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Patterns of regional firm mobility in Germany*

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Abstract: Although domestic establishment relocations are part of both the factor reallocation across regions and establishment dynamics within an economy, evidence on firm mobility in Germany is rather scarce. In this study, we therefore examine establishment- and regional-level patterns of firm mobility in Germany. Using rich administrative data, we document that most relocation flows go from major cities to the surrounding urban districts, suggesting sub-urbanization patterns. In terms of establishment-level characteristics, we find that middle-sized and knowledge-intensive establishments exhibit high relocation propensities. Further, establishments moving to major cities or urban districts are rather high-wage establishments while establishments moving to rural districts are rather low-wage establishments. Our regional analyses reveal that relocating establishments prefer nearby regions with (compared to their old locations) low tax burdens and low population densities.

Zusammenfassung: Obwohl inländische Betriebsumzüge sowohl Teil der Faktorreallokation zwischen Regionen als auch der Betriebsdynamik innerhalb einer Volkswirtschaft sind, gibt es nur wenig Evidenz über die Mobilität von Firmen in Deutschland. In dieser Studie untersuchen wir daher die Muster der Firmenmobilität in Deutschland auf betrieblicher und regionaler Ebene. Unter Verwendung umfangreicher administrativer Daten dokumentieren wir, dass die meisten Betriebsumzüge von kreisfreien Großstädten in die umliegenden städtischen Landkreise zu beobachten sind, was auf eine Suburbanisierung der Betriebslandschaft hindeutet. In Bezug auf die Betriebsmerkmale zeigen unsere Ergebnisse, dass mittelgroße und wissensintensive Betriebe eine hohe Umzugssneigung aufweisen. Außerdem handelt es sich bei Betrieben, die in kreisfreie Großstädte oder städtische Landkreise umziehen, eher um Hochlohnbetriebe, während Betriebe, die ihren Standort in ländliche Landkreise sind. Unsere regionalen Analysen zeigen, dass Betriebe, die ihren Standort verlagern, nahe gelegene Landkreise mit (im Vergleich zu ihrem alten Standort) niedriger Steuerbelastung und geringer Bevölkerungsdichte aufsuchen.

Keywords: Firm Mobility, Establishment Relocation, Firm Location, Germany **JEL classifications:** R10, R12, R30

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1. Introduction

Firm dynamics (that is the entry, growth, and exit of firms) and their consequences are well studied in the literature, both from a theoretical and an empirical perspective (see, for instance, Hopenhayn (1992), Clementi and Palazzo (2016) and Haltiwanger et al. (2013)). A prominent argument made in this literature is that firm dynamics (especially firm entry and exit) are an important source driving the factor (re)allocation within an economy. However, the life-cycle of a firm is not only determined by its entry, growth, and exit, but also by its location decisions. Usually, firms are thought of as making one location decision prior to their entry and then stick to it for their entire lifetime. This view neglects the possibility of changing its location, i.e. relocating. Relocating firms can then also be a source of factor reallocation across regions within an economy.

Why is it worthwile to study firm mobility? First, as already indicated above, we regard domestic relocations as part of the factor reallocation across regions within an economy. Second, relocations give insights about how firms perceive the geography surrounding them. Based on firm relocation flows, we get a glimpse into which factors attract a firm and which factors push firms away from a region. Third, we can learn something about location decisions in general when we examine relocations. In contrast to a location decision, which is always accompanied by the (arguably more important) market entry decision, a relocation is an isolated event that has to offer high benefits, considering the substantial relocation costs.

There is a growing body of research examining the reasons behind a relocation decision. Usually, establishment- or regional-level determinants of firm mobility are analyzed (see, e.g., Van Dijk and Pellenbarg (2000); Holl (2004); Manjón-Antolín and Arauzo-Carod (2011); Rupasingha and Marré (2020)). For Germany, the literature on firm relocations is rather scarce. Exemptions are recent studies by Krenz (2023) and Hellwig (2023) and older, survey-based work by Ahlers et al. (2007). Therefore, this paper provides a comprehensive assessment of the landscape of firm migration in Germany.

The contribution to the literature is threefold: First, we provide an exhaustive overview over frequency, distribution and patterns of firm relocations in Germany. To our knowledge, we are the first to present such comprehensive evidence for Germany. Second, we study establishment-level determinants of a relocation and focus not only on the role of size, age, and industry (as is standard in the literature) but also on the role of average wages and employment composition of an establishment. In all our estimations, we distinguish between moves to major cities, urban districts, and rural districts in order to examine differences with respect to the geographical position of the destination district. Using cox regression and taking all moves into account, we report a positive link between both wages and the share of high-skilled workers and the propensity to relocate, suggesting that highly productive and profitable establishments are more

likely to relocate. In contrast, establishments with higher wages have a lower propensity to relocate when only considering moves to rural districts, suggesting that these more peripheral districts attract other types of relocating establishments. Third, we additionally conduct a more aggregate analysis on the regional level, where we connect regional variables, such as housing price levels, tax rates, or population density, to the number of relocations between two districts. This analysis is very much in line with existing research by Rupasingha and Marré (2020) and Hellwig (2023) and uses Poisson regressions to estimate the parameters of interest. Guided by the discrete choice model by McFadden (1974), we include our explanatory variables as differences between origin and destination district. Our estimates suggest that relocating establishments prefer nearby districts that are less densely populated and exhibit lower tax burdens than their origin district. The impact of the tax burden is particularly high when examining moves to urban districts and can not be found for establishments moving to major cities.

The paper is organized as follows. Section 2 presents the relevant theoretical and empirical literature. In section 3 we introduce the data used and the measurement applied in the course of this study, while we present first descriptive evidence in section 4. Our econometric analysis on the establishment- and regional-level will be conducted in sections 5 and 6. Section 7 concludes.

2. Theoretical considerations and empirical evidence

Theoretical considerations. The new creation of a business as well as the exit from the market are the main events in the life-cycle of a firm. The dimension of firm existence is accompanied by other dimensions, maybe the most prominent being the geographical one. A new firm birth is automatically connected to a decision for a certain location where the firm is settling. Between birth and death of a firm, it has the possibility to change its location, hence, to relocate. However, if we assume a strategic location decision under optimization constraints and the existence of relocation costs, why would we ever observe a relocation?

Several theoretical contributions aim to resolve this puzzle. One strand of explanation (implicitly or explicitly) regards a relocation as a correction of the initial location decision. A prominent explanation in the literature is that an entrepreneur's location decision is partly guided by home bias, which can result in a location that is not optimal for the firm's evolving business model. While there are some advantages of settling locally, such as higher social capital or better access to financial resources (see, e.g., Figueiredo et al. (2002); Michelacci and Silva (2007); Dahl and Sorenson (2012)), it is also quite plausible that parts of the decision are guided by imperfect information on potential alternatives or imperfect mobility of entrepreneurs. However, also external reasons can render the original location as not optimal any more. For instance, the need to correct the initial location decision might also stem from unexpected shocks to the

distribution of regional cost or productivity differentials which then triggers spatial mobility of firms (Rupasingha and Marré, 2020). In principle, all factors that feed into location-specific cost (for instance, tax rates or price levels) or production functions (labor and capital input, technical progress) of firms could induce firm migration if the old region is no longer profit-maximizing. In the context of this study, the most plausible unexpected shock would be an adjustment of the local business tax rates.

In contrast, a relocation can also reflect an optimal location strategy for a firm. The reason is that the benefits of agglomeration externalities change during the life-cycle of firms. Duranton and Puga (2001) developed a model of process innovation where new firms first settle in diversified cities to experiment with prototypes of their potential products. Through agglomeration externalities such as learning or sharing, they reap benefits from the diverse structure of their urban environment, which facilitates the development of their products. After they decided on their product portfolio, or more generally, their optimal production technology, they move to a specialized city with lower production costs to scale their production. A model with similar implications, albeit with a focus on fragmentation within the firm, has been introduced by Rossi-Hansberg et al. (2009). The core idea is that firms react to increasing land prices in the city centers by splitting up their organization structure into a headquarter and one ore more production plants. The spatial allocation of their branches and their workforce then depends on the urban environment: while headquarters with high shares of high-skilled employees would remain in the city center where agglomeration externalities (such as knowledge spillovers) are higher, production plants would be relocated to the peripheries of a city where land is cheaper (since supply is not fixed). Both mechanisms would generate relocation flows of firms from a diversified urban environment to a more specialized or peripheral part of the urban structure.

Empirics. The empirical literature mostly focuses on the identification of firm- and regional-level determinants of a relocation decision. A joint analysis of these determinants is achieved by using micro data of firms of different sizes, sectors, countries, and time periods. In this branch of the literature most studies use binary regression models to examine relocation decisions of firms. Another approach is to use aggregate data on the regional level, counting the number of relocating firms by municipality or district, and study the impact of various regional-level characteristics on the number of relocating establishments in a regional unit. Here, it is common to use count data models, whose parameters are then estimated with exponential models, such as Poisson or negative binomial regressions.

Micro data analyses. A common finding in the literature using firm-level data is that relocation propensities decrease with firm size and age (Van Dijk and Pellenbarg, 2000; Brouwer et al., 2004; Knoben and Oerlemans, 2008; De Bok and Van Oort, 2011; Kronenberg, 2013; Weterings and Knoben, 2013; Nguyen et al., 2013; Yi, 2018). This can be explained by the argument that relocation costs and organizational adjustment costs associated with a move increase in firm size and the embeddedness in long-term networks in a region and the gains from it

increase with firm age (Van Dijk and Pellenbarg, 2000; Brouwer et al., 2004).¹ Kronenberg (2013) studies firm relocations in the Netherlands and distinguishes between firms in manufacturing and services, capital-intensive and labor-intensive firms, and knowledge-intensive and less knowledge-intensive firms. She finds differences in the (usually negative) relationship between firm size and relocation propensity and document that in less knowledge-intensive service firms it turns positive. Yi (2018) analyses establishments that move more than once, and distinguishes between the initial relocation and the subsequent one(s). She documents a positive relationship between, the change in firm size (hence employment growth) prior to relocation is associated with an increased relocation propensity, both when the firm increased or decreased its employment level (Kronenberg, 2013; Brouwer et al., 2004; Yi, 2018).

Generally, relocation propensities are not equally distributed across sectors. Kronenberg (2013) finds that less knowledge-intensive manufacturing and service firms have an increased relocation propensity. Brouwer et al. (2004), who analyse moving behaviour of larger firms (over 200 employees) find that firms in the quartiary service sector (knowledge-based economy) have the highest probability to move across space. Van Dijk and Pellenbarg (2000) document higher relocation propensities in the service sector compared to the manufacturing sector, however, the estimates lack statistical preciseness. The results of the point estimates, however, are confirmed by Weterings and Knoben (2013) and De Bok and Van Oort (2011). Only few studies have analyzed the impact of the wage level of a firm on its relocation probability. In this regard, Kronenberg (2013) finds that firms (especially low-tech manufacturing and knowledge-intensive service firms) paying a high salary have a higher probability to move.

An advantage of the firm-level data is that it is possible to study also the role of regional-level characteristics on the propensity to relocate by exploiting the information on the location of a firm. Much of the regional (re)location literature revolves around the role that agglomeration externalities play in business (re)location decisions. With respect to the industrial scope, (positive) agglomeration externalities can take two different forms: Firstly, localization economies (so-called Marshallian externalities) that stem from advantages of a concentrated or specialized industry structure in a region and secondly, urbanization economies (so-called Jacobian externalities) that stem from advantages of urban diversity (Rosenthal and Strange, 2004; Glaeser et al., 1992; Van der Panne, 2004). Duranton and Puga (2001) adopt these concepts and predict relocations going from cities with urbanization economies to cities with localization economies. Several empirical studies on the firm level examine the role of agglomeration externalities. Overall, the results are rather inconclusive. While Weterings and Knoben (2013)

¹Countering this view, Van Dijk and Pellenbarg (2000) additionally argue that the *relative* relocation costs might behave differently, and actually decrease in firm size. This might be due to advantages of larger firms in bargaining discounts for larger production sites or applying for government funding (Van Dijk and Pellenbarg, 2000). In line with this counter argument, certain parts of the fixed costs of relocating might be insensitive to firm size, such as the bureaucratic and legal process of relocating.

document - in line with Duranton and Puga (2001) - that high levels of specialization in a region decrease the propensity to relocate, the same holds true for high levels of urbanization. Related studies find no or ambiguous effects of specialization or urbanization on relocation decisions (see, e.g., Knoben and Oerlemans (2008); Yi (2018); Kronenberg (2013)). Hong (2014) studies relocations of manufacturing firms in Korea and finds that localization economies (high levels of specialization in the same industry) in the destination regions are a key driver of firm relocations, especially for long distance moves and older firms, consistent with the predications of Duranton and Puga (2001).

Related to agglomeration economies, Kronenberg (2013) analyzes the role of population density. She finds differences between the service and the manufacturing sector. Firms in the former sector seem to prefer densely populated areas while firms in the latter sector are attracted by regions with lower population densities. In terms of infrastructure, firms have been found to have a preference for regions with high accessibility to highways or train stations (Knoben and Oerlemans, 2008; Nguyen et al., 2013; De Bok and Van Oort, 2011; Krenz, 2023). Further, firms tend to move away from regions with high land prices (Nguyen et al., 2013) and high sector-specific wage levels (Kronenberg, 2013). Interestingly, Kronenberg (2013) finds that firms rather stay in regions with high general wage levels, possibly because high wages translate into high product demand. Krenz (2023) studies relocation patterns of German manufacturing plants and finds that worker remuneration is positively associated with relocation probabilities. Thereby, Krenz (2023) confirms the findings of Kronenberg (2013); however, she interprets high worker remuneration as a sign of high worker quality.

Regional data analyses. In contrast to micro studies, regional data analyses use aggregate counts of the number of relocations per regional unit (mostly municipality, district, or federal state) as a dependent variable and various regional characteristics as independent variables. Econometrically, these type of studies apply suitable count data models and estimate the parameters of interest with exponential models, such as Poisson regression, negative binomial regressions (NegBin) or zero-inflated versions of these. A linear OLS or fixed effects approach is usually avoided since a high fraction of the dependent variables' outcomes are zeros. Studies in this strand of literature either count the number of relocating firms for every destination region or for every origin-destination pair.² Accordingly, studies using the former approach examine the impact of the destination regions' characteristics (see Erickson and Wasylenko (1980); Charney (1983); Holl (2004); Manjón-Antolín and Arauzo-Carod (2011); Conroy et al. (2017)), while studies using the latter approach jointly examine the impact of both origin and destination regions' characteristics as well as the impact of the distance or similarity between the two exchanging regions (see Conroy et al. (2016); Pan et al. (2020); Rupasingha and Marré

²Alternative approaches in the literature are to use the number of relocating firms as a proportion of the total number of firms or of available land area (variations of this approach have been applied by Erickson and Wasylenko (1980) and Charney (1983)) or to create a dummy variable that indicates whether a regional unit experienced a positive net flow of relocating firms (see Conroy et al. (2017)).

(2020); Rupasingha (2023); Hellwig (2023)). Holl (2004), who studies patterns of the location of start-ups and the relocation of established firms in Portugal, finds that regions with a higher proximity to motorways (in line with the micro-level evidence) and a higher industry share experience a higher influx of relocating firms. In contrast, regions with high shares of low-skilled workers (schooling until 15) attract less relocating firms. In a similar approach, Manjón-Antolín and Arauzo-Carod (2011) investigate (re)location patterns in Spain. They find that urbanization economies increase the number of firms that relocate into a region, while population density decreases it.

The literature using region-to-region firm migration flows has applied several ways to measure their independent variables of interest. Hellwig (2023) and Rupasingha and Marré (2020) include both origin-region and destination-region characteristics in their preferred specifications, which they interpret as push- and pull-factors of relocation decisions. Conroy et al. (2016), Pan et al. (2020) and, in an additional analysis, Hellwig (2023) take differences between origin and destination-level variables and include these as regressors. Similarly, Rupasingha (2023) calculates ratios between destination- and origin-level regional characteristics. To inform about the impact of similarity between regions, Rupasingha and Marré (2020) additionally create a dissimilarity measure, based on the squared differences between origin- and destination-level variables. In addition to these regional variables, the literature mostly includes the physical distance between origin and destination region as a proxy for relocation costs. Every paper identifies a strong distance gradient of relocations, expressed by a negative and highly significant coefficient of the distance variable (Hellwig, 2023; Conroy et al., 2016; Rupasingha and Marré, 2020; Rupasingha, 2023). Additionally, Conroy et al. (2016) and Hellwig (2023) find that neighboring states or districts have a significant higher count of relocating establishments. Rupasingha and Marré (2020) examine urban to rural business relocation in the USA. Their core findings are that establishments value destination regions with a high proximity to an urban center, high population densities, and high levels of diversity in terms of the industry structure, which would rather contradict the prediction of Duranton and Puga (2001). Further, establishments move to regions with low local property taxes (confirmed by the findings of Pan et al. (2020)), while the evidence on the role of wages is mixed. An additional finding of Rupasingha and Marré (2020) is that establishments tend to favor destination regions that are fairly similar to the origin region.

3. Data & Measurement

The data base for this study is the Establishment History Panel (BHP), which is a 50% random sample of all German establishments with at least one employee subject to social security (self-employed are excluded). The data access was provided via on-site use at the Research Data

Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and remote data execution. The BHP is an administrative data set, covering establishment-level information as of 30th of June beginning in 1975. Since every establishment has one identifier which usually does not change over time, establishments can be followed over their entire life-cycle. In addition, it is possible to identify entries of new establishments and exit of incumbent establishments, following the approach proposed by Hethey-Maier and Schmieder (2013). For this study, we focus on the post-unification period in Germany and include the years 1994-2021. The BHP covers information on employment level and composition (regarding nationality, occupation, qualification, age, and gender), wage structure, sector, and district of German establishments. An overview over this data product is provided by Ganzer et al. (2023).

The core of this study is to identify relocating establishments. We apply a very simple approach: we measure a relocation by the change of the district (*Landkreis*) an establishment operates in. Thereby, we exploit the fact the establishments do not change their identification number in the data. Hence, we only observe relocations that occurred over the borders of two German districts. A relocation between two municipalities within a district is therefore not included in our analysis. Since we are interested in relocations into explicitly distinct geographical environments (and not in relocations triggered by idiosyncrasies, such as the expiry of rental or lease agreements or owner-based motivations), we argue that it is not worrisome that we do not observe relocations on a finer grained geographical level. Nonetheless, we excluded some types of relocation that we regard as not reliable or suitable for the purpose our this study. First, we excluded the sector of private households, since we are interested in firm migration. Second, geographical relocations that were associated with a change in the economic sector (based on a 1-digit classification) are excluded since we assume that these establishments underwent other restructuring apart from just switching districts. Third, the BHP contains observations of establishments that moved in their first year of existence and then exited in the period thereafter. We regard these data points as not reliable and excluded them from the sample.

For the regional part of our study, we gathered district-level information on various characteristics, such as GDP per capita, unemployment rates, median wages, and population densities from the INKAR data base which is provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). Classifications of districts as being rural, urban or major cities (*kreisfreie Großstadt*) are also based on the BBSR. We complement this data source with data on the scaling factors of local business tax rates (*Hebesätze der Gewerbesteuer*), provided by the Federal and state statistical offices of Germany. They are available on the municipality level, therefore we computed population-weighted averages for every district and year. As a regional price level measure, we use the Regional Real Estate Price Index for Germany, which is provided by RWI Essen and computes regional price levels for private real estate rents and purchases (see Klick and Schaffner (2021)). Additionally, we calculate distance in kilometres between every district pair in Germany by using the German Local Population Database which contains latitudes and longitudes of every municipality in Germany (Roesel, 2023). We decided to take the most populated municipality within each district as of the year 2019 to measure distances between districts. Data on the presence of universities of applied science (*Fachhochschulen*) and universities in the German districts are taken from the Hochschulkompass (Hochschulkompass, 2020).

4. Descriptive Analysis

In this section we provide an overview over frequency, distribution and regional and sectoral patterns of establishment relocations in Germany. The time period we consider here are the years 1994-2021. To our knowledge, this is the first analysis presenting a comprehensive picture of firm mobility in Germany. Let us start with the frequency of establishment relocations in

Number of moves	Number of establishments	Share of est.
0	3,808,902	96.33
1	127,852	3.23
2	15,020	0.38
3	1,849	0.05
4	252	0.01
5	55	0.00
6	< 20	0.00
7	< 20	0.00

Table 1: Frequency of establishment relocations in Germany, 1994-2021

Germany. How large is the share of establishments that moved at least once in their life time? Not surprisingly, Table 1 shows that most of the existing establishments do not move at all.³ In total, over 3.2% of all establishments moved once, another 0.38 % relocated twice in their life time while negligible few establishments (0.06%) relocated more than twice. Hence, nearly 4 in 100 establishments have actually moved from one district to another in the given time period. Similar numbers have been found by Duranton and Puga (2001) for France (4.7%) and by Rupasingha (2023) for the USA (4.4%), both using large business microdata sets. Studying relocation patterns in the Netherlands, Van Dijk and Pellenbarg (2000) found relocation propensities of between 6 and 8%. For Germany, Hellwig (2023) and Ahlers et al. (2007) document higher relocation

³Note that the results we present here are a lower bound of acutal relocations in Germany since we only observe them when they cross district borders.

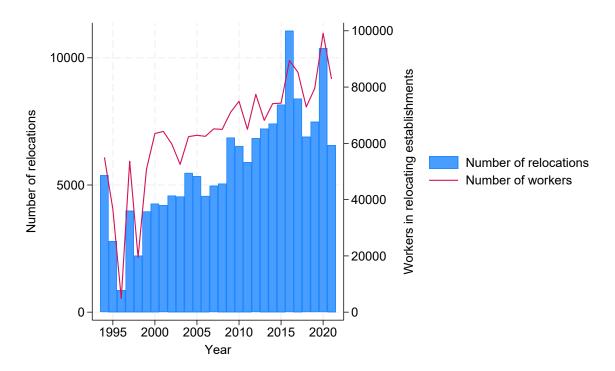


Figure 1: Establishment relocations per year

intensities (12.27 % and 9.2%, respectively). In contrast, Krenz (2023) documents substantially lower relocation fractions of around 0.16% in her sample.⁴

Next, we study the evolution of business relocations over time. Figure 1 presents the number of relocations in the blue bars (depicted on the left y-axis) and the number of workers in relocating establishments at the time of relocation on the red line (depicted on the right y-axis). As can be seen, there is an overall positive trend until the mid-2010s, after which the number of relocations declined again. The same holds true for the number of affected workers, albeit with a less pronounced decline. Hence, at the maximum we can observe up to 11,000 relocations and close to 100,000 affected workers per year. All in all, we can show that establishment relocations have become more prevalent over time in Germany. Figure A.1 in the Appendix further confirms this notion and shows that the share of establishments that have relocated has also increased over time.

In addition to the frequencies and the time trend presented above, we are interested in regional, sectoral and establishment-level patterns of business relocations in Germany. We begin by

⁴In general, it is difficult to make direct comparisons of the general propensity to relocate documented in the literature, as there are huge differences in data samples, structures and sources, as well as in the definitions of relocation and the exposition of the numbers. Nonetheless, the impression is that our numbers are rather located at the lower end of the distribution. Firstly, this can be explained by the fact that by construction we only observe a lower bound of actual relocations. Secondly, our dataset is a representative and large administrative sample of all German establishments and is therefore more robust to selection issues than a survey-based or less representative dataset.

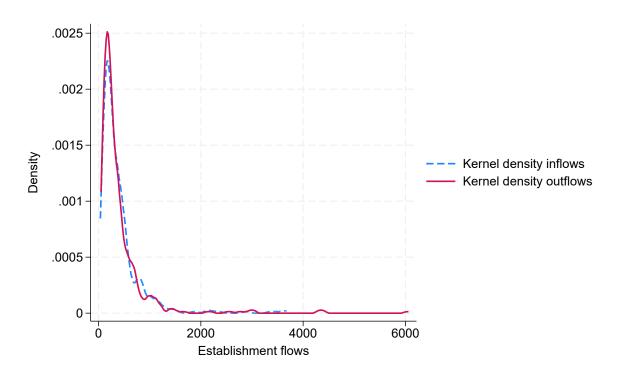


Figure 2: Distribution of inflows and outflows per district, 1994-2021

showing the regional distribution of establishment mobility. For that, we sum up inflows and outflows of establishments for every German district for the whole observation period (1994-2021). At first, we present the distribution of the inflow and outflow variable in Figure 2. It can be seen that most districts experience less than 1000 flows overall. The mean for both variables is around 400, while the 90th percentile is 810 (741) for inflows (outflows). However, there are some districts that exhibit a tremendously higher establishment mobility than the rest, as visible in the long tails of the distribution.

To depict regional relocation patterns, we present district-level net flows (inflows minus outflows), summed over the entire observation period in Figure 3. We cluster all districts into six quantiles, representing their respective position in the distribution of net flows. Figure 3 reveals a clear pattern: districts that are located close or next to large metropolitan centers are amongst the districts with the highest net flows, indicated by the dark red color. In contrast, these metropolitan centers themselves are among the districts with the lowest (most negative) net flows, indicated by the light red color. This pattern can essentially be observed for every large city in Germany, most importantly Berlin, Hamburg, Munich, Cologne and Frankfurt. Exact numbers on the districts with the highest and lowest net flows can be found in Table A.1 in the Appendix. We also show the inflows and outflows per district in the Appendix in Figure A.2.

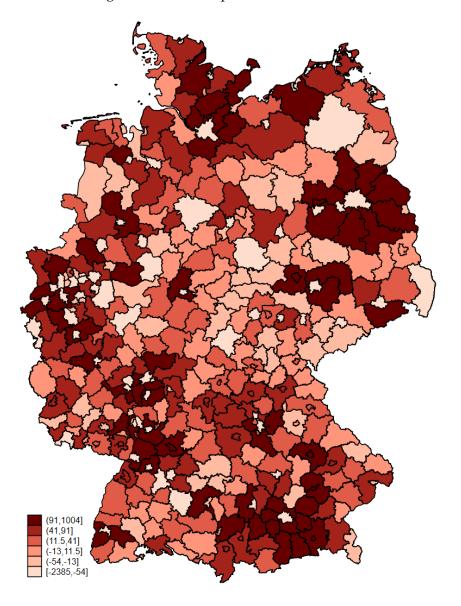


Figure 3: Net flows per district, 1994-2021

Even though the direction of the moves is not reflected in Figure 3, it indicates that there is a sub-urbanization in terms of business relocations in Germany. Hence, establishments tend to move out of the large metropolitan centres into the surrounding urban districts, consistent with the findings of Hellwig (2023) for Germany and Van Dijk and Pellenbarg (2000) for the Netherlands, who document a similar distribution. To further examine these patterns, Table 2 shows the distribution of the geographical direction of relocations in Germany. For that, we classify districts into three groups: major city (*kreisfreie Großstadt*), urban district and rural

Moving type	Number of moves	Share of moves
Geographical direction		
Major city to major city	14,539	8.98
Rural district to major city	10,884	6.72
Urban district to major city	22,070	13.62
Major city to urban district	32,484	20.05
Urban district to urban district	28,862	17.82
Rural district to urban district	7,620	4.70
Major city to rural district	16,248	10.03
Urban district to rural district	9 <i>,</i> 211	5.69
Rural district to rural district	20,070	12.39

Table 2: Directions of establishment relocations in Germany

Urban and rural classifications based on BBSR. Considered time period: 1994-2021.

district. These classifications are borrowed from the BBSR who classifies districts into four groups based on their settlement structure (*Siedlungsstruktur*).⁵

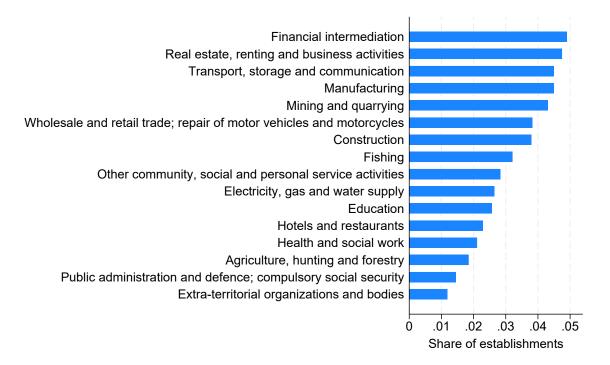
Table 2 reveals that the moving type *from major city to urban district* is indeed the most prevalent one, amounting to over 20% of all moves. The opposite direction, that is the moving type *from urban district to major city*, only amounts to over 13% of all moves, while the moves from or to rural districts are the rarest ones. In total, over 42% of relocating establishments move to an urban district, while around 29% move to a major city or to a rural district, respectively. Consequently, in our econometric analysis we will especially focus on the moves to urban districts.

We now turn to the establishment side and present novel evidence on establishment relocations by sector, size, and age. Let us start with the distribution of relocations across sectors.⁶ Figure 4 depicts the shares of relocating establishments per industry (absolute numbers can be found in Figure A.3 in the appendix). It can be seen that the relocation intensities vary strongly by industry. Among establishments operating in business-related services, such as financial intermediation and real estate, renting and business activities, close to 5% relocate at least once in their lifetime. These industries are followed by transport, storage and communication and the manufacturing sector. Hence, relocations are not a phenomenon that only occurs within the service sector. Also manufacturing plants with a presumably high amount of physical capital tend to relocate comparably often. In contrast, establishments in public administration, agriculture, or health and social work exhibit low relocation intensities, with only around 2% relocating establishments. All in all, these patterns align well with previous evidence from other countries. Van Dijk and Pellenbarg (2000) report the highest relocation propensities for

⁵The BBSR provides two categories for rural districts (rural district with densification and sparsely populated rural district), which we combine into one in our paper.

⁶We use the 3-digit code of the WZ 1993 classification system and further aggregate it to the 1-digit level, which gives us 16 different sectors. For more information on the industry classifications, see Eberle et al. (2011).





Dutch firms in the commercial services and wholesale sector, while firms in manufacturing and construction show moderate relocation behaviour. In contrast, Weterings and Knoben (2013) find that the relocation propensities of construction and business services firms are particularly high. Duranton and Puga (2001) document the highest relocation propensities for firms operating in innovative sectors, such as R&D and IT and consultancy services.

What types of establishments relocate? Much of this question will be dealt with in our econometric analysis in section 5. In the following, we will show establishment relocations by size and age. Note that this is a purely descriptive exercise, which does not give insights about size or age as determinants of relocations. Figure 5 shows the total number of relocations by establishment size class (at the time of relocation). We cluster the establishments into six size classes, based on their total employment level. As can be seen, most establishments are small when they move. This is mainly due to the establishment composition in the data since most establishment age (up to an age of 25), makes visible that most establishments are rather young at the time of relocation. The older establishments become, the less prevalent are relocations. Hence, the descriptive evidence presented here suggests that relocating establishments are rather young and small, which confirms the common finding in the literature that relocation propensities decrease in firm size and age (see, for instance, Van Dijk and Pellenbarg (2000); Kronenberg (2013); Weterings and Knoben (2013); Yi (2018)).



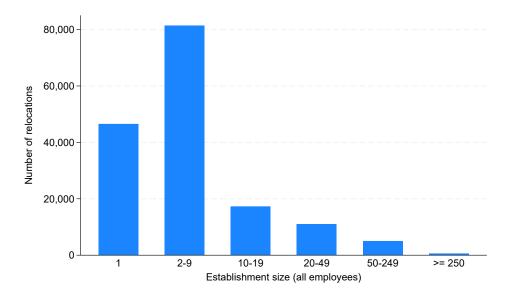
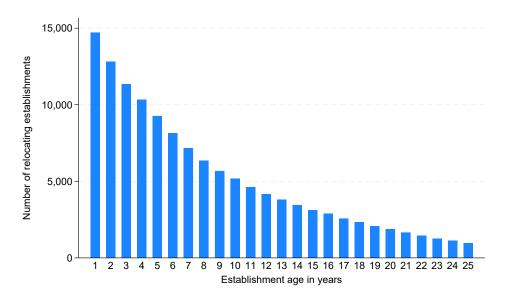


Figure 6: Relocations by establishment age, 1994-2021



5. Establishment-level analysis

In this section, we present methodology and results of our analysis on the establishment level. Specifically, we ask which establishment characteristics are associated with a lower or higher probability to relocate. To examine this question, we apply Cox proportional hazard regression techniques with time-varying covariates to model the time until the relocation (i.e., the event or failure) happens. A potential pitfall of using time-varying covariates in this model is that there

could be feedback effects of the duration until the event to the covariates.⁷ However, we do not see such problems within our application. In a second step, we examine the robustness of the results by applying a complementary log-log approach, which has been used by Weterings and Knoben (2013). To estimate the exact survival time, we follow establishments over time, beginning in their year of birth. Hence, we exclude all establishments for which we do not know when they entered the market.⁸

The basic Cox proportional hazard regression equation takes on the following form (Cox, 1972):

$$h(t|x_j) = h_0(t)exp(x_j\beta_x) \tag{1}$$

where β_x is the parameter vector that is estimated and $h_0(t)$ is the baseline hazard. An advantage of this method is that β_x can be estimated with consistency without making assumptions about the functional form of the baseline hazard. In other words, it does not matter whether the evolution of the hazard over time is constant, decreasing, increasing or any combination of the three. However, it is assumed that $h_0(t)$ is the same for every subject *j* (Cleves et al., 2016).

For this study, we chose several establishment-level variables as covariates x_j . More specifically, we include firm size and industry affiliation as well as the establishments' wage level (average gross daily wage, in real terms) as explanatory variables. Further, we exploit our rich administrative data set and include an exhaustive set of variables that reflect the employment composition of an establishment regarding skill, occupation, gender, nationality, and age. We are not aware of another study that uses establishment-level information of that kind. We consider the share of low-skilled and high-skilled workers to proxy for the knowledge intensity of an establishment.⁹ Additionally, the occupational structure of an establishment is accounted for by including the share of managers, technicians, engineers or natural scientists and apprentices. Further covariates are the share of female workers, the share of young workers (under 30), and the share of foreign workers. Additionally, we control for the average workers' age and include federal state and year dummies. Since we are also interested in the heterogeneity regarding the urban structure of the destination district, we differentiate between moves to a major city, moves to a urban district, and moves to a rural district.

Table 3 presents the results of the Cox proportional hazard regressions. We estimate the parameter vector for all moves as well as for every moving type alone and depict exponentiated coefficients. Starting with all relocations in model (1), it can be seen that there is a substantial size gradient in relocation "risks". For small establishments with less than 10 employees the risk to

⁷For instance, in an application for the duration of an unemployment spell, this duration may impact the search intensity. If search intensity is an independent variable, this procedure would give an biased estimate of the effect of this variable.

⁸Note that roughly 63% of establishments in the full sample of our data set are assigned a specific birth year (Schröpf, 2023).

⁹Low-skilled workers are workers without vocational qualifications, while high-skilled workers have a degree from a university of applied sciences or a university (Ganzer et al., 2023).

AllTo major cityTo urban districtTo rural districtSize: 1 0.712^{***} 0.627^{***} 0.697^{***} 0.697^{***} 0.697^{***} 0.697^{***} 0.893^{***} (0.01)(0.02)(0.02)(0.02)(0.03)Size: 10-19 0.957^{***} 0.937^{**} 0.966 0.954 (0.02)(0.03)(0.02)(0.03)(0.02)(0.03)Size: 20-49 (Reference) 1.000 1.000 1.000 1.000 (0.02)(0.04)(0.03)(0.04)Size: 50-249 0.857^{***} 0.889^{***} 0.827^{***} 0.852^{***} (0.02)(0.04)(0.03)(0.04)Size: ≥ 250 0.746^{***} 0.740^{***} 0.726^{***} (0.05)(0.09)(0.07)(0.10)Average wage (log) 1.669^{***} 1.266^{***} 1.073^{***} 0.915^{***} (0.00)(0.00)(0.00)(0.00)(0.00)(0.00)high-skilled workers 1.001^{***} 1.002^{***} 0.000 managers 1.005^{***} 1.006^{***} 1.004^{***} 1.002^{***} (0.00)(0.00)(0.00)(0.00)(0.00)(0.00)managers 1.005^{***} 0.996^{***} 0.997^{***} 0.998^{***} (0.00)(0.00)(0.00)(0.00)(0.00)(0.00)managers 1.005^{***} 1.006^{***} 1.004^{***} 0.005^{***} (0.00)(0.00)(0.00)(0.00)(0.00) </th <th></th> <th>(1)</th> <th>(2)</th> <th>(3)</th> <th>(4)</th>		(1)	(2)	(3)	(4)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$					
			city	district	district
$\begin{array}{llllllllllllllllllllllllllllllllllll$	Size: 1	0.712***	0.627***	0.697***	0.751***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.01)	(0.02)	(0.02)	(0.02)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Size: 2-9	0.885***	0.828***	0.896***	0.893***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.01)	(0.02)	(0.02)	(0.03)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Size: 10-19	0.957***	0.937**	0.966	0.954
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.02)	(0.03)	(0.02)	(0.03)
$\begin{array}{llllllllllllllllllllllllllllllllllll$	Size: 20-49 (Reference)	1.000	1.000	1.000	1.000
$\begin{array}{llllllllllllllllllllllllllllllllllll$		(.)	(.)	(.)	(.)
$\begin{array}{llllllllllllllllllllllllllllllllllll$	Size: 50-249	0.857***	0.889***	0.827***	0.852***
$ (0.05)$ (0.09) (0.07) (0.10) Average wage (log) 1.069^{***} 1.266^{***} 1.073^{***} 0.915^{***} (0.01) (0.02) (0.01) (0.01) (0.01) Employment shares of low-skilled workers 1.001^{***} 1.003^{***} 1.001 1.000 high-skilled workers 1.004^{***} 1.007^{***} 1.004^{***} 1.002^{***} (0.00) (0.00) (0.00) (0.00) (0.00) managers 1.005^{***} 1.006^{***} 1.004^{***} (0.00) (0.00) (0.00) (0.00) technicians 1.000 (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) engineers/natural scientists 0.997^{***} 0.996^{***} (0.00) (0.00) (0.00) (0.00) apprentice 0.984^{***} 0.982^{***} (0.00) (0.00) (0.00) (0.00) female workers 0.996^{***} 0.996^{***} (0.00) (0.00) (0.00) (0.00) young workers (under 30) 1.001^{***} 1.002^{***} (0.00) (0.00) (0.00) (0.00) foreign workers 1.005^{***} 1.007^{***} (0.00) (0.00) (0.00) (0.00) Average workers' age 0.995^{***} 0.994^{***} (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) $(0.$		(0.02)	(0.04)	(0.03)	(0.04)
Average wage (log) 1.069^{***} 1.266^{***} 1.073^{***} 0.915^{***} (0.01) (0.02) (0.01) (0.01) (0.01) Employment shares of 1.001^{***} 1.003^{***} 1.001 1.000 $[0w-skilled workers$ 1.001^{***} 1.003^{***} 1.001 1.000 high-skilled workers 1.004^{***} 1.007^{***} 1.004^{***} 1.002^{***} (0.00) (0.00) (0.00) (0.00) (0.00) managers 1.005^{***} 1.006^{***} 1.004^{***} (0.00) (0.00) (0.00) (0.00) technicians 1.000 (0.00) (0.00) (0.00) (0.00) (0.00) (0.00) engineers/natural scientists 0.997^{***} 0.996^{***} 0.998^{***} (0.00) (0.00) (0.00) (0.00) (0.00) apprentice 0.984^{***} 0.982^{***} 0.984^{***} 0.996^{***} (0.00) (0.00) (0.00) (0.00) (0.00) young workers (under 30) 1.001^{***} 1.002^{***} 1.000^{***} (0.00) (0.00) (0.00) (0.00) (0.00) foreign workers 1.005^{***} 1.007^{***} 1.006^{***} (0.00) (0.00) (0.00) (0.00) (0.00) Average workers' age 0.995^{***} 0.995^{***} 0.994^{***} (0.00) (0.00) (0.00) (0.00) (0.00)	Size: ≥ 250	0.746***	0.740***	0.726***	0.752**
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.05)	(0.09)	(0.07)	
Employment shares oflow-skilled workers 1.001^{***} 1.003^{***} 1.001 1.000 high-skilled workers 1.004^{***} 1.007^{***} 1.004^{***} 1.002^{***} (0.00)(0.00)(0.00)(0.00)(0.00)managers 1.005^{***} 1.006^{***} 1.004^{***} (0.00)(0.00)(0.00)(0.00)technicians 1.000 (0.00)(0.00)(0.00)(0.00)(0.00)(0.00)engineers/natural scientists 0.997^{***} 0.996^{***} 0.997^{***} (0.00)(0.00)(0.00)(0.00)(0.00)apprentice 0.984^{***} 0.982^{***} 0.984^{***} (0.00)(0.00)(0.00)(0.00)female workers 0.996^{***} 0.996^{***} 0.996^{***} (0.00)(0.00)(0.00)(0.00)(0.00)foreign workers (under 30) 1.001^{***} 1.002^{***} 1.006^{***} (0.00)(0.00)(0.00)(0.00)(0.00)foreign workers ' age 0.995^{***} 0.994^{***} 0.995^{***} 0.994^{***} (0.00)(0.00)(0.00)(0.00)(0.00)(0.00)Average workers' age 0.995^{***} 0.994^{***} 0.995^{***} 0.994^{***}	Average wage (log)	1.069***	1.266***	1.073***	0.915***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.01)	(0.02)	(0.01)	(0.01)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Employment shares of				
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	low-skilled workers	1.001***	1.003***	1.001	1.000
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.00)	(0.00)	(0.00)	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	high-skilled workers	1.004^{***}	1.007^{***}	1.004^{***}	1.002***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.00)	(0.00)	(0.00)	(0.00)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	managers	1.005***	1.006***	1.004***	1.004***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.00)	(0.00)	(0.00)	(0.00)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	technicians	1.000	0.999*	1.000	1.000
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.00)	(0.00)	(0.00)	(0.00)
apprentice 0.984^{***} 0.982^{***} 0.984^{***} 0.983^{***} (0.00) (0.00) (0.00) (0.00) (0.00) female workers 0.996^{***} 0.998^{***} 0.996^{***} 0.996^{***} (0.00) (0.00) (0.00) (0.00) (0.00) young workers (under 30) 1.001^{***} 1.002^{***} 1.000 (0.00) (0.00) (0.00) (0.00) foreign workers 1.005^{***} 1.007^{***} 1.006^{***} (0.00) (0.00) (0.00) (0.00) Average workers' age 0.995^{***} 0.994^{***} 0.995^{***} (0.00) (0.00) (0.00) (0.00)	engineers/natural scientists	0.997***	0.996***	0.997***	0.998***
11 (0.00) (0.00) (0.00) (0.00) female workers 0.996*** 0.998*** 0.996*** 0.996*** (0.00) (0.00) (0.00) (0.00) (0.00) young workers (under 30) 1.001*** 1.002*** 1.000 1.000 (0.00) (0.00) (0.00) (0.00) (0.00) foreign workers 1.005*** 1.007*** 1.006*** 1.003*** (0.00) (0.00) (0.00) (0.00) (0.00) Average workers' age 0.995*** 0.994*** 0.995*** 0.994*** (0.00) (0.00) (0.00) (0.00) (0.00)		(0.00)	(0.00)	(0.00)	(0.00)
	apprentice	0.984^{***}	0.982***	0.984***	0.983***
(0.00) (0.00) (0.00) (0.00) (0.00) young workers (under 30) 1.001*** 1.002*** 1.000 1.000 (0.00) (0.00) (0.00) (0.00) (0.00) foreign workers 1.005*** 1.007*** 1.006*** 1.003*** (0.00) (0.00) (0.00) (0.00) (0.00) Average workers' age 0.995*** 0.994*** 0.995*** 0.994*** (0.00) (0.00) (0.00) (0.00) (0.00) 0.00)		(0.00)	(0.00)	(0.00)	(0.00)
young workers (under 30) 1.001*** 1.002*** 1.000 1.000 (0.00) (0.00) (0.00) (0.00) foreign workers 1.005*** 1.007*** 1.006*** 1.003*** (0.00) (0.00) (0.00) (0.00) Average workers' age 0.995*** 0.994*** 0.995*** 0.994*** (0.00) (0.00) (0.00) (0.00)	female workers	0.996***	0.998***	0.996***	0.996***
(0.00) (0.00) (0.00) (0.00) foreign workers 1.005*** 1.007*** 1.006*** 1.003*** (0.00) (0.00) (0.00) (0.00) (0.00) Average workers' age 0.995*** 0.994*** 0.995*** 0.994*** (0.00) (0.00) (0.00) (0.00) (0.00)		(0.00)	(0.00)	(0.00)	(0.00)
foreign workers1.005***1.007***1.006***1.003***(0.00)(0.00)(0.00)(0.00)(0.00)Average workers' age0.995***0.994***0.995***0.995***(0.00)(0.00)(0.00)(0.00)(0.00)	young workers (under 30)	1.001^{***}	1.002***	1.000	1.000
(0.00)(0.00)(0.00)(0.00)Average workers' age0.995***0.994***0.995***0.994***(0.00)(0.00)(0.00)(0.00)(0.00)	-			(0.00)	
(0.00)(0.00)(0.00)(0.00)Average workers' age0.995***0.994***0.995***0.994***(0.00)(0.00)(0.00)(0.00)(0.00)	foreign workers	1.005***	1.007***	1.006***	1.003***
(0.00) (0.00) (0.00) (0.00)	-	(0.00)	(0.00)	(0.00)	
(0.00) (0.00) (0.00) (0.00)	Average workers' age	0.995***	0.994***		0.994***
		(0.00)	(0.00)	(0.00)	(0.00)
	N	11,407,665		10,945,109	10,833,895

Table 3: Results of Cox proportional hazard regressions

Notes: Exponentiated coefficients depicted. Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1 indicate the significance levels. Industry (1-digit), state, and year dummies included in every specification. Only establishments considered that relocated after the year 1993. Observation period: 1994-2021.

relocate is 11.5% to 28.8% lower than for middle-sized establishments with 20-49 employees (the reference category). However, the relocation propensities for larger establishments with more than 50 employees decrease again, such that the pattern resembles an inverse U. Hence, middle-sized establishments have the highest relocation propensities. This pattern can be found for every moving type and the differences are negligible, as can be seen in models (2)-(4). Therefore, we cannot fully confirm the results from the previous literature suggesting a monotonic decrease in relocation probability with firm size. Since most researchers included the employment level of firms as a continuous variable (linear or in logarithms), they ruled out the possibility of a non-linear relationship (see, for instance, Knoben and Oerlemans (2008); Kronenberg (2013); Weterings and Knoben (2013)). In contrast, Van Dijk and Pellenbarg (2000) considered three firm size classes and found that Dutch firms with less than 10 employees exhibit the lowest relocation probabilities. This finding is also at odds with the hump-shaped pattern we find.

Turning to the impact of the wage level, it can be seen that higher average wages translate into higher relocation risks. Hence, high-wage establishments are more likely to relocate than low-wage firms. This is consistent with the findings of Kronenberg (2013) and illustrates that establishments who can afford to pay relatively high wages, can also bear the costs of moving to another region. Interpreting this result is not straightforward, as pointed out by Kronenberg (2013). It might be that the high wages are the reason for the move: due to certain locationspecific conditions firms have to pay relatively high wages; they relocate to another location in order to save labor costs (Kronenberg, 2013). Another explanation would be that these high wages compensate the employees for the relocation and the associated costs. Kronenberg (2013) further argues that high salaries might reflect a high workforce quality. However, as we account for workforce composition in our estimations, we can exclude this explanation in our study. The wage level might also reflect potentially latent variables, such as an establishments' productivity or profitability or the potential of its business model. Profitable establishments with high wages would then have better opportunities to relocate to an optimal location due to a better financial situation.

The positive association between wages and relocation probabilities is particularly pronounced in establishments that move to a major city. Interestingly, the estimated coefficient in model (4) is smaller than one, which indicates that an increase in the average wage is associated with lower relocation risks. Therefore, establishments moving to rural districts are rather low-wage establishments, while establishments moving to major cities or urban districts, are rather highwage establishments. These findings speak against the explanation that a relocation is a strategy to save wages: Since wage levels are higher in cities than in rural areas, it is unlikely that establishments with high wage levels, which could save the most on labor costs, will move to districts with relatively high wage levels.

Table 3 additionally reveals that high shares of low-skilled *and* high-skilled workers increase relocation risks of establishments, especially for establishments that move to an urban district.

This indicates that highly polarized establishments with low amounts of middle-skilled workers exhibit high relocation propensities, especially when moving to major cities. The fact that the coefficients of the high-skill shares are higher than that of the low-skill shares suggests that relocating establishments have a comparably high knowledge intensity, which is not in line with the evidence of Kronenberg (2013) for the Netherlands who found that less knowledge-intensive firms have higher relocation probabilities. In addition, the coefficient of the high-skill share is highest when examining moves to major cities and lowest when examining moves to rural areas. Together with the evidence regarding the wage levels, this suggests that particularly strong, possibly highly productive and profitable establishments with high wages and a high share of high-skilled workers move to major cities or urban districts. This makes sense: urban areas are more competitive and therefore arguably require more successful and profitable business models.

Throughout every specification, a high share of employed managers and foreign workers in an establishment increases relocation risks. A high share of managers might reflect establishments with business models that are comparably mobile, location-independent and knowledgeintensive, while foreign workers might have limited power to oppose a relocation. This limited power might partly be rooted in the lower union density of non-native workers, as documented in a recent study of Pyka and Schnabel (2023) for 19 European countries. In contrast, a high share of engineers and natural scientists, a high share of apprentices, and a high share of female workers decrease relocation risks. Engineers and natural scientists exhibit high bargaining power and therefore might oppose potential relocation plans of their establishments, resulting in lower relocation rates. Establishments with high shares of apprentices presumably have strong local roots and ties, so it is plausible that they move less frequently. Also, apprentices could be reluctant to work for a firm with high relocation preferences, as they exhibit limited regional mobility due to financial restrictions. Female workers are less mobile and accept lower commuting times than male workers (see, for instance, White (1986); Van Ommeren and van der Straaten (2008); Casado-Díaz et al. (2023)), suggesting that women would rather oppose relocation plans or self-select into establishments with low relocation preferences. Due to the low mobility preferences of women, establishments with a high proportion of female workers would have to fear that they would lose a lot of firm-specific human capital if they relocated and therefore more often decide against it. These reasons would explain lower relocation propensities for establishments with a high share of female workers.

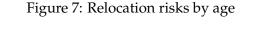
We validate our findings by applying another methodological approach. Following Weterings and Knoben (2013), we use a complementary log-log (*cloglog*) approach. Here, the dependent variable is binary and indicates whether an establishment has moved in a given year or not. It is often used when the dependent variable is very unequally distributed, hence, when most of the values are zero. Further, it can be regarded as a discrete time representation of a continuous time proportional hazards model with time-varying covariates (Jenkins, 2005). For these reasons, it fits

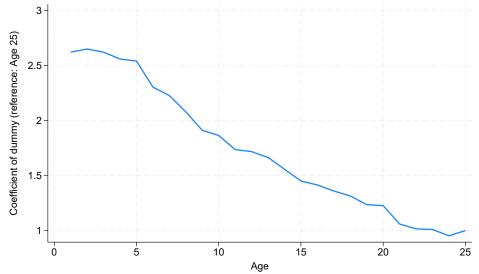
	(1)	(2)	(3)	(4)
	All	To major	To urban	To rural
		city	district	district
Size: 1	0.813***	0.712***	0.792***	0.862***
	(0.01)	(0.02)	(0.02)	(0.03)
Size: 2-9	0.901***	0.844***	0.911***	0.907***
	(0.01)	(0.02)	(0.02)	(0.02)
Size: 10-19	0.959***	0.940**	0.967	0.955
	(0.02)	(0.03)	(0.02)	(0.03)
Size: 20-49 (Ref.)	1.000	1.000	1.000	1.000
	(.)	(.)	(.)	(.)
Size: 50-249	0.854***	0.886***	0.824***	0.850***
	(0.02)	(0.04)	(0.03)	(0.04)
Size: ≥ 250	0.744***	0.738***	0.725***	0.749**
	(0.05)	(0.08)	(0.07)	(0.09)
Average wage (log)	1.057***	1.255***	1.060***	0.902***
	(0.01)	(0.02)	(0.01)	(0.01)
Employment shares of				
low-skilled workers	1.001***	1.003***	1.001^{*}	1.000
	(0.00)	(0.00)	(0.00)	(0.00)
high-skilled workers	1.004***	1.007***	1.004^{***}	1.002***
	(0.00)	(0.00)	(0.00)	(0.00)
managers	1.005***	1.005***	1.004^{***}	1.004^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
technicians	1.000	0.999*	1.000	1.000
	(0.00)	(0.00)	(0.00)	(0.00)
engineers/natural scientists	0.997***	0.996***	0.997***	0.998***
	(0.00)	(0.00)	(0.00)	(0.00)
female workers	0.996***	0.997***	0.995***	0.996***
	(0.00)	(0.00)	(0.00)	(0.00)
apprentices	0.983***	0.981***	0.983***	0.982***
	(0.00)	(0.00)	(0.00)	(0.00)
young workers (under 30)	1.001***	1.002***	1.001**	1.000
	(0.00)	(0.00)	(0.00)	(0.00)
foreign workers	1.006***	1.007***	1.006***	1.004***
	(0.00)	(0.00)	(0.00)	(0.00)
Average workers' age	0.994***	0.993***	0.995***	0.994***
	(0.00)	(0.00)	(0.00)	(0.00)
Ν	9,774,885	9,125,303	9,352,308	9,253.730

Table 4: Estimation results of complementary log-log regressions

Notes: Exponentiated coefficients depicted. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 indicate the significance levels. Industry (1-digit), state, age (one dummy for each age until 25, all establishments older than 25 are summarized in one dummy), and year dummies included in every specification. Only establishments considered that relocated after the year 1993. Observation period: 1994-2021.

very well into our study and data structure. The results are depicted in Table 4. It can be seen that the results for all variables are very similar to the results presented in Table 3. Even though some point estimates are slightly different, we can observe equivalent patterns when applying Cox proportional hazard or complementary log-log regressions. Another advantage of this appoach is that we can include age dummies as explanatory variables. For better clarity, the coefficients are not depicted in Table 4. However, we display them in Figure 7, where the substantial negative age gradient in the relocation risks can be nicely seen. Hence, relocation propensities strongly decrease with firm age, which is in line with our findings from the descriptive analysis (Figure 6) and the previous literature (Van Dijk and Pellenbarg, 2000; Weterings and Knoben, 2013; Nguyen et al., 2013).





Notes: Confidence intervals omitted for greater clarity. Coefficients of the age dummies depicted, with the reference category age 25.

6. Regional-level analysis

In this section we present the empirical strategy, considered variables, and the empirical results of our regional analysis. In contrast to the previous section, where we focused on establishmentlevel characteristics associated with a relocation decision, here we turn to the regional level. Our question is: which characteristics of a region are associated with a greater in- or out-migration of relocating establishments? However, we do not only focus on the destination region but also on the origin region. Therefore, we will not include the levels of the regional characteristics but their differences between origin and destination region in our econometric specifications. To analyse regional firm mobility patterns, we re-structured our dataset. For every district-pair, we counted the number of relocating establishments in a given year. For instance, for each year we counted the number of relocating establishments from Berlin to Hamburg and vice versa. Since our sample contains 400 German districts (*Landkreise*), we are left with a dataset with 160,000 district pairs for the years 2008-2020. We start in 2008 mainly because of data availability reasons. Our estimation strategy is to apply count data models which fit perfectly in this data structure. Therefore, our dependent variable will be the nonnegative number of relocating establishments between two districts. Additionally, since more than 99% of the relocation counts are zeros (similar to Hellwig (2023)) we need to account for this structure in our estimations. Therefore, we apply Poisson regressions in our main analysis. In our robustness estimations, we vary this approach by applying negative binomial regression models, which are similar but allow for special kinds of overdispersion in the data. As a further robustness check, we use hurdle models.

6.1 Empirical strategy

In contrast to the previous section, here we are interested in modelling the number of relocations in a given regional unit rather than the time until a relocation happens. However, both of the approaches are methodologically related. We follow Rupasingha and Marré (2020) to proceed from the establishment level decision of where to relocate to the estimation model on the regional level. Our framework is based on the discrete choice model of McFadden (1974). Each establishment has to decide whether to relocate to a specific destination region. To maximize profits, the establishments compare the profits of relocating to each available region from the origin region. Therefore, each available region is in the set of alternative location choices. Following Guimaraes et al. (2000), Davies et al. (2001) and Rupasingha and Marré (2020), we can formalize this decision by

$$\Pi_{ij} = Z_{ij} + \varepsilon_{ij}.\tag{2}$$

 Π_{ij} is the establishment's profit of relocating from region *i* to region *j*. This profit is determined by vector Z_{ij} . It captures the differences in the characteristics between region *i* and *j* and the distance between the regions. Moreover, there is a random error term ε_{ij} , which can be interpreted as an idiosyncratic matching parameter (Rupasingha and Marré, 2020).

Suppose *J* is the set of the potential destination regions. An establishment will prefer to move from origin region *i* to destion region *j* if

$$\Pi_{ii} > \Pi_{ik}, \forall k \neq j \text{ and } k \in J.$$
(3)

Thus, we can express the establishment's probability of moving from region *i* to region *j* as

$$P_{ij} = \operatorname{Prob}(\Pi_{ij} > \Pi_{ik}), \forall k \neq j \text{ and } k \in J$$
(4)

If we assume that ε_{ij} is an iid random variable following an Extreme Value Type I distribution, we can use the result of McFadden (1974) that the probability of moving from region *i* to region *j* is

$$P_{ij} = \frac{\exp(Z'_{ij}\beta_z)}{\sum_{j=1}^{J}\exp(Z'_{ij}\beta_z)}.$$
(5)

Equation (5) is known as the conditional logit model. Recall that the Cox proportional hazard model is related to a complementary log-log model. Thus, the approach presented here is related to our establishment level analysis shown in Section 5. An obstacle of this approach is that there is a larger number of destination regions to choose from. Therefore, estimating the model in this form could be computationally infeasible. Yet, Guimaraes et al. (2003, 2004) provide a work-around by demonstrating that a Poisson regression model is equivalent if the determinants are region-specific. Hence, we estimate the following Possion regression model on the regional level:

$$E[m_{ij}|Z_{ij}] = \exp(Z'_{ij}\beta_z).$$
(6)

 m_{ij} is the count of establishment relocations from region *i* to region *j*. Z_{ij} represents a vector of differences in characteristics between region *i* and region *j*, the distance between these regions as well as some region-specific dummy variables. In the next chapter, we describe the variables in Z_{ij} in greater detail. The estimated coefficients $\hat{\beta}_z \times 100$ give the percentage increase in the number of establishment relocations from region *i* to region *j* if the corresponding difference in Z_{ij} changes by one unit.

6.2 Explanatory variables

In this section we introduce the explanatory variables of interest in our study. We restrict our focus to six regional variables we regard as most relevant in the light of the existing empirical and theoretical literature. These variables are 1) the housing price level, 2) the scaling factors of the local business tax rates (*Hebesätze der Gewerbesteuer*), 3) the Herfindahl-Hirschman-Index, 4) population density, 5) average wages, and 6) GDP per capita. In addition, we include the physical distance in kilometers between two districts and a dummy, indicating whether two districts are neighbor districts.¹⁰ In line with Rupasingha and Marré (2020) and Hellwig (2023), these variables serve as our indicators for relocation costs: the higher the distance between two districts, the higher to costs of relocating. Apart from these main variables, our specifications will contain several control variables, such as regional employment shares (in terms of skill,

¹⁰We are indebted to Vanessa Hellwig who provided us with these data.

gender, age, and sector), regional shares of entering and exiting establishments, regional share of young population, unemployment rates, tax revenues as well as information on corporate bankruptcies, the presence of universities, average firm size and age, and the number of existing establishments. A more detailed description of all variables and their origins is provided in Table A.2 in the Appendix.

Turning to our variables of interest, housing price levels are measured by a housing purchase price index, gathered from the real estate platform *Immobilienscout24* (Klick and Schaffner, 2021). In the absence of commercial real estate data, this serves as our proxy for the regional housing price level faced by firms. It can reflect high operating costs for employers and therefore, high prices would rather dampen inflows of establishments. However, as Hellwig (2023) emphasizes, high-price regions can also be particularly attractive for firms as they offer, for instance, high agglomeration externalities.

To minimize costs, relocations could also be triggered by differences in relevant tax rates. Profitmaximizing firms may then have an incentive to move to a location, where the tax burden resulting from local business tax rates are lower. In Germany, the local business tax rates are composed of two components. First, the basic rate (which is set at the federal level) and second, the local scaling factor (which is set at the municipality level). The second component can basically be changed every year, while the first component is fixed at 3.5% since 2008. The total tax burden, accruing from the local business tax, then results from the product of the scaling factor and the basic rate. For more information on local business taxation in Germany, see Fuest et al. (2018). Since the scaling factors are determined on the municipality level, we compute population-weighted averages of these scaling factors for every German district.

A prominent theory explaining firm relocations revolves around the impact of agglomeration externalities in different phases of a firm's life cycle. Duranton and Puga (2001) provide a model describing that firms locate in diverse cities to profit from agglomeration externalities (such as learning) and, after the infant phase, then would relocate to a specialized city to scale production. We address this theoretical prediction by including a measure of regional specialization, more precisely the Herfindahl-Hirschman-Index (HHI), which is based on the regional industry structure. A higher value of the HHI indicates a higher industry concentration or specialization. According to the *nusery cities*-theory described above, we would expect to see more moves from rather diversified districts to rather specialized districts. Related work by Rupasingha and Marré (2020), Weterings and Knoben (2013), and Hong (2014) also includes measures of regional specialization. As Hellwig (2023) and Rupasingha and Marré (2020), we include population density as a measure for agglomeration economies, as it has been shown that location-specific productivity (arising from agglomeration economies) increase in population density (Combes and Gobillon, 2015; Rosenthal and Strange, 2008; Ciccone and Hall, 1996).¹¹ If establishments

¹¹Note that population density is sometimes also viewed as a measure of land costs since these increase in population density (Figueiredo et al., 2002; Guimaraes et al., 2004; Rupasingha and Marré, 2020).

seek these externalities, then they would relocate to a more densely populated region. However, if they rather seek more space and less congestion, they would relocate to less densely populated regions.

Lastly and in line with the previous literature, we study the impact of regional average wages and regional GDP per capita. The regional wage level is usually interpreted as a measure of labor costs and/or worker quality (Kronenberg, 2013; Krenz, 2023). However, as we already control for GDP per capita which can be thought of as a measure of labor productivity (and therefore worker quality), we interpret the wage level as a measure for labor costs. Therefore, profit-maximizing firms would move to regions where the labor costs are low. GDP per capita measures the economic power or the productivity of a region. From the lens of a gravity model, GDP would be positively related to firm migration flows, hence, establishments would move to regions with high GDP per capita (Hellwig, 2023).

6.3 Empirical results

In this section we present the estimation results from our preferred specifications. We include all variables described above and apply Poisson regressions in every column. However, in the following we only report the coefficients of our variables of interest. In Table 5 we display the baseline results for all moving types (column 1) and each moving type alone (column 2 for moves to major city, column 3 for moves to urban district, column 4 for moves to rural district). Guided by our derivation from section 6.1, we do not consider the levels of each variable but the differences of all variables between origin and destination district.¹²

The first column in Table 5 reveals that the only regional variable that is (marginally) significant is the average scaling factor of the local business tax. The coefficient has a positive sign which suggests that a higher tax difference between origin and destination district is associated with more relocation flows between these two districts. This makes sense: establishments search district where the tax burden is low, compared to their old district. In terms of magnitude, a one-point increase in the difference in the local scaling factors of the business tax between origin and destination district, is associated with a rise in the number of relocations by 0.8%. We cannot document a significant effect of the business tax burden for establishments that move to major cities. However, the effect is large and statistically significant for establishments that move to urban and rural districts. A one-point increase in the difference in the local scaling factors of the business tax is associated with an increase in the number of relocations by 1.7%. Framed differently, a district-pair with a one-point higher difference in the local scaling factor than another district-pair, is expected to exhibit 1.7% more relocations than the district-pair with the lower difference, while holding all other variables fixed. This would translate to an

¹²In the Appendix in Table A.3 we provide the estimation results for regressions in which we include all variables for origin and destination districts as levels instead of including their differences. The main takeaways are the same.

Dep. var.: Number of relocations	(1)	(2)	(3)	(4)
- · F · · · · · · · · · · · · · · · · ·	All	To major	To urban	To rural
		city	district	district
Differences (origin-destination)				
House purchase price index	0.0002	-0.0005	0.0012	0.0007
	(0.000)	(0.001)	(0.001)	(0.001)
Herfindahl-Hirschman Index	-0.0001	0.0001	0.0000	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Average gross monthly wages	0.0001	-0.0000	0.0002	0.0002^{*}
	(0.000)	(0.000)	(0.000)	(0.000)
GDP per capita	-0.0004	-0.0020	-0.0025	0.0013
	(0.002)	(0.003)	(0.003)	(0.003)
Population density	0.0000	0.0001**	0.0001**	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Average scaling factor	0.0008^{*}	-0.0002	0.0017**	0.0017^{*}
of business tax	(0.000)	(0.001)	(0.001)	(0.001)
Distance (log)	-1.1146***	-1.0746***	-1.1625***	-1.2607***
	(0.036)	(0.045)	(0.065)	(0.043)
Neighboring district (yes)	1.5838***	1.2385***	1.6813***	1.7271***
	(0.053)	(0.092)	(0.091)	(0.075)
Same state (yes)	0.9386***	1.0112***	0.7977***	0.8630***
	(0.051)	(0.076)	(0.088)	(0.052)
Additional Controls	Yes	Yes	Yes	Yes
Metropolitan area dummies	Yes	Yes	Yes	Yes
East-West dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	-12.2705***	-15.3843***	-9.7619***	-9.4686***
	(0.394)	(0.561)	(0.621)	(0.484)
R^2	0.6103	0.6294	0.6443	0.5368
Ν	2,073,206	347,395	689,605	1,036,206

Table 5: Estimation results of baseline specifications: Poisson regressions

Notes: Robust standard errors clustered on the district-pair level are displayed in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1 indicate the significance levels. Observation period: 2008-2020.

around 80% higher relocation count, if we increase the difference in the local scaling factors by one standard deviation (of the local scaling factor distribution, around 47 points). Hence, our estimates highlight that establishments systematically choose destination regions with lower local business taxes if they move to urban or rural districts. This is consistent with previous evidence on the role of property taxes of Rupasingha (2023), Rupasingha and Marré (2020) and Pan et al. (2020). However, if establishments move to major cities, our estimates suggest that they are not looking for locations that have lower tax rates than their previous locations.

The coefficients of the difference in population densities are positive and statistically significant for all moving types. Hence, an increase in the difference in the population densities between origin and destination district increases the relocation flows between these two districts. This suggests that establishments rather seek regions with comparably low population densities, even when they move to a major city. Therefore, it seems that the search for a new location is rather guided by the search for more space and less congestion than by the search for higher agglomeration externalities. Previous literature provided rather inconclusive results on the role of population density. The results of Rupasingha and Marré (2020) suggest that establishments rather move to new locations with high population densities, which would be the opposite of what we find. However, as they only study urban to rural business migration, their results are not directly comparable to ours. In her recent paper, Hellwig (2023) provides no clear evidence for the role of population density.

Turning back to Table 5, a one-point increase in the difference in the population densities is associated with an increase in the number of relocations by 0.1% for establishments that move to major cities or urban districts and by 0.2% for establishments moving to rural districts. Increasing the difference in population densities by one standard deviation of the population density distribution (roughly 680 inhabitants per km^2), would be associated with an increase in relocation flows by 68% when the destination districts are major cities or urban districts and by 136% when the destination districts. The differences between the moving types are quite plausible: moves to rural areas are more strongly driven by considerations regarding population density. We can also document a (marginally) significant and positive coefficient of the average gross monthly wages for establishments that move to rural districts. These establishments seem to search for rural regions with lower labor costs, compared to their old region. These results match our intuition: one motivation of establishments to move to rural districts is to save labor costs since wage levels are lower in rural and sparsely populated areas.

Surprisingly, the coefficient of the housing price index, proxying for the real estate price level differences between two districts, is not statistically significant. This result might reflect the fact that high prices can often be found in otherwise very attractive districts, which would explain the null effect. Based on these findings, we therefore cannot document a large impact of price differences on relocation patterns in Germany. Additionally, the coefficient of the HHI as a measure for the difference in the industrial specializations of a district-pair, also shows no significance. We, therefore, do not find evidence in favor of Duranton and Puga (2001), who predicted that relocation flows should go from diversified to specialized districts. Our work thus adds to the existing literature, on the basis of which no clear evidence for the theory of Duranton and Puga (2001) can be found.

We now turn to the impact of the variables measuring the physical distance between two districts. Most importantly, we find strong negative and highly statistically significant coefficients of the distance in kilometers between two districts. Hence, the higher the distance between two districts, the lower the number of relocating establishments. The same holds true for the dummy variable indicating if two districts are neighbors or not. Neighboring districts have a substantially higher number of relocating establishments. These findings are in line with Hellwig (2023) and Rupasingha and Marré (2020).

We present the full estimation table with all control variables included in Table A.4 in the Appendix. While most of the coefficients are not statistically significant, Table A.4 reveals some interesting additional findings which we will shortly discuss in the following. The share of young population in the age of between 18 and 25 is statistically significant for all moving types. However, it has a negative sign for the moves to major cities and a positive sign for the moves to urban and rural districts. This implies that establishments moving to major cities rather value regions with a high share of young population, compared to their old location, while establishments moving to urban or rural districts, rather value regions with comparably low shares of young population. This could be explained by the different motives behind relocations, depending on where they go. Establishments moving to less urbanized regions might rather search for a more settled and experienced labor force. An interesting additional finding in this context is that the share of high-skilled workers is highly significant when examining moves to major cities. Apparently, these establishments are considering cities with a lower proportion of highly qualified workers than in their old locations.

We also include variables that capture the presence of at least one public university in origin and destination district as well as the presence of at least one public university of applied sciences in origin and destination district.¹³ The results are as expected when looking at all moving types. The presence of a university and (or) a university of applied sciences in origin and destination district increases the number of relocating establishments. However, the positive coefficient of the variable capturing the presence of a university of applied sciences in the destination district is entirely driven by the moves to rural districts. Therefore, our estimates suggest that establishments moving to rural areas search for districts in which a university of applied sciences is located. This does not seem to be the case for establishments moving to more urbanized areas. In Germany, these universities of applied sciences are rather MINT and practically-oriented and are usually closely linked to local companies. Often, they provide the regions with a well educated and practical workforce. Relocating establishments might want to reap benefit of this structure and relocate to rural areas with rather low labor costs and less population density, but with access to this kind of workforce.

¹³Note that we include these variables as levels of origin and destination district.

6.4 Robustness analysis

This section presents the results of our robustness analysis. The aim is to show how our main results change when we alter the applied method. Instead of poisson regression, we apply negative binomial regressions and hurdle models. Negative binomial regressions (NegBin) are estimation techniques of count data models that take overdispersion into account. There are two types of assumptions that can be applied: firstly, $Var(y|x) = (1 + \eta^2)E(y|x)$, which is known as the NegBin I assumption, and secondly, $Var(y|x) = E(y|x) + \eta^2[E(y|x)]$, which is known as the NegBin II assumption (Wooldridge, 2010, ch.18).¹⁴ Since we have substantial overdispersion in our data, it might be sensible to pursue a negative binomial regression approach.

As an additional robustness check, we apply hurdle models. Hurdle models account for excessive amounts of zeros in the data and assume two independent processes underlying the data generating process. The first process is if a unit of observation ever had a positive count or not, while the second process is how many positive counts a unit of observation had, conditional on the count being positive (see Heilbron (1994) and Feng (2021) for an overview and Prümer and Schnabel (2019) for an application). Therefore, the parameters of two models are estimated: a logit model with a binary outcome variable and a poisson model for all positive relocation counts. The rationale for the use of this method for our study is that most district-pairs do not exhibit a single positive relocation count. It is very plausible that an establishment located in the northern part of Germany will never move to a district, located in the south-west of Germany. Hence, we argue that there might be two processes: first, if a district-pair ever exhibits a positive count and second, how many relocations can be observed, given that the count is positive.

We present the results of our robustness exercises in Table 6 for all moves and moves to a major city and in Table 7 for moves to an urban and rural district. The first column shows the results already displayed in Table 5. As can be seen, the results for the negative binomial regressions in the second and third column, are very similar to the results from the poisson regressions. A difference is that the coefficients from these regressions are partly estimated with greater precision. However, our main findings can be confirmed. High differences in population density and, for moves to urban and rural districts, the scaling factors of the business tax, are positively associated with the relocation flow between two districts. This can only partly be confirmed with the hurdle models, where, for instance, the coefficients of the scaling factors for the moves to urban and rural districts are not always statistically significant. Also, the hurdle models provide inconclusive results regarding the impact of population density for the moves to major cities (this can be seen in columns 4 and 5 of the lower part of Table 6).

¹⁴The parameter η^2 represents the variance of the unobserved heterogeneity component c_i ; $Var(c_i) = \eta^2$ (Wooldridge, 2010).

	(1)	(2)	(3)	(4)	(5)
	Poisson	NegBin I	NegBin II	Hurdle model	Hurdle mode
All moves				(1st stage)	(2nd stage)
Differences (origin-destination)					
House purchase price index	0.0002	0.0001	-0.0001	-0.0001	-0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Herfindahl-Hirschman Index	-0.0001	-0.0001	-0.0001	-0.0001	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average gross monthly wages	0.0001	0.0001	0.0001	0.0001^{**}	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP per capita	-0.0004	-0.0008	-0.0007	-0.0018*	-0.0005
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)
Population density	0.0000	0.0000	0.0000	-0.0000	0.0001
1	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average scaling factor	0.0008^{*}	0.0007*	0.0007**	0.0006***	0.0006
of business tax	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
R^2	0.6103	0.3662	0.3838	0.4070	0.2977
N	2,073,206	2,073,206	2,073,206	2,073,206	47,713
	(1)	(2)	(3)	(4)	(5)
	Poisson	NegBin I	NegBin II	Hurdle mode	Hurdle mode
Moves to major city				(1st stage)	(2nd stage)
Differences (origin-destination)					
Differences (origin-destination) House purchase price index	-0.0005	-0.0004	-0.0001	0.0003	-0.0003
-	-0.0005 (0.001)	-0.0004 (0.001)	-0.0001 (0.001)	0.0003 (0.001)	-0.0003 (0.001)
-					
House purchase price index	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
House purchase price index	(0.001) 0.0001	(0.001) 0.0001	(0.001) 0.0001	(0.001) 0.0000	(0.001) -0.0001
House purchase price index Herfindahl-Hirschman Index	(0.001) 0.0001 (0.000)	(0.001) 0.0001 (0.000)	(0.001) 0.0001 (0.000)	(0.001) 0.0000 (0.000)	(0.001) -0.0001 (0.000)
House purchase price index Herfindahl-Hirschman Index	(0.001) 0.0001 (0.000) -0.0000	(0.001) 0.0001 (0.000) -0.0001	(0.001) 0.0001 (0.000) -0.0001	(0.001) 0.0000 (0.000) -0.0000	(0.001) -0.0001 (0.000) -0.0001
House purchase price index Herfindahl-Hirschman Index Average gross monthly wages	(0.001) 0.0001 (0.000) -0.0000 (0.000)	(0.001) 0.0001 (0.000) -0.0001 (0.000)	(0.001) 0.0001 (0.000) -0.0001 (0.000)	(0.001) 0.0000 (0.000) -0.0000 (0.000)	(0.001) -0.0001 (0.000) -0.0001 (0.000)
House purchase price index Herfindahl-Hirschman Index Average gross monthly wages GDP per capita	(0.001) 0.0001 (0.000) -0.0000 (0.000) -0.0020	(0.001) 0.0001 (0.000) -0.0001 (0.000) -0.0011	(0.001) 0.0001 (0.000) -0.0001 (0.000) -0.0005	(0.001) 0.0000 (0.000) -0.0000 (0.000) -0.0000	(0.001) -0.0001 (0.000) -0.0001 (0.000) 0.0048
House purchase price index Herfindahl-Hirschman Index Average gross monthly wages	(0.001) 0.0001 (0.000) -0.0000 (0.000) -0.0020 (0.003)	(0.001) 0.0001 (0.000) -0.0001 (0.000) -0.0011 (0.003)	(0.001) 0.0001 (0.000) -0.0001 (0.000) -0.0005 (0.002)	(0.001) 0.0000 (0.000) -0.0000 (0.000) -0.0000 (0.002)	$\begin{array}{c} (0.001) \\ -0.0001 \\ (0.000) \\ -0.0001 \\ (0.000) \\ 0.0048 \\ (0.003) \\ -0.0001^* \end{array}$
House purchase price index Herfindahl-Hirschman Index Average gross monthly wages GDP per capita Population density	(0.001) 0.0001 (0.000) -0.0000 (0.000) -0.0020 (0.003) 0.0001**	(0.001) 0.0001 (0.000) -0.0001 (0.000) -0.0011 (0.003) 0.0001*	(0.001) 0.0001 (0.000) -0.0001 (0.000) -0.0005 (0.002) 0.0001**	(0.001) 0.0000 (0.000) -0.0000 (0.000) -0.0000 (0.002) 0.0000	$\begin{array}{c} (0.001) \\ -0.0001 \\ (0.000) \\ -0.0001 \\ (0.000) \\ 0.0048 \\ (0.003) \end{array}$
House purchase price index Herfindahl-Hirschman Index Average gross monthly wages GDP per capita Population density Average scaling factor	(0.001) 0.0001 (0.000) -0.0000 (0.000) -0.0020 (0.003) 0.0001** (0.000) -0.0002	(0.001) 0.0001 (0.000) -0.0001 (0.000) -0.0011 (0.003) 0.0001* (0.000) -0.0002	(0.001) 0.0001 (0.000) -0.0001 (0.000) -0.0005 (0.002) 0.0001** (0.000) 0.0001	(0.001) 0.0000 (0.000) -0.0000 (0.000) (0.002) 0.0000 (0.000) -0.0001	$\begin{array}{c} (0.001) \\ -0.0001 \\ (0.000) \\ -0.0001 \\ (0.000) \\ 0.0048 \\ (0.003) \\ -0.0001^* \\ (0.000) \\ -0.0007 \end{array}$
House purchase price index Herfindahl-Hirschman Index Average gross monthly wages GDP per capita Population density	(0.001) 0.0001 (0.000) -0.0000 (0.000) -0.0020 (0.003) 0.0001** (0.000)	(0.001) 0.0001 (0.000) -0.0001 (0.000) -0.0011 (0.003) 0.0001* (0.000)	(0.001) 0.0001 (0.000) -0.0001 (0.000) -0.0005 (0.002) 0.0001** (0.000)	(0.001) 0.0000 (0.000) -0.0000 (0.000) -0.0000 (0.002) 0.0000 (0.000)	$\begin{array}{c} (0.001) \\ -0.0001 \\ (0.000) \\ -0.0001 \\ (0.000) \\ 0.0048 \\ (0.003) \\ -0.0001^* \\ (0.000) \end{array}$

Table 6: Results of robustness analysis for all moves and moves to a major city

Notes: Robust standard errors clustered on the district-pair level are displayed in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1 indicate the significance levels. Additional controls, metropolitan area dummies, East-West dummies, and year dummies included in every specification. Observation period: 2008-2020.

	(1)	(2)	(3)	(4)	(5)
	Poisson	NegBin I	NegBin II	Hurdle mode	Hurdle model
Moves to urban district				(1st stage)	(2nd stage)
Differences (origin-destination)					
House purchase price index	0.0012	0.0012*	0.0005	0.0008*	-0.0001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Herfindahl-Hirschman Index	0.0000	0.0000	0.0000	0.0001	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average gross monthly wages	0.0002	0.0002	0.0001	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP per capita	-0.0025	-0.0029	-0.0027	-0.0058***	-0.0024
• •	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Population density	0.0001**	0.0001***	0.0001***	0.0001***	0.0002***
1	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average scaling factor	0.0017**	0.0016**	0.0011***	0.0004	0.0013*
of business tax	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
R^2	0.6443	0.3750	0.3910	0.4078	0.3683
Ν	689,605	689,605	689,605	689,605	18,686
	(1)	(2)	(3)	(4)	(5)
	Poisson	NegBin I	NegBin II	Hurdle mode	Hurdle mode
Moves to rural district				(1st stage)	(2nd stage)
Differences (origin-destination)					
House purchase price index	0.0007	0.0004	-0.0003	-0.0010**	-0.0009
House purchase price index	0.0007 (0.001)	0.0004 (0.001)	-0.0003 (0.000)	-0.0010** (0.000)	-0.0009 (0.001)
House purchase price index Herfindahl-Hirschman Index					
	(0.001) -0.0001	(0.001) -0.0001	(0.000) -0.0001	(0.000) -0.0001	(0.001) -0.0001
Herfindahl-Hirschman Index	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
	(0.001) -0.0001 (0.000) 0.0002*	(0.001) -0.0001 (0.000) 0.0002*	(0.000) -0.0001 (0.000) 0.0003****	(0.000) -0.0001 (0.000) 0.0003***	(0.001) -0.0001 (0.000) 0.0001
Herfindahl-Hirschman Index Average gross monthly wages	(0.001) -0.0001 (0.000)	(0.001) -0.0001 (0.000)	(0.000) -0.0001 (0.000)	(0.000) -0.0001 (0.000)	(0.001) -0.0001 (0.000)
Herfindahl-Hirschman Index	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0013	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0014	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0007	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0016	(0.001) -0.0001 (0.000) 0.0001 (0.000) 0.0022
Herfindahl-Hirschman Index Average gross monthly wages GDP per capita	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0013 (0.003)	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0014 (0.003)	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0007 (0.002)	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0016 (0.002)	$\begin{array}{c} (0.001) \\ -0.0001 \\ (0.000) \\ 0.0001 \\ (0.000) \\ 0.0022 \\ (0.003) \end{array}$
Herfindahl-Hirschman Index Average gross monthly wages	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0013 (0.003) 0.0002***	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0014 (0.003) 0.0001***	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0007 (0.002) 0.0001**	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0016 (0.002) 0.0001**	(0.001) -0.0001 (0.000) 0.0001 (0.000) 0.0022 (0.003) 0.0001***
Herfindahl-Hirschman Index Average gross monthly wages GDP per capita Population density	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0013 (0.003) 0.0002*** (0.000)	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0014 (0.003) 0.0001**** (0.000)	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0007 (0.002) 0.0001** (0.000)	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0016 (0.002) 0.0001** (0.000)	$\begin{array}{c} (0.001) \\ -0.0001 \\ (0.000) \\ 0.0001 \\ (0.000) \\ 0.0022 \\ (0.003) \\ 0.0001^{***} \\ (0.000) \end{array}$
Herfindahl-Hirschman Index Average gross monthly wages GDP per capita Population density Average scaling factor	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0013 (0.003) 0.0002*** (0.000) 0.0017*	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0014 (0.003) 0.0001*** (0.000) 0.0016*	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0007 (0.002) 0.0001** (0.000) 0.0015***	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0016 (0.002) 0.0001** (0.000) 0.0015***	(0.001) -0.0001 (0.000) 0.0001 (0.000) 0.0022 (0.003) 0.0001*** (0.000) 0.0004
Herfindahl-Hirschman Index Average gross monthly wages GDP per capita Population density	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0013 (0.003) 0.0002*** (0.000)	(0.001) -0.0001 (0.000) 0.0002* (0.000) 0.0014 (0.003) 0.0001**** (0.000)	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0007 (0.002) 0.0001** (0.000)	(0.000) -0.0001 (0.000) 0.0003*** (0.000) -0.0016 (0.002) 0.0001** (0.000)	$\begin{array}{c} (0.001) \\ -0.0001 \\ (0.000) \\ 0.0001 \\ (0.000) \\ 0.0022 \\ (0.003) \\ 0.0001^{***} \\ (0.000) \end{array}$

Table 7: Results of robustness analysis for moves to urban and rural district

Notes: Robust standard errors clustered on the district-pair level are displayed in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1 indicate the significance levels. Additional controls, metropolitan area dummies, East-West dummies, and year dummies included in every specification. Observation period: 2008-2020.

7. Conclusion

In this paper we analyze establishment-level and regional-level patterns of firm mobility in Germany, making use of relocations of German establishments. To this end, we first present descriptive evidence of firm mobility patterns in Germany. We document that roughly 3.5%

of German establishments relocated at least once during their lifetime and that the number of relocating establishments increased during the past 20 years. Further, regional patterns of establishment relocations reveal that districts that are major, mostly metropolitan, cities experience substantial net outflows of relocating establishments while the surrounding urban districts experience substantial net inflows. Hence, we can document a sub-urbanization of the establishment landscape in Germany: relocating establishments rather leave large metropolitan cities and locate in close urban districts.

For our second contribution, we study establishment-level determinants of a relocation decision by applying Cox proportional hazard models. We make use of our rich administrative dataset and include various covariates, such as firm size, industry affiliation, wage level, and employment composition regarding skill, occupation, gender, nationality, and age. Considering the regional patterns we unearthed in the descriptive analysis, we are interested in the heterogeneity regarding the urban structure the establishments relocate to and estimate the parameter vectors for moves to major cities, moves to urban districts, and moves to rural districts. Our results reveal that there is a firm size gradient in the relocation propensities in the form of an inverse U. Middle-sized establishments (20-49 employees) exhibit the highest propensities to move. In terms of the wage level, we find differences depending on the direction of the moves: while for establishments moving to major cities, the relocation propensities (substantially) increase with their wage level, the opposite is true for establishments moving to rural areas. Another finding is that establishments with a high knowledge intensity (as measured by the share of high-skilled workers) are more likely to relocate, this again is particularly true for establishments moving to a major city. Further, a high share of managers within an establishment increases the probability of relocating.

Finally, we turn to the regional side and study regional-level determinants of firm mobility. Therefore, we constructed a bilateral panel, containing the relocation flows between every district-pair in a given year. In our econometric analyses, we then apply Poisson regressions to connect the number of relocating establishments between a district-pair to their differences in various regional characteristics. Our estimations reveal that both the average scaling factor of the local business tax (proxying for the location-specific tax burden of establishments) and the population density have an impact on the number of relocating establishments between the two districts. Establishments that move to urban or rural districts seek districts with comparably (compared to their old district) low tax burdens, while establishments of all moving types seek districts with comparably low population densities. These findings suggest that the tax burdens represent crucial considerations in the relocation decision and optimization process of firms. In addition, establishments are rather attracted by regions that are less densely populated, which could indicate the search for more space and less congestion instead of the search for high agglomeration externalities. In contrast, we do not find evidence in favor of Duranton and Puga (2001), who predict relocation flows going from diversified to specialized districts. Quite

surprisingly, our results also do not support the notion that establishments seek regions with lower housing price levels. In all specifications, we find that the physical distance, which often is seen as a proxy for relocation costs, is negatively related to the relocation intensities between the two districts.

In summary, this study gives new and comprehensive insights about patterns of firm mobility in Germany. However, it is not straightforward to use these findings for clear-cut policy recommendations. Firm mobility can be a good thing as it is a potential source of factor reallocation and firm dynamics across regions that could lead to a more equal distribution of economic activity across space. From a firm dynamics perspective, relocations might accelerate an "up or out" dynamic when a relocation is a necessary condition for the future profitability of a firm. However, if firms relocate "too often" for external reasons, such as the tax burden, this might result in market inefficiencies and high macroeconomic adjustment costs since relocations are costly. Future research could address these questions by examining how relocation patterns shape the distribution of economic activity across space as well as the regional distribution of firm dynamics.



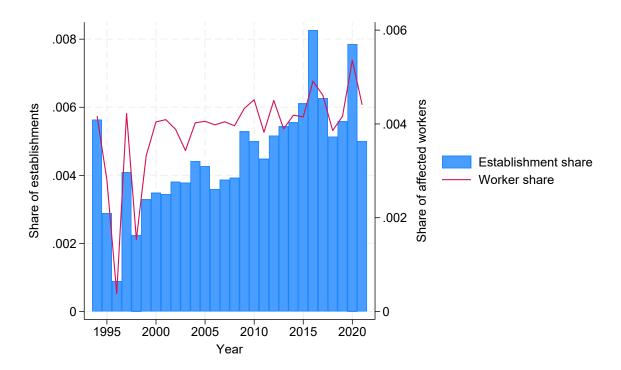


Figure A.1: Proportion of relocating establishments and relocating workers per year

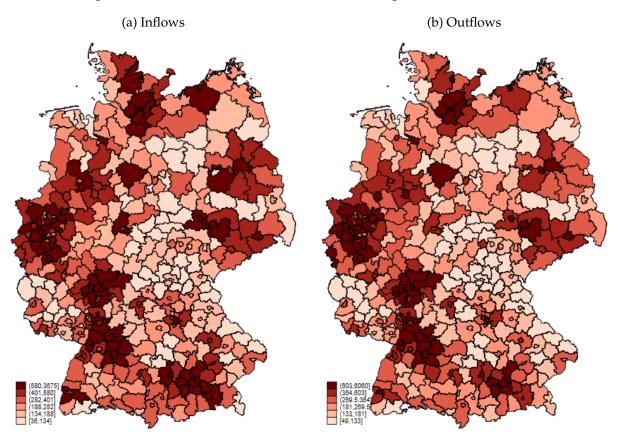


Figure A.2: Establishment inflows and outflows per districts, 1994-2021

Figure A.3: Establishment relocations by industry, 1994-2021



Rank	District	Net flows	District	Net flows
	Lowest net flows		Highest net flows	
1	Munich City	-2385	Munich district	1004
2	Hamburg City	-1437	Mettmann (near Düsseldorf)	428
3	Berlin City	-998	Stormarn (near Hamburg)	371
4	Frankfurt City	-864	Rostock district	349
5	Cologne City	-668	Segeberg (near Hamburg)	344
6	Stuttgart City	-641	Rhein-Erft-Kreis (near Cologne)	334
7	Düsseldorf City	-603	Leipzig district	333
8	Nuremberg City	-463	Rhein-Sieg-Kreis (near Bonn)	300
9	Bonn City	-336	Wesel (near Ruhr area)	283
10	Essen City	-301	Augsburg district	282

Table A.1: Lowest and highest net flows, by district

Variable	Description	Origin
House purchase price index	Regional Real Estate Price Index for house purchase	RWI-GEO-REDX database
Local business tax rate	Average scaling factors of the local business tax rate	Federal and state statistical
		offices of Germany
Herfindahl-Hirschman-Index	Concentration of the regional industry structure: ¹	BHP
	$HHI_r = \sum_{i=1}^n p_{ir}^2$, with $p_{ir} = \sum_{i=1}^n x_{ir}$	
Population density	Population per km^2	INKAR
Average wages	Gross monthly earnings of employees in euros ²	INKAR
GDP per capita	Gross domestic product in ℓ 1,000 per inhabitant	INKAR
Distance	Linear distance in kilometers ³ (as the crow flies)	Own calculations with the
		spdistance command in Stata
		GPOP database (coordinates of German municipalities)
Regional employment shares	Employment shares of high-skilled, low-skilled, female, young, and German workers;	BHP
	Share of workers employed in manufacturing and service sector	
	Share of workers employed in entering and exiting establishments	
Average establishment size	Average employment levels of establishments, considering all employees	BHP
Average establishment age		BHP
Number of existing establishments	Count of the total number of existing establishments	BHP
Share of young population	Share of residents aged 18 to under 25 of the population	INKAR
Unemployment rate	Unemployed as a percentage of the civilian labor force	INKAR
Value added tax	Value added tax per inhabitant	INKAR
Corporate bankcruptcies	Requested corporate insolvency proceedings per 1,000 companies	INKAR
Universities	Presence of at least one public university	Hochschulkompass
Technical universities	Presence of at least one public technical university	Hochschulkompass
¹ based on the WZ 1993 3-digit classification ² including civil servants, judges, and soldien ³ based on the coordinates of the most popul	¹ based on the WZ 1993 3-digit classification ² including civil servants, judges, and soldiers; excluding self-employed and freelancers ³ based on the coordinates of the most populated municipality (in the year 2019) of each district	

Table A.2: Variable description

Dep. var.: Number of relocations	(1)	(2)	(3)	(4)
	All	To major	To urban	To rural
		city	district	district
House purchase price index, orig	0.0008	0.0006	0.0003	0.0027***
	(0.001)	(0.001)	(0.001)	(0.001)
House purchase price index, dest	0.0005	0.0010	-0.0015	0.0014^{*}
	(0.001)	(0.001)	(0.001)	(0.001)
Herfindahl-Hirschman Index, orig	0.0003**	0.0005***	0.0002	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
Herfindahl-Hirschman Index, dest	0.0004^{***}	-0.0000	0.0002	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Average gross monthly wages, orig	-0.0002*	-0.0005**	0.0001	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Average gross monthly wages, dest	-0.0004***	-0.0006**	-0.0003*	-0.0003*
	(0.000)	(0.000)	(0.000)	(0.000)
GDP per capita, orig	0.0064^{***}	0.0038	0.0014	0.0036
	(0.002)	(0.004)	(0.004)	(0.003)
GDP per capita, dest	0.0084^{***}	0.0097**	0.0103**	0.0092
	(0.003)	(0.005)	(0.005)	(0.006)
Population density, orig	0.0001***	0.0001***	0.0001**	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Population density, dest	0.0001**	0.0000	0.0000	0.0003*
	(0.000)	(0.000)	(0.000)	(0.000)
Average scaling factor business tax, orig	0.0004	-0.0001	0.0015**	0.0007
	(0.001)	(0.001)	(0.001)	(0.001)
Average scaling factor business tax, dest	-0.0010*	0.0001	-0.0016*	-0.0033***
	(0.001)	(0.001)	(0.001)	(0.001)
Additional Controls	Yes	Yes	Yes	Yes
Metropolitan area dummies	Yes	Yes	Yes	Yes
East-West dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	-18.5822***	-26.9407***	-13.9745***	-13.8331***
	(1.581)	(4.106)	(2.384)	(2.154)
R^2	0.6141	0.6328	0.6462	0.5416
N	2,073,206	347,395	689 <i>,</i> 605	1,036,206

Table A.3: Estimation results of baseline specification: Poisson regression with variables in levels

Notes: Robust standard errors clustered on the district-pair level are displayed in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1 indicate the significance levels. Observation period: 2008-2020. Orig refers to the origin districts and dest refers to the destination districts.

Dep. var.: Number of relocations	(1)	(2)	(3)	(4)
	All	To major	To urban	To rural
		city	district	district
Differences (origin-destination)				
House purchase price index	0.0002	-0.0005	0.0012	0.0007
	(0.000)	(0.001)	(0.001)	(0.001)
Herfindahl-Hirschman Index	-0.0001	0.0001	0.0000	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Average gross monthly wages	0.0001	-0.0000	0.0002	0.0002^{*}
	(0.000)	(0.000)	(0.000)	(0.000)
GDP per capita	-0.0004	-0.0020	-0.0025	0.0013
	(0.002)	(0.003)	(0.003)	(0.003)
Population density	0.0000	0.0001**	0.0001**	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Average scaling factor business tax	0.0008^{*}	-0.0002	0.0017**	0.0017^{*}
	(0.000)	(0.001)	(0.001)	(0.001)
Share of young population (18-25)	0.0221	-0.0461**	0.0583**	0.0517**
	(0.017)	(0.023)	(0.024)	(0.025)
Unemployment rate	0.0097	0.0003	0.0087	-0.0198
	(0.009)	(0.013)	(0.014)	(0.012)
Value added tax revenue	0.0003	-0.0004	-0.0019	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Corporate bankruptcies	-0.0005	0.0126**	-0.0019	-0.0104
	(0.004)	(0.006)	(0.005)	(0.007)
Share high-skilled workers	0.0013	0.0289***	-0.0054	-0.0044
	(0.005)	(0.009)	(0.008)	(0.009)
Share low-skilled workers	-0.0040	-0.0041	0.0129	-0.0091
	(0.009)	(0.014)	(0.013)	(0.012)
Share female workers	0.0056	-0.0043	0.0184***	-0.0028
	(0.005)	(0.009)	(0.007)	(0.007)
Share German workers	-0.0021	-0.0148	0.0059	0.0136
	(0.006)	(0.010)	(0.008)	(0.008)
Share young workers (under 30)	-0.0029	-0.0037	-0.0099	-0.0066
	(0.007)	(0.011)	(0.011)	(0.011)
Manufacturing employment share	0.0044	-0.0175	0.0130**	0.0070
-	(0.006)	(0.012)	(0.007)	(0.008)
Service employment share	0.0026	-0.0104	0.0075	0.0076
	(0.006)	(0.012)	(0.007)	(0.008)
Employment share in entering est.	-0.0189	-0.0033	0.0035	-0.0147

Table A.4: Estimation results of baseline specification with all control variables: Poisson regressions

Same state (ves)	. ,	, ,	, ,	. ,
Neighboring district (yes)	1.5838*** (0.053)	1.2385*** (0.092)	1.6813*** (0.091)	1.7271*** (0.075)
Neighboring district (ves)	(0.036) 1.5838***	(0.045) 1.2385***	(0.065) 1.6813***	(0.043) 1.7271***
Distance (logs)				
	(0.030)	(0.060)	(0.052)	(0.059)
Number of establishments, in logs (dest)				
Number of establishments, in logs (dest)	, ,	, ,	, ,	0.7075***
	, ,	, ,	, ,	
	, ,	, ,	, ,	
	(0.031)	(0.044)	(0.044)	(0.050)
number of establishments, in logs (orig)				
Number of establishments, in logs (orig)	0.8088***	0.9876***	0.7578***	0.6877***
Number of establishments, in logs (orig)		, ,		
Number of establishments in lass (setablish	(0.046)	(0.092)	(0.065)	(0.089)
Number of establishments in loss (orig)		, ,		
Number of establisher on to in large (with)		, ,		
Number of establisher anter in lang (art)		, ,		
Number of establishments in loss (orig)		, ,		
Number of establishments, in logs (orig)	0.8088***	0.9876***	0.7578***	0.6877***
Number of establishments, in logs (orig)				
valuet of establishments, in logs (ong)				
			(0.044)	(0.050)
	(0.031)	(0.044)	(0.044)	(0.050)
	, ,	, ,	, ,	
Number of establishments in logs (dest)	, ,	, ,	, ,	
Number of establishments, in logs (dest)	0.8553***	1.1049***	0.6184***	0.7075***
(under of composition of the logs (uest)				
	(0.030)	(0.060)	, ,	(0.059)
	, ,	, ,	, ,	. ,
Distance (locs)	, ,	, ,	, ,	. ,
Distance (logs)	-1.1146***	-1.0746***	-1.1625***	-1.2607***
Distance (logs)	-1.1146***	-1.0746***	-1.1625***	-1.2607***
Distance (1023)				
~	(0.036)	(0.045)	(0.065)	(0.043)
	(0.036)	(0.045)	(0.065)	(0.043)
Neighboring district (ves)				
Neighboring district (yes)				
	(0.053)	(0.092)	(0.091)	(0.075)
	. ,	, ,	, ,	. ,
Same state (yes)	0.9386***	1.0112***	0.7977***	0.8630***
Sume state (yes)				
	(0.051)	(0.076)	(0.088)	(0.052)
Destination district=metropolitan region	-0.1631	-0.2946**	-0.1635 -0.2434	, ,
Desunation district=metropolitan region				
	(0.137)	(0.136)	(0.141)	(0.238)
Wast to East Cormany (rof : Wast Wast)	, ,			
West to East Germany (ref.: West-West)	-0.1190	0.2647	-0.8071***	-0.4793***
	(0.101)	(0.187)	(0.180)	(0.119)
Fact to Fact Commons	. ,	, ,	, ,	, ,
East to East Germany	-0.0561	0.0368	0.0354	-0.2737**
	(0.099)	(0.223)	(0.165)	(0.133)
East to West Commence	, ,	, ,		, ,
East to West Germany	0.1004	-0.1221	0.2841**	0.0690
	(0.094)	(0.163)	(0.134)	(0.139)
Constant				
Constant	-12.2705***	-15.3843***	-9.7619***	-9.4686***
	(0.394)	(0.561)	(0.621)	(0.484)
p?		, ,		. ,
R^2	0.6103	0.6294	0.6443	0.5368
Ν	2,073,206	347,395	689,605	1,036,206

Notes: Robust standard errors clustered on the district-pair level are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1 indicate the significance levels. Observation period: 2008-2020.

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