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Urbanization, Commuting and Regional Labor Markets

Peter Haller

Dissertationen

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Contents

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Last but not least, I would like to dedicate this dissertation to my parents for their constant support in every difficult situation of my life.

Nürnberg, April 2018
Peter Haller

List of Figures

List of Tables

Introduction

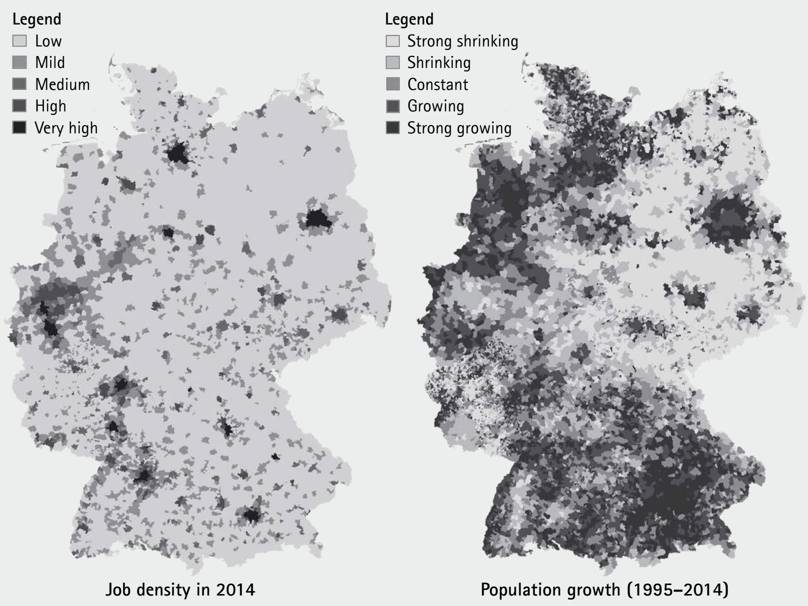
Spatial Economic Structure and Urbanization in Germany

Compared to other European countries, Germany has a highly dispersed spatial structure with many centers of dense economic activity. The left panel of Figure I.1 shows the job density in Germany in 2014. The unique polycentric structure is characterized by large employment centers, like Berlin, Hamburg or Munich. However, there are several other locations with a thick labor market. To a great extent this pattern is determined by location fundamentals, like access to amenities or natural resources, and path dependency from the countries' unique older and younger history. In the current literature these channels are of secondary importance, as the existence of booming and declining cities can be attributed to agglomeration and dispersion forces which also form the spatial structure (see Combes & Gobillon (2015) for a review). Today Marshall's (1890) ideas about the advantages of agglomerations can be summarized by *sharing* of inputs and common infrastructure, better *matching* of jobs and workers as well as knowledge spillovers and *learning* effects between workers and firms (Duranton & Puga, 2004).

Recently, the complex system of interactions within and across cities is given very much theoretical and empirical attention (e.g., Allen *et al.*, 2015; Davis & Dingel, 2017; Ahlfeldt *et al.*, 2015). Especially the New Economic Geography (e.g., Krugman, 1991; Fujita *et al.*, 1999) established a sound theoretical basis to explain those interactions by, e.g., monopolistic competition, price indices, increasing returns to scale. However, this literature falls short to establish a close connection between the theoretical predictions and the empirical data, which often reveals diverse and fragmented regional labor markets, including spatial fractions and heterogenous workers and firms. The improvements of quantitative models for spatial analyses were recently summarized by Redding & Rossi-Hansberg (2017). Besides the advances in quantitative spatial models, empirical evidence about spatial frictions and spatial interactions of workers and firms leave much room for regional and urban research. Its polycentric structure makes Germany an attractive country for empirical studies. Empirical research can give new evidence about the spatial mechanisms of the German economy by looking at the internal structure of cities and the interactions between regions.

One important phenomenon is the increasing population in cities. It is a decisive element in the analysis of spatial interactions. Urbanization is key in the political discussion about future spatial development. Politicians often fear the rural exodus in Germany, whereas many urban economists stress the chances that urbanization brings through agglomeration advantages. A prominent publication that evoked also public interest in the benefits of urbanization is Glaeser (2011). In fact, since 1995 the growth of urban areas in Germany is rather small. According to United Nation population data, the share of urban residents in Germany increased from 73.29 to 75.09 percent. However, this increase is spatially unequally distributed. The growth of workforce population shows a clear difference between East and West Germany. Population in non-metropolitan areas decreased by 16 percent from 1995 to 2014 in eastern municipalities, whereas there was a 1.8 percent increase in the western parts. The population in big cities increased by 3.3 percent in West Germany and remained almost unchanged in the east. In the right panel of Figure I.1 we can observe the population decline in East Germany. Also several municipalities in West Germany have a shrinking number of residents. The population seems to rise in and around employment centers. Bavaria (South Germany) is the state with highest growth in its municipalities. Overall, the increase is only less than half of the growth of US urban population. In newly developed countries the rise is even larger. For that reason, Brülhart & Sbergami (2009) are questioning whether the agglomeration economics are as expected in developed countries like Germany. Hence, there is room for additional empirical clarification whether all advantages from denser urban areas are applicable for the German spatial system with prospering southern and declining eastern regions.

Figure I.1: Job Density and Population Growth in German Municipalities



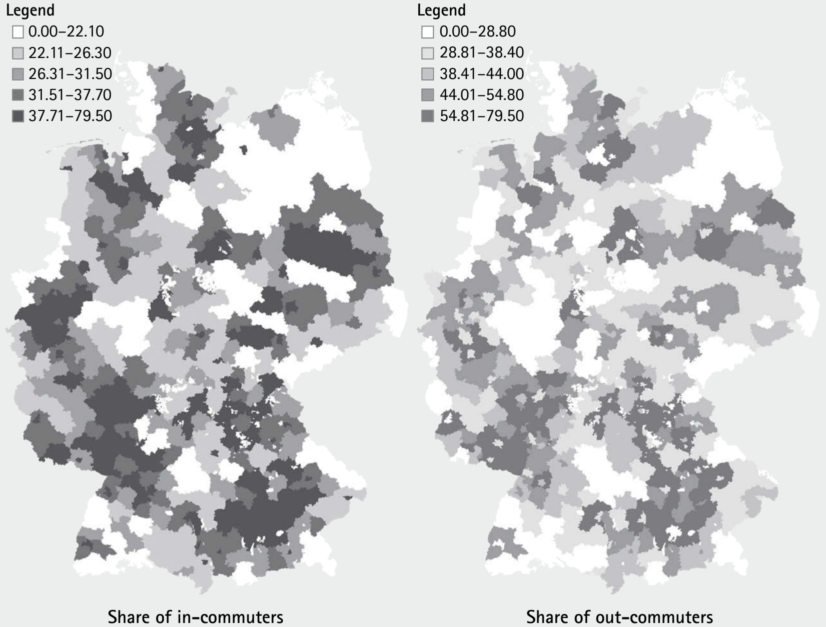
Notes: The left figure reports the job density ($full\ time\ employed/km^2$) in 2014 and the left figure the population growth from 1995 to 2014 in German municipalities. The data stems from the Statistics of the Federal Employment Agency.

Spatial Economic Interactions and Commuting

Despite of rising cities, yet not all economic activity is concentrated. The limitation of land and the following bidding up of land prices serves as suburbanization force for workers' and firms' locations (see, e.g., Duranton & Puga, 2015). The share of residential and commercial buildings, therefore, varies with the distance to the central business district. That is why dispersion and agglomeration forces of spatial economic activity depend highly on the transportation of people and goods (see Redding & Turner, 2015). For firms, higher prices for offices can lead to new business districts in other locations within a city. For workers, the differences in housing prices or certain preferences for neighborhoods are the main drivers in the decision about their residence and workplace location. In this sense, road access can be crucial to decide whether to commute and thus for the process of suburbanization (Baum-Snow, 2010). A downside of this dispersion is residential sorting of certain groups and segregation within cities, which can lead to disadvantages, e.g., in later labor market success (Brueckner & Zenou, 2003; Gobillon *et al.*, 2007). This suggests strong linkages of goods and factor markets between the agglomerations, suburbs and peripheral regions for which transport infrastructure is a central element.

Although the transport infrastructure in Germany is top-rated, a lack of investments today could be a bottleneck for future economic development (Kunert & Link, 2013). These investments can have direct effects (e.g., for its construction) and wider indirect economic effects. The latter are economically more important but very diverse. For instance, improvements in the transport infrastructure can cause regional economic development in rural areas, population growth, change in industry structure or commuter flows. In the past ten years there has been a vibrant discussion in regional and urban economic research (Redding & Turner, 2015). The main focus is on current and past road infrastructure (e.g., Michaels, 2008; Baum-Snow, 2007; Duranton & Turner, 2012; Duranton *et al.*, 2014) or railroads (Donaldson & Hornbeck, 2016) in the US. Another part of the literature discusses its effects in newly developed economies (Donaldson, 2017; Ghani *et al.*, 2016; Baum-Snow *et al.*, 2017) and developing countries (Storeygard, 2016; Jedwab & Moradi, 2016). For Germany, Heuermann & Schmieder (2017) investigate the effects of the rail network on the workers' mobility or Möller & Zierer (2014) of the autobahn network on regional employment levels and wages. In contrast to the previous literature, this thesis focuses on wider economic effects of spatial interaction with a given transport infrastructure.

Figure I.2: Percentage of In- and Out-commuters in 2014



Notes: The share is the percentage of in-commuter over the social-insured jobs in a county or the out-commuters over the social-insured jobs in the residence county. The figure's data stem from INKAR/BBSR.

Transporting people is costlier than transporting goods and therefore workers react more elastic to distance. Given this reasoning, spatial linkages in the factor market of workers can arise from the individual decision either to move close to their job, keep their current residence location and commute or do both. Commuting is important for the analysis of spatial economic activities, as it allows firms to hire workers who live in a region with lower housing costs or nicer amenities, but at the same time, work in highproductivity regions and earn higher wages. In the US commuting has huge economic effects on the country's GDP which are comparable in size with those of international trade. In a counterfactual scenario without commuting, welfare losses would mainly stem from firms' difficulties to extend production because they can only recruit from the local workforce (Monte *et al.*, 2015). Therefore, spatial interactions are economically efficient, however, economic policy still base their decisions on administrative areas. This raises the question whether these local regional policies fully account for the commuting of workers (see Petrongolo & Manning, 2017). Commuting forms the spatial interaction between local labor markets also in Germany. Figure I.2 shows the percentage share of in- and out-commuters in 2014. Not only the large cities have many in-commuters from other regions, also the surroundings attract commuters. The low share of out-commuters, workers who work in another administrative area, clearly emphasize cities as employment centers with a very low proportion of individuals working in other areas. In Germany the number of commuters increased over time along with urbanization. From the administrative employment data it is known that from the year 2000 to 2015 the share of commuters, who are crossing at least one municipality border on their way to work, increased from 54 percent to almost 60 percent. This imposes an increase of the average daily commuting distance from 14.6 to 16.6 kilometers (Pütz, 2015). The census of 2012 also detects a 11 percent increase in the commuting distance from 2004. Nevertheless, half of all employees worked within 10 kilometers to their residence and 70 percent of them needed less than 30 minutes to work (Wingerter, 2014). Albeit, this cannot be causally linked to the ongoing (sub)urbanization, it shows a rise of spatial flexibility within the German labor market and hence increased mobility through commuting. The share of in- and out-commuters in Figure I.2 further motivates questions about the mechanisms of spatial interactions between regions and individual valuation of commuting distance. On these grounds, it is worthwhile to identify and clarify the spatial mechanisms of regional labor markets and the spatial extent of density effects (Combes & Gobillon, 2015) in Germany. The spatial interaction in this thesis will rest upon commuting. The different chapters will empirically shed further light on the questions how local labor markets interact, how dense markets help in finding new employment given the interrelation with surrounding areas and how people respond to changes in commuting distances. Therefore, this dissertation contributes to a vivid academic and a recent political discussion about urbanization and spatial labor market interactions.

Chapter Overview

In three different parts this doctoral thesis contributes to the latter questions which are briefly summarized. Apart from the results, the chapters also concur to the methodology in empirical research of regional labor markets and apply different modern methods to capture the complex spatial interactions through commuting.

The first chapter is entitled '*Job Search and Hiring in Local Labor Markets: Spillovers in Regional Matching Functions*' and is published as Haller & Heuermann (2016). Herein, we account for the increasing integration of local labor markets through commuting and the resulting dependency structure in job matching functions. Looking at German counties (NUTS3) from 2000 to 2010, we provide new evidence on the geographical scope of job search and hiring behavior and how unemployed or vacant jobs affect hires within and across regions. By the means of spatial econometrics we capture local spillovers based on a set of neighboring regions. The neighboring relation is measured with a spatial weight matrix which values the (physical) distance between a pair of regions. From the methodological perspective, we present a clear empirical exercise to clarify the choice of weight matrices and the effects on spatial spillovers (see Gibbons *et al.*, 2015). Additionally, we conclude which statistical model describes the data generating process properly and whether the spillovers are of local or global nature. Our results show an elasticity between matches and unemployed ranges between 0.4 and 0.5. Spillovers accounts for 75 percent of the overall effect. The Spatial Durbin Error Model describes the regional job matching functions most appropriate which implicates the existence of underlying local spillovers. In line with the research on transport infrastructure, we also use weight matrices based on current as well as historic car and train travel time or distance. However, out of many different spatial weight matrices Bayesian estimations prefer the simple physical direct distance. Usually the commuting distance is expected to be more relevant in the literature. Furthermore, these spillovers arise exclusively after the labor market reforms in Germany, which suggests an increased mobility of unemployed through commuting.

In the light of this regional analysis of administrative tracts, chapter 2, with the title '*Opportunities and Competition in Thick Labor Markets: Evidence from Plant Closures*', evaluates the competing density mechanism within and across local labor markets on a smaller regional scale than the previous chapter. Empirically longer unemployment durations and unemployment rates in denser labor markets question the theoretical positive effect of thick labor markets on finding employment. In this chapter we use the incidences of involuntary unemployment from plant closures between 1999 and 2009 as a natural experiment to evaluate the relative importance of job opportunities and job competition density for the re-employment of displaced workers. Herewith the dissertation follows the call for more causal inference in urban and regional economics research (see Baum-Snow & Ferreira, 2015). In the underlying case we mitigate spatial sorting of individuals and firms. To create density indicators we not only consider the local labor demand and supply, we also account for the potential density which arises by commuting from neighboring regions. In contrast to previous studies, we use quarterly data to track the days in unemployment of the displaced individuals in detail and use the residence location based on municipalities, which is the smallest available administrative level in Germany. Furthermore, we control for unobserved individual and regional heterogeneity by the means of the panel structure of our data. Our results suggest that the negative effects of job competition in agglomerations reduce employment prospects. Thus, the advantages for unemployed job seekers of more job opportunities in cities are dominated by the density of other unemployed workers. The findings state that thick labor markets are not per se beneficial and urbanization can have disadvantages for unemployed workers.

Lastly, in chapter 3, '*Asymmetric wage responses to changes in commuting distances*', we analyze the causal effect of commuting on wages using georeferenced employment data of German job changers. This work appeared in an earlier and slightly different version as discussion paper (see Dauth & Haller, 2016). Within a simple job-search framework we analyze the wage-distance trade-off of job changers who can either increase or reduce their commuting distance. Our approach differs to previous findings in at least three regards. First, we distinguish positive and negative distance changes due to job transitions. Second, our panel structure allows us to control for unobserved individual heterogeneity. Furthermore, we also account for firm heterogeneity. Third, the addresses of workers' residence and work location allows us to calculate exact door-to-door commuting distances. This innovative feature of administrative employment data opens a very detailed view on the spatial dimension of the labor market. It can be seen as pioneering for future work as geo-information is more and more available in administrative and public data sources. This will lead to a very detailed view on regional labor markets without relying on aggregation based on administrative borders. We find an asymmetric effect along the distance change. Workers are willing to give up a larger fraction of their wage when reducing their daily commuting distance compared to the respective distance increase. This evidence suggests that individuals are only insufficiently compensated for their commuting costs and generally prefer to live closer to their residence location.

The intersection of all three parts is to get a comprehensive view on spatial linkages among regional labor markets. From chapter to chapter the definition of space is augmented, starting from county level, over municipalities and even continuous space without without administrative borders. From these different angles the thesis sheds novel empirical evidence on the spatial interactions among cities, suburbs and peripheral regions in Germany.

Chapter 1

Job Search and Hiring in Local Labor Markets: Spillovers in Regional Matching Functions

Abstract*

In this paper we take a fresh look at the job matching process within local labor markets in Germany. Drawing on smaller geographic units than the previous literature, we estimate regional matching functions on NUTS 3 level for the years 2000 to 2010. The elasticity between matches and unemployment ranges between 0.4 and 0.5 with 75 percent of this effect being driven by the impact that unemployment has on matches in neighboring regions. The effect of vacancies on matches is substantially smaller but also robustly positive. Bayesian model comparison tests suggest that spillovers from unemployment and vacancies are confined to local labor markets, which are best approximated by geographical distance rather than by present or past infrastructure or commuter numbers. Spillovers from unemployment arise exclusively after a series of major labor market reforms ('Hartz Reforms') have been implemented between 2003 and 2005, indicating that the reforms have contributed to an increased spatial mobility of the unemployed.

Keywords: local labor markets, matching function, commuting, transport infrastructure

JEL Codes: J61, J64, R12, R23

* This part is joint work with Daniel F. Heuermann. It is published as Haller & Heuermann (2016) by Elsevier in *Regional Science and Urban Economics* 60 (2016): p. 125–138.

1.1 Introduction

As one key trend in labor market dynamics, commuting is on the rise. In the US, the average one-way commuting distance has increased by 39 percent from 13.7 to 19.0 kilometers between 1980 and 2011 (United States Department of Transportation, 2009). In the UK, it has grown by 12 percent from 13.4 kilometers in 2001 to 15.0 kilometers in 2011 (UK Census, 2011). Similarly, in Germany it has risen by 14 percent from 14.6 to 16.6 kilometers between 1999 and 2009 (BBSR, 2012). As a consequence, a growing share of workers is employed outside their home region. In Germany, the share of workers crossing at least one county border on their way to work has increased from 28 percent in 2000 to 38 percent in 2013.

With a rising mobility of workers, administrative regions increasingly integrate into larger local labor markets. Within these local labor markets, the job matching process is strongly influenced by job search and recruitment activities of workers and firms in adjacent regions (Burda & Profit, 1996; Burgess & Profit, 2001; Hynninen, 2005; Fahr & Sunde, 2006a,b). In their pioneering work, Burda & Profit (1996) show for the Czech Republic that unemployment and vacancies affect the number of matches in neighboring regions. These effects decay in a non-linear way with distance. Burgess & Profit (2001) provide evidence that a rising number of unemployed within one region in Britain increases the number of filled vacancies in neighboring regions while reducing the outflow from unemployment therein. These findings are confirmed by Fahr & Sunde (2006a,b) for Germany and Hynninen (2005) for Finland.[1]

In this paper we take a fresh look at the job matching process within local labor markets in Germany. Estimating regional matching functions on NUTS 3 level for the years 2000 to 2010, we provide new evidence on the influence that unemployment and vacancies unfold on job matches within and across regions. In addition, we contribute to the literature in four major respects.

First, we shed light on how the specific definition of a local labor market shapes our estimates of spillover effects. Within most existing studies, local labor markets have been modeled by means of either contiguity or distance matrices.[2] As a key shortcoming, contiguity matrices ignore job search and hiring activities between more distant regions, which can hardly be reconciled with a rising incidence of (long-distance) commuting. In addition, neither contiguity nor distance matrices take into account regional accessibility by means of public

1 In a related literature, the matching function is disaggregated by industry and occupation (see, e.g., Anderson & Burgess, 2000; Stops, 2014).

2 Notable exceptions are Manning & Petrongolo (2011), who allow for labor markets of individual workers to overlap, and Schmutz & Sidibé (2015), who include sectoral dissimilarities between cities as an alternative measure of distance into a structural model.

and private transport or the real incidence of commuting. As a specific form of measurement error, this is likely to lead to biased estimates. Equally important, the lack of a comparative analysis can be regarded as a foregone opportunity to further our understanding of how the way we aggregate single regions into local labor markets influences our estimates of regional spillovers. Drawing on information on past and present infrastructure endowments and on commuter flows between regions, we construct nine different spatial weight matrices. These matrices reflect a broad range of definitions of local labor markets and differ substantially in the importance they assign to unemployment and vacancies in neighboring regions. Using Bayesian posterior model probabilities, we compare the results obtained from these matrices in order to examine whether the size of spillovers depends on how we model spatial dependencies between regions.

Second, we conduct a thorough comparison of the spatial models most commonly used in regional science in order to examine which of them fits the data generating process in regional matching functions best. Doing so, we devote particular attention to the question whether these spillovers are 'local' or 'global' in nature and thereby shed light on the geographical scope of spillovers from unemployment and vacancies. In addition, throughout all models we disentangle the effects of an increasing incidence of commuting on the number of matches from the confounding impact of worker relocation by controlling for local population numbers.

Third, we focus on NUTS 3 regions as the smallest geographical units that can be analyzed with the data currently available. Doing so, we address the problem that the spatial units employed in prior studies are rather large. Each of the 137 labor market regions used by Fahr & Sunde (2006a,b) covers on average an area of about 2,600 square kilometers with a radius of 29 kilometers. This not only stands in contrast to the finding by Manning & Petrongolo (2011) that local labor markets are relatively small. With an average commuting distance of about 17 kilometers, defining local labor markets of this size also severely restricts the insights that can be gained from an analysis of spillover effects from job search and hiring behavior, since most activities by construction take place within regions. NUTS 3 regions cover on average an area of 880 square kilometers, which is equal to 68 percent of the area of an average county in the US. As such, they are about 70 percent smaller than the labor market regions used so far, allowing for a more precise identification of spillover effects.[3]

Finally, specific to the German context, we shed first light on whether the labor market reforms of the early 2000s ('Hartz Reforms') have lived up to the

3 Due to a higher overall population density, the average number of persons living in each county (200,000) is about twice as large as the corresponding number for the US (100,000).

objective of increasing the regional mobility of the unemployed. In order to address this issue we examine whether the number of matches responds more strongly to unemployment in neighboring regions after the implementation of the reforms compared to the period before. While not to be taken as causal, these results provide tentative evidence on whether the reforms have increased the willingness of unemployed to commute longer distances for taking up a job. Our findings can be summarized as follows. First, the Spatial Durbin Error Model turns out as the best-fitting model in the context of regional matching functions. This supports the view that spillovers from unemployment and vacancies on matches are confined to local labor markets. Second, we find robust evidence for the existence of positive spillovers from unemployment, indicating that job seekers extend their job search into neighboring regions. These spillovers amount in size to about 75 percent of the total effect that unemployment has on matches. The effect of vacancies on matches within and across regions is smaller, but also significantly positive. These results are robust to the use of different spatial weight matrices. In fact, more realistic measures for neighborhood relations based on present and past rail and road connections yield largely the same results as physical proximity, which turns out as the most adequate way of modeling spatial interactions in regional matching functions. In line with the argument by LeSage & Pace (2014b), this finding puts the long-standing debate on how to correctly specify spatial weight matrices into perspective. Finally, we find that the size of regional spillovers from unemployment has increased after the Hartz-reforms, suggesting that in line with expectations the reforms have contributed to an increased regional mobility of the unemployed.

The paper is organized as follows. In the next section we derive the different spatial models, that we later test against each other, from matching theory. Section 3 contains a description of the data and provides first evidence on the spatial distribution of matches, unemployment and vacancies in Germany. In Section 4 we first evaluate the performance of the models and compare the results from using different spatial weight matrices. We then conduct different robustness checks and examine how the Hartz-reforms have influenced the matching process within and across regions. Section 5 concludes.

1.2 Empirical Approach

1.2.1 Specification of the Matching Function

In the context of labor markets, matching functions express the job finding process between workers and firms as a relation between hires, unemployment and vacancies

$$M = m(U, V) \tag{1.1}$$

where the number of successful matches M within one period is determined by the stock of unemployed U and the number of vacancies V (Petrongolo & Pissarides, 2001). Specifying m in Cobb-Douglas form yields the matching function

$$M = AU^{\alpha}V^{\beta} \tag{1.2}$$

where A denotes overall matching efficiency, which is constant across time and space. Applied to the level of regions $r = 1, \ldots, R$ and augmented by a time dimension $t = 1, \ldots, T$, equation (1.2) can be transformed into the regional matching function

$$M_{rt} = AU_{rt}^{\alpha}V_{rt}^{\beta} \tag{1.3}$$

As a structural difference to the national level, where only a small share of workers commutes across country borders, job search and hiring behavior on regional level are not confined to single spatial units.[4] As a result, the regional number of hires is likely to not only depend on unemployment and vacancies within regions, but also on unemployment and vacancies in neighboring regions. We account for this interrelation by defining the effective stock of unemployed U_{rt} as the product of the number of unemployment in region r, u_{rt}, and the number of unemployed in all other regions j. The latter is discounted by a time-invariant measure of the distance between j and r, denoted as w_{rj} with $w_{rj} \in [0,1]$ and $w_{rj} = w_{jr}$.

$$U_{rt} := u_{rt} \cdot \prod_{\substack{j=1 \\ j \neq r}}^{R} u_{jt}^{w_{rj}} = \prod_{j=1}^{R} u_{jt}^{w_{rj}},\ w_{rr} = 1 \tag{1.4}$$

Analogously, the effective number of regional vacancies is defined as

$$V_{rt} := \prod_{j=1}^{R} v_{jt}^{w_{rj}},\ w_{rr} = 1 \tag{1.5}$$

Writing equation (1.3) in logs and inserting (1.4) and (1.5) into (1.3) yields

$$\begin{aligned} \log(M_{rt}) &= \log(A) + \alpha\log\Big(\prod_{j=1}^{R} u_{jt}^{w_{rj}}\Big) + \beta\log\Big(\prod_{j=1}^{R} v_{jt}^{w_{rj}}\Big) \\ &= \log(A) + \alpha\sum_{j=1}^{R} w_{rj}\log(u_{jt}) + \beta\sum_{j=1}^{R} w_{rj}\log(v_{jt})) \end{aligned} \tag{1.6}$$

4 Only 0.07 percent of German workers, who have their permanent place of residence in Germany, commute across country borders to work. 0.18 percent of the workforce in Germany consists of workers who commute into the country while having their permanent place of residence abroad (European Parliament, 2014).

Equation (1.6) can be expressed in matrix form for each period t as

$$\mathbf{m}_t = \mathbf{a} + \alpha \mathrm{W}\mathbf{u}_t + \beta \mathrm{W}\mathbf{v}_t, \tag{1.7}$$

where

$$\mathbf{m}_t = \begin{pmatrix} \log(M_{1t}) \\ \vdots \\ \log(M_{Rt}) \end{pmatrix}, \mathbf{a} = \begin{pmatrix} \log(A) \\ \vdots \\ \log(A) \end{pmatrix}, \mathbf{u}_t = \begin{pmatrix} \log(u_{1t}) \\ \vdots \\ \log(u_{Rt}) \end{pmatrix} \text{ and } \mathbf{v}_t = \begin{pmatrix} \log(v_{1t}) \\ \vdots \\ \log(v_{Rt}) \end{pmatrix}.$$

The symmetric matrix W is defined as $\mathrm{W} = (w_{rj})_{\substack{j=1,\dots,R \\ r=1,\dots,R}}$. Entries on the main diagonal are equal to one, i.e, unemployment and vacancies within region r are assigned full weight. All other weights are constructed from exogenous and ex-ante defined measures of the distance between regions r and j, which accounts for the idea that the costs of job search and recruitment rise with distance. In order to disentangle the influence that unemployment and vacancies unfold within and across regions, we split up W into its main-diagonal elements and the elements outside the main diagonal. As a result, unemployment and vacancies within the same region as M_{rt} are multiplied by the unity matrix $\mathbf{I}$, while unemployment and vacancies in neighboring regions are discounted by a modified spatial weight matrix $\mathrm{W}^m = \mathrm{W} - \mathbf{I}$, where elements on the main diagonal are set to zero.

$$\begin{aligned} \mathbf{m}_t &= \mathbf{a} + \alpha_1 \mathbf{I}\mathbf{u}_t + \beta_1 \mathbf{I}\mathbf{v}_t + \alpha_2 \mathrm{W}^m \mathbf{u}_t + \beta_2 \mathrm{W}^m \mathbf{v}_t \\ &= \mathbf{a} + \alpha_1 \mathbf{u}_t + \beta_1 \mathbf{v}_t + \alpha_2 \mathrm{W}^m \mathbf{u}_t + \beta_2 \mathrm{W}^m \mathbf{v}_t \end{aligned} \tag{1.8}$$

By stacking the vectors $\mathbf{m}_t$, $\mathbf{a}$, $\mathbf{u}_t$ and $\mathbf{v}_t$ and defining $\mathrm{W}^\bullet = \mathbf{I}_T \otimes \mathrm{W}^m$, where $\otimes$ denotes the Kronecker product, and by adding an error term ε we can derive the empirical model

$$\mathbf{m} = \mathbf{a}^\bullet + \alpha_1 \mathbf{u} + \beta_1 \mathbf{v} + \alpha_2 \mathrm{W}^\bullet \mathbf{u} + \beta_2 \mathrm{W}^\bullet \mathbf{v} + \varepsilon \tag{1.9}$$

In this specification, α_1 and β_1 identify the influence that unemployment and vacancies in region r have on the number of matches M_{rt}. α_2 and β_2 yield the impact that unemployment and vacancies in neighboring regions have on M_{rt}. In line with existing evidence on matching functions, we expect to find a positive effect of local unemployment (α_1) and vacancies (β_1) on the number of matches. Similarly, the number of unemployed persons in neighboring regions (α_2) should raise the number of matches in r, since a larger labor supply increases the chances of a successful match. The number of vacancies in neighboring regions (β_2) should, in contrast, reduce matches in r as the probability of starting a job in a neighboring region rises with the number of job opportunities there (Burda & Profit, 1996).

Lottmann (2012) shows that the number of matches rises with the degree of agglomeration. In order to account for this, we include the logarithm of the regional population aged between 15 and 65, $\mathbf{x}_t = (\log X_{1t}, ..., \log X_{Rt})'$, and its spatial lag as control variables. Important in the present context, by including population numbers we also effectively rule out confounding effects from workers migrating to regions with better employment prospects. In addition, we control for unobserved heterogeneity across units by means of region fixed effects φ. Time fixed effects ϕ account for time-variant influences that affect all units to the same extent like, e.g., changes in labor market legislation.[5]

$$\mathbf{m} = \mathbf{a}^{\bullet} + \alpha_1\mathbf{u} + \beta_1\mathbf{v} + \gamma_1\mathbf{x} + \alpha_2\mathrm{W}^{\bullet}\mathbf{u} + \beta_2\mathrm{W}^{\bullet}\mathbf{v} + \gamma_2\mathrm{W}^{\bullet}\mathbf{x} + \phi + \varphi + \varepsilon \tag{1.10}$$

Equation (1.10) is usually referred to as SLX model (Elhorst, 2013; Halleck Vega & Elhorst, 2015). It was first applied by Baltagi & Levin (1992) and has become the workhorse model in the literature on spillovers in regional matching functions. As its defining feature, it contains spatial lags of the exogenous variables on the right-hand side. Conveniently, the coefficients in the SLX model can be interpreted as marginal direct (α_1, β_1) and indirect (α_2, β_2) effects.

The SLX model does, however, not account for potential spatial autocorrelation of the dependent variable or the error terms (Elhorst, 2010, 2014; LeSage & Pace, 2014a). In the presence of either, the SLX model will lead to biased or inefficient estimates of the direct and indirect effects (Gibbons *et al.*, 2015). Given such spatial autocorrelation, according to LeSage (2014a, p. 127), the 'only two *logically viable* specifications to select from [are] the SDM [Spatial Durbin Model] or SDEM [Spatial Durbin Error Model], with the SDM reflecting global spillovers and the SDEM local spillovers'.[6]

Augmenting the SLX model by a spatial lag of the dependent variable yields the SDM contained in equation (1.11). Alternatively, adding a spatial lag of the error term, $\mathrm{W}^{\bullet}\mathbf{u}$, provides the SDEM in equation (1.12).

$$\begin{aligned}\mathbf{m} = \rho\mathrm{W}^{\bullet}\mathbf{m} + \mathbf{a}^{\bullet} + \alpha_1\mathbf{u} + \beta_1\mathbf{v} + \gamma_1\mathbf{x} + \alpha_2\mathrm{W}^{\bullet}\mathbf{u} + \beta_2\mathrm{W}^{\bullet}\mathbf{v} + \gamma_2\mathrm{W}^{\bullet}\mathbf{x} + \phi + \varphi + \varepsilon,\\ \varepsilon \sim N(0, \sigma_\varepsilon^2\mathrm{I}_{RT})\end{aligned} \tag{1.11}$$

5 Note that in the empirical approach in Section 4, the logged overall matching efficiency ***log(A)*** is identified through the coefficient of the constant, which is defined as the average of all time and region fixed effects. Consequently, region and time fixed effects identify region- and time-specific deviations from this average.

6 The reason why only the SDM and the SDEM need to be considered is that they nest the spatial autoregressive model (SAR), the SLX model, and spatial error model (SEM) as the most relevant competing models.

As touched upon by LeSage (2014a), the defining difference regarding the suitability of either model lies in the stance we take on the nature of the spillovers. In the SDM, spillovers are 'global' in nature because a change in one exogenous variable in one region r is transmitted endogenously to all other regions by means of the spatially lagged endogenous regressor $\mathbf{W}^{\bullet}\mathbf{m}$. Translated to the context of matching functions, this implies that shocks in regional unemployment and vacancies may extend beyond the borders of local labor markets through the effect that matches in r indirectly have on matches in all other regions. The SDEM is, in turn, consistent with the notion of 'local' spillovers, where changes in the exogenous variables only affect the outcome in those neighboring regions that have a non-zero entry in the spatial weight matrix $\mathbf{W}$. Hence, the SDEM assumes the effect of unemployment and vacancies on matches to be confined to local labor markets, which are defined as clusters of regions that are connected to each other through positive entries in the spatial weight matrix.

Another difference between the two models, which is relevant for the interpretation of the results, is that while coefficients in the SDEM can be interpreted as marginal direct and indirect effects, this is not the case for the SDM (Anselin & Le Gallo (2006); Kelejian *et al.* (2006); see Elhorst (2014, p. 395–396) on how to calculate the size of direct and indirect effects in the SDM).

$$\begin{aligned}\mathbf{m} &= \mathbf{a}^{\bullet} + \alpha_1\mathbf{u} + \beta_1\mathbf{v} + \gamma_1\mathbf{x} + \alpha_2\mathrm{W}^{\bullet}\mathbf{u} + \beta_2\mathrm{W}^{\bullet}\mathbf{v} + \gamma_2\mathrm{W}^{\bullet}\mathbf{x} + \phi + \varphi + \varepsilon,\\ \varepsilon &= \lambda\mathrm{W}^{\bullet}\varepsilon + \varepsilon,\\ \varepsilon &\sim N(0,\ \sigma_{\varepsilon}^2\mathrm{I}_{RT})\end{aligned} \tag{1.12}$$

On theoretical grounds it seems that the SDEM suits the context of regional matching functions better than the SDM because commuting distances of job seekers are limited and, hence, spillovers should be confined to local labor markets. In Section 4, we apply a Bayesian approach to comparing static panel data models (LeSage, 2014b) in order to empirically examine which model fits the data generating process in spatial matching functions best.

1.2.2 Specification of the Spatial Weight Matrix

One key objective of this paper is to examine whether and to which extent the size of the direct and indirect effects hinges on the definition of the spatial weight matrix W. To shed light on this question, we construct nine different spatial weight matrices, which are summarized in Table 1.2.1.

The first category contains exogenous distance-based weight matrices, which provide the most common approach in the literature to model the proximity of regions. $W_{contig.}$ is a contiguity matrix based on the binary definition of sharing a common border ($w_{AB} = 1$ if sharing a common border, $w_{AB} = 0$ if not). The appeal of a border-based definition lies in its simplicity and, more importantly, in the exogeneity of unit contiguity. On the downside, both labor and product markets are in many respects prone to be interlinked in more complex ways than through sharing a common border. This in particular applies to the German labor market, where one out of four job matches are realized in regions which are not in direct vicinity of a worker's region of residence (own calculation based on individual-level data). The idea of a more realistic continuous spatial decay is captured by the inverse of the geographical distance between each pair of counties, $W_{dist.}$ with $w_{AB} = 1/d_{AB}$. As does the contiguity matrix, this measure exhibits the desirable property of exogeneity. Both measures have been widely used to define spatial weight matrices in different contexts. We use them as a baseline when estimating the size of direct and indirect effects in the matching function.

The second category draws on the idea put forth by Lottmann (2012) that commuting relations provide a more realistic approximation of the extent to which regional labor markets are integrated. Based on this notion, we use the average number of commuters between each pair of regions for all years between 2000 and 2010 as a measure for the degree to which regional labor markets are interconnected. As in Lottmann (2012), we construct a binary index which equals 1 if the ratio between in-commuters and residents (δ) exceeds a threshold of 0.005 and is zero otherwise. While this measure captures the degree of labor market interaction in a more realistic way, the resulting matrix is clearly endogenous as commuting intensity is itself a function of the number of regional matches.

Infrastructure-based weights provide an alternative approach to modeling local labor markets. Taking into account the real accessibility of regions might capture existing local labor markets more adequately than contiguity and physical distance. In fact, a highway or a direct train connection between two regions positively influences the degree of commuting even if regions are not direct neighbors (Baum-Snow, 2007; Heuermann & Schmieder, 2013b). Based on this notion, the third category contains three different infrastructure-based weight matrices. With a share of about 70 percent of workers commuting by car, individual motorized transportation is by far the most important mode of transportation (Hütter, 2013). We therefore employ the inverse of driving distance $W_{car(dist.)}$ and of driving time $W_{car(time)}$ by car between each pair of regions in 2014 as two alternative measures. In contrast, in 2012 only 4.6 percent of commuters used the train for their way to work. Although small in aggregate, this share varies substantially between locations, ranging from virtually zero percent in rural regions to well above thirty percent in highly agglomerated areas. Hence, especially in dense employment clusters the speed of train services should influence the extent to which counties integrate into one local labor market. Accounting for this, we use the inverted average travel time of the fastest train connection between each pair of regions from 2000 to 2010, $W_{train(time)}$, as a further alternative for the spatial weights.

Table 1.2.1: Alternative Definitions of the Spatial Weight Matrix

	Distance-Based
(1) $W_{contig.}$	contiguity, defined as sharing a common border
(2) $W_{dist.}$	geographic distance between counties
	Commuter-Based
(3) $W_{com.}$	average number of commuters, 2000–2010 *(binary)*
	Infrastructure-Based, Present
(4) $W_{car\,(dist.)}$	driving distance by car in 2014
(5) $W_{car\,(time)}$	driving time by car in 2014
(6) $W_{train\,(time)}$	average duration of fastest train connection, 2000–2010
	Infrastructure-Based, Historic
(7) $W_{car\,(dist.1957)}$	driving distance by car in 1957
(8) $W_{car\,(time1957)}$	driving time by car in 1957
(9) $W_{train\,(time1994)}$	duration of fastest train connection in 1994

Similar to commuter relations, measures based on present infrastructure endowments potentially bear the problem of endogeneity because investments in roads and tracks might to some extent be influenced by labor market considerations. With the papers by Duranton & Turner (2012) and Duranton *et al.* (2014) using lagged values of infrastructure has become a standard way to address this issue. The key idea is that historic infrastructure endowments are good predictors of present-day infrastructure while they are at the same time not determined by present labor market dynamics. Following this idea, we use information on historic infrastructure endowments. Theoretically, this information could be used to implement a two-stage procedure, where present infrastructure endowments are instrumented by past ones. Since we are, however, interested in a direct comparison of the results obtained from different spatial weight matrices, we estimate the spatial models with the lagged spatial weights, which is effectively the reduced form of the two-stage IV-estimator.

With respect to driving times and distances, the earliest available information dates back to 1957. At this time, the structure of the road system was still largely a result of military considerations in the run-up to the Second World War, when most highways were constructed, and of a very different economic environment. For instance, most parts of Bavaria were still dominated by agriculture, while the Rhine-Ruhr area was characterized by mining and steel industry. The economic structure of both regions has changed dramatically during the last sixty years with the Rhine-Ruhr area today being shaped by the service sector and Bavaria having become an industrial powerhouse. As a result, present labor market dynamics are unlikely to have influenced driving time and distance in the 1957 road system. Rows (7) and (8) therefore contain past driving distances and times as exogenous weights. With respect to travel times by train, the data only goes back to 1994. However, the period between the early 1990s and the year 2000 saw a massive expansion of the high speed rail system, which has reduced average travel times in Germany by ten percent. During the same period, the share of connections that entail the use of a high-speed train on at least one leg of the journey has doubled (Heuermann & Schmieder, 2013b). Making use of this transformation in rail transportation, we define $W_{train(time1994)}$ as the inverse of the fastest travel time by train in 1994.

When configuring the spatial weight matrices, we need to take a stand on what we mean by *local*. We define a local labor market in two ways. First, in contrast to earlier research, which has taken the centroid of each county as anchor point, we draw on precise geo-coordinates and define the location of the main train station within each county as the center of a local labor market. The advantage of this approach is that the main train station approximates the center of economic activities within each county much better than does the geographical center. This in particular applies to rural regions, where centroids often coincide with areas of farmland and woods (a map where we have plotted the respective locations of centroids and train stations for reasons of comparison is available upon request). Having set the center of a local labor market, we need to define its outer borders. This is necessary because the 'use of a distance-based weight matrix (without a cut-off that produces sparseness) blurs the distinction between local and global spillovers' (LeSage, 2014b, p. 28). We therefore truncate the spatial weight matrices at 90 minutes for commuting time by car and train, and at 100 kilometers for both geographic and driving distance. Beyond these thresholds entries in W are set to zero. With an average commuting distance of 17 kilometers in Germany, these settings can be interpreted as upper bounds. In the robustness section we examine whether changes in these restrictions influence the results. In the next section we describe the data in more detail and provide descriptive evidence on how the size of local labor markets varies with the definition of the spatial weights.

1.3 Data and Descriptives

1.3.1 Data

The analysis is based on annual data on county (NUTS 3) level in Germany for the years 2000 to 2010. Excluding counties with missing information provides a balanced panel of 352 counties (see Figure 1.3.1).[7] In total, the panel data set includes 3,872 observations for a period of eleven years.

As our key outcome variable, we construct the average monthly number of matches within each year and region from individual employment history data (see also Fahr & Sunde, 2006a,b). We draw on a 20 percent random sample from the German social security records (Integrated Employment Biographies (IEB)) provided by the Institute for Employment Research, which contains daily information on the employment status of each person (vom Berge *et al.*, 2013). In line with the tradition of papers on matching functions (see Pissarides (1986), Layard *et al.* (2005), and Shimer (2005) among others), we define the number of matches M as the regional aggregate outflow from unemployment into employment. In the individual-level data, this is indicated by a change in a worker's job status from unemployed to employed. Using daily information on individual employment status has two advantages. First, we avoid the problem of measurement error arising with (e.g., monthly) point-in-time data if matches are reversed within one period.[8] Second, the data allows to differentiate between hires of unemployed within their home county M_h and cross-border hires M_{nh}. We use the average monthly number of matches rather than annual sums in order to avoid the problem of time aggregation bias, which arises when regressing flow variables on stock variables. As argued by Petrongolo & Pissarides (2001, p. 422), 'the bias is not important whenever the data frequency is monthly or higher and the cycle frequency is yearly or higher' (see also Burdett *et al.*, 1994). By taking yearly averages of monthly values we effectively eliminate seasonality in the data. This allows us to explicitly focus on the spatial dimension in the matching function without having to consider confounding effects from seasonality and from within-year time lags between matches, unemployment and vacancies.

Information on the stock of registered unemployed u_{rt} and the number of vacancies v_{rt} within each county are taken from the Statistics of the Federal

7 Some cities are for historical reasons split up into a core city and the surrounding hinterland. In these cases, both counties together effectively constitute the overall city area and are served by the same main train station. This applies to 31 cities, out of which 17 are located in Bavaria (e.g., Munich, Wuerzburg, and Regensburg among others). In order to avoid bias from what is effectively a problem of measurement error, we have merged the two counties by adding up the respective numbers of matches, unemployed, and vacancies.

8 Nordmeier (2014) shows for the German case that the number of matches is underestimated by about ten percent when using monthly point-in-time data because employment contracts that are closed and dissolved within one month are not counted.

Employment Agency (2014). Both variables are provided as monthly total sums, i.e., as the sum of all persons that are registered as unemployed for at least one day in the respective month, and of all vacancies that are posted for at least one day. In order to avoid double counting, we define u_{rt} and v_{rt} as the average number of unemployed and vacancies per month within one year, rather than as annual sums.[9]

Since registration as unemployed is obligatory for receiving unemployment assistance, the data on regional unemployment cover all unemployed persons and are highly reliable. The data on vacancies in turn encompass all cases reported to the Local Employment Agency. As firms in Germany are not obliged to report open positions to the Federal Employment Agency, the data cover only around 43 percent of all vacant jobs in Germany.[10] Bias from measurement error might arise if regional differences in reporting behavior exist. In particular, the estimates are likely to be downward biased if the share of reported vacancies falls with the local intensity of informal hiring, which is likely to be the case. It would therefore be preferable to correct for such differences by means of information from alternative data sources. Unfortunately, even the most comprehensive data set reporting the number of vacancies on firm-level, the survey based *IAB-Erhebung des gesamtwirtschaftlichen Stellenangebots* (Kettner *et al.*, 2011), cannot be used on county level for lack of representativeness due to small sample size. To the best of our knowledge, no other data source exists on this level of regional disaggregation. As a result, virtually all existing studies employ the same data set on vacancies that we use here. As in all other papers, the results on vacancies should therefore be interpreted with some caution.

Information on county population is provided on annual basis by the Federal Institute for Research on Building, Urban Affairs and Spatial Development.

We have calculated the spatial weight matrices for contiguity, geographic distance, and historic driving times and distances using GIS software. The layer files for contiguity and geographic distance are taken from the Federal Agency for Cartography and Geodesy (BKG). Stelder *et al.* (2013) provide detailed GIS data for the highway and secondary road system in Europe for the year 1957. Present driving times and distances for road traffic are calculated using OpenStreetMap data (see Huber & Rust, 2016). With respect to passenger rail connections, we use annual information on travel times between all county pairs from 1994 to 2011 provided by Heuermann & Schmieder (2013a). The number of commuters between counties are obtained from the Statistics of the Federal Employment Agency (2014).

9 In this data set we cannot identify unemployed persons or vacancies individually. Annual sums would therefore be grossly inflated since all unemployed and vacancies being registered/posted for more than one month would be counted multiple times a year.

10 This is partly due to the fact that a large share of open positions are filled through informal hiring networks (see Casper & Murray (2005) for Germany and Ioannides & Datcher Loury (2004) for a survey of the literature).

1.3.2 Descriptive Evidence on Local Labor Markets

Table 1.3.1 contains summary statistics of the data. The upper part of the table summarizes the average monthly number of matches, unemployed and vacancies within German NUTS 3 regions. The lower part provides a first impression of how the size of a local labor market varies with the definition of the spatial weight matrix.

In each of the 352 counties, we observe on average 205 matches out of unemployment per month. Since we are drawing on a twenty percent random sample, this amounts to about 361,000 matches per month for the full population. 10,934 persons were on average registered as unemployed for at least one day in each county per month. Hence, 3.85 million persons were on average unemployed on national level in each month of the sample period. The average monthly number of registered vacancies in each county amounted to 921, yielding an average of about 324,000 vacancies per month on national level. Regarding population numbers, the fourth row shows that 151,181 persons between the age of 15 and 65 were on average living in each region during the sample period.

Table 1.3.1: Descriptive Statistics

Variable	Mean	SD	Min.	Max.
Matches	205	219	27	3,804
Unemployed	10,934	17,084	839	319,177
Vacancies	921	1,327	38	23,373
Population	151,181	171,191	21,972	2,435,508
Weight Matrix	**Neighbors within LLM**		**Mean of Non-Inverted W**	**Data Source**
	Mean	**SD**		
$W_{contig.}$	4.95	1.96	–	BKG 2013
$W_{dist.}$	28.92	10.23	64.71	BKG 2013
$W_{com.}$	6.90	2.35	–	FEA 2014
$W_{car\,(dist.)}$	16.68	7.63	65.72	OpenStreetMap
$W_{car\,(time)}$	29.58	12.14	62.56	OpenStreetMap
$W_{train\,(time)}$	15.06	9.64	59.08	H&S 2013
$W_{car\,(dist.1957)}$	16.93	8.96	65.74	Stelder *et al.* (2013)
$W_{car\,(time1957)}$	16.41	9.15	62.43	Stelder *et al.* (2013)
$W_{train\,(time1994)}$	14.17	9.26	58.77	H&S 2013

Notes: 'Population' refers to the number of persons per county between the age of 15 and 65. Commuting distances are truncated at 100 kilometers, commuting times at 90 minutes of a one-way commute, and commuter numbers at a value for δ of 0.005. Diagonal elements, which are all set to zero as a region cannot be its own neighbor, are not included in the calculations. The number of neighbors within a local labor market (LLM) is calculated as the average number of non-zero entries in the rows of each W. The mean of each non-inverted W is the mean of all non-zero entries.

The bottom part of the table provides evidence on how the size of local labor markets varies with the definition of the spatial weight matrix. On average, each county is surrounded by five direct neighbors ($W_{contig.}$). About 29 counties are located within a radius of 100 kilometers ($W_{dist.}$) from each region. Each county is connected on average to 7 other counties by means of commuter flows ($W_{com.}$). About 17 counties could be reached by car within 100 kilometers in both 1957 and 2014 ($W_{car(dist.)}$ and $W_{car(dist.1957)}$), indicating that investments in road infrastructure have left driving distances between counties virtually unaltered. Better roads have, however, dramatically reduced driving times. In 1957, 16 counties could on average be reached within a driving time of 90 minutes ($W_{car(time1957)}$). Until 2014, this number has nearly doubled to about 30 counties ($W_{car(time)}$). Reductions in travel time as a result of investments in rail infrastructure have – in the admittedly much shorter time period – been less pronounced. While 14 counties could on average be reached within a travel time of 90 minutes in 1994 ($W_{train(time1994)}$), this number has risen to 15 in 2010 ($W_{train(time)}$).

The comparison shows that the infrastructure-based matrices are remarkably similar in terms of their stability across time and regarding the size of the local labor market they define. As for the former, the correlation between past and present driving distances by car amounts to 0.987, between past and present driving time by car to 0.966, and between past and present travel times by train to 0.967. With the exception of present travel time by car, which yields substantially larger local labor markets, the infrastructure based-matrices all contain between 14 and 17 counties within a distance of 100 kilometers or 90 minutes of travel time. In Figure 1.3.1, we have plotted all major roads and railway tracks in order to check whether such homogeneity is plausible. The fact that most major roads and railway tracks connecting the county capitals run surprisingly parallel to each other is congruent with the relative homogeneity of the infrastructure-based matrices.

The third column contains average commuting time (in minutes) and average commuting distance (in kilometers) within the local labor markets defined by the different spatial weight matrices. Due to the truncation at 90 minutes and 100 kilometers, the infrastructure-based matrices are similar with respect to average commuting time and distance. Hence, the main source of variation across the nine matrices stems from the number of counties within one local labor market. This is of key importance for identification since the number of neighboring regions that potentially influence matches in r varies with the number of non-zero entries in each of the spatial weight matrices.[11]

11 Note that the local labor markets defined by the different W are similar in terms of their sociodemographic characteristics. The average share of persons below the age of 25 in the total population across all matrices is 25.60 percent (max: 25.79 ($W_{contig.}$), min: 25.24 ($W_{com.}$)); share of persons above the age of 50: 37.73 percent (max: 37.96 ($W_{car(time1957)}$), min: 37.39 ($W_{com.}$)); share of women: 51.11 percent (max: 51.17 ($W_{com.}$), min: 51.05 ($W_{contig.}$)); share of highly qualified workers in the workforce: 6.71 percent (max: 7.10 ($W_{com.}$), min: 6.55 ($W_{contig.}$)); share of workers without vocational training: 10.51 percent (max: 10.92 ($W_{contig.}$), min: 9.81 ($W_{com.}$)). This similarity makes it unlikely that the later findings are driven by systematic differences in the composition of the workforce within local labor markets. The number of unemployed varies, in contrast, substantially between the different definitions of local labor markets (average number: 25.554 persons (max: 30.794 ($W_{contig.}$), min: 21.907 ($W_{dist.}$))).

Figure 1.3.1: Counties and Transportation Network in Germany

Notes: The figure contains all major roads and railway tracks for the year 2012. Black dots represent county capitals. Grey solid lines are major roads, black dotted lines are major railroads. The shape files used in the figure are provided by the Federal Agency for Cartography and Geodesy (BKG), Stelder *et al.* (2013) and the Environmental Systems Research Institute, Inc. (2015).

In Figure 1.3.2, we have plotted the regional distribution of the shares of matches from resident (M_h) and non-resident (M_{nh}) job seekers. The two maps yield first insight into patterns of spatial autocorrelation as well as into the relative size of direct and indirect effects within local labor markets. The first map displays the regional share of matches from resident unemployed in 2010. The second map contains the share of matches from incommuters.[12] Overall, 54 percent of job matches are realized within an unemployed person's county of residence, while 21 percent are achieved in directly neighboring regions. The remaining 25 percent are located in non-neighboring regions. The maps show that these shares vary substantially across space. The maximum share achieved by resident unemployed amounts to 81 percent (Berlin), the minimum to 20 percent (Ludwigshafen). In one fifth of German regions, more than 64 percent of unemployed persons taking up a job are in-commuters. This number discards the notion that NUTS 3 regions are selfcontained labor markets and instead strongly speaks in favor of the existence of spillover effects from unemployment. This in turn emphasizes the need to aggregate regions into larger local labor markets by means of spatial weight matrices. When adding the direct neighbors to each county by means of $W_{contig.}$, the share of workers employed outside this larger local labor market falls to 25 percent. When defining all counties located within a radius of 100 kilometers as belonging to one local labor market, as in $W_{dist.}$, only 17 percent of workers turn out to be employed outside this area.[13]

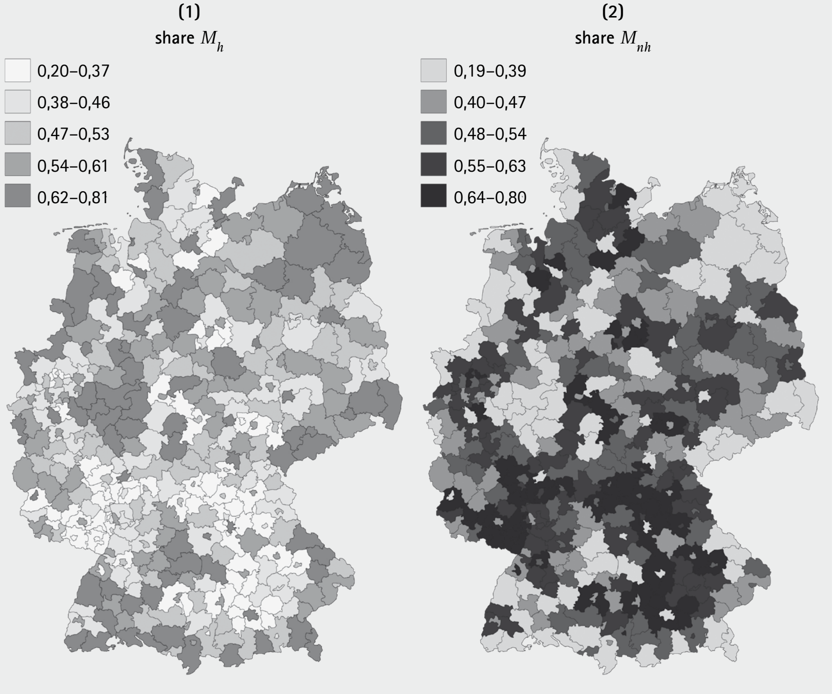
With respect to the spatial distribution, the two maps at first glance suggest a north-south divide with counties in the south being characterized by a larger share of in-commuters. A closer look reveals, however, that cross-border commuting is strongest within dense employment clusters like, e.g., the Munich area, the Rhine-Main area and the Ruhr area. Remote areas in the North-West and even more so in East Germany are, in contrast, shaped by high shares of unemployed persons finding work in their home region. Importantly, within labor market clusters it is not the case that unemployed persons more than proportionally commute into core cities for taking up a job. In fact, especially counties surrounding large cities exhibit high shares of in-commuters. Hence, in line with Moretti's (2011) notion of thick labor markets it seems that the density of economic activity within these clusters enables unemployed persons to look for jobs in neighboring regions independent on whether they live in the core city or not. This type of integration of local labor markets in turn emphasizes the potential role of infrastructure-based weights when trying to realistically model the relative distance between regions in regional matching functions.

12 In the interest of saving space, we provide a map only for the year 2010. The descriptive results are similar for all previous years.

13 The corresponding values for the other spatial weight matrices are 22 percent ($W_{com.}$), 19 percent ($W_{car\,(dist.)}$), 17 percent ($W_{car\,(time)}$), 21 percent ($W_{train\,(time)}$), 36 percent ($W_{car\,(dist.1957)}$), 35 percent ($W_{car\,(time1957)}$), and 22 percent ($W_{train\,(time1994)}$).

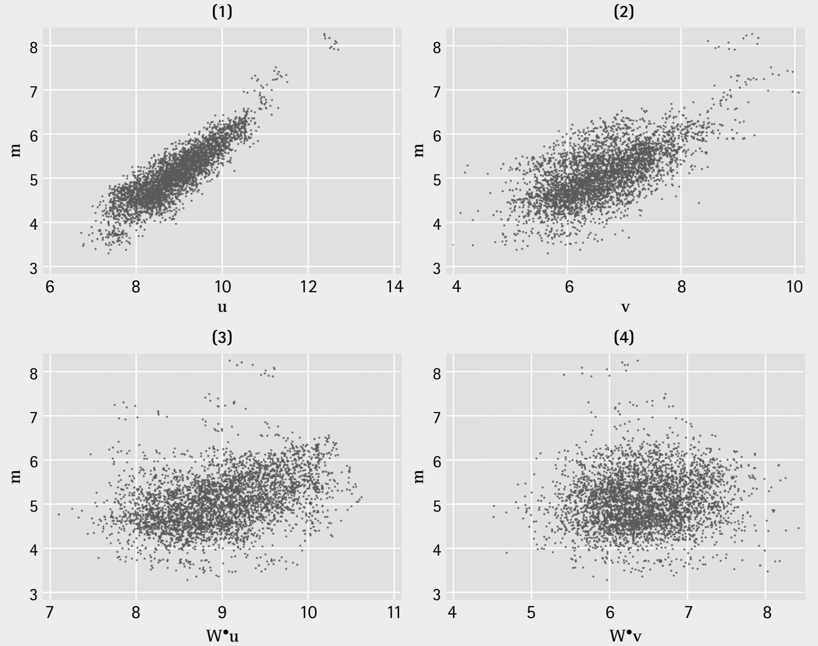
In Figure 1.3.3, we plot the number of matches against regional unemployment, vacancies, and their respective spatial lags in order to shed additional light on the relative importance of direct and indirect effects. Across the four plots, matches and regional unemployment exhibit the closest correlation (corr: .84). The relationship between matches and local vacancies is less pronounced (corr: .66) but in line with existing evidence still strongly positive. In line with the pattern found in Maps 1 and 2, local matches are positively correlated with the unemployment rate in neighboring counties (corr: .61), suggesting that unemployed persons also look for jobs in neighboring regions. In contrast, the correlation between matches and neighboring vacancies is much weaker (corr: .44). In addition, while the sign of the correlation between matches and unemployment, vacancies, and neighboring vacancies is in line with theoretical considerations, the positive correlation between matches and neighboring vacancies is surprising as it indicates that unconditional on further covariates the number of matches within a region rises with a higher labor demand in neighboring regions. We address this issue in more detail in the regression analysis in the next section.

Figure 1.3.2: Regional Distribution of Matches in 2010



Notes: Map 1 contains the percentage share of M_h over the total number of matches of unemployed (in quintiles). Map 2 is the mirror image, containing the percentage share of M_{nh} over the total number of matches of unemployed (also in quintiles).

Figure 1.3.3: Matches, Unemployment and Vacancies



Notes: Plots based on pooled data for 2000 to 2010; spatial lags based on contiguity matrix $W_{contig.}$

1.4 Results

We begin by estimating a non-spatial model, which we gradually extend to the SLX model, the SDM, and the SDEM. We conduct model comparison tests in order to examine which of the models is best suited to describe the data generating process in the context of regional matching functions.

The first two columns in Table 1.4.1 provide the results from estimating a non-spatial regional matching function. Column (1) contains the results from the model without any controls. Consistent with the existing literature, the number of matches rises significantly with both the number of unemployed and vacancies. The size of the coefficients is in line with results from similar specifications in Lottmann (2012), Klinger & Rothe (2012), Fahr & Sunde (2004), and Stops & Mazzoni (2010). The likelihood ratio test speaks strongly in favor of including time and region fixed effects.[14] When adding regional population numbers as well as region and time fixed effects in column (2), the coefficient of unemployment

14 LR-test: (i) H_0: 'No region fixed effects', 8,135.58, df = 352, p = 0.000; (ii) H_0: 'No time fixed effects', 2,792.87, df = 11, p = 0.000

decreases to 0.305 but remains significant. This result is close to Fahr & Sunde (2006b). The coefficient of vacancies decreases to 0.018 and also remains significant. In line with expectations, the number of matches within regions rises with the degree of agglomeration.

Table 1.4.1: Model Comparison

	Dependent Variable: m				
	non-spatial		SLX	SDM	SDEM
Coefficient	(1)	(2)	(3)	(4)	(5)
$\alpha_{1\mathbf{u}}$	0.572***	0.305***	0.150***	0.126***	0.157***
	(87.130)	(20.605)	(7.296)	(6.547)	(8.691)
$\beta_{1\mathbf{v}}$	0.167***	0.018**	0.017**	0.013*	0.015**
	(26.235)	(3.148)	(2.844)	(2.290)	(2.713)
$\gamma_{1\mathbf{x}}$		1.580***	1.365***	1.289***	1.265***
		(28.293)	(15.656)	(15.809)	(16.344)
$\alpha_{2\mathbf{W}\bullet\mathbf{u}}$			0.271***	0.099***	0.210***
			(10.212)	(3.890)	(7.337)
$\beta_{2\mathbf{W}\bullet\mathbf{v}}$			0.016	0.010	0.020
			(1.607)	(1.106)	(1.846)
$\gamma_{2\mathbf{W}\bullet\mathbf{x}}$			0.129	-0.480***	0.370**
			(1.175)	(-4.509)	(3.077)
$\rho_{\mathbf{W}\bullet\mathbf{m}}$				0.468***	
				(25.644)	
$\lambda_{\mathbf{W}\bullet\varepsilon}$					0.464***
					(25.244)
FE(region&time)	N	Y	Y	Y	Y
Log-Likelihood	-422.78	4373.90	4436.80	4751.50	4751.10
Bayesian post. prob.				0.0862	0.9138

Notes: N = 3,872; t-statistic in parentheses; W is defined as $W_{contig.}$; constant not reported; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In column (3) we extend the model by including spatially lagged independent variables based on the contiguity matrix frequently used in the literature.[15]

Columns (4) and (5) contain the SDM and the SDEM. We first examine which model most adequately captures spatial dependencies in regional matching functions before discussing the results of the best-fitting model in depth. The high significance level of the coefficients on both the spatially lagged dependent

15 For the regression analysis the spatial weight matrices are row-normalized throughout all models. Results obtained for eigenvalue-normalized matrices and a discussion thereof are contained in the Appendix.

variable (ρ in the SDM) and on the spatially lagged error term (λ in the SDEM) casts doubt on the suitability of the SLX model. As the SLX model is nested in both the SDM and the SDEM, we compare it to both models by means of the Log-Likelihood. The result contained in the lower part of the table shows that the Log-Likelihoods of both the SDM and the SDEM supersede that of the SLX model, discarding the latter as a relevant alternative.[16] As the SDM and SDEM are not nested in each other, we draw on the Bayesian comparison approach for static panel models proposes by LeSage (2014a).[17] With a value of 0.9138, the Bayesian posterior model probability clearly speaks in favor of the SDEM.[18]

The estimates from the SDEM suggest an elasticity between matches and local unemployment of 0.157. The spatial lag of unemployment enters with a highly significant coefficient of 0.210, lending support to the notion that unemployment affects the number of matches not only within but also across regions. With a value of 0.015, the direct effect of vacancies is substantially smaller. As indicated by the insignificance of β_2, there is no evidence for the existence of spillovers from vacancies. In line with the urban economics literature (see, e.g., Duranton & Puga, 2004), finding the coefficient of regional population to be larger than one and highly significant indicates the existence of local increasing returns. The significance of the spatial lag suggests that these effects transcend into neighboring regions. While intuitively plausible, the size of these two coefficients should be interpreted with caution since better matching prospects are likely to attract a larger number of workers. This problem of reverse causality cannot in general be alleviated by means of county fixed effects since matches and agglomeration are likely to follow a similar trend. The most common way in the literature to deal with this issue has been to use instrumental variables based on either historical or geological features. As this approach usually does not come without problems, different instruments would ideally be tested against each other (Combes & Gobillon, 2015) which is, however, beyond the scope of this article. While the estimates of γ_1 and γ_2 should therefore only be taken as indication that the number of matches rises with the degree of agglomeration, their joint inclusion with county fixed effects effectively addresses the problem that local shifts in population numbers might bias the estimates of α_i and β_i. In

16 For reasons of completeness, we have also tested the SDM against the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM) using Likelihood Ratio and Wald Tests. Both tests reject the H_0 ('The SDM can be simplified by the SAR or the SEM') at the 0.1 percent level. These results are independent of the spatial weight matrix used.

17 See Firmino Costa da Silva *et al.* (2017) for a similar comparison in the context of population growth models; we thank Paul Elhorst, who kindly shared the Matlab code for this approach on his website at http://www.regroningen.nl/elhorst/spatialeconometrics.shtml.

18 We have conducted the test for all specifications of W. In 7 out of 9 cases the probability is highest for SDEM. Only for $W_{com.}$ and $W_{train\,(time)}$ the SDM is the preferred model.

the robustness checks, we shed light on the extent to which the size of the direct and indirect effects of unemployment and vacancies depend on the inclusion of population numbers as a control variable. Finding the SDEM to be the most appropriate model indicates that spillovers in matching functions are likely to be of a local rather than a global nature. While unemployment and vacancies have a significant influence on matches in neighboring regions, their impact does not or only to a minor extent transcend the borders of local labor markets. Consequently, the obvious question is how to model local labor markets in a way that they cover most of the spillovers that arise between regions without being too large to be meaningful. In essence, this pertains to the question of how to adequately specify the spatial weights matrix in the context of regional matching functions.

In Table 1.4.2, we address this issue by comparing the results from using the different spatial weight matrices defined in Section 2.2 and evaluating their suitability by means of Bayesian posterior model probabilities. In order to avoid redundancies, we discuss the main insights that can be gained from a comparison of the models rather than going step by step through the single point estimates.

The first two columns contain the direct effects of unemployment and vacancies on matches. In line with the existing literature, all direct effects are positive and significant. Their size varies only little between the different spatial weight matrices. On average, the elasticities amount to 0.153 for unemployment and 0.016 for vacancies. The indirect effects contained in the next two columns are larger in size for both variables. Regarding unemployment, all coefficients are highly significant and range between 0.210 ($W_{contig.}$) and 0.440 ($W_{car\,(time)}$). Their average size is 0.307. For vacancies, only five out of the nine coefficients are significant on at least the five percent level of significance. With a mean of 0.050, these five coefficients range from 0.037 $W_{car(time1957)}$to 0.062 ($W_{(dist.)}$). The respective sums of direct and indirect effects suggest an overall elasticity of 0.460 between matches and unemployment and of 0.066 between matches and vacancies. Before discussing the relative importance of direct and indirect effects from unemployment and vacancies in more detail, we highlight a number of key insights that can be gained from this model comparison regarding the role of different spatial weight matrices and their adequate specification in the context of regional matching functions.

The Bayesian posteriors clearly assign the best fit to the model where spatial weights are defined as the inverse of the geographic distance between regions. At the same time, a comparison of the results shows that the size of the indirect effects does not vary much between the different matrices. These two findings bear three major implications. First, they corroborate the argument by LeSage (2014b, p. 31) that it is 'a myth that estimates and inferences from spatial regression models are sensitive to the specification of the weight matrix'. Consistently, using more complex spatial weights with the intent to model regional dependencies in a more realistic way adds little information to regional matching models. In fact, modeling neighborhood relations by means of physical distance, which is easier to calculate and for which data are readily available, provides virtually the same results.[19] Second, the fact that spatial weights based on historic infrastructure variables yield roughly the same results compared to present-day infrastructure suggests that infrastructure-based weights are largely unaffected by the problem of endogeneity. Hence, it is questionable whether the use of historic instruments for infrastructure endowments yields much benefit in the context of spatially augmented matching functions – especially if present infrastructure-based weights provide similar results as the simple and indisputably exogenous measure of geographical distance. Third, the evidence from the Bayesian posteriors combined with the fact that the results obtained on $W_{contig.}$ provide by far the lower bound of the estimates makes a strong case that the contiguity matrix frequently used in the literature constitutes an imperfect way to model local labor markets. Compared to the average of the other matrices, the indirect effect of unemployment is about 30 percent smaller, suggesting a systematic underestimation of the size of spillovers. In the present case, with about one out of four workers commuting into non-neighboring regions, a considerable share of labor market dynamics is not captured by contiguity relations.

In what follows, we discuss the relative importance of the direct and indirect effects from both unemployment and vacancies as determinants of the regional number of matches by means of a simple back-of-the-envelope calculation. We therefore draw on the results obtained on $W_{dist.}$ as spatial weight matrix.

We turn to unemployment first. The point estimate of the direct effect is 0.144. With 10,934 persons being unemployed on average in each region, an increase in local unemployment by one percent (109 persons) raises the number of matches by 15 persons. With respect to the indirect effect the estimates yield an elasticity between matches and neighboring unemployment of 0.353. In order to interpret this number, one has to bear in mind that each region is surrounded by 29 other regions within a distance of 100 kilometers (see Table 1.3.1). The average distance-discounted number of unemployed in these 29 regions amounts to 10,973 persons. A rise of unemployment in all neighboring regions by one percent (110 persons) yields 39 new matches in region r (0.353 x 110). Hence, the home region receives on average 1.34 persons from each neighboring region. These results suggest that the following adjustments take place if unemployment in an average region rises

19 In their study on the sensitivity of spatial wage equations, Ahlfeldt & Feddersen (2008) reach the same conclusion when comparing road travel times to straight line distances. LeSage & Pace (2014a) argue that the substantial differences found in estimates with different weight matrices often arise from an incorrect interpretation of the coefficients as marginal effects in the SDM.

by one percent: out of 109 newly unemployed persons, 15 find a job in their home region, 39 commute into neighboring regions and start a job there (about 1.34 in each of the 29 regions within a local labor market) and 55 persons remain unemployed or withdraw their labor supply. Overall, these numbers suggest that the indirect effect accounts for nearly 75 percent of the total effect that unemployment has on the number of matches.[20]

Table 1.4.2: Spatial Durbin Error Model

Dependent Variable: m					
Weight matrix	direct effect		indirect effect		Bayesian posterior model probability
	u	v	W•u	W•v	
Distance-Based					
(1) $W_{contig.}$	0.157***	0.015**	0.210***	0.020	0
	(8.691)	(2.713)	(7.334)	(1.845)	
(2) $W_{dist.}$	0.144***	0.017**	0.353***	0.062*	1
	(7.821)	(3.072)	(5.832)	(2.336)	
Commuter-Based					
(3) $W_{com.}$	0.144***	0.013*	0.270***	0.021	0
	(7.820)	(2.213)	(7.413)	(1.490)	
Infrastructure-Based, Present					
(4) $W_{car\,(dist.)}$	0.135***	0.015**	0.338***	0.047*	0
	(7.388)	(2.645)	(7.638)	(2.541)	
(5) $W_{car\,(time)}$	0.143***	0.017**	0.440***	0.055*	0
	(7.887)	(3.088)	(6.981)	(2.016)	
(6) $W_{train\,(time)}$	0.164***	0.018**	0.258***	0.010	0
	(8.986)	(3.146)	(7.131)	(0.645)	
Infrastructure-Based, Historic					
(7) $W_{car\,(dist.1957)}$	0.148*** (8.237)	0.015** (2.644)	0.324*** (8.203)	0.051** (3.067)	0
(8) $W_{car\,(time1957)}$	0.148***	0.016**	0.311***	0.037*	0
	(8.300)***	(2.906)	(7.97)	(2.279)	
(9) $W_{train\,(time1994)}$	0.165***	0.019**	0.251***	0.008	0
	(9.078)	(3.307)	(7.312)	(0.577)	
Notes: N = 3,872; t-statistic in parentheses; model specification is the SDEM contained in column (5) of Table 1.4.1; bias correction of Lee & Yu (2010) applied; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$					

Regarding vacancies, the effects are substantially smaller in magnitude. The direct effect amounts to 0.017 when using $W_{dist:}$ as spatial weight matrix. With

20 This result is in line with the descriptive evidence contained in Figure 1.3.2, where the number of matches achieved by non-resident job-seekers is particularly high around large cities, indicating a large number of out-commuters.

an average of 921 vacancies in each region, a rise by one percent (9.2) leads to 0.16 new matches (0.017 x 9.2). With respect to the indirect effect, the results yield an elasticity between vacancies and matches in neighboring regions of 0.062. Hence, from the perspective of an average region, a rise in the number of vacancies by one percent (9.2) leads to 0.16 additional matches in the home region and to 0.57 additional matches in all 29 neighboring regions within a local labor market (0.02 matches in each neighboring region). This implies that about 80 percent of the effect of vacancies on matches is driven by spillovers between regions.

Finding the indirect effect of vacancies to be positive warrants a brief discussion as this finding is hard to reconcile with standard matching considerations. Importantly, all existing studies on spillover effects from vacancies also report a significantly positive coefficient (see, e.g., Burgess & Profit, 2001; Hynninen, 2005). No explanation beyond the mere autocorrelation of vacancies has been provided for this result so far. The reason we regard as most plausible is the occurrence of reverse causality arising from an imperfectly elastic labor supply in regional labor markets and from spillover effects in the product market. As for the former, with labor supply being imperfectly elastic, a rising number of matches within one region implies that less vacancies are filled in neighboring regions. Framed differently, if more workers find jobs in one region, firms in other regions will find their labor demand unsatisfied, leading to more reported vacancies. Regarding product market effects, more matches in one region raise the demand for goods due to a higher purchasing power, which might induce a higher labor demand in neighboring regions. While both reasons are speculative in nature, they emphasize the need to model the interactions between labor demand, hiring behavior of firms, and product market effects in a more structural way than it is possible in reduced-form matching functions. At present, these interactions impede a precise and meaningful interpretation of the indirect effect of vacancies.

Fahr & Sunde (2006a,b) refrain from including spatial lags of vacancies in their estimation of a spatially augmented matching function, arguing that their inclusion leads to misspecification.[21] With spatial lags of vacancies being significant in most of our specifications, matching functions are, however, likely to also be misspecified if lagged vacancies are excluded. We address this issue empirically by estimating the SDEM without vacancies. The results are contained in column (1) of Table 1.4.3. They show that the coefficients of unemployment and the lag thereof remain virtually unchanged and, hence, do not depend on the inclusion or exclusion of vacancies.

21 Their line of reasoning is, however, somewhat different from ours. In both studies spatial lags are not included for the reason that 'a new match in a certain region implies a filled vacancy in that region, because regions are determined by the location of that employer' (Fahr & Sunde, 2006b, p. 814).

Table 1.4.3: Robustness Checks

		Dependent Variable: m						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		$W_{dist.100km}$	$W_{dist.100km}$	$W_{dist.50km}$	$W_{dist.150km}$	$W^{00-04}_{dist.100km}$	$W^{05-10}_{dist.100km}$	$W^{LMR}_{dist.100km}$
direct effect	u	0.140***	0.199***	0.135***	0.159***	0.127**	0.226***	0.220***
		(7.625)	(10.386)	(7.503)	(8.753)	(3.116)	(9.927)	(7.889)
	v		0.023***	0.015**	0.017**	0.001	0.005	0.005
			(3.975)	(2.691)	(3.048)	(0.181)	(0.770)	(0.572)
	x	1.376***		1.335***	1.426***	1.259***	1.575***	1.616***
		(19.190)		(18.688)	(19.885)	(6.575)	(12.265)	(17.089)
indirect effect	W•u	0.325***	0.533***	0.300***	0.458***	0.014	0.385***	0.271***
		(5.374)	(9.028)	(8.812)	(5.539)	(0.126)	(4.838)	(4.465)
	W•v		0.051	0.026	0.098**	0.018	0.152***	0.062*
			(1.778)	(1.939)	(2.715)	(0.563)	(4.020)	(2.471)
	W•x	0.187		0.198	-0.046	1.487*	0.134	-0.114
		(0.812)		(1.560)	(-0.152)	(2.132)	(0.377)	(-0.533)
Log-Likelihood		4821.68	4622.99	4796.78	4810.18	2499.92	3388.41	2209.37

Notes: N = 3,872 in columns (1)–(4); N = 1,760 in column (5); N = 2,112 in column (6); N = 1,518 in column (7); t-statistic in parentheses; all estimates are based on the SDEM; region and time fixed effects used in all specifications; bias correction of Lee & Yu (2010) applied; $W_{dist.50km}$, $W_{dist.100km}$, and $W_{dist.150km}$ are spatial weight matrices truncated at geographic distances of 50, 100, and 150 kilometers, respectively; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In column (2), we address the question whether the inclusion of regional population numbers as a control variable affects the results. As discussed in Sections 2 and 4, this amounts to examining whether they are driven by a potential migration of workers. A comparison to the results contained in column (5) in Table 1.4.1 shows that without regional population numbers the direct effects rise by about 30 percent, while the indirect effect of unemployment more than doubles. The highly significant coefficients of regional population and the larger Log-Likelihood for the longer model strongly speak against excluding this variable from the specification as otherwise the direct and indirect effects from unemployment and vacancies are largely overestimated.

In columns (3) and (4) we examine whether the results found for $W_{dist.}$ hinge on the truncation of the matrix at a maximum distance of 100 kilometers. The direct effects rise only slightly in size when raising the threshold from 50 kilometers to 100 kilometers and further to 150 kilometers. The indirect effects, in contrast, react more strongly. When reducing the threshold from 100 to 50 kilometers in column (3), the coefficients fall from 0.353 to 0.300 for unemployment, and from 0.062 to an insignificant size of 0.026 for vacancies. With an upper threshold of 150 kilometers in column (4), it rises to 0.458 for unemployment and to 0.098 for vacancies. These changes are plausible since more unemployed persons who potentially find jobs in neighboring regions and more vacancies to be filled are contained in larger local labor markets with a rise in radius.[22]

In columns (5) and (6) we address the question whether the major labor market reforms that were implemented in Germany between 2003 and 2005 ('Hartz Reforms') have influenced the job matching process for the unemployed. A number of contributions have already examined this issue in a framework of matching functions. Fahr & Sunde (2009) show that matching efficiency has risen by roughly 15 percent as a result of the reforms.[23] Controlling for changes in GDP-growth, Klinger & Rothe (2012) document a slightly lower increase in matching efficiency of ten percent, which they relate to the deregulation of the labor market ('Hartz I') and the re-organization of the Federal Employment Agency ('Hartz III'). Hertweck & Sigrist (2012) provide evidence that the reforms have accelerated the outflow out of unemployment. The key identification

22 In line with this notion, a Bayesian posterior model comparison indicates the best model fit for a radius of 150 kilometers. Addressing the question of how to set the upper bounds in the spatial weights matrices in an optimal way would be an interesting extension of this analysis and should ideally be conducted on municipality rather than county level in order to increase precision. This is, however, beyond the scope of this article and we leave it for further research.

23 Using higher-frequency data and disaggregating the matching function by types of occupations, Stops (2016) provides evidence that the main effects of the reform arise between 2006 and 2009 and affect all occupational groups.

approach in all papers has been to show in a log-linear specification that the regional number of matches exhibits an upward trend break between 2003 and 2005, i.e, at the time of the implementation of the reforms. We add a spatial dimension to this literature by examining whether there is evidence that the reforms have positively influenced the job search radius of the unemployed. The key idea is that the introduction of an improved placement service for long-term unemployed in the newly introduced job centers as well as stricter requirements on the acceptability of job offers should have raised the elasticity between matches and unemployment in neighboring regions as unemployed persons increasingly look for work beyond the borders of their home regions. Similar to Lottmann (2012), we therefore split up the sample into a pre-reform period (2000–2004) and a post-reform period (2005–2010) and estimate the SDEM separately for both periods.

The results are in stunning congruence with the intention of the reform. Compared to the pre-reform period, both the direct and the indirect effect of unemployment rise substantially after 2004. Before the reforms, the direct effect of unemployment ranges at 0.127 while the indirect effect is insignificant, indicating that unemployed were predominantly matched to jobs in their county of residence. With the reform, the direct effect increases to 0.226 while the indirect effect rises from insignificance to a highly significant size of 0.385, indicating that the spillover effects found in the prior analysis arise only after the reform. While these results should not be taken as causal, they are congruent with the idea that improved placement services combined with stricter requirements to take any adequate job has substantially raised the willingness of unemployed to commute into neighboring regions.

Lastly, we address the concern that NUTS 3 regions are ill-suited as a basis for defining local labor markets by means of different spatial weight matrices because their comparatively small size biases the estimates in favor of the indirect effects. In order to examine this issue we replace the NUTS 3 regions used so far by the 138 labor market regions (LMR, *Arbeitsmarktregionen*) defined by Kosfeld & Werner (2012). Based on information on commuter flows, these regions are obtained by merging NUTS 3 regions into larger travel-to-work areas. The results contained in column (7) show that in line with expectations the size of the direct effect of unemployment rises at the expense of the indirect effect. This is the result of more matches taking place within rather than between regions due to the larger size of regions. Finding the direct effect of vacancies to be insignificant when using travel-to-work areas is surprising given the high level of significance in the prior estimations. The fact that the specifications in the only available work that also draws on travel-to-work areas (Fahr & Sunde, 2006a,b) do not include spatial lags of vacancies impedes a comparison of the results. Importantly, although becoming smaller in magnitude, the spillovers from unemployment and vacancies do not cease to exist when using travel-to-work areas. On the one hand, this finding emphasizes that the relative size of direct and indirect effects naturally hinges on the specific definition of a region (to see this consider the extreme case of a national labor market containing only one region, which would by construction rule out any spillovers). On the other hand, it corroborates the key notion underlying this paper that a proper understanding of the matching process that takes place within increasingly integrated local labor markets requires looking beyond single regions and identifying spatial models that are well suited to capture the spatial dependencies prevailing between them.

1.5 Conclusion

In this paper we examine the effects that unemployment and vacancies have on the regional number of matches within and across regions. Doing so, we contribute to the literature in several respects. First, we provide fresh evidence on the geographical scope of job search and hiring behavior within local labor markets in Germany. Second, we examine which of the spatial models commonly employed in the empirical literature most appropriately describes the occurrence of spillovers in regional matching functions. Doing so, we shed light on the question whether these spillovers are 'local' or 'global' in nature. Third, we devote particular attention to the influence that the definition of the spatial weights matrix plays for the results. Fourth, we conduct the analysis on a finer geographical level then was previously available. Finally, we contribute to the discussion about the impact that the major labor market reforms implemented in Germany in the early 2000s have had on the matching process of unemployed job seekers.

In a nutshell, we find that the Spatial Durbin Error Model (SDEM), which models spillovers as being of local nature, is best suited to describe the data generating process in regional matching functions. The results from this model suggest that the elasticity between matches and unemployment ranges between 0.4 and 0.5, depending on the spatial weight matrix used. Spillovers between regions account for 75 percent of this overall effect. The direct and indirect effects from vacancies are small but significantly positive. The latter results are likely to be driven by the endogeneity of vacancies in neighboring regions. While these results are robust to the choice of the spatial weight matrix, Bayesian posterior model probabilities suggest that simple distance-based weights exhibit the best model fit. This finding puts the debate on the right choice of the spatial weight matrix into perspective. With respect to the German Hartz Reforms, we find that indirect effects of unemployment only arise after the reforms, suggesting that unemployed workers have extended their radius of job search into neighboring regions.

Gaining insight into the relation between matches, unemployment and vacancies within and across regions is not only crucial for understanding the functioning of local labor markets. It is also of key importance for the design of active labor market policies which aim to remediate regional imbalances between labor demand and supply. With job seekers increasingly finding work outside their home county, it seems recommendable for job centers to assist this process by providing job seekers with job offers from neighboring regions. The recent introduction of GIS software by the Federal Employment Agency, which is used to identify vacancies located within a certain driving distance, is a promising step in this direction.

With respect to further research it would be desirable to shed further light on the matching process on individual level using geo-referenced data on job seekers and vacancies. This type of analysis would allow for a true understanding of how the accessibility of local labor markets influences job search and the decision to accept or decline job offers. Such an analysis should be conducted separately for persons with different mobility patterns in order to better understand group-specific differences in job search behavior. One step further down the road, the role of infrastructure and local accessibility for the quality of job matches (as measured, e.g., by wages and the duration of employment relations) merits further attention.

1.A Appendix

Normalization of the Spatial Weight Matrices

In line with the argument by Halleck Vega & Elhorst (2014) that the way the spatial weight matrices are normalized may influence the results, we have estimated all models with eigenvalue-normalized and with row-normalized spatial weight matrices (see Kelejian & Prucha, 2010). A pairwise Bayesian posterior model comparison unambiguously identifies all row-normalized matrices as superior to their eigenvalue-normalized counterparts. In addition, with the exception of $W_{contig.}$ and $W_{com.}$ (which are both coded in a binary way and, hence, are not based on a continuous spatial decay function), the indirect effects for both unemployment and vacancies turn out as insignificant throughout all models and all spatial weight matrices. Given the substantial incidence of commuting between regions, this result is highly implausible and is effectively driven by the larger spatial discount factor resulting from normalizing the matrices by their largest eigenvalue. The downside of row-normalizing the matrices is that the interpretation of the results in terms of distance-decay vanishes (see Regelink & Elhorst, 2015). This interpretation is, however, largely irrelevant in the present context since the indirect effects from unemployment and vacancies are estimated as average effects within a pre-defined radius (90 minutes or 100 kilometers) without further consideration of how the size of the effects decays with distance.

Chapter 2

Opportunities and Competition in Thick Labor Markets: Evidence from Plant Closures

Abstract*

Since Marshall (1890), it has been widely held in urban economic theory that cities ensure workers against the risk of unemployment by offering a larger pool of potential jobs. Using a large administrative panel data set on workers affected by firm closures, we examine whether positive effects from a higher urban job density are offset by more intense competition between workers. When controlling for worker sorting, we find no evidence that the number of days workers spend in unemployment decreases with local job density. Instead, longer unemployment durations in cities are partly driven by more intense competition for available jobs.

Keywords: agglomeration, thick labor markets, displacement

JEL Codes: J63, J64, R12, R23

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* This part is joint work with Daniel F. Heuermann.

2.1 Introduction

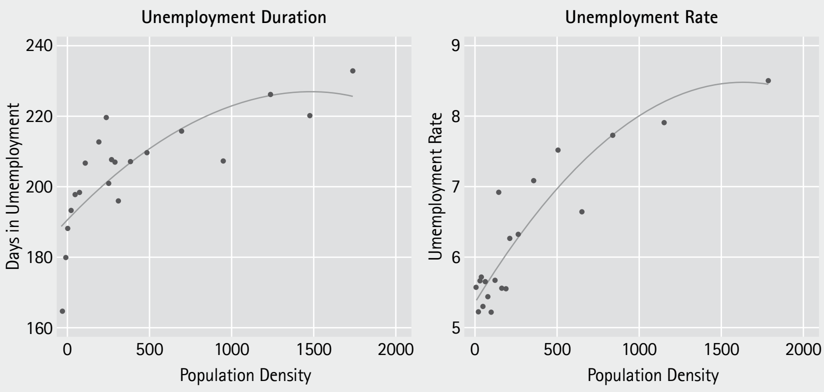
One key argument for the existence of cities is that denser labor markets insure workers against the risk of unemployment by offering them a larger pool of potential jobs. As a result, workers living in urban areas should benefit from shorter job search periods in case of involuntary job loss (Duranton & Puga, 2004). This way of reasoning stands, however, in stark contrast to the empirical observation that, at least in the US and Germany, the average duration of joblessness rises with the local degree of agglomeration. For the US, a large literature on spatial mismatch documents a higher incidence of unemployment in downtown areas than in less densely populated suburbs (see, e.g., Kain, 1968; Wasmer & Zenou, 2002; Gobillon *et al.*, 2007).[1] For the German case, we have plotted the number of days that displaced workers spend in unemployment against regional population density in the left panel of Figure 2.1.1. The figure shows that both variables exhibit a strong inverse relation, defying the notion that workers in cities find work more quickly. Consistently, the empirical literature has so far found little evidence in favor of an urban insurance effect. Overall, while access to jobs is of crucial importance for the re-employment process after periods of unemployment (Rogers, 1997), the density of the local labor market does not seem to shorten the time in unemployment (see, e.g., Petrongolo & Pissarides, 2006). This seeming contradiction might be explained by the prevalence of fiercer job competition between workers in cities for available jobs (Raphael, 1998; Détang-Dessendre & Gaigné, 2009). Kroft *et al.* (2013) show for the US labor market that the chances of unemployed to receive a callback for a job interview decrease with the tightness of the local labor market. In the right panel of Figure 2.1.1, we relate local unemployment rates to population density in order to examine whether the tightness of the local labor market rises with the degree of agglomeration. The graph shows that the average unemployment rate rises monotonically in size over the range of population densities, indicating that the tightness of the labor market increases with local density. In combination, the evidence from both panels suggests that the 'thickness' of urban labor markets may turn against workers by reducing individual chances of re-employment due to more intense job competition.

In the present paper, we examine how the degree of agglomeration affects the job search duration of workers who have involuntarily become unemployed. In particular, we shed light on the relative importance of job opportunities and job competition for the re-employment prospects of workers. We therefore construct

1 Given the large volume of studies, we refer the reader to the surveys by Ihlanfeldt & Sjoquist (1998) and Gobillon *et al.* (2011).

market potential-based indicators for both variables, which explicitly take into account that regions themselves are not closed labor markets. Identifying positive or negative effects of density on individual employment chances is complicated by a potential sorting of individuals and firms between locations. In order to address this issue, we exploit exogenous events of involuntary unemployment from plant closures, which we identify based on detailed information from the German social security records. From this data, we extract the employment biographies of all workers who became unemployed as a result of plant closures between 1999 and 2009. To further reduce the problem of worker selection and unobserved heterogeneity, we make use of the panel structure of the data and impose sample restrictions with regard to tenure and changes in places of residence and, in addition, employ individual and regional fixed effects. The frequency of the data in quarters allows for a detailed analysis of the effect that job opportunities and job competition have on the re-employment process of displaced workers. By drawing on the most disaggregated administrative level we make use of substantial variation in local densities resulting from the polycentric spatial structure in Germany. Germany.

Figure 2.1.1: Unemployment and Regional Agglomeration



Notes: The figure shows the average unemployment rate and unemployment duration per county in density bins (population per square kilometer). The graphs are based on data from the Statistics of the Federal Employment Agency and the Sample of Integrated Employment Biographies.

In line with previous findings, we find evidence for a persistent increase in aggregate unemployment levels over a period of four years after a displacement (e.g., Ruhm, 1991; Jacobson *et al.*, 1993; Couch & Placzek, 2010; Schmieder *et al.*, 2010). Regarding the effects of density, there is no indication that the local density of jobs has an effect on the number of days in unemployment once we control for the sorting of workers across regions. In contrast, we find that the time spent in unemployment rises significantly with the local density of unemployed workers. Overall, it seems that job seekers are effectively worse off in thick labor markets because competition effects dominate the opportunity value of cities. These negative effects are largest for workers who are least likely to resort to self-employment or to leave the labor market altogether.

In the next section, we review the existing literature. In Section 2.3, we outline our identification strategy. Section 2.4 describes the data and provides first descriptive evidence. The results are discussed in Section 2.5. Section 2.6 concludes.

2.2 Related Literature

The idea that a larger number of potential jobs in cities insures workers against the risk of unemployment goes back to Marshall (1890). Formalized by Duranton & Puga (2004), the mechanisms underlying this idea of risk sharing is that the variance of idiosyncratic productivity shocks incurred by firms rises with the degree of agglomeration. Workers who become unemployed are therefore better off in larger cities because of a higher probability that any other firm expands its production in consequence of a positive productivity shock and, hence, is in search of workers to hire.[2] This type of risk sharing between workers is commonly regarded as one main mechanism through which agglomeration externalities arise.

Despite this long-standing history of thought, the empirical evidence regarding the effect of labor market size on unemployment duration is far from conclusive. This literature, which is surveyed in Petrongolo & Pissarides (2001), reveals mainly constant returns to agglomeration, indicating that workers are not better off in larger labor markets in terms of their job search. Petrongolo & Pissarides (2006) point out that higher reservation wages in cities may offset potentially positive effects from higher job arrival rates. This argument is supported by Harmon (2013), who shows that while workers in Denmark do not find jobs faster in larger local labor markets, the degree of urbanization positively affects the wage level after a successful match. In contrast, Di Addario (2011) finds that the local degree of agglomeration does indeed raise the hazard rates of unemployed workers in Italy. Similarly, Bleakley & Lin (2012) provide support for positive scale effects from larger labor markets by showing that unemployed workers in densely populated areas are more likely to be re-employed in the same occupation.

2 On the labor demand side, firms should therefore benefit from lower vacancy times in cities as a result of better access to suitable workers (Rosenthal & Strange, 2001; Moretti, 2011). In line with this notion, Martín-Barroso *et al.* (2015, 2017) and Holl (2012) show that firms in cities are more productive due to an improved access to factor markets.

One argument for why agglomeration may not necessarily reduce unemployment durations in cities is that job opportunities in cities may partly be offset by a larger number of rivaling job seekers.[3] The only two papers which empirically address this issue are the ones by Détang-Dessendre & Gaigné (2009) and Andersson *et al.* (2014). Both estimate hazard models with a measure of regional job accessibility as independent variable, where the local number of jobs is discounted by the number of job seekers. Both papers find evidence that a rise in local job accessibility reduces the number of days a worker spends in unemployment, suggesting that the opportunity value of cities supersedes negative effects from fiercer job competition. There are, however, two drawbacks from using one combined measure for opportunities and competition. First, the complexity of the index inhibits a meaningful interpretation of the point estimates beyond their sign and level of significance. Second, the results do not allow for gaining insight into the relative importance of job opportunities and job competition for a successful recovery out of unemployment. A proper design of labor market policies requires, however, an understanding of the role that each of the two sides of the labor market - jobs and competing job seekers - has for the re-employment chances of workers who have become involuntarily unemployed. From the perspective of identification, another difficulty of both papers is that none of them controls for individual heterogeneity by means of individual fixed effects. This is, however, problematic if unobserved worker characteristics are correlated with local labor market conditions (Glaeser, 1996). Also related to our paper is the contribution by Neffke *et al.* (2017), which examines the effect of local industrial structure on employment probabilities of laid-off workers. In a nutshell, the authors find that employment chances rise with the presence of a worker's old industry in a region and decline with the presence of different but skill-related industries. As with the contributions by Détang-Dessendre & Gaigné (2009) and Andersson *et al.* (2014), one shortcoming of this paper is that it does not control for unobserved heterogeneity between workers. In the present paper, we build on these latter strands of the literature and add to their insights in two major respects. First, we disentangle the relative magnitude of opportunity and competition effects in thick labor markets. Secondly, we carefully control for sorting and unobservable heterogeneity between workers by means of a quasi-randomized experiment, by imposing different sample restrictions and by employing worker and region fixed effects.

3 Although differing in the underlying mechanisms, the literature on neighborhood effects of unemployment is closely to this paper (Hawranek & Schanne, 2014; Bayer *et al.*, 2008; Jahn & Neugart, 2017). The general idea of this literature is that higher local levels of unemployment impede access to local job-referrals networks for unemployed workers. The general finding in this literature is that living in a neighborhood with high unemployment rates raises the duration of job search for displaced workers.

2.3 Measurement and Identification Approach

2.3.1 Measuring Opportunities and Competition

Any attempt to determine the size and the sources of agglomeration economies crucially depends on the definition of a region and its respective degree of urbanization. In Germany, the smallest administrative units are municipalities. They constitute the fourth administrative layer and, as such, are similar to cities, towns and villages in the US. By the end of 2014, 11,194 of these municipalities existed with an average population of slightly more than 7,000 inhabitants. Out of these, 15 cities contained more than 500,000 residents and another 62 more than 100,000. According to a classification provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development, which takes into account the wider economic role of a region, 848 municipalities can be considered as urban while the rest is of rural nature.[4]

While these numbers provide a first glance on the number and the size of big cities in Germany, in the present context they are deficient in three respects. First, they only provide a binary classification of a distribution which by its nature is continuous. Second, they do not take into account the extent to which a local population is sprawled within a region. This is of particular relevance in the present context when taking into account the substantial variation of the size of municipalities, which cover a range between less than one (*Neuheilenbach*) and 890 (*Berlin*) square kilometers. In addition, Glaeser & Resseger (2010) among others argue that the density of workers might be at least of equal importance for agglomeration economies to materialize than absolute population or worker numbers alone. Third, focusing on single municipalities ignores potential labor market interactions between neighboring regions (Combes & Gobillon, 2015). On county level, Haller & Heuermann (2016) show that job search is far from being confined to single regions. In fact, since 38 percent of workers commute across regional borders, the relevant local labor market is effectively larger, in particular if a region is well connected to its surroundings. These problems can be accounted for by means of a continuous measure which takes into account the sprawl of a labor market within the wider region. Relating the number of residents, workers or unemployed in a region r at time t, which we denote as L_{rt}, to the area of a region A_r yields a measure for the density of a local labor market, M_{rt}.

4 One peculiarity of the city size distribution in Germany is that according to Zipf's law large cities are underrepresented, which is usually regarded as resulting from a decentralized spatial structure in Germany (Giesen & Südekum, 2011).

$$\text{Labor Market Density}_{rt} = M_{rt} = \frac{L_{rt}}{A_r} \tag{2.1}$$

In order to take into account the thickness of the labor market in the wider region, we augment this local density by the distance-discounted density of all neighboring municipalities *j* (Hansen, 1959; Brakman *et al.*, 2009).

$$\mathrm{M}_{rt}^{augm} = \underbrace{\frac{L_{rt}}{A_r}}_{\equiv \text{Local Density}} + \underbrace{\sum_{\substack{j=1 \\ j \neq r}}^{J} \frac{L_{jt}}{A_j} f(d_{rj})}_{\equiv \text{Neighboring Density}} = \sum_{\substack{j=1 \\ r \in J}}^{J} \frac{L_{jt}}{A_j} f(d_{rj}), f(d_{rr}) = 1 \tag{2.2}$$

This formulation requires several assumptions with regard to the relevance of neighboring regions. In particular, the impedance function $f(d_{rj})$ is determined by its functional form, the spatial decay parameter θ and the distance d_{rj} between localities (Reggiani *et al.*, 2011). We follow the literature (see, e.g., Andersson *et al.* (2014) and Ahlfeldt & Wendland (2016)) and employ an exponential decay function, $e^{-\theta d_{rj}}$, with $\theta = 0.1$. d_{rj} is measured by the driving time between the centroids of two municipalities in 2005.

Equation (2.2) provides the foundation for constructing measures of job opportunities and the degree of job competition within local labor markets. The most obvious proxy for job opportunities would be the distance-discounted number of vacancies per area unit. Data on vacancies are, however, not available on the level of municipalities. On county level, they are, in turn, notoriously unreliable because firms are not obliged to report their vacancies to the Federal Employment Agency. As a result, the existing data sets contain only 43 percent of all open positions. We therefore measure local job opportunities by means of the distance-discounted number of available jobs, which we approximate by the number of full-time employed workers within a region.

$$\mathrm{Opp}_{rt} = \sum_{\substack{j=1 \\ r \in J}}^{J} \frac{Workers_{jt}}{km_j^2} f(d_{rj}), f(d_{rr}) = 1 \tag{2.3}$$

Defined this way, Opp_{rt} is based on the assumption that workers aim to minimize commuting distances and therefore prefer jobs located close to their home. Within regions, the number of jobs is therefore discounted by the size of the area across which they spread. Between regions, the idea that the attractiveness of jobs decreases with distance is captured by the distance decay function $f(d_{rj})$.

Regarding the local degree of job competition, $Comp_{rt}$, it is ex ante an open question whether dismissed workers compete with all persons in the local workforce or only with other unemployed job seekers. In light of the literature inspired by Snower & Lindbeck (1989), it seems very likely that the latter is the more relevant peer group for unemployed workers when aiming to find a new job. From the perspective of identification, one additional problem that we encounter when using the local population of working age as a measure for competition is that this is highly correlated with the local number of jobs (corr.: 0.91). This results from the fact that a large share of workers are employed in the region they live in. When using regional fixed effects, the multicollinearity between both variables substantially reduces the precision of the estimates. For theoretical and econometric reasons, we therefore resort to the distance-discounted number of unemployed workers per region r normalized by the area of a municipality in square kilometers as our measure for job competition.

$$\text{Comp}_{rt} = \sum_{\substack{j=1 \\ r \in J}}^{J} \frac{Unemployed_{jt}}{km_j^2} f(d_{rj}), f(d_{rr}) = 1 \tag{2.4}$$

2.3.2 Identification Approach

Estimating the effect that job opportunities and job competition have on individual labor market outcomes is complicated by the fact that firms and workers are not distributed randomly in space (Combes *et al.*, 2011). This is problematic if the intensity of job search or other individual characteristics that are relevant for finding a job differ systematically between regions. In addition, unobservable regional characteristics are likely to lead to bias in the estimates if they are correlated with the local density of jobs or workers. We address this issue in three ways.

First, we quasi-randomize the place of residence of workers, and thereby the degree of job opportunities and competition, in order to render them orthogonal to individual characteristics. Finding a true randomized experiment where a large number of workers is allocated exogenously to regions is, however, hard to find (see for instance Katz *et al.* (2001) or Kling *et al.* (2007)). Starting with Ruhm (1991) and Jacobson *et al.* (1993), the literature has therefore resorted to incidences of mass layoffs in order to achieve an exogeneity of job search decision. In these studies, wages or earnings of displaced workers are compared to those of workers who have remained in the firm in order to gain insight into the costs of job loss in terms of earnings and income (see von Wachter (2010) for a survey).[5] This

5 In addition, effects on health (Sullivan & Von Wachter, 2009), fertility decision (Huttunen & Kellokumpu, 2016), divorce probabilities (Eliason, 2012) and the inter-generational transmission of these effects (Oreopoulos *et al.*, 2008) have been examined. Gathmann *et al.* (2014) provide evidence for sizeable negative spillovers of mass layoffs within local labor markets.

literature unanimously shows that a period of involuntary unemployment yields substantial income losses for displaced workers due to the loss of firm-specific knowledge (Couch & Placzek, 2010; Schmieder *et al.*, 2010) and occupational mismatch (Nedelkoska *et al.*, 2015; Holm *et al.*, 2016). In this paper, we apply a similar line of reasoning and focus on job displacements as a result of plant closures. We use incidences of plant closures rather than of mass layoffs because the latter are restricted to a small and selective subset of regions. Incidences of plant closures do, in turn, approximate the distribution of workers across locations rather well. In fact, 77 percent of workers who are displaced as a result of plant closures live in urban regions. This is similar to the population distribution in Germany, where 75 percent of individuals live in cities. The key idea of this design is that neither closing establishments nor dismissed workers differ systematically between regions in terms of their characteristics (Andersson *et al.*, 2014). In this setting, the local degree of labor market thickness is as good as randomly assigned to workers and the local number of job opportunities and job competition should therefore be unrelated to the individual intensity of job search. We discuss the plausibility of this assumption in Section 2.4.

Second, in order to further reduce potential bias from the selection of workers, we restrict the sample in terms of worker mobility and tenure. Specifically, we only include workers who have changed neither their place of residence nor their employer over a period of four years prior to the firm closure (Schmieder *et al.*, 2010). While this restriction may limit the external validity of our results, it reduces the threat of selective moves between firms and regions which would impede a correct identification of the causal effect of job opportunities and competition on unemployment. In order to shed light on the extent to which our results can be generalized, we compare the characteristics of the workers in our sample to the universe of all employed and unemployed workers in Section 2.4.

Finally, in our estimation approach we control for individual fixed effects which at the same time absorb all time-invariant regional characteristics because workers by definition do not change municipalities.[6] As discussed in Section 2.2, this provides a novel approach in the literature since in particular the studies by Détang-Dessendre & Gaigné (2009) and Andersson *et al.* (2014) do not control for the unobserved heterogeneity of workers. We compare our results to theirs when discussing our findings in Section 2.5.

Based on the resulting sample of workers, we examine the effect of job opportunities and job competition on individual employment prospects by means of an event study. Denote the number of days that a displaced worker i spends

6 Note that we impose a further restriction with regard to non-moving after dismissal in the robustness checks.

in unemployment per quarter q as d_{iq}, which is the dependent variable.[7] Note that since we observe workers for a period of four years after the incidence of involuntary displacement, q runs from $q = 0$ to $q = 16$. In addition, assume that worker i lives in region r, which is characterized among other things by a certain degree of job opportunities, Opp_{rq}, and of job competition, $Comp_{rt}$. The following equation relates the individual time in unemployment per quarter to both variables.

$$d_{iq} = \beta_1 Opp_{rq} + \beta_2 Comp_{rq} + X_{iq}\alpha + R_{rq}\gamma + \theta_i + \phi_t + \psi_q + \varepsilon_{iq} \tag{2.5}$$

The matrix X_{iq} contains covariates on individual level like age, gender, nationality, skill level, and a dummy for East Germany. R_{rq}, in turn, controls for systematic differences between regions in terms of GDP, amenities, and commuters. θ_i denotes individual fixed effects. Importantly, since workers in our sample by construction do not change regions, θ_i also controls for time-invariant characteristics of the municipalities. ϕ_t represents year-quarter fixed effects, which capture variation in re-employment chances over the business cycle. Since re-employment prospects vary with time spent in unemployment, we include fixed effects for each quarter after the incidence of displacement, ψ_q. Note that we standardize Opp_{iq} and $Comp_{iq}$ by their respective mean and standard deviation. Doing so allows for interpreting the coefficients as changes in days in unemployment per quarter as a result of a change in either Opp_{iq} or $Comp_{iq}$ by one standard deviation. As a result, we can directly compare the coefficients β_1 and β_2 to each other. Throughout all regressions, standard errors are clustered on the level of closed establishments.

2.4 Data and Descriptive Evidence

2.4.1 Data

We draw on administrative data from the German Federal Employment Agency, which are provided by the Institute for Employment Research in the IEB (Integrated Employment Biographies). The IEB contain information on a daily basis for all employed persons subject to statutory social security contributions, as well as all on all recipients of unemployment insurance or unemployment assistance (Antoni *et al.*, 2014). For these persons, information on education, age, gender, nationality, full-time vs. part-time, occupation, and wage, as well as on firm characteristics like establishment size and industry classification are provided.

7 An alternative approach would be to take the time to the next full-time employment as a measure for labor market success. Since, however, this first employment is often only of short duration, summing up the days in unemployment per quarter is a more informative measure of long-term labor market success after a displacement.

Based on this data, we identify in a first step all plants that were closed between 1999 and 2009 and have employed at least four employees at the time of closure.[8] The latter restriction accounts for the risk that otherwise the resulting unemployment needs not necessarily be involuntary but might rather be the result of the decision of one person or a small group of persons. We address the issue of changing firm identifiers by means of the method proposed by Hethey-Maier & Schmieder (2013). For the resulting set of firms, we take the employment biographies of all individuals between 25 and 50 years of age who were employed full-time at the firm and have not left earlier than six months before the firm disappears. In addition, we apply the restrictions discussed in Section 2.3, i.e., we only include workers into the sample who have changed neither their place of residence nor their employer over a period of four years prior to the closure.[9]

One problem we had to address is the one of sample attrition after displacement. In fact, around 12 percent of workers disappear from the data in the quarter after displacement. 27 percent drop out of the sample over the next four years. Potential reasons for such attrition are that workers become part-time or self-employed or leave the labor market altogether. In order to account for such temporary or permanent dropouts from the sample, we generate spells for those periods, mark them as 'neither full-time employed nor unemployed' and count the days per quarter that each individual spends in this status. We then convert the spell data into a balanced panel data set. This data set contains quarterly information on 97,743 workers who were employed in 34,946 establishments for a period of four years before and four years after the displacement.

On regional level, we consider all 11,194 municipalities that existed on 31^{st} of December 2014. We exclude 78 uninhabited units, which consist only of woods and lakes, as well as all islands, which due to their isolation are peculiar cases in terms of their labor markets. Information on the population of working age within each of these municipalities is provided by the Federal Statistical Office. The monthly number of unemployed per municipality is taken from the Statistics of the Federal Employment Agency (2017), which we aggregate to quarterly averages. The stock of employed individuals per municipality are contained in the Administrative Wage and Labor Market Flow Panel (Stüber & Seth, 2017). These data are based on the full universe of establishments in Germany. Aggregating them to the level of municipalities allows for a very precise measurement of the stock of employed workers. In addition, we are able to exactly match end of period values to quarters, which greatly reduces the problem of aggregation bias which

8 See Fackler *et al.* (2013) and Fackler & Schnabel (2015) for an overview of the characteristics of closing firms.

9 Table 2.A.1 shows how each of these restrictions affects the number of workers in the sample.

plagues other data sources. As regional controls on county level, we use the log of GDP, commuter balance and the number of hotel beds as a proxy for local amenities, which are all provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development.

2.4.2 Descriptive Evidence

Table 2.4.1 summarizes the characteristics of displaced workers, closed establishments and municipalities in Germany. The first two columns show the mean and the standard deviation of the main variables within each dimension. The median displaced worker is 40 years old, male, medium-skilled, of German nationality, lives in West Germany and has worked for six years (2,439 days) in a firm prior to its closure. The median establishment has existed for 15.9 years, was located in West Germany and has employed 17 workers out of which 13 were full-time employed. The average municipality covers an area of 80 square kilometers. The mean number of displaced workers per municipality per quarter in our sample is 3.3. On average, each municipality exhibits 719 jobs and 142 unemployed per square kilometer. One assumption of our identification design is that workers who have become involuntarily unemployed do not differ between regions in terms of their characteristics since otherwise we might capture a sorting effect rather than the causal effect of density. The remaining two columns show the mean of the main variables for workers and firms in the upper and the lower quartile of regions with regard to population density. Generally, workers and firms turn out to be relatively similar in regions shaped by high and low degrees of urbanization. Exceptions are the average degree of education and the nationality of the workforce. In denser areas, displaced workers are generally better educated and have a higher probability to be foreign born. This emphasizes the need to not only control these characteristics in the regression approach but to also include individual fixed effects since workers may also differ in terms of other unobservable characteristics.

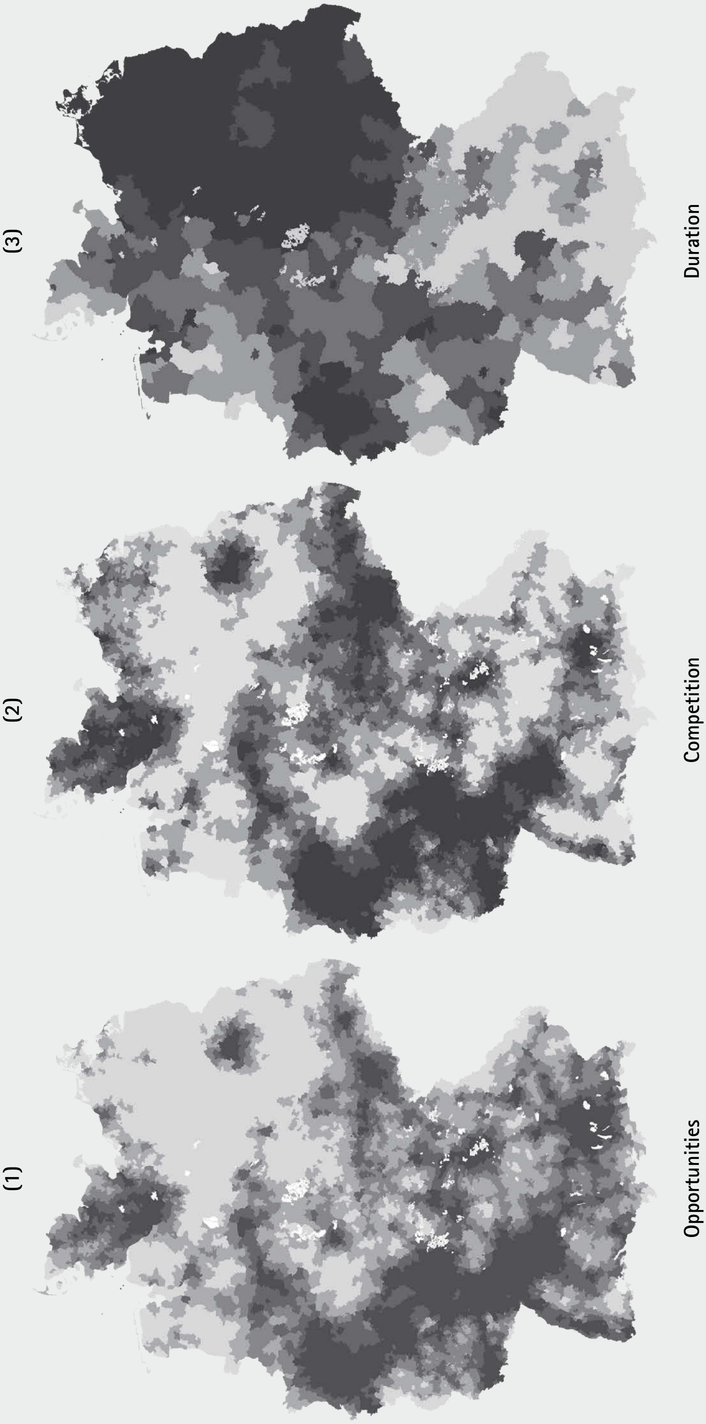
To shed light on the issue of external validity, we have summarized the characteristics of all employed and all unemployed workers in Germany in Table 2.A.2 in the Appendix. Overall, the workers in our sample are not very different from the two groups with the exception of the share of foreigners, which is higher in our sample, and the share of women, which is lower. While we condition on these variables, the populations of employed and unemployed workers may still differ from the individuals in our sample with regard to unobservable characteristics. The overall similarity between all groups shows, however, that the restrictions we have imposed with regard to tenure and place of residence have not yielded a sample that is disconnected from the universe of workers and unemployed in Germany.

Table 2.4.1: Summary Statistics

	Displaced Workers			
	Mean	**SD**	**25th Perc.**	**75th Perc.**
N	97,743		24,475	24,435
Age when displaced	39.89	6.49	39.73	39.90
Tenure (in days)	2,439	840	2,336	2,477
Female	0.27	0.44	0.24	0.29
Foreign	0.15	0.36	0.08	0.23
Low skilled	0.12	0.33	0.08	0.17
Medium skilled	0.79	0.40	0.87	0.73
High skilled	0.08	0.26	0.05	0.10
East Germany	0.34	0.47	0.45	0.35
	Closed Establishments			
	Mean	**SD**	**25th Perc.**	**75th Perc.**
N	34,946		8,499	8,476
Firm age (in years)	15.91	9.12	15.63	16.70
East Germany	0.29	0.46	0.36	0.28
All employed	17.70	35.51	17.86	17.03
Full-time employed	12.94	26.31	13.59	11.97
... of which are female	3.37	8.45	3.05	3.58
... of which are foreign	1.09	4.66	0.66	1.59
	Municipalities			
	Mean	**SD**	**25th Perc.**	**75th Perc.**
N	29,633			
Area (in km^2)	80.08	79.74	30.39	103.56
No. of Displaced Workers	3.30	11.02	1	2
Jobs per km^2	718.75	712.72	234.02	953.52
Unemployed per km^2	141.71	110.66	57.05	196.37

In Figure 2.4.1, we compare the regional distribution of job opportunities, job competition and unemployment duration. Maps (1) and (2) provide evidence for a close spatial correlation of job opportunities and job competition. Both variables closely follow the pattern of urbanization with densely populated regions like the Rhine-Ruhr and the Rhine-Main area and the regions in and around the large cities of Berlin, Hamburg, and Stuttgart exhibiting the highest values. The distribution of unemployment durations is dominated by a sharp divide between East and West Germany. It shows that local labor markets in the East have still not overcome the detrimental labor market effects of the German reunification. Within the West, the geographic distribution of unemployment durations largely follows the pattern of job opportunities and job competition. Overall, the evidence from the figure yields two main insights. First, it confirms the earlier finding that, at least in West Germany, the duration of unemployment rises with the degree of agglomeration. Secondly, it shows that job opportunities and job competition are two sides of the same coin in the sense that a 'thick' local labor market not only yields a large number of jobs, but at the same time also a large number of competitors for these jobs. In the following, we disentangle the influence that these two variables have on the number of days that laid-off workers spend in unemployment per quarter.

Figure 2.4.1: Job Opportunities, Job Competition and Duration of Unemployment

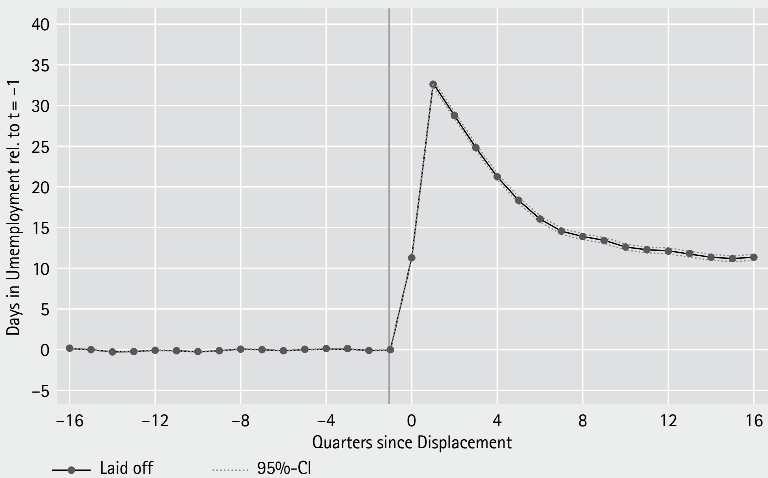


Notes: The three maps show the regional distribution of job opportunities as defined in Equation (2.3), of job competition as defined in Equation (2.4) and of the average number of days in unemployment. Map (3) is based on a representative sample of unemployed taken from the Sample of Integrated Employment Biographies. Coloring is in quintiles with darker colors indicating higher values.

2.5 Results

Figure 2.5.1 contains the estimated days in unemployment per quarter after a displacement, conditional on covariates on worker and regional level. It shows that workers are jobless on average for more than 30 days in the first quarter after displacement. This number decreases gradually and converges to a persistent level of around 11 days after four years.

Figure 2.5.1: Days in Unemployment before and after Displacement



Notes: The graph shows the estimated days per quarter in unemployment four years before and four years after a displacement conditional on nationality, gender, age, age^2, skill level, regional GDP, commuter balance, amenities, a dummy for East/West and year-quarter fixed effects.

In Table 2.5.1, we examine the effect that local job opportunities and job competition have on the number of days in unemployment per quarter. Column (1) provides the results for the specification contained in equation (2.5) with individual and regional controls as well as with year-quarter and time fixed effects, but without individual fixed effects. It shows that a rise in job opportunities by one standard deviation is associated with a decrease in the number of days in unemployment by 1.89 days. An increase in job competition by one standard deviation is, in turn, accompanied by 1.84 more days in unemployment per quarter. Both coefficients are highly significant and similar in size. The fact that they are not statistically different from each other indicates that the effects from higher job density and higher unemployment density in cities offset each other. When adding individual fixed effects in column (2), the coefficient on job density decreases to -1.4 and becomes insignificant. The coefficient on unemployment density, in contrast, rises to 3.5 and remains highly significant.

Taken together, these results are informative in at least three major respects. First, finding the effects from opportunities and competition to offset each other in the absence of individual fixed effects is consistent with the literature on matching functions, which has found no evidence for increasing returns to scale (Petrongolo & Pissarides, 2001). This absence of an overall effect of urbanization on the duration of joblessness hides, however, the potential existence of opportunities and competition as two underlying and opposing mechanisms which are both statistically significant as long as worker heterogeneity is not being controlled for.

Table 2.5.1: Regression Results

	Dependent Variable: ***Days Unemployed per Quarter***				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Job Opportunities	-1.8978***	-1.4236	0.8864	0.2630	-2.4379
	(0.165)	(2.010)	(2.093)	(2.351)	(2.078)
Job Competition	1.8441***	3.4932***	6.0307***	3.0925***	4.0422***
	(0.175)	(0.513)	(0.546)	(0.598)	(0.554)
East	5.2242***				
	(0.283)				
Female	1.0804***		0.9918***		
	(0.195)		(0.187)		
Foreign	5.3566***		5.1903***		
	(0.262)		(0.260)		
Age	-0.6438***	-3.8609***	-0.6550***	-1.8088***	-20.3583***
	(0.113)	(0.312)	(0.115)	(0.345)	(0.373)
Age^2	0.0130***	-0.0192***	0.0131***	-0.0235***	0.0022
	(0.001)	(0.002)	(0.001)	(0.003)	(0.003)
Low Skilled	6.9403***		6.8869***		
	(0.408)		(0.397)		
High Skilled	-4.1119***		-4.1482***		
	(0.227)		(0.226)		
log(GDP)	-0.2397**	-2.9006*	-1.6596	-4.4015**	-4.3105**
	(0.112)	(1.712)	(2.018)	(2.138)	(1.829)
Commuter Balance	0.0238***	0.0425	0.0462	0.0226	0.0682*
	(0.004)	(0.037)	(0.038)	(0.050)	(0.039)
Amenities	-0.0036	-0.0154	-0.0504***	0.0005	-0.0338**
	(0.004)	(0.015)	(0.015)	(0.025)	(0.016)
Year-Quarter FE	Y	Y	Y	Y	Y
Layoff-Quarter FE	Y	Y	Y	Y	Y
Individual FE	N	Y	N	Y	Y
Municipality FE	N	N	Y	N	N
R^2	0.0766	0.4709	0.1033	0.4807	0.5495
N	1,661,631	1,661,631	1,661,631	1,147,500	1,380,207

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors in parentheses; cluster correction on establishment-level; coefficients can be interpreted as change in days per quarter in unemployment with a change in job and workforce density by one standard deviation.

Second, the results emphasize the need to control for individual and regional heterogeneity by means of fixed effects. While finding a positive effect of job opportunities on unemployment duration in column (1) is in line with the findings by Andersson *et al.* (2014), this effect vanishes with the inclusion of individual fixed effects. This supports the argument by Petrongolo & Pissarides (2006) and Harmon (2013) that higher job arrival rates in cities might be offset by higher reservation wages. One peculiarity of our setting is that workers by construction of the sample do not change their region of residence prior to being laid off. As a result, individual fixed effects effectively also control for all time-invariant regional characteristics before dismissal. In order to disentangle the sources of unobserved heterogeneity, we estimate Equation (2.5) with municipality but without individual fixed effects. We assume that the most flexible specification in column (2), which contains both individual and regional fixed effects, is the correct one. Column (3) contains the results with municipality but without individual fixed effects. A comparison of columns (1), (2) and (3) shows that the effect of job competition on unemployment duration is underestimated in the absence of individual and regional fixed effects, but overestimated if only regional fixed effects are included. As such, the results suggest that while more dynamic urban labor markets partly offset negative effects from enhanced job competition in cities, individuals in cities tend to be negatively selected in terms of their probability of finding employment. This latter finding is consistent with a branch of the literature in sociology, which discusses a larger anonymity and less social pressure as main reasons for a higher incidence of long-term unemployment in cities (see, e.g., Siebel, 1997).

Third and most importantly, our findings provide a causal interpretation of the empirical regularity that unemployment rates and unemployment duration are both higher in urban than in rural areas in Germany. In line with the argument by Kroft *et al.* (2013) that job finding probabilities decrease with the tightness of the local labor market, we find that being exposed to a higher degree of job competition significantly raises the number of days that individuals spend in unemployment. At the same time, our results provide no evidence in support of the theoretical argument that workers benefit from sharing the risk of unemployment in thick labor markets. This combination of results is of key importance for the design of urban labor market policies because it emphasizes the importance of the labor supply side when considering additional efforts to fight higher unemployment rates in cities. Reducing the number of job seekers through, e.g., improved placement services, training measures and counseling services turns out to have external effect on all other job seekers by relieving competitive pressure.

Before conducting a number of robustness checks, we briefly summarize the coefficients of the individual and regional variables in column (1), which are informative in their own right. Generally, living in East Germany is associated with longer unemployment spells compared to West Germany, which is in line with a well-documented higher incidence of long-term unemployment in this part of the country (Bundesagentur für Arbeit, 2017b; Bauer *et al.*, 2016). The number of days that foreigners spend in unemployment per quarter after displacement exceeds those of German nationals by more than five days. Women are about one day longer unemployed per quarter than men. Age exhibits a negative effect in younger years, which turns positive around the age of 48. Low-skilled workers are 7 days longer unemployed than medium skilled workers and 11 days more than high skilled workers. Workers find jobs more quickly in more prosperous regions, while amenities do not significantly affect unemployment duration. The number of in-commuters, in turn, raises the duration of unemployment, which is likely the result of more intense competition for available jobs.

In order to further reduce the threat of bias from worker sorting we impose another restriction with regard to the continuity of a worker's place of residence in column (4). So far, we have only required that individuals exhibit a constant place of residence during the four years prior to displacement. We now extend this restriction to the full period of four years before *and* four years after the incidence of unemployment. In consequence, the effect of unemployment falls slightly in size from 3.5 to 3.1. This result provides evidence for a positive selection of stayers in the sense that dismissed workers with lower re-employment prospects in their home region tend to leave the region and look for work elsewhere. Those workers who decide to stay are, in turn, more likely to find a job in their home region.

In a second robustness check, we examine the sensitivity of our findings with regard to the artificial spells we have generated to avoid bias from panel attrition. As described in Section 2.4, about 27 percent of individuals are at some point during the four years after dismissal neither full-time employed nor registered as unemployed. In these cases, we have imputed unemployment spells of zero days. When we drop these artificial spells in column (5), the coefficient of job opportunities remains insignificant while the effect of job competition rises to 4.0. The direction of this change suggests that persons leaving the sample for part-time or self-employment are positively selected.

Table 2.5.2: Heterogeneity of Effects

	Dependent Variable: Days in Unemployment per Quarter				
		Gender		*Age*	
	Benchmark	Male	Female	< 40 years	≥ 40 years
Job Opportunities	-1.4236	-1.2635	-2.8619	1.4835	-4.1749
	(2.010)	(2.324)	(3.270)	(2.266)	(2.782)
Job Competition	3.4932***	3.7534***	2.8406***	4.3107***	2.8079***
	(0.513)	(0.592)	(0.851)	(0.601)	(0.666)
N	1,661,631	1,214,973	446,658	762,212	899,419
	Nationality		*Skill Level*		
	German	Foreign	Low	Medium	High
Job Opportunities	-2.9731	4.6168	5.3938	-3.5124	3.8584
	(2.166)	(4.157)	(5.086)	(2.138)	(5.137)
Job Competition	3.5412***	2.0085*	1.2977	3.8093***	1.6603
	(0.532)	(1.173)	(1.473)	(0.523)	(1.369)
N	1,406,682	254,949	201,178	1,335,911	124,542
	Region Type		*Firm Size*		
	Urban	Rural	< 18 Emp.	≥ 18 Emp.	
Job Opportunities	0.4196	1.5931	-0.8880	-1.8653	
	(2.287)	(5.032)	(2.405)	(3.166)	
Job Competition	3.5037***	5.2699***	3.5638***	3.3970***	
	(0.581)	(1.141)	(0.585)	(0.834)	
N	1,276,751	384,880	817,666	843,965	

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; clustered standard errors in parentheses; cluster correction on establishment-level; coefficients can be interpreted as change in days per quarter in unemployment with a change in job opportunities or job competition by one standard deviation.

In Table 2.5.2, we examine the effects of job opportunities and job competition on the unemployment duration of different subgroups of workers with regard to gender, age, nationality, skill-level, region type and firm size in greater detail. Since the effects of job opportunities are insignificant throughout, we only comment on the results obtained with regard to job competition. We begin by splitting the sample by individual characteristics, starting with gender. The first set of results shows that the effect of job competition is larger for men (3.7) than for women (2.8). This difference can be attributed to women being more likely to resort to part-time employment or to leave the workforce altogether if they become involuntarily unemployed (Bundesagentur für Arbeit, 2017a). When we split the sample by the median age of 40 years, we find the effect of job competition to be larger for younger (4.3) than for older workers (2.8).

Despite the upper ceiling of 50 years of age that we have imposed, this result is most likely driven by the drop-out of older workers to early retirement. In particular during the early years of the period of observation, which spans the years between 1999 and 2009, legal regulations still foresaw substantial room for early retirement under certain circumstances (Bellmann & Janik, 2010; Bonin, 2009). The third set of results indicates that the effect is larger for German nationals (3.5) than for foreigners (2.0). This results is counterintuitive at first glance since one would expect foreigners to be particularly disadvantaged in regions shaped by a high intensity of competition for available jobs. It can, however, be explained by a higher propensity of foreigners to resort to self-employment after jobs-loss (Brixy *et al.*, 2011). When differentiating the results by skill level, we find job competition to affect only the unemployment duration of medium-skilled workers but not of low-skilled and high-skilled workers.[10] For low-skilled workers, this finding probably results from one peculiarity in the German unemployment statistics, where participants in measures of active labor market policies are not counted as unemployed. If such measures are more prevalent in regions with higher levels of unemployment, then job competition will leave the days in unemployment unaffected since workers drop out of the unemployment statistics due to their participation in, e.g., training measures and public employment schemes. The insignificance for high-skilled workers is likely to be genuine in the sense that these workers are likely to compete within their own segment of the labor market and remain unaffected by a higher overall unemployment density.

We continue by shedding light on how the size of the effects varies with the overall degree of urbanization. We therefore categorize regions into rural and urban municipalities according to the classification provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development described in Section 2.3. About three quarters of the workers in our sample reside in urban municipalities. For these workers, negative effects from competition are about 35 percent smaller than for workers living in rural regions. This finding is in line with the notion that metropolitan areas provide better access to job referral networks (Jahn & Neugart, 2017) and offer a broader diversity of industries (Neffke *et al.*, 2017), which both shorten the periods that workers spend in unemployment. Lastly, we split the data with regard to the median size of closed establishments.[11] The negative effects of job competition are slightly larger for workers who were

10 Note that the category *low-skilled* contains all persons without job training. Workers with vocational training are classified as *medium-skilled* and workers holding a university degree are defined as *high-skilled*.

11 Note that the median size is calculated based on the 97,743 individuals and not on the 34,946 different firms contained in the sample.

employed in smaller firms. Similar to the regional differences we found, this result might be due to better job referral networks prevailing within and between larger firms.

2.6 Conclusion and Outlook

We have started off from the observation that both unemployment rates and unemployment durations are higher in urban than in rural areas in Germany, which stands in stark contrast to the argument posited by urban economic theory that workers benefit from sharing the risk of unemployment in larger labor markets. In this paper we have therefore examined to which extent the degree of local job opportunities and job competition influence the number of days that workers spend in unemployment after having become involuntarily unemployed. When controlling for regional and individual heterogeneity and for the sorting of workers across locations, we find that the degree of job competition substantially raises the number of days in unemployment while job opportunities have no significant effect. While these findings defy the notion of risk sharing in urban labor markets, they emphasize the detrimental effect of job competition on the re-employment prospects of unemployment workers. As such, they establish a causal link between observed higher unemployment rates and longer unemployment durations in urban areas.

With regard to the design of labor market policies, these findings emphasize the need for supply side approaches to fighting higher unemployment rates in cities since a decrease in overall unemployment reduces competitive pressures for all other job seekers and thereby unfolds external effects. It would therefore be desirable to better understand the local segregation of labor markets by skill level and occupation in order to better target active labor market policies to different types of unemployed in order to effectively relieve competitive pressures within specific segments of local labor markets. The contribution by Neffke *et al.* (2017), which complements our findings in this direction, provides a valuable starting point of further research.

2.A Appendix

Table 2.A.1: Summary of Sample Restrictions

	All	Leave < 6m.	Tenure > 4y.	Aged 25–50	$County^{const}$	$Munic^{const}$
1999	131,557	89,701	18,740	13,061	10,864	10,604
2000	184,104	129,352	31,249	22,185	15,563	14,908
2001	204,003	144,544	35,499	24,902	14,640	13,397
2002	195,753	139,985	35,988	25,281	13,422	11,767
2003	156,324	117,698	33,275	23,086	11,963	10,081
2004	143,285	103,510	27,820	19,215	9,789	8,265
2005	130,165	96,072	25,737	17,421	8,785	7,378
2006	92,388	67,430	16,745	11,520	5,933	4,984
2007	95,609	68,728	16,561	11,051	5,724	4,753
2008	127,353	87,174	18,570	12,142	6,193	5,130
2009	128,049	97,144	23,179	14,872	7,701	6,476
Total	1,588,596	1,141,338	283,363	194,736	110,577	97,743

Table 2.A.2: Summary Statistics – Reference Values

	Employed		Unemployed	
	Mean	SD	Mean	SD
N	19,274,600		2,251,352	
Age	40.17	10.70	41.23	13.06
Tenure (in days)	2,732.43	2,663.02	1,884.27	2,088.97
Female	0.35	0.48	0.40	0.49
Foreign	0.07	0.26	0.09	0.29
Low skilled	0.08	0.27	0.10	0.29
Mediumskilled	0.77	0.42	0.80	0.40
High skilled	0.14	0.35	0.10	0.30
East Germany	0.21	0.41	0.30	0.45

Chapter 3

Asymmetric Wage Responses to Changes in Commuting Distances

Abstract*

We analyze the causal effect of commuting on wages, using a large sample of German job changers. Information on their home and workplace addresses allows us to calculate exact door-to-door driving distances with an unprecedented degree of precision. With a simple spatial job search model, we motivate the wage-distance tradeoff individuals are facing during job changes. By focusing on job moves, we can control for unobserved individual heterogeneity. We find an asymmetric response to positive versus negative distance changes. Job changers forgo a larger fraction of their wage when reducing their commuting distance compared to the wage increase due to a rise of the commuting distance. Apparently, commuting enters the utility function differently for people with increasing distances compared to those with decreasing distances. A large part of this effect can be explained by sorting into certain firms at different distances and the remainder by a match specific wage component.

Keywords: commuting, job search, marginal willingness to pay

JEL Codes: J31, J64, R12, R40

* This part is joint work with Wolfgang Dauth. An earlier version is published as Dauth & Haller (2016).

3.1 Introduction

Commuting shapes the geography of labor markets as it allows individuals to consume cheap housing or amenities in rural regions and at the same time benefit from employment opportunities and higher wages in cities. This advantage comes at a cost: time spent on commuting is neither productive nor leisure time. Each additional kilometer of distance between home and workplace hence reduces an individual's utility (e.g., Stutzer & Frey, 2008). The standard urban model of a monocentric city suggests that differences in commuting costs are capitalized in housing prices. In reality, however, people from the same residential area work in different places - and colleagues from the same firm live in different areas. The mechanism that determines individual's decisions to commute must thus be more complex. Before accepting a job offer, individuals consider the bundle of a job's features, including wage and commuting distance. The empirical literature has yet to fully answer the question to what extent commuting costs are compensated in wages.

We contribute to this discussion by analyzing the valuation of commuting distance of job changers using precise georeferenced information on the places of residence and work. Focusing on workers who (voluntarily or involuntarily) change between jobs allows us to control for individual heterogeneity. Our main finding is that job changers are willing to forgo a larger fraction of their wage when reducing their commuting distance compared to the wage increase due to a rise of the commuting distance. Our results are robust even after accounting for the wage posting behavior of firms.

In urban economic theory (e.g., Fujita, 1989; Lucas & Rossi-Hansberg, 2002) commuting is the force that shapes cities. In short, it forms a city by determining the allocation of jobs and people. The implied welfare gains of commuting are large and, according to Monte *et al.* (2015), comparable to the GDP gains of moving from autarky to international trade for a country like the US. In a frictionless economy, the commuting costs of homogenous workers are fully compensated through wages and housing prices. Workers choose their place of work and residence from a set of residential areas and workplace locations. The spatial equilibrium is characterized by zero-profits of firms and spatially equalized utility among all workers. In this scenario, firms do not compensate their workers for longer commutes, while individuals decide to take up a job subject to the workplace and residence location (Lucas & Rossi-Hansberg, 2002). By contrast, in a model with search frictions, compensatory wage differentials do exist.

For instance, the individual's spatial job search radius is decreasing with distance (Borck & Wrede, 2009; Zenou, 2009a) which leads to efficiency losses in the matching process. This results in a reduction of the contact rate between firms and workers, giving firms some wage-setting power (Manning, 2003). Workers either take up jobs with fixed wages or bargain their wage (see Rogerson *et al.*, 2005; Hall & Krueger, 2012) in which a compensation for commuting might be included. Due to these numerous labor market frictions the marginal willingness of workers to pay for commuting derived from the gradient of the estimated relationship between wage and commuting distance in wage regressions might be biased (Gronberg & Reed, 1994; Hwang *et al.*, 1998, 1992). Hence, using this approach requires to explicitly control for search frictions and individual heterogeneity of workers and firms.

In the empirical literature, the estimation of the marginal willingness to pay for commuting is usually based on various job search models. Job seekers are differentiated by either on-the-job search for different jobs (e.g., Van Ommeren *et al.*, 2000; Van Ommeren & Fosgerau, 2009) or from unemployment (e.g., Van den Berg & Gorter, 1997). Both types of job seekers maximize their utility by simultaneous search on the labor market and in the housing market (see Van Ommeren *et al.*, 1997, 1999). They accept a job offer at a certain distance from their residence if either the wage or the housing price compensate for their commuting cost. Job offers are either posted with fixed wage (wage posting) independent of the commuting distance of a worker or individual negotiation (wage bargaining). While wage posting appears to dominate the wage determination, by-and-large, certain groups are more able to negotiate their wages. For on-the-job searchers in 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 Euro per day or Van Ommeren & Fosgerau (2009) 17 Euro for one additional hour of commuting. For Denmark, Gutiérrez-i Puigarnau *et al.* (2016) estimate a household's income elasticity with regard to distance of -0.18. Using two surveys for the UK, Manning (2003) find a semi-elasticity of commuting time on wages of around 0.057 for job movers. Van den Berg & Gorter (1997) also find a high negative utility from longer commutes for unemployed. Furthermore, an individual's experience with commuting can create habits. For instance, Simonsohn (2006) shows that individual commuting time can be influenced by the average commuting time in a region after a residential move. This suggests that individuals adapt their preferences with regard to their trip length, what should hence influence the monetary valuation of commuting.

The empirical analysis of the compensation of commuting costs is hampered by individual heterogeneity and residential sorting. Another strand of literature thus uses quasi-experimental strategies to determine the marginal commuting costs (e.g., firm relocation or unexpected changes in the legislation). Doing so for Denmark, Mulalic *et al.* (2014) estimate individual compensation by the employer by focusing on workers employed at a firm that moves but continues to exist. They find that each additional kilometer increases wage by 0.15 percent in the long run. For Germany, Heuermann *et al.* (2017) find no evidence that firms compensate their workers for an exogenous change in commuting costs caused by a tax reform. Boehm (2013) finds a 're-matching' effect of jobs and residences on municipality level after this tax reform in order to reduce distance.

The empirical literature is able to identify a (causal) positive long-run effect of distance and time on wage. Nevertheless the results strongly depend on whether the job seeker is employed or unemployed, whether spatial sorting in form of job or residential mobility is possible, or on the country. For Germany the evidence is rather scarce, but with its polycentric structure it is an ideal case to estimate the individual's marginal valuation of commuting.

In this paper, we run wage regressions for job changers. We derive the marginal valuation of commuting from the variation in both wage and commuting distance caused by the job change. We consider two groups of job changers: those who switch between two stable jobs seamlessly and those who either have an employment gap or register at the employment agency before the switch. We argue that the former switch jobs in order to increase their utility and the latter leave their old job involuntarily and are now forced to look for a new job.[1] We will analyze these groups separately, but assume the same individual considerations regarding the wage-distance trade-off. Our data allows us to observe the employment history of an individual before and after the job change. Due to this panel structure, we can account for individual heterogeneity and for self-selection. Using pre-estimated information on unobserved firm characteristics we can also control for employer heterogeneity (e.g., firm-specific wage-premia, wage posting, etc.).

Our paper contributes to the literature in at least three ways. First, we explicitly distinguish between positive and negative changes of the commuting distance due to a job transition. While there should be no asymmetric valuation in theory and possible differences have rarely been discussed in the empirical literature (e.g., Mulalic *et al.*, 2014, p. 1101), we do find a substantial difference. Second, we present a new approach to control for unobserved individual and firm heterogeneity in the decision to commute using panel data. Third, we use road navigation software and a large sample of German workers that provides information on their home and workplace addresses. This allows us to calculate exact door-to-door commuting distances with an unprecedented degree of precision.

We find an asymmetric valuation of distance changes. Both groups of job seekers value a reduction of their commuting distance higher than an increase.

1 Our identifying assumption is for both groups that the reference utility stems from the previous employment and not the unemployment benefits.

The average marginal effect for a reduction of commuting distance is -0.110 Euros (voluntary job change) or -0.089 Euros (involuntary job change) per kilometer. In contrast the effect of a positive distance change is 0.058 Euros or 0.037 Euros, respectively. Apparently, individuals are willing give up income in order to avoid the dis-utility of commuting. Conversely, they are not able to fully capitalize distance increases in their wages. The coefficient for the overall average semi-elasticity of 0.063 or 0.053 is in line with previous findings (Mulalic *et al.*, 2014; Manning, 2003). After controlling for the firm's wage posting, the size of the marginal valuation decreases but remains significant. The effect is more pronounced for voluntary job seekers. This is in line with the expectation that involuntary job seekers have a weaker position when looking for a new employment and cannot afford to be selective. The results remain robust after controlling for commuting time, long-run wage effects, certain industries, a stricter residence definition and the business cycle. We find heterogeneous effects among gender, age, skill-levels and regional structure.

In the main part of the paper we first discuss a simple job-search model that motivates our empirical approach. In section 3.3, we introduce the dataset and our empirical strategy. The main results as well as robustness checks are presented in section 3.4 and section 3.5 concludes.

3.2 Theoretical Motivation

In labor market search models (see Rogerson *et al.*, 2005), workers maximize their (discounted) lifetime utility from choosing between future employment or unemployment. Spatial job search models extend this basic framework by adding commuting costs. A utility maximizing person accepts the costs for commuting to work if the marginal commuting costs are compensated for by marginal benefits with regard to wage or housing costs (Zenou, 2009b). This implies that wages are a function of commuting costs, conditional on the place of residence. To motivate our subsequent empirical analysis, we consider a strongly simplified version of the standard framework in Rouwendal (1999) or Van Ommeren *et al.* (2000) with only one individual and one firm. We abstract from simultaneous search in the labor and the housing market. Hence, we analyze valuation of commuting distance based on job search decisions in the labor market, while keeping the residence constant.[2] Individual i is currently employed or has been employed recently at firm j. This job offers a utility which is a function of the wage rate w_{ij} and the firm's location

2 This implies that our analysis is in partial equilibrium. In general equilibrium, where residence is not kept constant, one would expect to observe additional adjustment along this margin. However, our results in section 3.4.3 suggest that this restriction is of minor empirical relevance.

which determines the distance z_{ij} (see eq. 3.1). We assume that there is only one job offer (i.e. $\lambda = 0$ in more general search models), which means that we only consider realized job matches.

$$u_{ij} = u(w_{ij}, z_{ij}) + \phi_i + \alpha_i, \tag{3.1}$$

where ϕ_i and α_i are time varying/constant individual characteristics (including attitudes towards commuting, accessibility of the residence, family commitments, etc.). We assume that u increases with w and decreases with z (see Stutzer & Frey, 2008).[3] This implies that, for a given level of utility u_{ij} and location, $\frac{\partial w}{\partial z} > 0$. In a setting with homogeneous workers, this relation is usually assumed to be linear (e.g., Lucas & Rossi-Hansberg, 2002). However, Berliant & Tabuchi (2017) argue that this relation is either concave, if z_{ij} enters u_{ij} in the form of monetary transport costs, or it is convex, if the utility is determined mainly by non-monetary costs. For instance, the job-search model with bargaining in Ruppert *et al.* (2009) suggests a convex wage-distance relation.

An empirical problem estimating the magnitude of $\frac{\partial w}{\partial z}$ is that α_i is arguably correlated to both wage and commuting distance. To solve this problem, we turn to employees who search for a new job. They do so for one of two reasons: they were either laid off at the previous job and are forced to search. Or they have taken up their current job under incomplete information. With updated information, they now voluntarily search for a new job in order to improve their utility. Both groups measure the expected utility of a new job against a reservation utility u_i^R.

$$u_i^R = u_{io}(w_{io}, z_{io}) + \phi_{io} + \alpha_i, \tag{3.2}$$

where u_{io} represents the utility from the previous job. Since we do not consider longterm unemployed, we assume their reference to be the previous employment rather than current unemployment benefits. We assume the unobserved influences on the utility ϕ_{io} to be time varying and the unobservable heterogeneity α_i to be constant during the job transition.

The worker accepts the new job offer n if the utility from the new employment exceeds the reservation utility:

$$u_{in}(w_{in}, z_{in}) + \phi_{in} + \alpha_i \geq u_i^R \tag{3.3}$$

3 The utility is also influenced by all other job characteristics x_{ij}, which we assume to be either homogeneous or controlled for in our empirical analysis.

Stated in first differences, the job offer is accepted if the change in utility from changing jobs $u_{in} - u_i^R \equiv \dot{u}_i(\dot{w}_i, \dot{z}_i)$ is non-negative:

$$\dot{u}_i(\dot{w}_i, \dot{z}_i) + \dot{\phi}_i \geq 0 \tag{3.4}$$

where $\dot{w}_i$ and $\dot{z}_i$ are the wage or distance differentials between the old job o and new job n. $\dot{\phi}$ is the change in the observable individual characteristics and α_i cancels out. As in equation (3.1) we assume that the utility differential increases with the wage change $\dot{w}$ and decreases with commuting distance change $\dot{z}$. For a non-negative utility change $\dot{u}$, $\partial\dot{w}/\partial\dot{z} > 0$. The magnitude of this term remains an empirical question. The model also makes no prediction of whether $\partial\dot{w}/\partial\dot{z}$ is constant or varies with $\partial\dot{z}$.

Finally, we are interested in what determines the relationship of changes in wage and commuting distance. A positive relationship could hint that workers choose a new employer who is willing to compensate them for their increased commuting costs (see Manning, 2011). An alternative explanation would be that workers with increasing commuting distances systematically sort into higher paying firms where they expect to be compensated to a larger extend. To shed light on this mechanism, we follow the empirical literature pioneered by Abowd *et al.* (1999) and Card *et al.* (2013) and assume that the expected wage of worker i at firm j can be multiplicatively decomposed into a workerspecific component, a firm-specific component, and a match specific component. The expected log wage then is: $\ln(w_{ij}) = \alpha_i + \psi_{j(i)} + \kappa_{ij}$. α_i is this worker's idiosyncratic wage component that she would receive at any firm, which comprises of her skills and any other characteristics that affect her wage. $\psi_{j(i)}$ is the proportional firm specific wage component that firm j pays to each of its employees because of rent-sharing, collective bargaining, efficiency wages, etc. κ_{ij} is a match specific component. Substituting into 3.4 gives:

$$\dot{u}_i(\dot{\psi}_{j(i)} + \dot{\kappa}_{ij}, \dot{z}_i) + \dot{\phi}_i \geq u_R \tag{3.5}$$

When looking at the job change, the worker specific term cancels out. $\dot{\psi}_{j(i)} \equiv \psi_{n(i)} - \psi_{o(i)}$ is the difference of the firm specific components and $\dot{\kappa}_i$ is the difference of the match specific components of the new and old jobs. For non-negative changes in utility, we can safely assume that either $\partial\dot{\psi}_{j(j)}/\partial\dot{z}_i$ or $\partial\dot{\kappa}_{ij}/\partial\dot{z}_i$ or both are larger than zero. While we do not know their relative influence, holding constant the firm specific wage component will reveal whether the match specific component is important.[4]

4 In our competitive framework, this wage component can implicitly result from a Nash-bargaining process. We will assess the importance of this element in our empirical analysis.

3.3 Empirical Approach and Data

3.3.1 Identification Strategy

We begin our empirical analysis with a cross sectional regression where we just consider each individual's first observation in the new job:

$$\ln(w_{i,t=0}) = \beta_0 + \beta_1 C_{i,t=0} + X'_{i,t=0}\beta + \alpha_i + \varepsilon_{i,t=0}, \tag{3.6}$$

where $\ln(w_{i,\ t=0})$ is the logarithm of worker i's daily wage, $C_{i,\ t=0}$ is the commuting distance in kilometers, and $X'_{i,\ t=0}$ is the vector of the control variables age, age squared, skill dummies, calendar year dummies, and dummies for the municipality of residence. The municipality dummies that the relation of commuting and wage is identified only by the variation between workers within the same small-scale region. β_1 would otherwise capture regional differences that might be correlated with both commuting times and wages, such as the urban wage premium (Glaeser & Maré, 2001).

α_i subsumes all unobserved individual characteristics that influence the wage. In the first specification, we omit α_i. Then, β_1 yields a naive estimate on how wages differ with commuting distances for workers with similar observable characteristics. However, as the model in section 3.2 suggests, the decision of taking up a job is jointly determined by wages and commuting distance. For example, individuals might differ with regard to how they value commuting distances and accordingly sort into more or less close distances. If α_i is systematically related to the commuting distance, β_1 will be biased.

To control for this unobserved heterogeneity, we exploit that our data consists of individuals who move between workplaces. A straightforward way to eliminate α_i is to use the observations before and after the job change and estimate (3.6) in first differences. Our main model is thus:

$$\Delta\ln(w_{i,t=0}) = \beta_1 \Delta C_{i,t} + \Delta X'_{i,t}\beta + \delta\Delta 1(t=0)_{i,t} + \Delta\varepsilon_{i,t}, \tag{3.7}$$

where $t = \{-1,0\}$. $\Delta\ln(w_{i,\ t})$ measures the difference of the log wages of the new vs. the old job and $\Delta C_{i,t}$ measures the change in commuting distances. β_1 is now tightly identified by the variation in both commuting distances and the wages caused by job changes. We additionally include an indicator variable for the new job, $\Delta 1(t=0)_{i,t}$. After differencing, this becomes the intercept and can be interpreted as the conditional average wage change for all job changers.

3.3.2 Data

Our data stems from registry data of all German workers subject to social security. All notifications to the pension insurance have been processed by the Institute for Employment Research (IAB) into the so called Integrated Employment Biographies[5]. This data source contains information on wages, place of residence and place of work, as well as the employment status of each worker on a daily basis. Wages are top-coded at the social security contribution ceiling (e.g., 177.53 Euros in 2009) and we use the imputation procedure introduced by Gartner (2005) to recover wages above this threshold. We draw a 20 percent random sample of all individuals who separated from a job and took up a new job within 365 days. Since, for administrative reasons, the BeH offers exact geo-referenced information only for the years 2007–2009, we further restrict the sample to workers who left their previous job anytime in 2007 or 2008. Another drawback of German administrative data is that we can only observe daily wages but have no information on working hours. Since the way how part time workers allocate their working hours over a week surely depends on their commuting distances, including them in our regressions but omitting hours would yield substantial bias. As a consequence, we only consider full time workers in our analyses.

In order to identify job transitions, we have to rely on changes of the establishment identifier. This might pose a problem since restructuring within a firm or plant relocations also cause changes in the establishment id. We use the approach of Hethey & Schmieder (2010) to discriminate supposedly true job transitions from firm restructuring by restricting the largest cluster of people who simultaneously change between plant ids. We then distinguish two types of job mobility: we define voluntary job movers as individuals who switched jobs within at most 31 days and who were not registered as job seekers at the German Federal Employment Agency. All others form the group of involuntary job switchers.[6]

We further clean the dataset to make sure we purge the actual effect of commuting on wages from possibly confounding sources of spatial or job mobility. First, we drop all observations with missing geo-coordinates. Since missings are mostly due to problems in the algorithm of string-matching coordinates to address information, we do not believe this will cause any bias. We also drop

5 BeH – Beschäftigtenhistorik V10.00.00, Nürnberg 2015

6 We cannot observe the actual reason for a job change. However, being registered as a job seeker is a strong indication that people did not quit their job voluntarily. According to the Social Code Book (SGB) III, registering as a job seeker is a precondition to receive unemployment benefits (§38). Those benefits are not paid for up to twelve weeks after the end of a job if it was terminated by the employee (§159). So people who change jobs voluntarily usually avoid the administrative inconvenience of registering since they know that they are not entitled to benefits anyway.

people whose old and new job are located at the same coordinates as this is likely to be an artefact of firm restructuring rather than an actual job change. We restrict our sample to individuals who were tenured for more than one year at both the old and new employers. We suspect that the utility maximization behavior of individuals with less stable job careers might differ from the one we have sketched in section 3.2. To make sure we measure daily commuting patterns, we drop workers with distances larger than 100 kilometers. As the distribution of commuting distances is highly right-skewed, this only affects a relatively small number of people. Next, we drop workers with extremely high wages, since we suspect that these are due to errors in the imputation procedure. Finally, we eliminate workers who changed their municipality of residence during the time between one year before or after the job change. We do this because measuring the causal relation of changes in wages and commuting distances requires us to condition on the place of residence (see section 3.2). As this might induce selection in our sample, we check the robustness of our results when we lift this restriction. Appendix table 3.A.1 summarizes these restrictions and their effect on the sample size.

Our data comprises the full employment biographies of the selected workers with daily precision. The main observation of each individual is the first spell at the new job. We then take the spell that includes the same date of the previous year as the second observation. Since we restricted the sample to workers with at least one year tenure at the old job and an employment gap of less than one year, this results in a panel with two observations for each individual, one at the old and one at the new job. Due to the availability of geo-coded data, these are the only observations where we definitely observe the exact places of work and residence.[7]

The BeH offers exact geo-referenced information on individuals' place of residence and place of work based on the addresses included in the social security information (Scholz *et al.*, 2012). With this address information, we can calculate exact commuting distances using OpenStreetMap Routing Machine (Huber & Rust, 2016). We can thus measure commuting distances with an unprecedented degree of precision. In previous research, commuting distance is often approximated by the distance between capitals of administrative units (e.g., municipalities or zipcode areas), assuming distances within regions to be zero. This might cause a severe measurement error since individuals might find jobs at the other side of a regional border to be closer than jobs within a region. In addition, the spatial

7 For a robustness check, we also use the average wage of up to $k = -3, \ldots, 0, \ldots, 3$ years before/after taking up the new job, conditional on the worker staying at this job.

scale of German administrative units varies across federal states and between urban and rural regions. In our sample 33 percent of commuting is within the same municipality. The median driving distance within a municipality is around five kilometers. Hence, using driving distance based on the municipalities would understate the commuting distance by 14 percent. In addition, we would neglect individual sorting within areas.

3.4 Results

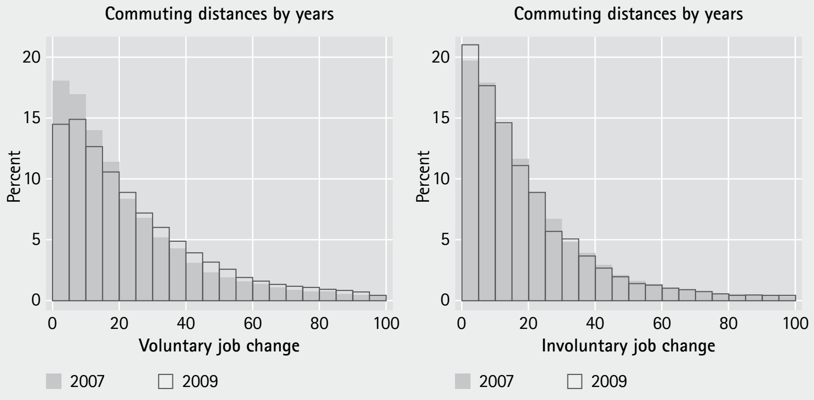
3.4.1 Descriptive Results

Table 3.4.1 reports summary statistics for the main variables. Voluntary job changers experience an increase in wages. This is intuitive as incumbent workers are more likely to change between jobs if they can realize a wage increase. On average, the daily wage increases by 7.95 Euros. More than 25 percent of the job changers also decide to accept a wage reduction. The mean commuting distance to the old employer is 20.28 kilometers and increases to 22.25. The average change is 1.97 kilometers, while the median change is only 0.64. Overall, 55 per cent of the 159,449 individuals have a positive distance increase implying the distribution is not skewed towards positive or negative distance changes. By contrast, involuntary job seekers experience a wage decrease, which corroborates our assumption that these changes are likely to be involuntary. The change in distance is slightly higher than in the first group, but on average, these individuals commute shorter distances both for the old and the new job. The share of persons with a positive distance change is exactly equal in both samples. To summarize, the search and job change behavior appears to result in similar patterns of the commuting distance change in both groups but a contrary wage trend.

Since the valuation of commuting time is likely to vary with worker characteristics, we also report summary statistics of possible control variables in a Appendix table 3.A.2. Our sample is quite balanced with regard to urban/rural municipality of residence, but involuntary job seekers are somewhat older, more often female, and less likely to have a university degree.

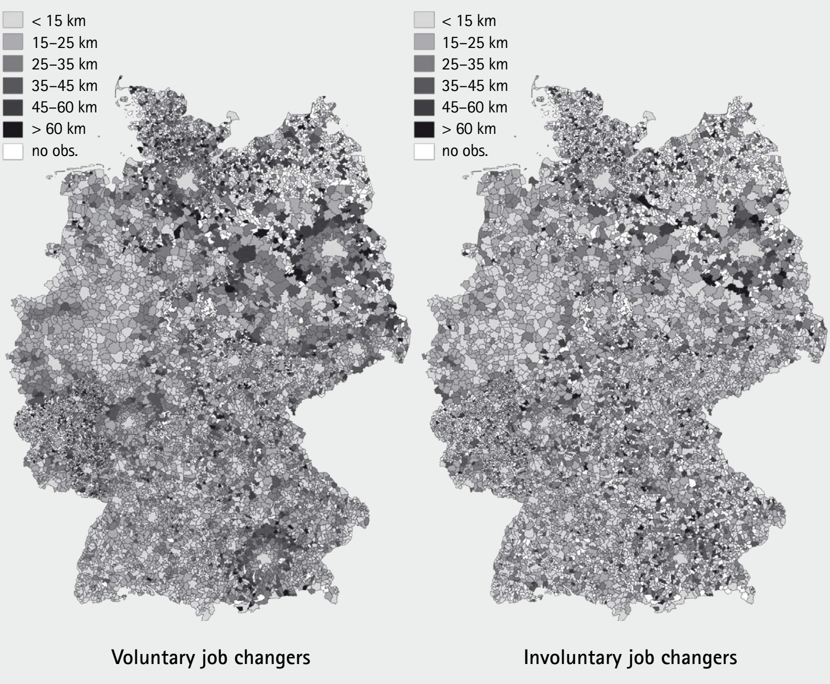
Figure 3.4.1 illustrates the distribution of commuting distances to the new job. The right tail is somewhat thicker for voluntary job changers. Differentiating the distribution by the years 2007 and 2009 we can only find obvious differences for voluntary job changers. The reasons for changes between these two years could be the change in the commuting allowances (see Heuermann *et al.*, 2017) or the international economic crisis which affected the German labor market in

Figure 3.4.1: Distribution of Commuting Distances



Notes: The figures report the commuting distance to the new employment. For comparison the figures distinguish jobs that started in 2007 and 2009.

Figure 3.4.2: Regional Distribution of Commuting Distances



Notes: The maps show the median commuting distance to the new job of all job seekers by municipality of residence in manually chosen distance categories. Municipalities with 'no obs.' emerge due to missing job matches in that region.

Table 3.4.1: Summary Statistics for Main Variables

Variable	Mean	Std.Dev.	25th Perc.	Median	75th Perc.
			Voluntary job seekers (N = 159,424)		
wage old job	101.64	62.92	62.72	86.86	120.79
wage new job	109.60	64.11	71.82	92.79	127.94
Δwage	7.95	44.93	-2.81	5.24	18.05
distance to old job	20.28	19.32	6.13	14.18	27.97
distance to new job	22.25	20.31	7.21	16.04	30.91
Δdistance	1.97	23.58	-6.93	0.64	10.96
dummy,1 = positive Δdist.	0.55	0.50	0	1	1
			Involuntary job seekers (N = 59,970)		
wage old job	77.32	46.76	49.90	67.91	90.00
wage new job	76.22	42.90	51.87	68.23	87.14
Δwage	-1.10	33.75	-11.48	-0.22	10.68
distance to old job	17.54	17.63	5.06	11.89	23.88
distance to new job	19.73	18.65	6.22	14.10	26.90
Δdistance	2.19	22.42	-6.60	0.82	11.05
dummy,1 = positive Δdist.	0.55	0.50	0	1	1

Looking at the regional distribution of commuting distances, we observe a distinctive spatial pattern. The left map of Figure 3.4.2 is dominated by the metropolitan areas of Munich (South), Frankfurt (Mid-West), Berlin (North-East) and Hamburg (North), which seem to attract the voluntary job changers particularly strongly. The distances in municipalities appears to be spread out more evenly in space for involuntary job changers. We conclude that there are somewhat different commuting patterns by type of job seeker and by type of region of residence (e.g., urban or rural).

3.4.1 Baseline Results

We first consider only each worker's first observation at the new job and regress the logarithm of daily wage on the commuting distance and observable worker characteristics. The results in Table 3.4.2 reveal a positive but concave relation of commuting distance and the log wage that declines with larger distances. While a cubic term is still statistically significant, it does not alter the shape of the regression curve substantially. Due to the non-linearity of the relation of commuting distance and log wages, we report semi-elasticities and marginal effects at the bottom of each results table. To this end, we derive the regression equation with respect to the commuting distance and insert the actual distance for each individual. Averaging over all individuals yields the average semi-elasticity of the wage with respect to a marginal change of distance in percent. We obtain the average marginal effect by first exponentiating equation 3.6 before deriving it with respect to the distance. Since the average wage is close to 100 for individuals without an employment gap, both values are often very similar for this group. The semi-elasticities indicate that when comparing two workers that differ only by one kilometer of commuting distance, we expect the worker with the higher distance to earn about 0.4 percent more. This conforms to an average marginal effect of around 0.44 Euros per kilometer for voluntary job changers and 0.29 Euros per kilometer for involuntary job changers.

However, these results do not indicate that the relationship of commuting distance and wage is actually concave, as it might stem exclusively from the log specification. To check this, we also calculate the second derivative of the linearized wage with respect to distance, which is small but negative for the average worker. This finding is in line with theoretical models on commuting (e.g., Berliant & Tabuchi, 2017), that assume commuting costs enter an individual's utility mainly as monetary costs. We illustrate this non-linearity in Appendix figure 3.A.1, where we plot the relationship of both the log and linear wage against the commuting distance, all purged from the control variables reported in Table 3.4.2. These figures confirm the concave relation of both the log and level wage and the commuting distance.

The control variables all have the expected signs. Interestingly, the indicator for jobs started in 2009 is large and positive for workers who voluntarily changed between jobs in 2009 but negative for those who changed involuntarily. This clearly captures the effects of the economic crisis on the German labor market and emphasizes the need to distinguish those two groups.

While the previous results confirm the expected positive relation between commuting distance and wages, they are at best descriptive. The decision to accept a job offer at a certain distance might depend on a number of individual characteristics, such as preferences, motivation, or family status, that are unobserved and possibly determine the wage as well. Since we observe job changers at both the old and the new job, we run the first-differences specification described in equation 3.7. As long as these characteristics and their valuation do not change during the job transition, this purges all unobserved heterogeneity that might cause omitted variable bias in the OLS model.

In Figure 3.4.3, we plot the change in log daily wage between the two successive jobs against the change in commuting distance, both residualized from age squared and dummies for educational attainment and the year of the job change. The striking result is that the non-linear valuation of commuting time becomes stronger: Voluntary job changers appear to value a reduction in commuting time much more than they do for the respective positive change.

Involuntary job changers do not show such a clear pattern. Apart from the instantaneous discontinuity at the zero-distance change threshold of around two percentage points, the slope of the fitted line appears to be more similar for positive and negative changes in distance.

Table 3.4.2: Baseline OLS Regressions – Commuting distance to new job and daily wages

	Dependent Variable: 100 x $log(dailywage)$			
Coefficient	**Voluntary job change**		**Involuntary job change**	
	(1)	**(2)**	**(3)**	**(4)**
Distance	0.5449***	0.6504***	0.5168***	0.5909***
	(0.026)	(0.039)	(0.032)	(0.058)
Distance^2	-0.0032***	-0.0066***	-0.0033***	-0.0058***
	(0.000)	(0.001)	(0.000)	(0.002)
Distance^3		0.0000***		0.0000
		(0.000)		(0.000)
Dummy, female = 1	-15.9270***	-15.9256***	-17.3947***	-17.3956***
	(0.790)	(0.790)	(0.985)	(0.985)
Age	5.0221***	5.0235***	3.1591***	3.1594***
	(0.196)	(0.196)	(0.187)	(0.187)
Age squared	-0.0552***	-0.0552***	-0.0379***	-0.0379***
	(0.002)	(0.002)	(0.002)	(0.002)
Dummy, 2008 = 1	2.4968***	2.4959***	-1.8168***	-1.8192***
	(0.555)	(0.555)	(0.400)	(0.400)
Dummy, 2009 = 1	14.4893***	14.4879***	-5.6942***	-5.6974***
	(1.194)	(1.194)	(0.625)	(0.625)
Dummy, low skilled = 1	-16.0576***	-16.0390***	-25.6604***	-25.6438***
	(0.861)	(0.860)	(1.247)	(1.249)
Dummy, high skilled = 1	41.9025***	41.9213***	43.0736***	43.0945***
	(0.474)	(0.475)	(0.909)	(0.909)
Constant	335.1810***	334.5427***	354.7965***	354.3876***
	(3.559)	(3.560)	(3.543)	(3.550)
N	159424	159424	59970	59970
R^2	0.422	0.422	0.405	0.405
semi elasticity	0.404***	0.431***	0.388***	.407***
marginal effect	0.427	0.453	0.286	0.3
curvature of $w(C)$	-0.005	-0.008	-0.004	-0.005

Notes: All models include fixed effects for municipality of residence. Standard errors, clustered by municipality in parentheses.
Levels of significance: * 10%, ** 5%, *** 1%

Table 3.4.3 reports more detailed results on this finding. In columns (1) and (3), we repeat the baseline specification. The semi-elasticity of an additional kilometer on daily wages drops to about 0.06 percent in both groups. To get an estimate of the slopes from Figure 3.4.3, we interact the distance terms with indicators for a positive or negative change of distance. Columns (2) and (4), show that the effect of a negative distance change on the daily wage is about four times larger as the effect of a positive change of distance, the difference being highly statistically significant. The average worker who reduces her commuting distance forgoes about 0.11 percent of her daily wage per reduced kilometer, which is in the same ballpark as the findings from many previous studies (e.g., Mulalic *et al.*, 2014) for all workers. By contrast, the average worker with a positive change of distance earns only 0.05 percent more per kilometer. In other words, people appear to value a reduction in commuting higher than an increase. This suggests some reverse loss aversion. Individuals might not be able to capitalize the full costs of commuting in their wages. Another interpretation relates to Berliant & Tabuchi (2017) and is more in line with the theory: commuting could enter the utility function differently for workers who commute further and those who decrease their commuting distance. The negative curvature of the relation between changes in wage and distance for those with a longer commuting distance indicates that they primarily consider monetary commuting costs. The convex shape for people with a shorter distance indicates that they also consider nonmonetary costs such as the opportunity cost of time neither spent productively nor on leisure. When taking up a job at a larger distance, people might be unaware of the actual dis-utility of commuting. After updating this information they might be willing to forgo a larger percentage of their wage if they are able to reduce their distance.

Figure 3.4.3: Changes of Commuting Distance and Daily Wage

Notes: The figures show binned scatterplots of 100 x *log(dailywage)* and commuting distances. Both variables have been first-differenced and purged from effects of age², year of job search and education. The dots represent the average values of 100 x *log(dailywage)* in 50 percentile categories of the commuting distance.

Table 3.4.3: Baseline First-differences Regressions – Changes of commuting distance and daily wages

	Dependent Variable: 100 x *log(dailywage)*			
Coefficient	**Voluntary job change**		**Involuntary job change**	
	(1)	**(2)**	**(3)**	**(4)**
Distance	0.0647***		0.0538***	
	(0.004)		(0.007)	
Distance^2	-0.0004***		-0.0001	
	(0.000)		(0.000)	
Neg. dist. change		0.1407***		0.1763***
		(0.016)		(0.033)
Neg. dist. change^2		0.0010***		0.0021***
		(0.000)		(0.001)
Pos. dist. change		0.0892***		0.0749**
		(0.015)		(0.031)
Pos. dist. change^2		-0.0010***		-0.0008
		(0.000)		(0.001)
N	159,424	159,424	59,970	59,970
R^2	0.024	0.024	0.025	0.025
semi elasticity	0.063***		0.053***	
marginal effect	0.064		0.041	
curvature of $\frac{w_{new}}{w_{old}}(\Delta C)$	-0.001		0.000	
semi elast. neg. change		0.111***		0.117***
semi elast. pos. change		0.058***		0.050***
p-value of diff.		0.001		0.025
marg. eff. neg. change		0.110		0.088
marg. eff. pos. change		0.058		0.038
curvature neg. change		0.002		0.003
curvature pos. change		-0.002		-0.001

Notes: All models estimated in first differences. Further control variables are age^2, calendar year and skill dummies.
Standard errors (clustered by municipality) in parentheses.
Levels of significance: * 1%, ** 5%, *** 10%

3.4.3 Further Results

Controlling for firm heterogeneity

Our main results indicate that German individuals value the benefits from a reduction of their commuting distance higher than the costs of an increase. However, the results do not reveal information about the underlying mechanism, that is whether the relation of wages and commuting stem from firms' wage setting behavior or the job changers' ability to bargain. In general, Brenzel *et al.* (2014) find that German wages are determined by about one third by bargaining and two thirds by wage posting. However, Heuermann *et al.* (2017) find that an unexpected repeal of tax breaks for German commuters in 2007 for distances below 20 kilometers had only a small effect on incumbent workers at this threshold.[8] This indicates that (incumbent) workers are not in the position to demand compensation for their increased commuting costs by the employers. Another mechanism might be that job seekers consider the firm itself in their optimization of lifetime utility. Card *et al.* (2013, henceforth CHK) show that wages of German workers are determined to a substantial part by their workplace establishment, who pay a proportional wage premium or discount to all their workers. Job seekers might be aware of this and be prepared to commute further to be able to work at a high paying firm. Or in contrast, abstain from working at such a firm to avoid a longer commuting distance.

Relating to the discussion in section 3.2, we assume that log wages can be split into three additive components: one worker-specific component, one firm-specific component and one component that is specific to the match of a certain worker and a certain firm. Assuming that the first component is time invariant, it will be eliminated by first differencing. If we explicitly account for firm heterogeneity, then the match specific component will be part of the error term. Since we only have a small sample of the total German workforce, including firm fixed effects would be futile. As an alternative, we use the pre-estimated coefficients of firm fixed effects from CHK. They stem from an Abowd *et al.* (1999) regression using almost a full sample of the total German workforce. These firm effects are available to researchers using IAB data and can be merged to our data using a unique establishment identifier. We use them as proxies for the firms' unobserved tendency to pay higher wages to all their employees, possibly due to higher productivity, rent sharing, or collective bargaining. This variable might be a "bad control" in a sense that workers arguably do consider this firm premium/discount in their decision to take up a job. If the effect of changes in commuting distances on wages were entirely driven by workers with different commuting distances sorting into specific firms, we would expect the coefficient of the commuting distance to drop to zero. A remaining match specific effect can then be the result of individual wage bargaining, rather than the firms' wage setting.

We report the results of this augmented model in Table 3.4.4.[9] We refrain from interpreting the magnitude of the coefficient on the CHK firm effects but note that the R^2 of the model increases by an order of magnitude. We are thus confident that this variable does pick up the heterogeneity of firms. The effects of the commuting

8 We also did not find an effect of this policy change on job search behavior in our data.

9 The sample size is smaller than in Table 3.4.3 because CHK had to restrict their analysis to the largest set of German plants interconnected by worker mobility.

distance on wages reduce sharply but remain significantly larger than zero. This indicates that the match specific wage component is important. We conclude that most of the relationship between the commuting distance and wage stems from workers increasing their commuting distances in order to work at firms that pay higher wages. Still, conditional on the firm's wage setting, there is at least some leeway for individual bargaining in the match specific wage component.

Table 3.4.4: First-differences Regressions – Control for firm heterogeneity

	Dependent Variable: 100 x $\Delta log(dailywage)$			
Coefficient	**Voluntary job change**		**Involuntary job change**	
	(1)	**(2)**	**(3)**	**(4)**
Distance	0.0342***		0.0245***	
	(0.003)		(0.005)	
Distance^2	0.0001		-0.0000	
	(0.000)		(0.000)	
Neg. dist. change		0.0718***		0.0747***
		(0.012)		(0.022)
Neg. dist. change^2		0.0007***		0.0008**
		(0.000)		(0.000)
Pos. dist. change		0.0253*		-0.0003
		(0.014)		(0.024)
Pos. dist. change^2		0.0001		0.0003
		(0.000)		(0.000)
CHK firm FE	72.8374***	72.8197***	87.6015***	87.5893***
	(0.603)	(0.603)	(0.790)	(0.792)
N	138,097	138,097	47,687	47,687
R^2	0.339	0.339	0.510	0.510
semi elasticity	0.035***		0.024***	
marginal effect	0.037		0.02	
curvature of $\frac{w_{new}}{w_{old}}(\Delta C)$	0.000		0.000	
semi elast. neg. change		0.051***		0.053***
semi elast. pos. change		0.030***		0.008
p-value of diff.		0.070		0.031
marg. eff. neg. change		0.052		0.043
marg. eff. pos. change		0.032		0.007
curvature neg. change		0.002		0.001
curvature pos. change		0.000		0.000

Notes: All models estimated in first differences. Further control variables are age^2, calendar year and skill dummies.
Standard errors (clustered by municipality) in parentheses.
Levels of significance: * 1%, ** 5%, *** 10%

Table 3.4.5: Robustness Checks: Semi-elasticities of wage changes with respect to changes of commuting distances

	Dependent Variable: 100 x $\Delta log(dailywage)$							
	Average semi-elasticity				Avg. marginal effects (in Euros)			No. of obs.
Group	Overall	Negative	Positive	Difference	Overall	Negative	Positive	
	Voluntary job change							
Benchmark	0.063***	0.111***	0.058***	***	0.064	0.110	0.058	159,424
Include residence movers	0.060***	0.109***	0.050***	***	0.060	0.108	0.050	176,057
Residence movers only	0.038***	0.078***	0.017		0.038	0.077	0.018	16,633
Constant grid cell of residence	0.063***	0.111***	0.057***	***	0.065	0.112	0.057	136,843
Commuting time	0.073***	0.114***	0.058***	***	0.074	0.115	0.058	159,424
Averaged wage	0.063***	0.102***	0.070***	**	0.062	0.100	0.069	159,424
Exclude industries	0.065***	0.112***	0.063***	**	0.067	0.114	0.063	120,058
Leaves job before 7/2007	0.074***	0.112***	0.083***		0.074	0.110	0.081	31,034
Different intercepts	0.047***	0.097***	0.047***	***	0.047	0.097	0.047	159,424
	Involuntary job change							
Benchmark	0.053***	0.117***	0.050***	**	0.041	0.088	0.038	59,970
Include residence movers	0.053***	0.116***	0.051***	**	0.041	0.087	0.038	67,278
Residence movers only	0.049***	0.111**	0.040		0.037	0.083	0.029	7,308
Constant grid cell of residence	0.056***	0.139***	0.040**	***	0.043	0.106	0.030	50,772
Commuting time	0.060***	0.116***	0.054***	**	0.046	0.087	0.041	59,970
Averaged wage	0.053***	0.119***	0.051***	**	0.041	0.089	0.039	59,970
Exclude industries	0.059***	0.130***	0.048***	**	0.047	0.101	0.038	41,723
Leaves job before 7/2007	0.060***	0.199***	0.023	**	0.048	0.156	0.018	13,103
Different intercepts	0.016**	0.064***	0.007	**	0.012	0.049	0.005	59,970

Notes: Semi-elasticities and marginal effects from first difference regressions of wage regressions analogous to the ones reported in Table 3.4.3. Further control variables are age^2, calendar year and skill dummies. Standard errors (clustered by municipality) in parentheses.

Levels of significance: * 10%, ** 5%, *** 1%

We still find a differential effect of positive and negative distance changes: conditional on an employer's wage-setting, workers still appear to be willing to forgo a higher amount of money to avoid commuting. Remarkably, the latter effect is much stronger for voluntary job changers. Involuntary job changers appear to be less likely in a position to select from job offers, and more often accept an inferior wage-distance relation.

Robustness checks

Our main findings from Table 3.4.3 prove to persist even when controlling for firm heterogeneity. There are still several issues that might influence our results. We thus conduct a series of robustness checks and summarize the results in Table 3.4.5.

Our main sample is restricted to people who change between jobs but not between residences. We do this because the optimization behavior of residence movers needs to take the cost of moving into account, which might distort the causal relation of wage and commuting distance. However, this might also introduce selection bias if residence movers react particularly sensitive to changes in commuting distances. The danger of such a bias in our data is small, as we do not find any significant differences in the wage changes comparing our main sample with residence changers after controlling for their observable characteristics. Still, we include those residence changers and re-estimate our baseline model as a robustness check. Reassuringly, we do not find any differences to the main results. When we restrict our sample only to people who simultaneously change both the workplace and the residence, the asymmetric effect of changes of the commuting distance on wage changes holds. However, there is no statistically significant effect of a positive distance change any more. This is likely because the higher dis-utility of commuting can now also be compensated by unobserved changes in housing costs.

So far, we define residence changers as people who change the municipality of residence. This means that our main sample contains people who move within municipalities. In most cases this should not pose a problem as municipalities are very small.[10] In this robustness check, we try to be even more conservative and restrict the sample to persons to live in the same 1000m x 1000m grid cell before and after the transition. The delineation of these cells is independent of a municipality's population density or area. This reduces the number of observations by around 22,500 and 9,200, respectively. The change in the marginal effects is very small for both groups of job seekers. We thus infer that, a stronger assumption regarding the residence location leaves our findings almost unchanged.

10 The mean (median) municipality has an area of 32 (19) km^2, which corresponds to a diameter of roughly 6.4 (4.9) km.

We obtained precise road commuting distances using the OpenStreetMap Routing Machine (Huber & Rust, 2016). This algorithm can also be used to estimate the commuting time based on parameters for the average velocity on different types of streets, waiting times at traffic lights, etc.[11] The estimated driving times are ideal driving times and can only insufficiently account for rush hours or traffic jams. We thus only use this as a robustness check. The difference in the valuation for positive and negative changes in commuting time is smaller between voluntary and involuntary job changers.

Our identification strategy builds on comparing the difference of daily wages at the end of the old and the start of the new job. This might yield an incomplete picture of the wage difference that actually enters an individual's considerations. For example, wages at the old job could have stagnated prior to the layoff or could rise quickly after a short tenure in the new job. Mulalic *et al.* (2014) find, in a somewhat different setting, that it takes until the next bargaining round for wages to adjust to changes in the commuting distance. To take this into account, we use the full employment biographies and calculate the average daily wage of the old (new) job during the three years prior to quitting the old job (after starting the new job). We then take the change of the average wage as the dependent variable and re-estimate our baseline models. A notable change is that the difference between the valuation of negative and positive distance changes shrinks but remains significant. This could be due to a steeper wage profile after the job move for voluntary job changers that makes up some of the age decline when entering the new job. Another difference is the intercept (not reported in Table 3.4.5). The intercept reflects the ceteris paribus wage increase due to the job change. It rises from 24.35 to 38.17 percent for voluntary job changers and from 17.75 to 29.15 percentage points for involuntary job changers. This indicates that wages do rise during the tenure of the new job but this mostly affects the constant and only slightly the effect of the distance change.

A possible concern in our data relates to the georeferencing of the workplace address. If a firm has several subsidiaries within the same municipality and with the same industry code, then each subsidiary is still assigned the same establishment ID. For example, a super market chain might hold several stores in the same city and it will not be possible to distinguish them in our data. This problem could be aggravated if a firm's employees are mobile across plants, for example in the construction or transport sectors. In both cases, commuting distances of individual workers will not be measured correctly. As a further robustness check, we thus drop those industries where we fear that this issue might be most severe: construction,

11 The original algorithm strongly understated the driving time within cities. We recalibrated the parameters so that a sample of estimated driving times conform to the results of a manual query using one of the prominent web mapping services. The resulting configuration file is available upon request from the authors.

transport (on land), temporary agency work, retail trade, financial intermediation, public administration, and defence. Almost 40,000 observations are dropped but in comparison to our initial results in Table 3.4.3 the results change only marginally.

A further concern might be that the world financial crisis happened right within our observation period of 2007 to 2009. Due to the availability of georeferenced data, we cannot choose a different time period. We thus drop all workers who left their job after June 2007 as they are more likely to be affected by the crisis. The somewhat unexpected result of this check is that the difference between the effects on reduced and increased commuting distances becomes more pronounced for involuntary job changers. We hypothesise that this might be because the composition of unemployed changed during the crisis. Before the crisis, unemployed were more of a negative selection who had even smaller chances to compensate their commuting costs or needed to make even stronger concessions when reducing their commuting distances.

Finally, we check if the wage increase from a job change differs between those with an increase of the commuting distance and those with a reduction, independent of the actual magnitude of the distance change. We do this by allowing for separate intercepts between the two groups. Individuals with a negative distance change have a significantly smaller intercept, i.e. 0.55 percentage points for voluntary and 2.09 percentage points for involuntary job changers. However, the effects of the magnitude of the distance change remain virtually unchanged.

Heterogeneous effects

Clearly, commuting patterns vary with the characteristics of individuals (see Wang, 2001). We document the different commuting patterns to the new employment in Appendix table 3.A.3. We see that men commute around 15 to 20 percent further than women. There is also an age pattern: Younger (than the median age) workers have 7 to 13 percent shorter commutes than older workers. Commuting distances clearly increase with education. High-skilled workers commute more than six kilometers further than low-skilled, i.e. 33 to 46 percent more. In the same way individuals differ when living in urban or more rural areas.[12] As expected, rural residents commute 33 to 34 percent more. We re-estimate our benchmark specification for each of those groups to see whether these commuting patterns are related to different valuations of the commuting distance. The results of the regressions for individual groups are summarized in Table 3.4.6. As the wages might differ between the subgroups, we focus our interpretation on the estimates for the semielasticities.

12 We define municipalities to be urban if they are classified as "large cities" in the 2014 classification of municipalities of the Federal Institute for Research on Building, Urban Affairs and Spatial Development.

Commuting patterns differ between men and women. For instance, household obligations influence the job location decisions of women more strongly than those of men (e.g., White, 1986). Comparing male and female job changers, we find higher elasticities for women than for men. While the effects of positive distance changes are more or less equal, the wages of women react more strongly to negative changes. The semi-elasticity differs only little between the voluntary and involuntary job seekers. These results are consistent with studies that find female labor supply to be more elastic (e.g., Hirsch *et al.*, 2010; Barth & Dale-Olsen, 2009). These differences might actually be even more pronounced if we could include part time workers since omitting women in part time jobs might yield a selective sample of the remaining women. Still, our main result holds and both sexes value distance reductions higher.

While searching for a new job, young and old workers might have different preferences with respect to commuting distance. For younger job seekers, the elasticity of changes in commuting distance is generally higher than for older workers. In case of a voluntary job change, people arguably seek to improve their career prospects. However, it appears that the distance change is a less important aspect for older workers. The desire to reduce the commuting distance is markedly higher for younger workers. In case of involuntary job search, the pattern changes slightly. Both young and old value a reduction almost twice as high as the comparable positive distance shift.

The residential location choice of workers highly depends on the their educational attainment (e.g., White, 1988; Gutiérrez-i Puigarnau *et al.*, 2016). When we split the sample by three skill groups, we find a very diverse picture. The asymmetric valuation for voluntary job seekers is driven by skilled workers. Unskilled workers do not significantly value closer jobs, but request more for commuting further. This group might be particularly adverse to losses in terms of nominal wages. High-skilled workers have the longest commuting distances, but they do value smaller and larger commuting distance differently only at the ten percent significance level. The results for involuntary job changers are somewhat puzzling. For unskilled workers the overall effect of a change in the commuting distance is zero. Since their jobs are usually less evenly distributed, matching effects might be of minor importance and hence yield few room for a match specific wage premium. Distinguishing positive and negative changes, the results even imply an increase of the wage if the distance decreases. The valuation pattern for skilled workers changes only slightly. For unemployed high-skilled individuals a reduction of the distance is now more pronounced. If they are forced to look for a new employment, they only value a reduction of the commuting distance. All of these results are in line with previous evidence that richer households prefer to live closer to their workplace (see Gutiérrez-i Puigarnau *et al.*, 2016).

Table 3.4.6: Heterogenous Effects by Sub-samples

	Dependent Variable: $\Delta log(dailywage)$							
	Average semi-elasticity				Avg. marginal effects (in Euros)			No. of obs.
Group	Overall	Negative	Positive	Difference	Overall	Negative	Positive	
	Voluntary job change							
Benchmark	0.063***	0.111***	0.058***	***	0.064	0.110	0.058	159,424
Gender								
Male	0.057***	0.093***	0.054***	**	0.061	0.099	0.057	109,214
Female	0.078***	0.147***	0.071***	***	0.068	0.127	0.061	50,210
Age above/below median of 36.9 years								
Young	0.078***	0.133***	0.074***	***	0.069	0.116	0.064	79,711
Old	0.049***	0.080***	0.048***	*	0.056	0.090	0.054	79,713
Skill								
Unskilled	0.007	0.000	0.067*		0.005	0.000	0.049	5,709
Skilled	0.064***	0.119***	0.061***	***	0.056	0.102	0.052	117,839
High-skilled	0.067***	0.091***	0.055***	*	0.102	0.136	0.085	35,876
Regional structure								
Urban	0.071***	0.131***	0.094***		0.076	0.139	0.096	53,247
Rural	0.060***	0.095***	0.051***	***	0.058	0.091	0.051	106,177
Distance to old job above/below median of 14.2 km								
Short	0.100***	0.356***	0.059***	***	0.091	0.327	0.054	79,711
Long	0.060***	0.094***	0.036***	***	0.065	0.097	0.041	79,713
	Involuntary job change							
Benchmark	0.053***	0.117***	0.050***	**	0.041	0.088	0.038	59,970
Gender								
Male	0.043***	0.089***	0.046**		0.035	0.071	0.036	38,882
Female	0.078***	0.163***	0.074***	**	0.054	0.111	0.050	21,088
Age above/below median of 38.0 years								
Young	0.062***	0.133***	0.053**	*	0.044	0.093	0.037	29,985
Old	0.046***	0.101***	0.051**		0.038	0.082	0.040	29,985
Skill								
Unskilled	-0.028	-0.246**	0.141*	**	-0.016	-0.145	0.077	2,340
Skilled	0.055***	0.132***	0.052***	***	0.038	0.091	0.035	47,054
High-skilled	0.066***	0.136**	0.026		0.075	0.150	0.034	10,576
Regional structure								
Urban	0.055***	0.148***	0.093**		0.045	0.116	0.072	19,709
Rural	0.054***	0.095***	0.049***	*	0.040	0.070	0.036	40,261
Distance to old job above/below median of 11.9 km								
Short	0.093***	0.867***	0.008	***	0.066	0.610	0.006	29,985
Long	0.044***	0.060***	0.052***		0.036	0.047	0.044	29,985

Notes: Semi-elasticities and marginal effects from first difference regressions of wage regressions analogous to the ones reported in Table 3.4.3. Further control variables are age^2, calendar year and skill dummies. Standard errors (clustered by municipality) in parentheses.
Levels of significance: * 10%, ** 5%, *** 1%

In larger cities public transport is better available and more frequent. Therefore, only every other worker uses a car for commuting, while in rural regions 70 percent use a car. By contrast, travel speed is usually higher in rural areas (see Wingerter, 2014). Against this background, another interesting finding is that city dwellers have higher semi-elasticities than their rural counterparts. A change of the commuting distance has presumably more impact in a city compared to the same change in an rural area, where the largest part of commuting is likely to take place on less congested country roads. Yet for urban resident, there is no statistically significant difference in the valuation of negative and positive distance changes. The estimates change only slightly for involuntary urban job changers. For rural residents the different valuation remains almost the same. Workers in less dense areas might be used to commuting and that is why it does not matter whether they are unemployed or employed while looking for a new job. This finding is in line with Reichelt & Haas (2015) who find that job changers prefer shorter distances in denser labor markets.

Finally, we distinguish according to the median commuting distance to the old job. This reveals that the differential valuation of positive and negative distance changes is largely driven by people who used to have a commuting distance below the median. For both voluntary and involuntary job changers with previously below median distances, the point estimate of the semi-elasticity is much larger for people with a negative distance change. So in spite of their short commutes ex ante, this group of people appears to be most eager to further reduce their commuting distances.

Overall, we can identify heterogeneity in all characteristics. Female, young and urban residents respond higher to distance changes. Future work should take a closer look at skill groups, as our results suggest a diverse picture in the valuation of commuting distance changes.

3.5 Conclusion

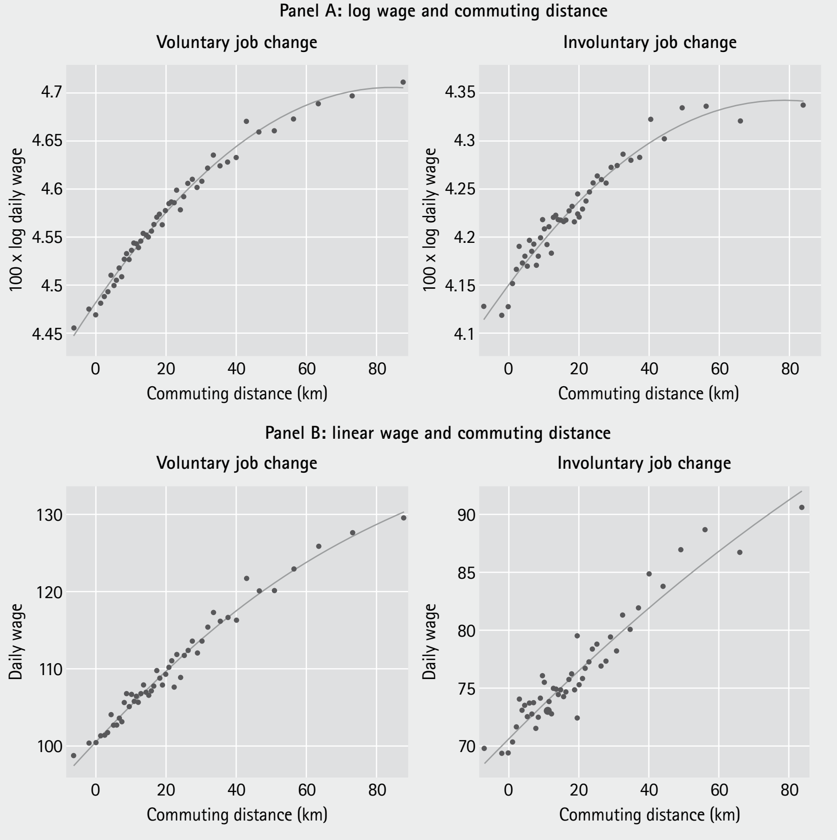
In this paper, we present a novel approach to measure the willingness to pay for commuting. We analyze the wage responses to changes in commuting distances of individuals who are changing between two jobs. This allows us to control for unobserved heterogeneity that would otherwise simultaneously affect both variables. In addition, we use very detailed georeferenced data of the exact locations of a large number of individuals' residences and workplaces. In combination with an algorithm that employs navigation software, we can measure each individual's road commuting distance with an unprecedented degree of precision.

The recurring finding of our study is that people are willing to forgo a larger share of their previous wage when they can reduce their commuting distance compared to what they would demand if they had to commute further. This is plausible when one acknowledges the high non-monetary dis-utility of commuting. All other things equal, when changing to a new job, people are willing to give up a larger part of their earnings possibilities in order to spend less time commuting. In the opposite case, they are either not in the position to capitalize a higher commuting distance in higher wages to the same extent, or they more naively focus only on the monetary costs of commuting. The largest part of the wage response to changes in the commuting distance is due to sorting into firms with different wage posting behaviors and only to a small degree due to match specific effects. Our results emphasize the large dis-utility of commuting. Especially urban residents with below-median commutes are zealous to further reduce their commuting distances. In our analysis, we hold the residence constant, but these findings imply that people should also be willing to accept over proportionally higher housing prices in order to live closer to their workplaces. While we have to leave a test of this conjecture to further research, it is well in line with the ongoing gentrification of the centers in many cities in industrialized countries. Urban policy makers should more strongly account for the high utility gains of reduced commutes in their decisions.

Our results stem from a rather small time window, where German georeferenced employment data is available. Future research could apply our approach to a larger time period. Analyzing the whole employment biographies of individuals and accounting for all changes of commuting distances due to changing residence or workplace would considerably increase the precision of the analysis. It would allow to better understand how wages and commuting jointly enter an individual's considerations to maximize lifetime utility.

3.A Appendix

Figure 3.A.1: Commuting Distance and Daily Wage



Notes: The figures show binned scatterplots of the partial effect of the commuting distance on the wage. Both variables have been purged from effects of sex, age, age², year of job search, education, and municipality of residence. The dots represent the average values of the wage in 50 percentile categories of the commuting distance. In panel A, the vertical axis reports residualized values of 100 x *log(dailywage)*. In panel B, the vertical axis reports values of the difference between the actual daily wage and its prediction obtained from the logarithmic specification.

Table 3.A.1: Summary of Sample Restrictions

	Voluntary job change	Involuntary job change
All	327,584	179,876
Nonmissing distance	295,240	176,698
Change of workplace coordinates	236,188	98,229
> 1 yr tenure new job	235,219	84,055
> 1 yr tenure old job	208,099	76,394
< 100 km commuting distance	177,088	67,402
No extreme wages	176,057	67,278
No change of residence	159,424	59,970

Table 3.A.2: Summary Statistics for Control Variables

Variable	Mean	Std.Dev.	25th Perce.	Median	75th Perce.
			Voluntary job change (N = 159,424)		
Female	0.31	0.46	0	0	1
Age	37.80	9.56	30	37	45
Low skilled	0.05	0.22	0	0	0
Medium skilled	0.75	0.43	0	1	1
High skilled	0.20	0.40	0	0	0
Urban	0.33	0.47	0	0	1
			Involuntary job change (N = 59,970)		
Female	0.35	0.48	0	0	1
Age	38.64	10.15	30	39	46
Low skilled	0.06	0.24	0	0	0
Medium skilled	0.79	0.41	1	1	1
High skilled	0.15	0.36	0	0	0
Urban	0.33	0.47	0	0	1

Table 3.A.3: Commuting Distances by Worker Groups

Group	Mean	Std.Dev.	25th Perce.	Median	75th Perce.
		Voluntary job change (N = 159,424)			
Gender					
Male	23.46	20.91	7.77	17.21	32.75
Female	19.62	18.66	6.25	13.79	26.77
Age above/below median of 36.9 years					
Young	20.94	19.37	6.72	15.06	28.91
Old	23.67	21.19	7.81	17.19	33.10
Skill					
Low skilled	19.03	18.86	5.84	12.83	25.32
Medium skilled	21.41	19.63	7.08	15.51	29.41
High skilled	25.53	22.27	8.00	18.85	36.64
Regional structure					
Urban	18.16	18.54	5.82	11.53	23.18
Rural	24.31	20.84	8.66	18.73	33.85
		Involuntary job change (N = 59,970)			
Gender					
Male	20.68	19.27	6.62	14.91	28.45
Female	17.97	17.32	5.62	12.72	24.53
Age above/below median of 36.9 years					
Young	19.11	18.10	5.95	13.67	26.14
Old	20.40	19.21	6.54	14.58	27.75
Skill					
Low skilled	16.03	17.04	4.49	10.90	20.96
Medium skilled	19.08	17.93	6.18	13.82	25.88
High skilled	23.40	21.45	6.92	16.61	33.33
Regional structure					
Urban	16.12	17.00	5.21	10.23	20.18
Rural	21.49	19.16	7.23	16.50	29.65

Overall Conclusion and Outlook

Regional integration of labor markets highly depends on the location of firms' labor demand and labor supply of workers in different (urban) areas. Many political decisions are made on the local level based on administrative units (Monte *et al.*, 2015). However, commuting as an increasing phenomenon can lead to a dilution of economic policy within regional administrative units (see Petrongolo & Manning, 2017). For instance, the local number of unemployed or jobs in a county or municipality can be influenced by mobile job seekers or vacancies in neighboring areas. In this case, an active labor market policy needs to take the spatial linkages with adjacent areas into account. In a way the creation of artificial labor market regions (for Germany, e.g., Kosfeld & Werner, 2012; Kropp & Schwengler, 2016) is an attempt to account for this interrelation. An aggregation of spatial units, however, would weaken the validity of empirical insights. Hence, the analysis of regional labor markets should take the spatial interactions into account. This dissertation sheds light on spatial interactions from three different perspectives.

In chapter 1 we find spatial spillovers in regional job matching functions. These interactions are not influenced by the transport infrastructure between two counties, but primarily depend on the physical distance. Unemployed workers are therefore competing with job seekers from neighboring regions about vacant jobs. This not only helps in understanding the regional job matching process but is also highly relevant for the design of labor market policies. An increasing number of job seekers who find work in other regions would suggest a stronger cooperation of job centers in neighboring counties. This is one way to remediate regional imbalances between labor demand and supply. From the methodology perspective, Spatial Econometrics provides excellent approaches to capture spatial interaction among regions (Gibbons *et al.*, 2015). Although, empirical work needs to sensibly assess the nature of spillovers and spatial grounds of regional economic mechanisms. Unfortunately, for the analysis of individuals or small scale areas these approaches are ineligible due to the long computation time of matrix calculations.

The sharing mechanism about the risk of unemployment in cities is the starting point of chapter 2. Longer unemployment durations and higher unemployment rates in dense labor markets question the theoretical presumption of risk sharing. We empirically evaluate this contradiction by looking at the labor market density of the residence municipality of involuntary unemployed. For this purpose, we evaluate the opposing density effects of job opportunities and job competition. To recognize the spatial interrelation with neighboring labor markets, we include the distance-weighted neighboring density in our indicators. The identification method allows us to control for spatial sorting and to apply individual and regional fixed effects to estimate the causal effect of job and unemployed density on the days being unemployed after a displacement. We find that job competition raises the days in unemployment per quarter, whereas job opportunities show no effects for displaced job seekers. Increasing competition in thick labor markets are therefore one of the forces behind longer unemployment durations and higher unemployment rates in denser markets. The finding of this chapter contributes to the discussion about the empirical validity of agglomeration advantages for workers. Our results suggest to work on the urban mechanism and possible advantages more closely. Future work can achieve it with a closer look at new data on cities to understand the spillover effects in denser labor markets. To do so, our identification approach can be applied to data which is not limited by aggregated regional information.

Although, the number of commuters as well as their commuting distance are increasing, individuals are reluctant about the daily travel to work. The asymmetric valuation of commuting distance changes in chapter 3 shows a larger forgoing of earnings when job changers can reduce their daily trip to work. Most of these effects stem from sorting of workers into firms with different wage posting schemes and a minor part due to a job match premium. We develop a novel approach to evaluate the marginal willingness to pay for commuting to answer further questions about the compensation for commuting. We detect heterogenous effects especially by education, which is an interesting topic for future research. Our georeferenced employment data is only available for the years 2007 to 2009. With more years available, we would be able to derive better conclusions on the effects over the business cycle. Economic policy needs to consider the welfare gains of reduced commuting distance in their decisions. Connecting rural amenities and urban employment opportunities by the gentrification of urban areas could be one solution. It would reduce the commuting distance and, as a byproduct, spatial interactions.

The last part shows how very detailed individual information of workplace and residence can broaden the knowledge about the interrelation of locations through commuting. Territories are thus continuous entities. Admittedly, administrative units will always be central for informative statistics and as a consequence in the political decision process (e.g., with regard to infrastructure investment). High disaggregation would further complicate the decision. Nevertheless, data with geo-information allows a detailed view on spatial linkages and agglomeration economies. Future empirical work in regional and urban economics will profit from the advancement in data availability and precision. This could boost recent theoretical advancements (Redding & Rossi-Hansberg, 2017).

New data will open up a novel view on upsides and downsides of cities and the mechanisms of agglomeration and dispersion. In this context, big data, which intends to combine several data sources of administrative, private and public origin, can be central (see Lohr, 2012, for an early review). The advantages in empirical social science or economics are obvious (Einav & Levin, 2014). For instance, projects like OpenStreetMap can supplement official statistics in order to get a superior representation of the local socio-economic structure. Another example is the use of satellite data (e.g., Henderson *et al.*, 2012; Donaldson & Storeygard, 2016) for the case official statistics are incomplete or absent. With a wider variety of such data we also need to develop new methods to analyze it (Varian, 2014). More observations complicates computing time and traditional methods. For instance, machine learning (Mullainathan & Spiess, 2017) is a promising approach which needs to be sharpened for purposes in regional and urban research. With these advancements new insights about spatial linkages, urbanization and commuting within and across regional labor markets are achievable. The reevaluation of proximity effects among good and factor markets in agglomeration economics, how cities and suburbs unify to metropolitan areas or segregation of social groups, e.g., refugees, are examples of future research questions, which should benefit from the recent advancements.

For Germany the most crucial issues in the future development of the spatial economics structure might be an aging society and the successful integration of immigrants in the (regional) labor market. So far knowledge about the mobility pattern of older workers is yet not fully discovered. However, this could have tremendous effects on the regional structure and spatial linkages. The mobility pattern of immigrants is known to a great extend. Yet, the influx of refugees in 2015 gives reasons to devote attention to their mobility pattern in order to prevent segregation and the development of parallel societies in cities. One possibility is to direct the immigration into regions with declining population. However, for long-term effects local jobs are basic prerequisite. Commuting might only partly balance the agglomeration forces. These issues will dominate economic policy in the next decade in many fields and most likely also research about spatial interaction among regions. The design of the spatial structure and spatial mobility needs to be addressed in current political decisions. In three chapters this doctoral thesis delivered valuable insights which help to understand the spatial interrelation among regional labor markets in Germany.

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Abstract

Compared to other European countries, Germany has a highly dispersed spatial structure with many centers of dense economic activity. Germany's polycentric structure is especially suitable for empirical studies about the spatial mechanisms of cities and the interactions between regions. With rising population in cities, commuting serves as a spatial equalization mechanism and forms spatial interactions between local labor markets in Germany. In different chapters this thesis will empirically shed further light on the questions, how local labor markets interact, how dense markets help finding new employment given the interrelation with surrounding areas and how people respond to changes in commuting distances.

The first chapter provides new evidence on the geographical scope of job search and hiring behavior. We answer the question, how the number of unemployed or number of vacant jobs affect hires within and across German counties (NUTS3) from 2000 to 2010. By the means of spatial econometrics we capture local spillovers based on a set of neighboring regions. The adjoining relation is measured with different spatial weight matrices (e.g. based on transport infrastructure) that vary in how they value the (physical) distance between a pair of regions. Our results show robust spillover effects, which are of local nature. Bayesian estimations prefer the simple physical direct distance. These spillovers arise exclusively after the labor market reforms in Germany in 2005, which suggests an increased mobility of unemployed through commuting.

In the light of this regional analysis of administrative tracts, chapter two, evaluates the competing density mechanisms within and across local labor markets on municipality level. Herein, we use involuntary unemployment from plant closures between 1999 and 2009 as a natural experiment to evaluate the relative importance of job opportunities and job competition density for the re-employment prospects of displaced workers. The results suggest that the negative effects of job competition in agglomerations reduce employment prospects. These findings state that thick labor markets are not per se beneficial and urbanization can have disadvantages for unemployed workers.

Lastly, in chapter three, we analyze the causal effect of commuting on wages using georeferenced employment data of German job changers. The addresses of workers' residence and work location allows us to calculate exact door-to-door commuting distances. We find an asymmetric effect along the distance change. Workers are willing to give up a larger fraction of their wage when reducing their daily commuting distance compared to the respective distance increase. This evidence suggests that individuals are only insufficiently compensated for their commuting costs and generally prefer to live closer to their work location.

The three chapters of the thesis provide a comprehensive view on spatial linkages among regional labor markets. From chapter to chapter the definition of a spatial labor market is augmented, starting from county level, over municipalities to ultimately continuous space independent of administrative borders. These perspectives provide novel empirical evidence on the spatial interactions among cities, suburbs and peripheral regions in Germany.

Kurzfassung

Im Vergleich zu anderen europäischen Ländern, weist Deutschland eine besondere räumliche Struktur mit vielen Zentren intensiver wirtschaftlicher Aktivität auf. Diese polyzentrische Struktur macht es zu einem interessanten Beispiel für empirische Studien über die räumlichen Mechanismen von Städten und den Wechselwirkungen zwischen Regionen. Mit steigender Bevölkerungszahl in den Städten dient das Pendeln zwischen Wohn- und Arbeitsort als räumlicher Ausgleichsmechanismus und führt so zu Interaktionen zwischen lokalen Arbeitsmärkten in Deutschland. In drei Kapiteln beschäftigt sich diese Arbeit mit den Fragen, wie lokale Arbeitsmärkte interagieren, wie stark besiedelte Märkte bei der Suche nach einem neuen Arbeitsplatz helfen und wie Beschäftigte auf Änderungen ihrer Pendlerdistanzen reagieren.

Das erste Kapitel liefert neue Erkenntnisse über den geografischen Einflussbereich der Arbeitsuche sowie dem Einstellungsverhalten. Es wird der Frage nachgegangen, wie sich die Anzahl der Arbeitslosen sowie der freien Stellen auf die Einstellungen von Arbeitslosen innerhalb und zwischen deutschen Kreisen auswirken. Mithilfe räumlicher Ökonometrie werden lokale Wechselwirkungen zwischen benachbarten Regionen analysiert. Diese Nachbarschaftsrelation wird mit unterschiedlichen räumlichen Gewichtungsmatrizen (z. B. basierend auf der Verkehrsinfrastruktur) getestet. Unsere Ergebnisse weisen robuste Wechselwirkungen lokaler Natur auf. Bayessche Schätzungen schlagen die Luftdistanz als optimales Gewichtungsschema vor. Weiterhin finden wir, dass die regionale Abhängigkeit erst nach den Hartz-Reformen entsteht, was auf eine erhöhte Pendelmobilität von Arbeitslosen nach den Gesetzesänderungen hindeutet.

Auf Basis der Gemeinden in Deutschland werden in Kapitel zwei Agglomerationsvorteile innerhalb und zwischen dicht besiedelten Arbeitsmärkten analysiert. Dabei nutzen wir das Ereignis unfreiwilliger Arbeitslosigkeit durch Betriebsschließungen zwischen 1999 und 2009 als natürliches Experiment. Damit können wir kausal bewerten, ob eine hohe Zahl an Beschäftigten oder die Konkurrenz um Stellen einen größeren Effekt auf die Wiederbeschäftigung von Entlassenen in Agglomerationen haben. Die Ergebnisse deuten darauf hin, dass die negativen Wettbewerbseffekte um freie Stellen die positiven Beschäftigungsaussichten in Ballungsräumen aufheben. Wie wir zeigen, können städtische Arbeitsmärkte Nachteile für Arbeitslose mit sich bringen.

In Kapitel drei analysieren wir den kausalen Effekt des beruflichen Pendelns auf die Löhne anhand georeferenzierter Beschäftigungsdaten von Jobwechslern in Deutschland. Die Adressen von Wohn- und Arbeitsort der Individuen erlauben uns die Berechnung exakter Tür-zu-Tür-Pendeldistanzen. Wir finden einen asym-

metrischen Effekt der Lohnänderung in Bezug auf die Änderung der Entfernung zur Beschäftigungsstelle. Das heißt, die Arbeitnehmer sind bereit, einen größeren Teil ihres Lohnes aufzugeben, wenn sie ihre tägliche Pendelstrecke reduzieren können. Dies deutet darauf hin, dass Beschäftigte nur unzureichend für ihre Pendelkosten entschädigt werden und in der Regel lieber näher an ihrem Zuhause arbeiten.

Die Gemeinsamkeit aller drei Kapitel ist die Analyse räumlicher Verflechtungen zwischen regionalen Arbeitsmärkten. Mit jedem Kapitel wird die Definition eines räumlichen Arbeitsmarkts erweitert. Ausgangspunkt ist die administrative Gliederung auf Kreis- und Gemeindeebene. Letztlich wird ein zusammenhängender Raum, unabhängig von administrativen Grenzen, betrachtet. Daraus ergeben sich neue empirische und methodische Erkenntnisse über die räumlichen Interaktionen zwischen Städten, Vororten und peripheren Regionen in Deutschland.

Flexibilität im Stellensuchprozess

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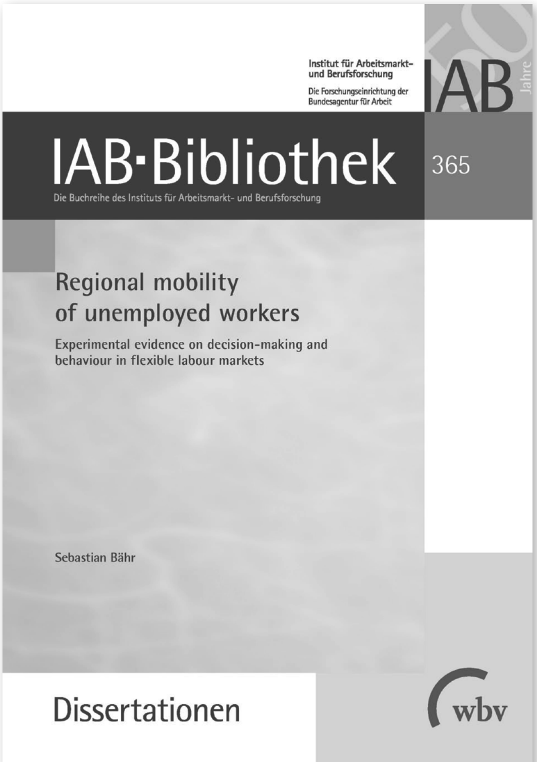

Sebastian Bähr

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Experimental evidence on decision-making and behaviour in flexible labour markets

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Due to its regional structure, with numerous centers of intensive economic activity, Germany lends itself particularly to analyses of spatial mechanisms of cities and interrelationships between regions. As a result of the increase in urban population, commuting serves as a spatial dispersion mechanism and leads to interactions between regional labor markets. The author studies how local labor markets interact, how densely populated markets facilitate the search for a new job and how employees react to changes in their commuting distance. The different perspectives and the use of micro and geo-referenced data provide new empirical insights into the interactions between regional labor markets and mobility patterns in Germany.

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