Commuting behavior of employees in Germany with a focus on georeferenced data

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vorgelegt von:
Ramona Jost

Berichterstatter: Prof. Dr. Dr. h.c. Joachim Möller
Prof. Dr. Wolfgang Dauth

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Chapter 1

Introduction

New productive techniques and the increase in welfare resulted in the spatial separation of work and residence locations. In particular, in order to benefit from agglomeration effects like knowledge spillover, availability of labor and the proximity to suppliers, firms in the same industry often locate together at the same place (Rosenthal, 2004; Krugman, 1991). However, space near this concentration of employment is limited, which means that not all workers can live close to their jobs. To overcome this spatial separation of residence and workplace, individuals have to commute, because commuting provides the opportunity to link both locations (Lux and Sunega, 2012; Zabel, 2012).

In general, commuting is considered to be a burden as commuting costs money, takes time, causes stress and has a negative effect on the well-being and health of individuals (Frey and Stutzer, 2007; Hansson et al., 2011; Künn-Nelen, 2016). Nevertheless, commuting is associated with a lot of benefits. For individuals, increased mobility leads to better labor accessibility and to better job and career opportunities. Additionally, commuting offers some flexibility as individuals can change jobs while staying in the same house without the need to move. This prevents people from having to pay high relocation costs and from having to give up their familiar surroundings and family ties (Rouwendal, 2004; Cameron and Muelbauer, 1998; Bergantino and Madio, 2018).
On the individual level, commuting therefore has two sides: individuals might dislike commuting, but at the same time appreciate the job opportunities of far away jobs. Thus, for the decision to commute and for the intensity of commuting, individuals need to balance the costs and benefits of commuting. In this context, previous studies find profound differences between individuals' commutes. In particular, research shows that commuting is higher for males and for workers with a higher income as well as for home owners. The same applies to workers who are older, work in specific occupations and qualification levels (Giménez-Nadal et al., 2020; Ross and Zenou, 2008; Dargay and Clark, 2012; Hanson and Johnston, 1985). At the same time, empirical evidence indicates that individuals want to be compensated for the

disutility of commuting either by cheaper housing prices or higher wages (Van Ommeren et al., 2000; Van Ommeren, 2005; Zax, 1991). This allows all workers to reach the same utility level although they face different intensities of commuting (Rouwendal, 2021).

In addition to the benefits for workers, employers can profit from higher mobility. Higher worker mobility provides firms' access to both more labor overall and to more specialized labor. Thus, higher mobility can contribute to a better and more efficient matching of local demand and supply of labor. This enhances productivity and can reduce disparities between labor markets (Rice et al., 2006; Buch et al., 2009). From an economic perspective, commuting is therefore essential for a well-functioning labor market.

1.1 Commuting in Germany

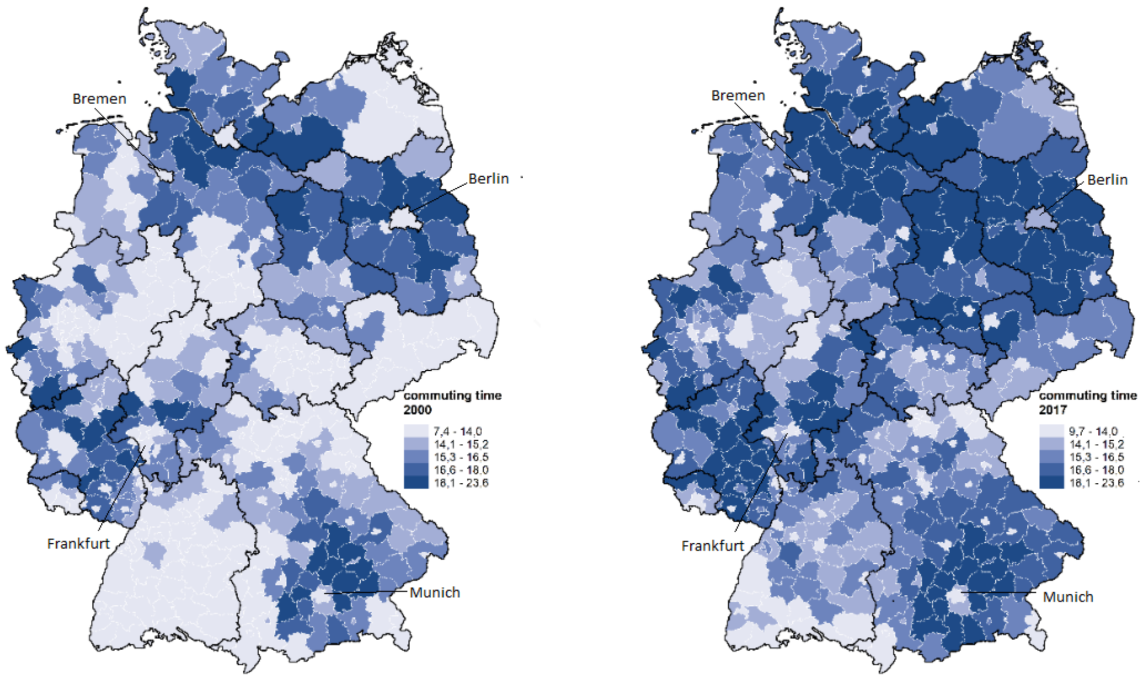
Prior research document increasing trends in commuting in developed countries in recent years (Rouwendal and Rietveld, 1994; Kirby and LeSage, 2009; Giménez-Nadal et al., 2018*a*; Susilo and Maat, 2007; Giménez-Nadal et al., 2014). In Germany, the commuting distance has increased from 14.8 kilometer in 2000 to 17 kilometers in 2018.[1] This can also be observed comparing both maps in Figure 1.1, where I calculated the average commuting time for each NUTS-3 region in Germany for the year 2000 and 2017. Comparing the two maps shows that the commuting times increased substantially. Many factors contribute to this development, including the rising labor market participation of women, higher education levels, greater specialization among workers, improved infrastructure, the availability of faster travel modes, lower migration propensity and the suburbanisation of the population in urban areas (Rouwendal, 1998, 1999).

Commuting is also not the same everywhere: commuting is higher in suburban and rural areas than in urban regions. This can be observed in Figure 1.1, where workers living in metropolitan cities like Munich, Berlin, Frankfurt or Bremen, have shorter average commuting times than those in the surrounding regions. In particular, while the average commuting time in urban areas ranges between 11 and 19 minutes, employees from the surrounding regions commute up to 29 minutes to work. This implies that workers who live in large cities are most likely to work there as well, while those living in the suburbs commute from the surrounding regions into the city center to work.

In addition, average commuting times seem to vary between federal states, especially the northern states of Germany show on average higher commuting times. Those regions of Brandenburg and Mecklenburg-Vorpommern (MV) are characterized by less urbanised regions with less employment opportunities and lower wages. Workers living in those rural areas might therefore search in more centralized areas for jobs where they benefit from a wide array of job possibilities (Klärer and Knabe, 2019; McGranahan, 1988). As a consequence, workers who live in rural areas face longer commuting trips to work than workers in

[1] See `https://www.thelocal.de/20200207/why-are-more-and-more-people-in-germany-commuting-to-work`.

Figure 1.1: Regional distribution of the commuting time in the year 2000 and 2017



Notes: The map shows the mean commuting time of workers place of residence by NUTS-3 regions in manually chosen time categories. Source: Own calculation and presentation.

urban areas (Alonso, 1964; Wang, 2001).

This phenomenon, in which people commute from one region to another, known as inter-regional commuting, has attract much attention in recent years. For example, in Germany, the number of workers leaving their communities to work has increased from 14.8 million in 2000 to 19.3 million in 2018, which is nearly half of the entire German labor force.[2] The explanation for this increase in inter-regional commuting trips can be seen as a reduced propensity to relocate.[3] The reason is that commuting provides a valuable alternative to relocation, as it offers access to employment opportunities in a larger geographic labor market without forcing people to leave their familiar surroundings and family ties (Green et al., 1999; Van Ham, 2002).

Commuting is thus becoming increasingly important in Germany as it continues to rise not only on average but also the number of inter-regional commuting trips increase. It also appears that individuals do not commute the same everywhere. In particular, individuals in rural areas show on average the highest

[2]See `https://www.thelocal.de/20200207/why-are-more-and-more-people-in-germany-commuting-to-work`.
[3]Less than two percent of the population moves from one municipality to another from one year to another (Lundholm, 2007).

commuting times. Therefore, it seems important to include the regional component when studying commuting.

1.2 Contribution to previous literature

Given the fast changes in economies and labor markets becoming more flexible, policies aim to develop measures and instruments that increase the geographic mobility of the workforce, such as tax allowances or investments in transport infrastructure (Krieger and Fernandez, 2006). Increased mobility allows workers to better adapt to these new conditions and to take jobs that are further away from their current place of residence. This improves the match between job vacancies and job searchers by increasing productivity and contributing thus to a sustainable economic growth. In order to identify policies that facilitate commuting, it is necessary to understand the factors that encourage and discourage commuting because commuting decisions are likely to be influenced by a complicated interaction between personal motivations and external conditions.

Numerous research therefore addresses various topics regarding commuting. In particular, a number of studies analyse the willingness to commute in terms of commuting patterns considering differences between men and women, occupation, education level and family situation (Sandow and Westin, 2010; Lee and McDonald, 2003; Hanson and Hanson, 1993; Camstra, 1995; Giménez-Nadal et al., 2020; McQuaid and Chen, 2012; Börsch-Supan, 1990). They find that commuting varies between different sociodempgraphic characteristics. Whereas, studies of job search theory estimate the marginal willingness to pay for commuting (Van Ommeren et al., 2000; Mulalic et al., 2014; Dauth and Haller, 2020; Le Barbanchon et al., 2021; Van Ommeren and Fosgerau, 2009). While models of urban economic theory focus on how urban spatial structure and job-housing balance affect commuting patterns (Lin et al., 2015; Bento et al., 2005; McFadden, 1974).

This cumulative thesis adds to this literature and contributes - with four studies - in several ways.

First, the thesis extends the explanation of the commuting behavior and the commuting decision by a behavioral economic perspective, which I focus on in Chapter 2. Previous research shows that previously observed options can influence individuals' perception and therefore their subsequent decision-making behavior (Simonson and Tveresky, 1992). The consideration of this theory in analysing commuting decisions allows to get a deeper understanding of the commuting behavior and the factors that influence commuting decisions of people.

Recent studies on commuting find that the commuting behavior of workers can be explained by gender, wage, age, education, occupations and household responsibilities (Giménez-Nadal et al., 2018*b*, 2020; Ross and Zenou, 2008; Hanson and Johnston, 1985; Dargay and Clark, 2012; McQuaid and Chen, 2012) and neglect that commuting might also depend on previously observed commuting options. This, however, is an important factor in the analysis of commuting decisions, as the results in Chapter 2 indicate. In particular, workers choose longer commuting times in the region they recently moved to when the average commute in the region they left was longer. Individuals thus behave in such a way that previous observed options influence their current marginal utility when facing commuting decisions. Additionally, the results show that this is only short-lived, as the new options of the new region replace earlier options in their role as background against which options are evaluated. Thus, individual' preferences for commuting can change and depend on the context individuals' observed in the past. These results have important implications for empirical studies - not only in terms of commuting preferences, but also to derive preferences in a number of different areas, such as wage differentials in labor economics or travel costs in environmental economics.

Second, this thesis contributes to the literature on inter-regional as well as on long distance-commuting in Chapter 3 taking a closer look at a particular eastern German region: the Federal State MV.
Many firms in Germany are short of qualified workers, whereby East German regions are particularly affected because of the out-migration to West Germany after the reunification and the aging population. This gives rise to an important debate for regional policy as the shortage of workers is a major challenge for each region and firm. In this context, out-commuters – workers who commute to work in another region – become an important group of employees to potentially satisfy local labor needs. Chapter 3 takes a closer look at out-commuters and analyses what individual and firm characteristics cause individuals to live in MV while working in another region by commuting long distances (Castelli and Parenti, 2020; Parenti and Tealdi, 2019; Sandow and Westin, 2010). Since wages are a key factor why workers commute over long distances (Bergantino and Madio, 2018), we additionally investigate the wage differential between out-commuters and workers who are living and working in MV (home employees). The determination of the factors that explain this wage gap can provide new insights and a deeper understanding of the labor market in MV. This can provide a basis to work out potential strategies to attract the group of out-commuters for a workplace in MV to reduce the complained labor shortage.
We find that out-commuters are typically older and more likely to work as specialists and experts indicating a lack of more advanced jobs in MV. For women however, we additionally find a higher likelihood of being an out-commuter and working in low-skilled jobs. Although the wage of these group of women is less and commuting seems not to be very lucrative they commute out and face high costs of commuting. This is also confirmed analysing the wage gap as men profit more from out-commuting than women.
Our results thus contribute to a diverse debate by showing that men commute out to earn more money, whereas women commute out to find a job in general.

Third, the thesis contributes to the literature on the effects of job displacement on workers' labor market outcomes by shedding a new light on the commuting behavior. Previous studies on job displacement often only focus on the effect on wages and earnings (Jacobson et al., 1993; Davis and von Wachter, 2011; Bertheau et al., 2022) and neglect a significant additional cost factor - the costs of commuting - which is why they underestimate the costs due to job displacement. Chapter 4 therefore focuses on the consequences of job displacement on workers' commuting costs.

To identify the effects of job displacement on commuting, we use an event study design (Jacobson et al., 1993) by comparing the outcomes of workers who are displaced in a mass layoff event with a matched group of non-displaced workers who exhibit similar pre-displacement characteristics. The analysis shows that while wages decrease, workers' commuting distances increase after job displacement. Both negative effects diminish in the long run and recover towards the pre-displacement level. These dynamic effects are driven by workers moving from less to more productive firms and by workers switching from distant to nearby firms rather than relocating their homes.

To rationalize the empirical findings and to quantify the monetary value of increased commuting we build a job search model. With on-the-job search, workers can increase their job match surplus by moving from less to more productive firms and from distant to proximate firms, which explains the empirical findings of joint recovery of wages and commuting after job displacement. In addition, as unemployed workers trade off higher wages and shorter commuting, we exploit this positive correlation to identify workers' willingness-to-pay (WTP) for commuting. Along the reservation wage curve, any change in commuting costs is exactly compensated for by wage changes. Therefore, the slope of the curve identifies workers' WTP for commuting. To quantify the monetary cost of commuting, we structurally estimate the job search model using the simulated method of moments. We find that workers incur an average commuting cost of 18 euros per day, and increased commuting exacerbates the wage losses due to job displacement by 14 percent in total. To understand the overall costs of job displacement it is therefore important to quantify the increased commuting costs in monetary terms as displaced workers suffer not only a wage loss but also face higher commuting costs.

Fourth, Chapter 5 extends the knowledge of the the gender commuting gap in a regional dimension. It is a styled fact that women commute less than men and work closer to home (Madden, 1981; Crane, 2007; Sang et al., 2011). The consequences can be profound: since women restrict themselves to a smaller area than men in their job search, they are in danger of spatial entrapment at their place of residence (England, 1993; Wheatley, 2013) and might therefore benefit less from better jobs and higher wages in other regions (Crane, 2007; Petrongolo and Ronchi, 2020). This might be particularly relevant in rural areas where job opportunities are less and workers have to commute longer distances to work than in urban regions (Rouwendal, 2004; Lin et al., 2015).

While gender differences among commuters are acknowledged not only in general, but also in specific spatial respect, only few studies explicitly examine spatial characteristics of commuting patterns and

investigate simultaneously whether they have diverging effects on men and women (Sang et al., 2011; Bergantino and Madio, 2018). Chapter 5 closes this research gap and analyses the gender commuting gap for rural and urban regions by explicitly considering the place of residence and the place of work. This allows for a comprehensive investigation of women's and men's commuting behaviour between as well as within urban and rural regions, which leads to six-journey to work flows.
The results provide evidence for a triple gap in commuting to the disadvantage of women. The regional disaggregation of the overall gap uncovers two additional gaps that open up between rural and urban commuters on the one hand and between intra- and inter-regional commuters on the other hand. Decomposition results assign the strongest effects on commuting gaps to occupational segregation and the sorting into establishment of different sizes.

Georeferenced data

In addition to the above contributions, this dissertation highlights the importance using appropriate data when studying commuting.
Most existing research analysing commuting uses survey data (Sang et al., 2011; Giménez-Nadal and Molina, 2016; Bergantino and Madio, 2018; Albert et al., 2019) or identifies workers and firms at some regional level (Meekes and Hassink, 2019). This, however, generates serious issues. While survey data cannot represent the population of workers and establishment in a regional perspective as administrative data can, the measurement of commuting distances between regional centers omits commutes within the same region. This leads to a censoring problem where within-regional commuters are assumed to bear zero commuting costs. Further, the distance traveled by individuals rarely coincides with the distance between regional centers. For example, workers living near regional borders could be more likely to commute out of the region.
To overcome this issue, the thesis illustrates that the use of georeferenced administrative data provides substantial advantages over previous approaches. Georeferenced data includes the exact mailing address of individuals and establishments. Thus, for each worker the commuting distance between the exact place of residence and place of work along actual routes can be calculated. This enables to precisely capture workers' commuting patterns, especially for within-city, short-distance commuters (Ostermann et al., 2022).
In particular, investigating individuals' responses to job displacement, the study in Chapter 4 shows that using regional-level data like the shortest distance between two municipalities overstate the causal effect of job displacement by 42 percent in the short run and 13.5 percent in the long run.

In summary, this thesis provides new aspects regarding the commuting decision of people, the differences between men's and women's commuting behavior in a regional perspective, the factors that increase the probability of inter-regional commuting, and the effects of job displacement on commuting. Thereby highlighting the importance to distinguish between urban and rural regions and the necessity of using georeferenced data when analysing commuting.

1.3 Conceptual framework

Until now, there are many theoretical frameworks to study the commuting behavior of individuals. This section presents some theoretical considerations that are relevant and serve as a basis for the empirical approaches of the four studies in this thesis.

Previous studies show that urban spatial structure and the spatial relationship between residence and workplace location are correlated with commuting (McFadden, 1974; Lin et al., 2015; Bento et al., 2005; Rouwendal, 2004; Sandow and Westin, 2010). The first theoretical model that formalises this correlation between housing and jobs is the monocentric city model as conceptualized by Alonso (1964), Muth (1969) and Mills (1972). The monocentric city model offers an equilibrium solution that is remarkably consistent with some important aspects of urban reality. It implies that cities have an unique center – the Central Business District – where all employment is concentrated leading to higher prices in those concentrated areas. Thus, the model assumes a gradual decrease in prices from the center to rural areas. Employees can choose to live either in the center were commuting costs are low and housing costs are high or locate in rural areas with higher commutes but cheaper housing. This implies a negative relationship between commuting and residential density, leading workers to trade-off housing prices against commuting costs (Fujita, 1989). This relationship is not only found by several empirical studies investigating how urban form influences the commuting distance, but also illustrated in Chapter 5. These studies find a significant negative effect of urban density on commuting distances (Grazi et al., 2008; Ewing and Cervero, 2010; Schwanen, 2002; Lin et al., 2015). In addition, the results of Chapter 3 indicate that workers in rural areas commute out of their region and commute over long distances, the reasons for this are fewer job opportunities, especially for high skilled. Rural regions also seem to have greater effects on the commuting time of displaced workers than urban regions. In particular, the results of Chapter 4 show that displaced workers in rural areas have longer commuting times after job displacement than workers in urban regions. Hence, there are major differences between rural and urban regions in terms of commuting.

Additionally, the monocentric city model can be extended towards a polycentric model that considers further centers alongside the central business district. It can explain a variety of commuting flows beyond the monocentric commuting pattern within urban or between rural and urban regions (Gordon et al., 1989; Schwanen et al., 2004; Meijers, 2007). Indeed, for Germany, although Germany has a rather polycentric structure, the monocentric model provides a robust explanation for urbanisation patterns in metropolitan areas, with subcenters being of local relevance only (Krehl, 2018; Schmidt et al., 2021). Related, a further explanation of diversified commuting patterns across space can be deduced from suburbanisation of employment that has led to the emergence of suburban employment centers, thereby changing commuter flows (Heider and Siedentop, 2020).

However, the assumptions of the standard urban model are quite unrealistic as markets are not perfect. Market imperfections are defined as the presence of job and housing relocation costs and the absence of perfect information on job opportunities and available housing. In particular, due to relocation costs, workers are unwilling to change their residence or workplace to reduce commuting (Crane, 1996). This sub optimal combination of home and work location leads to excessive commuting, defined as the difference between actual and theoretical commuting (Hamilton, 1982).

Another anomaly of the standard urban economic theory is that housing prices decline with the distance of residence from the city center. Workers who choose to live outside the city center and bear greater commuting costs are, according to theory, fully compensated by the housing market for these commutes - regardless of wages. However, this form of compensation cannot be found empirically (Dubin and Sung, 1987; Söderberg and Janssen, 2001), as empirical studies show that in a given workplace, the wage might also depend on the place of residence (Zax, 1991).

Many studies try to address these labor market and housing market imperfections. For example, Van Ommeren and Rietveld (2007) consider labor market imperfections, imperfect residential mobility, and wage bargaining by combining urban economics with job search theory. The job search theory, which builds on the work of Stigler (1961, 1962), is one of the main theoretical framework for analysing labor markets by allowing market imperfections, such as moving costs and lack of intimations (Van den Berg and Uhlendorff, 2015). Thus, it avoids some problems associated with the standard urban economic model. In job search models, commuting is incorporated as a source of labor mobility that allows workers to access geographically dispersed labor markets.

According to the standard job search model, an unemployed worker is searching for a new job. Job offers arrive at a constant arrival rate. The jobs offered differ in the net income. Such differences in net income can result from the fact that the same wage is paid in several employment centers, located at different distances from the searchers place of residence. Each time a job offer arrives, the searcher has to decide to accept it or not. Acceptance means the end of the search process; refusal denotes that the search process continues, which usually implies the possibility of a better job offer in the future. Commuting costs are important determinants of workers' behavior: if they are high, individuals may prefer to reject an offer of a far away job in favor of a job around the corner, even if the former job offers a much higher wage. The standard job search model has been extended in many ways: by incorporating on the job search, by adding the demand side, or by considering the heterogeneity of individuals.

The job search model also provides the basis for the analysis in Chapter 4, and, consistent with other empirical research, shows that workers attach great importance to commuting costs when accepting a job (Rouwendal, 1999; Van den Berg and Gorter, 1997; Van Ommeren et al., 2000). Interestingly, these studies show that workers' sensitivity to commuting costs depends on a variety of characteristics. For example, a repeated finding is that women attach a greater weight to commuting distance than men (Rouwendal, 1999; Van den Berg and Gorter, 1997).

Besides gender differences in commuting, previous literature presents that commuting over different distances tends to be dominated by certain groups, which is also shown in the studies of this thesis. In particular, individuals with different sociodemographic characteristics have different preferences and thus vary in terms of commuting distances.

In this context, Ding and Bagchi-Sen (2019) show that some occupations and industry sectors increase the likelihood of commuting longer distances, like working in mining and constructions or in agriculture and transportation sectors.

Another factor that influences the commuting distance is the education level: more educated workers are more mobile (Eliasson et al., 2003; Sandow, 2008; Börsch-Supan, 1990). They have to search longer for jobs because their job market is concentrated to a limited number of locations and are thus not evenly distributed across space (Börsch-Supan, 1990). Moreover, higher educated workers often earn more money which can compensate for higher commuting costs (Dargay and Clark, 2012).

As mentioned before, gender is a significant factor that influence the length of commuting (Madden, 1981; Hanson and Johnston, 1985; McQuaid and Chen, 2012; Dargay and Clark, 2012; Giménez-Nadal et al., 2022). Several determinants have been brought forward to explain this gender gap in commuting. Among individual and sociodemographic factors, differences in age, education, or household responsibilities play a large role. Likewise, job-related factors such as working part-time or in sectors located close to home or earning low wages make commuting long distances less attractive for women (Crane, 2007; Rouwendal, 2004; Giménez-Nadal and Molina, 2016; Bergantino and Madio, 2018; Hanson and Johnston, 1985).

The age level is also seen as a determinant in commuting. Previous studies find differences in the commuting behavior between younger and older workers. Generally, commuting decreases with age, as younger workers need to gain labor market experience (Sandow, 2008). However, there are variations for men and women. For example, Bergantino and Madio (2018) show an inverted U-shaped relation between age and commuting for men, but not for women.

Additionally, the wage might affect individuals' commuting through the trade-off effect, as individuals request wage compensations to work for a more distant employer (Van Ommeren et al., 2000; Laird, 2006).

In summary, commuting is influenced by a variety of factors and markets. Specifically, commuting depends on the housing and the labor market, such as the wage structure of the local labor market combined with accessible and affordable housing. Further, commuting and urban form influence each other: while commuting behavior affects urban development, urban development itself affects commuting. In addition, commuting depends on preferences, and these preferences vary among different sociodemographic groups. Therefore, I attempt to consider all those factors when investigating the commuting behavior of employees in Germany in this thesis.

The following four chapters contain the studies that are designated for publication in scientific journals. A conclusion closes this thesis.

Chapter 2

Persistence of commuting habits: Context effects in Germany

Abstract In this study, I investigate the commuting behavior of workers in Germany. Using comprehensive georeferenced administrative employee and firm data, I can calculate the exact commuting time and the distance between workers' residence and workplace locations. Based on a behavioral economic approach (Simonson and Tveresky, 1992), I show that individual commuting decisions are influenced by wages and individual heterogeneity as well as depending on the context individuals observed in the past. In particular, my results show that previously observed commutes have an impact on subsequent commuting behavior: workers choose longer commuting times in the region they recently moved to when the average commute in the region they left was longer. The results indicate that while selectivity and sorting do not influence the effect of the context, the inclusion of individual fixed effects is crucial.

JEL Classification J60, R10, R19, R23

Keywords commuting, behavioral economics, context effects, movers, georeferenced data, commuting decision

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Acceptance for Publication in The annals of Regional Science

2.1 Introduction

The importance of commuting is growing rapidly– both the number of commuters and the distance they commute are growing steadily (Giménez-Nadal et al., 2014, 2018*a*). From an economic perspective, commuting is essential for a well-functioning labor market as it is an important measure to overcome spatial separations (Lux and Sunega, 2012; Zabel, 2012). At the individual level, commuting implies better labor accessibility and subsequently improves job and career opportunities, leading to better outcomes and improved individual utility. However, commuting also has negative impacts on both the environment and the infrastructure (Brueckner, 2000; Rouwendal and Rietveld, 1994), as well as on individuals' well-being as it is associated with congestion and high costs (Frey and Stutzer, 2007). Understanding the determinants of and the reasons for commuting is thus an important topic for policymakers dealing with economic and labor market issues.

Studies on commuting find different factors and effects that influence individuals' commuting behavior, for example commuting is more common among males and among workers with higher incomes as well as among homeowners. The same applies to workers who are older and work in specific occupations and have specific skill levels (Giménez-Nadal et al., 2020, 2018*b*; Ross and Zenou, 2008; Hanson and Johnston, 1985; Dargay and Clark, 2012; McQuaid and Chen, 2012).

However, individuals' commuting behavior might also be explained from a behavioral economic perspective. In particular, previous research shows that previously observed options can influence individuals' perceptions and therefore their subsequent decision-making behavior (Simonson and Tveresky, 1992). Applied to individuals' commuting behavior this means that previously observed commuting options influence their preferences for commuting and consequently their own commuting decisions. This approach can explain, for example, why individuals who move to Munich commute 30 percent less than the average in Munich if they come from regions with shorter average commuting times, while individuals commute 35 percent more than the average in Munich if they previously lived in regions with longer commuting times than those typical in Munich. This might indicate that commuting decisions are influenced by the context of commuting options observed in the past, such as other individuals' commutes.

This study analyzes such commuting behavior, based on the study conducted by Simonsohn (2006) for the US, and contributes to the literature in at least four ways: first, it contributes to the literature on commuting behavior and the factors that are important for explaining commuting (Giménez-Nadal et al., 2020; Dargay and Clark, 2012; McQuaid and Chen, 2012). In particular, I show that the context of commuting options observed in the past is crucial for analyzing individuals' commuting behavior. In this context I show that the results obtained by Simonsohn (2006) are biased due to the omission of individual fixed effects and the consideration only of migrants between two metropolitan areas. Second, I reveal effects for different groups, discussing effect heterogeneity for age, gender, skill level, as well as rural and urban areas, for an entire country. Third, I use georeferenced employer-employee data. These administrative registry data possesses higher validity than survey data and provides precise information about individuals' residence and workplace locations with a high number of observations. This makes it possible to calculate the exact commuting distance and time for German workers. Fourth, the study contributes to the migration literature (Van Ham and Hooimeijer, 2009; Brueckner and Stastna, 2020; Shuai, 2012). In particular, I show that the greater the difference between a worker's individual commuting time and the average commuting time at their place of residence, the more likely they are to move again.

When individuals choose where to live, they face the difficult decision of how far they are willing to commute, weighing up the benefits and costs of commuting. Advantages of commuting may include cheaper rents and housing prices outside the city center, resulting in a higher disposable income. Furthermore, commuting can provide more job opportunities for individuals who live in rural areas where there may be no or no adequate employment offers. However, commuting also has disadvantages; it takes up time, causes stress, and impacts the reconciliation of work and family. It can therefore have a negative effect on individuals' well-being (Frey and Stutzer, 2007). When deciding how far they wish to commute, individuals have to trade off the benefits with the disutility of commuting. Indeed, costs and benefits do not have the same effect on utility: the response to losses is stronger than the response to the corresponding benefits (loss aversion, Kahneman and Tversky (1979). In the context of commuting decisions, however, Dauth and Haller (2020) find no sign of loss aversion, which contradicts previous experimental evidence (Tversky and Kahneman, 1991).

Empirical evidence from urban economics reveals the disutility of commuting for which individuals wish to be compensated. For the Netherlands, Van Ommeren et al. (2000) and Van Ommeren (2005) find a marginal willingness to pay for an additional kilometer of commuting of 0.15 euros per day or 17 euros for one additional hour of commuting (Van Ommeren and Fosgerau, 2009). With regard to compensation by the employer, Heuermann et al. (2016) find that employers compensate only few employees directly for additional commuting costs. Hence, the decision to commute is mainly an individual one, which can be strongly influenced by prior experiences.

However, individuals are often unable to assess correctly the disutility of commuting and are frequently uncertain about their preferences, which contradicts the standard economic theory (Kahneman and Tversky, 1979). Instead, they form their preferences as and when they are needed, for instance when making choices (Bettman et al., 1998). For example, in the context of commuting decisions, individuals rely on a wide range of possible cues, such as other individuals' commutes. Moreover, in the literature on decision-making (Bettman et al., 1998; Huber et al., 1982) it becomes fundamental that an individual's decision can be influenced by the context: individuals interpret information by comparing it not only to other available options, but also to what was recently observed. According to Hartzmark and Shue (2017), these context effects have the potential to affect a variety of important real-world decisions. They not only distort judicial perceptions of the severity of crimes, leading to unfair sentencing, but also affect employee hiring, medical diagnoses as well as housing and commuting decisions.

The context effect that is relevant for this study is the background context effect, according to which choices depend on options encountered in the past – preferences can change with the history of choices. The intuition behind this is that the same product may seem more attractive against the background of less attractive alternatives and unattractive compared to more attractive alternatives (Simonson and Tveresky, 1992). Simonson and Tveresky (1992) document this effect in an experiment comprising two stages in which subjects have to make choices in sequence. In the first stage, half of the subjects are confronted with two options that have a relative high cost for one attribute, and the other half should make a choice with a relatively low cost for the same attribute. In the second stage, all subjects are confronted with the same choice. In line with the background context effect, subjects who are confronted with a relatively high cost for an attribute in the first stage are more likely to choose the more expensive option in the second stage because it appears cheaper to them.

There is ample evidence of the background context effect. Bhargava and Ray (2014) demonstrate this effect in the context of speed dating. They show that the attractiveness of previous partners reduces the probability of finding a date. Moreover, Hartzmark and Shue (2017) demonstrate that today's earnings impress investors more when previous earnings were poor. Furthermore, Simonsohn and Loewenstein (2006) present the effect with regard to housing choices: individuals who move from cities with relatively high housing costs are more likely to pay higher prices in the new city compared to individuals coming from cities with cheaper markets. Applied to commuting behavior, this means that commuting options encountered by individuals in the past affect their current commuting decisions. However, relatively little research has been conducted into when and why the background context effect influences commuting decisions. The only such study was conducted by Simonsohn (2006). He considers individuals relocating between two metropolitan areas in the US and takes the average commuting time in the previous city as a proxy for commuting options encountered in the past to examine how previously observed commutes influence commuting decisions when moving to a new city. He finds that individuals choose longer commutes in the new city, the longer the average commute was in the city they came from. Commuting decisions are thus influenced by commuting options encountered by individuals in the past, which is in line with the background context effect.

In this study I consider workers who relocate between NUTS-3 regions in Germany and examine the context effect for German workers for an entire country, which is why I deviate from the approach of Simonsohn (2006) and use the average commuting time at the NUTS-3 level for the proxy of commuting options encountered in the past. The results show that individuals coming from backgrounds with longer average commuting times initially choose longer individual commutes in the destination region compared to individuals from regions with shorter average commutes. In contrast to Simonsohn (2006), I additionally differentiate between individuals moving between different region types of rural and urban regions and thus I show that the context effect is strongest for workers who move from rural to urban areas. Further, the robustness checks show that selectivity of a relocation does not influence the effect of the context and I find no evidence of workers selecting themselves into regions because of their taste for commuting. However, my results do indicate that it is very important to control for individual fixed effects. Moreover, I find no sign of stable taste difference as traditional economic theory would suggest.

The remaining paper is structured as follows. Section 2.2 provides the theoretical motivation for the background context effects. Section 2.3 discusses the data and the sample. The identification strategy used is shown in Section 2.4. The empirical results are presented in Section 2.5, and Section 2.6 concludes.

2.2 Theoretical motivation for the Background Context Effects

As empirical evidence shows, decisions are preference-dependent (Bettman et al., 1998; Huber et al., 1982; Hartzmark and Shue, 2017; Bhargava and Ray, 2014; Simonsohn and Loewenstein, 2006). However, these preferences change with previously observed options. As Simonson and Tveresky (1992) demonstrate in their background contrast experiment, individuals' previous experiences influence their perceptions and therefore their subsequent decision-making behavior. For commuting decisions, this implies that commuting options encountered previously affect current commuting preferences and thus individuals' commuting behavior. The following approach is based on this concept, which is also used by Simonsohn (2006). The idea is that the disutility of commuting decreases when a person was only confronted with longer commuting options in the past, whereas, the disutility increases when individuals were only exposed to short commutes.

To investigate this approach and to measure the effect of the context, I use relocations involving individuals moving between two NUTS-3 regions in Germany. According to the background contrast experiment conducted by Simonson and Tveresky (1992), the commuting behavior after the move should be affected by previously observed commuting options. This concept is formally represented as:

$$\alpha_t^* = (1 - \beta)\alpha_{t-1} + \beta(\alpha_t) \tag{2.1}$$

with $\beta \in [0, 1]$. Abstracting all other influences, such as sociodemographic factors, α_t^* represents a person's individually chosen commuting time as a weighted sum of the observed commuting options in the present α_t and the past α_{t-1}, with the weights decreasing exponentially into the past (Ryder and Heal, 1973). More precisely, under the assumption of $\beta = 1$ there is no impact of commutes observed in the past on the current commuting time, since $\alpha_t^* = \alpha_t$ and thus no impact of the context. In contrast, if $\beta = 0$

the current commuting preferences are determined only by the previously observed commuting times, corresponding to $\alpha_t^* = \alpha_{t-1}$. In the following, I expect β to take values between 0 and 1 ($0 < \beta < 1$), such that two otherwise identical individuals with different numbers of previously observed commuting options will have different levels of α_t^*, when moving to the same region. Moreover, I use the average commuting time in the region of residence before the move as a proxy for previously observed commuting options (Simonsohn, 2006).[4] According to equation (2.1), individuals moving from regions with longer average commutes accept a longer commuting time α_t^* when choosing places of work and residence in the destination region compared to individuals coming from regions with shorter average commuting times. This is the first prediction I investigate in this study:

1. The average commuting time in the region a person leaves has a positive influence on the individually selected commuting time in the destination region.

However, if individuals stay in the new region and observe the commuting options in the new region, their preferences for commuting change due to the new observed commutes in the new region. This leads to a change in the desired commuting duration. For example, movers who relocate from regions with longer commutes to regions with shorter ones initially have a greater tolerance for long commutes and prefer cheaper and larger living space outside the city center. Therefore, they initially commute longer than the average commute in the new region. If they remain in this region and observe shorter commutes, however, their preferences for shorter commutes grow and the disutility for commuting increases. They thus become dissatisfied with the commutes they chose initially and might move again within the new region to reduce their commuting time, thereby correcting an originally excessive amount of commuting. This relationship is illustrated by the second prediction:

2. Individuals readjust their commuting times and move again when remaining in the new region.

The second prediction is therefore useful for ruling out explanations based on stable unobserved differences across individuals who move from different regions. Because if individuals who come from regions with longer average commutes travel more after relocating because they are different from those coming from regions with shorter average commutes, I would not expect them to revise their commutes by moving again.

[4] In contrast, Simonsohn (2006) uses the average commuting time on the city level, as he only analyzes movers between two metropolitan areas. Thus, while the predictions are quite similar to those of Simonsohn (2006), the objects of investigation differ due to the different target group of movers

2.3 Data and sample selection

2.3.1 Data

For the analysis, I use the employment biographies of a 6-percent random sample of all German workers subject to social security contributions. The administrative registry data does not include self-employed persons or civil servants; however, it covers more than 80 percent of the German labor force. The Employment History (BeH – Beschäftigenhistorik V10.01.00, 2016) collated by the Institute for Employment Research (IAB) provides exact information about periods of employment based on the status reports submitted to the pension insurance. Besides the sociodemographic characteristics, information at the firm level are included, which comes from the Establishment History Panel (BHP). This dataset contains information about the branch of industry, the establishment location, number of employees and marginal part-time employees. As daily wages are top-coded at the social security contribution ceiling, I use the imputation procedure developed by Card et al. (2013) to recover wages above this threshold.
A unique feature of this dataset is the supplement IEB GEO, which provides anonymized address information in the form of geocodes for the locations of an individual's residence and place of work for the years 2000 to 2014 (Ostermann et al., 2022). Combining this address information with road network data from OpenStreetMap, I calculate door-to-door commuting distances (Huber and Rust, 2016; Dauth and Haller, 2020; Duan et al., 2022). It is only possible to determine distances for individuals traveling by car in this way; those for users of public transport may differ. However, the car is the most important mode of transport. Almost 70 percent of workers commute to work by car (Destatis, 2017), whereas only 14 percent of commuters use the public transport system.[5] In addition, to calculate the commuting time I take average values for highways, primary, and residential roads. By using geocodes, the commuting time is not limited by administrative units, which reduces measurement error for individuals close to administrative borders and mitigates the problem of spatial sorting within areas. Yet, using driving time can cause issues regarding the experienced commuting time: for example, the algorithm cannot recognize dense traffic in the daily rush hours. Nevertheless, as the time is measured before and after the regional move, the change in the duration might be affected less by this measurement problem.[6]

2.3.2 Sample

In this study, I investigate the commuting behavior of German workers, excluding persons in marginal and part-time employment as well as workers older than 57 and younger than 18 years of age. Regarding

[5] However, the results by Simonsohn (2006) show that the context has almost the same effect for people who use public transport.

[6] For the analysis in this study I consider commuting time. However, all the results are very similar when commuting distance is used.

the commuting time, I restrict the sample to workers with a commuting time between 1 and 90 minutes. I choose 1 minute as the minimum because this represents the first percentile of the data and hence ensures that outliers who do not commute are not considered. The restriction to 90 minutes is because the data does not provide any information about the number of commuting trips. Thus, the data could also include workers who commute weekly and have a second place of residence. To exclude those workers, I restrict the data to workers with commuting times of up to 90 minutes. This is comparable to other German studies that restrict the commuting distance to 100 km (Dauth and Haller, 2020; Duan et al., 2022) and ensures that commuting is conducted on a daily basis.

To test prediction 1, whether the average commuting time in the region a person leaves has a positive influence on the individually selected commuting time in the destination region, several restrictions have to be considered. First, to be able to analyze commuting decisions, I have to consider only those individuals who face such a decision. This group comprises individuals who are required to make a new commuting decision due to moving home or changing their job. For my study, however, I consider individuals who simultaneously change both their place of residence and their place of work. The reason for this is, first, that for individuals who only change their place of work it is not possible to examine the influence of the context of commutes observed in the past, because for job changers the region of the place of residence does not change.[7] Second, if individuals only change their place of residence they might, for example, be relocating due to dissatisfaction with commuting and I would therefore not be able to identify the influence of the context correctly.[8] To avoid this, I restrict the sample to workers who change both residence and workplace locations, which further guarantees a relocation of the entire center of their lives. In addition, I restrict the sample to those movers who relocate between two of the 402 German NUTS-3 regions.[9] I also keep the NUTS-3 region of the place of work and the place of residence constant for two years before and after the move. This guarantees that movers are able to adopt the commuting options as well as the commuting behavior of the region they lived in. In addition, this assumption means that it is possible for movers to relocate again within the target region to readjust their initially chosen commuting time. After these restrictions I identify 15,671 workers who move between two NUTS-3 regions. Furthermore, the time periods are categorized to $t-1$ for the year before the move, $t=0$ for the year of the relocation and $t+1$ for the year after the move.

To test prediction 2, I look at workers who relocate again within the new region in period $t+1$ (one year after the move), keeping the place of work constant. The number of second-time movers is 4,267.

[7] In a robustness check, I investigate the effect of the context for this group, then also provide evidence of a context effect for this group of movers.

[8] Estimating the model for the group of movers who only change their place of residence also reveals an effect of the context. The results can be provided additionally on request.

[9] However, investigating movers between German labor market regions generates almost the same results (see Appendix 2.A.7).

2.4 Identification Strategy

To test the first prediction, I estimate how the average commuting time in the region of residence before the relocation $\bar{C}_{i,t-1}$ influences the individually chosen commuting time in the target region $C_{i,t=0}$, I consider a dynamic fixed effects model, where the lag of the dependent variable $C_{i,t-1}$ is used as an explanatory variable:[10]

$$lnC_{i,t=0} = \beta_1 ln(C_{i,t-1}) + \beta_2 ln(\bar{C}_{i,t-1}) + \beta_3 X'_{i,t} + \mu_i + \varepsilon_{i,t} \tag{2.2}$$

where $C_{i,t=0}$ represents the dependent variable, the logarithm of the individual chosen commute in minutes after the relocation $t = 0$, while $ln(C_{i,t-1})$ – the lag of the dependent variable – is added as an independent variable. The variable of interest $ln(\bar{C}_{i,t-1})$ shows the logarithm of the average commuting time in the region of residence before the relocation $t - 1$. The average commuting time is calculated for each NUTS-3 region and represents the context of previously observed commutes. Further, I include $X'_{i,t}$ as a vector of control variables. This vector includes the log wage, calendar years, occupational status and indicator variables for firm size (number of employees, 4 categories), age group (4 categories), occupation (12 categories), industry (9 categories) and region type of the place of residence as well as of the place of work (according to the classification of the Federal Institute for Research on Building, Urban Affairs and Spatial Development BBSR). These region types represent whether individuals live and work in a metropolitan city, city, large town, small town or in a rural area (5 categories). Moreover, $X'_{i,t}$ incorporates several dummies indicating whether a worker is a supervisor, has a leading position, is a trained/professional, specialist/expert or has an auxiliary job. In addition, $X'_{i,t}$ incorporates a dummy for women, migrants, western Germany and for being low-skilled (without vocational training) medium-skilled (with vocational training) or high-skilled (academic degree). And μ_i shows the time invariant individual-specific effects.

According to prediction 1, β_2 should be positive because individuals with stronger observed commuting backgrounds have a lower disutility of commuting and thus prefer to live outside the city center, thereby facing longer commutes.

However, in the case of *unobserved heterogeneity, omitted variable bias and selectivity* which can influence the estimates of $ln(\bar{C}_{i,t-1})$ or *sorting* – meaning that movers relocate to certain regions because of their taste for commuting – my results would not be valid. First, to address the issue of unobserved heterogeneity regarding, for example, commuting preferences, the estimates control for individual fixed effects μ_i (equation 2.2). Thus, unobserved heterogeneity regarding individual commuting should not

[10] In this sample, I include all workers who relocate between two NUTS-3 regions. For all workers I have 5 observations, two observations before the move, the period of the relocation, and two after.

impact my results. Second, to deal with the issue of omitted variable bias, I conduct several robustness checks excluding observable individual and firm characteristics in my analysis. The results are presented in the robustness checks in Section 2.5.3 (Table 2.8) and confirm my presented results, as the results barely change. Third, workers might endogenously choose whether or not to move. To control for this selectivity, I use a two-stage Heckman selection method (Heckman, 1979) where I first account for the decision to move, which can be estimated as a latent variable model:

$$P_i^* = \delta_1 S_i + \varepsilon_i \tag{2.3}$$

With the decision to move:

$$P_i = \begin{cases} 1 & \text{if } P_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.4}$$

P_i^* srepresents the latent variable for the propensity to move between two NUTS-3 regions and S_i is a vector of sociodemographic characteristics and information on industry and firm size, which influence individual i. To estimate whether or not a worker moves, I use a probit estimation. These results are then taken to construct an inverse Mills ratio. This inverse Mills ratio is then included in the second step equation to correct for selection bias (equation 2.2).

The third issue is sorting: For example, individuals who dislike (like) commuting choose regions with shorter (longer) commuting times. To face this selectivity issue, I include the individual's own commuting time in the region before the relocation $C_{i,t-1}$ (see equation 2.2), and perform a robustness check.

In line with selectivity, individuals select themselves into a region because of their commuting taste. If people select themselves into regions with longer average commutes because of their taste for long commuting, they should also have commuted longer in the region before the move. To exploit this fact, I perform a reversed regression in which I regress the individual commute in the previous region on the average commuting time in the target region – after the relocation.

$$ln(C_{i,t-1}) = \beta_0 + \beta_1 ln(\bar{C}_{i,t=0}) + \beta_2 X'_{i,t=0} + \varepsilon_i \tag{2.5}$$

In line with the above argument indicating selectivity, I should find a positive effect of the average commutes in the destination region $\bar{C}_{i,t=0}$ on the individuals' commuting time in the region before the movement $C_{i,t-1}$. The results are presented in the robustness checks in Section 2.5.3 (Table 2.9).

Another neglected effect could be due to imperfect information: when moving to a new region workers have no information about the commuting situation there. Therefore, they might commute longer initially and then change their commutes by relocating again within the new region – thereby explaining the second prediction. However, information about commuting and the local housing market is relatively cheap. Nevertheless, the commuting costs are high: commuting takes time, causes stress, and is very expensive. I would thus expect workers to obtain information about the commuting situation in the new region before they move.

In addition, the decision regarding accommodation might be made under time pressure, thus representing a random event. For example, when individuals have found a new job but then have little time left to find a new apartment. In this case, they might be willing to take any accommodation, wherever it is located, as long as it seems to be acceptable. However, if it appears to be the case that the new commuting time is a random event, first I would not expect the individual's own previous commuting time as well as the average commuting time in the region before the move to have a significant influence on the selected commuting time in the target region. And second, I would not expect those workers to move again within the new region and adjust their commuting time to the average commuting time in the new region.

The travel time budget – and thus the commuting decision – might also be influenced by trip chaining or by the fraction of remote work. In particular, with the Covid-19-shock remote work has increased and there is some consistency in remote work. Due to the possibility of working from home the travel-time budget becomes more relaxed and thus longer commuting distances might be expected and accepted. However, as my observation period is restricted (2000-2014) and the data does not include the fraction of remote work, I cannot analyze how the results might be affected by the Covid-19-shock. In addition, Brunow and Gründer (2013) found that the daily allocation of time in Germany is affected by trip chaining, such that unobserved factors may influence the time budget. In particular, after migration not just the trip "home-to-work" influences the persistence of habits but also other factors such as shop accessibility or child care institutions leading to a potential bias in estimates. However, I suspect that this bias is negligible in this study, because people living in the destination area still form the daily activity chains.

To test prediction 2, I restrict the sample to workers who move again within the new region, one period after the first move $t+1$. I use the following identification strategy, in which only changes are analyzed. Because of these differences, individual fixed effects are canceled out:

$$ln(C_{i,t+1} - C_{i,t=0}) = \beta_1 ln(\bar{C}_{i,t=0} - \bar{C}_{i,t-1}) + \beta_2 ln(W_{i,t+1} - W_{i,t=0}) + \varepsilon_i \tag{2.6}$$

The dependent variable $(C_{i,t+1} - C_{i,t=0})$ is the change in the individual chosen commuting time after the second and the first move within the new region. The control variable is the change in wages

$(W_{i,t+1} - W_{i,t=0})$ between the second and the first move. And the key predictor is represented by the difference between the observed commuting time in the new region $t = 0$ and the region before the move $t - 1$, corresponding to $(\bar{C}_{i,t=0} - \bar{C}_{i,t-1})$. This classification of the reference point presupposes that the workers' perceptions have fully adjusted after one period.

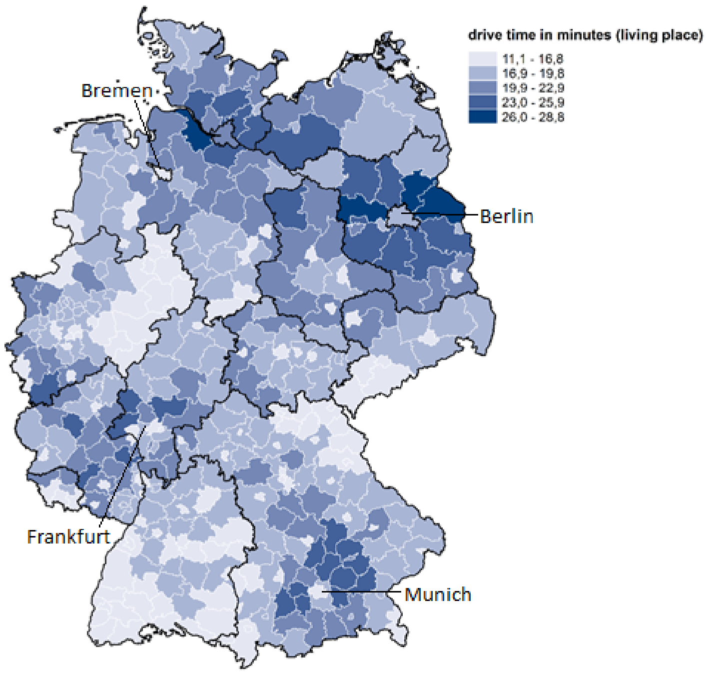
However, this might still not be a correct estimate of the change in the commuting time as workers might endogenously choose whether to move a second time. Therefore, I again use a two-step Heckman selection method (see equation 2.3 and 2.4). If workers decide to move a second time within the new region, in line with prediction 2, the coefficient β_1 (equation 2.6), should be positive: individuals moving from regions with observed long commutes to a new region (with shorter average commutes) commute too long at first. This leads to a change in the desired commuting durations. Therefore, if they move again within this new region, they reduce their commutes and adopt the commuting behavior prevalent in the new region.

2.5 Empirical analysis of the commuting behavior

2.5.1 Descriptive statistics

Figure 3.1 presents the distribution of the average commuting times for the place of residence for each NUTS-3 region in Germany. Workers living in metropolitan cities, like Munich, Berlin, Frankfurt or Bremen, have shorter average commuting times than those in the surrounding regions. Specifically, the average commuting time in metropolitan cities is 16.8 minutes, while workers in rural areas commute almost 20 minutes to work on average. This implies that workers who live in large cities are most likely to work there as well, while workers living in the suburbs travel from the surrounding regions into the city center to work. This may be because job opportunities are better in the city center and housing costs are cheaper in the suburbs (Alonso, 1964).

Figure 2.1: Regional distribution of the commuting time in the year 2014



Notes: The map shows the mean commuting time of workers place of residence by NUTS-3 regions in manually chosen time categories. Source: Own calculation and presentation.

Comparison of movers and non-movers

To demonstrate how the characteristics of workers who relocate differ from those who do not, I compare the two groups. The results are represented in the Appendix 2.A.1 and 2.A.2. They show that movers and non-movers differ especially in terms of their productivity-related characteristics: employees who relocate are more highly qualified (academic degree) than non-movers. Differences also become obvious with regard to industries, occupations, and age groups. While the share of movers is much larger between 18 and 34, non-movers are mainly between 35 and 56 years old. Moreover, movers tend to drive an average of 1.2 minutes longer to work than non-movers. This comparison therefore shows considerable heterogeneity between movers and non-movers.

Comparison of movers before and after the movement

In the following, I examine summary statistics of workers who move. Table 2.1 shows the difference between the drive time and the wage of movers before $t = -1$ and after the relocation $t = 0$. The average mover experiences an increase in wages (+12.8 euros per day), which supports the idea that workers are more likely to move if they can achieve a wage increase, as non-movers on the other hand only experience an average wage increase of about 3.4 euros per day between two periods. Not only wages rise due to the relocation, the commuting time does so too. On average, the commuting time among movers increases by 3.9 minutes.

Table 2.1: Summary statistics of the daily wage and commuting time

Variables	Mean	S.d.	25th perc.	50th perc.	75th perc.
Commuting time t=-1 in minutes	18.8	16.6	6.9	13.9	25.1
Δ Commuting time t=0 in minutes	+3.9	23.8	-8.2	2.7	14.9
Wage t=1 (euro/day)	85.9	55.9	49.7	74.2	106.5
Δ Wage t=0 (euro/day)	+12.8	41.0	-2.7	8.5	27.1
Workers			15,671		

Notes: Means, standard deviation, 25th, 50th, 75th percentiles of commuting time and the wage. Comparison of movers before and after the relocation.

Motivation of movers

As already mentioned, when workers move to a new region, they achieve an increase in wages, which could be an important motivation to move. Furthermore, Table 2.2 shows that 33 percent of workers change their occupation after the move. In addition, almost 34 percent of movers work in a different industry after relocating. Workers might therefore move in particular for job-related reasons. Simonsohn (2006) obtains a similar finding. He reports that more than 36 percent of individuals in the US move for job-related reasons. Moreover, in many cases (12.7 percent) the move is associated with a promotion, for example from trained/professional assistant to specialist/expert (see Table 2.2).

Table 2.2: Summary statistics of changes in occupation, industry, and promotion

Variable	Occupation	Industry	Promotion
Change as a percentage	33.0	33.9	12.7
Workers	5,238	5,372	2,009

Notes: Percentage of workers who change occupation or industry, or are promoted after the relocation $t = 0$.

Comparison of movers and second-time movers

In the following, I take a closer look at second-time movers. These are workers who relocate a second time within the new region. Table 2.3 compares these second-time movers with the share of regular movers (workers who move once) after the first and before the second move. Of the 15,671 movers in $t = 0$ 4,267 relocate a second time in $t = 1$. Especially medium-skilled workers tend to move again within the new region (see Table 2.3). In addition, the shares of men, migrants, and workers in western Germany are higher for second-time movers, and they are younger on average (between 18 and 24 years old).

Table 2.3: Summary statistics of main variables

Variable	Movers	Second-time movers
Woman	50.6%	47.6%
Migrant	3.9%	4.3%
West Germany	86.4%	89.0%
Age groups		
18-24	14.5%	18.4%
25-34	47.9%	46.8%
35-44	26.8%	24.9%
45-56	10.8%	10.0%
Skill level		
Low-skilled	6.5%	7.9%
Medium-skilled	63.1%	68.5%
High-skilled	30.4%	23.6%
Workers	11,597	4,267

Notes: Means of main variables. Comparison of movers and second-time movers after the first move $t = 0$.

Table 2.4 shows the difference between the daily wages and the commuting times of movers and second-time movers after the first relocation $t = 0$. Compared to movers, second-time movers have much longer commuting times after the first move in $t = 0$. Workers who move only once have a commuting time of 18.7 minutes in $t = 0$, while those who move a second time drive over 14 minutes longer to work after the first relocation. This results not only from the fact that second-time movers come from regions with longer commutes compared to movers, but also that they are more likely to move from rural regions with longer average commuting times. According to the background context effect, this leads to a higher tolerance for commuting and thus to a longer chosen individual commuting time after the move. This could explain why especially these workers move again within the new region and reduce their commuting time by more than 13 minutes (see Table 2.5).

Table 2.4: Summary statistics of commuting time and wage

	Variables	Mean	S.d.	25th perc.	50th perc.	75th perc.
Movers	Commuting time (min.)	18.7	15.5	7.7	14.6	25.0
Second-time movers	Commuting time (min.)	33.4	22.6	15.2	28.1	48.1
Movers	Wage (euro/day)	99.7	58.6	61.6	84.1	122.4
Second-time movers	Wage (euro/day)	96.0	55.0	62.7	82.0	113.8

Notes: Means, standard deviation, 25th, 50th, 75th percentiles of driving time and the wage. Comparison of movers and second-time movers after the first move $t = 0$.

Table 2.5 shows the difference between wages and commuting times before the first move $t = -1$ after the first move $t = 0$ and after the second move $t = +1$ for individuals who moved a second time. As explained above, the increase in the commuting time after the first move is far higher for individuals moving twice than for those moving only once. Second-time movers increase their commuting time by over 13 minutes in $t = 0$. However, they shorten their commuting time by the same amount after the second relocation in $t = +1$. This corrects the originally excessive commuting time, and confirms prediction 2.

Table 2.5: Summary statistics of commuting time and wage

Variables	Mean	S.d.	25th perc.	50th perc.	75th perc.
Commuting time $t = -1$ in minutes	19.9	17.1	7.6	15.1	26.4
Δ Commuting time $t = 0$ in minutes	+13.4	27.7	-2.7	10.7	29.7
Δ Commuting time $t = +1$ in minutes	-13.5	24.8	-28.0	-6.6	2.3
Wage $t = -1$ (euro/day)	81.8	51.7	47.4	72.1	101.7
Δ Wage $t = 0$ (euro/day)	+14.3	36.4	-0.6	9.2	27.5
Δ Wage $t = +1$ (euro/day)	+4.9	29.9	0.2	3.6	9.09
Workers			4,267		

Notes: Means, standard deviation, 25th, 50th, 75th percentiles of commuting time and the wage. Comparison of second-time movers before and after the first move and after the second move.

2.5.2 Empirical analysis

1. The average commuting time in the region a person leaves has a positive influence on the individually selected commuting time in the destination region.

In the following, I test the first prediction, in which I investigate how the average commuting time in the region before the relocation influences the individually selected commuting time in the target region (equation 2.2). As workers may endogenously choose to move, I use a two-step regression (Heckman, 1979). In the first step I estimate a probit regression for the decision to relocate (equation 2.3). The results for this probit regression are provided in the Appendix 2.A.3 and show, for example, that workers with higher wages, high-skilled workers and workers in western Germany are more likely to relocate. In the second step, I use the inverse Mill's ratio from the first step as an additional control variable and analyze how the average commuting time in the region before the relocation influences the commuting time in the new region (equation 2.2). Table 2.6 shows the results of 4 specifications.

According to Table 2.6, model 1, which includes the lag of the individual commuting time $t-1$, the longer the commuting time was in the region before the relocation, the longer the individually selected commuting time is in the target region. In addition, the wage has a positive significant effect, which might be the result of compensatory wages for longer commutes as shown by Mulalic et al. (2014). In the second model I include the average commuting time in the region in which the previous place of residence was located $\bar{C}_{i,t-1}$ as a proxy for commuting options observed in the past. Consistent with the first prediction, Table 2.6, model 2 shows a positive significant effect on the individual commuting time. Moreover, the effect can be interpreted as causal, as I control for selectivity and unobserved heterogeneity, and can rule out the issue of omitted variable bias and sorting (see Section 2.5.3). Hence, mobile workers coming from NUTS-3 regions with longer observed commutes have a greater tolerance for commuting

Table 2.6: Individually selected commuting time after relocation

NUTS-3 region	Dependent variable: $\ln(C_{i,t=0})$			
	Model	1 Model 2	Model 3	Model 4
$\mathrm{Ln}(C_{i,t-1})$	0.228***	0.225***	0.225***	0.225***
	(0.006)	(0.006)	(0.006)	(0.006)
$\mathrm{Ln}(\bar{C}_{i,t-1})$		0.216***	0.222***	0.212***
		(0.030)	(0.029)	(0.029)
Inverse of Mill's ratio*	0.620***	0.560***	0.143	0.531***
	(0.205)	(0.206)	(0.144)	(0.206)
Ln(wage)	0.107***	0.100***		0.117***
	(0.034)	(0.034)		(0.034)
$\mathrm{Ln}(wage_{t-1})$				-0.103***
				(0.015)
Medium-skilled	0.172***	0.163***	0.103**	0.165***
	(0.047)	(0.047)	(0.042)	(0.047)
High-skilled	0.231***	0.211***	0.093	0.206***
	(0.079)	(0.079)	(0.066)	(0.079)
Migrant	-0.106	-0.098	-0.044	-0.092
	(0.066)	(0.066)	(0.063)	(0.066)
Specialist/expert	0.036	0.035	0.032	0.037
	(0.044)	(0.044)	(0.044)	(0.044)
Trained/professional assistant	0.003	0.002	0.004	0.005
	(0.038)	(0.038)	(0.038)	(0.038)
Age groups	Yes	Yes	Yes	Yes
Occupation dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Occupational status	Yes	Yes	Yes	Yes
Firm size (Number of workers)	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Place of residence type	Yes	Yes	Yes	Yes
Place of work type	Yes	Yes	Yes	Yes
Constant	-0.667	-1.030	0.841	-0.560
	(0.830)	(0.827)	(0.508)	(0.830)
Workers	45,232	45,232	45,232	45,232
Workers (cluster)	15,262	15,262	15,262	15,262
R^2	0.5773	0.5777	0.5775	0.5783
Adj. R^2	0.3607	0.3614	0.3611	0.3622

Notes: The table reports regressions of the individually selected log commuting times after the first relocation on the average log commuting time in the region before the relocation and control variables. Standard errors clustered by individuals, below parameter estimates. Levels of significance: *1%. **5%. ***10%. *Inverse of Mill's ratio is obtained from the first stage probit estimation of the move.

and choose longer individual commutes in the target region. This indicates the presence of a context effect and is therefore consistent with the result obtained by Simonsohn (2006). However, a comparison of the effects with those found by Simonsohn (2006) shows that he overestimates the effect of the context (see Section 2.5.3 Table 2.8). This is because he does not include individual unobserved fixed effects. In addition, comparing R^2 reveals that the model I consider performs much better than that of Simonsohn (2006) (0.36 vs. 0.15).

Since commuting may be endogenous with respect to wages, model 4 excludes daily wages, which has little impact on the size of the coefficient of $\bar{C}_{i,t-1}$. In addition, in Table 2.6, model 5 I include time-lagged wages $t-1$. In this estimation, too, the result shows no change for the variable of interest $\bar{C}_{i,t-1}$.
Thus, the results indicate that workers' current commuting behavior is affected not only by their own previous commuting time but also by the average commuting time in the region they moved from.

2. Individuals readjust their commuting times and move again when remaining in the new region.

If workers relocate from regions with longer commutes to regions with shorter average commuting times ($\bar{C}_{i,t-1} > \bar{C}_{i,t=0}$), they initially commute longer than the average in the target region. The reason for this is that they have a greater tolerance for commuting as they come from regions where long commutes are common. Nevertheless, if they remain in the new region and observe fewer commutes, they become dissatisfied with their initially chosen commutes and their desired commuting time changes. Therefore, I expect them to reduce their commutes by relocating again within the new region. To analyze the adjustment of the commuting time after a second move, I consider only individuals who move again within one year after relocating to the new region. A total of 4,135 individuals move again within the new NUTS-3 region in $t = 1$.
The regression estimates of equation 2.6 are presented in Table 2.7, where $(C_{i,t+1} - C_{i,t=0})$, the dependent variable, measures the change in the individual commuting time after the second and the first relocation. Therefore, it represents the adjustment of the individual commuting time between $t = 0$ and $t = +1$. The key predictor is the difference between the average commuting time in the new region and that in the previous region $(\bar{C}_{i,t=0} - \bar{C}_{i,t-1})$. Moreover, as workers may endogenously choose whether to move a second time, I use a two-step regression Heckman (1979): in the first step, I estimate a probit regression for the decision to relocate a second time in the new region (equation 2.3). The results of this probit regression can be found in the Appendix 2.A.4. They show, for example, that the greater the difference between the average commuting time and the individual's own selected commuting time in the target region, the more likely a second move is. In the second step, I use the inverse Mill's ratio from the first step as an additional control variable. The results are presented in Table 2.7 and are seen to be in line with prediction 2, the greater the difference between the new and the old region $(\bar{C}_{i,t=0} - \bar{C}_{i,t-1})$ the stronger the adjustment of the individually chosen commuting time after the second move is. Comparing the estimated effect of β_2 (Table 2.7) with the estimation of β_2 in prediction 1 (Table 2.6, model 2) it can be seen that the coefficient β_2 of the first prediction is twice as large as β_2 in the second prediction. Thus, second-time movers do not fully reverse the original impact of $\bar{C}_{i,t-1}$ but it is moving in that direction.
With this result, I can therefore rule out an explanation for the commuting behavior that is based on stable unobserved differences across movers from different regions, as individuals readjust their commuting time by moving again within the new region – they adopt the commuting behavior of the new region.

Table 2.7: Adjustment of the commuting time in $t+1$

NUTS-3 region	Dependent variable: $\ln(C_{i,t+1} - C_{i,t=0})$
Change in ln(wage)	0.049
	(0.108)
$\mathrm{Ln}(\bar{C}_{i,t=0} - \bar{C}_{i,t-1})$	0.100*
	(0.046)
Inverse of Mill's ratio*	1.971***
	(0.084)
Constant	-2.729***
	(0.084)
Workers	4,135
R^2	0.3531
Adj. R^2	0.3526

Notes: The table reports the regression of the adjustment of the individually selected commuting time after the second move on the difference between the average commutes in the new and the old region. Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%. **5%. ***10%. *Inverse of Mill's ratio is obtained from the first stage probit estimation of moving again within the new region.

2.5.3 Robustness checks

Although the presence of stable unobserved differences can be ruled out by confirming prediction 2, there could be other explanations for the presented results and several issues that might influence the outcome, such as unobserved heterogeneity, omitted variable bias, selectivity, and sorting. However, in the following, I am able not only to reject other explanations, but also to confirm my results by means of several robustness checks. Therefore, the effect of $\bar{C}_{i,t-1}$ on $C_{i,t=0}$ can be interpreted as causal.

Unobserved heterogeneity

In fact, unobserved heterogeneity can have an influence on the estimates of $\bar{C}_{i,t-1}$, thereby driving the effect of the context (see Section 2.4). To deal with this issue, I include individual fixed effects in my analysis (see equation 2.2). This is especially important, and failure to do so generates a bias. This can be observed in Table 2.8, model 1. Excluding individual fixed effects overestimates the effect of the individual previous commuting time $C_{i,t-1}$ and underestimates the influence of the context of previously observed commutes $\bar{C}_{i,t-1}$. It is therefore important to include individual fixed effects. Failure to do so leads to a bias, as in the study by Simonsohn (2006) which does not include individual fixed effects in the analysis and therefore underestimates the effect of the context.

Table 2.8: Robustness check: individually selected commuting time after the move

NUTS-3 region	Dependent variable: $\ln(C_{i,t=0})$				
	Model	1 Model 2	Model 3	Model 4	Model 5
$\text{Ln}(C_{i,t-1})$	0.531***	0.226***	0.226***	0.227***	0.225***
	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
$\text{Ln}(\bar{C}_{i,t-1})$	0.154***	0.224***	0.220***	0.223***	0.224***
	(0.023)	(0.029)	(0.029)	(0.029)	(0.029)
Inverse of Mill's ratio*	0.092	-0.009	0.292**	-0.021	
	(0.078)	(0.032)	(0.132)	(0.032)	
Ln(wage)	0.061***		0.088***		0.034
	(0.013)		(0.027)		(0.024)
Medium-skilled	0.039**		0.119***		0.078**
	(0.018)		(0.040)		(0.035)
High-skilled	0.035		0.124**		0.040
	(0.028)		(0.062)		(0.048)
Migrant	-0.037*		-0.063		-0.027
	(0.019)		(0.063)		(0.060)
Specialist/expert	0.026		0.016		0.027
	(0.024)		(0.044)		(0.044)
Trained/professional assistant	0.001		-0.012		0.001
	(0.021)		(0.038)		(0.038)
Age groups	Yes		Yes		Yes
Occupation dummies	Yes		Yes		Yes
Industry dummies	Yes	Yes			Yes
Occupational status	Yes		Yes		Yes
Firm size (Number of workers)	Yes	Yes			Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Place of residence type	Yes	Yes	Yes	Yes	Yes
Place of work type	Yes	Yes	Yes	Yes	Yes
Constant	0.190	1.438***	-0.042	1.476***	1.194***
	(0.310)	(0.134)	(0.533)	(0.132)	(0.139)
Workers	45,232	45,232	45,232	45,232	45,232
Workers (cluster)	15,262	15,262	15,262	15,262	15,262
R^2	0.3415	0.5768	0.5763	0.5753	0.5776
Adj. R^2	0.3407	0.3606	0.3595	0.3586	0.3612

Notes: The table reports regressions of the individually selected log commuting times after the first relocation on the average log commuting time in the region before the move and control variables. Standard errors clustered by individuals, below parameter estimates. Levels of significance: *1%. **5%. ***10%. *Inverse of Mill's ratio is obtained from the first stage probit estimation of the move.

Omitted variable bias

In addition, I conduct several robustness checks excluding individual and firm characteristics. In model 2 (Table 2.8) I exclude firm characteristics, which yields similar results for the context of previously observed commutes to those in Table 2.6, model 2, which included all control variables. Also, almost the same results are obtained when firm characteristics are excluded and when both individual and firm characteristics are excluded (Table 2.8, model 3 and 4). Thus, the results on the previous average commuting time are very robust and do not seem to be influenced by observed individual or firm characteristics. This leads me to conclude that there is no evidence of omitted variable bias.

Selectivity

To control for the selectivity of a relocation – as workers may endogenously choose to relocate – I use a two-step Heckman selection model (Heckman, 1979), in which I control for the selectivity of a relocation (equation 2.3). To gain an impression of whether selectivity is important I estimate the model without controlling for selectivity. The results are provided in Table 2.8, model 5 and show almost the same effects for previously observed commutes as those in Table 2.6, model 2. Only the coefficients for wages and the skill-level variables change. Thus, controlling for the selectivity of the relocation is not important for interpreting the variable of interest but influences other control variables.

Sorting

Another issue might be sorting, as workers select themselves into certain regions because of their taste for commuting. To address this issue, I run a reversed regression of equation 2.5. In line with the definition of sorting, I should find a positive correlation between the average commuting time in the destination region and the individual commuting time in the region before the move. However, my results show no significant effect of the average commuting time in the destination regions (Table 2.9). Thus, there is no sign of a sorting process – individuals do not select themselves into regions because of their taste for commuting – but this once again shows the presence of the context effect.

Table 2.9: Robustness check: individuals select themselves into regions because of their taste for commuting

NUTS-3 region	Dependent variable $\ln(C_{i,t-1})$
$\text{Ln}(C_{i,t=0})$	0.082***
	(0.008)
$\text{Ln}(\bar{C}_{i,t=0})$	-0.109
	(0.077)
$\text{Ln}(C_{i,t-1})$	0.951***
	(0.059)
Ln(wage)	0.086***
	(0.021)
Medium-skilled	0.049*
	(0.029)
High-skilled	0.078**
	(0.034)
Migrant	-0.109**
	(0.043)
Specialist/expert	0.053
	(0.047)
Trained/professional assistant	-0.005
	(0.042)
Women	-0.070***
	(0.019)
Age groups	Yes
Occupation dummies	Yes
Industry dummies	Yes
Occupational status	Yes
Firm size (Number of workers)	Yes
Year dummies	Yes
Place of residence type	Yes
Place of work type	Yes
Constant	-0.658**
	(0.297)
Workers	15,262
R^2	0.056
Adj. R^2	0.052

Notes: The table reports the regression of the individual commuting time in the previous region on the average commuting time in the target region (after the relocation). Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%. **5%. ***10%.

Moreover, workers might also move for job-related reasons, such as higher wages. As wages are highly correlated with commuting in theory, I consider only workers who earn almost the same wage before and after the first relocation.[11] Table 2.10 shows that the average commuting time in the region before the move has a positive and significant influence on the commuting time of workers who do not achieve an increase in wages after the relocation.

Table 2.10: Robustness check: movers, who earn almost the same wage before and after relocating (1) and who have the same wage as well as the same task level (2) before and after relocating

NUTS-3 region	(1) Dependent variable $\ln(C_{i,t=0})$	(2) Dependent variable $\ln(C_{i,t=0})$
$\text{Ln}(C_{i,t-1})$	0.202***	0.199***
	(0.013)	(0.015)
$\text{Ln}(\bar{C}_{i,t-1})$	0.381***	0.361***
	(0.071)	(0.081)
Ln(wage)	-0.164*	-0.125
	(0.088)	(0.109)
Medium-skilled	-0.089	-0.073
	(0.102)	(0.117)
High-skilled	-0.033	-0.042
	(0.151)	(0.196)
Migrant	0.161	0.060
	(0.108)	(0.138)
Specialist/expert	0.066	0.014
	(0.103)	(0.197)
Trained/professional assistant	0.063	0.018
	(0.081)	(0.155)
Age groups	Yes	Yes
Occupation dummies	Yes	Yes
Industry dummies	Yes	Yes
Occupational status	Yes	Yes
Firm size (Number of workers)	Yes	Yes
Year dummies	Yes	Yes
Place of residence type	Yes	Yes
Place of work type	Yes	Yes
Constant	1.745***	1.687***
	(0.449)	(0.559)
Workers	9,193	7,473
Workers (cluster)	3,094	2,514
R^2	0.5797	0.5833
Adj. R^2	0.3603	0.3645

Notes: The table reports regressions of the individually selected log commuting time after the first relocation on the average log commuting time in the region before the move and control variables. Standard errors clustered by individuals, below parameter estimates. Levels of significance: *1%. **5%. ***10%.

[11] Wages are rounded to the nearest ten.

This indicates that endogeneity issues with respect to wages do not drive the results. In addition to restricting the sample to persons earning the same wage before and after relocating, I also restrict it to workers who do not change their task level. Once again, the coefficient of the average commuting time in the previous region does not change.

To sum up, the robustness checks show that it is crucial to include the individual fixed effects when investigating the individual commuting behaviors. In addition, the robustness checks indicate that my results on the average commuting time are not driven by omitted variable bias – as the coefficient is very robust when individual and firm-specific characteristics are excluded. Furthermore, sorting does not seem to influence my results, either. Therefore, the investigated influence of the previously observed commutes on the individually chosen commuting time (Table 2.6) can be interpreted as causal.

2.5.4 Effect heterogeneity

In the following, I investigate the heterogeneous effects of the context on the individual selected commuting time. I differentiate movers by different age groups, skill levels, and gender. In addition, I consider movers between different types of regions – urban and rural areas – as well as movers between labor market regions.

Age groups, gender, and skill level

Since it is possible that individuals differ in their behavior due to their age, gender, or skill level, I take up this point by performing the estimation for different interactions (Appendix 2.A.5). In particular, I interact the average commuting time in the region before the relocation $\bar{C}_{i,t-1}$ with age, gender, and skill level. The results show no significant group differences in terms of age and skill level. Nor can any significant differences be observed between women and men. Thus, there is no effect heterogeneity for different groups regarding age categories, skill level, or gender.

Movers between different types of rural and urban regions

Considering movers between different types of place of residence, I interact the average commuting time in the previous location $\bar{C}_{i,t-1}$ with the different types of rural and urban regions before and after the move.[12] The results are shown in the Appendix 2.A.6 and indicate that the effect of the context of previously observed commutes is strongest for those moving to urban areas, especially for the group moving from a rural to an urban area.[13] This is related to the fact that workers who previously lived in a rural area with long average commutes are used to commuting long distances. Therefore, when moving to urban regions such workers have a higher tolerance for commuting and choose longer than

[12] I consider only the location of the place of residence.

[13] However, as I cannot take into account dense traffic or congestion when calculating the commuting time, the results might underestimate the commuting costs especially in dense urban areas.

average commutes in the urban region. However, for movers to rural areas the results indicate a smaller or insignificant effect of the context. The reason could be that the majority of workers moving from urban to rural areas do not only relocate their place of residence but also take up a new job in the rural area. Thus, other conditions, such as job availability, are more important than commuting preferences for this group of movers.

Hence, the results indicate that the size of the effect of the context depends particularly on the region type of the place of residence before and after the relocation. Considering only movers between metropolitan areas (Simonsohn, 2006) might therefore lead to a bias in the estimated effect.

Labor market regions

Next, I show the results for individuals moving between German labor market regions (Kosfeld and Werner, 2012). The restrictions are the same as for movers between NUTS-3 regions, i.e., workers have to relocate both their place of work and their place of residence to a different German labor market region. Moreover, the labor market region of the place of work and the place of residence must be constant for two years before and after the move. In contrast to the consideration of individuals moving between NUTS-3 regions, I calculate the average commuting time at the level of labor market regions (as a proxy for previously observed commuting options). The results are shown in Appendix 2.A.7 and are comparable with the effect of the context for persons moving between NUTS-3 regions (Table 2.6).

2.6 Conclusion

This study investigates for the first time commuting behavior in terms of a behavioral economic concept based on georeferenced data for Germany. The basis of this investigation is the approach developed by (Simonsohn, 2006), who examines commuting behavior for the US. However, I can show that his estimated effects are biased due to the absence of individual fixed effects and the consideration only of individuals moving between metropolitan areas.

The presented results show that workers' commuting decisions are influenced by commuting options observed in the past. This explains why individuals who move from different regions to one and the same region initially commute differently: individuals moving from areas with long average commutes have a greater tolerance for commuting and therefore commute more than individuals coming from regions with shorter commutes. However, if they remain in the new region, they adjust their initially chosen commuting times to the average commutes in the new region. This refutes the assumption of stable unobserved differences across individuals. Instead, individuals change their marginal utility of commuting when moving to a new region, as they adjust their commuting time by means of a second relocation within the new region. The reason for this behavior is the change in the context: The original context was seen as the average commuting time in the previous region, but the context changes with the relocation to a new region. Thus, commuting preferences change. In addition, the results indicate that selectivity and sorting do not influence the effect of the context, but it is crucial to include individual fixed effects. Moreover, the context has different effects depending on the region type of the place of residence: the context effect is greatest for those moving from rural to urban areas.

However, the travel time budget can be influenced by remote work that increased during the Covid-19-shock and might increase the expected and acceptable commuting distance. Future research could examine whether such increase in remote work influences the effect of the context. Additionally, for future investigation that examine consumer preferences and other labor market decisions, the study highlights the importance of identifying the context of previously observed options and including them in the analysis. Finally, the results indicate the essentiality of including individual fixed effects, as they influence the outcome of commuting decisions.

Appendix

A Additional Figures and Tables

Table 2.A.1: Summary statistics of main variables

Worker characteristics	Movers		Non-Movers	
	Mean	S.d.	Mean	S.d.
Wage (Euro/day)	85.9	55.9	86.7	55.1
Commuting time in minutes	18.8	16.6	17.6	14.7
Women	49.8%		45.5%	
Migrant	4.0%		6.0%	
West Germany	87.1%		81.5%	
Supervisor	2.5%		2.1%	
Leading position	0.2%		0.7%	
Education				
Low-skilled	15.8%		15.1%	
Medium-skilled	64.6%		72.2%	
High-skilled	28.6%		12.7%	
Age groups				
18-24	15.5%		10.7%	
25-34	47.6%		23.0%	
35-44	26.3%		31.3%	
45-56	10.6%		35.1%	
Tasks				
auxiliary activity	30.4%		20.4%	
Trained/professional assistant	64.4%		71.2%	
Specialist/expert	2.5%		6.4%	
Workers	15,671		18,002,997	

Notes: Comparison of movers and non-movers before the movement in $t = -1$.

Table 2.A.2: Summary statistics of main variables

Firm characteristics	Movers	Non-movers
Industries		
Primary sector	2.0%	3.0%
Food manuf.	2.1%	2.4%
Consumer goods	2.0%	2.6%
Industrial goods	6.0%	6.0%
Capital goods	9.2%	11.6%
Construction	3.3%	6.0%
Personal services	21.9%	19.4%
Business services	27.2%	21.5%1
Public sector	26.3%	24.1%
Occupations		
Agricultural workers	0.8%	1.2%
Lower manual occupations	5.9%	12.3%
Higher manual occupations	8.4%	14.9%
Technicians	5.2%	5.2%
Engineers	6.4%	3.0%
Lower services	7.8%	11.6%
Higher services	7.0%	5.8%
Semi-Professionals	11.4%	9.3%
Professionals	5.5%	2.0%
Lower administrative occupations	7.7%	8.1%
Higher administrative occupations	28.0%	22.9%
Managers	5.4%	3.1%
Firm size		
0-9	12.9%	13.4%
10-49	25.8%	24.6%
50-249	28.6%	28.7%
250-499	10.3%	10.9%
$\geq$ 500	22.4%	22.3%
Workers	15,671	18,002,997

Notes: Comparison of movers and non-movers before the movement in $t = -1$.

Table 2.A.3: Probit regression whether workers move in $t = 0$ (first movement)

NUTS-3 region	Worker relocate in $t = 0$
Ln(wage)	0.113***
	(0.007)
Women	0.067***
	(0.006)
High-skilled	0.334***
	(0.014)
Medium-skilled	0.160***
	(0.011)
Migrant	-0.139***
	(0.017)
Supervisor	0.042**
	(0.019)
Leading position	0.058**
	(0.028)
Specialist/expert	0.018
	(0.015)
Trained/professional assistant	0.009
	(0.013)
West Germany	0.116***
	(0.014)
Age groups	Yes
Occupation dummies	Yes
Industry dummies	Yes
Occupational status	Yes
Firm size (Number of workers)	Yes
Year dummies	Yes
Place of residence type	Yes
Place of work type	Yes
Constant	-5.443***
	(0.115)
Workers	17,789,084

Notes: The table reports the results of the probit regression whether a worker moves in $t = 0$ (first step of the Heckman selection model). Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%. **5%. ***10%.

Table 2.A.4: Probit regression whether workers move for a second time

NUTS-3 region	Workers move for a second time
$\text{Ln}(\bar{C}_{i,t=0})$	0.237
	(0.246)
$\text{Ln}(C_{i,t=0} - \bar{C}_{i,t=0})$	0.502***
	(0.044)
Ln(wage)	-0.029
	(0.040)
Women	-0.086***
	(0.032)
High-skilled	-0.246***
	(0.054)
Medium-skilled	-0.058
	(0.037)
Migrant	0.132**
	(0.064)
Supervisor	-0.046
	(0.067)
Leading position	0.087
	(0.111)
Specialist/expert	-0.030
	(0.0945)
Trained/professional assistant	-0.020
	(0.076)
West Germany	0.154***
	(0.028)
Age groups	Yes
Occupation dummies	Yes
Industry dummies	Yes
Occupational status	Yes
Firm size (Number of workers)	Yes
Year dummies	Yes
Place of residence type	Yes
Place of work type	Yes
Constant	-5.443***
	(0.115)
Workers	15,262

Notes: The table reports the results of the probit regression whether a worker moves in $t = 0$ (first step of the Heckman selection model). Standard errors clustered by NUTS-3 regions, below parameter estimates. Levels of significance: *1%. **5%. ***10%.

Table 2.A.5: Individually selected commuting time after the movement (interaction effects)

Dependent variable: $\text{Ln}(C_{i,t=0})$	Model 1	Model 2	Model 3
$\text{Ln}(C_{i,t-1})$	0.225***	0.225***	0.225***
	(0.006)	(0.006)	(0.006)
$\text{Ln}(\bar{C}_{i,t-1})$	0.224***	0.194***	0.263**
	(0.081)	(0.039)	(0.113)
Inverse of Mill's ratio*	0.559***	0.561***	0.556***
	(0.206)	(0.206)	(0.206)
Ln(wage)	0.099***	0.100***	0.099***
	(0.034)	(0.034)	(0.034)
$\text{Ln}(\bar{C}_{i,t-1})$ # 25-34	-0.198		
	(0.254)		
$\text{Ln}(\bar{C}_{i,t-1})$ # 35-44	-0.140		
	(0.282)		
$\text{Ln}(\bar{C}_{i,t-1})$ # older than 44	0.010		
	(0.354)		
$\text{Ln}(\bar{C}_{i,t-1})$ # Women		0.045	
		(0.055)	
$\text{Ln}(\bar{C}_{i,t-1})$ # Medium-skilled			-0.064
			(0.119)
$\text{Ln}(\bar{C}_{i,t-1})$ # High-skilled			-0.019
			(0.123)
Medium-skilled	0.163***	0.163***	0.346
	(0.047)	(0.047)	(0.340)
High-skilled	0.211***	0.211***	0.265
	(0.079)	(0.079)	(0.358)
Migrant	-0.098	-0.098	-0.097
	(0.066)	(0.066)	(0.066)
Specialist/expert	0.034	0.034	0.034
	(0.044)	(0.044)	(0.044)
Trained/professional assistant	0.002	0.002	0.002
	(0.038)	(0.038)	(0.038)
Occupation dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
Occupational status	Yes	Yes	Yes
Firm size (Number of workers)	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Place of residence type	Yes	Yes	Yes
Place of work type	Yes	Yes	Yes
Constant	-0.896	-1.035	-1.148
	(0.808)	(0.827)	(0.878)
Workers	45.232	45.232	45.232
Workers (cluster)	15.262	15.262	15.262
R^2	0.5777	0.5777	0.5777
Adj. R^2	0.3614	0.3614	0.3613

Notes: The table reports regressions of the individually selected log commuting time after the first relocation on the average log commuting time of the region before the movement. Standard errors clustered by individuals, below parameter estimates. Levels of significance: *1%. **5%. ***10%. *Inverse of Mill´s ratio is obtained from the first stage probit estimation of the movement.

Table 2.A.6: Relocation between different types of regions (interaction effects)

NUTS-3 region Dependent variable	Ln($C_{i,t=0}$)
Ln($C_{i,t-1}$)	0.226***
	(0.006)
Ln($\bar{C}_{i,t-1}$)	0.218***
	(0.066)
Inverse of Mill's ratio*	0.570***
	(0.206)
Ln($\bar{C}_{i,t-1}$) # rural to rural	-0.134*
	(0.080)
Ln($\bar{C}_{i,t-1}$) # urban to rural	-0.368***
	(0.087)
Ln($\bar{C}_{i,t-1}$) # rural to urban	0.510***
	(0.090)
Ln(wage)	0.101***
	(0.034)
Medium-skilled	0.162***
	(0.047)
High-skilled	0.209***
	(0.079)
Migrant	-0.096
	(0.066)
Specialist/expert	0.035
	(0.044)
Trained/professional assistant	0.003
	(0.038)
Occupation dummies	Yes
Industry dummies	Yes
Occupational status	Yes
Firm size (Number of workers)	Yes
Year dummies	Yes
Place of residence type	Yes
Place of work type	Yes
Constant	-1.064
	(0.829)
Workers	45.232
Workers (cluster)	15.262
R^2	0.5787
Adj. R^2	0.3628

Notes: The table reports regressions of the individually selected log commuting time after the first relocation on the average log commuting time of the region before the movement and control variables. Standard errors clustered by individuals, below parameter estimates. Levels of significance: *1%. **5%. ***10%. *Inverse of Mill´s ratio is obtained from the first stage probit estimation of the movement.

Table 2.A.7: Relocation between German labour market regions

Labor market region level Dependent variable	$\text{Ln}(C_{i,t=0})$
$\text{Ln}(C_{i,t-1})$	0.198***
	(0.006)
$\text{Ln}(\bar{C}_{i,t-1})$	0.217***
	(0.040)
Inverse of Mill's ratio*	0.562***
	(0.214)
Ln(wage)	0.095***
	(0.035)
Medium-skilled	0.135***
	(0.052)
High-skilled	0.182**
	(0.088)
Migrant	-0.155**
	(0.074)
Specialist/expert	-0.019
	(0.048)
Trained/professional assistant	-0.035
	(0.041)
Occupation dummies	Yes
Industry dummies	Yes
Occupational status	Yes
Firm size (Number of workers)	Yes
Year dummies	Yes
Place of residence type	Yes
Place of work type	Yes
Constant	-0.920
	(0.862)
Workers	45.232
Workers (cluster)	15.262
R^2	0.5593
Adj. R^2	0.3323

Notes: The table reports regressions of the individually selected log commuting time after the first relocation on the average log commuting time of the region before the movement and control variables. Standard errors clustered by individuals, below parameter estimates. Levels of significance: *1%. **5%. ***10%. *Inverse of Mill´s ratio is obtained from the first stage probit estimation of the movement.

Chapter 3

Being a long distance out-commuter or home employee in a rather peripheral region: Evidence of a German federal state

with Stephan Brunow [14]

Abstract Many firms in Germany are short of qualified workers, whereby East German regions are particularly affected because of the out-migration to West Germany after the reunification. This gives rise to an important debate for regional policy as the shortage of workers is a major challenge for each region and firm. In this context, out-commuters – workers who commute to work in another region – become an important group of employees to potentially satisfy local labor needs. In this study, we take a closer look at out-commuters in a particular eastern German region – the Federal State Mecklenburg-Vorpommern (MV)– and address the question whether out-commuters are a selective group of individuals working in e.g. occupations or industries that are rarely needed for labor market requirements in MV. Further, we focus on the wage differential between out-commuters and workers who live and work in MV (home employees). The determination of the factors that explain this wage gap can provide new insights and a deeper understanding of the labor market in MV. This can provide a basis to work out potential strategies to attract the group of out-commuters for a workplace in MV to reduce the complained labor shortage. The derived evidence suggests that only few out-commuters can be recalled, as the labor demand in MV and the respective wage level are too low and the economic structure is too weak to sufficiently gain back out-commuters. Especially females suffer from the job-market weakness in MV.

[14] University of Applied Labour Studies, Department of Labour Economics, Schwerin

JEL Classification J21, R23

Keywords long-distance commuting, rural region, economic conditions

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3.1 Introduction

Within countries, inter-regional commuting is increasing in the EU (European and Comission, 2017), i.e. workers leave the region of residence and commute to another region for job related reasons. In Germany, for example, the number of workers leaving their communities to work increased from 14.9 million in 2010 to 19.3 million in 2018, which is nearly half of the German labor force. Such inter-regional commuting can lead not only to personal, environmental and societal changes, like lower life satisfaction and increased congestion, but it also results in a loss of workforce for the region of emigration. This outflow of labor can be particularly serious for regions that complain of labor shortages.

One of these regions is East Germany. After the German re-unification in 1991, East Germany was characterised by high unemployment, low wages and less growth perspectives compared to the western parts (Blien et al., 2016). As a result, especially, young people out-migrated from East Germany (Kröll and Niebuhr, 2008; Fuchs-Schnündeln and Schündeln, 2009). Although, economic conditions in East Germany have improved and out-migration reached balanced levels (Nadler and Wesling, 2003), there is still a large number of workers commuting out of eastern German regions and working in the West. Out-migration from East Germany and a low birth rate in the 1990th have left its mark: the age structure is characterised by a higher proportion of elderly people who will retire in the next years, resulting in a shortage of young workers (Schwengler and Hirschenauer, 2015). This is already asserted by Burkard (2010) and showing in an analysis of the IAB-Establishment Panel (2018): firms in eastern Germany were unable to fill 33 percent of training places and around 4 out of 10 vacancies. This situation gives rise to an important debate for regional policy and policy makers as the shortage of workers can be seen as a major challenge to regional development and social welfare. In this context, out-commuters – workers who commute to work in another region – become an important group of employees to satisfy local labor needs as they are already available in the particular "home" region. The win back of this workforce can reduce local labor shortages.

Generally, commuting between different regions might be the result of strategic choices that balance housing and living costs, family, wage differentials, employment opportunities as well es job accessibility and job availability (Bunel and Tovar, 2014; Eliasson et al., 2003; Reggiani et al., 2011; Bergantino and Madio, 2018). This could be especially important for workers commuting between regions that differ in labor market conditions, like East and West Germany. In particular, regarding wages and unemployment[15], the differences to West Germany are still visible (Brenke, 2014). People living in East Germany are consequently disadvantaged in many respects: (i) they face lower wages, (ii) working conditions are not comparable (work council, career possibilities), and (iii) they face higher unemployment resulting in

[15] Although the unemployment rate has fallen significantly in East Germany in recent years, it is still higher than in West Germany (Granato et al., 2009). And this decline is particularly due to the increasing number of eastern German employees retiring.

fewer job opportunities (Blien et al., 2010). Such factors push workers to cross regional borders (Van Ham and Hooimeijer, 2001; Reggiani et al., 2011), either by migration or commuting.

However, migration flows between East and West Germany are now balanced, but both out-commuting (commuting from East to West Germany) and the distances workers commute are increasing. This increase in long-distance commuting can be seen as a reason for the decrease in inter-regional migration decisions (Lundholm, 2009). The lower migration propensity can be explained by the fact that individuals who live for a long period in the same place develop social networks, have families and children as well as home ownership. Their attachment to this region is therefore very strong, which is why they decide to commute and not to migrate. This is also further enhanced by the improvements in infrastructure and the information and communication technology (Sandow and Westin, 2010) that makes it easier for employees to cover long distances and cross regional borders. Thus, long-distance commuting can be regarded as an alternative to migration (Green et al., 1999; Lundholm et al., 2004).

In order to win back this group of long-distance out-commuters it is important to understand why those people commute out and face the costs of long-distance commuting. The aim of this study is therefore to investigate factors – individual, job-related and establishment characteristics – that distinguish the group of long-distance out-commuters from the group of workers who live and work within the same region (home employees).

A qualification-related mismatch results, if we find that both groups, out-commuters and home employees differ in terms of individual and firm characteristics. If both groups are however more identical, it would be easier for policy measures to win back the group of out-commuters. Additionally, as theory and empirical evidence show that wages are a main factor for long-distance commuting (Van Ommeren and Fosgerau, 2009; Brueckner, 2000; Manning, 2003; Green et al., 1999), we pay particular attention on the wage differential between the group of out-commuters and home employees (Bergantino and Madio, 2018). Investigating individual and firm-specific factors that explain the wage gap can provide new insights and a deeper understanding of the labour market of the region of migration and emigration in terms of occupational and individual characteristics that could be influenced by policy measures to gain back the group of long-distance out-commuters. And can thus show what regions with worse labour market conditions might be able to do to attract back skilled workers who are working outside their residence region. In particular, if wages of both regions are not competitive a win-back campaign is potentially less successful.

For this study, we consider a particular region of East Germany, namely Mecklenburg-Vorpommern (MV). This region is not only characterised by workers leaving their regions for job related reasons, but MV is also still worse to the West in terms of economic conditions, like the wage level and labor market opportunities (Blien et al., 2016). In addition, MV offers a particularly good basis for investigation, since it is located at the boarder to West Germany that provides workers a good opportunity living in MV and working in the west. Close to the western parts of MV is the metropolitan area of Hamburg, which has good labor market opportunities as well. In general, MV has a high proportion of peripheral regions with low population densities. In the west of MV there is the capital city Schwerin, with almost 100,000 inhabitants, surrounded by rather peripheral regions. Rostock as a harbour city is the largest city with about 245,000 inhabitants. Stralsund (Vorpommern-Rügen), Greifswald (Vorpommern-Greifswald), Neubrandenburg (Mecklenburgische Seenplatte) and Wismar (Nordwestmecklenburg) are other cities with about 30-70,000 inhabitants and are spread all over the federal state. In total, about 1.6 Mio people live currently in MV and the population density is less than 70 people per square kilometer including the cities (about 35 excluding cities).

Figure 3.1: Map of Meckenburg-Vorpommern

Notes: The map shows the Federal State of Meckenburg-Vorpommern. Source: `https://www.regierung-mv.de/Landesregierung/wm/Technologie/Hochschulen-in-MV`.

Our study contributes to the literature in several ways. First, we contribute to the literature on inter-regional commuting and analyse individual and firm characteristics that cause individuals to live in one region and work in another region (Castelli and Parenti, 2020; Parenti and Tealdi, 2019; Sandow

and Westin, 2010). Second, our study adds to the literature on long-distance commuting by examining commuting between extensive labor markets rather than focusing only on commuting within cities, as is usually the case in the literature (Andersson et al., 2018). Third, we determine individual and firm-specific characteristics that explain the wage gap between the group of out-commuters and home employees by showing how the wage setting differs between the region of migration and emigration (Bergantino and Madio, 2018). Forth, we make use of a vast data basis provided by the Institute for Employment Research, the Integrated Employment Biographies, IEB. This data basis covers all individuals working subject to social security contributions and represents a comprehensive source of individual as well as firm information. Last, due to the distinction between men and women we reveal gender-specific differences in individual and firm-specific characteristics which explain out-commuting and wage disparities.
In fact, our results indicate different reasons why women and men commute long distances and cross regional borders. While men commute out for higher wages and better career opportunities, the results for women indicate that they commute out to avoid unemployment. MV has not only weak labor market conditions, but especially for women there is a low demand for labor and thus it is rather difficult to win back the group of out-commuters.

The remaining paper is structured as follows. Section 3.2 provides insights into long-distance commuting and related literature. Section 3.3 discusses the empirical design, describes the data and the methodological approach. The descriptive analysis is shown in Section 3.4, while Section 3.5 reports the results of the probit model and the Oaxaca-Blinder decomposition. Finally, Section 3.6 concludes.

3.2 Literature review and theoretical considerations

Whenever the place of work differs from the place of residence, commuting is necessary. Commuting is hence an elementary, time-consuming part of most workers' day and an important requirement to match employees and employers. Commuting can also occur in a wide-ranging regional setting as workers can cross regional borders and commute long-distances leading workers to reach an even more distant labour market. Many studies have investigated factors that are important in explaining long-distance commuting finding that the labor market, housing market as well as individual and job characteristics are important determinants.
In particular, the standard urban theory implies a negative relationship between urban density and commuting distances: people living in sparsely populated labor markets commute longer than those in urbanised areas because urban areas are denoted the centre of employment opportunities (Rouwendal and Nijkamp, 2004). Since land prices decrease gradually from the centre to rural areas and housing is limited in the centre, workers are faced with a trade-off between living in the centre and paying higher

rents or living outside where rents are lower, but commuting ways are longer.

In this context, literature on housing market characteristics find that high housing prices increase long-distance commuting in-flows because of their deterrent effect on in-migration (Muellbauer and Cameron, 1998). The reason is that regions with high wage levels attract workers, but high housing prices in these regions cause workers to live outside. In this sense, Bergantino and Madio (2018) find that regional wage differentials lead to inter-regional commuting. Similar, Renkow and Hoover (2002) show that longer commutes are traded for lower housing prices in rural areas, which increases long-distance commuting between rural and urban regions (Andersson et al., 2018; Zax, 1991). Housing prices, especially in rural regions such as in MV are significantly lower than in the neighbouring larger cities in western Germany such as in Hamburg, what makes commuting a more attractive way than migration into these regions.

Gender plays also a fundamental role on commuting patterns as men commute longer distances than women (Hanson and Hanson, 1993; Camstra, 1995). Women earn less than men (MacDonald, 1999) what makes commuting long distances less attractive according to the willingness-to-commute literature (Le Barbanchon et al., 2021; Dauth and Haller, 2020). Females work more frequently in occupations that are geographically more evenly distributed (Halfacree, 1995; Hanson and Pratt, 1995), leading to smaller commuting distances. Women's commuting patterns are also constrained by household and family involvements (Giménez-Nadal and Molina, 2016). In addition, commuting distance increases for full-time workers (McQuaid and Chen, 2012), but females are more often engaged in part-time work, which is lower paid and thus results in lower commuting distances.

Age is another important determinant of commuting decisions; however, the relationship is not entirely evident. While older workers have longer working experience, which would lower the willingness to accept longer commuting distances (Booth et al., 1999), older workers are home-owners or have family obligations that could increase the propensity to commute (Van Ham and Hooimeijer, 2001).

Another common finding is that commuting increase with the education level: more educated workers are more mobile. They have to search longer for jobs because their job market is concentrated to a limited number of locations (especially to larger centres) and are thus not evenly distributed across space (Börsch-Supan, 1990; Sandow, 2008). In this context, Huber (2014) derives theoretical arguments of the impact of individual education on being a commuter or home employee and provides empirical evidence that out-commuters are better skilled. According to Dargay and Clark (2012) high educated workers earn better than low skilled workers, which makes it more profitable for them to commute longer distances. Additionally, high earning households have preferences for larger living space, so they choose to live in suburbs where housing prices and rents are cheaper and accept longer commutes (Brueckner, 2000).

However, when out-commuters work in distinct regional labor markets, differences in wages may be driven by differences in productivity, caused by differences in firm, industrial and occupational structure. This is confirmed by several studies explicitly showing that individual wages are affected by firm characteristics

(Brixy et al., 2022; Schmid, 2023; Dostie et al., 2020; Brunow and Jost, 2022).

The literature review provides theoretical and empirically justified arguments for long-distance commuting. The complexity of mobility choices depends on sociodemographic characteristics, such as age and gender, education attainment, job characteristics and the occupation, labor market aspects, wages and firm productivity. With MV being a rather rural region in Germany with relatively poor labor market conditions, it offers a good object of study to foresee potential future problems regarding labor supply in MV and East Germany.

3.3 Empirical design

3.3.1 Data and sample

In this study, we use the Integrated Employment Biographies (IEB, version V13.01.01-190111) provided by the Institute for Employment Research (IAB) of the Federal Employment Agency in Germany. This data results from the administrative process of the German Social Security System and is highly reliable. The data covers individuals working subject to social security contributions; self-employed and civil servants are excluded. It can be aggregated to any higher level of aggregation, such as firm and region because of unique identifiers.

The sample comprises all individuals who live in MV at some moment in time since 1999, as the place of residence is collected since then. However, in the analysis we restrict to the day of September 15, 2017[16]. Additionally, we draw a 10 percent sample of all individuals working in the destination regions of out-commuters. Although the analysis is built on a cross-section of individuals, we use the entire individual labor market biographies to construct measures of individual past performance, such as job-changing behaviour and unemployment periods. These measures control for unobserved heterogeneity in part.

Further, we perform two proven data corrections. The first one corrects the education-related variable following the procedure suggested by Fitzenberger et al. (2005). For the second, we follow Card et al. (2013) and use an imputation method that overcomes the truncation of wages top-coded at the social security contribution ceiling. From the sample, we excluded individuals with unknown education (i.e. missing information) and individuals working in so called “mini-jobs”. These are jobs without social security contributions and earnings of up to 400 Euro per month. We restrict the sample to German employees only, because less than 2 percent of all employees are foreigners, but of those 90 percent out commute. Thus, 10,592 foreigners are excluded.

The group of out-commuters comprises all employees living in MV and working outside MV and commute

[16] The reference day is chosen to balance seasonal frictions (summer-winter employment levels) and because most of young individuals start their apprenticeship and are not potentially registered as unemployed.

at least 34 kilometer. We exclude the group of out-commuting workers with commuting distances up to 34 kilometer (approximately 8,000 cases, 11 percent of all out-commuters), as we find that 75 percent of all home employees, commute up to 34 kilometer. Therefore, we assume that commuting distances up to 34 kilometer are acceptable and that each out-commuter with commuting distances up to 34 kilometer would accept a job offer within MV immediately. Hence, this group does not represent our target group to win back for a job in MV. In addition, this restriction excludes people who live outside MV but may move to MV because of lower housing costs and thus become out-commuters. The 34 kilometer restriction is further comparable to other studies, e.g. Sandow and Westin (2010) who investigate long-distance commuting in sparsely populated areas in Sweden. We further rever long-distance out-commuters to out-commuters.

After data preparation, the data set comprises 485,673 home employees and another 58,554 out-commuters.

3.3.2 The comparison groups in detail

This study has two objectives. First, the study aims to identify individual and firm characteristics that increase the likelihood that workers are living in MV while working in another German region and commute long distances. Second, we are interested in the explanation of the wage gap between the group of out-commuters and home employees. For this purpose, we compare the group of out-commuters with the group of home employees.

In addition, we compare the group of out-commuters with two other groups. First, with a group of home employees with commuting distance of more than 34 kilometers. We refer this group as long-distance home employees. Out-commuters and long-distance home employees should be similar regarding commuting costs and thus after theory similar regarding their sociodemographic characteristics (see Section 3.2). This additional comparison allows us to draw even better conclusions why workers are leaving their region and commute out. In particular, if there are only small or even insignificant differences between these two long-distance commuting groups, it would indicate less job opportunities within MV, leading to the need to out-commute in order to avoid unemployment. If there are still significant differences, then it indicates, that their qualification is not requested in MV. For example, it is possible to draw conclusions about occupations not offered in MV and therefore cause workers to commute out.

Second, we compare out-commuters with those workers in the destination region. This shows, if the group of out-commuters is similar in their characteristics compared to workers in the destination region and gives additional insights into push and pull factors of out-commuting.

Thus, we compare the group of out-commuters with three groups: home, long-distance home and destination employees.

3.3.3 Variables

There are two variables which are subject of our investigation. The first one is the binary variable of being an out-commuter. The second variable is the wage gap between the group of out-commuters and the considered control groups. It is calculated as the differences between log daily wages.

To explain the wage gap and the likelihood of being an out-commuter, we consider individual, establishment and regional determinants that are included in Table 3.1, and that have been identified in previous studies (see Section 3.2).

Table 3.1: Individual, Job and Firm characteristics

	Characteristics
Occupations	Indicators for 36 distinct occupations (based on the classification of occupations 2010 KldB2010, equiv. to ISCO-08; excluding military services)
Tasks	Indicator for unskilled labor – skilled labor (reference) – specialists/experts
Leading responsibility	Indicator fro supervision responsibility
	Indicator for leading responsibility (reference: neither of both)
Vocational training	Indicator for no vocational training – vocational training (reference) – university degree
	Indicator for working as foreman (German Meister/Polier) (Additional training)
Firm characteristics	Firm size (indicators for number of employees)
	Proportions of human capital, females, foreigners and young employees
	Indicators for industry (NACE, 2-digit)
Individual age	Age (indicators for 5 age groups)
Full-time	Indicator for full-time or part-time
Unemployment	Indicator representing the share of time spent in unemployment (<5%, 5%-<10%, 10%-<25%, ≥25%)
Experience	Duration at the current employer (firm experience)
	Average employment duration at different employers (work experience)
Regional indicators	5 labor market region indicators measured at the place of residence

3.3.4 Methodological approach

Who is an out-commuter?

We use a probit model to identify the individual and firm characteristics listed in Table 3.1 that increase the likelihood that workers live in MV and commute to another region. The estimates allow us to identify significant group differences. Further, to identify differences regarding gender, we consider separate estimates for women and men.

What explains the wage gap?

To explain the wage difference between the group of out-commutes and (long-distance) home/destination employees, we use the Oaxaca-Blinder decomposition (OB-decomposition) according to Jones and Kelley (1984). The estimation relies on the Mincerian earnings function as a theoretical workhorse for the wage setting on the labor market. To perform the OB-decomposition, for both groups – out-commuters and home employees – a separate wage equation is estimated by OLS. The OB-decomposition splits the wage differential into an explained part consisting of differences in endowments, an unexplained part consisting of differences in coefficients and an interaction term. The endowment effect states: *how much more/less would a home/destination employee earn adjusting the average endowment (i.e. the average x-values) to the level of out-commuter.* Differences in endowments therefore indicate an unequal distribution of characteristics and would thus indicate a mismatch for out-commuters, i.e. their qualification/characteristics are not as frequent demanded in MV. The coefficient effect indicates differences in slopes of the estimated Mincerian wage equations. The interpretation of the coefficient effect is as follows: *how much would an average home/destination employee earn more/less adjusting the coefficient to the level of out-commuter.* We relate these different returns to characteristics as structural differences in payment schemes. Employers in MV might become more competitive, when returns to characteristics are treated in a way as for out-commuters. Lastly, the interaction effect considers the simultaneous adjustment of differences in endowments and coefficients. Concerning the interpretation, we adjust the wage level of home employees to the level of out-commuters. This is a matter of choice and does not bias results in any respect. From a policy perspective, it provides insights on potential, required wage increases to become competitive with other regions; at least with payment levels of out-commuters.

3.4 Descriptive analysis

According to Table 3.2, the number of out-commuters is more than twice as high for males as for females. Comparing female and male long-distance home employees, there can also be observed a larger number of males. Thus, men commute longer distances than women. Various studies confirm this gender specific commuting pattern (Dargay and Clark, 2012; McQuaid and Chen, 2012; Giménez-Nadal et al., 2020).

Table 3.2: Age distribution, task level and median wages

	Home employee		Out-commuter		Long-distance home employee		Destination employee	
	Women	Men	Women	Men	Women	Men	Women	Men
Age structure %								
<25	5.6	7.3	7.1	3.6	7.9	7.5	5.2	5.5
25-34	18.7	21.7	23.4	18.1	20.1	20.8	20.5	22.9
35-44	20.3	21.7	21.7	21.6	20.3	21.3	21.0	22.3
45-54	29.2	26.0	25.9	30.3	27.7	26.7	31.0	28.9
55-64	26.4	23.3	21.9	26.5	24.0	23.8	22.2	20.4
Task levels %								
unskilled labor	14.0	12.5	15.2	8.9	13.2	10.5	13.8	11.6
skilled labor	64.4	66.6	57.3	61.3	61.1	65.1	63.2	57.0
specialist/expert	21.6	20.9	27.5	29.9	25.7	24.5	23.0	31.4
Median wage in euro/day								
<25	36.3	33.5	36.2	42.8	34.4	34.1	70.0	79.4
25-34	61.8	70.5	77.0	92.0	68.6	75.4	83.8	100.8
35-44	64.1	76.3	80.7	105.1	74.6	82.2	74.0	114.8
45-54	69.2	78.9	81.6	109.9	78.9	86.5	76.4	121.0
55-64	70.1	78.6	0.	1 104.7	82.0	86.2	74.1	115.3
unskilled labor	47.6	59.2	46.0	70.3	45.4	59.0	50.3	76.5
skilled labor	62.4	70.9	73.06	92.2	69.0	74.8	74.5	100.9
specialist/experts	103.04	117.9	115.4	153.4	105.8	122.4	110.6	159.1
Median wage in euro/day	64.7	73.8	76.6	101.6	72.5	80.0	77.1	110.8
N	252,591	233,082	16,523	42,031	36,082	48,560	1,143,825	1,268,436

Source: IEB version V13.01.01-190111, own calculation.

Considering the age structure of home employees and out-commuters in Table 3.2, shows slightly higher proportions of older workers among male out-commuters. In contrast, female out-commuters are slightly younger. The age structure of long-distance home employees is comparable to the age structure of home employees. In addition, the comparison of out-commuters with destination employees shows that male out-commuters are older, while female out-commuters are younger.

Out-commuting may be a result of mismatch of job characteristics at the labor market. Table 3.2 therefore includes the distribution according to tasks. Indeed, there are relative more employees working as specialists/experts among male and female out-commuters, indicating a specific brain drain. However, for women we also observe a slightly higher share of unskilled labor.

Further, Table 3.2 reveals substantial wage differences between home employees and out-commuters: gross daily wages are about 28 Euro higher (approximately 840 Euro monthly) for males. For females, wages of out-commuters are higher, but with about 12 Euro (357 Euro monthly), less lucrative for out-commuting. In addition, out-commuting is beneficial for better skilled. Surprisingly, out-commuting unskilled females earn even 5 Euro less per day. In comparison with long-distance home commuters, out-commuting males earn still substantially more. For females, there is a benefit as well but less pronounced. Sandow and Westin (2010) confirm such findings considering long-distance commuters in Sweden. Further, comparing the wage of out-commuters with the wage of destination employees, male commuters earn about 10 Euro less, depending on the age group, for out-commuting females' wages are slightly higher.

The descriptive results show first evidence of group differences in characteristics and especially between men and women. For men, out-commuting seems to be more lucrative, as they benefit even more from higher wages. The results show that wages in MV are lower even for those workers who commute long distances in MV.

3.5 Results

3.5.1 Who is an out-commuter?

Table 3.3 presents the estimates of the probit model to identify group differences between out-commuters and (long-distance) home/destination employees separated by gender. Within each gender block, the first column considers differences between out-commuters and home employees. The second column shows differences between out-commuters and long-distance home employees, while the third column reveals the results comparing out-commuters with employees in the destination region. In each estimation, all coefficients are jointly significant. Since we are not interested in the magnitude to become an out-commuter, but in the differences in characteristics between both groups, we only interpret the signs of the estimates.

The results show that out-commuters are relatively older than home employees. Younger workers – men and women – are less likely to be out-commuters. This holds for the comparison with the group of long-distance home employees and destination employees. Since the economic conditions have improved in the last years, the necessity for young individuals to leave MV is reduced (Nadler and Wesling, 2003; Schwengler and Hirschenauer, 2015; Burkard, 2010).

Table 3.3: Probit regression on being an out-commuter

	Men			Women		
	home employees	long dist. home empl.	destination employees	home employees	long dist. home empl.	destination employees
			Individual characteristics			
<25	-0.737***	-0.662***	0.849***	-0.385***	-0.405***	1.112***
	(0.019)	(0.026)	(0.018)	(0.023)	(0.033)	(0.023)
25-34	-0.177***	-0.128***	-0.020*	-0.079***	-0.040**	0.004
	(0.010)	(0.014)	(0.012)	(0.013)	(0.019)	(0.016)
35-44	0.139***	0.077***	0.105***	0.052***	-0.001	0.007
	(0.009)	(0.013)	(0.011)	(0.012)	(0.018)	(0.016)
55-64	0.175***	0.099***	0.159***	0.084***	0.035*	0.071***
	(0.010)	(0.013)	(0.012)	(0.013)	(0.019)	(0.017)
Unskilled labor	-0.086***	0.005	0.239***	0.109***	0.175***	0.258***
	(0.013)	(0.018)	(0.020)	(0.015)	(0.023)	(0.026)
Specialist/expert	0.126***	0.071***	0.287***	0.139***	0.144***	0.221***
	(0.013)	(0.018)	(0.022)	(0.016)	(0.023)	(0.032)
No vocational training Employees working as						
unskilled labor	0.235***	0.238***	-0.537***	0.170***	0.113***	-0.485***
	(0.025)	(0.036)	(0.039)	(0.029)	(0.041)	(0.047)
skilled labor	0.011	0.071***	0.096***	0.006	0.035	0.000
	(0.016)	(0.022)	(0.023)	(0.021)	(0.030)	(0.034)
specialist/expert	0.086**	0.169***	0.564***	0.168***	0.299***	0.113
	(0.034)	(0.048)	(0.043)	(0.045)	(0.066)	(0.083)
University degree holders working as						
unskilled labor	0.286***	0.344***	2.773***	0.092	0.117	2.486***
	(0.085)	(0.128)	(0.027)	(0.084)	(0.125)	(0.031)
skilled labor	0.119***	0.061**	3.076***	0.031	0.003	2.397***
	(0.023)	(0.031)	(0.013)	(0.022)	(0.031)	(0.018)
specialist/expert	-0.173***	-0.152***	1.757***	-0.107***	-0.176***	1.377***
	(0.014)	(0.018)	(0.020)	(0.018)	(0.025)	(0.029)
Full-time	-0.060***	0.046**	-0.162***	-0.039***	-0.003	-0.133***
	(0.013)	(0.018)	(0.015)	(0.009)	(0.013)	(0.012)
Additional training	0.070	0.080	0.054	0.008		
	(0.075)	(0.107)	(0.096)	(0.141)		
Leadership responsibility	-0.038**	-0.001	-0.111***	-0.047*	0.098**	-0.098***
	(0.019)	(0.026)	(0.018)	(0.028)	(0.040)	(0.032)
Supervision responsibility	0.130***	0.100***	-0.254***	0.025	0.072	-0.143***
	(0.021)	(0.029)	(0.022)	(0.035)	(0.051)	(0.041)
Unemployed 5%-<10%	-0.098***	-0.059***	0.216***	-0.110***	-0.103***	0.231***
	(0.010)	(0.014)	(0.013)	(0.013)	(0.020)	(0.017)
Unemployed 10%-<25%	-0.227***	-0.178***	0.321***	-0.232***	-0.208***	0.412***
	(0.010)	(0.014)	(0.013)	(0.013)	(0.019)	(0.017)
Unemployed $\geq$25	-0.517***	-0.395***	0.488***	-0.428***	-0.376***	0.761***
	(0.013)	(0.018)	(0.017)	(0.016)	(0.023)	(0.020)
Log(firm experience)	-0.061***	0.006	-0.315***	-0.085***	-0.009	-0.382***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)
Log(work experience)	-0.256***	-0.179***	0.268***	-0.243***	-0.193***	0.461***
	(0.006)	(0.009)	(0.007)	(0.008)	(0.012)	(0.010)

(continue on next page)

Table 3.3: Probit regression on being an out-commuter (continued)

	Men			Women		
	home employees	long dist. home empl.	destination employees	home employees	long dist. home empl.	destination employees
			Firm characteristics			
10-49 employees	0.283***	0.090***	0.200***	0.156***	0.022	0.149***
	(0.010)	(0.015)	(0.014)	(0.013)	(0.020)	(0.017)
50-249 employees	0.621***	0.314***	0.310***	0.469***	0.234***	0.310***
	(0.011)	(0.015)	(0.014)	(0.013)	(0.020)	(0.017)
250+ employees	0.948***	0.702***	0.255***	0.789***	0.610***	0.327***
	(0.012)	(0.017)	(0.015)	(0.015)	(0.022)	(0.018)
Proportion of females in firm	-0.923***	-0.726***	-0.687***	-0.245***	-0.251***	0.283***
	(0.021)	(0.029)	(0.026)	(0.023)	(0.033)	(0.029)
Proportion of high-skilled in firm	0.747***	0.659***	-0.059***	0.214***	0.089***	-0.219***
	(0.018)	(0.024)	(0.019)	(0.021)	(0.030)	(0.025)
Constant	-1.559***	-0.495***	-2.466***	-1.422***	-0.420***	-3.084***
	(0.042)	(0.061)	(0.089)	(0.071)	(0.107)	(0.136)
N	275,113	90,591	1,285,833	269,114	52,605	1,129,683
Pseudo R^2	0.139	0.090	0.632	0.118	0.091	0.557

Notes: Robust Standard errors in (). Level of significance: * 1%, ** 5%, ***10%. Source: IEB version V13.01.01-190111, own calculation. Labor Market Region fixed effects, Industry fixed effects, Occupation fixed effects included.

Table 3.3 reports relevant results considering the task levels. The presented parameters relate to the reference group of individuals holding a vocational training degree (interaction effects will be discussed next): relative to skilled labor, the proportion of specialists/experts is higher among male and female out-commuters compared to home and destination employees. Further, female out-commuters are more frequently working in unskilled labor positions compared to all three comparison groups.

Going into detail, the interaction effect with the vocational-degree background reveals the following pattern: men and women without a vocational training degree out commute more often compared to home employees. In addition, high-skilled, male out-commuters are more frequently employed as unskilled or skilled labor compared to home and long-distance home employees. This indicates downward mobility to jobs that do not require such high formal qualification. In comparison with the destination employees, the large and positive coefficients consolidate this picture of downward mobility for males and females.

Commuting long distances is costly and therefore only profitable for those working in full-time (McQuaid and Chen, 2012). Our results confirm this picture, as out-commuters are more frequently full-time employed relative to part-time work. However, in comparison with long-distance home employees, male out-commuters work more frequently part-time.

The fraction of taking a supervision position is higher for male out-commuters, but in comparison with the destination employees, supervision positions are relative less frequent.

Considering measures of the employment biography, we find that compared to home employees, male and female out-commuters are less often employed, and compared to destination employees, they are on average more often unemployed. Home employees are on average longer employed at their current employer compared to out-commuters. As a result, the average employment duration within firms is highest for female and male home employees and lowest for destination employees. Out-commuters are somewhere in between, indicating a more dynamic labor market outside MV.

Regarding firm characteristics, out-commuters of both genders are more frequently employed in larger firms irrespective of the comparison group. Compared to home employees, out-commuters work in firms with a higher fraction of high-skilled employees. However, the evidence suggests a brain-drain and downward mobility of high-skilled. Therefore, it is not surprising that out-commuters work in firms with a lower share of high-skilled workers in comparison with destination employees.

3.5.2 On the monetary benefits of out-commuting

A first overview of the results of the OB-decomposition is provided in Table 3.4. Male out-commuters earn on average 36.4 percent (26.7 percent) more than home employees (long-distance home employees). However, they earn about 8.3 percent less compared to employees in the destination region. For females, the results show less pronounced wage differentials. Female out-commuters earn about 11.2 percent more relative to home employees. There is no difference compared to long-distance home commuters. Relative to females in the destination region, out-commuters earn 2.9 percent less. With respect to the economic magnitude, a one percent wage increase accounts for approximately 0.74 euros for males and 0.65 euros for females in gross daily income (about 22.20 euros for males and 19.50 euros for females per month). The endowment effect is positive for out-commuting males and insignificant for females, in comparison to home employees. For men in particular, this confirms the results of the probit model for group differences in favor of out-commuters. Interestingly, the coefficient effect is positive for females and males, indicating that returns on endowments are better evaluated outside MV. In comparison with destination employees, males show a slightly disadvantageous effect of 3.3 percent; for females the coefficient effect is insignificant.

Table 3.4: Evaluation of the Oaxaca-Blinder decomposition

	Men			Women		
	home employees	long dist. home empl.	destination employees	home employees	long dist. home empl.	destination employees
Difference	1.364***	1.267***	0.917***	1.112***	1.049	0.971***
	(0.013)	(0.008)	(0.002)	(0.036)	(0.040)	(0.005)
Endowments	1.137***	1.093***	0.939***	1.034	0.989	1.028***
	(0.008)	(0.007)	(0.002)	(0.025)	(0.030)	(0.004)
Coefficients	1.168***	1.135***	0.960***	1.051***	1.033***	0.986
	(0.006)	(0.001)	(0.003)	(0.007)	(0.007)	(0.008)
Interaction	1.027***	1.022***	1.018***	1.024***	1.027***	0.958***
	(0.005)	(0.002)	(0.003)	(0.007)	(0.003)	(0.008)

Notes: Cluster robust s.e. at labor-market-region level in (), * 0.1, ** 0.05, *** 0.01; all control variables included.

Endowment effect

Table 3.5 reports the endowment effect in detail. The effect of the difference in the occupational mix is very tiny. This aspect is important as it reveals that after controlling for other characteristics, the average wage differential is not caused by the unequal occupational mix. However, compared to destination employees, both men and women experience a wage disadvantage of about one percent, depending on the occupational group. Thus, out-commuters work in occupations, which are payed less compared to destination employees.

The probit model reveals a relative higher proportion of specialists/experts among out-commuters compared to home and destination employees, which makes it less surprising that adjusting the task structure of home employees to the level of out-commuters leads to a wage increase of about 1.8 percent for men, and 0.6 percent for women. However, although the share of specialist/experts is higher among out-commuters compared to destination employees, there is no positive wage effect.

Little or no wage effects can be found adjusting leadership responsibility and vocational training information.

Moreover, we find no significant effect for labor market experience related variables for males, but a significant negative effect of almost 3.1 percent for females. Although out-commuting females are less frequent unemployed, show shorter firm tenure and are on average more frequently job-changers, they earn less. Because out-commuters are slightly older compared to home employees, higher wages are paid supporting to the Mincerian wage equation. Thus, wages are higher for out-commuters. For females such age-related effect is not observed.

There is also a substantial wage increase of about 2 percent for men and women caused by full-time work. Regarding firm characteristics, the results show that they are associated with a substantive wage increase of about 4.4 percent for males and 4.7 percent for females. Especially the employment size of firms in

MV is smaller and firms employ less human capital.

Lastly, there are small industry-related effects for males in favour of out-commuters. Contrary, out-commuting females work in industries that pay less.

Table 3.5: Detailed results of the endowment effect

	Men			Women		
	home employees	long dist. home empl.	destination employees	home employees	long dist. home empl.	destination employees
Occupations	1.001	1.001	0.992***	0.990**	0.988**	0.989***
	(0.001)	(0.002)	(0.000)	(0.004)	(0.005)	(0.001)
Tasks	1.018***	1.011***	1.000	1.006***	1.000	1.002***
	(0.004)	(0.004)	(0.000)	(0.001)	(0.001)	(0.001)
Leadership responsibility	1.002***	1.001***	1.000	1.001***	1.001*	1.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Full-time	1.020***	1.008***	1.012***	1.018***	1.007***	1.047***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
Age	1.017***	1.020***	1.004***	0.996	1.004	0.997***
	(0.002	) (0.002)	(0.000)	(0.004)	(0.004)	(0.000)
Vocational training	1.013***	1.007***	0.995***	0.996**	0.991***	1.002***
	(0.003)	(0.002)	(0.000)	(0.002)	(0.002)	(0.001)
Unemployment	1.007***	1.006***	0.983***	1.005	1.002	0.985***
	(0.001)	(0.002)	(0.000)	(0.005)	(0.005)	(0.000)
Experience	0.992*	1.005	0.970***	0.969***	0.985	0.963***
	(0.005)	(0.005)	(0.000)	(0.009)	(0.010)	(0.001)
Firm characteristics	1.044***	1.023***	1.002***	1.047***	1.011***	1.035***
	(0.005)	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)
Industry	1.008***	0.999	0.988***	0.988***	0.981***	0.989***
	(0.003)	(0.002)	(0.000)	(0.004)	(0.004)	(0.001)

Notes: Cluster robust s.e. at labor-market-region level in (), * 0.1, ** 0.05, *** 0.01; all control variables and regional indicators included.

Coefficient effect

The coefficient effect relates to differences in the parameters of characteristics on the effect on wages. Thus, potentially structural differences in the wage setting can be identified. The results of the coefficient effect are provided in Table 3.6. Small values indicate a rather equal wage setting and evaluation among MV employers and firms employing out-commuters outside MV. However, this is rarely the case. In particular, compared to home employees tasks outside MV are evaluated better for female and male out-commuters, which may be due to the observed brain drain.

Further, working full-time outside MV provides about 9.5 percent higher wages for males and 7.4 percent higher wages for females.

There are also substantive age effects – the associated returns are much higher outside MV – compared to home, long-distance home and destination employees.

Table 3.6: Detailed results of the coefficient effect

	Men			Women		
	home employees	long dist. home empl.	destination employees	home employees	long dist. home empl.	destination employees
Occupations	1.001	1.042***	0.962**	0.989	1.029	1.080***
	(0.017)	(0.013)	(0.016)	(0.022)	(0.023)	(0.019)
Tasks	1.045***	1.016*	1.005	1.065**	1.036	1.008
	(0.002)	(0.009)	(0.006)	(0.031)	(0.028)	(0.010)
Leadership responsibility	0.999	0.999*	0.999*	1.000	0.999	0.999*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Full-time	1.095***	1.112***	1.011*	1.074***	1.077***	0.977***
	(0.029)	(0.030)	(0.007)	(0.010)	(0.015)	(0.004)
Age	1.087***	1.057***	1.426***	1.090***	1.067***	1.453***
	(0.017)	(0.020)	(0.013)	(0.025)	(0.024)	(0.023)
Vocational training	0.882***	0.863***	1.121***	0.930***	0.864***	1.181***
	(0.005)	(0.014)	(0.007)	(0.025)	(0.021)	(0.013)
Unemployment	0.997	1.001	1.011***	0.999	0.999	0.994***
	(0.002)	(0.001)	(0.001)	(0.004)	(0.005)	(0.002)
Experience	0.993**	0.987***	1.010***	1.009*	0.992	1.024***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.008)	(0.007)
Firm characteristics	1.037***	1.090***	0.978***	0.933***	0.963***	0.941***
	(0.005)	(0.010)	(0.006)	(0.013)	(0.014)	(0.015)
Industry	1.054*	1.065*	1.038***	1.039	1.037	1.042***
	(0.033)	(0.039)	(0.014)	(0.026)	(0.028)	(0.010)
Constant	0.970	0.924	0.681**	0.956	1.019	0.793
	(0.059)	(0.045)	(0.111)	(0.092)	(0.101)	(0.322)

Notes: Cluster robust s.e. at labor-market-region level in (), * 0.1, ** 0.05, *** 0.01; all control variables and regional indicators included.

For education related variables, the coefficient effect is not in favour of out-commuting. However, in terms of the relative wage dispersion, it is the case that unskilled workers in MV suffer a higher wage loss than skilled workers in MV; consequently, the coefficient effect is in favour of home employees. Thus, unskilled out commuting might be seen as a chance to improve the wage position. Finally, we argue that outside MV, formal qualification is of less importance and thus employers not necessarily pay relatively less for unskilled (as is the case within MV).

Regarding the firm characteristics, a different picture emerges for males and females: for males, the returns are higher, relative to home employees and for females the coefficient effect is negative. Compared to destination employees, respective firm effects are smaller for men and women.

Interaction effect

The interaction effect captures the joint change in endowments and coefficients. The results are provided in the Appendix 3.A.1. Although some effects are significant from a statistical point of view, their magnitude is rather small from an economic point of view.

3.5.3 Discussion

The results so far indicate a certain brain drain of better skilled people out of MV and obviously a lack of more advanced jobs in MV. This becomes obvious comparing out-commuters with long-distance home employees. Although both face similar commuting costs, out-commuters are different. In particular, we find a higher likelihood of being an out-commuter and working as specialist/experts compared to long-distance home employees. The lack of advanced jobs in MV is also confirmed, as we find that high skilled males are more frequently employed as unskilled or skilled labor compared not only to home but also to destination employees. Thus, such better skilled out-commuters tend to work overqualified outside MV, which indicates a brain drain. This could be a reaction to a weak labor market in MV, not providing enough employment opportunities, especially for high skilled workers. Further, the results provide evidence of a qualification related spatial mismatch, as the results show that out-commuters work in larger firms with a higher fraction of high-skilled workers compared to home employees. However, in comparison with destination employees, out-commuters work in firms with a lower share of high-skilled workers.

In addition, the results imply that individuals out commute to prevent unemployment – what especially affects women. In particular, we find that although women work in unskilled jobs with lower wages, they commute out and face higher commuting costs – comparing out-commuters with home and long-distance home employees. Further, the results show that employers in MV more frequently request formal qualification also for tasks, that not necessarily need formal qualification – for men and women. Thus, workers without formal qualification have to commute out to might prevent long-lasting unemployment. In addition, considering the comparison with the destination region the fraction of individuals without formal qualification working in unskilled tasks is higher among the destination employees. Again, here the demand for unskilled labor is given and out-commuters are more frequently recognized as a resource of labor. However, out-commuting is an individual choice. Those, who accept jobs outside MV under their individual qualification may be still satisfied, although they work overeducated, they still earn more – which is confirmed in the Oaxaca-Blinder decomposition – and potentially these higher wages compensate the potential disadvantage of working over-qualified.

Further, the results indicate weak career opportunities in MV: we not only find a lack of supervision and leadership positions in MV, but out-commuters also more frequently change firms. Jobs in MV potentially may not allow for carrier opportunities and therefore, those who want to pursuer carrier must commute out – which affects men in particular.

With respects to potential labor shortage, there should also be an increase in full-time jobs, as we find that out-commuters are more likely to work in part-time compared to long-distance home employees. However, we find that out-commuters are typically older. Therefore, we expect a decline in out-commuting flows in the future when these workers retire.

Regarding the wage gap, the results show that out-commuters earn higher wages than home and long-distance home employees, which is especially the case for men. This wage difference is explained by a higher proportion of specialists/experts, older workers, workers in full-time jobs and by the fact that out-commuters more often work in larger firms that employ more human capital. Therefore, potential gains of increasing returns to scale and benefits of human-capital-intensive production are missing in MV, leading to lower wages. Thus, firms outside MV are relatively more productive.

In addition, there are significant differences in coefficients indicating that the wage setting behaviour outside MV honours full-time work, task levels and age relatively more. This indicates that male and female out-commuters must be a specific, valuable group for example regarding human capital that explains the substantive higher wages, although we provide evidence of over-qualification of out-commuters.

Comparing out-commuters with destination employees, the wage dispersion between different educational levels is higher between out-commuters and smaller among destination employees. There is obviously a "fading" effect, i.e., employers outside MV do not differentiate as strongly between the different skill levels as it is the case in MV. For males and females, the wage spread is larger outside MV, as the coefficients of the occupational indicators differ significantly. Thus, firms within MV set wages more equally among occupations, whereas the wage spread is larger outside MV. For females, the results additionally indicate that they select themselves into less productive firms outside MV, which in turn may indicate a reaction to avoid unemployment.

3.5.4 Robustness checks

Several modifications underpin the robustness of our findings. In particular, we identify out-commuters as workers with commuting times between (i) 30 and 60 minutes, (ii) 30 and 90 minutes and (iii) more than 90 minutes. The results are in line with the findings presented so far, only the magnitude slightly differs.

To better understand the potential skill-mismatch, especially for the high-educated individuals, the analysis is performed by the different task levels separately, which supports the previous findings. Especially for males working as specialists/experts, we find supportive evidence of the skill-mismatch.

The relative wage gap might also be explained by differences in housing prices[17]; especially, when commuting is the chosen alternative to migration into the region outside MV. For out-commuters, the ratio of average housing prices at the place of work and residence is expected to be higher. We test several

[17] Housing prices are included as the regional median basic rent (excluding heating costs) (Mense et al., 2019; Mense, 2021).

specifications on the impact of housing-prices on the wage gap, i.e. the ratio of prices at workplace and residence, only the prices at workplace and finally at the place of residence. First, the ratio is always insignificant, although in favour of out-commuters. Second, considering the endowment effect, the housing price is positive for out-commuters, indicating that especially out-commuters earn higher wages caused by higher housing prices at the place of work. This provides a general evidence that employers take local housing prices in their wage setting into account, irrespective of the regions, where their employees live. Third, adding simply housing prices of the place of residence, no endowment effect become significant. However, the coefficient effect is significant and in favour of individuals' living and working in MV. Because the coefficients are identified by within-group comparison, obviously an extra Euro of housing prices in MV raises individual wages within MV stronger compared outside MV. However, because MV is very peripheral with low housing costs in the rural areas but relative higher prices in the towns and cities, obviously, employers compensate for such differences. Outside MV the differences are smaller and a coefficient effect in favour of MV employees results.

3.6 Conclusion

In this study, we consider out-commuters from a particular eastern German region, MV, and compare them with employees within MV and the destination region. We analyse individual, job-related and firm characteristics that increase the likelihood that men and women cross regional borders by commuting long-distances; and take a closer look at factors that explain the wage gap between both groups. These findings can be important against the background that regions in East Germany are complaining about labor shortage, especially in the course of the aging population who will retire in the next years (Kroll and Niebuhr 2014). Policy measures which aim to employ current out-commuters within MV could be a smart way to compensate labor shortages.

Our findings show that especially high skilled, older workers, and men and women working in larger firms out commute. For women, we additionally show a higher share of women working in unskilled labor. Thus, less job opportunities, less labor demand – especially for women – are the key factors why workers live in MV and commute in other regions to work.

Regarding the wage gap between out-commuters and home employees we find that especially males benefit from out-commuting as they earn about 37 percent more than home employees. This can be explained by differences in the age structure, task levels and firm characteristics. Moreover, we show that the wage setting behaviour outside MV honours full-time work, tasks and leadership responsibilities more. Additionally, the returns of firm characteristics are larger for out-commuters. Thus, firms outside MV are relatively more productive.

This brings us to the conclusion: if employers and policy makers within MV want to gain back out-commuters, such that they provide their work capacity within MV, structural changes at the labor market have to occur first. Especially job opportunities for high-skilled individuals are not enough, leading to a brain drain. Females partly out commute and accept even lower wages to avoid unemployment. Employers have to rethink their wage setting behaviour in general to become competitive with the wage setting of firms outside MV. Lastly, the firm productivity is relatively lower within MV, indicating structural differences and lead at least to the relative lower labor demand for highly skilled individuals. Thus, to make MV more attractive for individuals, significant economic improvements have to be done. We suspect that our results can be partly transferred to other East German regions, which face similar problems.

Appendix

A Additional Figures and Tables

Table 3.A.1: Detailed results of the interaction effect

	Men			Women		
	home employees	long dist. home empl.	destination employees	home employees	long dist. home empl.	destination employees
Occupations	1.007***	1.002	1.005***	0.998	0.996	0.995***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)
Tasks	1.001	0.999	1.000	1.001	1.000	1.001**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Leading responsibility	1.000*	1.000*	1.000	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Full-time	1.005***	1.003***	1.000*	1.010***	1.003**	0.995***
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)
Age	1.007***	1.004***	1.004***	0.996***	1.000	0.991***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Vocational training	0.996***	0.997***	1.003***	1.001**	1.003***	0.999
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Unemployment	1.001**	1.001***	1.005***	1.001	1.000	0.995***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Experience	1.000	1.000	0.999	0.998	1.001	0.996*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Firm characteristics	1.016***	1.014***	1.006***	1.008**	1.013***	0.992***
	(0.005)	(0.004)	(0.001)	(0.004)	(0.002)	(0.001)
Industry	0.998	1.004**	1.003**	1.016**	1.010	1.007***
	(0.002)	(0.002)	(0.001)	(0.007)	(0.007)	(0.002)

Note: Cluster robust s.e. at labor-market-region level in (), * 0.1, ** 0.05, *** 0.01; all control variables and regional indicators included.

Chapter 4

Beyond Lost Earnings: The Long-Term Impact of Job Displacement on Workers' Commuting Behavior

with Yige Duan [18] *and Oskar Jost*

Abstract Job displacement causes large and persistent earning losses, but less is known about its non-monetary impacts or workers' valuation for such consequences. This paper examines the effects of job displacement on workers' commutes to subsequent jobs. Using German employer-employee matched data with geocoordinates of workers' workplaces and residences, we find workers commute longer distances to post-displacement jobs by up to 21 percent. The effect diminishes over time as workers move from distant to proximate jobs. Structural estimation of a job search model suggests sizeable commuting costs of 18 euros per day or 14 percent of the contemporaneous wage losses after job displacement.

JEL Classification J3, J6, R23, R41.

Keywords commuting, mobility, displacement, job search

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[18] Vancouver School of Economics, University of British Columbia

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4.1 Introduction

Job displacement has profound consequences on individual workers. In the past decades, a large body of literature has documented substantial earning losses following job displacement (e.g., Jacobson et al., 1993; Davis and von Wachter, 2011; Schmieder et al., 2020). However, recent research also finds broader effects of job displacement beyond earnings, such as deteriorated health (Black et al., 2015), greater mortality (Sullivan and Von Wachter, 2009), and increased crime rates (Britto et al., 2022). To evaluate the welfare consequences of job displacement, it is therefore important to identify and quantify such non-monetary costs.

In this paper, we investigate one important consequence of job displacement: the cost of commuting to subsequent jobs. For most workers, commuting is an indispensable part of everyday life.[19] For displaced workers, particularly, commuting costs may discourage them from looking for jobs in larger geographic areas and delay their recovery from job loss (Manning and Petrongolo, 2017; Marinescu and Rathelot, 2018). Nevertheless, we show that workers' commuting distances *increase* after job displacement, consistent with a frictional labor market where wage differentials do not compensate for variation in commuting costs. We also find that workers have a large willingness to pay (WTP) for shorter commuting. Therefore, accounting for the value of increased commuting would significantly add to the total cost of job displacement beyond lost wages.

Our study contributes to the literature in two major ways. First, we exploit unique geocode data to measure workers' commuting patterns and estimate the commuting responses to job displacement. The data contains geocoordinates of each worker's place of residence and place of work, from which we calculate her commuting distance and time along actual routes. This helps us avoid non-trivial measurement errors in regional-level data (e.g., the shortest distance between two municipalities), especially for within-city, short-distance commutes. Correcting for such errors could reduce the estimated effects on commuting distance by 42 percent in the short run and 13.5 percent in the long run.

Second, we use a structural approach to estimate the cost of commuting in monetary value, i.e., in terms of workers' WTP. We provide empirical evidence that job search frictions result in utility dispersion across jobs, so that the observed wage differentials across jobs do not elicit differences in commuting costs (Hwang et al., 1998; Van Ommeren and Fosgerau, 2009; Sorkin, 2018). To address this problem, we develop a job ladder model and derive workers' reservation wage curve as an increasing function of commuting distances. The slope of the curve identifies workers' WTP for shorter commuting, holding the utility of jobs constant. Accounting for utility dispersion, our estimated commuting cost is significantly larger than reduced-form estimates based on compensating differentials (Rosen, 1974; Roback, 1982).

[19] In Germany, for example, the number of workers leaving their communities to work increased from 14.9 million in 2010 to 19.3 million in 2018. This is nearly half of the entire German labor force. In the meantime, the average commuting distance of German workers rose from 14.8 kilometers to 17 kilometers. See `https://www.thelocal.de/20200207/why-are-more-and-more-people-in-germany-commuting-to-work`.

Our analysis is carried out in two steps. First, we estimate the effects of job displacement on workers' wages and commuting outcomes simultaneously. Using an event study design, we compare the outcomes of workers displaced in mass layoffs with a matched group of non-displaced workers exhibiting similar pre-displacement characteristics. To rule out selection into mass layoffs, we control for worker fixed effects and focus on stable, full-time workers at displacing firms. Our estimates show that job displacement increases workers' average commuting distance to subsequent jobs by 20.9 percent (3.35 kilometers one-way) in the short run and 14.8 percent (2.37 kilometers one-way) in the long run. While the effect declines over time, workers still commute longer distances 10 years after displacement. The dynamic effects are driven by workers' switching from distant to nearby firms rather than relocating their homes.

Overall, the estimated effect on commuting distances exhibits limited variation across workers. However, we do find that workers displaced from more productive firms experience a larger increase in commuting. This is consistent with a job ladder model where workers higher on the job ladder accumulate more search capital, and thus are hurt more when they lose their jobs (Fackler et al., 2021). In addition, our estimates are robust to various threats to identification and different model specifications, including selection into mass layoffs and re-employment, spillover effects of large layoff events, under-identification of dynamic and heterogeneous effects, and alternative measures of commuting time.

In the second step, we develop an on-the-job search model (Burdett and Mortensen, 1998) with heterogeneous firm productivity and commuting distances to rationalize the empirical findings. The model establishes a job ladder where employed workers keep searching for higher-productivity and lower-distance jobs, consistent with the empirical findings of joint recovery. Moreover, we derive the reservation wage curve of unemployed workers as an increasing function of commuting distances. Along the reservation wage curve, any change in commuting costs is exactly compensated for by wage changes. Therefore, the slope of the curve identifies workers' WTP for shorter commuting.

We structurally estimate the model to quantify the monetary cost of commuting. First, we document that displaced workers rarely accept low-wage and long-distance jobs, consistent with our model prediction that such jobs fall below workers' reservation wage curves. As such, jobs accepted by displaced workers exhibit positively correlated wages and commuting distances. Exploiting a truncated regression framework, we prove that a steeper reservation wage curve increases the observed correlation between wages and commuting distance through truncation. Hence, the commuting cost is indirectly identified from (though not equal to) the observed correlation.

Using the simulated method of moments and indirect inference, we find that each kilometer of commuting is worth 1.25 percent of a worker's daily wage. Therefore, the average worker incurs a commuting cost of 18 euros per day. This amount is substantial, exceeding the opportunity cost of commuting time (15 euros per day), and close to one-fifth of the German average daily wage. After job displacement, the short-run increase in commuting costs amounts to 17.9 percent of the contemporaneous wage loss, and the long-run increase is equivalent to 14.1 percent of the wage loss. Therefore, accounting for the increase in commuting costs significantly adds to the total cost of job displacement. Finally, we show that women have a higher marginal cost of commuting but a lower commuting cost out-of-pocket, as they commute shorter distances and earn lower wages on average.

To summarize, our paper makes both empirical and methodological contributions. We document a substantial increase in commuting distances after job displacement and the joint recovery of wages and commuting in the long run. We also propose a structural approach to estimating workers' WTP for shorter commuting in the presence of job search frictions. Our findings suggest that the increased commuting cost exacerbates the overall cost of job displacement. Finally, we combine route planning algorithms with geocoordinate data to precisely measure commuting distances and commuting time. This allows us to distinguish commuting from migration and overcome a sizeable estimation bias in regional-level data.

4.1.1 Related Literature

Our paper is related to a long literature on the cost of job displacement. While most of the work focuses on lost earnings and wages (e.g., Jacobson et al., 1993; Davis and von Wachter, 2011; Schmieder et al., 2020; Bertheau et al., 2022), several studies also consider non-monetary outcomes such as health (Black et al., 2015), mortality (Sullivan and Von Wachter, 2009), and crime (Britto et al., 2022). In particular, Meekes and Hassink (2019, 2022) investigate how job displacement impacts cross-regional commuting, while Fackler and Rippe (2017) and Huttunen et al. (2018) examine the effect on migration.

Our work differs from the above in three ways. First, we study commutes both within and across regions and distinguish between commuting and migration. We show that due to the large share of commutes within regions, focusing on cross-regional commuting could overestimate the displacement effects. Second, we demonstrate that the long-term recovery of commuting is driven by job change rather than relocation, and develop a job ladder model to rationalize the findings. Third, we estimate not only the increase in commuting distance but also workers' WTP for commuting. Combining both estimates, we quantity that the increased commuting distance implies a large monetary cost, thereby worsening the wage losses after job displacement.

Next, we contribute to the literature on the monetary cost of commuting. Existing estimates exhibit varying magnitudes and differ in their identification assumptions. On one hand, Mulalic et al. (2014) and Dauth and Haller (2020) estimate the commuting cost in Germany using compensating differentials and find it close to negligible. On the other hand, Le Barbanchon et al. (2021) and Van Ommeren and Fosgerau (2009) find substantial commuting costs of 11–13 euros per day, respectively, using survey and structural methods based on job search models.[20] Our analysis shows that the observed relationship

[20] Mulalic et al. (2014) exploit variation in commuting distances due to firm relocation to identify workers' WTP for shorter commuting. Le Barbanchon et al. (2021) compare the actual job search outcomes of unemployed workers in French

between wages and commuting distances is confounded by job search frictions and the resulting utility dispersion across jobs. Hence, we propose a novel structural approach to identifying the commuting cost. More generally, a number of studies attempt to identify the value of non-wage job amenities in the presence of market friction (e.g., Hwang et al., 1998; Sorkin, 2018; Taber and Vejlin, 2020; Lehmann, 2023). Our paper focuses on a specific (dis)amenity, the commuting distance, which is observed from geocoordinate data. An important difference between commuting distances and other job amenities is that the former varies across workers at the same firms. As we show later, the extra variation is useful to identify the monetary cost of commuting from the joint distribution of wages and commuting distances. Finally, our paper belongs to the burgeoning literature that exploits georeferenced data in spatial and labor economics. Granular geodata enables investigation of novel topics such as migration and commuting (Dauth and Haller, 2020; Jost, 2020; Chu et al., 2021), agglomeration and city structure (Ahlfeldt et al., 2015; Leonardi and Moretti, forthcoming), and labor market monopsony (Hirsch et al., 2021). Combining georeferenced data with route planning algorithms, we can measure workers' commuting distance and commuting time with high precision, and thus avoid a large estimation bias using aggregate data.

The rest of the paper is organized as follows. Section 4.2 discusses the data and causal identification. Section 4.3 reports the estimated effects of job displacement. Section 4.4 illustrates the value of granular commuting data. Sections 4.5 develops a job search model to rationalize the findings. Sections 4.6 and 4.7 structurally identify and estimate the model to quantify the monetary cost of commuting. Finally, Section 4.8 concludes.

4.2 Data and Identification Strategy

Our study exploits two administrative data sets provided by the Institute for Employment Research in Germany: The Integrated Employment Biographies (IEB) and the Establishment History Panel (BHP). The IEB data covers a representative sample of German workers subject to social security, and contains information on each individual's age, gender, educational attainment, employment history, and receipt of unemployment benefits. However, the data does not include civil servants and the self-employed. Meanwhile, the BHP provides information on all establishments in Germany, including their industries (2008 edition), employment on June 30 each year, and locations by municipalities, districts, and labor market regions.[21] Hereafter, we will use "firm" and "establishment" interchangeably.

with their claimed reservation outcomes collected from a survey. Their estimates imply that commuting the sample-average distance (18.6 kilometers) is worth 242 euros per month, which is 11 euros per day assuming 22 working days in each month. Van Ommeren et al. (2000) and Van Ommeren and Fosgerau (2009) develop a job search model where the cost of commuting is identified from the relative responsiveness of workers' job-moving behavior to wages and commuting distances. Van Ommeren and Fosgerau (2009) estimate the cost of one hour's commuting at 17 euros per day in the Netherlands. At the sample-average daily commuting time (0.77 hours), the cost is $17 \times 0.77 = 13.09$ euros.

[21] Germany is divided into 141 labor market regions (equivalent to U.S. commuting zones, Glitz, 2012), which are further divided into 401 administrative districts and 11,014 municipalities. The average size of a district is 890 square kilometers

We complement the employee-employer data with geocoordinates of each worker's residence and workplace (Ostermann et al., 2022). Combining the granular location data with route planning algorithms by OpenStreetMap.org (Huber and Rust, 2016; Dauth and Haller, 2020; Jost, 2020), we can calculate the door-to-door driving distance and driving time for all employed workers. We argue that driving distance is a plausible measure of commuting distance, as 68 percent of German commuters drive to work (Destatis, 2017). Besides, driving distances are highly correlated with distances via other means of transportation obtained from Google Maps. By contrast, driving time might underestimate the true commuting time if workers commute on foot, by bike, or by public transit. To address this problem, we average the walking, cycling, and driving time for each trip weighted by the share of commuters using each mode of transportation (see Appendix A, Table 4.A.1 for details). Following Scheiner (2010), we allow the shares to vary with distance to capture the fact that workers walk or ride more often for shorter trips. Figure 4.A.1, panels (a) to (c) plot the distribution of driving distances, driving time, and the weighted-average commuting time in our sample. We validate that the weighted average predicts longer commuting time for short trips.

As in Schmieder et al. (2020) and Illing et al. (2021), our analysis focuses on workers of both genders aged from 20 to 54. The sample period spans from 2000 to 2017, as the location information is only available from 2000 onward. We transform the employment spells from the IEB into a worker-year panel (Dauth and Eppelsheimer, 2020). For each year, we calculate the worker's total earnings, the number of days in full-time, part-time, and mini jobs[22], the main employer on June 30, commuting distance and time to the main employer, and the average daily wage paid by the main employer. If a worker has multiple employers on June 30, we choose the one with the highest daily wage as the main employer. In addition, we impute wages that are top-coded due to the social security threshold (Card et al., 2013) and missing education variables (Fitzenberger et al., 2005). Finally, we exclude workers whose maximum commuting distance exceeded 100 kilometers, as they are unlikely to commute on a daily basis (Dauth and Haller, 2020).

4.2.1 Mass Layoffs and Displaced Workers

On the establishment side, we consider mass layoffs as the source of involuntary job displacement (Blien et al., 2021; Burdett et al., 2020; Fackler et al., 2021; Jarosch, 2022). Later on, we also use establishment closure as an alternative strategy to examine the robustness of our results. Following the standard approach (Davis and von Wachter, 2011), we define a mass layoff event in calendar year τ if (i) an establishment has at least 50 workers on June 30 of year τ; (ii) the number of workers decreases by at

and that of a municipality is only 32 square kilometers.

[22]Mini jobs are a form of marginal employment in Germany with a monthly income of 450 euros or less (Illing et al., 2021).

least 30 percent from June 30 of year τ to June 30 of year $\tau + 1$; and (iii) the number of workers on June 30 of year τ is not higher than 130 percent of that on June 30 of year $\tau - 1$. Using worker-flow data between establishments, we also distinguish mass layoffs from firm reorganizations and outsourcing (Hethey-Maier and Schmieder, 2013; Goldschmidt and Schmieder, 2017). In total, we identify 22,490 mass layoffs between 2002 and 2012. By focusing on layoffs up to 2012, we can track each displaced worker for at least five years after displacement.

Figure 4.A.2 reports the number and size of mass layoff events by year. Panel (a) shows that, except for a hike in 2010, mass layoffs are dispersed over time and hardly correlated with business cycles. Panel (b) further shows that the average establishment has 153.6 workers prior to the layoff and 59 percent of workers are displaced during the mass layoff. Since most layoff events are small relative to the size of local labor markets, they are unlikely to impact aggregate labor demand at the market level. Section 4.3.2 further shows that our estimates are not confounded by unobserved labor market conditions or spillover from large layoffs.

While establishment-level mass layoffs provide plausibly exogenous shocks to workers' employment status, workers within the same establishment could still select into job displacement. For example, part-time and less productive workers might be displaced first during mass layoffs. To address potential endogeneity at the worker level, we include worker fixed effects in the regression to compare outcomes of the same worker before and after job displacement. Besides, we follow the literature and impose additional restrictions on the sample: we define a displaced worker in year τ if she (i) has worked full-time at the displacing firm for three consecutive years before the mass layoff; (ii) has ever registered as unemployed between June 30 of year τ and that of year $\tau + 1$; and (iii) does not return to the displacing firm after the mass layoff. The first condition, by focusing on stable employment, rules out the concern that marginal or low-productivity workers face higher displacement risks (Burdett et al., 2020). The second restriction ensures that workers do not voluntarily quit their jobs and thus mitigates the concern of pre-layoff search (Simmons, 2021). The third condition excludes recalled workers. Lastly, if a worker experiences multiple mass layoffs during the sample period, we only consider the first displacement for our analysis. In total, we identify 9,949 first-time displaced workers.

Table 4.1, column (a) provides summary statistics of the displaced workers in the year before displacement. Almost one-third of the workers are female, and the average age before mass layoffs is 40.5 years old. The majority of those workers have vocational training (71.5 percent) and live in western Germany (83.2 percent). At the time of the mass layoff, an average worker has 14.1 years of total work experience and 7.6 years of experience with the current employer, and she earns roughly 100 euros per day. Consistent with the statistics of Giménez-Nadal et al. (2022), the average worker travels 16 kilometers or 23.5 minutes one-way between home and work. Moreover, a sizeable share of commutes occurs within administrative regions. Only 37.3 percent of workers commute across districts, and 59 percent commute

Table 4.1: Pre-Layoff Worker Characteristics

	(a) Displaced workers	(b) Matched control workers
Female	0.330	0.303
	(0.470)	(0.460)
Age	40.46	40.81
	(8.435)	(8.267)
High school or less	0.220	0.224
	(0.414)	(0.417)
Vocational training	0.715	0.722
	(0.451)	(0.448)
University or above	0.053	0.045
	(0.224)	(0.207)
East Germany	0.168	0.159
	(0.374)	(0.365)
Working experience	14.12	14.94
	(7.712)	(7.801)
Firm tenure	7.614	8.290
	(6.126)	(6.597)
Annual earnings	30,212	31,324
	(11,203)	(10,962)
Daily wage	99.66	100.7
	(41.64)	(37.29)
Commuting distance	16.02	14.76
	(16.69)	(15.32)
Commuting time	23.50	22.20
	(15.90)	(14.66)
Commuting across districts	0.373	0.338
	(0.484)	(0.473)
Commuting across municipalities	0.590	0.594
	(0.492)	(0.491)
Workers	9,949	384,071

Notes: The table reports the average characteristics of displaced workers during mass layoffs and matched non-displaced workers in the year before displacement. The sample is obtained using exact matching on gender, education qualification, one-digit industrial sector, and indicator of eastern Germany, and coarsened matching on age, firm tenure, firm size, and average daily wage two years before displacement. Standard deviations are reported in parentheses.

across municipalities. Table 4.A.2, column (a) further shows that the majority of workers are displaced from manufacturing (47.4 percent), trade (18.8 percent), construction (7.9 percent), and administrative services (7.0 percent) industries.

4.2.2 Matching Non-Displaced Workers

Besides displaced workers, we construct a control group of workers who are not displaced but have similar characteristics to displaced workers. As discussed in Borusyak et al. (2022), including non-displaced workers is important to identify heterogeneous or dynamic effects of job displacement.

The control group is obtained using coarsened exact matching (CEM, Iacus et al., 2012). For workers displaced in year τ, we firstly identify potential matches as those not displaced in year τ and having been full-time employed by the same employer for three years before τ. Following Krolikowski (2018), we allow the workers to be displaced in later years. Next, we match displaced and non-displaced workers year by year using their characteristics in the year before displacement. The matching variables are selected following Schmieder et al. (2020): we use exact matching on gender, education, one-digit industrial sector, and living in western versus eastern Germany in year τ, coarsened matching on age, firm tenure, and firm size in year τ, as well as daily wages in year $\tau - 1$. The procedure yields a matched control group of 384,071 workers. Table 4.1 shows that the matched control group exhibits similar characteristics to those of the displaced workers.

Finally, we combine displaced and matched control workers to form a worker-year panel for analysis. Each worker is tracked for up to five years before and 10 years after displacement. It is worth noting that we observe a worker's wage or commuting outcomes only if she is employed. As a result, our estimates should be interpreted as the conditional average treatment effect—the effect conditional on employment or re-employment (Jarosch, 2022; Meekes and Hassink, 2019, 2022).[23] Section 4.3.2 confirms that our empirical findings are not driven by endogenous selection into re-employment.

4.2.3 Event Study

To identify the effect of mass layoffs on worker wages and commuting behavior, we exploit the event study approach following Jacobson et al. (1993). For displaced workers, we define $\tau(i)$ as the year of displacement. For workers in the matched control group, $\tau(i)$ is the year of matching. The outcome Y_{it} for worker i in year t is given by

$$Y_{it} = \sum_{\substack{k=-4, \\ k \neq -1}}^{10} [\alpha_k I\{t = \tau(i) + k\} + \beta_k I\{t = \tau(i) + k\} ML_i] + X'_{it}\gamma + \phi_i + \psi_t + \epsilon_{it}. \tag{4.1}$$

In equation (4.1), ML_i indicates that worker i is displaced according to the criteria in Section 4.2.1. The indicator $I\{t = \tau(i) + k\}$ equals one if the focal year t is the k-th year after displacement. As such, α_k captures the outcome of non-displaced workers k years after displacement relative to the year immediately before displacement ($\tau(i) - 1$). For displaced workers, this is captured by ($\alpha_k + \beta_k$). Therefore, β_k represents the partial effect of job displacement on Y_{it} after k years. In addition, X_{it} controls for time-varying worker characteristics, i.e., a cubic polynomial of age. Other time-invariant characteristics,

[23] In our treated group, employed workers, unemployed workers, and missing observations (civil service, self-employment, etc.) make up 81.7 percent, 13.3 percent, and 5.0 percent of the balanced panel, respectively. In the matched control group, the share of employed workers exceeds 97 percent.

such as gender and education, are absorbed by the worker fixed effect ϕ_i. Finally, ψ_t is the calendar-year fixed effect and ϵ_{it} is the error term clustered by the displacing establishment.

Additionally, we estimate the average displacement effects across all post-displacement years. The estimates are obtained from a standard difference-in-differences (DID) regression:

$$Y_{it} = \alpha Post_{it} + \beta(ML_i \times Post_{it}) + X_{it}'\gamma + \phi_i + \psi_t + \epsilon_{it}, \tag{4.2}$$

where $Post_{it}$ equals one for all $t > \tau(i)$ so that β represents the average effect of job displacement across all subsequent years. Other terms remain the same as equation (4.1).

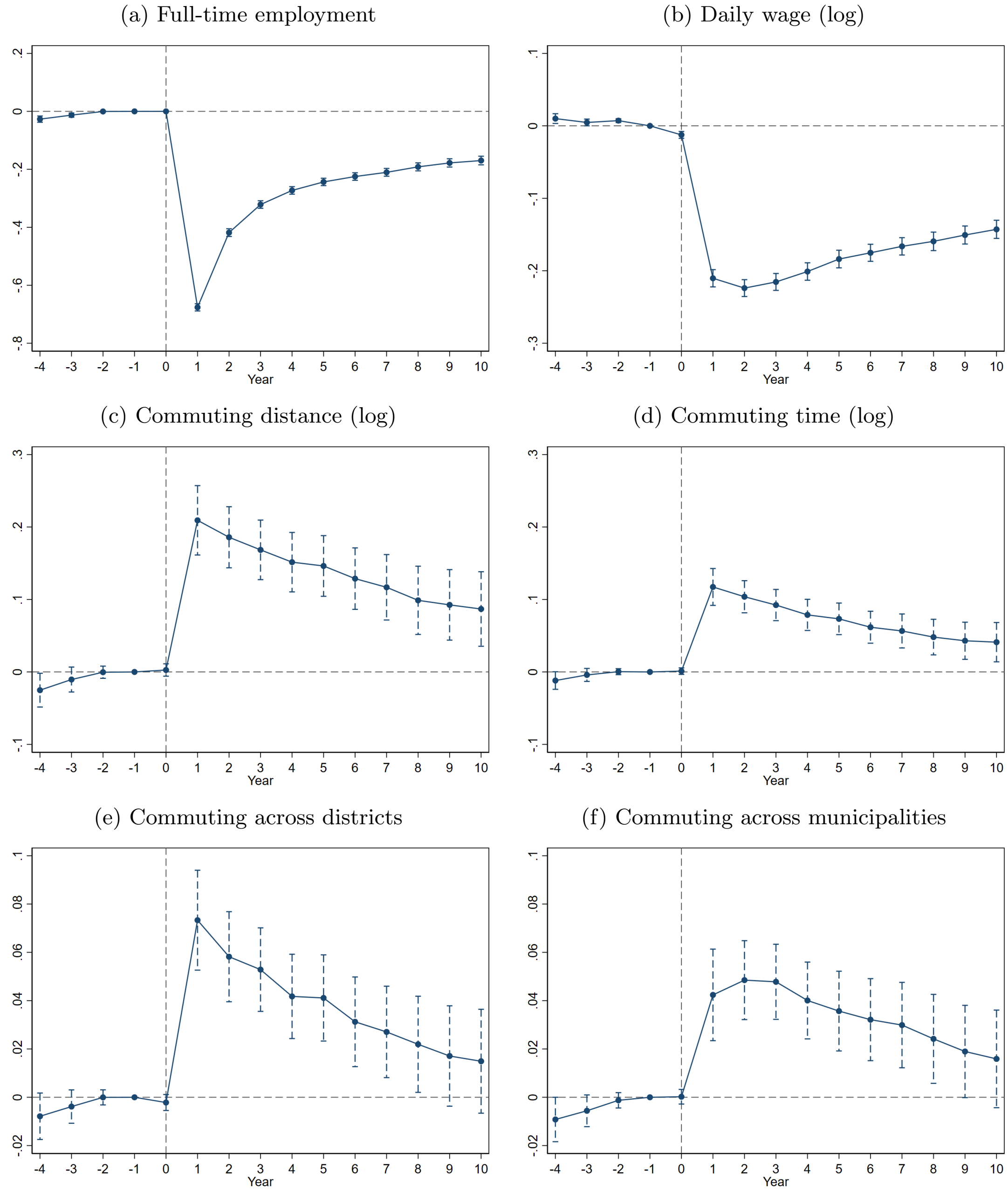
To identify the causal effect of job displacement on workers' outcomes, we rely on the unconfoundedness assumption that mass layoff events are uncorrelated with workers' characteristics relevant to their labor market outcomes. This assumption is justified as follows. First, mass layoffs occurred at the establishment level rather than the worker level, so they are "as good as random" for workers, especially given their sizes and distribution over time. Second, by including worker fixed effects and focusing on stable full-time workers prior to mass layoffs, we essentially compare the same worker before and after displacement and rule out the concern that less productive workers or workers with unstable employment contracts face higher displacement risks. Third, mass layoffs at small-to-medium establishments are unlikely to generate spillover effects to the local labor market, which would worsen the situation of displaced workers. Fourth, we compare the sample of displaced workers with a large, matched control group. According to Borusyak et al. (2022), this enables us to identify the dynamic and potentially heterogeneous effects of job displacement. In Section 4.3.2, we perform various robustness checks to support our argument.

4.3 The Effects of Job Displacement

In this section, we present the estimated effects of job displacement. To begin with, Figure 4.1, panel (a) plots estimates of equation (4.1) using the balanced worker-year panel and the indicator of full-time employment as the dependent variable. We find that mass layoffs significantly impact workers' employment trajectories. In the first year after displacement, displaced workers are 67.6 percent less likely to be full-time employed than non-displaced workers. Although the employment gap diminishes over time, displaced workers are still 17 percent less likely to be employed 10 years after displacement. Table 4.2, column (a) shows the corresponding DID estimates from equation (4.2). Averaged across all post-displacement years, job displacement reduces workers' employment probability by 33.9 percentage points.[24]

[24] In addition, Figure 4.A.3 and Table 4.A.3 show that workers' annual earnings decrease by roughly 20,000 euros in the first year after displacement and recover by one-half after five years. Besides, displaced workers reduce full-time employment by over 200 days in the first year after displacement, and the lost full-time employment is partially offset by increasing days

Figure 4.1: Effects of Job Displacement on Employment, Wage, and Commuting



Notes: Each plot depicts estimates of equation (4.1) with dependent variable in the subtitle. The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year. The vertical dashed line indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by establishments.

working in part-time and mini jobs. In the long run, employment in part-time and mini-jobs declines as workers get back to full-time employment. The results suggest that displaced workers take part-time and mini jobs as stepping stones back to full-time employment.

Table 4.2: Effects of Job Displacement

	(a) Full-time employment	(b) Daily wage (log)	(c) Commuting distance (log)	(d) Commuting time (log)
ML × Post	-0.339***	-0.189***	0.148***	0.077***
	(0.005)	(0.005)	(0.019)	(0.010)
Observations	4,593,491	4,316,096	4,316,096	4,316,096
Workers	394,020	394,020	394,020	394,020
R^2	0.311	0.898	0.817	0.808
	(e) Across districts	(f) Across municipalities	(g) Job change	(h) Relocation
ML × Post	0.042***	0.038***	0.270***	0.038***
	(0.008)	(0.007)	(0.004)	(0.003)
Observations	4,316,096	4,316,096	4,316,096	4,316,096
Workers	394,020	394,020	394,020	394,020
R^2	0.826	0.837	0.076	0.067

Notes: Each column represents estimates of equation (4.2) with dependent variable in the column title. The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year (except column (a) which uses a balanced panel). All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors in parentheses clustered by establishments. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

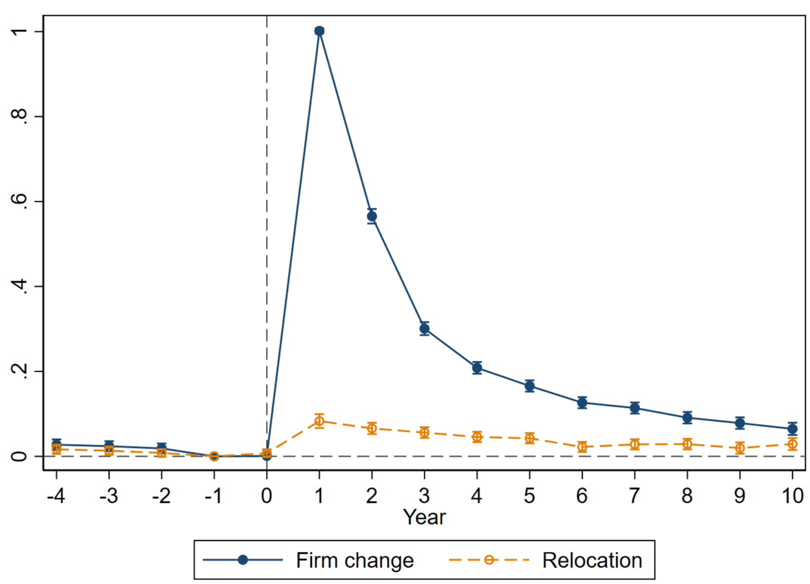
Next, Figure 4.1, panel (b) illustrates the job displacement effects on wages of subsequent jobs. Hereafter, we focus on years when the workers are full-time employed. Conditional on being reemployed, workers' average daily wage drops sharply by 21 percent in the first year after displacement. This large wage loss persists in the first few years and modestly recovers in subsequent years. Ten years after job displacement, displaced workers still earn 14.3 percent lower wages than non-displaced workers. Table 4.2, column (b) shows that the average daily wage of displaced workers falls by 18.9 percent over the entire post-displacement period. The estimated effect magnitude is comparable with existing studies (Burdett et al., 2020; Jarosch, 2022; Schmieder et al., 2020).

Figure 4.1, panels (c) and (d) report estimates on commuting distance and commuting time, respectively. Both outcomes increase significantly upon job displacement and gradually decline in subsequent years. In the first year after displacement, the average commuting distance of displaced workers raises by 20.9 percent and the average commuting time by 11.7 percent. The smaller increase in commuting time is likely because workers switched to faster modes of commuting in response to longer trips. Evaluated at the pre-layoff sample means (Table 4.1), the increases are equivalent to 3.35 kilometers and 2.75 minutes one-way, respectively. Ten years after displacement, however, the increase is only 8.7 percent for commuting distance and 4.1 percent for commuting time. Table 4.2, columns (c) and (d) show that the long-run increases in commuting distance and commuting time are 14.8 percent and 7.7 percent (2.37 kilometers and 1.81 minutes one-way), respectively.

Besides commuting longer distances and time, displaced workers also commute out of their area of residence more often. Figure 4.1, panels (e) and (f) show the impacts of job displacement on the probabilities of commuting out of one's residing municipality and district, respectively. In both cases, we observe an increase in cross-regional commuting by 4.2 to 7.3 percentage points right after job displacement. In subsequent years, the probabilities declined similarly as in panels (c) and (d).

Margins of Adjustment. The above analysis reveals that job displacement increases workers' commuting to subsequent jobs, but the effects are mitigated over time. To reduce commuting, workers could either switch to an employer closer to their homes or move their homes closer to the employer (relocate). To determine which mechanism explains the dynamics of commuting, we estimate equation (4.1) using indicators of job change and relocation as dependent variables. Job changes are identified from changes in the firm identifier and address, and relocation from changes in the worker's place of residence. As shown in Figure 4.2, job changes and relocation both increase in the first few years after job displacement, but the increase in relocation has a much smaller magnitude and does not persist in subsequent years.

Figure 4.2: Effects of Job Displacement on Worker Mobility



Notes: Each plot depicts estimates of equation (4.1) with indicators of relocation and firm change as dependent variables. The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year. The vertical dashed line indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by establishments.

Therefore, the estimated long-term increase in commuting distance and recovery must be driven by job changes. This validates the argument of Huttunen et al. (2018) and Meekes and Hassink (2019) that the relocation of displaced workers is driven by non-economic factors and that commuting is a more effective response to job displacement.

4.3.1 Effect Heterogeneity

Next, we explore the effect heterogeneity of job displacement across workers. The event study and DID estimates are reported in Figure 4.3 and Table 4.3, respectively.

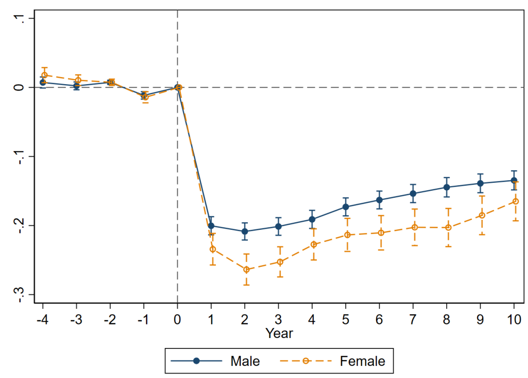
The effects of job displacement could differ across workers for three reasons. First, some workers might have greater disutility from commuting and would rather accept lower wages. To explore this possibility, we estimate the job displacement effects on wages and commuting distances by gender and age groups. Figure 4.3, panels (a) and (b) show that women suffer from a greater wage penalty than men after job loss; however, their commuting pattern recovers faster. Ten years after displacement, women's average commuting distance almost reaches the pre-displacement level. This is consistent with findings by Illing et al. (2021) and Meekes and Hassink (2022). Similarly, Figure 4.3, panels (c) and (d) reveal that older workers experience greater wage losses and smaller increases in commuting than younger workers. Taken together, female and older workers likely face higher commuting costs, so they are willing to accept lower wages to avoid commuting. Nevertheless, Table 4.3, panels I–II show that the long-run effects on commuting distances exhibit no statistical difference across gender or age groups.

Second, proximity to jobs with better skill matches could make job search easier and mitigate the cost of job displacement. For example, when a manufacturing worker is displaced in a manufacturing region (e.g., Bavaria), it would be easier for her to find another local job with similar task contents. As such, her commuting distance would increase less and her wage penalty due to skill mismatch would be smaller. To test this hypothesis, we calculate the employment share of workers‘ pre-layoff industry within labor market regions. A lower share indicates a stronger skill mismatch—that it is harder for a worker to find a new job in the same region and the same industry. Figure 4.3, panels (e) and (f) demonstrate that workers displaced from low-share industries not only experience greater wage losses but also commute relatively longer after displacement. This is consistent with Macaluso et al. (2017) that skill mismatch amplifies job search frictions facing displaced workers. However, Table 4.3, panel III shows that the long-run differences are again statistically insignificant.

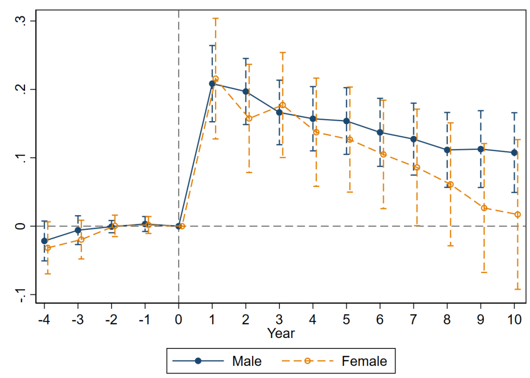
Third, the job displacement effects could be more salient if workers are displaced from more productive or proximate firms. Following Abowd et al. (1999, AKM hereafter) and Card et al. (2013), we use estimated firm and worker fixed effects from a log wage regression to measure worker- and firm-specific wage premiums.

Figure 4.3: Effect Heterogeneity

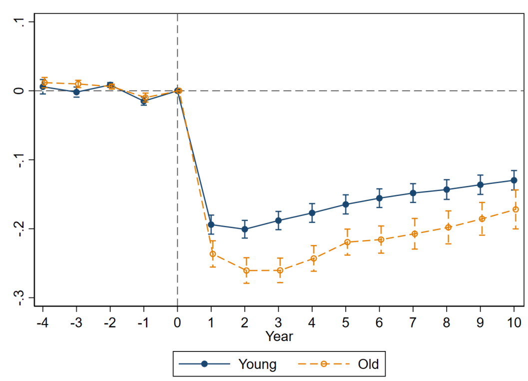
(a) Daily wage (log): Gender



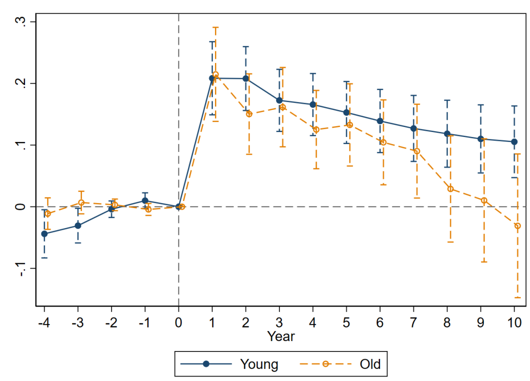
(b) Comm. dist. (log): Gender



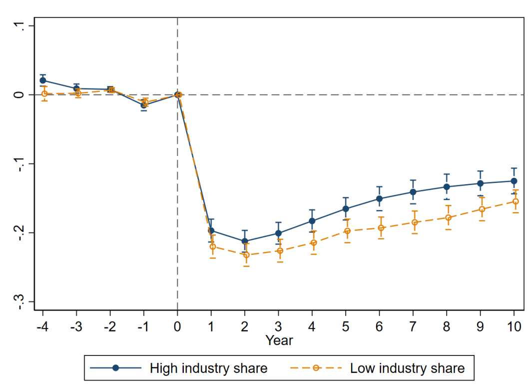
(c) Daily wage (log): Age



(d) Comm. dist. (log): Age



(e) Daily wage (log): Local industry share



(f) Comm. dist. (log): Local industry share

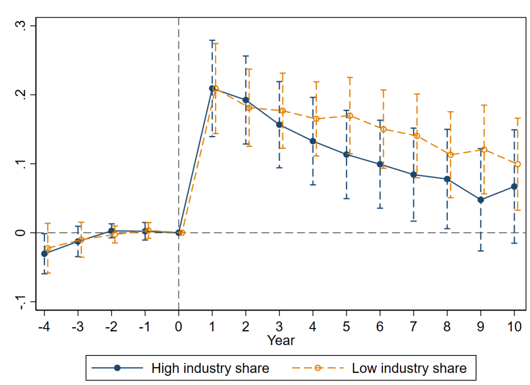


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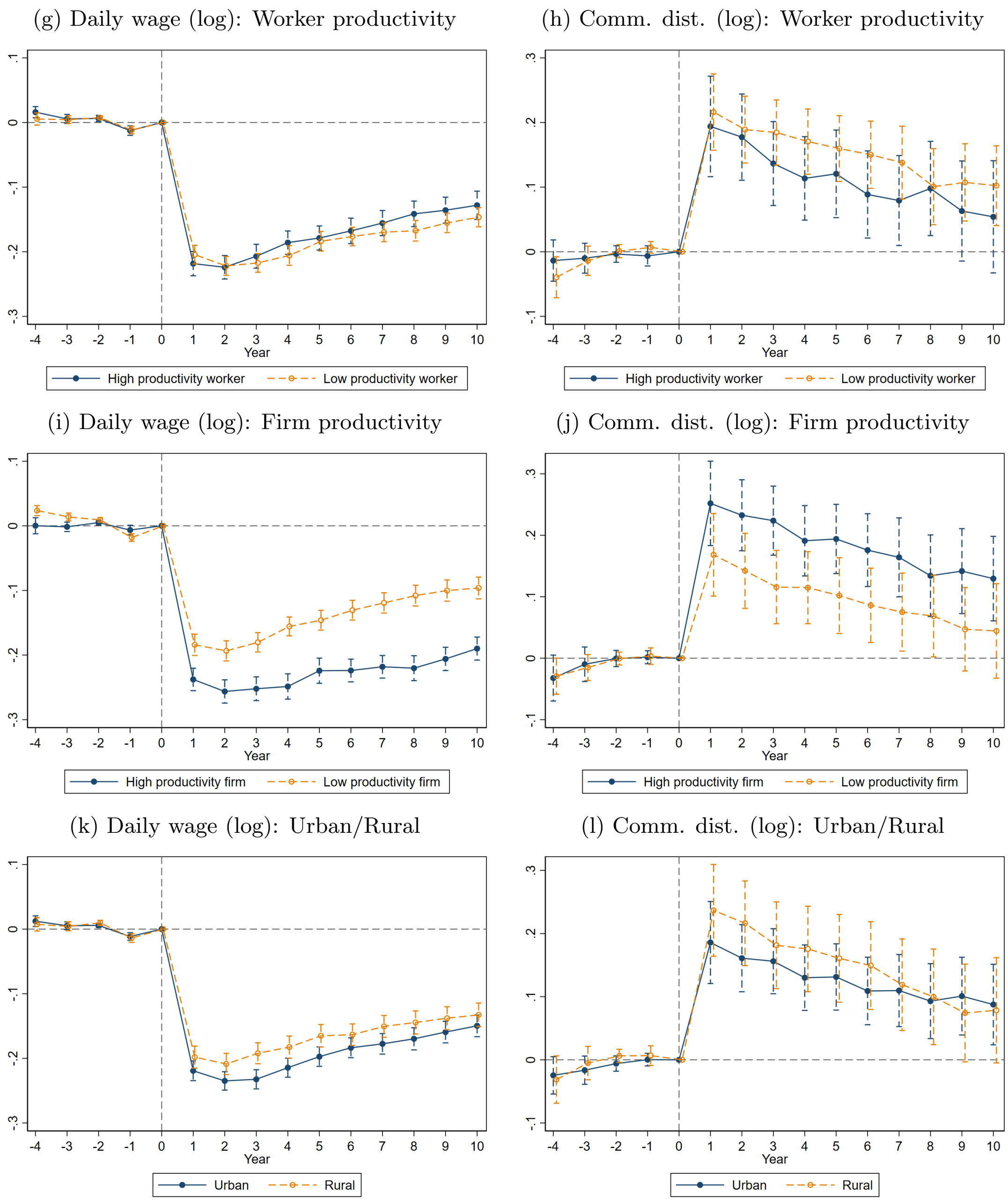
Figure 4.3: Effect Heterogeneity (Continued)



Notes: Each plot depicts estimates of equation (4.1) with dependent variable in the subtitle. The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year, separated by gender (panels (a)–(b)), age (panels (c)–(d), below or above the sample median in the year before displacement), local industry share (panels (e)–(f), employment share of the displacing industry below or above the median of the labor market region), worker and firm productivity (panels (g)–(j), AKM effects below or above the sample median, Abowd et al., 1999), and urban/rural residence (panels (k)–(l)). The vertical dashed line indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by establishments.

Table 4.3: Effect Heterogeneity

	(a) Daily wage (log)	(b) Commuting distance (log)
I. Gender		
ML × Post × Male	-0.176***	0.155***
	(0.006)	(0.022)
ML × Post × Female	-0.228***	0.129***
	(0.010)	(0.034)
Difference	-0.053***	-0.026
	(0.010)	(0.040)
Observations	4,316,096	4,316,096
Workers	394,020	394,020
R^2	0.898	0.817
II. Age		
ML × Post × Young	-0.164***	0.160***
	(0.006)	(0.023)
ML × Post × Old	-0.237***	0.127***
	(0.008)	(0.029)
Difference	-0.072***	-0.033
	(0.009)	(0.035)
Observations	4,316,096	4,316,096
Workers	394,020	394,020
R^2	0.898	0.817
III. Local industry share		
ML × Post × Low share	-0.201***	0.161***
	(0.007)	(0.025)
ML × Post × High share	-0.174***	0.131***
	(0.007)	(0.028)
Difference	0.026***	-0.030
	(0.010)	(0.038)
Observations	4,316,096	4,316,096
Workers	394,020	394,020
R^2	0.898	0.817

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Table 4.3: Effect Heterogeneity (Continued)

	(a) Daily wage (log)	(b) Commuting distance (log)
IV. Worker productivity		
ML × Post × Low productivity	-0.191***	0.161***
	(0.006)	(0.023)
ML × Post × High productivity	-0.181***	0.126***
	(0.008)	(0.030)
Difference	0.010	-0.035
	(0.010)	(0.037)
Observations	4,316,096	4,316,096
Workers	394,020	394,020
R^2	0.898	0.855
V. Firm productivity		
ML × Post × Low productivity	-0.150***	0.107***
	(0.006)	(0.027)
ML × Post × High productivity	-0.233***	0.196***
	(0.008)	(0.026)
Difference	-0.083***	0.089**
	(0.010)	(0.038)
Observations	4,316,096	4,316,096
Workers	394,020	394,020
R^2	0.898	0.817
VI. Urban/Rural residence		
ML × Post × Rural	-0.174***	0.158***
	(0.007)	(0.032)
ML × Post × Urban	-0.201***	0.139***
	(0.006)	(0.024)
Difference	-0.027***	-0.018
	(0.009)	(0.040)
Observations	4,316,096	4,316,096
Workers	394,020	394,020
R^2	0.898	0.817

Notes: Each column represents estimates of equation (4.2) with dependent variable in the column title. The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year, separated by gender (panel I), age (panel II, below or above the sample median in the year before displacement), local industry share (panel III, employment share of the displacing industry below or above the median of the labor market region), worker and firm productivity (panels IV–V, AKM fixed effects below or above the sample median, Abowd et al., 1999), and urban/rural residence (panel VI). The industry classification is based on the first-digit German Classification of Economic Activities, Edition 2008 (WZ08). All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors in parentheses clustered by establishments. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

In Figure 4.3, panels (g) and (h), we find that high-productivity and low-productivity workers experience similar changes in wages and commuting distances after job displacement. However, Figure 4.3, panels (i) and (j) show that workers displaced from higher-productivity firms suffer from greater wage losses and larger increases in commuting distances. In particular, the long-term differences are large and statistically significant (Table 4.3, panel V). The differences by firm productivity are consistent with a job ladder model, which predicts that displacement from "better" firms is more costly as workers lose more firm-specific wage premiums (Fackler and Rippe, 2017) and amenities in terms of shorter commuting distances.

Finally, Figure 4.3, panels (k)–(l) compare the effects of job displacement in urban versus rural areas. In urban areas, the wage losses are greater likely because urban firms are more productive (Fackler and Rippe, 2017), whereas commuting distances increase slightly less. Nonetheless, the long-term differences are small in magnitude and statistically insignificant (Table 4.3, panel VI).

To summarize, we find at best modest heterogeneity in the effects of job displacement across workers. Consistent with a job ladder model, we find workers displaced from more productive firms experience larger effects on both wages and commuting distances. However, our findings should be interpreted with caution as other unobserved differences across workers might still confound the heterogeneous estimates.

4.3.2 Robustness

To conclude this section, we perform various robustness checks for the estimated job displacement effects. The results are presented in Figure 4.A.4–4.A.5 and Tables 4.A.4–4.A.5.

Endogenous job displacement. To address the concern that less productive workers face higher unemployment risks in mass layoffs, we use establishment closures as an alternative source of job displacement. Closure events are identified when an establishment ID becomes unavailable and no successor (spin-off or ID change) can be identified from the worker flow (Ganzer et al., 2021). As before, we impose the same sample restrictions on workers displaced due to establishment closures, use CEM to obtain a matched sample of non-displaced workers, and re-estimate equations (4.1) and (4.2). Figure 4.A.4, panels (a)–(b) and Table 4.A.4, panel I show that the effects of job displacement are similar to the baseline results. Besides, Table 4.A.6 presents the pre-layoff worker characteristics in the new sample.

Spillover effects. Second, we rule out the spillover effects of mass layoffs on local labor markets. In Figure 4.A.4, panels (c)–(d) and Table 4.A.4, panel II, we exclude layoffs involving more than 500 workers. Such events might generate a large negative shock to the local labor market, make it harder for displaced workers to find a new job, and hence overstate the true effect (Gathmann et al., 2020). As an alternative, Figure 4.A.4, panels (e)–(f) and Table 4.A.4, panel III report estimates controlling for labor market region by year fixed effects to absorb such spillover effects. Both specifications produce quantitatively similar estimates to the baseline results. This is expected because most mass layoffs in our sample are too small to generate any spillover effects.

Selection into re-employment. Since we only observe outcomes of full-time employed workers, the decline in wages and increased commuting distances could be driven by changing composition of reemployed workers. In Figure 4.A.4, panels (g) and (h) and Table 4.A.4, panel IV, we restrict our sample to displaced workers who find a full-time job within two years after displacement and remain employed until the fifth year. For workers with stable employment after displacement, the estimates exhibit similar magnitudes and recovery patterns.

Measurement errors. Fourth, we address the concern that some workers' workplaces are not clearly identified. For multi-location firms, establishments in different municipalities are separately identified, but those in the same municipality are not. Hence, we re-estimate equations (4.1) and (4.2) excluding workers in finance, trade, and transportation industries, where firms are more likely to operate at multiple locations within a municipality (Ostermann et al., 2022). Figure 4.A.4, panels (i)–(j) and Table 4.A.4, panel V, show that these restrictions have little impact on our estimates.

Effect heterogeneity and dynamics. In addition, we use the imputation method of Borusyak et al. (2022) to explicitly account for dynamic and heterogeneous treatment effects. In Figure 4.A.4, panels (k)–(l), we find little difference between the imputed estimates and the baseline estimates. This is because we compare displaced workers with a much larger group of comparable non-displaced workers, which allows us to identify the dynamic effects of job displacement.

Alternative measures of commuting time. Finally, we estimate the job displacement effects on alternative measures of commuting time. The results are reported in Figure 4.A.5 and Table 4.A.5. On one hand, we follow Van Ommeren and Dargay (2006) and predict commuting time from commuting distance, assuming a constant elasticity of speed with respect to distances of 0.4. As we allow commuting speed to increase in distance and reflect changes in the mode of transportation, the new measure has a similar distribution as the baseline measure (Figure 4.A.1, panels (c)–(d)) and the estimated effects are quantitatively close. On the other hand, we estimate the job displacement effect on driving time directly calculated from OpenStreetMaps. The effect magnitudes are larger because driving time is roughly proportional to driving distances.

4.4 The Value of Granularity

As mentioned above, a major advantage of our study is the use of granular commuting data. For each worker, we calculate the commuting distance between her exact place of residence and place of work along actual routes. However, most existing research identifies workers and firms at some regional level and measures commuting distances between regional centers.

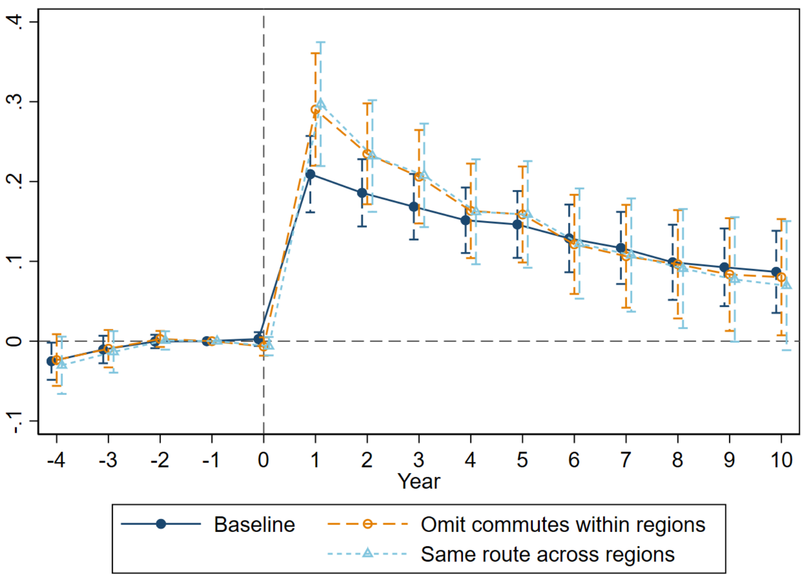
We argue that measuring distances at the regional level can be associated with two types of errors. First, it omits commutes within the same region. This leads to a censoring problem where within-region commuters are assumed to bear zero commuting costs. Second, the distance traveled by individual workers rarely coincides with the distance between regional centers. For example, if workers living near regional borders are more likely to commute out of the region, regional distance data will overstate the actual commuting distance. In what follows, we quantify the magnitudes of both errors.

In Figure 4.4, panel (a), we compare estimates of equation (4.1) using our baseline measure of commuting distances versus distances measured at the district level. First, we "omit" within-district commutes by forcing their distances to zero. In the first year after displacement, this leads to an overestimation of the job displacement effect by 8.1 percentage points, which is almost 40 percent of the baseline effect. Table 4.4, panel I shows that the long-term effect of job displacement is overestimated by 12.8 percent.

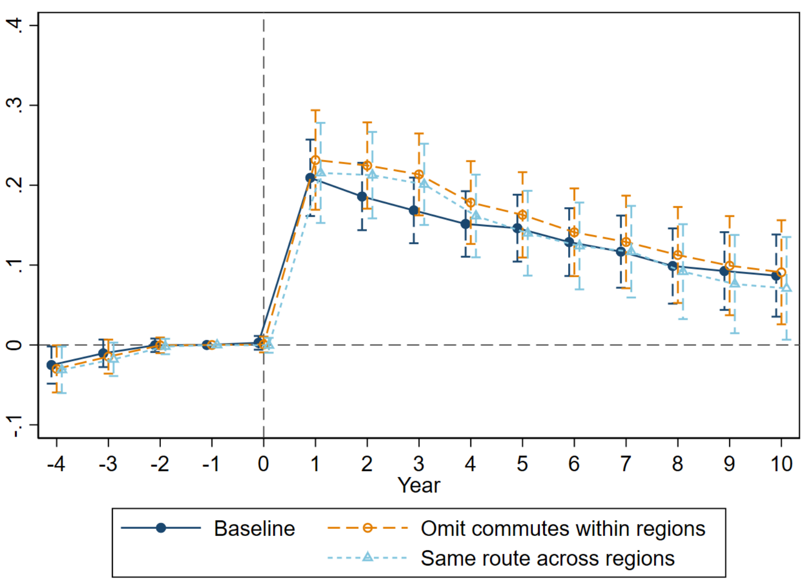
Next, we assume that commuters from one district to another all take the same route, for which the driving distances are calculated using OpenStreetMaps between district centers. As shown in Figure 4.4, panel (a), this also inflates the estimates but to a less severe extent. Combining both biases, the short-run and long-run effects of job displacement are overestimated by 41.9 percent and 13.5 percent, respectively. In Figure 4.4, panel (b) and Table 4.4, panel II, we repeat the comparison at the geocoordinate versus the municipality levels and obtain similar results. Considering both errors, measuring commuting at the municipality level overestimates the short-term effects of job displacement by 19.4 percent (in the fourth year after displacement) and the long-term effects by 6.1 percent. If anything, measuring commuting at a more granular level mitigates the bias, especially in the first few years after displacement. Therefore, we conclude that using regional-level commuting measures could significantly overestimate the effect of job displacement, and it is mainly because such measures omit commutes within the same region.

Figure 4.4: The Value of Granularity

(a) Commuting distance by district



(b) Commuting distance by municipality



Notes: The figure depicts estimates of equation (4.1). The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year. In panel (a), the dark blue line represents the driving distance between geocoordinates of an individual's residence and workplace (preferred specification); the orange line assigns zero log distance for commutes within districts and thus ignores commutes within districts; and the light blue line further replaces the commuting distances of all commuters between two districts by the commuting distance between district centers (assuming commuters take the same route). Panel (b) replicates the comparison at the municipality level. The vertical dashed line indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by establishments.

Table 4.4: The Value of Granularity

	(a) Baseline commuting distance (log)	(b) Omit commutes within regions	(c) Same route across regions
I. By Districts			
ML × Post	0.148***	0.167***	0.168***
	(0.019)	(0.028)	(0.030)
Observations	4,316,096	4,316,096	4,316,096
Workers	394,020	394,020	394,020
R^2	0.817	0.817	0.823
II. By Municipalities			
ML × Post	0.148***	0.173***	0.157***
	(0.019)	(0.024)	(0.024)
Observations	4,316,096	4,316,096	4,316,096
Workers	394,020	394,020	394,020
R^2	0.817	0.830	0.830

Notes: Each column represents estimates of equation (4.2). The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year. Dependent variables: log commuting distance at the worker level (column (a)); log commuting distance set to zero for within-region commutes (column (b)); and log commuting distance set to zero for within-region commutes and calculated between regional centers for cross-regional commutes (column (c)). Panels I and II define regions by the districts and municipalities, respectively. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors in parentheses clustered by establishments. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

4.5 A Job Search Model

In this section, we develop a job search model to rationalize the empirical findings and derive the monetary cost of commuting. Readers are referred to Appendix B for proofs.

Environment. Consider a continuum of infinitely-lived workers and firms in a linear city $\mathbf{R}_+$. Without loss of generality, assume that all workers reside at the origin and do not relocate.[25] Workers have ex-ante homogeneous human capital $h \in \mathcal{H}$. In contrast, firms are heterogeneous in productivity $y \in [\underline{y}, \bar{y}]$ and location $r \in \mathbf{R}_+$. A firm's type is denoted as $\theta = (y, r)$.

Time is discrete. In every unemployed period, the worker receives unemployment benefits z and draws a job offer with probability λ_0. Meanwhile, her human capital h depreciates and that in the next period h' follows the distribution $H_0(h'|h)$. When the worker is employed at firm θ, she earns a flow wage $w(\theta, \hat{\theta}, h)$, incurs commuting cost cr, and receives a job offer with probability λ_1. The wage $w(\theta, \hat{\theta}, h)$ depends on the current firm type θ, the worker's outside option $\hat{\theta}$, and her human capital h. The commuting cost is linear in distance r with $c > 0$ being the marginal cost of commuting. The worker's human capital in the next period follows the distribution $H_1(h'|h)$. All workers receive job offers from

[25]Both assumptions can be relaxed in a generalized model where workers optimally choose their residence in a symmetric linear city $\mathbf{R}$. In equilibrium, since all locations are symmetric, workers have no incentive to relocate and it suffices to consider one place of residence for analysis. The fact that job displacement hardly increases relocation (see Figure 4.2) also suggests that relocation does not play a role in workers' response to job displacement.

an exogenous distribution F_θ[26], and job matches dissolve with probability δ.

When a firm of type θ meets a worker with outside option $\hat{\theta}$ and human capital h, the value of a match is equal to $J(\theta, \hat{\theta}, h)$ for the firm and $W(\theta, \hat{\theta}, h)$ for the worker. When unmatched or unemployed, the firm gets zero value and the worker gets $U(h)$. A job offer turns into a job match if and only if the resulting joint surplus

$$S(\theta, h) \equiv \max\{0, W(\theta, \hat{\theta}, h) - U(h) + J(\theta, \hat{\theta}, h)\}, \tag{4.3}$$

is strictly positive. Note that S does not depend on $\hat{\theta}$ because the latter only affects how the surplus is split between the firm and the worker. No surplus is created by an unemployed worker or a vacant firm so that $S(u, h) = 0$.

The timing of events is summarized as follows. In each period, workers first update their human capital, and job matches are formed or separated. Next, wages are determined for successful job matches. Then employed workers produce outputs and pay commuting costs. Finally, all workers consume either wages or unemployment benefits.

Wage Bargaining. With on-the-job search, bargaining takes the form of sequential auctions (Postel-Vinay and Robin, 2002*a*,*b*). When an unemployed worker with human capital h meets a firm of type θ, the worker bargains for an exogenous share $\alpha \in [0, 1]$ of the joint surplus:

$$W(\theta, u, h) - U(h) = \alpha S(\theta, h). \tag{4.4}$$

When the worker is currently employed at firm θ_1 with outside option $\hat{\theta}$ and receives an offer from firm θ_2, one of the following will happen. If $S(\theta_2, h) > S(\theta_1, h)$, the worker will move to the new firm, and the new wage is determined by

$$W(\theta_2, \theta_1, h) - U(h) = S(\theta_1, h) + \alpha(S(\theta_2, h) - S(\theta_1, h)), \tag{4.5}$$

so that the worker gains α share of the increase in surplus. If $S(\hat{\theta}, h) < S(\theta_2, h) < S(\theta_1, h)$, firm θ_1 retains the worker at a higher wage to match the better outside option θ_2. The renegotiated wage satisfies

$$W(\theta_1, \theta_2, h) - U(h) = S(\theta_2, h) + \alpha(S(\theta_1, h) - S(\theta_2, h)). \tag{4.6}$$

Finally, if $S(\theta_2, h) \leq S(\hat{\theta}, h)$, the worker remains at the old firm at the current wage. For the sake of convenience, we define $M_1(\theta_1, h) = \{\theta : S(\theta, h) > S(\theta_1, h)\}$ as the set of firms that successfully poach the worker from θ_1, and $M_2(\theta_1, \theta_2, h) = \{\theta : S(\theta_2, h) < S(\theta, h) \leq S(\theta_1, h)\}$ as those triggering wage renegotiation at firm θ_1 when the worker's original outside option is θ_2. The corresponding probability measures are

[26] Recall that the average size of mass layoffs is small and unlikely to have general equilibrium effects on the job offer distribution or labor market tightness (see Sections 4.2 and 4.3.2).

$p_1(\theta_1, h)$ and $p_2(\theta_1, \theta_2, h)$, respectively. In later analysis, we also denote $p_3(\theta_2, h) = p_1(\theta_1, h) + p_2(\theta_1, \theta_2, h)$.

Value Functions. In the steady state, the value functions U, W, and J are given as follows. For unemployed workers,

$$U(h) = z + \beta \int_{\mathcal{H}} \left\{ \lambda_0 \int_{M_1(u,h')} W(x, u, h') dF_\theta(x) + (1 - \lambda_0 p_1(u, h')) U(h') \right\} dH_0(h'|h). \tag{4.7}$$

The first term in the braces represents the expected continuation value of being employed at some firm x, provided that the worker meets the firm and that the firm generates a positive surplus. The second term describes when the worker receives no job offer or the job offer creates zero surplus.
Similarly, the value function of an employed worker at firm θ with outside option $\hat{\theta}$ is

$$\begin{aligned} W(\theta, \hat{\theta}, h) = w(\theta, \hat{\theta}, h) - cr + \beta \int_{\mathcal{H}} \Bigg\{ \delta U(h') + (1-\delta) \Bigg[\lambda_1 \int_{M_1(\theta,h')} W(x, \theta, h') dF_\theta(x) \\ + \lambda_1 \int_{M_2(\theta,\hat{\theta},h')} W(\theta, x, h') dF_\theta(x) + (1 - \lambda_1 p_3(\hat{\theta}, h')) W(\theta, \hat{\theta}, h') \Bigg] \Bigg\} dH_1(h'|h), \end{aligned} \tag{4.8}$$

and the value function of the firm is

$$\begin{aligned} J(\theta, \hat{\theta}, h) = y + h - w(\theta, \hat{\theta}, h) + \beta(1-\delta) \int_{\mathcal{H}} \Bigg\{ \lambda_1 \int_{M_2(\theta,\hat{\theta},h')} J(\theta, x, h') dF_\theta(x) \\ + (1 - \lambda_1 p_3(\hat{\theta}, h')) J(\theta, \hat{\theta}, h') \Bigg\} dH_1(h'|h). \end{aligned} \tag{4.9}$$

4.5.1 Job Match Surplus and the Cost of Commuting

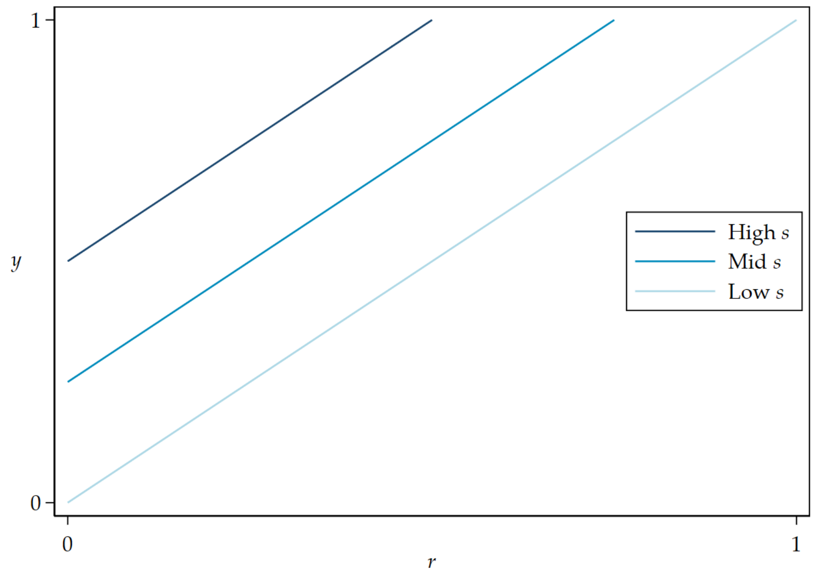
To investigate the relationship between wage and commuting costs after job displacement, we associate both outcomes with the job match surplus. Plugging the value functions (4.7)-(4.9) and wage bargaining rules (4.4)-(4.6) into (4.3), we obtain an expression of the surplus function. For $S(\theta, h) > 0$, we have

$$\begin{aligned} S(\theta, h) = y + h - cr - z + \beta \left(\int_{\mathcal{H}} U(h') dH_1(h'|h) - \int_{\mathcal{H}} U(h') dH_0(h'|h) \right) \\ + \beta(1-\delta) \int_{\mathcal{H}} S(\theta, h') dH_1(h'|h) - \alpha\beta\lambda_0 \int_{\mathcal{H}} \int_{M_1(u,h')} S(x, h') dF_\theta(x) dH_0(h'|h) \\ + \alpha\beta(1-\delta)\lambda_1 \int_{\mathcal{H}} \int_{M_1(\theta,h')} \left(S(x, h') - S(\theta, h') \right) dF_\theta(x) dH_1(h'|h). \end{aligned} \tag{4.10}$$

Proposition 1. *Holding h fixed, the surplus function S strictly increases in y and strictly decreases in r.*

Proposition 1 establishes a job ladder where more productive and proximate firms are preferred to less productive or distant ones. This partial order can be characterized using "isosurplus curves". To illustrate this idea, Figure 4.5 plots three hypothetical isosurplus curves over the space $[\underline{y}, \bar{y}] \times \mathbf{R}_+$.

Figure 4.5: Hypothetical Isosurplus Curves



Notes: This figure depicts three hypothetical isosurplus curves. The surplus level increases in productivity y and decrease in commuting distance r.

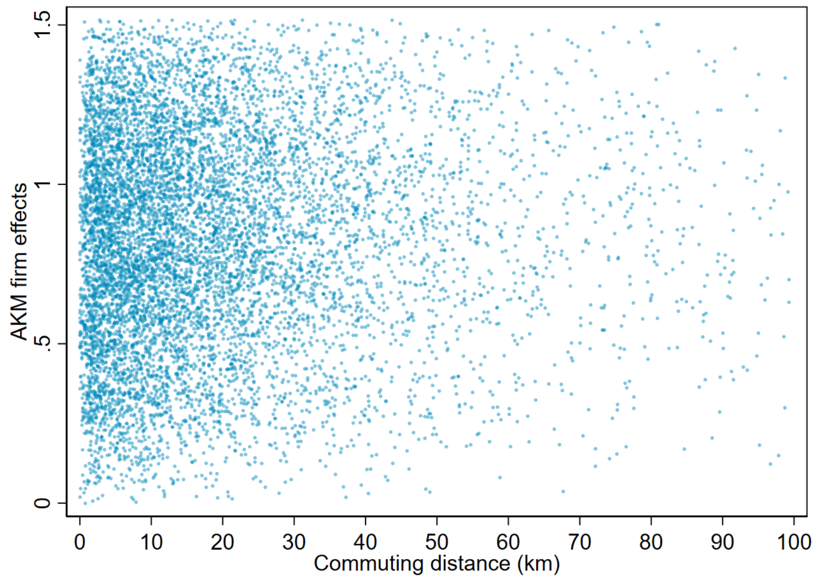
All jobs on the same curve yield the same surplus, and curves on higher positions represent greater surplus levels. Analogously, we can define indifference curves for individual workers by relating the flow wage w to the commuting distance r. Conditional on h and the worker's outside option $\hat{\theta}$, jobs on the same indifference curve yield the same value W for the worker, and jobs with higher wages and short distances yield higher W.

Our model also implies that displaced workers will accept a job offer only if it yields a positive surplus. This is validated in Figure 4.6, panel (a), which depicts productivity y and commuting distance r of all first jobs accepted by displaced workers in our data. Firm productivity is approximated by the AKM firm effects. As distance increases, workers are less likely to accept low-productivity jobs. In particular, very few accepted jobs have low wages and long commuting distances, which we interpret as truncation by the upward-sloping zero surplus curve. The same pattern is observed when the firm effects are replaced by log wages in Figure 4.6, panel (b).

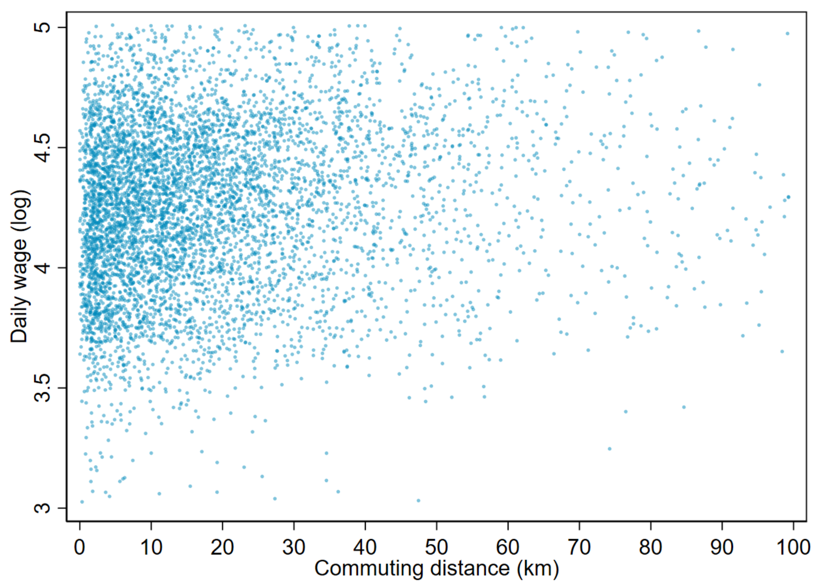
Moreover, the slope of isosurplus curves, c, measures workers' valuation for commuting. It represents, for an infinitesimal increase in commuting, the change in firm productivity or wage needed to hold S or W constant (see equations (4.8) and (4.10)). Our results generalize the "reservation wage curve" in Le Barbanchon et al. (2021) by (i) incorporating on-the-job search and establishing a job ladder for employed workers and (ii) showing that the slope of the curves identifies the valuation for commuting for both employed and unemployed workers.

Figure 4.6: First Jobs after Displacement

(a) Productivity and Distance



(b) Wage and Distance



Notes: Panel (a) plots the AKM firm effects against commuting distances for first jobs taken by displaced workers (the minimum firm effect is normalized to zero); Panel (b) plots the daily wages against commuting distances for the same sample.

4.5.2 Recovery from Job Displacement

Given Proposition 1 and the upward-sloping curves, we argue that workers with a greater surplus are expected to match with more productive and more proximate firms. This is obvious when y and r are uniformly distributed, as the expectation of y and r conditional on the surplus level is given by the midpoint of the corresponding isosurplus curve (see Figure 4.5), However, we can extend this result to a general class of distributions. We fix h as before and let $\mathbf{E}[y|s]$ and $\mathbf{E}[r|s]$ denote the expected firm productivity and distance, respectively, conditional on surplus s.

Proposition 2. $\mathbf{E}[y|s]$ *increases in* s *and* $\mathbf{E}[r|s]$ *decreases in* s*, if*
(i) F_y *and* F_r *are twice differentiable;*
(ii) the density functions f_y *and* f_r *are log-concave;*
(iii) y *and* r *are independent.*

With on-the-job search, employed workers either stay at their current jobs or move to higher-surplus jobs. Proposition 2 implies that whenever they move to another job, the new firm is expected to be more productive and more proximate. Jarosch (2022) argues that when a worker's bargaining power α is sufficiently large, wages will increase in productivity so that the expected wage is also higher. Additionally, employed workers accumulate human capital which increases the joint match surplus (4.10) and their wages. Taken together, the model characterizes how workers climb up the job ladder and recover from job displacement, consistent with our empirical findings.

Corollary 1. *For a worker employed in periods* $t = 1, 2, \cdots, T$*, let* (y_t, r_t) *denote the matched firm type in period* t*. Under the assumptions of Proposition 2,* $\mathbf{E}[y_t]$ *increases in* t *and* $\mathbf{E}[r_t]$ *decreases in* t*.*

Finally, we discuss cases where y and r are not independent. If y and r are negatively correlated, i.e., more productive firms locate closer to workers, results of Proposition 2 could still hold, because recovery along the productivity dimension naturally reduces commuting distances and vice versa. However, if y and r are positively correlated, it is possible that higher-surplus jobs are more productive but also further away in distribution. As a result, either $\mathbf{E}[y|s]$ could decrease in s or $\mathbf{E}[r|s]$ could increase in s, and joint recovery breaks down.

4.6 Structural Estimation

To quantify the monetary cost of commuting, we structurally estimate the job search model in Section 4.5 using the simulated method of moments (SMM). Essentially, we choose a set of model parameters to simulate workers' job search behavior and match moments in the simulated data with their counterparts in the actual data.

4.6.1 Identification

The model parameters are identified as follows. First, we choose the offer arrival rates for the unemployed and employed (λ_0 and λ_1) to match the empirical job finding (U-E) rate of the unemployed and the employer-to-employer transition (E-E) rate of the employed, respectively. The separation probability $\delta = 0.007$ matches the separation (E-U) rate in the data. We assume worker's human capital h takes 20 discrete values $h_1 < \cdots < h_{20}$. In each period, h_k depreciates to $\min\{h_{k-1}, h_1\}$ with probability ρ_0 if the worker is unemployed, and increases to $\max\{h_{k+1}, h_{20}\}$ with probability ρ_1 if employed. Following Jarosch (2022), we set $\rho_0 = 0.236$, $\rho_1 = 0.052$, and worker's bargaining power $\alpha = 0.962$. The monthly discount factor $\beta = 0.996$ corresponds to an annual factor of 0.95.

Next, we parameterize the distribution of firm types. Let $\underline{y} = 0$ and $\bar{y} = 1.47$ to match the 99th-1st percentile gap of the AKM firm effects. Then we assume firm productivity $y = \bar{y}Y$ where $Y \sim \text{Beta}(\eta_{y1}, \eta_{y2})$, and commuting distance be $r = 100R$ where $R \sim \text{Beta}(\eta_{r1}, \eta_{r2})$. The distributional parameters η_{y1}, η_{y2} are identified by the 90th-50th and 50th-10th percentile gaps of AKM firm effects, and η_{r1}, η_{r2} by the same percentile gaps of commuting distances. We use the lower bound of matched job-type distribution to identify z, for which Appendix C.1 provides more details.

Most importantly, we identify the marginal commuting cost c using indirect inference. As Figure 4.6 suggests, the first jobs of displaced workers are likely truncated by some zero surplus curves. When the isosurplus curves become steeper (c is higher), the truncation will be more severe and the observed correlation between y and r will become more positive. Therefore, the observed correlation between firm productivity provides information to identify c.

To fix ideas, let $m(r)$ denote the expectation of y conditional on r among all potential job matches, and assume that $m(r)$ is differentiable. This yields

$$y = m(r) + \epsilon, \quad \mathbf{E}[\epsilon|r] = 0. \tag{4.11}$$

By Proposition 1, a potential job match is realized only if $y - cr > c_0 + \upsilon$ for some $c_0 \in \mathbf{R}$. The idiosyncratic term υ may stem from variations in workers' human capital or measurement errors. Conditional on realized job matches, we have

$$\mathbf{E}[y|r, y - cr > c_0 + \upsilon] = m(r) + \underbrace{\mathbf{E}[\epsilon|\epsilon > c_0 - m(r) + cr + \upsilon, r]}_{\xi(r)}. \tag{4.12}$$

Note that the truncated expectation of residuals ξ is a function of r. Therefore, the slope coefficient γ_1 of the linear projection

$$y = \gamma_0 + \gamma_1 r + \epsilon, \tag{4.13}$$

is determined by the first-order derivatives of both $m(r)$ and $\xi(r)$. The formal represents the relationship between y and r among potential job matches, and the latter captures the effect of truncation by zero surplus curves among realized matches.

In Appendix C.2, we prove that

$$\frac{\partial^2 \xi}{\partial r \partial c} > 0. \tag{4.14}$$

Hence, greater commuting cost c leads to a more positive relationship between ξ and r, and thus between y and r, among realized job matches. For fixed $m(r)$, c is identified from γ_1 which can be estimated using all first jobs of displaced workers.

4.6.2 Validating the Identification Assumptions

Our structural method identifies the commuting cost c under two assumptions: (i) the dependence between y and r among potential job matches is fixed, and (ii) there is no unobserved job attribute correlated with both y and r. In what follows, we present empirical evidence to validate both assumptions.

First of all, we attempt to back out the set of potential job matches facing each displaced worker. Using the locations of all workers and firms in the same labor market, we calculate the commuting distance between each worker-firm pair and recover the joint distribution of (y, r) among all potential job matches. Table 4.C.1, Panel I shows that the Pearson correlation coefficient between y and r is almost zero (-0.0171), indicating no linear relationship. Moreover, higher-order polynomials of y and r are uncorrelated either, suggesting that they are independent.[27] Table 4.C.1, Panels II and III also show that y and r are independently distributed within both urban and rural areas.

At first glance, the result seems counter-intuitive as workers and firms often locate endogenously. It is possible that productive firms and workers sort into downtown whereas unproductive ones sort into peripheral areas. Thus, firm productivity will be negatively correlated with commuting distances. However, our findings can be supported by a quantitative spatial model where production and residential amenities are dispersed across locations (e.g., Ahlfeldt et al., 2015; Heblich et al., 2020) so that firms and workers spread out over space. As a result, the distribution of commuting distances depends very little on the specific location of firms. Since we focus on commutes mostly within a few kilometers, it is also possible that workers and firms cannot perfectly sort at such a granular scale.

[27] Independence of y and r is equivalent to uncorrelatedness of $f(y)$ and $g(r)$ for any measurable functions f and g. Hence, we approximate f and g each with a fourth-order Taylor series. Since the polynomials are pairwise uncorrelated, their sums (the Taylor series) are uncorrelated as well.

Finally, our job search model abstracts away other unobserved amenities such as job stability and non-wage benefits. We argue that such amenities are unlikely to confound the relationship between firm productivity and commuting distances and bias the estimated commuting cost. On one hand, if firms and workers are sufficiently dispersed over the space, firms offering different productivity or amenities are expected to face the same distributions of distances to workers at large. On the other hand, we can consistently estimate equation (4.13) as long as amenities are uncorrelated with distance. Using firm-average job separation rates as a proxy for unobserved amenities, we find that high- and low-separation firms face the same distribution of distance to workers.[28]

4.6.3 Comparing Structural and Reduced-form Methods

Before presenting the estimates, we discuss the difference between our structural approach with reduced-form estimates based on compensating differentials. In the presence of job search frictions, the observed correlation between y and r is given by equation (4.12). Even if the marginal cost of commuting is constant, the parameter c enters the equation in a non-linear way through the truncated error term $\xi(r)$. As such, the cost of commuting cannot be directly identified.

Worse yet, exogenous changes in commuting distances can also affect the surplus of jobs and render c unidentified. Suppose a worker's commuting distance increases exogenously due to firm relocation (Mulalic et al., 2014). With job search frictions, the relocation will reduce the job match surplus and the extra commuting cost will be shared between the worker and her employer. As a result, wages may not adjust for the changing commuting cost in such a way that the worker stays on the same isosurplus curve.

In contrast, in a competitive labor market without search friction, we expect all jobs to deliver the same surplus. This implies

$$y - cr = c_0 + \upsilon, \tag{4.15}$$

Plugging condition (4.15) into equation (4.12) yields

$$\mathbf{E}[y|r, y - cr = c_0^* + \upsilon] = c_0^* + cr. \tag{4.16}$$

Therefore, c is identified by an OLS regression of y against r.

[28] Note that at the worker level, job separation is expected to increase in commuting distance. However, we show that commuting distance is independent of the average job separation rate of firms. This provides further evidence that good (bad) firms do not endogenously locate closer to (further away from) workers.

4.7 The Monetary Cost of Commuting

We implement the SMM estimation in three steps. First, for a given vector of parameters, we solve the job ladder model for the value functions, surplus functions, and flow wages. We approximate the distributions of Y and R by 50 grid points each on the unit interval, so there are 2501 firm types (including unemployment) and 20 human capital levels. We solve for S and U at 2501×20 states, and W, J, and w at $2501 \times 2501 \times 20$ states. Second, we use the model to simulate a monthly panel of $100,000$ workers and 240 months (20 years) and obtain workers' employment and wage trajectories. We drop the first 60 months (5 years) to focus on the steady state. Then we calculate data moments from the actual monthly panel and model moments from the simulated panel. At last, we estimate the structural parameters by minimizing the L^2-distance between the model and data moments.

To obtain the actual data moments, we convert the IEB data described in Section 4.2 into a monthly panel. As before, we focus on the years 2000 to 2017, impose the age restriction of 20 to 54 years old, and a maximum commuting distance of 100 kilometers. However, employment status, daily wage, and commuting variables are now defined with respect to the main employer on the 15th of each month. In addition, we no longer distinguish displaced and non-displaced workers or match their characteristics. Hence, the monthly panel captures the employment and wage dynamics of the entire labor force.

Table 4.5 shows the full estimation results. Panel I lists parameters determined outside of the model, and Panel II reports structurally estimated parameters and the corresponding moments. To begin with, we

Table 4.5: Simulated Method of Moments: Full Results

I. External/Calibrated Parameters

Parameter	Value	Source
δ	0.007	E-U rate
$\bar{y}$	1.470	$y_{99} - y_1$
ρ_0	0.236	Jarosch (2022)
ρ_1	0.052	Jarosch (2022)
α	0.962	Jarosch (2022)
z	-0.018	$S(\underline{y}, 0), h_1) = 0$

II. Estimated Parameters

Parameter	Value	Moment	Model	Data
λ_0	0.104	U-E rate	9.13%	9.14%
λ_1	0.023	E-E rate	0.70%	0.71%
η_{y1}	1.650	$y_{50} - y_{10}$	0.500	0.497
η_{y2}	2.000	$y_{90} - y_{50}$	0.353	0.367
η_{r1}	0.650	$r_{50} - r_{10}$	0.080	0.078
η_{r2}	2.900	$r_{90} - r_{50}$	0.240	0.234
$c/100$	1.250	$\gamma_1/100$	0.137	0.137

Notes: Panel I lists externally calibrated parameters and the source of information. Panel II reports estimates using the Simulated Method of Moments, the corresponding model moments, and data moments.

find the job arrival rate for the unemployed and employed are $\lambda_0 = 0.104$ and $\lambda_1 = 0.023$, respectively. Note that the matched U-E rate is only 87.8 percent of the offer arrival rate λ_0, so when an unemployed worker meets a firm, the probability that the firm lies above the worker's reservation wage curve is 0.878. Similarly, when an employed worker meets a new firm, the probability of the firm delivering greater surplus and thereby inducing an E-E transition is $0.71/2.6 = 0.27$. In addition, Figure 4.A.6 shows that the estimated distribution of y is roughly bell-shaped, whereas the distribution of r is heavily right-skewed. That is, workers draw fewer job offers from distant firms regardless of their willingness to commute.

Most importantly, we estimate the marginal commuting cost $c = 0.0125$. As shown in Table 4.6, column (a), the monetary cost of commuting for one kilometer is equal to 1.25 percent of workers' daily wage.

At the sample-average daily wage (100.4 euros) and commuting distance (14.39 kilometers), the monetary

Table 4.6: Willingness-to-Pay for Commuting

	(a) All workers	(b) Male workers	(c) Female workers
(1) Average daily wage	100.4	118.8	78.80
(2) Average commuting distance	14.39	15.96	12.56
(3) OLS slope	1.37‰	1.12‰	1.76‰
(4) Semi-elasticity c	1.25%	1.17%	1.39%
(5) Commuting cost per km	1.255	1.395	1.094
(6) Commuting cost per day	18.06	22.26	13.74
(7) Elasticity	0.180	0.187	0.174

Notes: Rows (1)–(2) report the average daily wages and commuting distances calculated from the monthly panel described in Section 4.7. Row (3) reports OLS estimates of equation (4.13) representing the reduced-form relationship between log daily wages and commuting distances. Row (4) reports the estimated marginal cost of commuting c interpreted as semi-elasticity (the percentage change in daily wages to compensate for one kilometer of commuting). Rows (5)–(6) report the average commuting cost per kilometer and per day, respectively, calculated from rows (1)–(2) and (4). Row (7) reports the elasticity at sample means (the percentage change in daily wages to compensate for one percentage increase in commuting distance relative to the sample-average distance), calculated from rows (2) and (4). Columns (a)–(c) report statistics using all workers, male workers, and female workers separately.

cost of commuting is 1.26 euros per kilometer and 18.06 euros per day. Recall that job displacement increases workers' average commuting distances by 20.9 percent in the first year after displacement. For an average worker, the effect is equivalent to $14.39 \times 20.9\% = 3.01$ additional kilometers or $3.01 \times 1.26 = 3.77$ euros per day. In comparison, the contemporaneous average loss in daily wage is $100.4 \times 21\% = 21.08$ euros. Therefore, the increased commuting cost is equivalent to 17.9 percent of the wage loss in the short run, and 14.1 percent of that in the long run.[29]

The estimated commuting cost reflects workers' subjective disutility from commuting, hence it differs from the opportunity cost of lost working hours. Recall that the average commuting time of a German worker is 0.75 hours per day (Giménez-Nadal et al., 2022) and the average hourly wage is approximately

[29] Using the DID estimates in Table 4.2, we calculate the long-run wage losses $100.4 \times 18.9\% = 18.98$ euros and long-run increase in commuting distance $14.39 \times 14.8\% = 2.13$ kilometers, which is worth 2.67 euros.

20 euros. Hence, the opportunity cost of commuting equals 15 euros per day. The gap between the WTP and the opportunity cost reflects additional disutility such as the cost of the vehicle, fuel, or tickets, as well as the subjective distaste for commuting long hours.

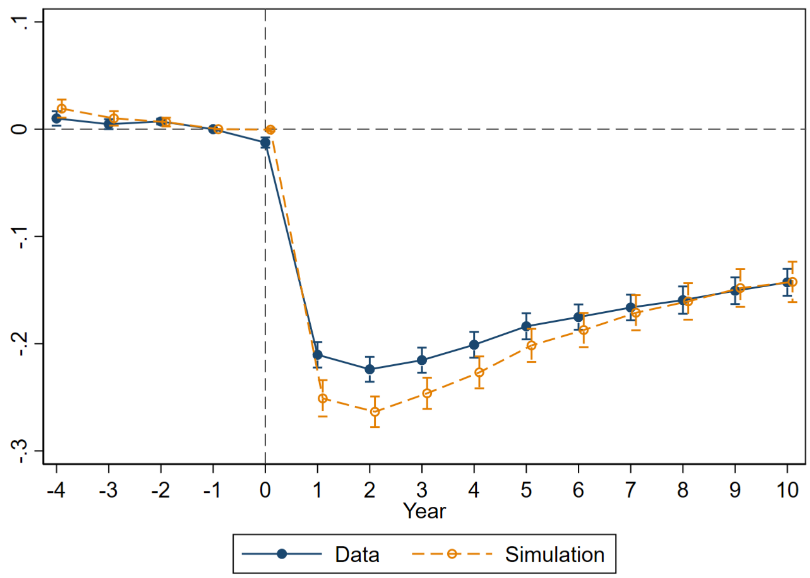
4.7.1 External Validity

We compare our estimated commuting cost with estimates in existing studies. Since c represents the trade-off between commuting distance in levels and daily wage in percentage (log) points, we interpret it as semi-elasticity and convert it to elasticity at the aforementioned sample means. As shown in Table 4.6, column (a), the average elasticity of distance with respect to daily wage is 0.188. It means that each percentage increase in commuting distances must be compensated by a 0.188 percent increase in daily wages to hold the worker's utility constant. This is in line with Le Barbanchon et al. (2021) who exploited a similar identification strategy that compares jobs on and above the reservation wage curve, and estimates of Van Ommeren and Fosgerau (2009) based on a structural model. By contrast, our estimate is one magnitude larger than the reduced-form estimates of Mulalic et al. (2014) and Dauth and Haller (2020) where utility might not be equalized across jobs.

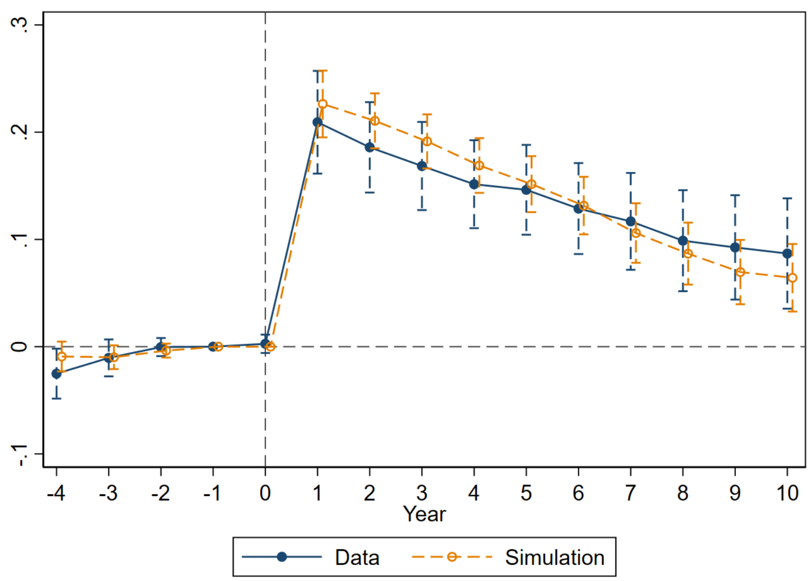
In addition, we use simulated data from the model to re-estimate the effects of job displacement on wages and commuting distances. We convert the simulated monthly panel into a yearly panel by focusing on one representative month per year. Figure 4.7 compares estimates of equation (4.1) using actual and simulated data, respectively. It turns out that simulated effects of job displacement on both wages and commuting are closely aligned with estimates using real data. The simulated regression slightly overstates the short-term effect on wages but replicates the long-term effects very well. In the meantime, the simulated effects on commuting distances align closely with the actual effects. Therefore, our structural model provides a decent fit for the empirical patterns documented in previous sections.

Figure 4.7: Actual and Simulated Effects of Job Displacement

(a) Daily wage (log)



(b) Driving distance (log)



Notes: Each plot depicts estimates of equation (4.1) with dependent variable in the subtitle. The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year (in dark blue) and a simulated panel of workers from the structural estimation (in orange). The estimates control for a polynomial of age (for actual data only), worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by establishments.

4.7.2 Gender Gaps in the Cost of Commuting

Finally, we estimate the structural model by gender, targeting gender-specific data moments. Table 4.6, columns (b)–(c) report the estimated marginal commuting cost c and the corresponding elasticity for men and women, respectively. The estimates are larger for women than for men, suggesting that women exhibit greater WTP for shorter commuting (Le Barbanchon et al., 2021). However, since an average woman in our sample earns a lower wage and commutes a shorter distance than an average man, the out-of-pocket commuting cost exhibits a reverse gender gap. On average, the commuting cost per day is 22.26 euros for working men but only 13.74 euros for working women.

4.8 Conclusion

In this paper, we investigate the impact of job displacement on workers' commuting behavior. Using an event study approach, we estimate the short-term and long-term effects of being displaced during mass layoffs on commuting distances and commuting time to subsequent jobs. We find that displaced workers commute up to 21 percent longer distances and 12 percent longer time after displacement, and their commuting patterns gradually recover towards the pre-displacement level in later years. Like the scarring effect of wage losses, the increase in commuting persists for at least 10 years after displacement. Further analysis reveals that the recovery is driven by workers' moving from distant to proximate firms rather than relocation.

To rationalize the empirical findings, we build a job search model with heterogeneous firm productivity and commuting distance. With on-the-job search, workers can increase their job match surplus by moving from less to more productive firms and from distant to proximate firms. This explains the long-run recovery of wages and commuting after job displacement. However, the existence of a job ladder (utility dispersion across jobs) complicates the reduced-form relationship between wages and commuting distances. As such, we propose a structural approach to quantify the monetary cost of commuting and empirically validate the key identifying assumptions. We find that workers incur an average commuting cost of 18 euros per day, and increased commuting exacerbates the wage losses due to job displacement by 14 percent in total.

A large literature has documented the profound consequences of job loss on individual workers. We contribute to the literature by emphasizing the multi-dimensional nature of the impacts of job loss. Not only do displaced workers experience lower wages or earnings, but they also face increased commuting costs to subsequent jobs. More importantly, the increased commuting cost is yet priced in the lost earnings. As such, it is important to quantify the monetary value of increased commuting to understand the overall cost of job displacement. It would be interesting for future research to consider the effect of job displacement on other outcomes and evaluate the monetary value of such effects.

For policymakers, our paper sheds light on the value of transportation infrastructure, working-from-home, and employment assistance programs. Except for cash transfers and skill training, measures to reduce commuting costs and job search frictions would particularly benefit unemployed workers, as they face higher commuting costs to find new jobs. Future research could examine whether such policies could facilitate job search and employment, and whether they reduce the persistence of the cost of job displacement (Franklin, 2018; Paetzold, 2019). It would also be valuable to study how job search frictions impact the effectiveness of employment assistance programs.

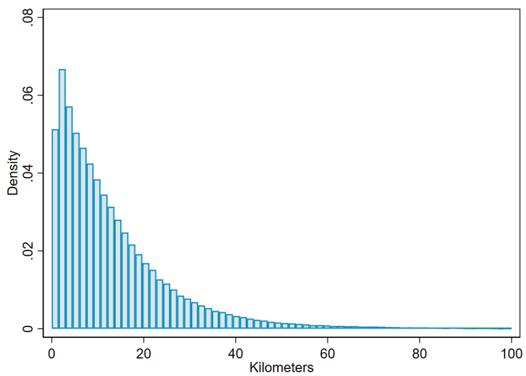
Finally, our study highlights the importance of granular commuting data for studying individuals' responses to job displacement. In other research areas, we also expect a great value in individual-level measures of commuting. For example, studies of job search, labor market frictions, monopsony, and social networks are all related to individuals' commuting decisions. The granular location and commuting data provide new venues for those research.

Appendix

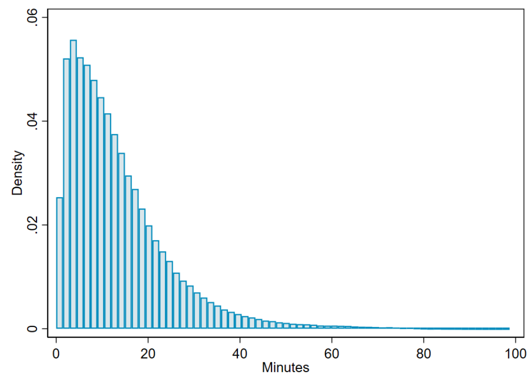
A Additional Figures and Tables

Figure 4.A.1: Distribution of Commuting Distance and Commuting Time

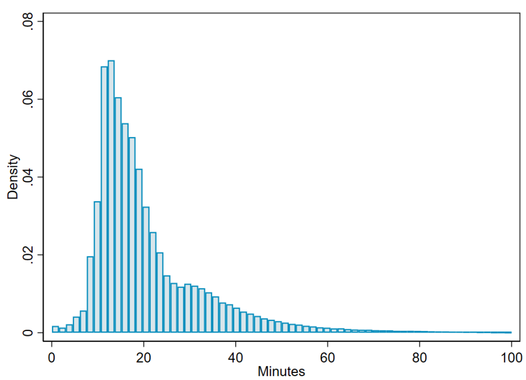
(a) Commuting distance



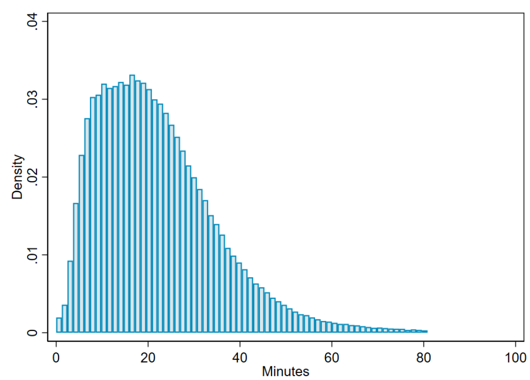
(b) Commuting time (driving speed)



(c) Commuting time (weighted average)



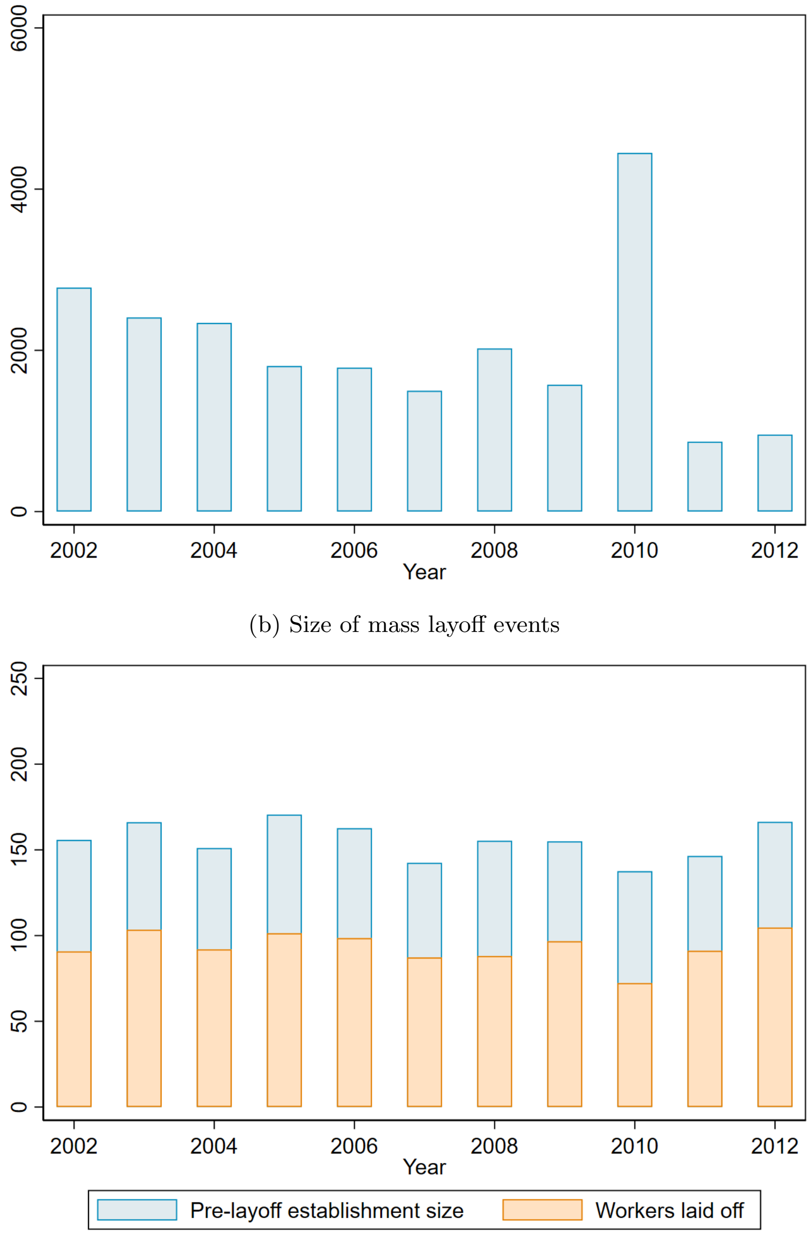
(d) Commuting time (speed elasticity)



Notes: Panels (a)–(b) plot the distributions of driving distances and driving time, respectively, calculated by OpenStreetMaps. Panel (c) plots the distribution of commuting time calculated as the weighted average of walking, cycling and driving time, with distance-dependent weights reported in Table 4.A.1 (Scheiner, 2010). Panel (d) plots the distribution of commuting time predicted from driving distances, assuming a constant elasticity of speed to distance of 0.4 (Van Ommeren and Dargay, 2006). The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year.

Figure 4.A.2: Mass Layoff Statistics

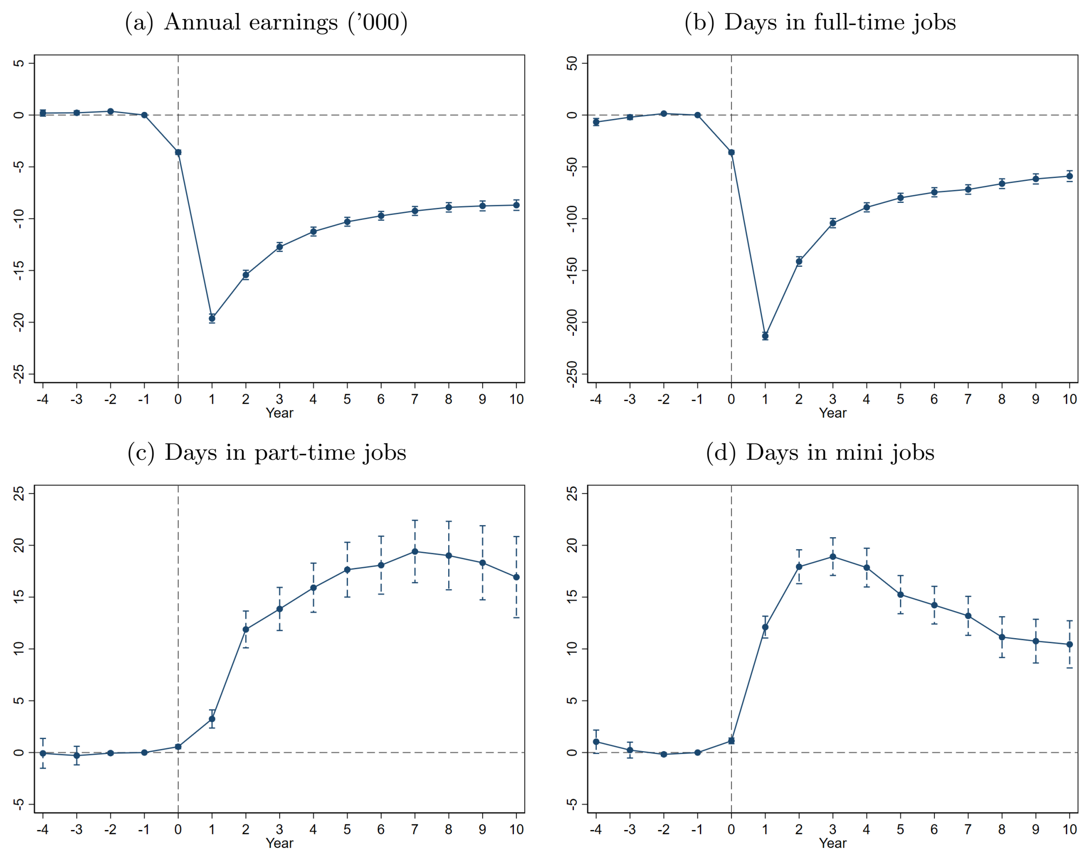
(a) Distribution of mass layoff events



(b) Size of mass layoff events

Notes: The sample comprises all establishments in the BHP data that went through a mass layoff event in 2002–2012. Panel (a) plots the number of mass layoff events by year. Panel (b) plots the average pre-layoff establishment size and the number of workers laid off by year.

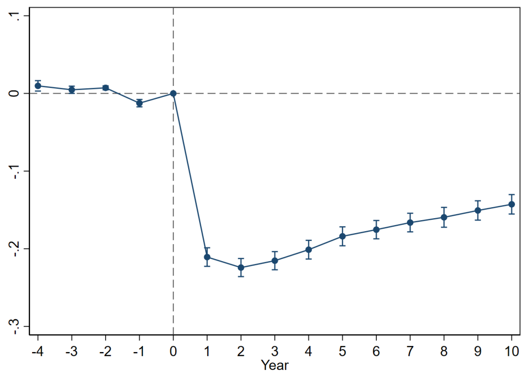
Figure 4.A.3: Effects of Job Displacement on Earnings and Labor Supply



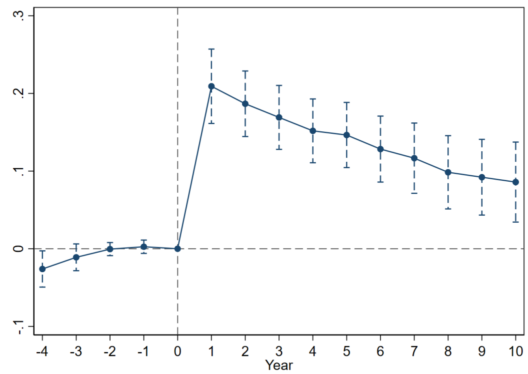
Notes: Each panel depicts estimates of equation (4.1) with dependent variables in subtitles. Annual earnings are measured in thousand euros. The sample comprises a balanced yearly panel of workers. The vertical dashed line indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by establishments.

Figure 4.A.4: Effects of Job Displacement: Robustness

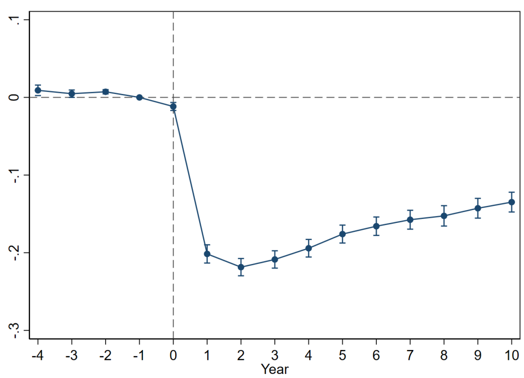
(a) Daily wage (log): Closure



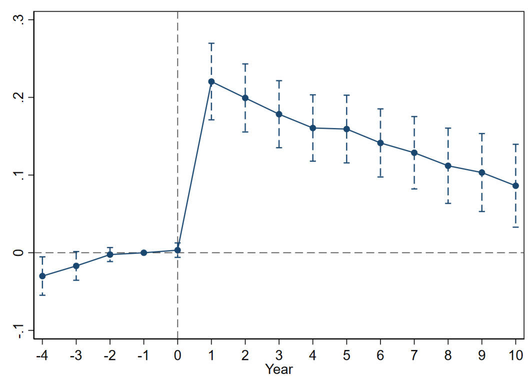
(b) Comm. dist. (log): Closure



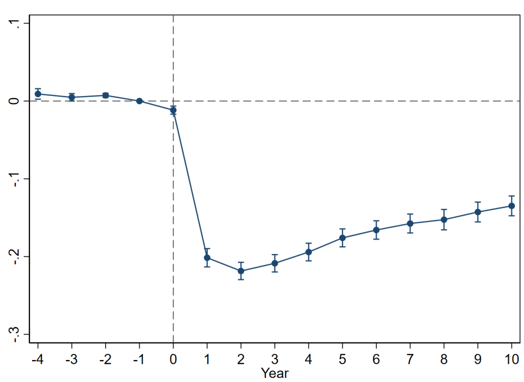
(c) Daily wage (log): Excl. large layoffs



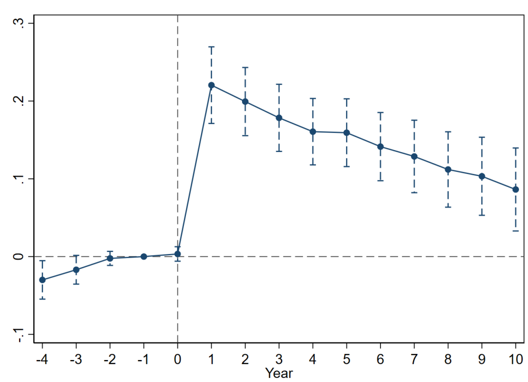
(d) Comm. dist. (log): Excl. large layoffs



(e) Daily wage (log): Region-year F.E.



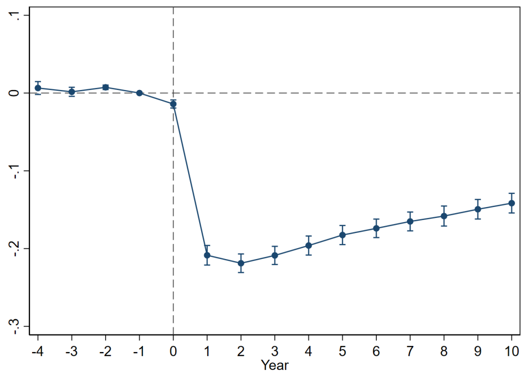
(f) Comm. dist. (log): Region-year F.E.



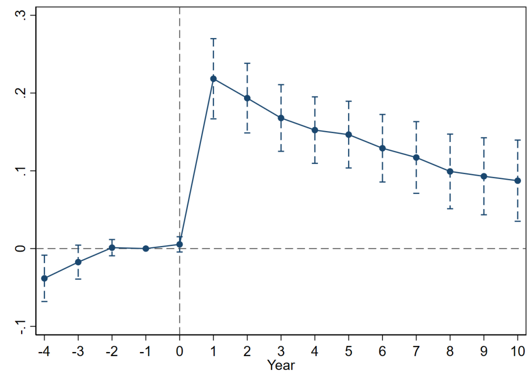
(continue on next page)

Figure 4.A.4: Effects of Job Displacement: Robustness (Continued)

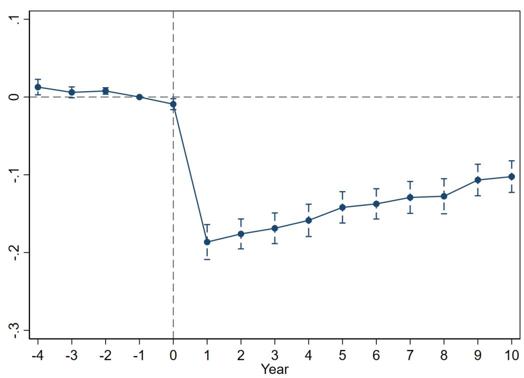
(g) Daily wage (log): Stable employment



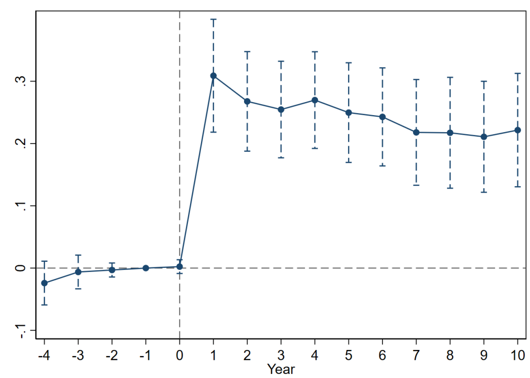
(h) Comm. dist. (log): Stable employment



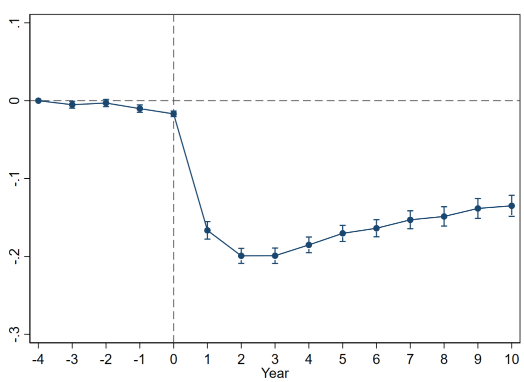
(i) Daily wage (log): Excl. multi-location



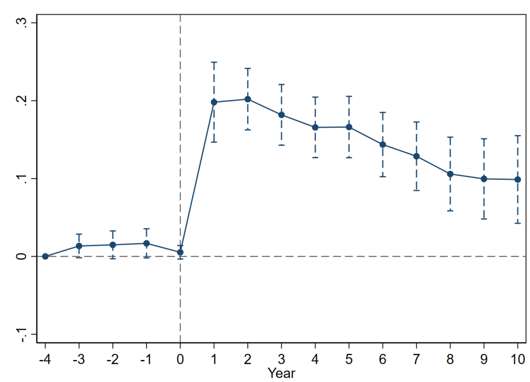
(j) Comm. dist. (log): Excl. multi-location



(k) Daily wage (log): Imputation

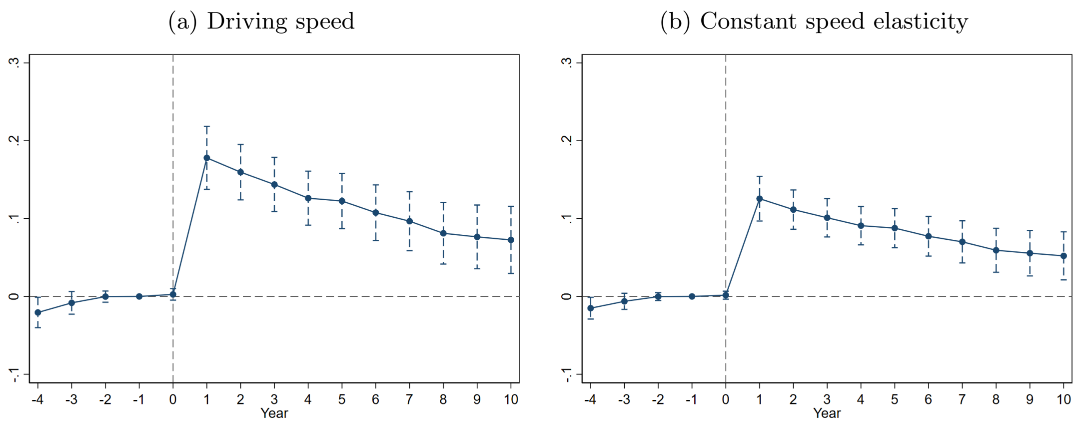


(l) Comm. dist. (log): Imputation



Notes: Each panel depicts estimates of equation (4.1) with dependent variables in subtitles. The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year. Panels (a)–(b) use establishment closures to identify displaced workers; Panels (c)–(d) excluded mass layoffs of more than 500 workers; Panels (e)–(f) control for labor market region by year fixed effects; Panels (g)–(h) focus on workers with regular employment from the second to the fifth year after displacement; Panels (i)–(j) exclude firms in finance, trade, and transportation industries as they are more likely to operate at multiple locatiosn within a municipality; Panels (k)–(l) use the imputation method of Borusyak et al. (2022) to estimate dynamic treatment effects. The vertical dashed line indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by establishments.

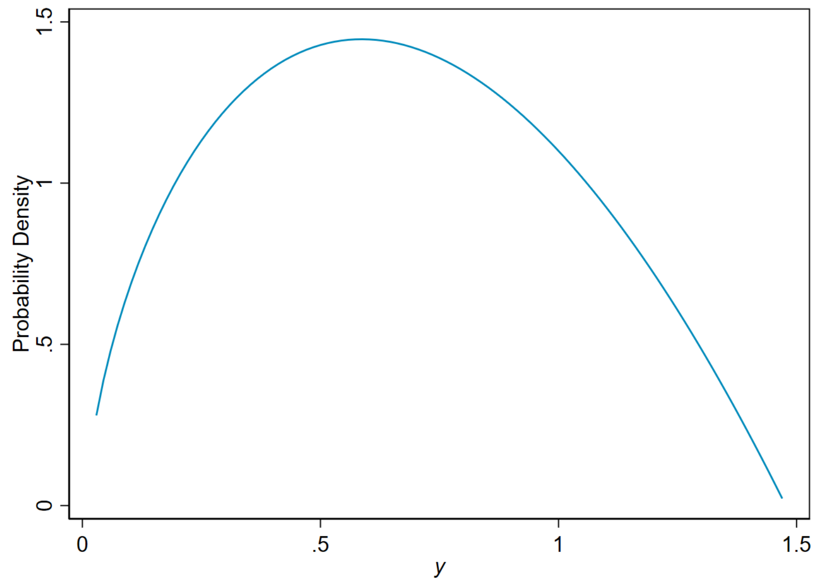
Figure 4.A.5: Effects of Job Displacement: Alternative Measures of Commuting Time



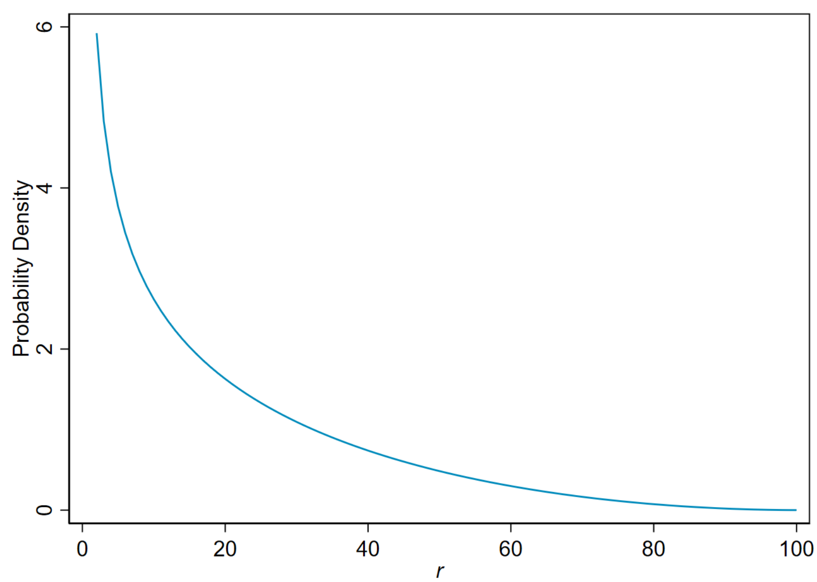
Notes: Panels (a)–(b) depict estimates of equation (4.1) with log driving time and log commuting time predicted from commuting distances with a speed elasticity of 0.4, respectively, as dependent variables. The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year. The vertical dashed line indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by establishments.

Figure 4.A.6: Estimated Firm Type Distributions

(a) Distribution of y



(b) Distribution of r



Notes: Panel (a) plots the probability density of firm productivity $y = 1.47Y$ where $Y \sim \text{Beta}(1.65, 2.00)$. Panel (b) plots the probability density of commuting distance $r = 100R$ where $R \sim \text{Beta}(0.65, 2.90)$. The distributional parameters are estimated using the simulated method of moments.

Table 4.A.1: Share of Commuters by Modes of Commuting and Distance Segments

(1) Distance (km)	(2) Walking (%)	(3) Cycling (%)	(4) Driving (%)
$\leq$0.2	94	5	1
0.2–0.4	81	11	8
0.4–0.6	64	19	17
0.6–0.8	56	21	23
0.8–1.0	38	19	43
1.0–1.5	25	19	56
1.5–2.0	18	17	65
2.0–3.0	10	14	76
3.0–5.0	4	9	87
5.0–7.0	1	6	93
7.0–10.0	1	4	95
10.0–20.0	0	2	98
>20.0	1	1	98

Notes: The table lists the share of commuters by modes of commuting in 2002. Driving includes public transit, motorcycles, and private cars. Source: Table 2, Scheiner (2010).

Table 4.A.2: Distribution of Displaced Workers by Industry

Industry	(1) Displaced workers (%)	(2) Matched control workers (%)
Agriculture, Foresty, and Fishing	0.171	0.142
Mining and quarrying	0.291	0.254
Manufacturing	47.44	52.80
Electricity, gas, steam, and air conditioning supply	0.402	0.338
Water supply, waste management, and remediation	0.734	0.595
Construction	7.900	7.702
Wholesale and retail trade; repair of motor vehicles	13.81	12.71
Transportation and storage	5.699	4.935
Accommodation and food service activities	0.352	0.307
Information and communication	3.910	3.367
Financial and insurance activities	2.865	2.431
Real estate activities	0.332	0.296
Professional, scientific, and technical activities	3.066	2.643
Administrative and support services	6.955	6.256
Education	0.764	0.671
Health and social work	2.643	2.227
Arts, entertainment, and recreation	0.121	0.095
Other service and administration activities	2.543	2.225

Notes: The table lists the share of displaced workers and matched control workers by industry, based on the first-digit German Classification of Economic Activities, Edition 2008 (WZ08). The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year.

Table 4.A.3: Effects of Job Displacement on Earnings and Labor Supply

	(1) Annual earnings ('000)	(2) Days full-time	(3) Days part-time	(4) Days mini-jobs
ML × Post	-12,063.3***	-103.9***	14.20***	14.52***
	(192.8)	(1.847)	(0.904)	(0.606)
Observations	4,593,491	4,593,491	4,593,491	4,593,491
Workers	394,020	394,020	394,020	394,020
R^2	0.760	0.356	0.336	0.245

Notes: Each column represents estimates of equation (4.2) with dependent variable in the column title. Annual earnings are measured in thousand euros. The sample comprises a balanced yearly panel of workers. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors in parentheses clustered by establishments. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 4.A.4: Effect of Job Displacement: Robustness

	(1) Daily wage (log)	(2) Commuting distance (log)
I. Establishment closure		
ML × Post	-0.190***	0.149***
	(0.005)	(0.019)
Observations	4,304,403	4,304,403
Workers	391,722	391,722
R^2	0.898	0.817
II. Excluding large layoffs		
ML × Post	-0.182***	0.161***
	(0.005)	(0.020)
Observations	3,822,703	3,822,703
Workers	346,950	346,950
R^2	0.896	0.816
III. Region-year fixed effects		
ML × Post	-0.189***	0.152***
	(0.005)	(0.018)
Observations	4,316,096	4,316,096
Workers	394,020	394,020
R^2	0.900	0.821
IV. Stable employment		
ML × Post	-0.183***	0.149***
	(0.005)	(0.020)
Observations	3,785,205	3,785,205
Workers	306,356	306,356
R^2	0.890	0.800
V. Excluding multi-location establishments		
ML × Post	-0.176***	0.211***
	(0.007)	(0.026)
Observations	3,699,967	3,699,967
Workers	336,615	336,615
R^2	0.906	0.836

Notes: Each column represents estimates of equation (4.2) with dependent variable in the column title. The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year. Panel I uses establishment closures to identify displaced workers; Panel II excludes mass layoffs of more than 500 workers; Panel III controls for labor market region by year fixed effects; Panel IV focuses on workers with regular employment from the second to the fifth year after displacement; Panel V exclude firms in finance, trade, and transportation industries as they are more likely to operate at multiple locations within a municipality. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors in parentheses clustered by establishments. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 4.A.5: Effect of Job Displacement: Alternative Measures of Commuting Time

	(1) Commuting time (log): Driving speed	(2) Commuting time (log): Constant speed elasticity
ML × Post	0.125***	0.089***
	(0.016)	(0.011)
Observations	4,316,096	4,316,096
Workers	394,020	394,020
R^2	0.817	0.817

Notes: Each column represents estimates of equation (4.2) with dependent variable in the column title. The sample comprises a matched yearly panel of workers with full-time jobs on June 30 of the year. Columns (1) and (2) use log driving time and log commuting time predicted from commuting distances with a speed elasticity of 0.4, respectively, as dependent variables. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors in parentheses clustered by establishments. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 4.A.6: Pre-Layoff Worker Characteristics: Establishment Closure

	(1) Displaced workers	(2) Matched control workers
Female	0.329	0.303
	(0.470)	(0.459)
Age	40.46	40.81
	(8.434)	(8.265)
High school or less	0.219	0.223
	(0.414)	(0.416)
Vocational training	0.715	0.722
	(0.451)	(0.448)
University or above	0.053	0.045
	(0.224)	(0.207)
East Germany	0.168	0.159
	(0.374)	(0.365)
Working experience	14.13	14.95
	(7.712)	(7.774)
Firm tenure	7.630	8.296
	(6.160)	(6.603)
Annual earnings	30,204	31,326
	(11,189)	(10,960)
Daily wage	99.69	101.1
	(41.84)	(38.53)
Commuting distance	16.03	14.75
	(16.70)	(15.30)
Commuting time	23.51	22.19
	(15.91)	(14.64)
Workers	9,928	382,990

Notes: The table reports the average characteristics of displaced workers during establishment closures and matched non-displaced workers in the year before displacement. The sample is obtained using exact matching on gender, education qualification, one-digit industrial sector, and indicator of eastern Germany, and coarsened matching on age, firm tenure, firm size, and average daily wage two years before displacement. Standard deviations are reported in parentheses.

B Proof

B.1 Proof for Proposition 1

Proposition 1 is implied by the following two lemmas.

Lemma 1. *Define $\vartheta \equiv y - cr$. Then for all h and $\theta = (y, r)$, $S(\theta, h) = S(\vartheta, h)$.*

Proof. Replace $y - cr$ by ϑ everywhere in (4.10). □

Lemma 2. *$S(\vartheta, h)$ is strictly increasing in ϑ.*

Proof. See Appendix A.1, Part I of Jarosch (2022). □

B.2 Proof for Proposition 2

Because h is a conditioning variable, we suppress h as implicit hereafter. By Lemma 2, there exists a strictly increasing function g such that $\vartheta = g(S(\vartheta))$. Let $L_s = \{(y, r) : S(y, r) = s, r \geq 0\}$ denote the isosurplus curve corresponding to the surplus level s. Along this curve, we have $y - cr = g(s)$.

The expectation of y conditional on s is given by

$$\mathbf{E}[y|s] = \int_{L_s} y dF(y, r|s), \tag{4.B.1}$$

where $F(y, r|s)$ is the conditional distribution of (y, r) given L_s. By independence of y and r, the density function is

$$f(y, r|s) = \frac{f_y(y) f_r(r)}{\displaystyle\int_{L_s} dF(y, r|s)} = \frac{f_y(y) f_r\left(\frac{y - g(s)}{c}\right)}{\displaystyle\int_{g(s)}^{\bar{y}} f_y(y) f_r\left(\frac{y - g(s)}{c}\right) \frac{\sqrt{2}}{c} dy}. \tag{4.B.2}$$

Plug (4.B.2) into (4.B.1),

$$\mathbf{E}[y|s] = \frac{\displaystyle\int_{g(s)}^{\bar{y}} y f_y(y) f_r\left(\frac{y - g(s)}{c}\right) dy}{\displaystyle\int_{g(s)}^{\bar{y}} f_y(y) f_r\left(\frac{y - g(s)}{c}\right) dy} \equiv \frac{Y_1}{Y_2}. \tag{4.B.3}$$

The derivatives of Y_1 and Y_2 with respect to s are, respectively,

$$Y_1' = -g'(s) \left[\int_{g(s)}^{\bar{y}} \frac{y f_y(y)}{c} f_r'\left(\frac{y - g(s)}{c}\right) dy + g(s) f_y(g(s)) f_r(0) \right], \tag{4.B.4}$$

$$Y_2' = -g'(s)\left[\int_{g(s)}^{\bar{y}} \frac{f_y(y)}{c} f_r'\left(\frac{y-g(s)}{c}\right) dy + f_y(g(s))f_r(0)\right]. \tag{4.B.5}$$

Notice that

$$\begin{aligned} Y_1'Y_2 - Y_2'Y_1 =& g'(s)f_y(g(s))f_r(0)\int_{g(s)}^{\bar{y}} [y-g(s)]\, f_y(y)f_r\left(\frac{y-g(s)}{c}\right) dy \\ &+ \frac{g'(s)}{c}\left[\int_{g(s)}^{\bar{y}} yf_y(y)f_r\left(\frac{y-g(s)}{c}\right) dy \int_{g(s)}^{\bar{y}} f_y(y)f_r'\left(\frac{y-g(s)}{c}\right) dy\right. \\ &\left.-\int_{g(s)}^{\bar{y}} f_y(y)f_r\left(\frac{y-g(s)}{c}\right) dy \int_{g(s)}^{\bar{y}} yf_y(y)f_r'\left(\frac{y-g(s)}{c}\right) dy\right]. \end{aligned} \tag{4.B.6}$$

The first line on the right-hand-side is non-negative because g is increasing and $y = g(s) + cr \geq g(s)$. Meanwhile, dividing the second and third lines by

$$\frac{g'(s)}{c}\left(\int_{g(s)}^{\bar{y}} f_y(y)f_r\left(\frac{y-g(s)}{c}\right) dy\right)^2 > 0, \tag{4.B.7}$$

yields

$$\underbrace{\frac{\int_{g(s)}^{\bar{y}} yf_y(y)f_r\left(\frac{y-g(s)}{c}\right) dy}{\int_{g(s)}^{\bar{y}} f_y(y)f_r\left(\frac{y-g(s)}{c}\right) dy}}_{\mathbf{E}[y|s]} \times \underbrace{\frac{\int_{g(s)}^{\bar{y}} f_y(y)f_r'\left(\frac{y-g(s)}{c}\right) dy}{\int_{g(s)}^{\bar{y}} f_y(y)f_r\left(\frac{y-g(s)}{c}\right) dy}}_{\mathbf{E}\left[\frac{f_r'(r)}{f_r(r)}\middle|s\right]} - \underbrace{\frac{\int_{g(s)}^{\bar{y}} yf_y(y)f_r'\left(\frac{y-g(s)}{c}\right) dy}{\int_{g(s)}^{\bar{y}} f_y(y)f_r\left(\frac{y-g(s)}{c}\right) dy}}_{\mathbf{E}\left[y\frac{f_r'(r)}{f_r(r)}\middle|s\right]} \tag{4.B.8}$$

Along the curve L_s, y is increasing in r and decreasing in $f_r'(r)/f_r(r)$. Thus,

$$\mathbf{E}\left[y\frac{f_r'(r)}{f_r(r)}\middle|\, s\right] - \mathbf{E}\left[\frac{f_r'(r)}{f_r(r)}\middle|\, s\right]\mathbf{E}\left[y|\, s\right] = \mathrm{Cov}\left(y, \frac{f_r'(r)}{f_r(r)}\middle|\, s\right) \leq 0. \tag{4.B.9}$$

Together, we find

$$\frac{\partial \mathbf{E}[y|s]}{\partial s} = \frac{Y_1'Y_2 - Y_2'Y_1}{Y_2^2} \geq 0. \tag{4.B.10}$$

The case of $\mathbf{E}[r|s]$ can be proved analogously.

C Supplementary Materials for Structural Estimation

C.1 Identifying the Unemployment Benefit

Here, we describe how to identify the unemployment benefits z. Since we normalize the minimum firm productivity $\underline{y} = 0$, z has to be determined within the model.

Recall in equation (4.10) that the surplus function decreases in z. In the simpler case with homogeneous workers, we can identify z from the position of the zero-surplus curve in the job space $[\underline{y}, \bar{y}] \times \mathbf{R}_+$. As shown in Figure 4.C.1, a higher zero-surplus curve (the dark blue line) will truncate the distribution of (y, r) more heavily than a lower zero-surplus curve. In panel (a), the zero-surplus curve passes the origin, so that the truncated firm-type distribution has a triangular support (shaded in light blue). In contrast, the zero-surplus curve in panel (b) crosses the y-axis below the origin, and the truncated firm-type distribution has a trapezoidal support.

We empirically distinguish the two scenarios by running a threshold regression of y against r Hansen2000. The green lines in Figure 4.C.1 depict the hypothetical fitting lines. In panel (b), we expect a strictly positive threshold (marked by the vertical gray line) corresponding to the shape of the trapezoidal support. The estimated slope to the left of the threshold represents the generic correlation between untruncated y and r, and the slope to the right becomes more positive due to the truncation. In panel (a), however, the firm-type distribution is truncated for all $r > 0$ and there is no positive threshold.

Our estimates using all first jobs taken by displaced workers cannot reject a threshold at $r = 0$ (panel (a)). Thus, we choose the value of z such that the zero-surplus curve of workers with the lowest human capital h_1 crosses the origin:

$$\begin{cases} S((\underline{y}, r), h_1) = 0 & \text{for all } r \geq 0, \\ S((y, 0), h_1) = 0 & \text{for all } y \geq \underline{y}. \end{cases} \tag{4.C.1}$$

Moreover, it turns out that our structural estimates are not sensitive to the choice of human capital levels in equation (4.C.1).

C.2 Identifying the Marginal Commuting Cost

We prove equation (4.14) as follows. First, let F_υ be the distribution of υ. Provided that F_y is differentiable, the density function of ϵ exists and is written as $F'_\epsilon = f_\epsilon$. Notice that

$$\xi(r) = \int \frac{\int_{c_0 - m(r) + cr + t}^{\infty} x f_\epsilon(x) dx}{\int_{c_0 - m(r) + cr + t}^{\infty} f_\epsilon(x) dx} dF_\upsilon(t). \tag{4.C.1}$$

Hence, $\xi(r)$ is differentiable if $m(r)$ is so. Write $t' = c_0 - m(r) + cr + t$ and calculate

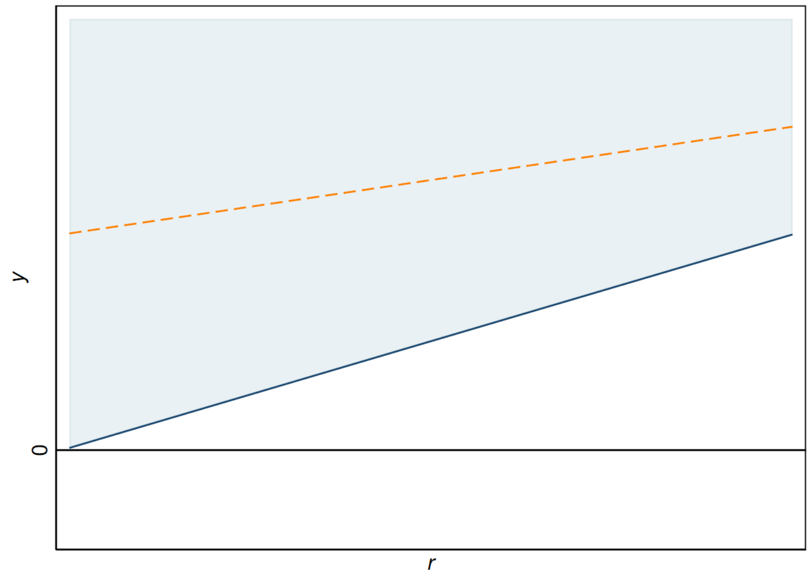
$$\frac{\partial \xi}{\partial r} = (c - m'(r)) \underbrace{\int \frac{f_\epsilon(t') \int_{t'}^{\infty} (x - t') f_\epsilon(x) dx}{(1 - F_\epsilon(t'))^2} dF_\upsilon(t')}_{A}, \tag{4.C.2}$$

where $A > 0$. As such,

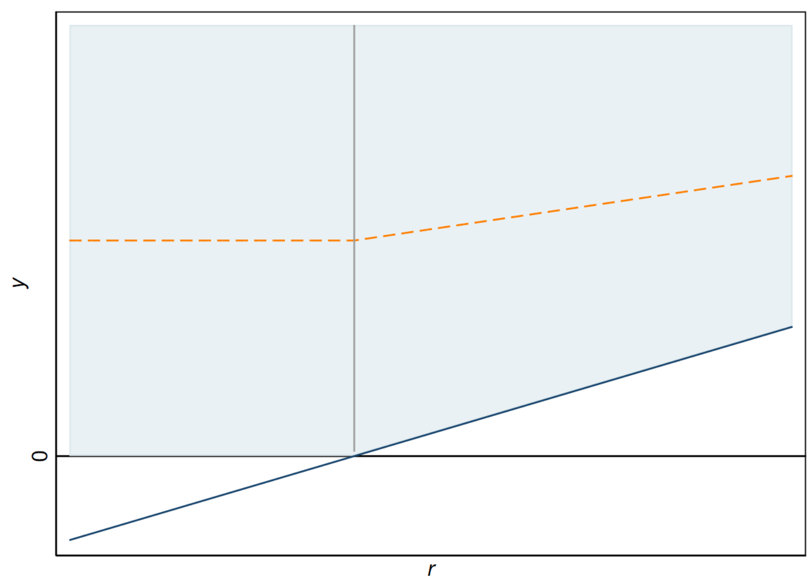
$$\frac{\partial^2 \xi}{\partial r \partial c} = A > 0. \tag{4.C.3}$$

Figure 4.C.1: Zero-Surplus Curves and Support of Firm-Type Distribution

(a)



(b)



Notes: Panels (a)–(b) plot two scenarios with different positions of the zero-surplus curve. The dark blue lines represent the zero surplus curve. The shaded areas represent the support of firm-type distributions. The dashed orange lines represent the best-fitting lines from threshold regressions. The vertical gray line in panel (b) represents the threshold.

Table 4.C.1: Independence between y and r

I. All potential job matches				
Obs: 431,215	y	y^2	y^3	y^4
r	-0.0171	0.0022	-0.0053	0.0012
r^2	-0.0186	0.0037	-0.0071	0.0029
r^3	-0.0175	0.0040	-0.0073	0.0035
r^4	-0.0160	0.0039	-0.0070	0.0036
II. Urban firms				
Obs: 272,292	y	y^2	y^3	y^4
r	-0.0108	-0.0003	-0.0019	-0.0016
r^2	-0.0150	0.0022	-0.0048	0.0006
r^3	-0.0156	0.0033	-0.0059	0.0018
r^4	-0.0149	0.0037	-0.0062	0.0025
III. Rural firms				
Obs: 158,923	y	y^2	y^3	y^4
r	-0.0168	0.0082	-0.0122	0.0107
r^2	-0.0152	0.0073	-0.0113	0.0101
r^3	-0.0131	0.0061	-0.0099	0.0089
r^4	-0.0113	0.0053	-0.0088	0.0080

Notes: This table reports Pearson correlation coefficients between polynomials of AKM firm effects y and polynomials of commuting distance r between displaced workers and firms in the same labor market region. Panel I: all potential job matches; Panel II: job matches between displaced workers and urban firms; Panel III: job matches between displaced workers and rural firms.

Chapter 5

How many gaps are there?

Investigating the regional dimension in the gender commuting gap

with Michaela Fuchs[30] *and Antje Weyh*[31]

Abstract This paper investigates the gender gap in commuting by differentiating between the place of residence and work in urban and rural regions. Using administrative geo-referenced data for Germany, we provide evidence for a triple gap in commuting to the disadvantage of women. The regional disaggregation of the overall gap uncovers two additional gaps that open up between rural and urban commuters on the one hand and between intra- and inter-regional commuters on the other hand. Explaining the gaps with decomposition techniques, occupational segregation and establishment size turn out to be the most relevant factors.

JEL Classification R10, J60, R19

Keywords Commuting, gender, labor markets, regional differences

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[30] Institute for Employment Research, Germany
[31] Institute for Employment Research, Germany

5.1 Introduction

Commuting is essential to bridge the spatial separation of workers' place of residence and place of work, thereby improving the spatial matching of jobs and workers and contributing to well-functioning local labor markets. For workers, commuting results in better labor accessibility, improves job and career opportunities and boosts job satisfaction (Clark et al., 2020). However, there are substantial differences between workers in terms of the decision to commute and the intensity of commuting. Specifically, women commute less than men and work closer to home (Madden, 1981; Crane, 2007; Sang et al., 2011; Giménez-Nadal et al., 2022). Prominent reasons for their lower spatial mobility are gender differences in occupational choice, wages or household responsibilities (McQuaid and Chen, 2012; Giménez-Nadal and Molina, 2016; Bergantino and Madio, 2018). The consequences can be profound: since women restrict themselves to a smaller area than men in their job search, they are in danger of spatial entrapment at their place of residence (England, 1993; Wheatley, 2013) and might therefore benefit less from better jobs and higher wages in other regions (Crane, 2007; Petrongolo and Ronchi, 2020).

Besides affecting men and women in different ways, commuting also has a distinctly spatial component along the urban-rural divide. In urban regions, workers benefit from thick labor markets and a wide array of job options, whereas rural areas provide only a limited number and variety of employment opportunities (Rouwendal and Nijkamp, 2004; Partridge et al., 2010; Andersson et al., 2018). As a consequence, workers who live in rural areas tend to face longer commutes than those who live in urban areas (Lin et al., 2015). Due to their lower spatial mobility, women might be even more disadvantaged in rural regions, where they face more monopsonistic labor markets than men and may be more willing to accept lower wages for shorter commutes (Hirsch et al., 2013). Hence, an additional commuting gap might exist that prevents women living in rural regions from fully participating in the labor market to a larger degree than women living in cities. It has to be taken into consideration, however, that the place of living per se does not provide information on whether workers have to undertake long work trips or not. Specifically, in analysing mobility across regional labor markets in the UK, (Bergantino and Madio, 2018) find a trade-off of commuting towards other labor markets that is higher for women, resulting in a cross-regional gender commuting gap. As a consequence, whether women have their place of work in their region of residence or whether they have to commute to another region might give rise to a further gender gap in commuting along the intra- and inter-regional divide.

There is a vast body of literature that addresses the spatial dimension in the analysis of commuting patterns in general, confirming a significant negative effect of urbanity on commuting distances (Schwanen et al., 2004; Bento et al., 2005; Ewing and Cervero, 2010). Attention has also been paid to distinctive commuting patterns between rural and urban regions (Sandow, 2008; Sandow and Westin, 2010; Partridge et al., 2010; Andersson et al., 2018). While gender differences among commuters are acknowledged not only in general, but also in specific spatial respect (Sandow, 2008; Dargay and Clark, 2012; Andersson et al., 2018), only few studies explicitly examine spatial characteristics of commuting patterns and investigate simultaneously whether they have diverging effects on men and women (Sang et al., 2011; Bergantino and Madio, 2018). Specifically, in light of profound spatial disparities between urban and rural regions, the question as to whether there are gender differences in commuting between urban and rural regions has been largely neglected. What is more, there has been no explicit consideration of both the place of work and place of residence so far, which would enable a comprehensive investigation of commuting behaviour between as well as within urban and rural regions. To our knowledge, only Green and Meyer (1997) have undertaken a descriptive analysis of commuting patterns in a detailed urban-rural framework to date. However, such insights could be very important for policy measures, such as designing instruments to encourage women in certain regions to expand their commuting, which could lead to gender equalisation in the labor market, for example in terms of the wage gap. Therefore, additional research on this aspect is vital.

This paper fills the research gap on regional differences in the gender commuting gap. We take Germany as a case study, which is characterised by striking regional disparities on the labor market (e.g., OECD, 2005). With respect to the inter- and intra- rural-urban setup, we investigate gender differences in six journey-to-work flows. Differentiating between the place of residence and place of work in an urban or rural region gives us the following commuting directions: women and men (i) living and working within the same urban area, (ii) living and working in different urban areas (iii) living in urban and working in rural areas, (iv) living in rural and working in urban areas, (v) living and working in different rural areas, and (vi) living and working within the same rural area. In order to contextualise the six regional results, we relate them to the overall picture for Germany. For the empirical analyses, we use novel geocoded administrative data for the year 2017 that enable calculating the commuting distance between the exact places of residence and work for each worker. This enables us to capture workers' commuting patterns precisely. In addition, the use of administrative data has the distinct advantage of providing the population of workers and establishments in a small-scale regional perspective, going beyond the survey data or data on exemplary regions used by related studies (e.g., Sang et al., 2011; Giménez-Nadal and Molina, 2016; Bergantino and Madio, 2018; Albert et al., 2019). In order to identify the determinants of gender differences in the six commuting directions, we resort to the decomposition technique introduced by Oaxaca (1973) and Blinder (1973) and consider individual, establishment, and regional factors relevant for both gender and spatial differences in commuting.

Our results provide evidence for a triple commuting gap. Women have shorter commuting times than men, but this first gender commuting gap differs depending on the place of residence and work in urban or rural regions. Compared to men, women who live and work in the countryside are more restricted in their job search than women who either live and work in cities or who commute between the countryside and cities, which represents the second gap. The further disaggregation into commuting within urban areas and within rural areas uncovers the third gap that opens up for those women whose place of residence and place of work are located in different rural areas. Gender differences in occupations and in the selection into establishments of different sizes are the most relevant factors for explaining these patterns.

The remainder of the paper is organised as follows. Section 5.2 provides background information on regional commuting patterns and gender differences in commuting. In Section 5.3, we discuss the empirical setup, including the data, regional delineations and methodological approach. Section 5.4 presents the results, and Section 5.5 draws conclusions.

5.2 Background

There are manifold reasons why workers commute, with complex interrelations between the place of residence and the place of work (see Rouwendal and Nijkamp, 2004; Chen et al., 2021; Giménez-Nadal et al., 2022).[32] From a regional perspective, commuting is strongly determined by the urban spatial structure (McFadden, 1974; Rouwendal and Nijkamp, 2004; Bento et al., 2005; Lin et al., 2015). A prominent explanation is provided by the monocentric city model (Alonso, 1964; Muth, 1969; Mills, 1972), which assumes that urban production and employment are concentrated in a single Central Business District. Since land prices decrease gradually from the centre to rural areas and housing is limited in the centre, workers are faced with a trade-off between living in the centre and paying higher rents, or living outside where rents are lower but commutes are longer. The monocentric city model can be extended to a polycentric model that takes into consideration further centres in addition to the Central Business District. This can explain a variety of commuting flows beyond the monocentric commuting pattern within urban regions or between rural and urban regions (Gordon et al., 1989; Schwanen et al., 2004; Meijers, 2007).[33] Related to this, a further explanation of diversified commuting patterns across space can be seen in the suburbanisation of employment that has led to the emergence of suburban employment centres and subsequently to changes in commuter flows (Wang, 2001; Heider and Siedentop, 2020). However, cities provide not only employment and housing, but also urban amenities (Brueckner et al., 1999) that make them attractive for consumption activities. Since consumption aspects are an additional key determinant of residential location and commuting behaviour, they provide an explanation as to why some workers reside in urban areas, but work in rural areas outside cities (Rouwendal and Nijkamp, 2004; Partridge

[32] A large number of theoretical models deal with the determinants as well as the spatial pattern of commuting. For example, job search models broach the marginal willingness to pay for commuting (e.g., Dauth and Haller, 2020; Le Barbanchon et al., 2021), and in transportation economics, commuting is seen as one of the main causes of urban traffic congestion (Rouwendal and Nijkamp, 2004).

[33] Although Germany has a rather polycentric structure, the monocentric model provides a robust explanation for urbanisation patterns in metropolitan areas, with subcentres being of local relevance only (Krehl, 2018; Schmidt et al., 2021). However, this does not imply that there is no commuting within rural regions.

et al., 2010). The relationship between commuting and urban form has been subject to a vast body of empirical research (e.g., Gordon et al., 1989; Schwanen, 2002; Ewing and Cervero, 2010; Melo et al., 2012; Lin et al., 2015).

The monocentric city model principally assumes that workers are homogeneous (Rouwendal and Nijkamp, 2004). This stands in strong contrast to gender differences in commuting that manifest themselves primarily in women's shorter commutes and that have been widely established as a stylised fact (Madden, 1981; Hanson and Johnston, 1985; McQuaid and Chen, 2012; Dargay and Clark, 2012; Giménez-Nadal et al., 2022). Consequently, these differences have been theoretically modelled in several ways (Madden, 1977, 1981; White, 1986; Hanson and Johnston, 1985), and a broad range of determinants have been brought forward as explanations. First, the gender commuting gap can be caused by heterogeneity in sociodemographic characteristics. Generally, commuting decreases with age, as younger workers need to gain labor market experience (Sandow, 2008). While there are no major differences between men and women at labor market entry, Petrongolo and Ronchi (2020) document a rapidly increasing gender commuting gap throughout women's child-bearing years. Similarly, Bergantino and Madio (2018) find an inverted U-shaped relationship between age and commuting for men, but not for women. Longer commutes are also positively correlated with the level of education, as highly educated workers might have fewer local job opportunities than those with lower educational levels and thus have to undertake longer commutes (McQuaid and Chen, 2012; Giménez-Nadal et al., 2022). Still, according to Sandow (2008), women have shorter commutes than men who have the same educational level.

A second reason for women's shorter commutes is connected with occupational segregation between men and women. This refers to the stable and widely documented pattern of women dominating occupations in the service and health sector and men dominating occupations in production and construction (Perales and Vidal, 2015). As regional labor markets differ substantially in their sectoral and establishment composition, they provide different employment opportunities for men and women (Sang et al., 2011; Perales and Vidal, 2015; Petrongolo and Ronchi, 2020). In particular, the female-dominated public sector is geographically more evenly distributed than men's industrial jobs (Hanson and Johnston, 1985; Hanson and Pratt, 1995; Shearmur, 2015; Sandow, 2008). These regional differences are enhanced by gender differences in the way individuals sort themselves into firms. In particular, women prefer to work in smaller firms, whereas men are more likely to work in larger firms that generally offer more career opportunities and pay higher wages (Barth et al., 2016; Card et al., 2016).

A further source of gender differences in commuting is related to social roles within the household. As women still take on most of the household and childcare responsibilities, their commutes are constrained to a larger degree than those of men (England, 1993; Wheatley, 2013; Giménez-Nadal and Molina, 2016). Specifically, women commute less and for shorter periods when they have dependent children (McQuaid and Chen, 2012; Sakanishi, 2020). Related to this, women are more likely to work part-time, which is associated with lower wages and thus again with shorter commutes (Madden 1981, McQuaid and Chen 2012). Gender roles might also be one reason why women are less sensitive to wage increases induced by commuting than men (Bergantino and Madio, 2018) and why they are more likely to work close to home in lower-paid jobs (Le Barbanchon et al., 2021).

To summarise, a large strand of literature explains commuting in general and emphasises the inherent spatial component. Another strand of literature attempts to explain differences in the commuting behaviour of women and men. More concretely, women's less pronounced mobility can be explained by differences in sociodemographic and establishment characteristics. In the following, we combine both literature strands and analyse the gender commuting gap in a detailed regional perspective.

5.3 Empirical setup

5.3.1 Data

To analyse the commuting patterns of male and female workers, we use extensive administrative data for Germany based on social security notifications provided by the Institute for Employment Research (IAB). We combine two sources, namely the Integrated Employment Biographies (IEB) and the Establishment History Panel (BHP), to create a comprehensive data set that allows us to use information on workers as well as on the establishments they work in. Detailed daily information on all workers in Germany subject to social security contributions is collected in the IEB, covering age, sex, education, wages and the place of residence and place of work. The BHP contains all establishments with at least one employee subject to social security contributions. It includes information on establishment size, sector, location and workforce composition as of 30 June of a given year. Due to legal sanctions for misreporting, the data are very reliable.

For our analysis, we use a six percent random sample of all workers in Germany from the IEB as of 30 June 2017 (Dauth and Eppelsheimer, 2020). We focus on workers in regular employment subject to social security contributions, excluding trainees, marginal part-time workers and interns. Furthermore, we have to take into consideration two constraints that arise from the specific purpose for which the administrative data were collected. First, the data do not contain information on the exact number of hours worked. This means that we have to explicitly exclude one important source of gender differences in commuting that are due to female part-time employment (Dauth and Haller, 2020). As an advantage, the restriction to full-time workers allows us to investigate the gender commuting gap for a more homogeneous group. Assuming that part-time workers commute less than full-time workers (see McQuaid and Chen, 2012), our calculated commuting gaps can be regarded as the minimum gaps. We refer to this issue in the sensitivity analyses in Section 5.4.3. Second, we cannot directly observe the family context. In order to take into account the fact that household responsibilities constitute an important factor for women's lower spatial mobility (Sandow, 2008), we draw on the identification strategy developed by (Müller et al., 2022) and consider the marital status as an additional sensitivity check in Section 5.4.3. Our final data set covers a total of 34,344,288 observations.

5.3.2 Considerations regarding space

In the IEB, information on the place of residence and the place of work is generally provided along administrative units. For our purposes, the exact mailing addresses of individuals and establishments that constitute the respective background information are available as geocoded point data (Ostermann et al., 2022). Based on the precise longitude and latitude position of the respective place of residence and place of work, we calculate the distance between residence and workplace location with the algorithm used by Huber and Rust (2016) (Dauth and Haller, 2020; Jost, 2020, 2022). This program calculates the commuting distance using Open Source Routing Machine (OSRM), which is a high-performance open-source routing software for identifying the shortest routes on road networks. OSRM can determine the commuting distance between two places and finds the most suitable road and the fastest route for cars. Focusing on cars as the mode of transport, it can be argued that the commuting distance for users of public transport may differ. However, cars are the most important mode of transport in Germany, as almost 70 percent of workers drive to work. This even holds for commuting small distances (Destatis, 2020).

In our analyses, we utilise commuting time instead of distance, as is done, for example, by Schmidt et al. (2021). Commuting time is also calculated with OSRM by taking the average driving time on highways, primary and residential roads. Although the algorithm cannot recognise specific traffic situations that impact commuting time, for example daily rush hours, these issues are likely to affect women and men equally. What is more, using commuting time makes it easier to compare commuting in terms of spatial factors. This is particularly important when comparing commuters within and between specific types of regions. For example, since commuters between rural and urban areas are more likely to use motorways than commuters in urban areas, they might take less time than urban commuters for travelling the same distance.[34] A restriction arises from the use of our administrative data, as it does not contain information on a primary or secondary residence or on the number of commuting trips. Consequently, it might include workers who commute on a weekly basis and have a second residence close to their place of work, which might bias the commuting time. In order to ensure the measurement of daily commuting patterns, we

[34] A robustness check using commuting distance yields very similar results. The unadjusted and adjusted commuting gaps increase slightly in all cases, with no changes in the spatial patterns and in the impact of explanatory factors.

therefore exclude workers whose maximum commuting time exceeds 90 minutes one way.[35]

In order to analyse workers' commuting behaviour in a comprehensive framework of the urban-rural setup we assign their places of residence and work to either an urban or rural region. Besides covering commuting flows between these two region types, we check whether the place of residence and place of work are in the same urban or rural region, or whether commuters have to cross regional borders to get to their job. Hence, we subdivide commuting into intra- and inter-regional flows. Urban-rural differentiations have been used by a sizeable number of studies investigating issues of inter-regional mobility and related outcomes (e.g., Lehmer and Ludsteck, 2011; Hirsch et al., 2013; Perpiña Castillo et al., 2022). In empirical terms, urban structure can be approximated by residential density, which serves as a good indicator for the accessibility of jobs, goods and services (Rouwendal and Nijkamp, 2004; Bento et al., 2005).

We use the definition of the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR), which categorises the NUTS-3 regions in Germany into urban and rural regions based on the absolute number of inhabitants and on population density.[36] Consequently, we analyse women's and men's commuting behaviour along the six spatial delineations of intra-urban, inter-urban, urban-to-rural, rural-to-urban, inter-rural and intra-rural commuting.

5.3.3 Variables

The main variable of interest is the gap in commuting time between female and male workers in full-time employment. It is calculated as the difference between the log average commuting time in minutes for men and women. To explain the gender gap in commuting time, we consider individual, establishment and regional determinants that have been found to be relevant for both gender and spatial differences in commuting (see Section 5.2). Individual characteristics include age (in five groups) and occupation, distinguishing between 14 occupational segments (Statistik Statistik der Bundesagentur für Arbeit (2021)). They are complemented by the task level of the occupation, which serves as an indicator of vertical occupational segregation (Brunow and Jost, 2022). It is based on the skill level required for the occupation (unskilled, skilled, expert) and depicts the various degrees of complexity within those occupations which have a high similarity of occupational expertise (Paulus and Matthes, 2013).[37] We further consider the level of education (no vocational training, vocational training, university degree) to control for systematic gender differences in holding positions within one skill level.[38] Since prior work experience also impacts

[35]This affects 6 percent of all commuters or 2,233,448 observations.

[36]See `https://www.bbsr.bund.de/BBSR/DE/forschung/raumbeobachtung/Raumabgrenzungen/deutschland/kreise/staedtischer-laendlicher-raum/kreistypen.html` for furthre information.

[37]Generally, the complexity of an occupation is captured by four skill requirement levels that range from unskilled (low skills) and specialist (medium skills) to complex specialist (specialist skills) and highly complex activities (expert skills). For the analyses, we aggregate specialist and expert skills together into expert.

[38]The qualification variable in the IEB is based on reports submitted by employers, which has missing information for some spells in the data set. To improve the information in this variable, we follow the procedure developed by Fitzenberger

on subsequent labor market success, we include work experience via a continuous variable that cumulates all employment episodes. Furthermore, there are profound regional gender differences in wages (Fuchs et al., 2021) that are strongly interrelated with commuting (Dauth and Haller, 2020; Le Barbanchon et al., 2021). To take this into account, we include the individuals' daily wage level in the regressions.

Establishment characteristics comprise establishment size (aggregated to four groups) to consider gender differences in the way workers sort themselves into firms (see Section 5.2). Indicators on the employment structure within establishments cover the demand side for workers. The share of young workers controls for the higher mobility of this age group, while the share of skilled and expert workers represents the human capital intensity of the establishment's workforce.

As discussed in Section 5.2, rents are assumed to decrease with increasing distance from the centre, leading to a trade-off between rents and commuting. In order to take into account the fact that workers living in regions with higher rents are more likely to commute shorter distances (Bergantino and Madio, 2018), we include the regional median basic rent (excluding heating costs) at the place of residence for each NUTS-3 region (Mense et al., 2019; Mense, 2021).[39] Appendix 5.A.1 presents descriptive statistics for all variables.

5.3.4 Methodological approach

To identify the determinants of gender differences in commuting, we apply an approach pioneered by Oaxaca (1973) and Blinder (1973), which has been widely used to explain gender differences in labor market issues such as mobility (Albert et al., 2019) or wages (Fuchs et al., 2021; Brunow and Jost, 2022). The Oaxaca-Blinder (OB) decomposition technique divides the gender gap in commuting time into two parts. The explained part quantifies the share of the gap that can be traced back to observed gender differences in endowments. The unexplained part shows which part of the commuting gap is due to the fact that the same endowment generates different returns in terms of mobility for male and female workers. As an additional advantage, the OB decomposition permits a detailed decomposition of the explained part into the relative influence of each determinant.

Formally, the OB decomposition consists of two estimation steps. First, OLS regressions of the determinants of commuting time are carried out separately for male (m) and female (f) workers. In a log-linear model, log commuting times (C) are regressed on a set of explanatory factors (X) that comprise individual, establishment and regional characteristics as discussed in Section 5.3.3. They are henceforth referred to as endowments and are viewed as observable indicators of gender differences partly explaining the commuting gap. The two regression equations are as follows, with β^j representing the estimated

et al. (2006) and impute the likely qualification from past or future values.

[39] The data were collected from the three largest online real estate market places, Immowelt, Immonet and Immoscout24 (see Mense, 2021).

coefficient of the characteristic indexed by j and ε denoting the error term, which is adjusted to produce robust standard errors:

$$lnC_m = \beta_m^0 + \sum\nolimits_j \beta_m^j X_m^j + \varepsilon_m \tag{5.1}$$

$$lnC_f = \beta_f^0 + \sum\nolimits_j \beta_f^j X_f^j + \varepsilon_f \tag{5.2}$$

Second, the resulting coefficient estimates, in combination with the gendered endowments, are used to decompose gender differences in the average commuting time $\bar{C}$. This is achieved by replacing gender-specific log mean commuting times with the right-hand side regression results of equations 5.1 and 5.2. Following Blinder (1973) and using male workers as the reference group, rearranging terms yields the following expression, assuming $E[\varepsilon_{f/w}|X_{f/w}] = 0$.

$$ln(\bar{C}_m) - ln(\bar{C}_f) = \underbrace{\sum\nolimits_j (\bar{X}_m^J - \bar{X}_f^J)\beta_m^j}_{explained-part} + \underbrace{\sum\nolimits_j (\beta_m^j - \beta_f^j)\bar{C}_f^J + (\beta_m^0 - \beta_f^0)}_{unexplained-part} \tag{5.3}$$

The unadjusted commuting gap is thus split into two components. The first component represents the part that can be attributed to gender differences in observed endowments, with $\bar{X}$ denoting the average characteristics by sex. It is therefore termed the explained part. The second component is called the unexplained part or the adjusted commuting gap and shows what part of the gap is due to the fact that the same endowment generates different returns for male and female workers. This component also includes the constant. It captures the influence of all unobserved determinants on the commuting gap that we cannot control for in our model. Examples for such determinants may be household responsibilities or individual preferences.

In the subsequent empirical analysis, we conduct the OB decomposition as specified in equation 5.3. To incorporate gender differences in commuting between and within rural and urban regions, we estimate equations 5.1 to 5.3 for commuting within urban and within rural regions as well as between urban and rural regions respectively.

When estimating equations 5.1 and 5.2, we have to take into account that women and men might endogenously choose whether to live and work in a rural or urban region. In particular, a seminal study by Madden (1981) shows that unmarried women without children are more likely to live in urban areas, while Sang et al. (2011) emphasise that cities are more important as employment locations for women than for men. To control for this selectivity, we apply the two-stage Heckman selection method (Heckman, 1979). It takes into consideration the places of residence and work in rural or urban areas and can be estimated as a latent variable model:

$$P_i^* = \delta_1 S_i + \varepsilon_i \tag{5.4}$$

with the following decision for the places of residence and work:

$$P_i = \begin{cases} 1 & \text{if } P_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{5.5}$$

P_i^* represents the latent variable for the propensity of men and women to live and work in either a rural or an urban region. S_i includes the unemployment rate at the place of residence and the place of work which is assumed to influence individual i's decision concerning where to live and work. To estimate equation 5.4, we use a probit model for each of our six spatial combinations. The results are then used to construct an inverse Mills ratio, which is included in the OB decomposition.

5.4 Results

5.4.1 Descriptive evidence

Women in Germany commute an average of 10.4 minutes to their workplace, while for men it takes 12.0 minutes to get to work on average. The resulting gender commuting gap amounts to 14.3 percent. This generally lower spatial mobility of women coincides with evidence for other countries (Bohman et al., 2019; Giménez-Nadal et al., 2022) as well as with other studies on Germany (Dauth and Haller, 2020).[40] Commuting times and thus commuting gaps can be expected to differ depending on where in space individuals live and work. Table 5.1 shows the share of men and women with their place of residence in urban and rural regions and who commute within or between these two types of region. In general, most commuting takes place within an urban region. 32.7 percent of all male and 39.9 percent of all female workers live and work within the same urban area, while 16.8 percent and 15.7 percent, respectively, commute between different urban areas. A similar pattern can be discerned for rural areas. There, 17.2 percent of men and 15.7 percent of women live and work within the same rural area, but only 5.7 percent and 4.2 percent, respectively, undertake work trips to other rural areas. Another 19.3 percent of men and 18.2 percent of women commute from the countryside to cities. Comparatively few workers travel in the opposite direction from urban to rural regions, comprising 8.3 percent of all male and 6.4 percent

[40] Based on commuting distance, Dauth and Haller (2020) report a commuting gap of 16 percent.

of all female commuters. The dominance of intra-urban as opposed to inter-urban commuting and the very small share of urban-to-rural and inter-rural commuting is also documented for Canada by Green and Meyer (1997).

Table 5.1: Share of commuters within and between urban and rural regions, 2017 (as %)

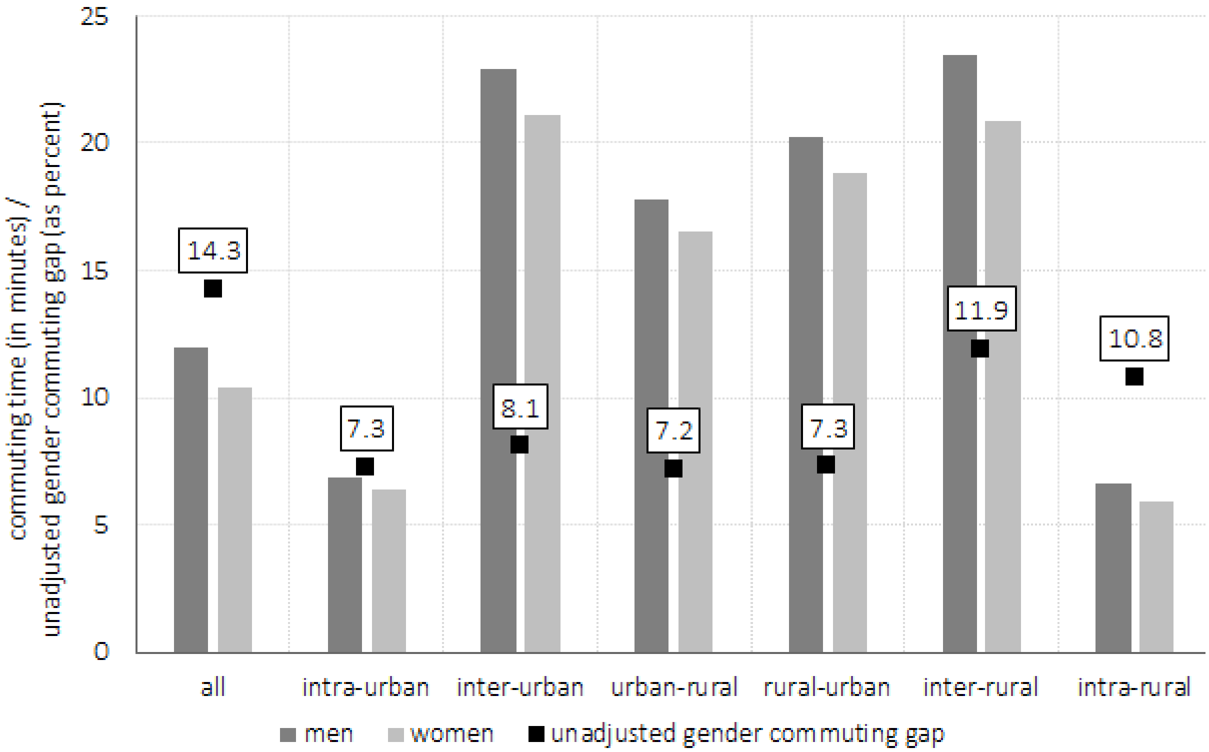
place of residence - place of work	men	women
intra-urban	32.7	39.9
inter-urban	16.8	15.7
urban-rural	8.3	6.4
rural-urban	19.3	18.2
inter-rural	5.7	4.2
intra-rural	17.2	15.7
all commuters	100.00	100.00

Source: IEB, own calculations.

This first result highlights the necessity to consider the location of both the place of residence and the place of work in analyses of commuting patterns. As emphasised by monocentric and polycentric city models outlined in Section 5.2, special relevance can be assigned to urban regions for the provision of jobs and as commuting destinations. Urban regions also provide the place of residence for the majority of commuters, although this pattern is not as pronounced as for the place of work. Concerning gender differences, especially women seem to value working in cities (Hanson and Pratt, 1995; Sang et al., 2011), as is indicated by the larger share of intra-urban commuters and the smaller share of intra-rural and inter-rural commuters among women. Still, a sizeable share of commuters lives and works in rural areas, although this is more common among men.

Figure 5.1 provides an overview of average commuting times and the gender commuting gap in the urban-rural setup. A look at commuting times shows that work trips solely within urban or rural regions take considerably less time than work trips beyond the region of residence. The relatively short intra-urban commuting time is consistent with the availability of better transport infrastructure, more roads and a higher job density in cities (Bento et al., 2005). Interestingly, intra-rural commuting time is even slightly shorter. Evidently, workers in rural areas are unwilling to spend much time on commuting to work and thus choose to work close to their places of residence (Rouwendal and Nijkamp, 2004). This view is consistent with the low shares of inter-rural commuters in Table 5.1, who take on average about three times as long to get to their workplace as compared to intra-rural commuters. Taken together with equally high work trips of inter-urban commuters, this pronounced pattern of commuting times hints towards systematic differences between workers with their place of residence and work in the same region and workers with their place of work in another region, regardless of it being urban or rural. This is corroborated by an above-average commuting time of urban-to-rural commuters, which suggests a high unwillingness to trade off the benefits of city life against residing in the countryside (Rouwendal and Nijkamp, 2004). Rural-to-urban commuting time is slightly higher and compatible with a trade-off between low costs of living in the countryside and having well-paid jobs in agglomerations (Sandow, 2008; Partridge et al., 2010).

Figure 5.1: Average commuting time for men and women (in minutes) and commuting gap (as %) for different combinations of place of residence and place of work



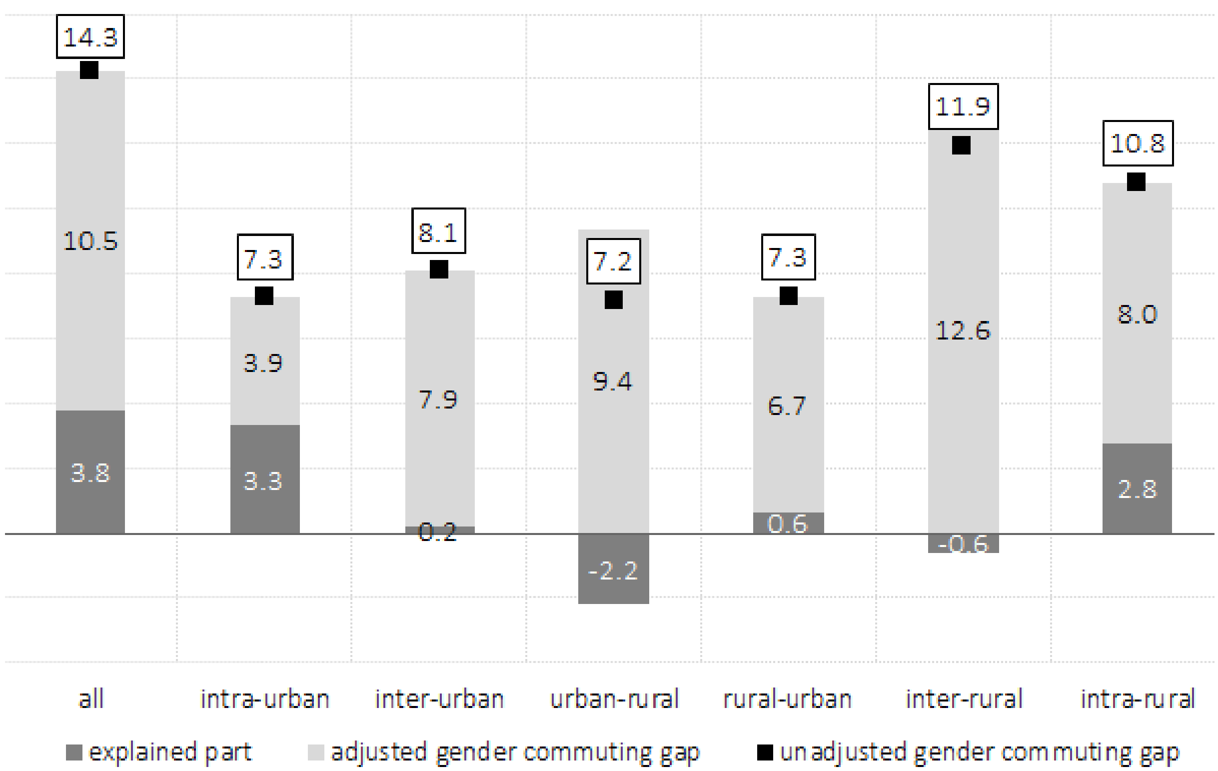
Source: IEB, own calculations.

Turning to gender differences in regional commuting patterns in Figure 5.1, it becomes obvious that the gender commuting gap is pervasive throughout all six combinations of the place of residence and the place of work. The overall gap of 14.3 percent conceals a bandwidth of almost five percentage points, with the highest gaps among inter-rural and intra-rural commuters (11.9 % and 10.8 %, respectively). The commuting gaps of the other four combinations are considerably lower and, with the exception of inter-urban commuters, of a similar magnitude. The high rural-rural gaps support the view that women who live and work in the countryside are more restricted in their job search than women who either live and work in cities or who commute between the countryside and cities. Hence, this implies a systematic disadvantage of women who live and work in rural regions that is consistent with the spatial entrapment thesis (England, 1993; Petrongolo and Ronchi, 2020). What is more, if the region type of the place of residence and place of work is identical, the inter-commuting gap is always higher than the intra-commuting gap. This leads to a triple disadvantage for those women whose place of residence and place of work are located in different rural areas, as can be seen by the highest gap of 11.9 percent. In the following, we turn to decomposition techniques to further investigate the reasons underlying these patterns.

5.4.2 Decomposition results

The results of the OB decomposition are shown in Figure 5.2 for the overall gender commuting gap as well as for the gaps in the six regional combinations of the places of residence and work. Overall, 3.8 percentage points or about 27 percent of the unadjusted gap of 14.3 percent can be traced back to gender differences in the explanatory factors included in our analysis, whereas 10.5 percentage points (73 %) remain as the unexplained part or the adjusted gender commuting gap. The positive sign of the explained part indicates that men are better endowed than women with observable characteristics that determine commuting time. Consequently, differences in explanatory factors work in favour of men and increase the commuting gap. In other words, if women and men possessed comparable observable characteristics, the commuting gap would be 3.8 percentage points lower. Turning to the commuting gap in the urban-rural

Figure 5.2: Decomposition of the gender commuting gap for different combinations of place of residence and place of work



Source: IEB, own calculations.

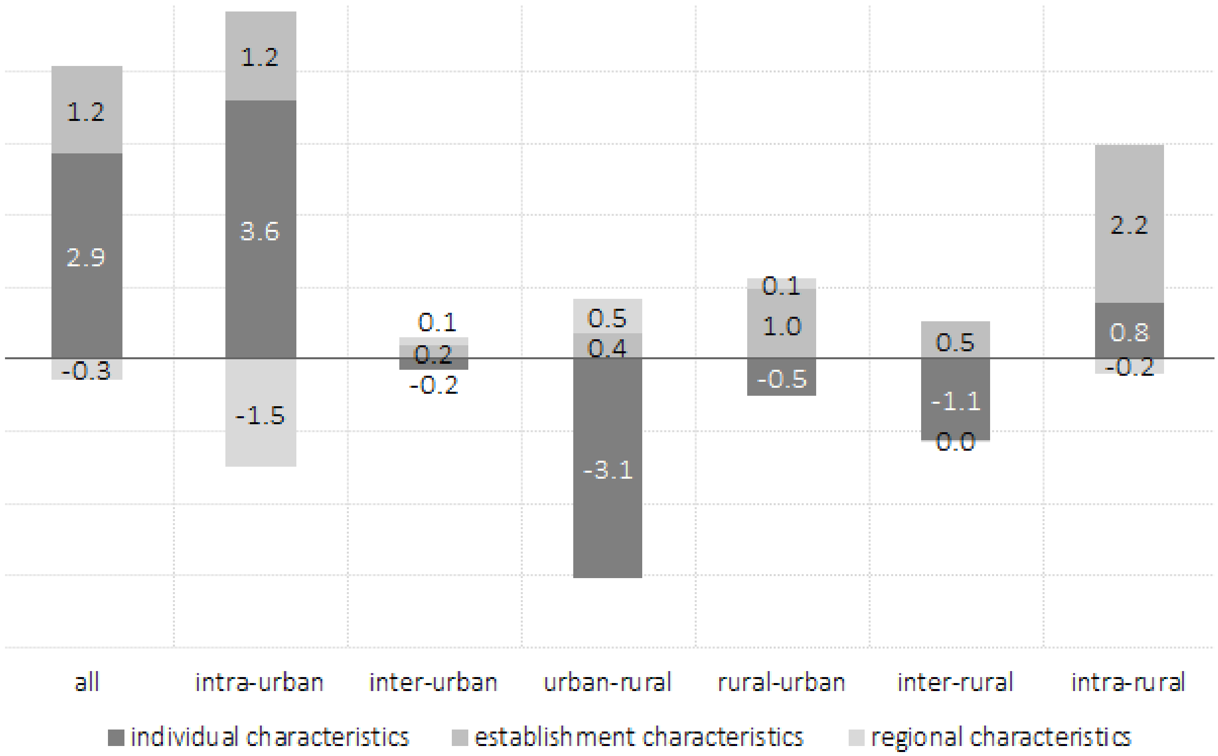
setup, the explained part is particularly large for intra-urban commuting. Here, 3.3 percentage points or almost half of the commuting gap can be explained by the factors included in the decomposition. The picture is quite similar for intra-rural commuting, where the explained part constitutes about one quarter of the unadjusted gap. The decompositions for the other four regional combinations yield rather different results. Foremost, the negative sign of the explained part in the case of urban-to-rural commuting implies that female urban-to-rural commuters are better endowed with observable characteristics than their male counterparts. Hence, gender differences in the explanatory factors reduce the commuting gap in favour of women. Turning towards rural-to-urban commuting, the unadjusted gap is similar to that of urban-to-rural commuters, but the explanatory factors in sum have a slightly positive overall effect, i.e. they work in favour of men. Small explained parts also emerge for the inter-urban and the inter-rural commuting gap, again emphasising the necessity to analyse the six groups of inter-and intra-urban/rural commuters separately.

A closer examination of the explained part in Figure 5.3 reveals profound differences regarding the role of individual, establishment and regional factors. Overall, gender differences in individual characteristics increase the gender commuting gap by 2.9 percentage points. In addition, gender differences with regard to establishment characteristics explain 1.2 percentage points of the overall gap. In contrast, gender differences in the regional factor reduce the gap by 0.3 percentage points. The positive contribution of establishment characteristics holds in all six regional combinations, whereas gender differences in individual and regional factors differ in their impact.

Turning towards the results for the respective regional combinations, the explanatory pattern of the two groups of intra-urban and intra-rural commuters again coincides with the overall picture. Still, differences emerge with respect to the relevance of the three groups of characteristics. In explaining the intra-urban commuting gap, gender differences in individual characteristics stand out, as they contribute 3.6 percentage points to the gap. For the intra-rural gap, in contrast, gender differences in establishment features play a prominent role. They account for 2.2 percentage points.

The results in Figure 5.3 show further that the impact of the three groups of explanatory factors differs profoundly between intra- and inter-urban as well as between intra- and inter-rural commuters. Foremost, gender differences in individual characteristics increase the gap among commuters working within their region of residence, but reduce it among commuters undertaking work trips to other regions. While this change of sign features prominently in the case of intra- and inter-rural commuting, the negative impact on the inter-urban gap is low. A further noteworthy result emerges for the urban-rural gender gap, where gender differences in individual characteristics reduce the gap by 3.1 percentage points, i.e. the individual characteristics work in favour of women here. Slight advantages of women in individual features can also be discovered among rural-to-urban commuters, but they are completely offset by disadvantages mainly in establishment features.

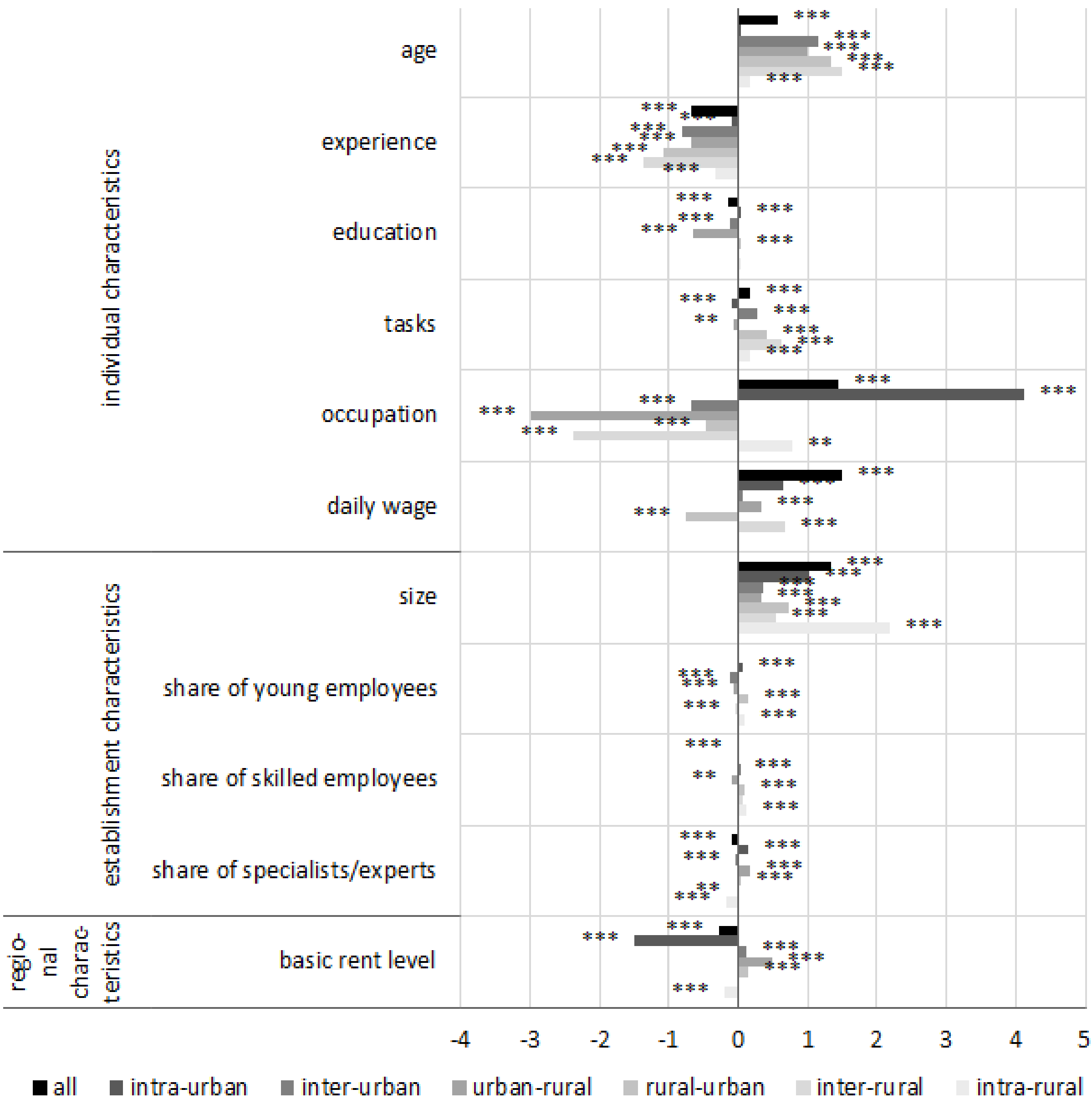
Figure 5.3: The role of individual, establishment and regional characteristics in the explained part of the gender commuting gap



Source: IEB, own calculations.

Before turning to the impact of each single variable contained in the broad groups of individual and establishment characteristics, it is worthwhile to investigate gender differences in these variables contained in Appendix 5.A.1. First of all, the share of women under the age of 35 is larger than the respective share of men. Turning towards occupations, a profound gender pattern becomes visible that mirrors the general occupational segregation of women and men (Perales and Vidal, 2015). Men predominantly work in production technology as well as in transport and logistics occupations, whereas the largest share of women can be found in business management and in medical and non-medical health care occupations. Furthermore, relatively more male commuters are employed in expert jobs, whereas the share of female commuters holding a university degree is slightly larger. Men also have more labor market experience and earn higher wages. As for workplace characteristics, relatively more men work in larger establishments with more than 50 workers. In contrast, there are comparatively more female commuters working in small establishments and in establishments with a young and highly qualified workforce. Finally, women live on average in regions with a higher basic rent level. This is mainly due to the fact that women are more likely than men to live in urban regions, as shown in Table 5.1. In the countryside men live in more expensive regions than women. When looking at the six regional combinations, further gender differences become apparent, which we discuss in the following in the context of the detailed decomposition results. For each combination of the place of residence and the place of work, Figure 5.4 dissects the results for the three groups of characteristics contained in Figure 5.3 and presents decompositions of the explained part for each variable separately.

Figure 5.4: Detailed decomposition results of the explained part of the gender commuting gap for different combinations of place of residence and place of work



Notes: Coefficients multiplied by 100. *** significant at the 1%-level, ** significant at the 5%-level, * significant at the 10%-level. IEB, own calculations.

Of the individual characteristics, the most important explanatory factors for the commuting gaps are gender differences in age, work experience, occupations and wages. The coefficient for age is positive and significant overall and for five of the six regional combinations, implying that gender differences in the age structure increase the commuting gap. One explanation might be women's family obligations, which begin when they start a family and which subsequently restrict their spatial mobility (England, 1993; Petrongolo and Ronchi, 2020). Consistent with this interpretation, female commuters have less work experience on average than male commuters in all commuting types (see Appendix 5.A.1). However, these gender differences have a significant and negative impact on the commuting gap. We interpret this result such that male commuters can use their more extensive work experience to find work closer to their place of residence, thereby reducing their commuting time (Booth et al., 1999).

While gender differences in age and work experience have a consistently positive or negative impact regardless of the places of residence and work being in urban or rural regions, this changes for occupations. Overall, the commuting gap increases significantly due to gender differences in occupations. This result is in line with Sang et al. (2011), who find a large impact of differences in workers' occupations by gender for explaining commuting patterns. In the case of intra-urban commuting, they contribute 4.1 percentage points to the unadjusted gap of 7.3 percent. Occupational segregation also increases the intra-rural gap by 0.7 percentage points. In contrast, it has a negative impact among those workers who have to cross regional borders to get to work. In Figure 5.4 , this is of special relevance for urban-to-rural and for inter-rural commuters. This pronounced difference between commuters who remain in their region of residence and those who do not is presumably related to the even more pronounced occupational segregation among commuters between the respective region types. In order to test this, we calculate the widely used Index of Dissimilarity (ID) proposed by Duncan and Duncan (1955) to quantify the uneven distribution of women and men across occupations.[41]

Overall, the ID reaches a value of 0.49, indicating that about half of all female commuters would have to change their occupations in order to achieve a balanced gender distribution. Among intra-urban commuters, the ID reaches 0.47, implying a slightly smaller degree of segregation. As Appendix 5.A.1 shows, the share of both men and women with jobs in medical, social, and business-related occupations is higher than among all commuters. This is compatible with the specific features of urban labor markets, which are characterised more strongly by the service sector than rural labor markets (Perpiña Castillo et al., 2022). Still, these comparatively small gender differences in occupations explain the generally longer commuting time of men to a large degree. Inter-urban commuters are even more similar in their occupations, as shown by an ID of 0.44. Obviously, the concentration of both sexes on occupations in the service sector (commerce and trade, business management and services, services in the IT sector)

[41]The ID was developed to determine the socio-spatial segregation of population groups and has been widely used in empirical labor market research (Perales and Vidal, 2015). It quantifies the share of men and women who would have to change their occupation in order to reach a balanced gender distribution in the labor market, measured along the overall proportions of men and women. The index reaches the value 0 if women and men are evenly distributed across all occupations and 1 if only one gender group is represented in all occupations.

reduces the commuting gap here. While the ID for both urban-to-rural and rural-to-urban commuters is identical to the overall value, it reaches 0.51 for inter-rural and 0.54 for intra-rural commuters. In these two groups, gender differences with regard to occupation are most profound, mirroring the specific occupational structure of rural labor markets. Notably, men tend to work in occupations related to agriculture, manufacturing, and construction, while women rather hold occupations in commerce and trade (see Appendix 5.A.1). Still, the occupational structure has a different impact on the intra-rural and inter-rural commuting gap. Notwithstanding a lower ID, we find a comparable pattern among intra-urban and inter-urban commuters. Among inter-urban and inter-rural commuters, there is a negative correlation between gender differences in the occupational structure and the commuting gap, while commuting time is high for both sexes. Among intra-urban and intra-rural commuters, the correlation between the occupational structure and the commuting gap is positive, while commuting time is low for both sexes. Consequently, we suppose that the occupational structure is more closely related to commuting time than to gender differences in commuting.

Turning to gender differences in wages, the observation that men earn more than women contributes 1.5 percentage points to the overall gender commuting gap. On the one hand, this can be interpreted as a higher willingness of men to commute longer for higher wages (Le Barbanchon et al., 2021; Dauth and Haller, 2020). On the other hand, it might pay off to commute longer in order to earn higher wages, which is easier to realize for men than for women (Bergantino and Madio, 2018). In a regional perspective, higher wages of men are positively related to the intra-urban and intra-rural gap by about 0.7 percentage points.

Gender differences in education and tasks explain the gender commuting gap to a smaller degree. In concordance with the stronger regional mobility of more highly educated workers (McQuaid and Chen, 2012), the larger share of women with a university degree reduces the gap. This is of particular relevance for urban-to-rural commuters. Somewhat in contrast with this result, gender differences in the complexity of the job increase the commuting gap, with men being employed in expert jobs more often than women in almost all groups of commuters (see Appendix 5.A.1). This suggests the existence of vertical occupational segregation going along with a potential overqualification of women for their jobs.

Among establishment characteristics, the different distribution of men and women across establishment size significantly increases the commuting gap, regardless of whether the places of residence and work are in urban or rural regions. Overall and in all six regional combinations (see Appendix 5.A.1), women are more likely to work in small establishments, whereas relatively more men have jobs in larger establishments that provide more career opportunities and pay higher wages (Card et al., 2016; Barth et al., 2016). Gender differences in establishment size are of special importance for the intra-rural commuting gap, explaining 2.2 percentage points of the unadjusted gap of 10.8 percent.

Gender differences in the region of residence, as measured by average basic rents in the region of residence, have an ambiguous influence on the gender commuting gap. Overall and for intra-urban commuting, the observation that women live in more expensive regions than men reduces the commuting gap. This might be explained by the larger share of women living in large cities with high rents and with more job opportunities than in rural areas. Consequently, they might trade off higher costs of living for short commutes (Bergantino and Madio, 2018). A small negative impact is also found for intra-rural commuters, among whose women live in slightly cheaper regions on average. These findings underline the descriptive results on the place of residence and work in urban regions in Table 5.1.

Summing up, the variables included in the decomposition have the largest contribution in explaining the gender gap among intra-urban and intra-rural commuters, who at the same time have the lowest average commuting times. By and large, the lower commuting time of women can be explained most strongly by gender differences in individual factors. They increase the gap among intra-urban and intra-rural commuters, and they decrease the gap among commuters who cross regional borders to get to work. Gender differences in establishment factors increase the commuting gap throughout. Among the individual factors, differences between men and women in terms of occupation are most important for explaining the commuting gap. Men's and women's workplaces in firms of different sizes has the largest impact among the firm-specific factors.

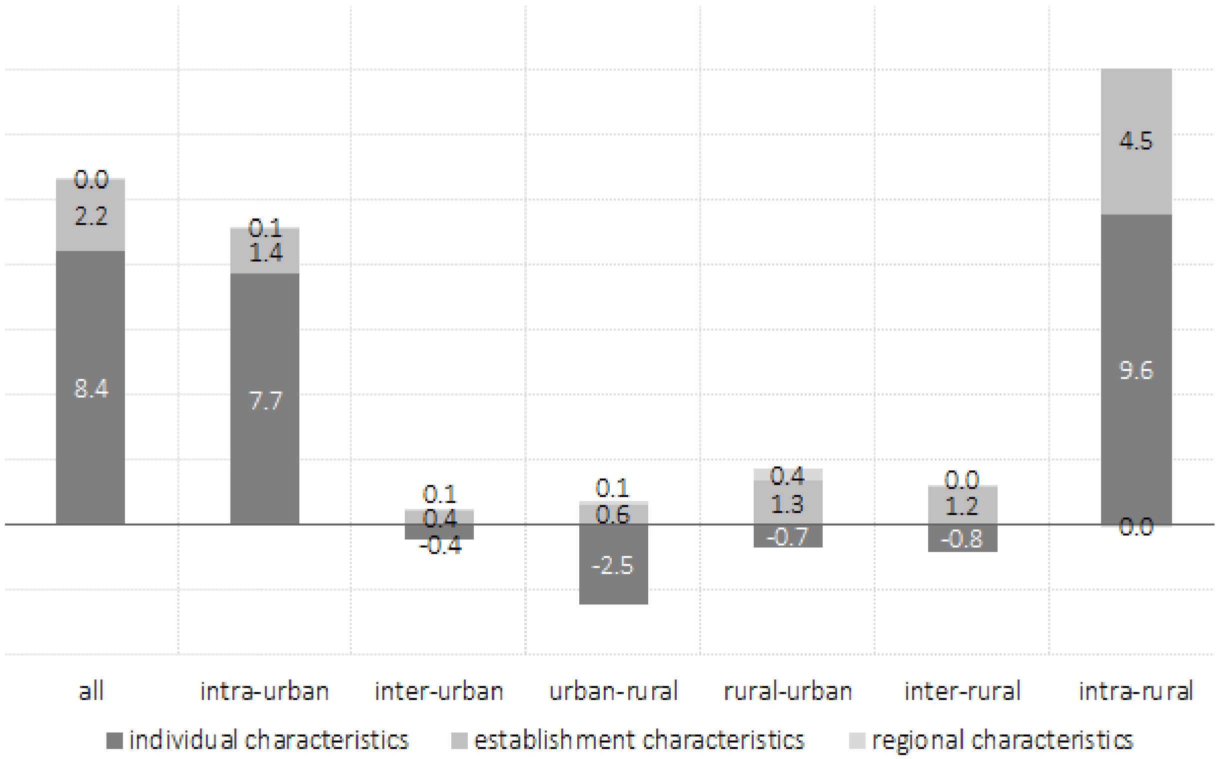
5.4.3 Sensitivity analyses

To check the validity of our results, we perform several robustness checks that also provide additional information on the commuting gap between women and men. They relate to the inclusion of part-time employment, the household context, removing limits on commuting time, and the endogeneity of wages.

Since the administrative data do not include information on the hours worked by part-time workers, which affects men's and women's commuting time, we have restricted the main analysis to full-time workers only (see Section 5.3.1). In order to facilitate a comparison with other studies that investigate the commuting gap (McQuaid and Chen, 2012), we additionally conduct our analyses with the inclusion of part-time workers and a dummy variable for being employed part-time. However, the results should be interpreted with caution, as they could be biased due to the lack of information on working hours. As expected, when we include part-time workers in the analysis, the commuting gap widens. The overall commuting gap increases from 14.3 percent to 21.9 percent. The largest increase in the gap is among workers commuting within the same rural region, from 10.8 percent to 20.2 percent.

The inclusion of information on part-time employment in the OB decomposition enlarges the explained part considerably, to about 50 percent overall and in the intra-urban and intra-rural commuting cases. Thus, the overall explanatory power of the individual factors increases substantially (see Figure 5.5).

Figure 5.5: The role of individual, establishment and regional characteristics in the explained part of the gender commuting gap (including part-time workers)



Source: IEB, own calculations.

Moreover, the establishment factors in total can explain a larger part of the commuting gap, too. This could be due to the fact that, by considering part-time workers, we included more women in our analysis and thus more information about the establishments in which they work. The generally low impact of the regional basic rents is also confirmed here.

As we know from the literature, the family context plays an important role in the decision to commute, especially for women (Sakanishi, 2020). Unfortunately, we only have information on whether a person is married or not, and this information is also only available reliably until 2013. However, when we estimate the 2013 results and take into consideration the information on marital status, we find only little difference from our main results. Overall, the coefficient of this variable is significantly positive, meaning that the fact that relatively more men than women are married increases the commuting gap slightly.

Furthermore, to address only daily commuting, we limited the maximum commuting time to 90 minutes in our main results. As expected, if this limit is removed, commuting times increase. However, the commuting gap also increases, because men are more likely to commute longer and beyond the daily commuting range. The pattern with the largest commuting gap between rural areas remains constant, but the smallest gap is measured now for intra-urban commuting. Hardly any differences are found with regard to the influence of our explanatory factors.

Although we do not interpret the relation between commuting and wages in a causal way, we address the endogeneity of the daily wage as a last sensitivity check. At least in terms of commuting time or commuting distance, it is not clear whether the wage is the reason for commuting or the result of commuting (Bergantino and Madio, 2018; Le Barbanchon et al., 2021). Therefore, we also run the analyses with the lagged daily wages. As a result, all the general patterns remain identical with the main results, but in all six cases considered the size of the commuting gap decreases slightly.

5.5 Conclusion

In this paper, we have analysed regional differences in the commuting pattern of men and women by considering different combinations of residence and workplace locations in urban and rural regions. For this we have used administrative georeferenced data for Germany to calculate the exact commuting time for men and women and have applied decomposition techniques to identify the determinants of gender differences in six locational combinations.

We find an overall gender commuting gap of 14.3 percent for the year 2017, confirming the lower spatial mobility of women as evidenced by previous studies. Going one step beyond existing knowledge, the breakdown into the place of residence and place of work uncovers not only rural-urban differences in the size of the commuting gap, but also systematic differences in the travel time of workers commuting within and between regions. Foremost, the commuting gap is highest among women and men who live and work in rural regions, unveiling the second gender commuting gap at the disadvantage of women in the countryside. This finding underlines the spatial entrapment thesis for women especially in rural areas. What is more, further disaggregating commuting within urban areas and within rural areas, we find that the respective inter-commuting gap is always higher than the intra-commuting gap. This leads to a third disadvantage for those women whose place of residence and place of work are located in different rural areas.

The decompositions of the commuting gaps have shown that the included variables have the largest contribution in explaining the gap among intra-urban and intra-rural commuters, who at the same time have the lowest average commuting times. Generally, the lower commuting time of women can primarily be explained by gender differences in individual factors, among which the occupational structure stands out. Gender differences in establishment factors are foremost driven by establishment size selection. They increase the commuting gap throughout.

All in all, by combining the two stands of literature on spatial determinants and on gender differences in commuting, our results clearly emphasise the necessity to analyse the gender gap in commuting on a spatially disaggregated level. Specifically, it is important to distinguish whether both the place of residence and the place of work are located in an urban or a rural region and whether commuters have to cross regional borders, reflecting differences in commuting times.

The differentiated picture of the regional gender commuting gap drawn by our analysis entails valuable implications for policies aimed at increasing women's mobility in certain regions, thereby reducing disparities in the regional labor markets. In this regard, specific focus should be put on women living in rural areas, who might be more restrained by their social role within the household than women living in cities. For example, securing the provision of all-day childcare facilities (by local municipalities or by firms) enables mothers longer commutes and thus the benefit from larger job markets. Furthermore, the result that men sort into larger establishments than women close to their place of living calls for more information about local job opportunities specifically for women. Women's lower spatial mobility can further be compensated by working from home, which can allow women to expand their job search radius especially in rural areas. In this context, employers have to provide the necessary technical equipment. Furthermore, political actors are called for to enable faster deployment of digital infrastructure.

The results of this article leave ample scope for further research. Given the restriction of our data, future work should investigate the role of part-time work in more detail. In addition, the interrelation between the existence of children and the commuting time of mothers merits further investigation. In addition, information from qualitative surveys might provide deeper insights into other factors like the mode of transport or time devoted to childcare activities that are not contained in administrative data and that also influence gender differences in commuting.

Appendix

A Additional Figures and Tables

Table 5.A.1: Descriptive statistics for men and women, 2017 as percentages

	All commuters		Inter-urban		Intra-urban		Urban-rural	
	men	women	men	women	men	women	men	women
Individual characteristics								
Age								
<25	3.9	5.5	3.8	6.2	4.7	5.9	5.1	7.5
25-34	21.6	25.3	24.5	32.8	25.8	28.7	26.8	31.2
35-44	22.8	19.0	24.6	20.7	23.5	19.6	24.1	19.6
45-54	30.4	28.5	29.0	24.9	27.1	25.9	26.6	25.0
55-64	21.4	21.8	18.2	15.4	19.0	20.0	17.4	16.8
Occupation								
Agriculture, forestry & horticulture	1.9	1.0	0.9	0.6	1.7	0.7	1.8	1.1
Manufacturing	13.0	4.1	9.1	2.8	11.7	3.5	15.7	5.6
Production technology	20.7	4.7	20.2	4.1	18.1	3.7	20.6	6.9
Building & interior constr.	10.7	1.0	7.8	1.0	10.1	1.1	10.7 0	.9
Food ind., gast. & tourism	4.1	7.3	3.3	5.6	4.9	7.2	4.2	7.7
Medical & non-medical health care	2.9	16.1	3.1	14.3	3.7	17.4	2.1	13.7
Social sector & cultural work	2.8	8.4	3.4	8.2	3.6	9.4	2.1	8.5
Commerce & trade	6.2	11.2	7.6	11.0	6.1	10.5	6.0	12.7
Business manage. & organis.	8.2	20.5	10.9	23.7	8.5	20.3	7.0	19.5
Business-related services	5.9	14.5	8.2	17.4	6.9	15.4	3.4	10.0
Services in the IT sector & the natural science	5.2	2.3	7.6	3.2	5.3	2.2	4.8	2.9
Safety & security	1.8	1.0	2.4	1.2	2.0	1.0	1.4	1.0
Transport & logistics	15.0	4.9	13.6	4.4	15.2	4.3	18.0	6.0
Cleaning services	1.8	3.0	2.0	2.5	2.4	3.2	2.2	3.5
Task levels								
unskilled	11.3	10.2	11.1	8.6	15.0	11.5	14.5	14.0
skilled	57.8	62.9	52.0	59.2	57.3	61.4	58.7	58.8
expert	30.9	26.9	36.9	32.3	27.8	27.0	26.8	27.3
Education								
no vocational training	5.9	5.5	7.1	5.8	8.9	7.1	7.4	6.9
vocational training	74.6	73.5	66.8	66.7	71.9	69.7	75.0	70.5
university degree	19.5	21.0	26.2	27.6	19.2	23.2	17.6	22.7
Work experience (in years)	17.8	16.1	17.5	15.3	17.	1 16.1	16.4	14.9
Daily wage (in €)	123.08	102.05	128.9	107.7	114.6	99.2	110.9	94.9
Firm characteristics								
Size								
1 to 9 workers	13.0	18.6	9.8 1	4.3	13.9	19.4	16.0	20.0
10 to 49 workers	24.5	24.9	22.4	22.8	23.6	24.3	28.8	29.0
50 to 249 workers	29.2	27.3	30.8	29.3	29.0	25.9	31.0	30.1
$\geq$ 250 workers	33.3	29.2	37.0	33.7	33.6	30.5	24.2	20.9
Employment structure								
Share young workers	29.4	30.7	30.1	33.1	31.0	32.5	31.2	32.6
Share skilled workers	58.8	58.4	54.3	54.7	57.0	56.9	60.0	56.5
Share expert workers	28.6	30.0	33.0	34.5	28.3	31.1	24.5	27.8
Regional characteristics								
Basic rent level (in €)	541.2	549.8	559.9	577.3	561.6	579.4	523.9	532.9

Table 5.A.1: Descriptive statistics for men and women, 2017 as percentages (continued)

	Rural-urban		Inter-rural		Intra-rural	
	men	women	men	women	men	women
Individual characteristics						
Age						
<25	5.2	8.4	5.9	9.5	7.0	7.8
25-34	21.4	27.4	23.9	28.5	23.0	22.6
35-44	22.7	19.3	22.7	19.0	21.3	17.7
45-54	30.2	27.2 2	8.6	26.9	28.0	29.1
55-64	20.6 1	7.8	19.0	16.2	20.7	22.9
Occupation						
Agriculture, forestry & horticulture	1.4	0.9	2.3	1.6	3.8	1.9
Manufacturing	11.6	3.8	15.3	5.9	18.8	6.6
Production technology	24.9	5.2	23.2	6.2	20.6	5.9
Building & interior constr.	9.1	0.9	11.6	0.8	16.2	0.9
Food ind., gast. & tourism	43.0	6.0	3.8	8.1	4.6	10.3
Medical & non-medical health care	2.6	16.3	2.0	15.1	2.0	15.6
Social sector & cultural work	2.5	7.0	1.9	7.6	1.6	7.9
Commerce & trade	6.8	10.9	6.5	13.6	4.3	12.1
Business manage. & organis.	9.1	21.7	6.6	18.5	5.1	17.6
Business-related services	6.7	16.9	3.1	9.8	2.9	9.4
Services in the IT sector & the natural science	5.6	2.5	4.1	2.4	2.6	1.5
Safety & security	2.0	1.0	1.2	1.1	0.9	0.7
Transport & logistics	13.5	5.0	17.4	6.0	15.3	6.2
Cleaning services	1.2	2.2	1.1	3.2	1.3	3.7
Task levels						
unskilled	11.0	10.3	12.4	14.9	15.2	17.2
skilled	57.0	65.0	61.1	63.1	66.9	66.0
expert	332.0	24.7	26.5	22.0	17.9	16.7
Education						
no vocational training	4.3	4.6	4.3	5.3	5.6	6.3
vocational training	77.9	78.3	82.3	80.4	86.7	83.3
university degree	17.8	17.1	13.4	14.4	7.7	10.5
Work experience (in years)	19.1	16.5	18.1	15.6	18.4	17.2
Daily wage (in €)	127.31	99.9	114.5	88.6	103.8	82.2
Firm characteristics						
Size						
1 to 9 workers	9.4	16.4	14.5	20.2	21.1	27.9
10 to 49 workers	22.2	23.8	28.9	29.8	30.6	31.6
50 to 249 workers	30.2	28.8	30.6	30.0	21.1	27.9
$\geq$ 250 workers	38.3	31.1	25.8	20.0	28.0	26.2
Employment structure						
Share young workers	29.9	32.2	31.0	32.2	20.3	14.3
Share skilled workers	56.9	58.0	62.0	59.3	30.4	29.9
Share expert workers	30.3	29.8	23.4	24.0	65.4	63.1
Regional characteristics						
Basic rent level (in €)	562.2	556.4	522.2	525.4	485.0	482.4

Source: IEB, own calculations

Chapter 6

Conclusion

This thesis focuses on a central topic of the labor market: the commuting behavior of employees. In Germany, the importance of this subject is growing as both the number of commuters as well as the distance they commute continues to rise steadily. However, increased mobility leads not only to better labor accessibility and to better career opportunities as it broadens the access to labor markets, but it also has some negative aspects. In particular, commuting costs money and time, causes stress and has a negative impact on the well-being and health of individuals. Therefore, the study of this phenomenon is becoming increasingly important to gain deeper insights into the factors that explain people's commuting behavior. Using novel georeferenced administrative data for employees in Germany which allows to calculate accurate commuting distances between work and home, this paper offers four new contributions.

Chapter 2 discuses the first study and analyses for the first time the commuting behavior in terms of a behavioral economic concept for Germany. The results show that workers' commuting decisions are not only influenced by wages and individual heterogeneity but depend also on the context individuals' observed in the past. In particular, the results show that previously observed commutes have an impact on subsequent commuting behavior: workers choose longer commuting times in the region they recently moved to when the average commute in the region they left was longer. In addition, if they remain in the new region, they adjust their initially chosen commuting times to the average commutes in the new regions, which refutes the assumption of stable unobserved differences across individuals. Instead, individuals change their marginal utility of commuting when moving to a new region, as they adjust their commuting time by means of a second relocation within the new region.
Chapter 3 studies out-commuters from a particular eastern German region, MV, and compares them with employees living and working in MV. In particular, the individual, job-related and firm characteristics are investigated that increase the likelihood that men and women cross regional borders by commuting long distances. In addition, the factors explaining the wage gap between the group of out-commuters

and home employees are examined in more detail. As regions in eastern Germany complain of labor shortages, especially in the context of an aging population that will retire in the next few years, these findings may be important for policies aimed at employing current out-commuters of MV to compensate for such shortages. The results indicate that especially high skilled, older workers and women and men working in larger firms out-commute. For women, we additionally show a higher share of women working in unskilled labor. Regarding the wage gap between out-commuters and home employees, we find that men in particular benefit from out-commuting, which can be explained by differences in task levels and firm characteristics. Hence, if policy makers and employers want to gain back out-commuters structural changes at the labor market have to occur, especially job opportunities for high-skilled are not enough and wages are not comparable with wages outside MV.

Chapter 4 investigates the impact of job displacement on workers' commuting behavior. Using an event study approach, we analyse the short-term and long-term effects of being displaced during a mass layoff event on commuting distances to subsequent jobs. The results show that displaced workers commute up to 21 percent longer distances after displacement. The effect diminishes over time as workers move from distant to proximate jobs. Using georeferenced data, we further show that studies using regional-level data for the calculation of commuting distances overstate the causal effect of job displacement by up to 42 percent. To rationalize the empirical findings, we build a job search model with heterogeneous firm productivity and commuting distances. With on-the-job search, workers can increase their job match surplus by moving from less to more productive firms and from distant to proximate firms. This explains the empirical findings of joint recovery of wages and commuting after job displacement. Further, the structural estimates of the job search model suggest that workers incur an average commuting costs of 18 euros per day, and increased commuting exacerbates the wage losses due to job displacement by 14 percent in total.

The last study included in Chapter 5 analyses regional differences in the commuting pattern of men and women by considering different combinations of residence and workplace locations in urban and rural regions. The results provide evidence for a triple gap in commuting to the disadvantage of women. First, we find an overall gender commuting gap of 14.3 percent. Additionally, the regional disaggregation of the overall gap into rural and urban places of work and residence uncovers two additional gaps. In particular, the commuting gap is highest among women and men who live and work in rural regions, unveiling the second gender commuting gap at the disadvantage of women in the countryside. Further disaggregating commuting within urban areas and within rural areas, we find that the respective inter-commuting gap is always higher than the intra-commuting gap. This leads to a third disadvantage for those women whose place of residence and place of work are located in different rural areas. Using decomposition techniques to identify the determinants of gender differences in commuting shows that the lower commuting time of women can primarily be explained by gender differences in individual factors, among which the occupational structure stands out. Gender differences in establishment factors are foremost driven by establishment size selection. They increase the commuting gap throughout.

Based on the research findings of these studies, I can derive several important policy implications. First, the results provide new evidence improving the integration of unemployed workers into the labor market. Unemployed workers could benefit more from easier commuting as they incur, in line with the results of Chapter 4, greater commuting costs and are financially more constrained. In this context, policy measures such as the expansion of transportation infrastructure that allows workers to access job opportunities more easily or working-from-home that removes the commuting costs of remote-job workers would attenuate the negative impact of job displacement. Further, these findings point to the benefits of commuting subsidies. Implemented in several European countries, the subsidy directly lowers the cost of commuting and can thus decrease the difficulties unemployed workers face in finding a new job.
Second, this work sheds new light on policies aimed at reducing the inequality that still exists between women and men in the labor market. In particular, the gender commuting gap identified in Chapter 5 can help policymakers develop measures to increase women's mobility in certain regions. In fact, increased mobility allows women to expand their job market, which can lead to more and better job opportunities and thus decrease gender disparities. In this regard, specific focus should be paid to women living in rural areas, as this group shows the highest commuting gap. For example, securing the provision of all-day childcare facilities or the opportunity of working-from-home might enable women longer commutes. Furthermore, the result that men sort into larger establishments than women close to their place of living calls for more information about local job opportunities specifically for women in rural areas. Nevertheless, rural areas are still subject to distance penalties. In this context, new technologies and faster deployment of digital infrastructure can improve not only the access to e-health and e-learning services, but also the possibility of working-from-home.
Thus, the possibility of working-from-home - and in this context the expansion of digital infrastructure - as well as commuter subsidies could be very important for certain groups in the labor market and policy makers should take this into account in their future interventions.
Finally, highlighting the importance of granular commuting data for studying individuals' commuting behavior, the thesis provides a starting point for future research. Research areas such as job search, labor market frictions, monopsony or social networks, all of which are related to individuals' commuting decisions, could benefit from individual-level measures of commuting. However, as a result of the Covid-19-shock, the commuting behavior may have changed. In fact, the increase in working-from-home influences the travel time budget and the expected and acceptable commuting distances. It is up to future research whether such increase in working-from-home influences the commuting outcomes.

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