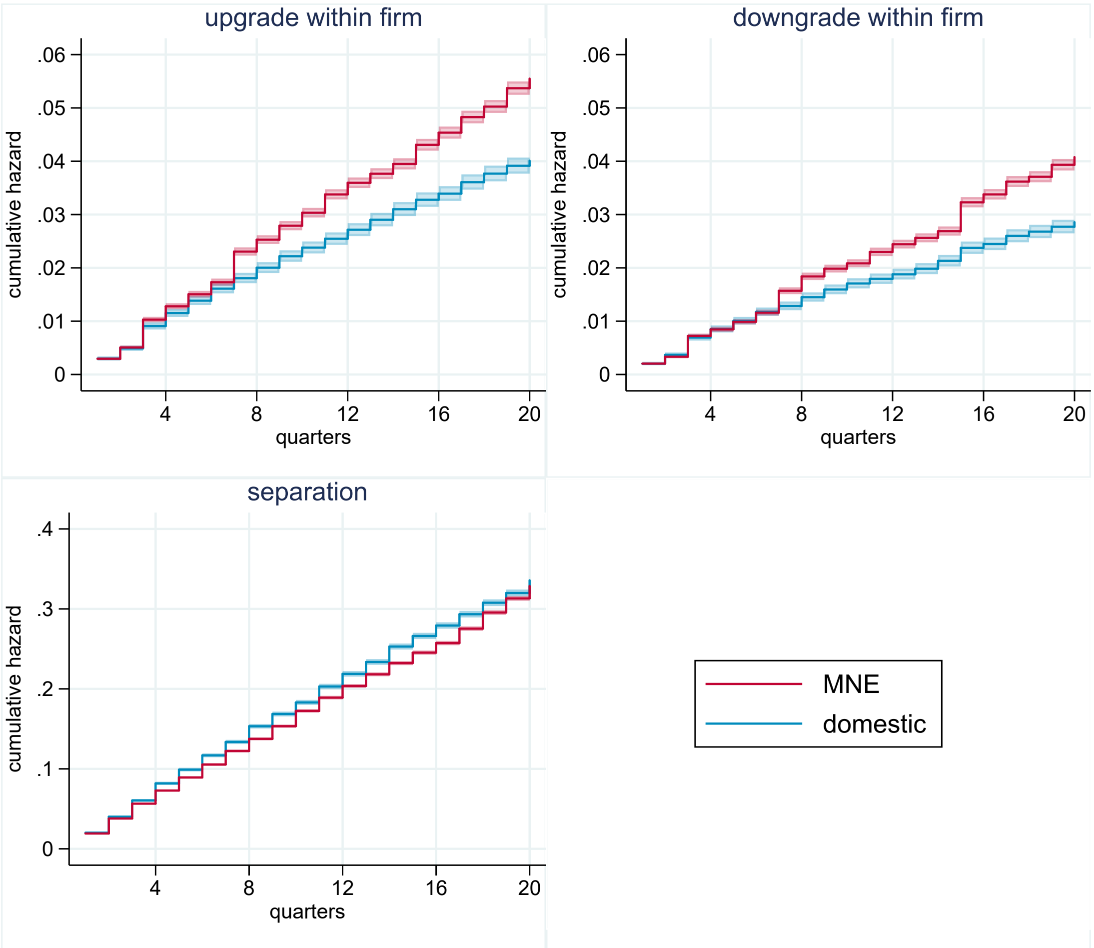


Notes: The figure shows the distribution of up- and downgrades by percentage point changes of the share of analytical and interactive tasks for job switches within investing (MNE) and domestic firms. We define job upgrades (downgrades) as firm-internal job transitions to occupations with a higher (lower) share of analytical and interactive tasks. Therefore, all upgrades are found to the right of the zero line and all downgrades to its left.
Source: ReLOC, IEB and BHP, own calculations.

shows that for the majority of workers, an occupational switch changes the complexity of their job by up to 40 percentage points. Of all up- and downgrades, 60% entail changes in complexity of more than 10 percentage points.

Having defined up- and downgrades, let us now descriptively assess their relative frequencies in MNEs and domestic firms. Figure 3.3.3 illustrates the cumulative hazards of separations and up- and downgrades. The cumulative hazard indicates the probability of an event within a given timeframe. The upper-left panel of Figure 3.3.3 shows that the hazard of receiving a job upgrade is larger for workers in investing firms than for those in domestic firms. In the quarters immediately following the investment, the difference is negligible. However, approximately two years after the investment, the likelihood of a job upgrade in MNEs clearly exceeds that in the control group. After 20 quarters, the probability of receiving an occupational upgrade is 5.7% in MNEs. In domestic firms, it is only 4%. The development of the risk of downgrades is similar. However, the hazard of a downgrade is lower than the hazard of an upgrade. Figure 3.3.3 further illustrates that the risk of separation is higher than the likelihood of both types of occupational changes within the firm. However, separation rates differ only barely between MNEs and domestic

Figure 3.3.3: Cumulative hazards of up- and downgrades and separations in MNEs and domestic firms



Notes: The figure shows the cumulative hazards for the three events, *separation from the firm* as well as *internal up- and downgrades*, by quarters after the (pseudo) investment, distinguishing between investing (MNE) and domestic firms. Light blue and light red colors indicate 95% confidence bands. The cumulative hazard indicates the probability of an event within a given timeframe. For instance, the individual hazard of receiving an occupational upgrade within 20 quarters in FDI firms is 5.7% (first panel). Hazards of occupational up- and downgrades are significantly larger in MNEs than in domestic firms. By contrast, the hazard of separations is slightly larger in domestic firms.
Source: ReLOC, IEB and BHP, own calculations.

firms. In fact, they are slightly lower in MNEs than in domestic firms.

In summary, Figure 3.3.3 suggests that most of the adjustments over the course of FDI take place within the firm. Although the described hazards only provide descriptive evidence, they mirror well our multivariate findings that follow in the next sections.

Table 3.4.1: Effects of FDI on the hazard ratios of separations and up- and downgrades

	separation		upgrade		downgrade	
	(1)	(2)	(3)	(4)	(5)	(6)
FDI	0.9630	0.8092**	1.2422**	0.9960	1.3413**	0.9781
	(0.0440)	(0.0691)	(0.1315)	(0.1896)	(0.1980)	(0.2094)
FDI × quarter		1.0190**		1.0252*		1.0352*
		(0.0083)		(0.0141)		(0.0205)
Subjects	383,098	383,098	383,098	383,098	383,098	383,098
Events	102,661	102,661	15,880	15,880	11,731	11,731

Notes: The table presents exponentiated coefficients (hazard ratios) and cluster robust standard errors at the firm level (in parentheses). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Additional control variables in all models are: age, age squared, experience, tenure, a foreign dummy, skill dummies, firm age and a dummy if the firm existed in 1975 (all interacted with quarters since treatment), as well as occupation, year, and state dummies. The deviation of the estimated hazard ratios from one can be interpreted as changes in the probabilities of the events attributable to FDI. For example, an estimated hazard ratio for separation of 0.8092 indicates that FDI reduces the individual risk of separation by 19.08% in the quarter of investment. Estimates are based on a matched sample of MNEs and domestic firms. The full table, including estimates on control variables, can be found in the Appendix (Table 3.A.4).
Source: ReLOC, IEB and BHP, own calculations.

3.4 Results

Main results

This section presents the estimation results for the impact of FDI on the job stability of the average worker in the investing firm. We distinguish between effects on the likelihood of separations of workers and firms and upgrades into more-complex jobs and downgrades into less-complex jobs within the firm. Table 3.4.1 summarizes the main results. Columns 1, 3 and 5 show the time-independent impact of FDI on the hazard of separation and up- and downgrades, respectively (see Equation (3.1)). Columns 2, 4 and 6 provide the results from a dynamic specification. Here, the FDI indicator is interacted with the quarters since the investment (see Equation (3.2)). The table denotes the effects as hazard ratios, which have the same interpretation as odds ratios.

As Column 1 indicates, we find no effect of FDI on separations in the static model. In contrast, the hazard ratios of 1.24 and 1.34 imply that FDI increases the likelihood of a job upgrade by 24% and the likelihood of a downgrade by 34%. Table 3.4.1 further shows that the absolute number of promotions and demotions in our sample is much lower than the number of separations. Nevertheless, the estimated hazard rations indicate that MNEs adjust their workforce to meet changing labor demand over the course of FDI mainly through internal occupational changes. However, separations do not seem to be an important adjustment channel.

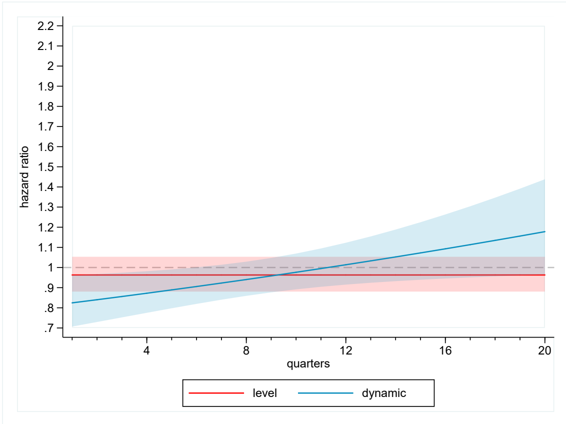
The static model provides average hazard ratios over the five-year period after (pseudo) investment. However, it is possible that the hazard of each event changes over time. Because estimates from the dynamic models are not directly interpretable from Table 3.4.1, we illustrate the time-varying impact of FDI on job stability in Figure 3.4.1. The blue lines in Panels A, B and C show time-dependent hazard ratios for separations and up- and downgrades. For comparison, the horizontal red lines indicate estimates from the static models. Shaded areas show 95% confidence intervals. The dashed line in each panel has an intercept of one and therefore serves as reference to a scenario with no influence of FDI.[10]

While time-invariant hazard ratios indicate no effect of FDI on workers' separation rates, more flexible time-variant estimates imply a short lock-in effect immediately after the investment. Specifically, the hazard of separation is 19% lower in MNEs in the quarter of the investment. It increases by 1.9% in each following quarter. However, over five years, the effect never becomes significantly positive. We conclude that there is no evidence that FDI increases the risk of separations for the average worker. On the contrary, FDI has an advantageous lock-in effect, which, however, vanishes approximately six quarters after the investment.

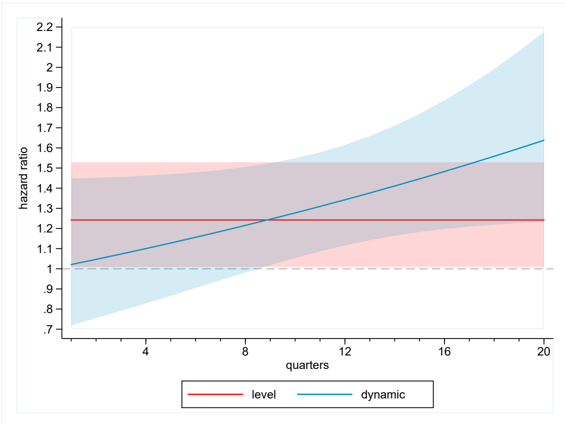
Panels B and C of Figure 3.4.1 illustrate the effect of FDI on the hazard ratios of up- and downgrades. Both graphs show that there is no instantaneous effect of FDI on the likelihood of job switches within the firm. Instead, the effects evolve over time and become statistically significant approximately two years after the investment. The likelihood of upgrading to a more-complex job increases by 2.5% every quarter due to FDI. The risk of downgrading to a less-complex job increases by 3.5% per quarter. There are several possible explanations for the time lag between FDI and the occurrence of job switches. For instance, it might well be that firms do not restructure their domestic plants immediately after the investment. Further, it takes time to negotiate new positions with incumbent workers, and it might be necessary to re-train workers before they can fill new positions.

10 Because hazard ratios are exponentiated coefficients, the impact of FDI on the hazard ratio t quarters after the investment is $\exp(\gamma_0) \times \exp(\gamma_1)^t$. As an example, the hazard ratio for job upgrades due to FDI eight quarters after the investment increases by a factor of $0.996 \times 1.025^8 = 1.21$. Note that confidence intervals depend on the variance of the estimands γ_0 and γ_1, as well as their covariance. Thus, standard errors from Table 3.4.1 do not suffice to infer the significance of the effects.

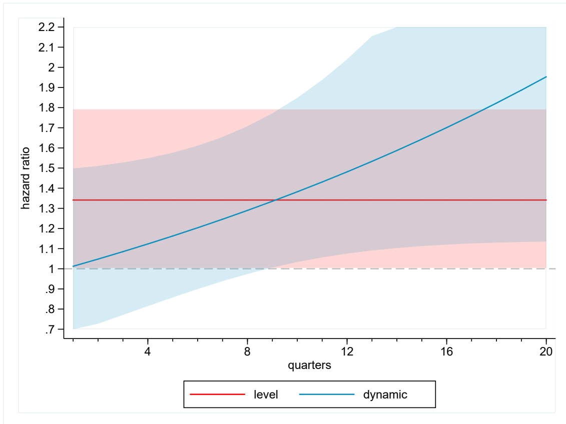
Figure 3.4.1: Dynamic effects of FDI on the hazard ratios of separations and up- and downgrades



PANEL A: Separations



PANEL B: Upgrades



PANEL C: Downgrades

Notes: The figures provide a graphical representation of the hazard ratios and 95% confidence intervals of the estimated effects of FDI on separations and up- and downgrades. The results are obtained from the Cox regressions presented in Table 3.4.1. The red lines display the level effects of FDI, i.e., the average effects over five years after investment. The blue lines show the development of the estimated hazard ratios over time (see the interaction effects of FDI $\times$ quarter in Table 3.4.1). The deviation of the estimated hazard ratios from one can be interpreted as changes in the probabilities of the events attributable to FDI. For example, an estimated hazard ratio for separation of 0.8092 indicates that FDI reduces the individual risk of separation by 19.08% in the quarter of investment.
Sources: ReLOC, IEB and BHP, own calculations.

Job stability and tasks

Not all workers in the investing firms might be equally affected by FDI. Recent literature shows that the effects of offshoring depend substantially on the tasks that are performed on a job (e.g., Blinder, 2006; Grossman & Rossi-Hansberg, 2008). In particular, scholars classify routine (Levy & Murnane, 2004), codifiable (Leamer & Storper, 2001), and non-interactive tasks (Blinder, 2006) as easily offshorable. In this section, we therefore explore heterogeneous effects of FDI depending on the offshorability of the tasks of the initial job. Following the literature, we define the level of offshorability for every occupation as the share of routine and non-interactive tasks.

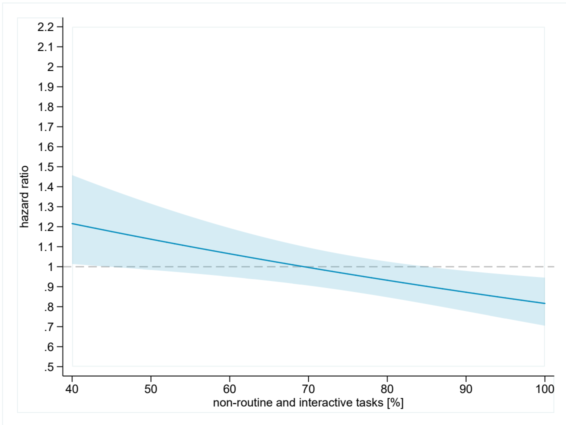
Figure 3.4.2 illuminates the impact of FDI on job stability depending on the initial offshorability of jobs. For ease of interpretation, the share of non-routine and interactive tasks increases from left to right. Thus, more easily offshorable jobs are on the left and jobs that are theoretically more resistant to offshoring on the right of the x-axis. Technically, the graphs show the interaction effect of FDI with the share of non-routine and interactive tasks (see Table 3.A.5 in the Appendix). Note that the x-axis scale ranges from 40% to 100% because there are practically no occupations comprising less than 40% non-routine and interactive tasks (see Figure 3.A.1 in the Appendix).

As can be seen from Panel A of Figure 3.4.2, the likelihood to separate from the firm increases with the offshorability of occupations (right to left). While FDI significantly reduces the hazard of separation for workers in highly non-routine and interactive jobs, FDI barely increases the risk of separations for workers in offshorable occupations. These results are in line with what we would expect theoretically. Internationalization means that investing firms require more administration, management and supervision. Because these tasks are mainly undertaken by workers with highly non-routine and interactive jobs, it seems plausible that they stay. On the contrary, workers with jobs with a high share of offshorable tasks could lose their jobs due to FDI. However, as argued by Grossman & Rossi-Hansberg (2008), foreign activity can increase a firm's productivity. This productivity effect can save workers with offshorable jobs from dismissal. This argumentation might explain why we barely observe an effect of FDI on the separation rate for employees with routine and non-interactive jobs.

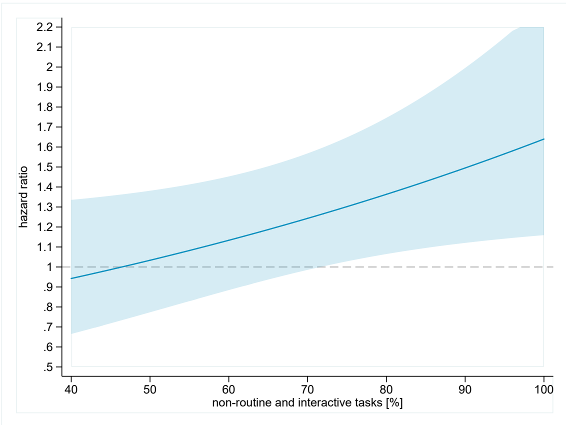
The results for up- and downgrades in Panels B and C imply that the probability of switching positions within the firm increases with the share of non-routine and interactive tasks. In the following, we discuss several explanations for this pattern. Generally, switching occupations requires adaptations. The share of non-routine and interactive tasks presumably also reflects a worker's ability and willingness to adopt. Therefore, the likelihood of switching should be higher for workers with non-routine and interactive jobs.

Moreover, occupational upgrades requires further training and are therefore more expensive than downgrades, which merely require a reduction in tasks. Thus, to fill jobs with medium complexity, it is less expensive to downgrade workers with initially high shares of non-routine and interactive tasks than to upgrade workers with initially low shares. Our data reflect this argumentation. For instance, common downgrades in our data are locksmiths (very non-routine) to welders. Welders typically only carry out some of the

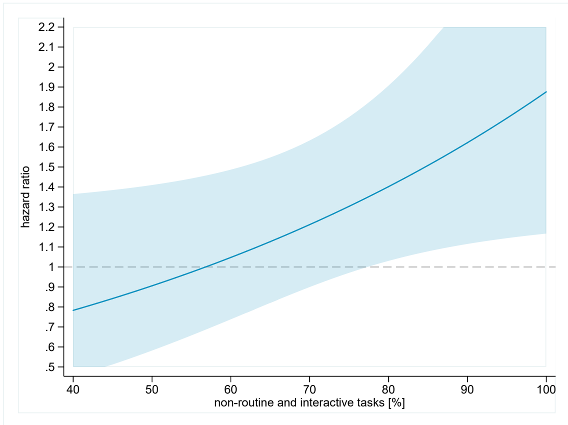
Figure 3.4.2: Effects of FDI on the hazard ratios of separations and up- and downgrades depending on the share of non-routine and interactive tasks



PANEL A: Separations



PANEL B: Upgrades



PANEL C: Downgrades

Notes: The figures provide a graphical representation of the hazard ratios and 95% confidence intervals of the estimated effects of FDI on separations and up- and downgrades. The blue lines plot these estimated hazards against a worker's share of offshorable tasks, i.e., routine and non-interactive tasks, before investment. The results are obtained from Cox regressions presented in Table 3.A.5 in the Appendix with an interaction between FDI and the share of non-routine and interactive tasks. The estimated hazard ratios are averages over the five-year post-investment period. As Figure 3.A.1 in the Appendix shows, the share of non-routine and interactive tasks ranges between 40% and 100% in the data. The range of non-routine and interactive tasks in Figure 3.4.2 is restricted accordingly.
Sources: ReLOC, IEB and BHP, own calculations.

locksmiths' tasks. This reduction in the complexity of tasks is a plausible reaction to the fragmentation of production processes where only some tasks of the locksmiths remain at the home firm, while others become obsolete.

Similarly, to fill jobs with high complexity it is cheaper to upgrade workers with initially high shares of non-routine and interactive tasks than to upgrade workers with lower shares. Furthermore, if FDI raises the demand for management and coordination, and only non-routine and interactive workers possess the abilities to take over such complex tasks, the likelihood additionally increases for these workers.

In summary, these arguments imply that firms have strong incentives to up- and downgrade workers in non-routine and interactive jobs. Moreover, our results reveal that firms adopt their workforce after FDI by relocating their most flexible individuals. Separations do not appear to be a popular adjustment channel.

Job stability and unobserved worker productivity

In this section, we shed further light on the mechanisms of separations, promotions and demotions by investigating whether unobserved worker productivity influences the likelihood of these events. To this end, we first obtain residual wages from Mincer-type wage estimates. We use standard controls from the labor literature, such as age, experience, tenure (and their squares), skill level as well as dummies for foreign nationality, two-digit occupations and year. We then rank all workers according to their estimated wage residual within the firm (in bins of 100). Technically, the wage residual captures positive or negative wage premiums that workers earn compared to workers with identical observable characteristics (e.g., same education, work experience, occupation). Ranking residual wages within firms additionally nullifies all time-invariant firm-specific effects on wages. Economically, the ranking of residual wages within the firm should reflect unobserved worker productivity. We expect that workers with high (low) unobserved productivity have better (lower) chances of upgrades and be less (more) likely to downgrade or leave the firm.

Table 3.4.2 presents estimates of our main specification extended with the workers' position in the wage ranking and an interaction of the ranking with the FDI indicator. Compared to our baseline estimates (Table 3.4.1), the sizes of the coefficients on FDI change somewhat. However, these changes are simply the result of the interaction of FDI and the wage ranking. For workers exactly in the middle of the ranking, the effects are identical to our baseline estimates (e.g, for upgrades, $1.3918 \times 0.9981^{50} = 1.2656 \approx 1.2422$). In particular, we find no effect of FDI on separations. At the median of the wage ranking, FDI increases the likelihood of up- and downgrades by 27% and 36% percent, respectively. Both effects are statistically significant.

The main coefficients on the wage ranking indicate that the job stability of workers indeed depends on their unobserved ability. These results are in line with what we would expect, i.e., more productive workers are less likely to be dismissed or demoted and more likely to receive occupational upgrades. Specifically, an increase in the residual wage

Table 3.4.2: Effects of FDI on the hazard ratios of separations and up- and downgrades depending on unobserved worker productivity

	separation (1)	upgrade (2)	downgrade (3)
FDI	0.9477	1.3918**	1.2723
	(0.0492)	(0.1937)	(0.2167)
FDI × wage rank	1.0002	0.9981	1.0013
	(0.0006)	(0.0012)	(0.0018)
Wage rank	0.9962***	1.0093***	0.9914***
	(0.0005)	(0.0010)	(0.0014)
Subjects	376,411	376,411	376,411
Events	99,866	15,687	11,611

Notes: The table presents exponentiated coefficients (hazard ratios) and cluster robust standard errors at the firm level (in parentheses). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. "Wage rank" indicates the ranking of a worker's unobserved productivity within the firm. Additional control variables in all models are: age, age squared, experience, tenure, a foreign dummy, skill dummies, firm age and a dummy if firm existed in 1975 (all interacted with quarters since treatment), as well as occupation, year, and state dummies. Estimates are based on a matched sample of MNEs and domestic firms.
Source: ReLOC, IEB and BHP, own calculations.

ranking of one (on a scale between one and 100) reduces the hazard of separations by 0.38% and that of demotions by 0.86%. The likelihood of promotions increases by 0.93%. However, this effect does not differ between firms that invest abroad and domestic firms.

The insignificant interaction effects of FDI and wage ranking in all three models indicate that MNEs follow the same patterns as domestic firms when choosing whom to upgrade, downgrade or dismiss in terms of individual productivity. This result is not surprising. Although this paper finds that MNEs are more likely to restructure, restructuring is comparable to the dynamics in domestic firms. Workers with lower productivity always face higher risks of dismissals and downgrades independent of FDI.[11]

Discussion of the empirical findings

In the following, we discuss our findings and derive their main implications. Contrary to the widespread concern that MNEs substitute foreign for domestic labor, our main findings suggest no effect of FDI on average separation rates. However, further investigations with time-sensitive models and heterogeneous groups of workers reveal some exceptions. First, we find a brief lock-in effect that saves workers from separations immediately after their employers go multinational. Second, the positive effect on employment security is significant only for workers in highly non-routine and interactive occupations. These

[11] In Appendix 3.A.5, we present additional results for different skill and age groups.

workers experience a 10% to 20% greater likelihood of remaining employed at the firm over the course of FDI.

Overall, the results on separations are in line with the literature, which generally finds no or very limited employment effects of FDI. For instance, Bachmann *et al.* (2014) find no significant evidence that industry-level FDI affects individual separation rates.[12] In line with our results, Becker & Muendler (2008) find lower separation rates in MNEs, particularly among high-skilled workers.[13] Empirical evidence on the employment effects of FDI by tasks is scarce. Thus, we compare our findings with the offshoring literature. Comparable to our results, Baumgarten (2015) finds no significant effect of offshoring on the hazard of non-employment on average. Moreover, he also shows that over the course of offshoring, workers in non-routine occupations experience a decrease in the hazard of non-employment.

Generally, our results are in line with the theoretical predictions by Grossman & Rossi-Hansberg (2008). They argue that the positive productivity effect of offshoring could outweigh the negative effects for workers with offshorable jobs. Thus, even if firms want to save labor costs and offshore parts of their production abroad, this does not necessarily lead to dismissals of domestic workers. Additionally, our results are in line with the predicted employment effects of market-seeking FDI. To serve the foreign market on-site, more complex coordination and management services are required at the headquarters, and there is thus no need for separations. We show that instead of separations, MNEs adjust their workforce internally through promotions and demotions. For the average worker, the likelihood of upgrading to a more-complex job increases by 24% due to FDI. The likelihood of downgrading to a less-complex job increases by 34%. Both effects become measurable with a time lag of two years after the investment. Explanations for the time lag of up- and downgrades include, e.g., time-intensive negotiations between firms and employees over occupational changes. Moreover, it might be necessary to re-train workers before they can fill new positions. Further, the positive impact of FDI on internal job transitions applies only to workers in occupations with at least moderate shares of non-routine and interactive tasks. Their likelihood of upgrading to more-complex jobs increases by between 30% and 60%. For the same group of workers, the probability of

[12] In their paper, separation rates comprise both transitions to other firms and to non-employment. When Bachmann *et al.* (2014) exclusively consider transitions to non-employment, which is their main measure of employment security, they find that FDI—especially to CEEC—significantly increases workers' risk of non-employment.

[13] We also estimate occupational hazard ratios by skill levels; see Table 3.A.6 and Figure 3.A.2 in the Appendix. Our results support the findings by Becker & Muendler (2008) inasmuch as the positive lock-in effect of FDI exists among high-skilled workers. We additionally find an impact for medium-skilled workers.

downgrading to less-complex jobs increases by between 30% and 80%. The likelihood of both types of switches does not increase for workers performing mostly routine and non-interactive tasks.

The greater opportunities to climb the career ladder through occupational upgrades in MNEs are in line with the theoretical expectations that MNEs require more administration and management tasks and with our hypothesis that these firms attempt to fill these vacant complex positions internally. Moreover, the increased risk of demotions through FDI is in line with our expectation that MNEs might avoid the costs of dismissals by demoting workers whose tasks become redundant over the course of FDI. Generally, the positive effect of FDI on firm-internal job switches speaks in favor of our hypothesis that internal labor markets are an important way in which MNEs can meet the changes in labor demand due to FDI.

The task-specific analyses show that the hazard of up- and downgrades is significant only for workers in jobs with medium-to-high initial shares of non-routineness and interactivity. As explained in Section 3.4, they have the opportunity to upgrade to new and more-complex positions because routine and non-interactive workers might not possess the prerequisites for these positions. However, highly non-routine and interactive workers also face an increased risk of downgrades. A possible explanation for this is that in the case of fragmentation, jobs at the middle of the complexity scale of tasks need to be filled, and it might be less expensive for MNEs to downgrade these workers than to upgrade workers with a low initial level of non-routine and interactive tasks.

There is no comparable study in the FDI literature that analyzes effects on job switches. Instead, we take up some results of the offshoring literature. However, the offshoring literature considers imports of intermediate inputs mostly at the industry level and does not specifically examine firm-internal transitions. Our results are in line with the positive effect of offshoring to CEEC on job-to-job transitions observed by Baumgarten (2015). Additionally, our results on job switches are, to some extent, comparable with studies on workforce composition. In line with our results Becker *et al.* (2013) and Hakkala *et al.* (2014) find evidence for a shift in tasks in German and Swedish MNEs. In contrast to our results for FDI to the Czech Republic, Becker *et al.* (2013) do not find significant effects on the workforce composition for FDI to CEEC.

Overall, our results provide unique evidence that firms restructure their labor forces internally over the course of FDI. Some incumbent workers are promoted, while others are demoted. Although demotions are per se not a positive occupational change, they might be a more minor career disruption than dismissals. Further, the results suggest that although FDI opens career opportunities for some workers, it might also exert pressure to adapt and keep up for others. The perceived pressure to adapt might partly explain the fear of globalization in the public debate.

3.5 Robustness checks

In this section, we perform several robustness exercises. Specifically, we assess the competing risk assumption, employ alternative estimators and test further definitions of occupational up- and downgrades. The section concludes with a brief description of additional robustness checks.

Non-competing risks

In Section 3.2, we argue that separations and up- and downgrades follow distinct causal mechanisms. Therefore, we treat these events as competing risks and estimate separate models in which we remove workers from the risk set after any other event. As a robustness exercise, we now test an alternative specification for separations in which we retain individuals after job switches within the firm. Table 3.5.1 shows the results (Column 2) and repeats the estimates from our baseline specification (Column 1) for comparison. Both models yield the same results and obtain no effect of FDI on job separations. Thus, our conclusions from the main specification are not driven by the assumption of competing risks.

Moreover, we control for preceding up- and downgrades within the firm in Column 2 of the same table. Independent of FDI, a promotion reduces the hazard of a separation by 25%. This finding is in line with the expectation that only *good* workers receive promotions and are therefore less likely to be dismissed. The robustness exercise further indicates that past downgrades do not influence separations.

Alternative estimators

To ensure that our findings are independent of the chosen estimator, we further compute the effects of FDI on job stability with simple logit and multinomial logit models. To do so, we construct a cross-sectional dataset that assigns the first event $e \in \{\text{separation, upgrade, downgrade}\}$ within five years after the (pseudo) investment to individuals. Obviously, logit estimates ignore the chronological order of events. In the simple logit models, we estimate each event separately, as we also do in our baseline specification. In the multinomial logit model, we jointly estimate the likelihood of all events

Table 3.5.1: Effect of FDI on separations: competing vs. non-competing risks model

	baseline	no competing risks
	(1)	(2)
FDI	0.9630	0.9595
	(0.0440)	(0.0437)
Upgrade		0.7471***
		(0.0291)
Downgrade		0.9525
		(0.0504)
Subjects	383,098	383,098
Events	102,661	106,613

Notes: The table presents exponentiated coefficients (hazard ratios) and cluster robust standard errors at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Additional control variables in all models are: age, age squared, experience, tenure, a foreign dummy, skill dummies, firm age and a dummy if a firm existed in 1975 (all interacted with quarters since treatment), as well as occupation, year, and state dummies. Estimates are based on a matched sample of MNEs and domestic firms.
Source: ReLOC, IEB and BHP, own calculations.

Table 3.5.2: Logit estimates of the effect of FDI on separations and up- and downgrades

	separate logit models by events			multinomial logit model (base category: no event)		
	separation	upgrade	downgrade			
	(1)	(2)	(3)	(4)		
				separation	upgrade	downgrade
FDI	0.9722	1.2607**	1.4248**	0.9868	1.2968**	1.3973**
	(0.0534)	(0.1236)	(0.2236)	0.0541	0.1375	0.2232
N	383,097	382,776	382,664	383,098		
Log lik.	-211949.4449	-61383.9606	-48363.6299	-316837.68		
Chi-squared	3624.3332	3388.7212	4093.1349	6064.85		

Notes: The table presents exponentiated coefficients (odds ratios) and cluster robust standard errors at the firm level (in parentheses). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Additional control variables in all models are: age, age squared, experience, tenure, a foreign dummy, skill dummies, firm age and a dummy if a firm existed in 1975, as well as occupation, year, and state dummies. The multinomial logit does only include one-digit occupational dummies. Estimates are based on a matched sample of MNEs and domestic firms.
Source: ReLOC, IEB and BHP, own calculations.

(against the baseline outcome *no event*). Table 3.5.2 summarizes the results.

Overall, the estimates of the separate logit models and the multinomial logit model are well in line with our main findings. The computed odds ratios are only marginally larger than in the proportional hazard models. We conclude that our results are independent of the chosen estimator. Nevertheless, we prefer hazard models because they allow us to explicitly model the time structure of the impact of FDI.

Alternative definitions of up- and downgrades

Throughout the paper, we interpret switches to occupations with higher (lower) shares of analytical and interactive tasks as upgrades (downgrades). We now corroborate the validity of this interpretation with a range of alternative definitions.

We begin with the possible concern that switches with only marginal changes in the complexity of tasks might not reflect real up- or downgrades. For instance, a switch from metalworker to mechanic increases the share of complex tasks by only five percentage points and thus might not be considered a significant promotion. As a robustness exercise, we therefore define *significant* up- and downgrades as job switches with changes in complex tasks of at least ten percentage points. In Figure 3.3.2, these switches are in the bins to the left of -10% and in the bins to the right of +10%. The estimates for significant up- and downgrades in Panel B of Table 3.5.3 are comparable in sign and significance to our baseline results (Panel A). We conclude that our main findings are not biased by including job switches with only marginal changes in the complexity of tasks.

Next, we assess whether considering an alternative definition of the complexity of tasks alters our results. In our main specification, we measure the complexity of tasks as the share of analytical and interactive tasks. We now quantify the complexity of occupations by the share of all non-routine tasks. Accordingly, workers receive upgrades (downgrades) if the percentage of routine tasks decreases (increases). As the share of routine tasks is analogous to one minus the share of interactive, analytical and non-routine manual tasks, our alternative definition essentially extends our original definition of complexity along the manual dimension. Importantly, this definition also corresponds to the definition of offshorable tasks in the trade literature. As Panels A and C of Table 3.5.3 indicate, adding the manual dimension to our task measure does not affect the results.

Finally, inspired by Liu & Trefler (2011), we completely refrain from a task-based classification and identify occupational up- and downgrades based on wages. Therefore, we use a large, representative register sample of workers in Germany (Sample of Integrated Labour Market Biographies, SIAB) and compute yearly median wages in two-digit occupations. To remove noise, we further fit a quadratic time trend to the data. The result is an occupational panel with smooth median wages over the time frame of our analysis. We link the occupational panel to our main dataset and re-define upgrades (downgrades) as job switches within the firm to occupations with higher (lower) median wages. Panel D of Table 3.5.3 summarizes the according estimates. Both our task-based definition from the baseline model and the alternative wage-based definition of job switches lead to similar results. Overall, our main finding that FDI leads to notably more up- and downgrades

Table 3.5.3: Effects of FDI on the hazard ratios of up- and downgrades (alternative definitions)

	upgrade		downgrade	
	(1)	(2)	(3)	(4)
Panel A: Baseline model (complex tasks):				
FDI	1.2422**	0.9960	1.3413**	0.9781
	(0.1315)	(0.1896)	(0.1980)	(0.2094)
FDI × quarter		1.0252*		1.0352*
		(0.0141)		(0.0205)
Subjects	383,098	383,098	383,098	383,098
Events	15,880	15,880	11,731	11,731
Panel B: Significant up- and downgrades with at least 10 percentage points changes:				
FDI	1.3448***	1.2031	1.4476**	1.0333
	(0.1231)	(0.1786)	(0.2489)	(0.2731)
FDI × quarter		1.0121		1.0365
		(0.0109)		(0.0246)
Subjects	383,098	383,098	383,098	383,098
Events	10,580	10,580	6,255	6,255
Panel C: All non-routine tasks:				
FDI	1.2501**	0.9847	1.3248*	0.9962
	(0.1267)	(0.1662)	(0.1903)	(0.2435)
FDI × quarter		1.0270**		1.0321
		(0.0135)		(0.0205)
Subjects	383,098	383,098	383,098	383,098
Events	14,017	14,017	13,594	13,594
Panel D: Median wages:				
FDI	1.2533**	1.1140	1.3137*	0.8730
	(0.1305)	(0.2039)	(0.1898)	(0.1905)
FDI × quarter		1.0132		1.0467***
		(0.0154)		(0.0180)
Subjects	383,098	383,098	383,098	383,098
Events	14,006	14,006	13,605	13,605

Notes: The table presents exponentiated coefficients (hazard ratios) and cluster robust standard errors at the firm level (in parentheses). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Panel A repeats our main findings, where upgrades (downgrades) are defined as increases (decreases) in non-routine and analytical tasks. Panel B classifies upgrades (downgrades) as job switches with at least a ten percentage points increase (decrease) in analytical and interactive tasks. Panel C identifies upgrades (downgrades) as job switches with increases (decreases) in analytical, non-routine manual and interactive tasks. Panel C specifies job switches as upgrades (downgrades) if the occupational median wage increases (decreases) with the job switch. Control variables in all models are: age, age squared, experience, tenure, a foreign dummy, skill dummies, firm age and a dummy if the firm existed in 1975 (all interacted with quarters since treatment), as well as occupation, year, and state dummies. Estimates are based on a matched sample of MNEs and domestic firms.
Source: ReLOC, IEB and BHP, own calculations.

within the firm, holds independent of the exact definition of up- and downgrades.[14]

[14] Figure 3.A.4 in the Appendix present the unconditional hazard rates for the alternative definitions of

Additional robustness checks

In an additional robustness check, we test whether our main findings are driven by small firms. To ensure that the investment decision is independent of the individual worker, we exclude small firms with fewer than 50 employees in Panel B of Table 3.A.8 in the Appendix. The results point in the same direction, and deviations from our main specification are minor (see Panel A of the same table). We conclude that small firms do not drive our results.

While for workers in MNEs, the onset of the risk of job changes naturally begins with FDI, there is no such inherent start date for domestic firms. For this and other reasons, we match domestic firms to MNEs and assign the investment quarter of the MNE to its domestic counterpart. To determine whether this assignment influences our findings, we now randomly change the pseudo investment date of domestic firms. In particular, we randomly draw pseudo investment quarters from a uniform distribution ranging from four quarters before to four quarters after the initial assignment. We do not alter the investment dates of MNEs. As Table 3.A.8 in the Appendix shows, this robustness exercise does not affect the results on separations. In the static model, the effects on job switches are also stable and even larger for upgrades. However, the dynamic effects on up- and downgrades are insignificant. If the likelihood of job switches within the firm follows time-dependent trajectories, it is substantial for a dynamic analysis to compare temporal twins of MNEs and domestic firms and not just time-averaged twins. Shuffling pseudo investment dates breaches such a prerequisite and therefore potentially leads to insignificant estimates.

To identify the causal effects of FDI on job stability, we restrict our sample to workers who were already employed two years prior to the (pseudo) investment. This restriction ensures that individuals do not self-select into future MNEs. However, it also removes 20% of workers from our sample, to whom our findings might not be applicable. To test the generalizability of our findings to workers with less than two years' tenure, we discard this restriction and re-estimate our models. The resulting estimates are almost identical to our main findings (see Table 3.A.8 in the Appendix). Although the unrestricted estimates should not be interpreted causally, they suggest that our findings also apply to workers with less than two years' tenure.

---

up- and downgrades.

3.6 Conclusion

The objective of this paper is to analyze how FDI affects the job stability of workers. In an extension of the results in the previous literature, we suggest that firms use internal reorganizations of their workforce as an important adjustment channel to the changes in labor demand induced over the course of FDI. Particularly, we consider occupational up- and downgrades of workers to more- or less-complex jobs, respectively. Especially in labor markets with strong labor protection laws and rigid wages, internal labor markets offer investing firms the opportunity to adjust their incumbent workforce to changes in labor demand. Internal restructuring circumvents the costs of hires and dismissals and information asymmetries and retains firm-specific human capital. To identify occupational switches within and out of the firm, we use employer-employee data on German firms that invest in the Czech Republic and those on comparable domestic firms.

Our results show that workers in MNEs have a significantly greater likelihood of upgrading to more-complex jobs over the course of FDI. However, the risk of downgrading to less-complex occupations also increases. The probability of up- and downgrades grows with the workers' share of non-routine and interactive tasks in their job before FDI. Both effects become significant two years after investment. Further, we show that FDI has no impact on separations of workers and firms on average. At most, we find a temporal lock-in effect of FDI shortly after investment.

In summary, our results imply that MNEs use internal restructuring rather than dismissals as an important adjustment channel to meet labor demands that change over the course of FDI. Our findings therefore rebut the common fear that foreign labor substitutes for domestic labor in MNEs. However, workers in investing firms need to be more flexible and willing to take on new tasks. As further training is indispensable for successful occupational transitions, this paper underpins the importance of lifelong learning.

3.A Appendix

3.A.1 Iterative matching algorithm

Algorithm 1: Iterative matching

input : List with three potentially best matches: **P**.
output: List with single best matches: **M**

define : Match of treatment firm t and control firm c: m_{tc}
Distance of logit propensity scores of m_{tc}:
$\Delta_{tc} = |logit(\text{PS}_t) - logit(\text{PS}_c)|$

repeat $3\times$
  for *each treatment firm* t
    find best match $\tilde{m}_{t\cdot} \in \mathbf{P}_t$ with smallest $\Delta_{t\cdot}$
    add match $\tilde{m}_{t\cdot}$ to **M**
  for *each control firm* c
    find best match $\tilde{m}_{\cdot c} \in \mathbf{M}$ with smallest $\Delta_{\cdot c}$
    drop other matches $m_{\cdot c} \neq \tilde{m}_{\cdot c}$ from **M**
  for *each treatment firm* t
    if *match* $\tilde{m}_{t\cdot} \notin \boldsymbol{M}$
      drop match $\tilde{m}_{t\cdot}$ from $\mathbf{P}_t$
drop matches $m_{\cdot\cdot}$ with $\Delta_{\cdot\cdot} < [0.2 \times sd(logit(\text{PS}))]$ from **M**

3.A.2 Matching results

Table 3.A.1 illustrates the distribution of firm characteristics of (future) MNEs and domestic firms in our raw data. Notably, the sizes and average wages of MNEs are considerably larger and show higher variability.

To create a homogeneous dataset of MNEs and domestic firms with equal probabilities of investing, we propose an iterative matching procedure. We match firms between 1990 and 2010. Firms with just one employee in the year of treatment are excluded. Further, we restrict our sample to MNEs smaller than 30,000 employees because the largest control firm has only 23,000 workers. We also drop firms in the public sector as well as private households and extra-territorial organizations.

First, we estimate propensity scores based on the following variables: log number of employees, average age and wage of the workers, the share of female, regular, German, unskilled-manual, full-time, low-, medium- and high-skilled employees, the share

Table 3.A.1: Firm characteristics (unmatched sample)

	MNEs two years prior FDI			MNEs two years after FDI			domestic firms		
	obs.	mean	std.	obs.	mean	std.	obs.	mean	std.
No. of employees	1,996	383.8868	1133.8480	2,164	382.5873	1113.0740	7,767	185.5134	420.8820
Employment growth rate	1,992	0.3699	2.4167	1,870	0.3816	5.0398	7,767	0.6443	4.2290
Firm age	1,996	15.2169	8.5461	2,164	17.4205	9.5959	7,767	16.0055	8.8191
Av. wage of emp.	1,996	88.8361	38.0267	2,164	98.4771	43.4784	7,767	82.9027	32.1573
Wage growth rate	1,992	0.0717	0.1748	1,867	0.0736	0.1796	7,767	0.0584	0.1252
Av. age of emp.	1,996	38.3412	4.9081	2,164	39.4725	4.8128	7,767	39.3095	4.4908
Share of female emp.	1,996	0.3539	0.2322	2,164	0.3559	0.2239	7,767	0.3828	0.2589
Share of trainees	1,996	0.0341	0.0507	2,164	0.0362	0.0595	7,767	0.0445	0.0620
Share of regular emp.	1,996	0.9141	0.1255	2,164	0.8912	0.1381	7,767	0.8496	0.1537
Share of full-time emp.	1,996	0.8609	0.1509	2,164	0.8367	0.1639	7,767	0.7707	0.2082
Share of low-sk. emp.	1,996	0.1486	0.1396	2,164	0.1358	0.1257	7,767	0.1519	0.1280
Share of med.-sk. emp.	1,996	0.7065	0.1922	2,164	0.7007	0.1897	7,767	0.7289	0.1720
Share of high-sk. emp.	1,996	0.1304	0.1794	2,164	0.1499	0.1839	7,767	0.1019	0.1447
Share of German emp.	1,996	0.9160	0.1101	2,164	0.9188	0.1076	7,767	0.9258	0.1077
Share of unsk.-man. emp.	1,996	0.2197	0.2585	2,164	0.1986	0.2429	7,767	0.1786	0.2399
Share of engineers etc.	1,996	0.0303	0.0800	2,164	0.0311	0.0758	7,767	0.0226	0.0671

Notes: The table compares the number of firms, the means and standard deviations of various characteristics of investing and domestic firms in the raw data before matching. For MNEs we report the values two years prior to investment and two years after the investment. For the control group of domestic firms we show averages over all years they are in the data. Source: ReLOC and BHP, own calculations.

of trainees, the share of engineers and scientists, wage and employment growth rates over the last two years, firm age, a dummy for whether the firm existed before 1975 and federal state, year and industry dummies. These variables either directly affect the firms' probability of investing (e.g., firm age) or are a good proxy for variables that have a direct impact on the firms' decision to conduct FDI (e.g. firm-size for productivity.) All variables are measured two years prior to investment to avoid adjustments to FDI already having been made. If a firm did not exist two years before, we do not receive a growth rate of wage and employment. Growth rates in these firms are imputed with the average growth rate for the year in question. We include a dummy to tag these observations in the logit model.

We match every MNE two years before investment to its three nearest neighbors according to the estimated propensity score among the control firms exactly in the same year.

To obtain an unambiguous start date for domestic firms, we need to ensure that every control firm is only matched once to a treatment firm (see Section 3.2). Therefore, we propose an iterative matching procedure (see Algorithm 1) to identify the single best pairs of MNEs and domestic firms over the entire observation period. To ensure that nearest neighbors are not too far away, we calculate the optimal caliper width as recommended

Table 3.A.2: Balancing test results after matching

	standardized mean differences			variance ratios		
	raw	1st match	2nd match	raw	1st match	2nd match
Log no. employees	0.0126	-0.0129	-0.0055	1.4268	1.3381	1.3067
Av. wage	0.2569	0.0714	0.0872	1.6021	1.1804	1.1692
Firm age	-0.1861	-0.0238	0.0233	0.9263	0.9375	0.9036
Av. age	-0.0674	-0.0229	-0.0023	0.9634	1.0325	1.0416
Share female emp.	-0.0690	0.0133	0.0384	0.7704	0.8431	0.8521
Share trainees	-0.1850	0.0216	0.0273	0.5424	1.0195	1.0923
Share regular emp.	0.2035	0.0043	0.0330	0.6570	0.9031	0.8697
Share full-time emp.	0.2973	0.0047	0.0217	0.5262	0.8325	0.7948
Share low-skilled emp.	-0.1044	-0.0480	-0.0356	0.8927	0.9241	0.9718
Share medium-skilled emp.	-0.1477	-0.0397	-0.0362	1.1235	1.0230	0.9784
Share high-skilled emp.	0.2666	0.0859	0.0690	1.6013	1.1090	1.0281
Share german emp.	-0.0464	0.0229	0.0141	0.8735	0.8854	0.9236
Share unskilled-manual emp.	0.1155	-0.0677	-0.0518	1.0628	0.9187	0.9261
Share engineers etc.	0.1206	0.0130	0.0154	1.3399	0.9416	0.9979
Employment growth	-0.0201	-0.0204	-0.0348	0.0491	0.2411	0.1758
Av. wage growth	0.0348	0.0159	-0.0025	0.2527	1.1729	0.8502

Notes: The table compares the standardized mean differences and variance ratios of the variables used for matching. "Raw" represents the standardized mean differences and variance ratios before matching. "1st match" give the results for the first part of our matching procedure two years prior to investment with three-nearest neighbor propensity score matching exactly by year. "2nd match" presents the results after applying our iterative matching algorithm (1). The cells with the best balance statistic are highlighted, i.e., figures closest to zero in case of the standardized mean differences and figures closest to one for variance ratio.
Source: ReLOC and BHP, own calculations.

by Austin (2011b).[15]

Table 3.A.2 presents the balancing test results of our matching approach. We calculate the standardized differences and variance ratios of our resulting sample according to Austin (2011a). Standard propensity score matching (1st Match) and Algorithm 1 (2nd Match) reduce the standardized differences of almost all variables (expect for the log number of employees and employment growth) and lead to a variance ratios closer to one. The results indicate that matching substantially improves the balancing of firm characteristics.

Further, Table 3.A.3 shows that the distribution of firms across industries is also remarkably similar after matching. The matched dataset consists of 1,876 matched treatment and control pairs.

[15] We use a logit of the estimated propensity score for matching. Here, we follow Austin (2011b), who recommend setting the optimal caliper width to 0.2 of the standard deviation of the logit of the propensity score.

Table 3.A.3: Balance of industries after matching

Industry	No. domestic f.	No. MNEs	Total
Manuf. food products, beverages and tobacco	21	28	49
Manuf. textiles and textile products	35	34	69
Manuf. pulp, paper and paper products; publishing and printing	30	38	68
Manuf. chemicals, chemical products and man-made fibres	48	44	92
Manuf. rubber and plastic products	79	66	145
Manuf. other non-metallic mineral products	36	32	68
Manuf. basic metals and fabricated metal products	147	142	289
Manuf. machinery and equipment n.e.c.	130	130	260
Manuf. electrical and optical equipment	129	147	276
Manuf. transport equipment	30	25	55
Manuf. n.e.c.	21	25	46
Construction	79	72	151
Wholesale/retail; repair of motor vehicles/household goods etc.	262	247	509
Transport, storage and communication	95	83	178
Real estate, renting and business activities	130	150	280
Total	1,344	1,340	2,684

Notes: The table presents the balance of firms over industries after applying our iterative matching algorithm. For reasons of data protection the table only includes industries with more than 20 firms.
Source: ReLOC and BHP, own calculations.

3.A.3 Main results of Cox regression

Table 3.A.4: Effects of FDI on the hazard ratios of separations and up- and downgrades (full table)

	separation		upgrade		downgrade	
FDI	0.9630	0.8092**	1.2422**	0.9960	1.3413**	0.9781
	(0.0440)	(0.0691)	(0.1315)	(0.1896)	(0.1980)	(0.2094)
FDI × quarter		1.0190**		1.0252*		1.0352*
		(0.0083)		(0.0141)		(0.0205)
Age	0.7875***	0.7875***	1.0070	1.0068	0.9761	0.9762
	(0.0156)	(0.0155)	(0.0333)	(0.0335)	(0.0543)	(0.0552)
Age squared	1.0030***	1.0030***	0.9997	0.9997	1.0003	1.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0006)	(0.0006)
Experience	0.9999***	0.9999***	1.0000	1.0000	1.0000	1.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Tenure	0.9998***	0.9998***	1.0000	1.0000	0.9999***	0.9999***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Foreign	1.2165***	1.2170***	0.8614	0.8646	1.2759	1.2687
	(0.0915)	(0.0892)	(0.1359)	(0.1351)	(0.2026)	(0.1976)
Medium skilled	0.9779	0.9788	1.3636***	1.3647***	0.9639	0.9646
	(0.0460)	(0.0458)	(0.1141)	(0.1154)	(0.1086)	(0.1105)
High skilled	1.2300***	1.2449***	2.9824***	3.0368***	0.5418**	0.5494**
	(0.0851)	(0.0871)	(0.6202)	(0.6263)	(0.1373)	(0.1405)
Firm age	1.0201*	1.0206**	1.0623**	1.0629**	1.0388	1.0398
	(0.0106)	(0.0105)	(0.0273)	(0.0271)	(0.0394)	(0.0390)
Dummy firm < 1975	0.7874	0.8074	0.5501**	0.5779*	0.5013*	0.5394
	(0.1825)	(0.1854)	(0.1559)	(0.1624)	(0.1932)	(0.2087)
Interaction with quarters since treatment:						
Age	1.0050***	1.0050***	0.9920**	0.9920**	0.9970	0.9970
	(0.0011)	(0.0011)	(0.0033)	(0.0033)	(0.0053)	(0.0054)
Age squared	0.9999***	0.9999***	1.0001**	1.0001**	1.0000	1.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Experience	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	1.0000***	1.0000***	1.0000	1.0000	1.0000**	1.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Foreign	1.0013	1.0013	0.9921	0.9917	1.0118	1.0126
	(0.0079)	(0.0077)	(0.0136)	(0.0134)	(0.0137)	(0.0132)
Medium skilled	1.0007	1.0006	0.9889	0.9888	0.9610**	0.9609**
	(0.0048)	(0.0048)	(0.0073)	(0.0072)	(0.0171)	(0.0170)
High skilled	0.9884*	0.9871*	0.9772	0.9752	0.9531	0.9517
	(0.0067)	(0.0069)	(0.0203)	(0.0203)	(0.0310)	(0.0311)
Firm age	1.0002	1.0001	1.0011	1.0010	1.0027	1.0027
	(0.0010)	(0.0010)	(0.0023)	(0.0022)	(0.0035)	(0.0035)
Dummy firm < 1975	0.9846	0.9819	0.9915	0.9859	1.0071	0.9992
	(0.0225)	(0.0224)	(0.0225)	(0.0230)	(0.0354)	(0.0359)
Subjects	383,098	383,098	383,098	383,098	383,098	383,098
Events	102,661	102,661	15,880	15,880	11,731	11,731

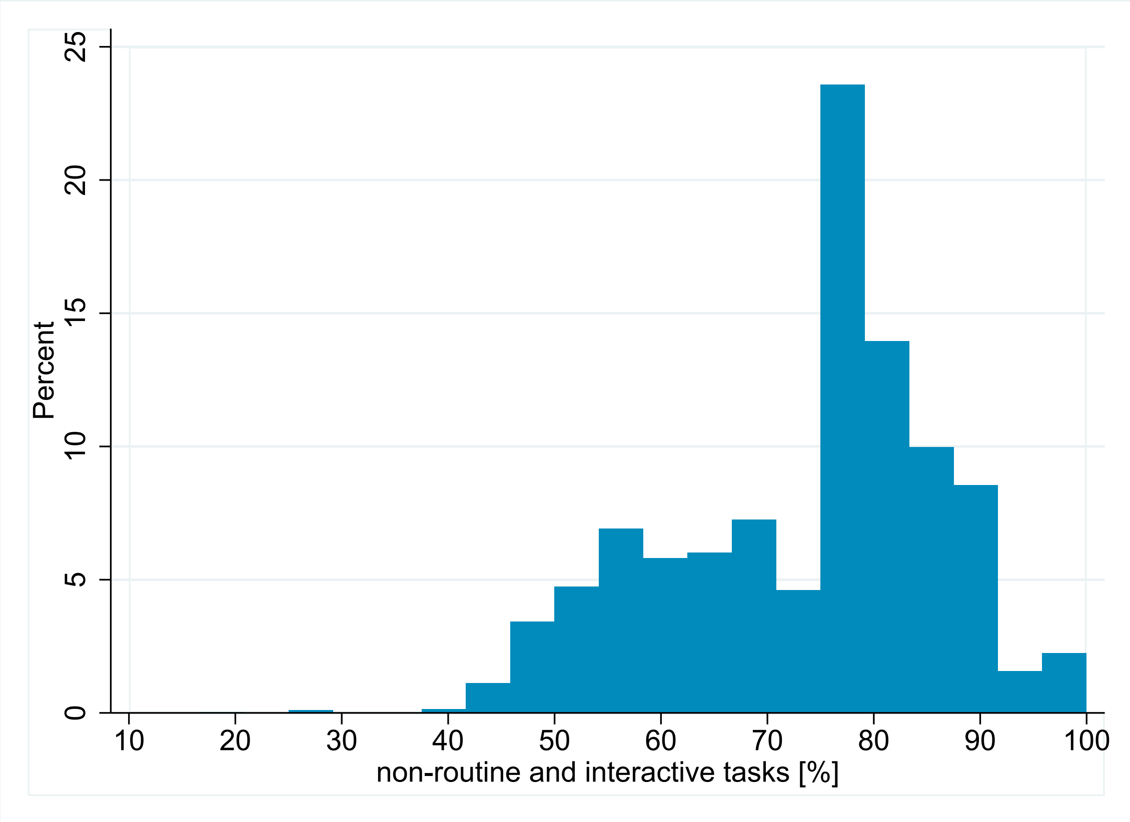
Notes: The table presents exponentiated coefficients (hazard ratios) and cluster robust standard errors at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The models further include occupation, year, and state dummies.

Source: ReLOC, IEB and BHP, own calculations.

3.A.4 Additional material on job stability and tasks

Distribution of non-routine and interactive tasks

Figure 3.A.1: Histogram of non-routine and interactive tasks



Notes: The histogram shows the share of non-routine and interactive tasks that workers perform in our data (in the quarter of the (pseudo) investment). The actual range of non-routine and interactive tasks is between 40% and 100%. Only 0.1% of workers are in occupations with less than 40% non-routine and interactive tasks.
Source: ReLOC, IEB and BHP, own calculations.

Job stability by initial share of non-routine and interactive tasks

Table 3.A.5: Effects of FDI on the hazard ratios of separations and up- and downgrades depending on the share of non-routine and interactive tasks

	separations		upgrades		downgrades	
	(1)	(2)	(3)	(4)	(5)	(6)
FDI	1.5853***	1.9558	0.6514	0.6542	0.4373	0.2429
	(0.2825)	(1.4482)	(0.2155)	(0.7855)	(0.2399)	(0.6932)
Non-routine & interactive	1.0100***	0.9997	0.9805***	0.9511*	1.0078	1.0414
	(0.0017)	(0.0143)	(0.0027)	(0.0284)	(0.0051)	(0.0565)
FDI $\times$ non-routine	0.9934***	0.9872	1.0093**	1.0096	1.0147**	1.0308
& interactive	(0.0023)	(0.0206)	(0.0044)	(0.0375)	(0.0073)	(0.0792)
FDI $\times$ (non-routine		1.0000		1.0000		0.9999
& interactive)squared		(0.0001)		(0.0003)		(0.0005)
Subjects	383,009	383,009	383,009	383,009	383,009	383,009
Events	102,626	102,626	15,862	15,862	11,730	11,730

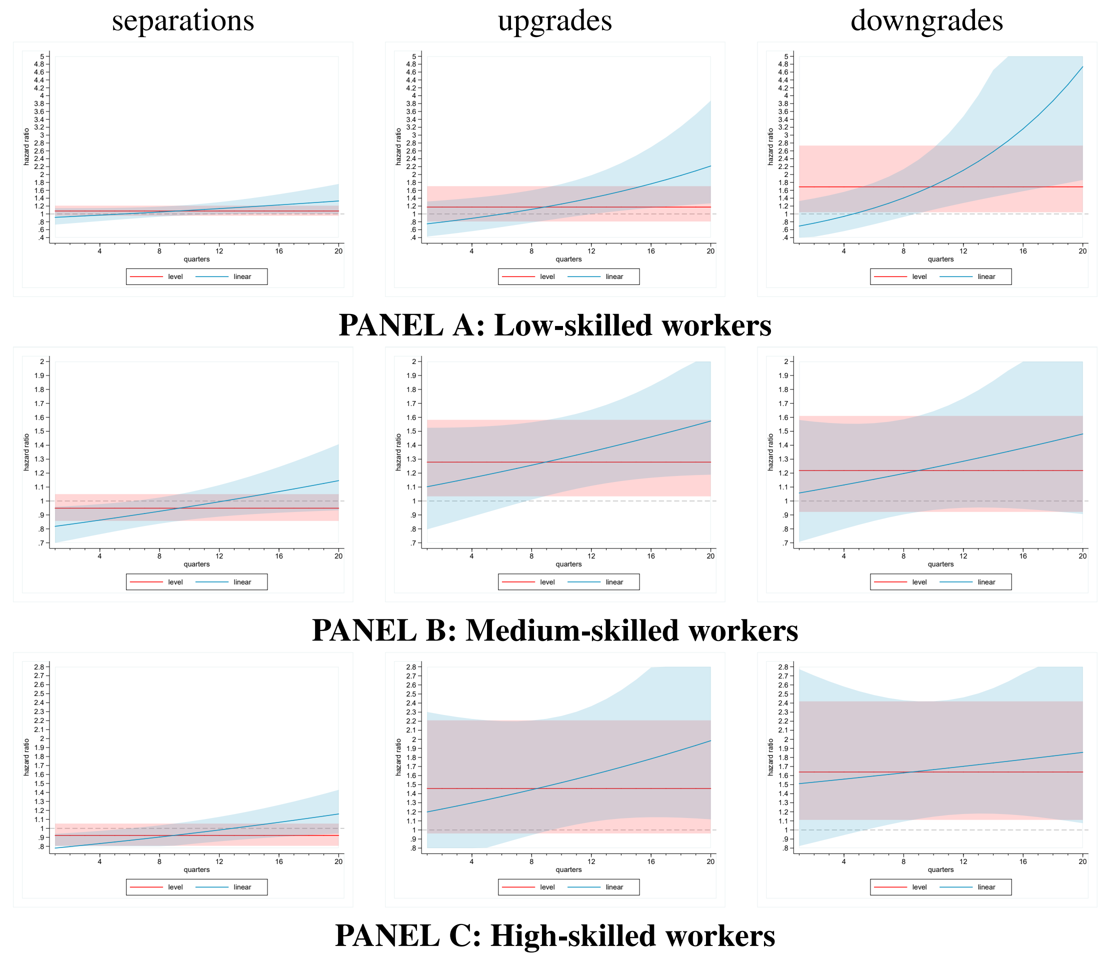
Notes: The table presents exponentiated coefficients (hazard ratios) and cluster robust standard errors at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Additional control variables in all models are: age, age squared, experience, tenure, foreign dummy, firm age and a dummy if firm existed in 1975 (all interacted with quarters since treatment), as well as year and state dummies. Estimates are based on a matched sample of MNEs and domestic firms.
Source: ReLOC, IEB and BHP, own calculations.

3.A.5 Additional results

Job stability by skill level

Figure 3.A.2 shows the effect of FDI on job stability by skill level. We distinguish between low-skilled workers, without any occupational degree, medium-skilled workers, with an occupational degree, and high-skilled workers, who hold a university degree. The graphs show the estimated hazard ratios and 95% confidence bands for the Cox models presented in Table 3.A.6.

Figure 3.A.2: Dynamic effects of FDI on the hazard ratios of separations and up- and downgrades by skill groups



Notes: The figures provide a graphical representation of the hazard ratios and 95% confidence intervals of the estimated effects of FDI on separations and up- and downgrades by skill groups. The regression results are shown in Table 3.A.6 in the Appendix. The red lines display the level effects of FDI, i.e., the average effect over the five years after investment. The blue lines show the interaction effects of FDI and time, i.e., quarters.
Source: ReLOC, IEB and BHP, own calculations.

Table 3.A.6: Effects of FDI on the hazard ratios of separations and up- and downgrades by skill groups

	separations			upgrades			downgrades		
	low	medium	high	low	medium	high	low	medium	high
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Level estimates:									
FDI	1.0742	0.9484	0.9210	1.1738	1.2786**	1.4573*	1.6877**	1.2183	1.6393**
	(0.0652)	(0.0489)	(0.0629)	(0.2236)	(0.1389)	(0.3093)	(0.4155)	(0.1733)	(0.3254)
Panel B: Time-variant estimates:									
FDI	0.8960	0.8039**	0.7639***	0.7075	1.0818	1.1674	0.6255	1.0388	1.4946
	(0.1124)	(0.0698)	(0.0765)	(0.2171)	(0.1897)	(0.4129)	(0.2256)	(0.2275)	(0.4922)
FDI × quarter	1.0199	1.0179**	1.0211***	1.0588**	1.0189	1.0269	1.1065***	1.0179	1.0109
	(0.0122)	(0.0082)	(0.0079)	(0.0254)	(0.0124)	(0.0262)	(0.0397)	(0.0190)	(0.0241)
Subjects	52,591	282,017	48,490	52,591	282,017	48,490	52,591	282,017	48,490
Events	14,461	73,104	15,096	2,353	12,348	1,179	2,120	8,476	1,135

Notes: The table presents exponentiated coefficients (hazard ratios) and cluster robust standard errors at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Additional control variables in all models are: age, age squared, experience, tenure, foreign dummy, firm age and a dummy if firm existed in 1975 (all interacted with quarters since treatment), as well as year and state dummies. Estimates are based on a matched sample of MNEs and domestic firms and separably shown by the skill-level of workers. "Low" classifies all workers without an occupational degree, "medium" all workers with a vocational degree and "high" all workers with a degree from an university or an university of applied sciences.
Source: ReLOC, IEB and BHP, own calculations.

None of the average separation rates of the skill groups is significantly affected by FDI (red lines). However, the time-flexible models (blue curves) show that low-skilled workers in MNEs face a small but significantly higher risk of separation that sets in with some delay. This result is in line with theoretical considerations (e.g., Feenstra & Hanson, 1996a) that predict that to save labor costs, FDI in low-wage countries is particularly harmful to low-skilled workers. By contrast, medium- and high-skilled workers in MNEs face significantly lower risk of losing employment immediately after the investment than comparable workers in domestic firms. This outcome is in line with the expectation that MNEs require more communication, management and organizational tasks, which are typically possessed by workers with at least a vocational degree. These findings are also in line with earlier studies, e.g., Görg & Görlich (2015), who find that offshoring increases the risk of unemployment for low-skilled workers and reduces the risk for high- and medium-skilled workers.

Investigating job changes within the firm, we find a significant level effect of FDI on job upgrades only for medium-skilled workers. Their likelihood of experiencing an upgrade increases by 28% following FDI. However, time-flexible estimates show that after some delay, the likelihood for low- and high-skilled workers to upgrade to more-complex jobs increases due to FDI. Overall, five years after investment, all skill groups have 20% to 30% greater likelihoods of occupational upgrades than workers in domestic firms.

For low- and high-skilled workers, we also find a significant effect on the risk of downgrades through FDI. On average, low-skilled workers in MNEs face a 69% higher risk of switching to a less-complex job than workers in domestic firms. This large effect might explain why we do not observe a significant effect on average separation rates for this group and only find a slight increase in their separation rates some years after investment. Although they might perform labor-intensive tasks that can be offshored easily, low-skilled employees without any occupational degree are rather inexpensive. Thus, instead of dismissing them, the investing companies may retain the most productive low-skilled employees and assign them new tasks. Following such a strategy would allow MNEs to preserve their firm-specific human capital.

Job stability by age

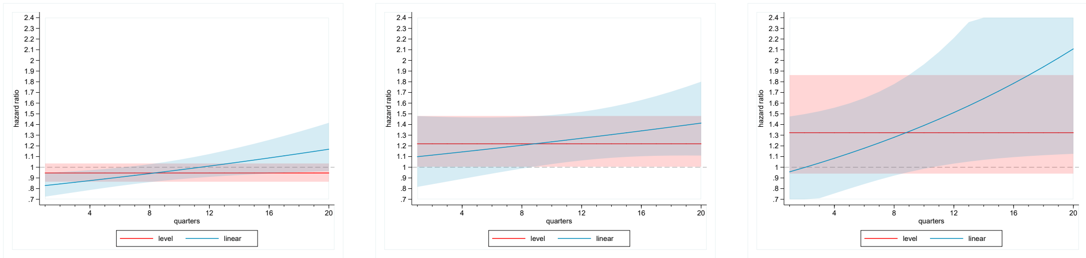
In our paper, we have shown that the effects of FDI depend on the task composition of employees. We might also expect the results to vary by worker age. Medoff & Abraham (1981), e.g., find that younger workers are more likely to receive a promotion than older workers. In this section, we therefore separate the sample into three age groups. We categorize workers as "young" if they are younger than 33, "medium" if they are between 33 and 45, and "older" if they are older than 45. We expect young workers in particular to have less firm-specific human capital given their lower seniority. They might not be as valuable for the firm as older workers and might face a higher risk of being fired.[16] Moreover, we expect that young workers might be particularly likely to be promoted after their firm goes multinational because firms might invest in further training these workers to benefit from their new knowledge for the longest possible time.

Figure 3.A.3 provides the results that support the hypotheses discussed above. On average, we find no effect of FDI on the probability of separations for all age groups. However, young and middle-aged workers in MNEs have a significantly lower risk of losing employment in the year of investment (19% and 22%; see also Table 3.A.7). Thus, we refute our hypothesis that younger workers, who likely have less firm-specific human capital, are among those dismissed over the course of FDI. The risk of separation due to FDI does not seem to depend on workers' age. Across all age groups, we find a significant positive effect of FDI on the likelihood of experiencing a job upgrade that appears with a

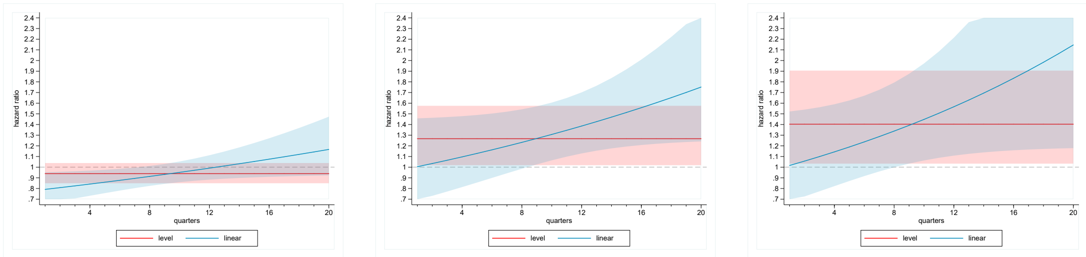
16 All workers in the sample have seniority of at least two years with the firm because one prerequisite of our estimation is that all workers already worked for the firm two years prior to investment. Thus, the estimates for separations cannot depend on lower employment protection rules during a probation period. Panel D in Table 3.A.8 includes a robustness check without the tenure restriction. The results are highly comparable with our main findings in Table 3.4.1.

Figure 3.A.3: Dynamic effects of FDI on the hazard ratios of separations and up- and downgrades by age groups

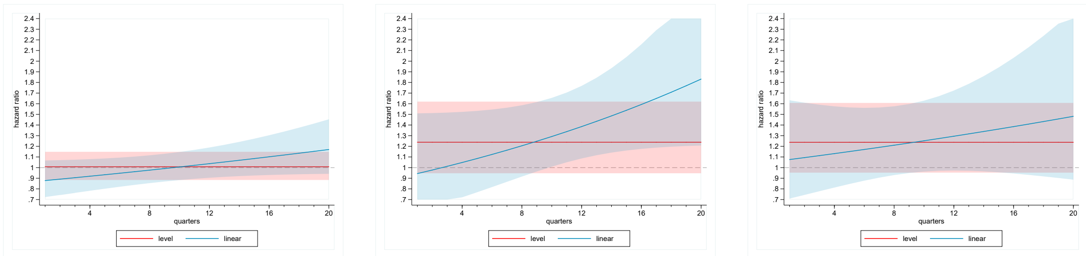
separations | upgrades | downgrades



PANEL A: Younger than 33



PANEL B: Between 33 and 45



PANEL C: Older than 45

Notes: The figures provide a graphical representation of the hazard ratios and 95% confidence intervals of the estimated effects of FDI on separations and up- and downgrades by age groups. The regression results are shown in Table 3.A.7 in the Appendix. The red lines display the level effects of FDI, i.e., the average effect over the five years after investment. The blue lines show the interaction effects of FDI and time, i.e., quarters.
Source: ReLOC, IEB and BHP, own calculations.

delay of approximately 2.5 years after investment. This result contradicts our consideration that firms might be particularly likely to offer promotions to younger employees. On the contrary, the last column of Figure 3.A.3 shows that younger and middle-aged workers face a higher risk of demotion. Older workers, however, are not affected. Overall, FDI primarily affects the job stability of young and middle-age workers. They face a lower risk of separation from the firm, but at the same time, their risk of demotion is higher in MNEs after investment. Moreover, we find that independent of age, all workers seem to have a higher chance of promotion due to FDI.

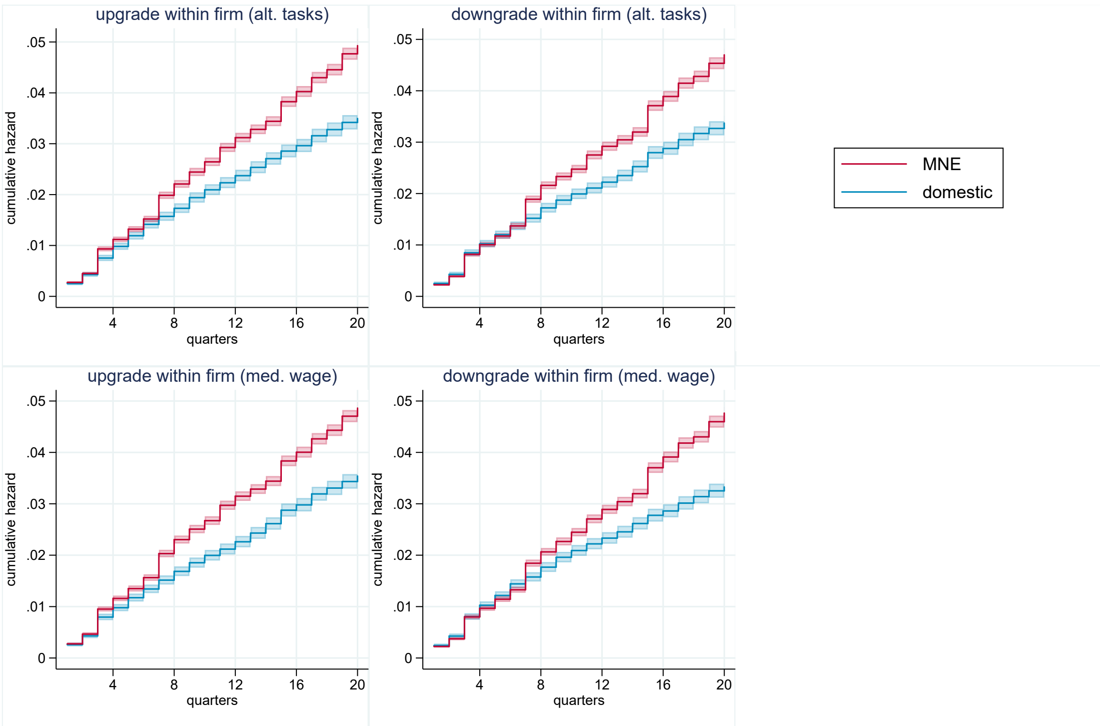
Table 3.A.7: Effects of FDI on the hazard ratios of separations and up- and downgrades by age groups

	separations			upgrades			downgrades		
	< 33	$33 - 45$	> 45	< 33	$33 - 45$	> 45	< 33	$33 - 45$	> 45
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Level estimates:									
FDI	0.9461	0.9392	1.0075	1.2194**	1.2669**	1.2385	1.3234	1.4030**	1.2376
	(0.0435)	(0.0482)	(0.0673)	(0.1204)	(0.1410)	(0.1697)	(0.2308)	(0.2191)	(0.1651)
Panel B: Time-variant estimates:									
FDI	0.8138***	0.7758**	0.8652	1.0844	0.9755	0.9114	0.9181	0.9768	1.0577
	(0.0601)	(0.0797)	(0.0915)	(0.1741)	(0.1985)	(0.2341)	(0.2162)	(0.2166)	(0.2426)
FDI $\times$ quarter	1.0183**	1.0206**	1.0152*	1.0133	1.0297*	1.0355*	1.0424*	1.0401*	1.0170
	(0.0074)	(0.0100)	(0.0087)	(0.0110)	(0.0163)	(0.0206)	(0.0228)	(0.0224)	(0.0210)
Subjects	96,579	181,562	104,957	96,579	181,562	104,957	96,579	181,562	104,957
Events	30,530	42,924	29,207	5,460	7,103	3,317	3,309	5,329	3,093

Notes: The table presents exponentiated coefficients (hazard ratios) and cluster robust standard errors at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Additional control variables in all models are: age, age squared, experience, tenure, foreign dummy, skill dummies, firm age and a dummy if firm existed in 1975 (all interacted with quarters since treatment), as well as occupation, year, and state dummies. Estimates are based on a matched sample of MNEs and domestic firms and separably shown by the age of workers. Source: ReLOC, IEB and BHP, own calculations.

3.A.6 Alternative definitions of job up- and downgrades

Figure 3.A.4: Cumulative hazards for alternative definitions of up- and downgrades



Notes: The figure shows the cumulative hazards for the two events *internal up- and downgrades* by quarters after (pseudo) investment and by investing (MNE) and domestic firms. The graphs depict the cumulative hazards for alternative definitions of up- and downgrades. The graphs in the first row include switches defined by changes in the share of analytical, interactive and non-routine manual tasks. The graphs in the second row show switches defined by changes to jobs with a higher or lower median wage. For details, see Section 3.5. Light blue and light red colors indicate 95% confidence bands. The cumulative hazard indicates the probability of an event within a given timeframe.
Source: ReLOC, IEB and BHP, own calculations.

3.A.7 Additional robustness checks

Table 3.A.8: Estimated hazard ratios for the effect of FDI on separations and up- and downgrades

	separations		upgrades		downgrades	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Main results:						
FDI	0.9630	0.8092**	1.2422**	0.9960	1.3413**	0.9781
	(0.0440)	(0.0691)	(0.1315)	(0.1896)	(0.1980)	(0.2094)
FDI × quarter		1.0190**		1.0252*		1.0352*
		(0.0083)		(0.0141)		(0.0205)
Subjects	383,098	383,098	383,098	383,098	383,098	383,098
Events	102,661	102,661	15,880	15,880	11,731	11,731
Panel B: Without small firms (>50 employees):						
FDI	0.9576	0.8019**	1.2463**	1.0019	1.3425**	0.9756
	(0.0450)	0.0700	(0.1337)	(0.1928)	(0.2013)	(0.2123)
FDI × quarter		1.0193**		1.0249*		1.0354*
		0.0085		(0.0143)		(0.0208)
Subjects	376,847	376,847	376,847	376,847	376,847	376,847
Events	100,316	100,316	15,708	15,708	11,592	11,592
Panel C: Random starts (plus minus 4 quarters):						
FDI	0.9494	0.8573**	1.3317***	1.2961	1.3600**	1.1711
	(0.0427)	(0.0620)	(0.1331)	(0.2140)	(0.2028)	(0.2160)
FDI × quarter		1.0112*		1.0030		1.0166
		(0.0064)		(0.0112)		(0.0170)
Subjects	264,427	264,427	264,427	264,427	264,427	264,427
Events	71,722	71,722	11,157	11,157	8,073	8,073
Panel D: No restriction to workers' tenure:						
FDI	0.9395	0.8027**	1.2523**	1.0484	1.3209*	0.9930
	(0.0541)	(0.0805)	(0.1244)	(0.1843)	(0.1888)	(0.1976)
FDI × quarter		1.0190**		1.0205		1.0323*
		(0.0083)		(0.0131)		(0.0189)
Subjects	490,679	490,679	490,679	490,679	490,679	490,679
Events	158,350	158,350	19,471	19,471	14,049	14,049

Notes: The table presents exponentiated coefficients (hazard ratios) and cluster robust standard errors at the firm level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Panel A repeats our main findings. Panel B shows estimates without firms with less than 50 employees. Panel C summarizes estimates where we randomly shuffled the pseudo investment quarter of domestic firms. Panel D shows estimates without restrictions on the tenure of workers. Control variables in all models are: age, age squared, experience, tenure, foreign dummy, skill dummies, firm age and a dummy if a firm existed in 1975 (all interacted with quarters since treatment), as well as occupation, year, and state dummies. Estimates are based on a matched sample of MNEs and domestic firms.

Source: ReLOC, IEB and BHP, own calculations.

Overall Conclusions

This dissertation contributes to two distinct research areas on human capital in labor economics. First, I contribute to the literature on human capital externalities. In particular, this thesis aims to add new perspectives on the dynamics and the spatial scope of human capital externalities. Second, I contribute to the literature on the labor market effects of globalization. Here, I present initial evidence that firms internally restructure their workforce after investing abroad. Furthermore, the thesis proposes new estimation frameworks to explore these perspectives empirically.

The first chapter of this dissertation, for the first time, analyzes human capital externalities from the internal migration of high-skilled workers. In particular, we use rich administrative panel data to estimate externalities from the regional immigration and emigration of high-skilled workers on individual wages simultaneously. We also investigate the impact of labor market entries of graduates and labor market exits of retiring high-skilled workers. To disentangle spillovers from labor market demand and supply effects and to address the sorting of workers, we control for an extensive set of time-varying fixed effects. We find that immigration and labor market entries of high-skilled workers raise the wages of incumbent workers. Contrarily, emigration and labor market exits of high-skilled workers decrease the wages of locals. Over a period of ten years, positive externalities from immigration and negative externalities from emigration compensate each other. However, positive externalities from inflows grow over time, whereas negative externalities from outflows remain stable. A possible explanation for this pattern might be that spillovers mainly transmit through personal networks, which develop over time. In the short run, negative externalities from emigration outweigh positive externalities from immigration. It takes approximately three years until the inflow of high-skilled workers compensates an outflow of equal size. In the long run, the immigration of high-skilled workers eventually overcompensates the emigration of high-skilled workers of the same size. The latter observation is in line with the hypothesis that diversity, i.e., the knowledge that individuals accumulate in other regions, amplify human capital externalities.

The second chapter studies the impact of knowledge spillovers from the regional concentration of high-skilled workers on the wages of neighboring workers. We are the first to use precise geocoded social security data of an entire economy and a novel estimation framework from the field of functional data analysis (FDA) to compute the spatial decay of knowledge spillovers. Similar to the first chapter, we address labor market demand and supply effects and sorting of workers with an extensive set of time-varying fixed effects. Primarily two developments in modern social science allow us to derive a precise functional relationship between the concentration of high-skilled workers and individual earnings. First, newly available geospatial data enables us to describe the distribution of high-skilled workers around workplaces as functional objects with high resolution. Second, FDA provides tools to fully exploit such detailed data. Our findings imply that knowledge spillovers from the local concentration of high-skilled workers attenuate with distance. Spillovers from the direct neighborhood of firms are roughly twice as large as those from ten kilometers away are. After fifteen kilometers, the effects vanish.

The results from the first two chapters are in line with the common view that attracting and training skilled individuals is beneficial for regions. However, although spillover effects cover entire cities, workers and firms benefit most from the skill distribution in their immediate neighborhood. To maximize external returns from human capital, firms should, therefore, settle close to one another. Firms in remote regions do not gain from knowledge spillovers. Because knowledge spillovers accrue over time, regions should also aim to retain their human capital as long as possible. Migration increases diversity. Therefore, on the national level, internal migration of high-skilled workers is, in sum, beneficial for the economy if the frequency of relocation is not too high. Otherwise, the frictional costs of building new local personal networks vitiate potential human capital externalities.

To further illuminate the mechanisms of local knowledge spillovers a promising research avenue may be exploring potential mediators, such as industry parks, local firm networks, forums, and places for informal meetings (e.g., cafés). Importantly, identifying mediators promises to generate highly practical policy recommendations. Finding mediators would also contribute to our theoretical understanding of knowledge spillovers. Potential data sources to explore mediators might be publicly available geodata or administrative geodata on firms.

The third chapter investigates how foreign direct investment (FDI) affects the job stability of workers. Novel to the literature on globalization, the chapter suggests that firms use internal reorganizations of their workforce as an adjustment channel to altered labor demands induced over the course of FDI. Particularly, the chapter analyzes the effect of FDI on occupational up- and downgrades of workers to more- or less-complex jobs, respectively. We base our analysis on employer-employee data on German firms that invest in the Czech Republic and those on comparable domestic firms. To address endogeneity issues, we propose a novel matching algorithm and carefully design a panel dataset with comparable treatment and control firms.

Our results imply that FDI raises the likelihood that workers upgrade to more-complex occupations. However, FDI also increases the risk of downgrading to less-complex jobs. Furthermore, the probability of up- and downgrades grows with the workers' share of non-routine and interactive tasks in their initial job. We find no evidence that FDI raises the hazard of separations of workers and firms on average. These findings imply that firms use internal restructuring rather than dismissals as an adjustment channel to meet labor demands that change over the course of FDI. Therefore, workers in firms that invest abroad need to be more flexible and take on new tasks. Further training might help individuals to manage such occupational transitions.

Similar to FDI, digitization can be a mean to fragment tasks and to increase the efficiency of production processes. Digitization might, therefore, have a similar impact on the job stability of workers. Because firms likely use both, FDI and digitization, jointly investigating labor market effects from globalization and digitization, constitutes a promising avenue for future research.

Generally, all three chapters of this dissertation investigate novel perspectives on traditional topics in labor economics and propose new research strategies. Therefore, it would be important to corroborate the described findings with data from other countries and to refine the proposed empirical strategies further.

Bibliography

Abadie, Alberto, Athey, Susan, Imbens, Guido, W., & Wooldridge, Jeffrey. 2017 (Nov.). *When Should You Adjust Standard Errors for Clustering?* Working Paper 24003. National Bureau of Economic Research.

Abowd, John, M., Kramarz, Francis, & Margolis, David, N. 1999. High Wage Workers in High Wage Firms. *Econometrica*, **67**(2), 251–333.

Acemoglu, Daron. 1996. A Microfoundation for Social Increasing Returns in Human Capital Accumulation. *The Quarterly Journal of Economics*, **111**(3), 779–804.

Acemoglu, Daron. 1998. Why do new technologies complement skills? Directed technical change and wage inequality. *The Quarterly Journal of Economics*, **113**(4), 1055–1089.

Acemoglu, Daron, & Angrist, Joshua. 1999 (December). *How Large are the Social Returns to Education? Evidence from Compulsory Schooling Laws*. Working Paper 7444. National Bureau of Economic Research.

Acemoglu, Daron, & Angrist, Joshua. 2000. How Large Are Human-Capital Externalities? Evidence from Compulsory Schooling Laws. *Pages 9–74 of:* Bernake, Ben S., & Rogoff, Kenneth (eds), *NBER Macroeconomics Annual 2000*, vol. 15. MIT Press.

Ahlfeldt, Gabriel, M., Redding, Stephen, J., Sturm, Daniel, M., & Wolf, Nikolaus. 2015. The economics of density: Evidence from the Berlin Wall. *Econometrica*, **83**(6), 2127–2189.

Andersson, Martin, Larsson, Johan P, & Wernberg, Joakim. 2019. The economic microgeography of diversity and specialization externalities - firm-level evidence from Swedish cities. *Research Policy*.

Antoni, Manfred, Ganzer, Andreas, & vom Berge, Philipp. 2016. *Sample of Integrated Labour Market Biographies (SIAB) 1975-2014*. Institute of Employment Research, Nuremberg. FDZ-Datenreport 04/2016.

Arrow, K., J., Chenery, H., B., Minhas, B., S., & Solow, R., M. 1961. Capital-Labor Substitution and Economic Efficiency. *The Review of Economics and Statistics*, **43**(3), 225–250.

Arzaghi, Mohammad, & Henderson, J. Vernon. 2008. Networking off madison avenue. *The Review of Economic Studies*, **75**(4), 1011–1038.

Austin, Peter C. 2011a. An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies. *Multivariate Behavioral Research*, **46**(3), 399–424.

Austin, Peter C. 2011b. Optimal Caliper Widths for Propensity-Score Matching when Estimating Differences in Means and Differences in Proportions in Observational Studies. *Pharmaceutical Statististics*, **10**(2), 150–161.

Autor, David, H., Katz, Lawrence, F., & Kearney, Melissa, S. 2008. Trends in U.S. wage inequality: revising the revisionists. *The Review of Economics and Statistics*, **90**(2), 300–323.

Bachmann, Ronald, & Braun, Sebastian. 2011. The Impact of International Outsourcing on Labour Market Dynamics in Germany. *Scottish Journal of Political Economy*, **58**(1), 1–28.

Bachmann, Ronald, Baumgarten, Daniel, & Stiebale, Joel. 2014. Foreign Direct Investment, Heterogeneous Workers and Employment Security: Evidence from Germany. *Canadian Journal of Economics*, **47**(3), 720–757.

Barba Navaretti, Giorgio, & Castellani, Davide. 2004. *Investments Abroad and Performance at Home: Evidence from Italian Multinationals*. CEPR Discussion Papers 4284. Centre for Economic Policy Research.

Barba Navaretti, Giorgio, Castellani, Davide, & Disdier, Anne-Celia. 2010. How Does Investing in Cheap Labour Countries Affect Performance at Home? Firm-Level Evidence from France and Italy. *Oxford Economic Papers*, **62**(2), 234–260.

Baumert, Jürgen, Benkmann, Rainer, Fuchs, Jochen, Hopf, Diether, Köhler, Helmut, Krais, Beate, Krappmann, Lothar, Leschinsky, Achim, Naumann, Jens, Roeder, Peter Martin, & Trommer, Luitgard. 1994. *Das Bildungswesen in der Bundesrepublik Deutschland: Strukturen und Entwicklungen im Überblick*. Vollständig überarbeitete und erweiterte neuausgabe edn. Reinbeck bei Hamburg: Rowohlt Taschenbuch Verlag.

Baumgarten, Daniel. 2015. Offshoring, the Nature of Tasks, and Occupational Stability: Empirical Evidence for Germany. *The World Economy*, **38**(3), 479–508.

Baumgarten, Daniel, Geishecker, Ingo, & Görg, Holger. 2013. Offshoring, tasks, and the skill-wage pattern. *European Economic Review*, **61**, 132–152.

Becker, Gary S. 1962. Investment in human capital: A theoretical analysis. *Journal of political economy*, **70**(5, Part 2), 9–49.

Becker, Sascha O., & Muendler, Marc-Andreas. 2008. The Effect of FDI on Job Security. *The B.E. Journal of Economic Analysis & Policy*, **8**(1).

Becker, Sascha O., Ekholm, Karolina, & Muendler, Marc-Andreas. 2013. Offshoring and the Onshore Composition of Tasks and Skills. *Journal of International Economics*, **90**(1), 91–106.

Ben-Porath, Yoram. 1967. The production of human capital and the life cycle of earnings. *Journal of political economy*, **75**(4, Part 1), 352–365.

Berry, Christopher R., & Glaeser, Edward L. 2005. The divergence of human capital levels across cities. *Papers in Regional Science*, **84**(3), 407–444.

Blien, Uwe, Möller, Joachim, Van, Hong, Brunow, Stephan, *et al.* . 2016. Long-Lasting Labour Market Consequences of German Unification. *Jahrbücher für Nationalökonomie und Statistik*, **236**(2), 181–216.

Blinder, Alan S. 2006. Offshoring: The Next Industrial Revolution? *Foreign Affairs*, **85**(2), 113–128.

Blundell, Richard, Dearden, Lorraine, & Meghir, Costas. 1996. *The determinants and effects of work-related training in Britain*. IFS Reports, Institute for Fiscal Studies.

Borjas, George J. 2003. The Labor Demand Curve Is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market. *The Quarterly Journal of Economics*, **118**(4), 1335–1374.

Bratti, Massimiliano, & Leombruni, Roberto. 2014. Local human capital externalities and wages at the firm level: Evidence from Italian manufacturing. *Economics of Education Review*, **41**, 161–175.

Broersma, Lourens, Edzes, Arjen J., & Van Dijk, Jouke. 2016. Human Capital Externalities: Effects for Low- Educated Workers and Low-Skilled Jobs. *Regional Studies*, **50**(10), 1675–1687.

Bronzini, Raffaello. 2015. The Effects of Extensive and Intensive Margins of FDI on Domestic Employment: Microeconomic Evidence from Italy. *The B.E. Journal of Economic Analysis & Policy*, **15**(4), 2079–2109.

Burgess, Simon, Lane, Julia, & Stevens, David. 2000. Job Flows, Worker Flows and Churning. *Journal of Labor Economics*, **18**(3), 473–502.

Caldeira, JoÃo, & Torrent, Hudson. 2017. Forecasting the US term structure of interest rates using nonparametric functional data analysis. *Journal of Forecasting*, **36**(1), 56–73.

Card, David, & Lemieux, Thomas. 2001. Can falling supply explain the rising return to college for younger men? A cohort-based analysis. *The Quarterly Journal of Economics*, **116**(2), 705–746.

Card, David, Heining, Jorg, & Kline, Patrick. 2013. Workplace Heterogeneity and the Rise of West German Wage Inequality. *The Quarterly Journal of Economics*, **128**(3), 967–1015.

Cardot, Hervé, Mas, André, & Sarda, Pascal. 2007. CLT in functional linear regression models. *Probability Theory and Related Fields*, **138**(3-4), 325–361.

Che, Yi, & Zhang, Lei. 2017. Human Capital, Technological Adoption and Firm Performance: Impacts of China's Higher Education Expansion in the Late 1990s. *The Economic Journal*, **128**, 2282–2320.

Ciccone, Antonio, & Peri, Giovanni. 2005. Long-run substitutability between more and less educated workers: evidence from U.S. states, 1950-1990. *The Review of Economics and Statistics*, **87**(4), 652–663.

Ciccone, Antonio, & Peri, Giovanni. 2006. Identifying Human-Capital Externalities: Theory with an Application to US Cities. *The Review of Economic Studies*, **488**(73), 381–412.

Clemens, Michael A. 2016. Losing our minds? New research directions on skilled emigration and development. *International Journal of Manpower*, **37**(7), 1227–1248.

Cornelissen, Thomas, Dustmann, Christian, & Schönberg, Uta. 2017. Peer Effects in the Workplace. *American Economic Review*, **107**(2), 425–456.

Cox, David, R. 1972. Regression Models and Life-Tables. *Journal of the Royal Statistical Society, Series B*, **34**(2), 187–220.

Crambes, Christophe, Kneip, Alois, & Sarda, Pascal. 2009. Smoothing splines estimators for functional linear regression. *The Annals of Statistics*, **37**(1), 35–72.

Crinò, Rosario. 2009. Offshoring, Multinationals and Labour Market: A Review of the Empirical Literature. *Journal of Economic Surveys*, **23**(2), 197–249.

Crinò, Rosario. 2010. Employment Effects of Service Offshoring: Evidence from Matched Firms. *Economics Letters*, **107**(2), 253–256.

Dalmazzo, Alberto, & de Blasio, Guido. 2007. Production and consumption externalities of human capital: an empirical study for Italy. *Journal of Population Economics*, **20**(2), 359–382.

Dauth, Wolfgang, & Haller, Peter. 2018 (Oct.). *Berufliches Pendeln zwischen Wohn- und Arbeitsort*. IAB-Kurzbericht. Institute for Employment Research (IAB), Nuremberg.

Davis, Donald, R., & Dingel, Jonathan, I. 2019. A spatial knowledge economy. *American Economic Review*, **109**(1), 153–70.

De la Roca, Jorge, & Puga, Diego. 2017. Learning by Working in Big Cities. *Review of Economic Studies*, **84**(1), 106–142.

Debaere, Peter, Lee, Hongshik, & Lee, Joonhyung. 2010. It Matters Where You Go: Outward Foreign Direct Investment and Multinational Employment Growth at Home. *Journal of Development Economics*, **91**(2), 301–309.

Demougin, Dominique, & Siow, Aloysius. 1994. Careers in Ongoing Hierarchies. *The American Economic Review*, **84**(5), 1261–1277.

Deutsche Bundesbank. 2014 (April). *Bestandserhebung über Direktinvestitionen*. Statistische Sonderveröffentlichung 10.

Docquier, Frédéric, & Rapoport, Hillel. 2012. Globalization, Brain Drain, and Development. *Journal of Economic Literature*, **50**(3), 681–730.

Docquier, Frédéric, Özden, Çaglar, & Peri, Giovanni. 2010. *The Wage Effects of Immigration and Emigration*. Working Paper 16646. National Bureau of Economic Research.

Docquier, Frédéric, Özden, Çaglar, & Peri, Giovanni. 2014. The labour market effects of immigration and emigration in OECD countries. *The Economic Journal*, **124**(579), 1106–1145.

Dustmann, Christian, Ludsteck, Johannes, & Schönberg, Uta. 2009. Revisiting the German Wage Structure. *The Quarterly Journal of Economics*, **124**(2), 843–881.

Ebenstein, Avraham, Harrison, Ann, McMillan, Margaret, & Phillips, Shannon. 2014. Estimating the Impact of Trade and Offshoring on American Workers using the Current Population Surveys. *The Review of Economics and Statistics*, **96**(4), 581–595.

Eberle, Johanna, & Schmucker, Alexandra. 2017. *The Establishment History Panel—Redesign and Update 2016*. FDZ-Methodenreport 03/2017. Institute for Employment Research, Nuremberg.

Eberle, Johanna, Jacobebbinghaus, Peter, Ludsteck, Johannes, & Witter, Julia. 2014. *Generation of time-consistent industry codes in the face of classification changes*. Institute of Employment Research, Nuremberg. FDZ-Methodenreport 05/2011.

Egger, Peter, & Pfaffermayr, Michael. 2003. *The Counterfactual to Investing Abroad: An Endogenous Treatment Approach of Foreign Affiliate Activity*. Working Papers in Economics 2003/02. University of Innsbruck.

Egger, Peter, Pfaffermayr, Michael, & Weber, Andrea. 2007. Sectoral adjustment of employment to shifts in outsourcing and trade: evidence from a dynamic fixed effects multinomial logit model. *Journal of applied Econometrics*, **22**(3), 559–580.

Eppelsheimer, Johann, & Möller, Joachim. 2019. Human capital spillovers and the churning phenomenon: Analysing wage effects from gross in- and outflows of high-skilled workers. *Regional Science and Urban Economics*, **78**, 103461.

Feenstra, Robert C., & Hanson, Gordon H. 1996a. Foreign Investment, Outsourcing and Relative Wages. *Pages 89–127 of:* Feenstra, Robert C., Grossman, Gene M., & Irwin, Douglas A. (eds), *The Political Economy of Trade Policy: Papers in Honor of Jagdish Bhagwati*. Cambridge: MIT Press.

Feenstra, Robert C., & Hanson, Gordon H. 1996b. Globalization, Outsourcing, and Wage Inequality. *The American Economic Review*, **86**(2), 240–245.

Feenstra, Robert C, & Hanson, Gordon H. 1997. Foreign direct investment and relative wages: Evidence from Mexico's maquiladoras. *Journal of international economics*, **42**(3-4), 371–393.

Feenstra, Robert C, & Hanson, Gordon H. 1999. The impact of outsourcing and high-technology capital on wages: estimates for the United States, 1979–1990. *The Quarterly Journal of Economics*, **114**(3), 907–940.

Ferraty, Frédéric, & Vieu, Philippe. 2006. *Nonparametric Functional Data Analysis - Theory and Practice*. New York: Spinger.

Fisher, Irving. 1897. Senses of "Capital". *The Economic Journal*, **7**(26), 199–213.

Fitzenberger, Bernd, Osikominu, Aderonke, & Völter, Robert. 2005. *Imputation Rules to Improve the Education Variable in the IAB Employment Subsample*. Institute of Employment Research, Nuremberg. FDZ-Methodenreport 03/2005.

Frosch, Katharina H. 2011. Workforce Age and Innovation: A Literature Survey. *International Journal of Management Reviews*, **13**, 414–430.

Fu, Shihe. 2007. Smart Café Cities: Testing human capital externalities in the Boston metropolitan area. *Journal of Urban Economics*, **61**(1), 86–111.

Gathmann, Christina, & Schönberg, Uta. 2010. How general is human capital? A task-based approach. *Journal of Labor Economics*, **28**(1), 1–49.

Geishecker, Ingo. 2008. The impact of international outsourcing on individual employment security: A micro-level analysis. *Labour Economics*, **15**(3), 291–314.

Glaeser, Edward L., Ponzetto, Giacomo A. M., & Tobio, Kristina. 2014. Cities, Skills and Regional Change. *Regional Studies*, **48**(1), 7–43.

Glaeser, Edward, L., & Mare, David, C. 2001. Cities and Skills. *Journal of Labor Economics*, **19**(2), 316–342.

Görg, Holger, & Görlich, Dennis. 2015. Offshoring, Wages and Job Security of Temporary Workers. *Review of World Economics*, **151**(3), 533–554.

Greenwald, Bruce C. 1986. Adverse Selection in the Labour Market. *The Review of Economic Studies*, **53**(3), 325–347.

Grossman, Gene M., & Rossi-Hansberg, Esteban. 2008. Trading Tasks: A Simple Theory of Offshoring. *American Economic Review*, **98**(5), 1978–97.

Hakkala, Katariina Nilsson, Heyman, Fredrik, & Sjöholm, Fredrik. 2014. Multinational Firms, Acquisitions and Job Tasks. *European Economic Review*, **66**, 248–265.

Hall, Anja, & Tiemann, Michael. 2006. *BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2006, suf 1.0.* Research Data Center at BIBB (ed.); GESIS Cologne, Germany (data access). Federal Institute of Vocational Education and Training, Bonn.

Hall, Peter, & Horowitz, Joel L. 2007. Methodology and convergence rates for functional linear regression. *The Annals of Statistics*, **35**(1), 70–91.

Heap, SP Hargreaves. 1980. Choosing the Wrong 'Natural Rate': Accelerating Inflation or Decelerating Employment and Growth? *The Economic Journal*, 611–620.

Hecht, Veronika, Hohmeyer, Katrina, Litzel, Nicole, Moritz, Michael, Müller, Jo-Ann, Phan thi Hong, Van, & Schäffler, Johannes. 2013a. *Motive, Strukturen und Auswirkungen deutscher Direktinvestitionen in Tschechien. Erste Untersuchungsergebnisse aus dem IAB-Projekt ReLOC—Research on Locational and Organisational Change*. IAB-Forschungsbericht 01/2013. Institute for Employment Research, Nuremberg.

Hecht, Veronika, Litzel, Nicole, & Schäffler, Johannes. 2013b. *The ReLOC Project—Method Report for Implementing a Cross-Border Company Survey in Germany and the Czech Republic*. IAB-Forschungsbericht 04/2013. Institute for Employment Research, Nuremberg.

Helpman, Elhanan. 1984. A Simple Theory of International Trade with Multinational Corporations. *Journal of Political Economy*, **92**(3), 451–471.

Helpman, Elhanan, Melitz, Marc J., & Yeaple, Stephen R. 2004. Export versus FDI with Heterogeneous Firms. *American Economic Review*, **94**(1), 300–316.

Henningsen, Arne, & Henningsen, Géraldine. 2012. On estimation of the CES production function - revisited. *Economic Letters*, **115**, 67–69.

Heuermann, Daniel. 2011. Human Capital Externalities in Western Germany. *Spatial Economic Analysis*, **6**(2), 139–165.

Hijzen, Alexander, Inui, Tomohiko, & Todo, Yasuyuki. 2007. *The Effects of Multinational Production on Domestic Performance: Evidence from Japanese Firms*. RIETI Discussion Paper Series 07-E-006. The Research Institute of Economy, Trade and Industry, Tokyo.

Hijzen, Alexander, Jean, Sébastien, & Mayer, Thierry. 2011. The Effects at Home of Initiating Production Abroad: Evidence from Matched French Firms. *Review of World Economics*, **147**(3), 457–483.

Horváth, Lajos, & Kokoszka, Piotr. 2012. *Inference for Functional Data with Applications*. New York: Springer.

Hsing, Tailen, & Eubank, Randall. 2015. *Theoretical Foundations of Functional Data Analysis, with an Introduction to Linear Operators*. Chichester: John Wiley & Sons.

Hummels, David, Munch, Jakob R, Skipper, Lars, & Xiang, Chong. 2012. Offshoring, transition, and training: Evidence from Danish matched worker-firm data. *American Economic Review*, **102**(3), 424–28.

Hummels, David, Jørgensen, Rasmus, Munch, Jakob, & Xiang, Chong. 2014. The wage effects of offshoring: Evidence from Danish matched worker-firm data. *American Economic Review*, **104**(6), 1597–1629.

Hummels, David, Munch, Jakob R., & Xiang, Chong. 2016. *Offshoring and Labor Markets*. NBER Working Papers 22041. National Bureau of Economic Research, Cambridge.

Hummels, David, Munch, Jakob R, & Xiang, Chong. 2018. Offshoring and labor markets. *Journal of Economic Literature*, **56**(3), 981–1028.

Imbens, Guido W., & Rubin, Donald B. 2015. *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction*. Cambridge: Cambridge University Press.

Katz, Lawrence, F., & Murphy, Kevin, M. 1992. Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *The Quarterly Journal of Economics*, **107**(1), 35–78.

Kleinert, Jörn, & Toubal, Farid. 2007. *The Impact of Locating Production Abroad on Activities at Home*. Tübinger Diskussionsbeitrag 314. Tübingen.

Kmenta, J. 1967. On estimation of the CES production function. *International Economic Review*, **8**(2), 180–189.

Kosfeld, Reinhold, & Werner, Alexander. 2012. Deutsche Arbeitsmarktregionen - Neuabgrenzung nach den Kreisgebietsreformen 2007-2011. *Raumforschung und Raumordnung*, **70**(1), 46–64.

Krueger, Alan B, & Lindahl, Mikael. 2001. Education for growth: why and for whom? *Journal of economic literature*, **39**(4), 1101–1136.

Krusell, Per, Ohanian, Lee, E., Rios-Rull, Jose-Victor, & Violante, Giovanni, L. 2000. Capital-skill complementarity and inequality: a macroeconomic analysis. *Econometrica*, **68**(5), 1029–1053.

Laffineur, Catherine, & Mouhoud, El Mouhoub. 2015. The Jobs at Risk from Globalization: The French Case. *Review of World Economics*, **151**(3), 477–531.

Leamer, Edward E., & Storper, Michael. 2001. The Economic Geography of the Internet Age. *Journal of International Business Studies*, **32**(4), 641–665.

Lehmer, Florian, & Möller, Joachim. 2009. Interrelations between the urban wage premium and firm-size wage differentials: a microdata cohort analysis for Germany. *The Annals of Regional Science*, **45**(1), 31–53.

Levy, Frank, & Murnane, Richard J. 2004. *The New Division of Labor: How Computers Are Creating the Next Job Market*. Princeton: Princeton University Press.

Liu, Runjuan, & Trefler, Daniel. 2011. *A Sorted Tale of Globalization: White Collar Jobs and the Rise of Service Offshoring*. NBER Working Papers 17559. National Bureau of Economic Research, Cambridge.

Liu, Zhiqiang. 2014. Human capital externalities in cities: evidence from Chinese manufacturing firms. *Journal of Economic Geography*, **14**(3), 621–649.

Lucas, Robert E. 1988. On the mechanics of economic development. *Journal of Monetary Economics*, **22**, 3–42.

Mankiw, N Gregory, Romer, David, & Weil, David N. 1992. A contribution to the empirics of economic growth. *The quarterly journal of economics*, **107**(2), 407–437.

Manning, Alan, & Petrongolo, Barbara. 2017. How local are labor markets? Evidence from a spatial job search model. *American Economic Review*, **107**(10), 2877–2907.

Maré, David C, & Glaeser, Edward L. 2001. Cities and Skills. *Journal of Labor Economics*, **19**(2), 316–342.

Markusen, James R. 1984. Multinationals, Multi-Plant Economies, and the Gains from Trade. *Journal of International Economics*, **16**(3-4), 205–226.

Markusen, James R. 2002. *Multinational Firms and the Theory of International Trade*. Cambridge: MIT Press.

Marshall, Alfred. 1890. *Principles of Economics*. London: MacMillan.

Matthes, Britta. forthcoming. *Berufsspezifische Arbeitsplatzanforderungen auf dem westdeutschen Arbeitsmarkt 1979 bis 2012*. IAB-Discussion Paper. Institute for Employment Research, Nuremberg.

Medoff, James L., & Abraham, Katharine G. 1981. Are Those Paid More Really More Productive? The Case of Experience. *The Journal of Human Resources*, **16**(2), 186–216.

Mellander, Charlotta, Stolarick, Kevin, & Lobo, José. 2016. Distinguishing neighbourhood and workplace network effects on individual income: evidence from Sweden. *Regional Studies*, 1–16.

Mincer, Jacob. 1958. Investment in human capital and personal income distribution. *Journal of political economy*, **66**(4), 281–302.

Möller, Joachim. 1990. Unemployment and Deterioration of Human Capital. *Pages 91–107 of:* Franz, Wolfgang (ed), *Hysteresis Effects in Economic Models*. Heidelberg: Physica-Verlag HD.

Moretti, Enrico. 2004. Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data. *Journal of Econometrics*, **121**, 175–212.

Morris, Jeffrey S. 2015. Functional Regression. *Annual Review of Statistics and Its Application*, **2**, 321–359.

Munch, Jakob R. 2010. Whose job goes abroad? International outsourcing and individual job separations. *Scandinavian Journal of Economics*, **112**(2), 339–360.

Muravyev, Alexander. 2008. Human capital externalities: Evidence from the transition economy of Russia. *Economics of Transition*, **16**(3), 415–443.

Nelson, Richard R, & Phelps, Edmund S. 1966. Investment in humans, technological diffusion, and economic growth. *The American Economic Review*, **56**(1/2), 69–75.

Ottaviano, Gianmarco, I. P., & Peri, Giovanni. 2005. Cities and cultures. *Journal of Urban Economics*, **58**(2), 304–337.

Pflüger, Michael, Blien, Uwe, Möller, Joachim, & Moritz, Michael. 2013. Labor Market Effects of Trade and FDI—Recent Advances and Research Gaps. *Jahrbücher für Nationalökonomie und Statistik*, **233**(1), 86–116.

Phelps, E.S. 1972. *Inflation policy and unemployment theory: the cost-benefit approach to monetary planning*. Macmillan London.

Ramsay, J.O., & Silverman, B.W. 2005. *Functional Data Analysis*. 2. edn. New York: Springer.

Ramsay, James, O., & Ramsey, James, B. 2002. Functional data analysis of the dynamics of the monthly index of nondurable goods production. *Journal of Econometrics*, **107**(1-2), 327–344.

Rauch, James E. 1993. Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities. *Journal of Urban Economics*, **34**(3), 380–400.

Romer, Paul M. 1990. Endogenous technological change. *Journal of political Economy*, **98**(5, Part 2), S71–S102.

Rosenthal, Stuart S., & Strange, William C. 2008. The attenuation of human capital spillovers. *Journal of Urban Economics*, **64**(2), 373–389.

Schäffler, Johannes. 2014. *ReLOC Linkage: A New Method for Linking Firm-Level Data with the Establishment-Level Data of the IAB*. FDZ-Methodenreport 05/2014. Institute for Employment Research, Nuremberg.

Schäffler, Johannes. 2016. German Direct Investments in the Czech Republic – Employment Effects on German Multinational Enterprises. Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel - Session: Trade and Employment, nos. D19–V2. Kiel und Hamburg: ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft.

Schimpl-Neimanns, Bernhard. 2003. *Mikrodaten-Tools: Umsetzung der Berufsklassifikation von Blossfeld auf die Mikrozensen 1973-1998*. ZUMA, Mannheim. ZUMA-Methodenbericht 2003/10.

Schmucker, Alexandra, Seth, Stefan, Ludsteck, Johannes, Eberle, Johanna, & Ganzer, Andreas. 2016. *The Establishment History Panel 1975-2014*. Institute of Employment Research, Nuremberg. FDZ-Methodenreport 03/2016.

Schultz, Paul, T. 1988. Education investments and returns. Handbook of Development Economics, vol. 1. Elsevier.

Schultz, Theodore W. 1961. Investment in human capital. *The American Economic Review*, 1–17.

Shapiro, Jesse M. 2006. Smart Cities: Quality of Life, Productivity, and the Growth Effects of Human Capital. *The Review of Economics and Statistics*, **88**(2), 324–335.

Smith, Adam. 1776. *An Inquiry into the Nature and Causes of the Wealth of Nations*. W. Strahan and T. Cadell, London.

Südekum, Jens. 2008. Convergence of the skill composition across German regions. *Regional Science and Urban Economics*, **38**(2), 148–159.

Südekum, Jens, Wolf, Katja, & Blien, Uwe. 2014. Cultural Diversity and Local Labour Markets. *Regional Studies*, **48**(1), 173–191.

Taylor, Alva, & Greve, Henrich R. 2006. Superman or the fantastic four? Knowledge combination and experience in innovative teams. *Academy of Management Journal*, **49**(4), 723–740.

Thursby, Jerry G., & Lovell, Knox C. A. 1978. An Investigation of the Kmenta Approximation to the CES Function. *International Economic Review*, **19**(2), 363–377.

Timmermans, Bram, & Boschma, Ron. 2014. The effect of intra-and inter-regional labour mobility on plant performance in Denmark: the significance of related labour inflows. *Journal of Economic Geography*, **14**(2), 289–311.

Ullah, Shahid, & Finch, Caroline F. 2013. Applications of functional data analysis: A systematic review. *BMC Medical Research Methodology*, **13**(1), 43.

Verstraten, Paul. 2018 (Sept.). *The scope of the external return to higher education*. Discussion Paper 381. CPB Netherlands Bureau for Economic Policy Analysis.

von Thünen, Johann Heinrich. 1826. *Der isolierte Staat in Beziehung auf Landwirtschaft und Nationalökonomie*. Perthes, Hamburg.

Waldman, Michael. 1984. Job Assignments, Signalling, and Efficiency. *The RAND Journal of Economics*, **15**(2), 255–267.

Waldorf, Brigitte S. 2009. Is human capital accumulation a self-propelling process? Comparing educational attainment levels of movers and stayers. *The Annals of Regional Science*, **43**(2), 323–344.

Wang, Shanshan, Jank, Wolfgang, & Shmueli, Galit. 2008. Explaining and forecasting online auction prices and their dynamics using functional data analysis. *Journal of Business & Economic Statistics*, **26**(2), 144–160.