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The valuation of changes in commuting distances: An analysis using georeferenced data

Wolfgang Dauth
Peter Haller

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Wolfgang Dauth (University of Wuerzburg and IAB)
Peter Haller (IAB)

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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 in combination with road navigation software allows us to calculate exact door-to-door commuting distances with an unprecedented degree of precision. We use a theoretical model on spatial job search to motivate our empirical strategy. By focusing on job moves, we can use panel data techniques and control for unobserved individual heterogeneity. We find an asymmetric valuation of distance changes. Job changers value a reduction of their commuting distance higher than an increase. Apparently, individuals are not able to capitalize the full costs of commuting in their wages. A large part of this effect can be explained by sorting into certain firms at different distances and the rest by individual wage bargaining.

Zusammenfassung

In diesem Beitrag untersuchen wir den kausalen Effekt der Pendeldistanz auf das Tagesentgelt mit Hilfe eines großen Datensatzes von Arbeitsplatzwechslern in Deutschland. Wir nutzen „Navi-Software" und berechnen, anhand der geografischen Koordinaten von Wohn- und Arbeitsorten, die genauen Tür zu Tür Pendeldistanzen mit dem PKW. Wir motivieren unsere empirische Strategie anhand eines theoretischen Modells der räumlichen Arbeitsplatzsuche. Durch den Fokus auf Arbeitsplatzwechsel beobachten wir dieselben Personen mehrmals, was uns erlaubt, für deren nicht beobachtbare Heterogenität zu kontrollieren. Die Ergebnisse zeigen eine asymmetrische Bewertung von Änderungen der Pendeldistanz. Nach einem Arbeitsplatzwechsel bewerten Personen eine Reduktion ihrer Distanz höher als eine Verlängerung. Dies deutet darauf hin, dass Arbeitnehmer nicht vollständig durch den Arbeitgeber für ihre Pendelkosten entschädigt werden. Ein Großteil des Effekts kann durch die Selbstselektion von Personen in bestimmte Firmen erklärt werden. Der Rest lässt sich auf individuelle Lohnverhandlungen zurückführen.

JEL classification: J31, J64, R12, R40

Keywords: commuting, job search, marginal willingness to pay, loss-aversion

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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 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 detailed georeferenced information on the places of residence and work. Focusing on workers who (voluntarily or involuntarily) change between jobs allows us to use panel data models and control for individual heterogeneity. In addition, we are able to control for firm heterogeneity. Our main finding is that job changers value a reduction in commuting distance higher than an increase. This result is robust even after controlling for firm characteristics.

In urban economics 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. Furthermore, according to Monte/Redding/Rossi-Hansberg (2015), the welfare gains of commuting are large and comparable to the GDP gains of international trade for a country like the US. In a frictionless economy, the commute of homogenous workers is fully compensated through wages and housing. Workers choose their place of work and residence from a set of residential areas and workplace locations of firms. 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). In a model with search frictions, compensatory wage differentials exist.[1] For instance, the individual's spatial job search radius is decreasing with distance (Borck/Wrede, 2009; Zenou, 2009a) which could lead to efficiency loses in the labor market. The contact rate between firms and workers is limited which allows firms to have some wage-setting power (Manning, 2003) or workers can face jobs with either fixed wages or can bargain their wage (see Rogerson/Shimer/Wright, 2005). In this case, the marginal willingness of workers to pay for commuting can be derived from the gradient of the estimated relation between wage and commuting distance in wage regressions. Using this approach we need to explicitly control for search frictions and individual heterogeneity of workers and firms. Otherwise the estimated relationship might be biased

[1] In many countries, hence, commuting subsidies in the form of tax breaks aim for compensating workers for their costly commute (Borck/Wrede, 2005; Heuermann et al., 2016) The existence of commuting allowances proves that the compensation is empirically not optimal.

(Gronberg/Reed, 1994; Hwang/Mortensen/Reed, 1998; Hwang/Reed/Hubbard, 1992).

In various search models from labor economics, the estimation of the marginal willingness to pay for commuting is differentiated by either on-the job search for different jobs (e.g. Van Ommeren/Van den Berg/Gorter, 2000; Van Ommeren/Fosgerau, 2009) or job take-ups from unemployment (e.g. Van den Berg/Gorter, 1997). Usually, duration models in continuous time are used to estimate the marginal willingness to pay for job attributes (e.g. Van Ommeren/Fosgerau, 2009; Gronberg/Reed, 1994). For both types of job seekers, the search in the labor market and in the housing market can also be simultaneous (see Van Ommeren/Rietveld/Nijkamp, 1997, 1999).
The empirical literature about the marginal willingness to pay for commuting is largely shaped by a job-search perspective of individuals. It is derived from the decision to take up a job at a certain distance in order to maximize the individual utility. The job offers can be 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/Van den Berg/Gorter (2000) find a marginal willingness to pay for commuting of 0.15 Euro per day (Van Ommeren, 2005) or Van Ommeren/Fosgerau (2009) 17 Euro for one additional hour of commuting. For Denmark, Gutiérrez-i Puigarnau/Mulalic/van Ommeren (2016) estimate an income elasticity of distance of -0.18. Unemployed have a high negative utility from longer commutes (Van den Berg/Gorter, 1997). The empirical problem remains that the compensation is related to the individual decision. Hence, another strand of literature uses exogenous events to determine the marginal commuting costs (e.g. firm relocation, unexpected changes in the legislation). Doing so for Denmark, Mulalic/Van Ommeren/Pilegaard (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. (2016) 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. Reichelt/Haas (2015) find that job changers prefer shorter distances in denser labor markets.

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 considered 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 a job change. We consider two groups of job changers: those who switch between two stable jobs with or without an employment gap. We argue that the latter switch jobs in order to increase their utility and the former leave their old job involuntarily and are now forced to look for a new job.[2] We will analyze these groups separately, but assume the same search process. Our data allows us to follow the employment history of an individual five years before and after the job change. With the panel structure we can control for individual heterogeneity and for self-selection. Using an pre-estimated information on unobserved firm characteristics we can also control for employer heterogeneity.

Our paper is contributing to the literature in at least three aspects. First, we explicitly distinguish between positive and negative distance changes due to a job transition. While there should be no asymmetric valuation in theory and possible differences have rarely been discussed in the literature, 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. The average marginal effect for a reduction of commuting distance is 0.24 Euro (voluntary unemployed) or 0.19 Euros (involuntary unemployed) per kilometer. In contrast the effect of a positive distance change is 0.08 Euro or 0.06 Euro, respectively. Apparently, individuals are willing to pay in order to avoid the dis-utility of commuting. Conversely, they are not able to capitalize this in their wages. The coefficient for the overall average semi-elasticity of 0.148 or 0.142 is in line with previous findings (Mulalic/Van Ommeren/Pilegaard, 2014). After controlling for firm characteristics the size of the marginal valuation decreases, but remains significant. Most interestingly, the differences in valuation remains significant only 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. 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 heterogenous effects among skill-levels, age and regional structure. Overall the valuation pattern turns out to be less robust for involuntary job seekers.

In the main part of the paper we first discuss a simple job-search model that motivates our empirical approach. In section 3, we introduce the dataset and our empirical strategy. The main results as well as robustness checks in section 4 and section 5 concludes.

2 Search for new employment

In labor market search models (see Rogerson/Shimer/Wright, 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.

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

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.

We adapt a standard framework of a spatial job search model based on theoretical considerations in Rouwendal (1999), Van Ommeren/Rietveld/Nijkamp (1997),Van Ommeren/Van den Berg/Gorter (2000) and Van Ommeren (2005).[3] In contrast to these papers, however, we abstract from simultaneous search in the labor and the housing market. We hence analyze valuation of commuting distance based on job search decisions in the labor market, while keeping the residence constant.

We assume that utility u is a function of the (daily) wage w, the commuting distance z and a vector $\mathbf{x}$ of other job characteristics (e.g. career prospects).

$$u = u(w, z, \mathbf{x}) \tag{1}$$

We assume that u increases with the w and $\mathbf{x}$, and decreases with z. All individuals search for a new job for one of two reasons: either because they have been laid off, or because they have decided on taking up their current job under incomplete information which are now updated. They have a current utility u_0 from being unemployed or employed in the current job.

Job offers arrive with a constant rate λ and vary with regard to w , z, and $\mathbf{x}$. The individuals consider job offer packages which can be regarded as random draws from a multivariate distribution $F(w, z, x)$ with the corresponding probability density function $f(w, z, x)$.[4] Hence, wage, commuting distance, and other job characteristics may depend on each other. The variables are limited by a certain range for wage (e.g. minimum expected wage), commuting distance (e.g. daily commute) and further job characteristics in order to stress that the relevance of offers is limited. Based on the utility function in (1), individuals value different offers in the three dimensions.

$$m(u) = \frac{\partial}{\partial u} \int\limits_{\underline{w}}^{\bar{w}} \int\limits_{\underline{z}}^{\bar{z}} \int\limits_{\underline{x}}^{\bar{x}} f(w, z, x)\, dw\, dz\, dx \tag{2}$$

This density function of utilities $m(u)$ based on the characteristics of the job offers allows us to reduce the three-dimensional job-search decision into one dimension and still capture the (spatial) diversity of job offers in the labor market.

Job seekers maximize their net present value (discounted with ρ) of the expected lifetime utility they gain through a job change. Individuals search for a new job and consider their acceptance conditional on their reservation utility. The reservation utility u_R in (3) is a function of the density of utilities $m(u)$ (which is based on the job offer distribution) and the current utility u_0 drawn from either the current job or unemployment. Given a constant job

[3] A comprehensive review of (spatial) job search theory can be found in Sonnabend (2013).

[4] Although probably unrealistic, we assume the vector of job characteristics $\mathbf{x}$ to be subsumed in a single continuous variable.

arrival rate and density function over time, there is a utility threshold u_R which is the sum of u_0 and the expected life-time utility from an accepted job. In this framework the first job offer that equals the threshold will be accepted.

$$u_R = u_0 + \lambda \frac{1}{\rho} \int_{u_R}^{\infty} (u - u_R) m(u)\, du \tag{3}$$

The individual decision, based on utilities, cannot be measured directly. We hence substitute the unknown utility by a function of observable wages, commuting distance, and other job characteristics using (1) and (2).

$$u_R = u_0 + \lambda \frac{1}{\rho} \int_{w_R}^{\bar{w}} \int_{z>0}^{\bar{z}} \int_{\underline{x}}^{\bar{x}} (u(w,z,x) - u_R) f(w,z,x)\, dw\, dz\, dx \tag{4}$$

We assume the current utility u_0 to be determined either by the current job or, in the case of unemployed job seekers, by the previous job. As taking up this job has been subject to a similar maximization problem, u_0 includes all individual characteristics that affect the decision to accept a job with characteristics w, z, and x. As this also comprises unobserved individual heterogeneity, Rouwendal (1999) includes this term along with a term for uncertainty. Our empirical specification, by contrast, allows us to directly control for unobserved individual heterogeneity and hence we assume that current utility takes the form:

$$u_0 = u_0^{'} + \phi + \gamma \tag{5}$$

, where ϕ includes all observable characteristics such as skills and age. γ represents the unobservable individual heterogeneity, which we assume to be constant during the job transition, for example the attitude towards commuting, family circumstances, or accessibility and location of the residence. $u_0^{'}$ represents the residual utility from unemployment (e.g. unemployment benefits) or current employment. Including these parts in (4) yields the new reservation utility.

$$u_R = u_0^{'} + \phi + \gamma + \lambda \frac{1}{\rho} \int_{w_R}^{\bar{w}} \int_{z>0}^{\bar{z}} \int_{\underline{x}}^{\bar{x}} (u(w,z,x) - u_R) f(w,z,x)\, dw\, dz\, dx \tag{6}$$

The reservation utility now consists of the initial utility, the individual heterogeneity and the expected net-present value from an acceptable job offer.

The utility maximizing individual will decide to take a new job and receive the lifetime utility u_{new} if the new job offer equals the reservation utility. Otherwise she will continue searching and remains unemployed or in the current job.

$$u_{new}(w_R, z, x) = u_R \tag{7}$$

In order to hold the equality for the new lifetime utility in (7), the reservation wage w_R has to rise with increasing commuting distance z, conditional on individual heterogeneity and the job characteristics x. Hence, from each individual's perspective, more distant jobs have to offer higher wages than closer jobs in order to be acceptable. Analogously, job seekers will accept jobs with lower wages as long as they require a shorter commute. This framework thus internalizes the spatial component of a job offer, where the wage is the compensating differential for different commuting distances. Both, an increase and a decrease of the commuting distance should have symmetric effects on wages.

3 Empirical Approach & Data

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:

$$w_{i,t=0} = \beta_0 + \beta_1 C_{i,t=0} + \boldsymbol{X'_{i,t=0}\beta} + \alpha_i + \varepsilon_{i,t=0} \tag{8}$$

, where $w_{i,t=0}$ is 100 times 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^2, skill dummies, calendar year dummies, and dummies for the municipality of residence. The latter imply 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 wages. 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 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 our data that 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 (8) in first differences. Our main model is thus:

$$\Delta w_{i,t} = \beta_1 \Delta C_{i,t} + \boldsymbol{\Delta X'_{i,t}\beta} + \gamma \Delta 1(t=0)_{i,t} + \Delta\varepsilon_{i,t} \tag{9}$$

, where $t = \{-1, 0\}$. $\Delta w_{i,t}$ measures the difference of 100 times 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.

3.2 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 (BeH - Beschäftigtenhistorik V10.00.00, Nürnberg 2015). This spell 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). 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.

A problem of administrative data is that one has to rely on changes of the firm identifier to indicate job transitions. We use the approach of Hethey/Schmieder (2010) to discriminate supposedly true job transitions from firm restructuring. 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.[5]

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. Next, we keep only workers who did not change their municipality of residence during the time between one year before or after the job change. This ensures that our results are not biased by workers sorting into more accessible locations. We also drop 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 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. Finally, we drop workers with extremely high wages, since we suspect that these are due to errors in the imputation procedure. Appendix table 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

[5] We cannot observe the actual reason for a job change. However, since being registered is a precondition to receive unemployment benefits, people who do not register presumably have already a new job in prospective.

an employment gap of less than one year, this results in a panel with two observations for each individual, one of the old and one of 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.[6]

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 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 five kilometers. Hence, using driving distance based on the municipalities would understate commuting distance by 14 percent. In addition, we would neglect individual sorting within areas.

4 Results

4.1 Descriptive Results

Table 1 reports summary statistics for the main variables. Voluntary job seekers 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 8.16 Euros. More than 25 percent of the job changers also decide to accept a wage reduction. The median commuting distance to the old employer is 14.18 kilometers and increases to 16.04. The average change is 1.96 kilometers, while the median change is only 0.639. Overall, 54.6 per cent of the 159,446 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 similar 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 valuation of commuting time is likely to vary with worker characteristics, we also report summary statistics of possible control variables in appendix table A.2. Our sample

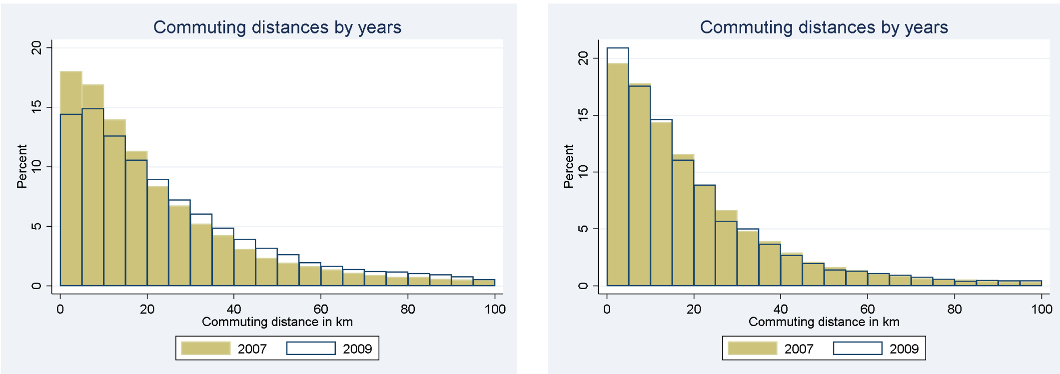
[6] For a robustness check, we also construct a larger panel with the observations exactly $k = -5, \ldots, 0, \ldots, 5$ years before/after taking up the new job.

Table 1: Summary statistics for main variables

Variable	Mean	Std.Dev.	25th Perc.	Median	75th Perc.
Voluntary job seekers (N=159,446)					
wage old job	101.706	63.339	62.716	86.848	120.788
wage new job	109.871	65.089	71.821	92.789	127.940
Δwage	8.165	45.810	-2.799	5.238	18.086
distance to old job	20.287	19.325	6.135	14.176	27.977
distance to new job	22.250	20.302	7.208	16.044	30.906
Δdistance	1.963	23.575	-6.928	0.639	10.958
dummy,1=positive Δdist.	0.546	0.498	-	-	-
Involuntary job seekers (N=59,983)					
wage old job	77.400	47.046	49.896	67.908	90.010
wage new job	76.338	43.713	51.871	68.231	87.140
Δwage	-1.062	34.600	-11.470	-0.223	10.693
distance to old job	17.526	17.617	5.055	11.889	23.875
distance to new job	19.720	18.640	6.225	14.097	26.889
Δdistance	2.194	22.416	-6.595	0.819	11.053
dummy,1=positive Δdist.	0.549	0.498	-	-	-

Source: Own calculations.

is quite balanced with regard to age, sex, and urban/rural municipality of residence, but involuntary job seekers are somewhat less likely to have a university degree.



Voluntary job change

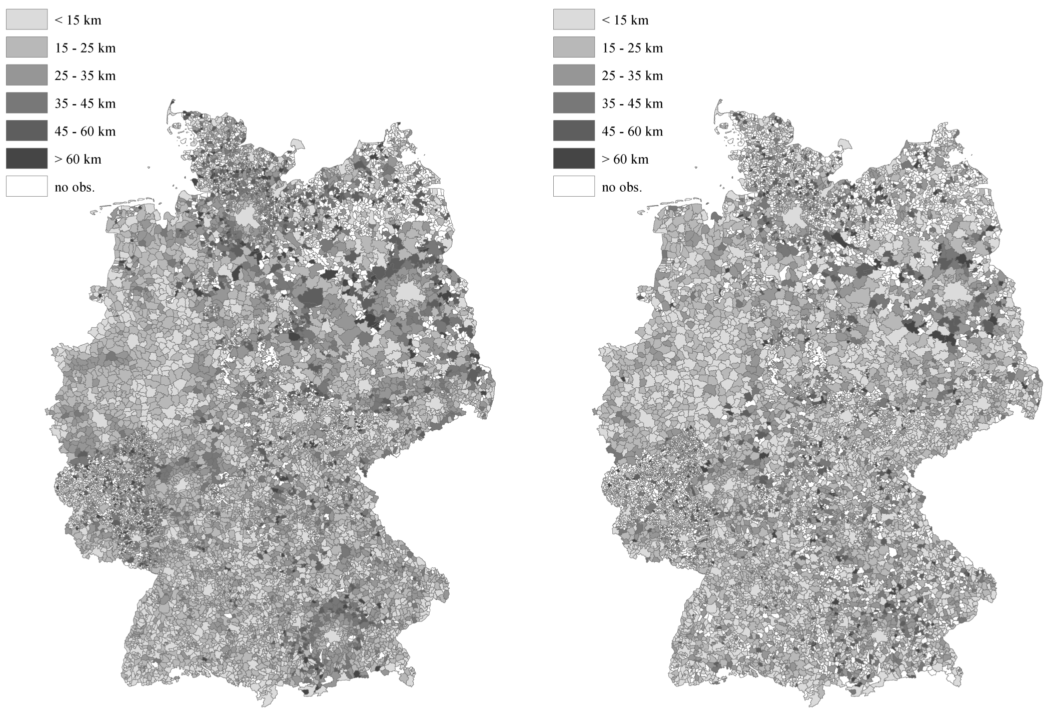
Involuntary job change

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

Figure 1: Distribution of commuting distances

Figure 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 changes for voluntary job changers. During the two years the reasons could be the change in the commuting allowances (see Heuermann et al., 2016) or the economic crisis which affected the German labor market in 2009.

Looking at the regional distribution of commuting distances, we observe a distinctive spatial pattern. The left map of figure 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 looks spatial more evenly spread for involuntary job changers. We can conclude a different pattern by type of job seeker and by type of region of residence (e.g. urban or rural).



Voluntary job changers — Involuntary job changers

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. Absent municipalities ('no obs.') could emerge due to missing job matches in that region. Source: Own calculations; The shape files used in the figures are provided by the Federal Agency for Cartography and Geodesy (BKG).

Figure 2: Regional distribution of commuting distances

4.2 Baseline Results

We first consider only the observation of the new job and regress the logarithm of daily wage on the commuting distance and observable worker characteristics. The results in table 2 reveal a non-linear positive relation of commuting distance and 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. We illustrate this non-linearity by plotting the residualized values of both variables in appendix figure A.1. In line with theoretical models on commuting (e.g. Berliant/Tabuchi, 2015), the relation of distance and wages is steep but concave at first. At distances larger than about 5 km it becomes linear. To account for this shape, we interact the quadratic terms for distance with indicator variables for distances larger or smaller than 5 km.

Due to the non-linearity of the relation of commuting distance and 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 change of 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 then obtain the average marginal effect by multiplying the semi elasticity by the average daily wage in the old job of the respective group and dividing by 100. Since the average wage is close to 100 for individuals without an employment gap, both values are often very similar.

These results indicate that the daily wage increases by 0.41 percent for each additional kilometer of commuting distance for the average worker. This effect becomes 2.215 percent for each additional kilometer for the average commuter with a distance less than 5 km and only one sixth the magnitude for larger distances. For involuntary job changers, these effects are slightly smaller.

The control variables also 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.

Table 2: Baseline OLS regressions - Commuting distance to new job and daily wages

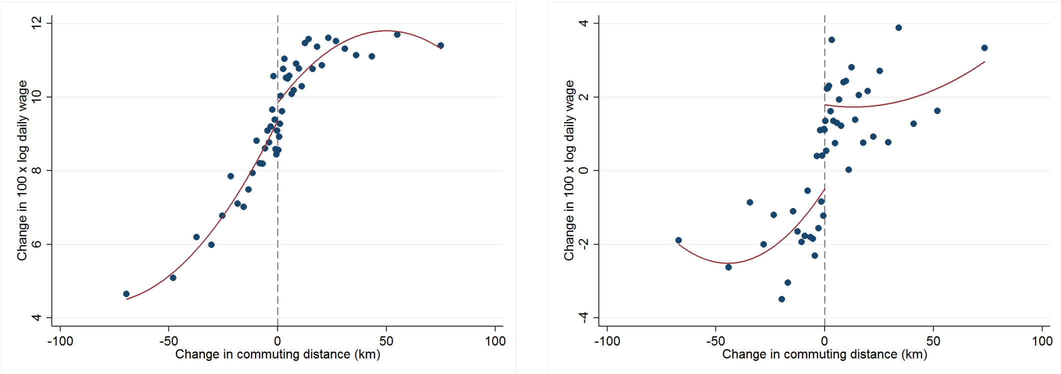
Dependent Variable: 100 x $log(dailywage)$

Coefficient	Voluntary job change			Involuntary job change		
	(1)	(2)	(3)	(4)	(5)	(6)
Distance	0.5589***	0.6794***		0.5282***	0.5894***	
	(0.026)	(0.038)		(0.033)	(0.057)	
Distance^2	-0.0034***	-0.0073***		-0.0034***	-0.0055***	
	(0.000)	(0.001)		(0.000)	(0.002)	
Distance^3		0.0000***			0.0000	
		(0.000)			(0.000)	
Dummy, 1= if dist. $>$5 km			12.4961***			9.9877***
			(1.234)			(1.635)
distance if $<$5 km			8.5682***			7.4816***
			(0.833)			(1.284)
distance^2 if $<$5 km			-1.2008***			-1.0882***
			(0.148)			(0.239)
distance if $>$5 km			0.4929***			0.4782***
			(0.033)			(0.040)
distance^2 if $>$5 km			-0.0027***			-0.0029***
			(0.000)			(0.000)
Dummy, female=1	-16.5660***	-16.5640***	-16.5262***	-17.1208***	-17.1216***	-17.1094***
	(0.784)	(0.785)	(0.781)	(0.938)	(0.938)	(0.937)
Age	4.8463***	4.8481***	4.8458***	3.1505***	3.1508***	3.1469***
	(0.183)	(0.184)	(0.184)	(0.189)	(0.189)	(0.188)
Age^2	-0.0550***	-0.0550***	-0.0550***	-0.0393***	-0.0393***	-0.0392***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dummy, 2008=1	2.5766***	2.5753***	2.5791***	-1.6615***	-1.6633***	-1.6608***
	(0.499)	(0.499)	(0.499)	(0.391)	(0.392)	(0.391)
Dummy, 2009=1	13.5048***	13.5026***	13.5248***	-6.1605***	-6.1629***	-6.1390***
	(1.161)	(1.161)	(1.162)	(0.637)	(0.637)	(0.635)
Dummy, low skilled=1	-17.0753***	-17.0540***	-17.0471***	-26.1678***	-26.1541***	-26.0860***
	(0.863)	(0.862)	(0.862)	(1.320)	(1.322)	(1.313)
Dummy, high skilled=1	44.5303***	44.5515***	44.5146***	45.0343***	45.0515***	45.0092***
	(0.456)	(0.457)	(0.453)	(0.917)	(0.918)	(0.906)
N	159,446	159,446	159,446	59,983	59,983	59,983
R^2	0.435	0.435	0.436	0.414	0.414	0.415
Average semi elasticity	0.410***	0.440***		0.394***	0.411***	
Avg. marginal effect (in Euros)	0.450	0.481		0.305	0.317	
Avg. semi elast. $<$5 km			2.215***			1.833***
Avg. semi elast. $>$5 km			0.353***			0.341***
p-value threshold diff.			0.000			0.001
Avg. marg. eff. $<$5 km			1.986			1.216
Avg. marg. eff. $>$5 km			0.401			0.272

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

While the previous results indicate a 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 both the old and the new job, we run the first-differences specification described in equation 9. As long as these characteristics and their valuation does not change during the job transition, this purges all unobserved heterogeneity that might cause omitted variable bias in the OLS model.

In figure 3 we plot the change in commuting distance and the change in daily wage between the two successive employments, both residualized from age^2 and dummies for educational attainment and the year of the job change. The striking result is that non-linear valuation of commuting time still persists: Voluntary job changers appear to value a reduction in commuting time much more than they do for the respective positive change. In contrast, 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.



Voluntary job change

Involuntary job change

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 age^2, 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. Source: Own calculations.

Figure 3: Changes of commuting distance and daily wage

Table 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 0.15 percent in both groups, which is in the same ballpark as the findings from many previous studies (e.g. Mulalic/Van Ommeren/Pilegaard, 2014). To get an estimate of the slopes from figure 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 0.24 percent of her daily wage per reduced kilometer. By contrast, the average worker with a positive change of distance earns only 0.08 percent more per kilometer. In other words, people appear to value a reduction in commuting higher than an increase. This reverse loss aversion indicates that individuals apparently are not able to capitalize the full costs of commuting in their wages.

Table 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	0.1525***		0.1476***	
	(0.009)		(0.018)	
Distance^2	-0.0012***		-0.0013***	
	(0.000)		(0.000)	
Negative Δdistance		0.1958***		0.1998***
		(0.016)		(0.032)
Negative Δdistance^2		-0.0014***		-0.0018***
		(0.000)		(0.000)
Positive Δdistance		0.1126***		0.1044***
		(0.016)		(0.032)
Positive Δdistance^2		-0.0010***		-0.0009**
		(0.000)		(0.000)
Constant	23.9911***	24.4425***	17.5985***	17.9477***
	(0.407)	(0.434)	(0.816)	(0.893)
N	159,446	159,446	59,983	59,983
R^2	0.024	0.025	0.025	0.025
Average semi elasticity	0.148***		0.142***	
Avg. marginal effect (in Euros)	0.149		0.109	
Avg. semi elast. neg. Δdist.		0.236***		0.250***
Avg. semi elast. pos. Δdist.		0.082***		0.077***
p-value of diff.		0		0.027
Avg. marg. eff. neg. Δdist.		0.239		0.194
Avg. marg. eff. pos. Δdist.		0.082		0.059

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. Source: Own calculations.
Levels of significance: * 1%, ** 5%, *** 10%

4.3 Further results

4.3.1 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. Heuermann et al. (2016) do not find that an unexpected repeal of tax breaks for commuters in Germany in 2007 for distances below 20 kilometers had any effect on incumbent workers at this threshold.[7] This indicates that (incumbent) workers do not have the bargaining power to have their employers compensate them for their differential commuting costs. Another mechanism might be that job seekers consider the firm itself in their optimization of lifetime utility. Card/Heining/Kline (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.

We check this by explicitly accounting for firm heterogeneity in our model. 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/Kramarz/Margolis (1999) regression using almost a full sample

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

Table 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	0.0557***		0.0322**	
	(0.009)		(0.014)	
Distance^2	-0.0002**		-0.0000	
	(0.000)		(0.000)	
Negative Δdistance		0.1117***		0.0500**
		(0.013)		(0.023)
Negative Δdistance^2		-0.0009***		-0.0002
		(0.000)		(0.000)
Positive Δdistance		0.0106		0.0179
		(0.015)		(0.025)
Positive Δdistance^2		0.0003*		0.0001
		(0.000)		(0.000)
CHK firm effect	72.9070***	72.9470***	87.3971***	87.3940***
	(0.571)	(0.574)	(0.760)	(0.759)
Constant	12.0138***	12.2886***	9.4009***	9.5142***
	(0.439)	(0.464)	(0.487)	(0.510)
N	138,117	138,117	47,702	47,702
R^2	0.337	0.337	0.505	0.505
Average semi elasticity	0.055***		0.032***	
Avg. marginal effect (in Euros)	0.058		0.026	
Avg. semi elast. neg. Δdist.		0.139***		0.056**
Avg. semi elast. pos. Δdist.		0.020**		0.021*
p-value of diff.		0.000		0.193
Avg. marg. eff. neg. Δdist.		0.146		0.046
Avg. marg. eff. pos. Δdist.		0.022		0.017

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. Source: Own calculations.
Levels of significance: * 1%, ** 5%, *** 10%

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 firm 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. Any remaining effect can then be attributed to individual wage bargaining with the firms, rather than the firms' wage setting.

We report the results of this augmented model in table 4.[8] We refrain from interpreting the magnitude of the coefficient on the CHK firm effects but note that the R^2 of the model increased considerably. We are thus confident that this variable does pick up the heterogeneity of firms. The effects of the commuting distance on wages reduce sharply but remain significantly larger than zero. This indicates that there must be some individual bargaining. 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 negotiate over their wage with the new employer.

[8] The sample size is smaller than in table 3 because CHK had to restrict their analysis to the largest set of German plants interconnected by worker mobility.

Table 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	Positive	Negative	Difference	Overall	Positive	Negative	
			Voluntary job change					
Benchmark	0.148***	0.082***	0.236***	***	0.149	0.082	0.239	159,446
Commuting time	0.158***	0.084***	0.257***	***	0.159	0.085	0.258	159,446
Averaged wage	0.150***	0.087***	0.245***	***	0.149	0.086	0.244	159,435
Exclude industries	0.153***	0.093***	0.223***	***	0.158	0.095	0.230	120,098
Strict residence	0.142***	0.074***	0.237***	***	0.146	0.076	0.243	136,874
Leaves job before 7/2007	0.160***	0.107***	0.196***		0.159	0.106	0.194	31,047
Different intercepts	0.130***	0.070***	0.216***	***	0.131	0.071	0.218	159,446
			Involuntary job change					
Benchmark	0.142***	0.077***	0.250***	**	0.109	0.059	0.194	59,983
Commuting time	0.167***	0.097***	0.283***	*	0.128	0.074	0.218	59,983
Averaged wage	0.149***	0.075***	0.287***	**	0.114	0.057	0.222	59,980
Exclude industries	0.156***	0.072***	0.316***	***	0.123	0.057	0.253	41,729
Strict residence	0.143***	0.070***	0.266***	***	0.111	0.054	0.209	50,785
Leaves job before 7/2007	0.169***	0.054	0.400***	**	0.133	0.043	0.321	13,104
Different intercepts	0.082***	0.035*	0.171***	**	0.063	0.026	0.133	59,983

Notes: Semi-elasticities and marginal effects from first difference regressions of wage regressions analogous to the ones reported in table 3. Further control variables are age^2, calendar year and skill dummies. Standard errors (clustered by municipality) in parentheses. Source: Own calculations.
Levels of significance: * 1%, ** 5%, *** 10%

4.3.2 Robustness checks

Our main findings from table 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 5.

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.[9] 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. The different valuation is only significant on the ten percent level for workers with a period of non-employment.

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. To take this into account use the full employment biographies and calculate the average daily wage of the old (new) job during the four 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. The estimates remain

[9] 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.

qualitatively unchanged for both types of job changers. If anything, the semi elasticity of a positive distance change decreases and the one for a negative change increases slightly. One notable change is the intercept (not reported in table 5). The intercept reflects the ceteris paribus wage increase due to the job change. It rises from 24.44 to 38.48 percent for voluntary job changers and from 17.95 to 29.14 percentage points for involuntary job changers. This indicates that wages do rise during the tenure of the new job but this only 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 the this issue might be most severe: construction, transport (on land), temporary agency work, retail trade, financial intermediation, public administration, and defence. Almost 40,000 observations are dropped. In comparison to our initial results in table 3 the valuation for voluntary job changers change only slightly. For involuntary job changers the valuation of an additional kilometer less rises from 0.19 Euros to 0.25 Euros. This is larger in the group of voluntary job changers. The valuation of an additional kilometer remains the same. As we do have slightly more high-skilled workers in the sample of voluntary job transitions (see appendix table A.2), these changes might stem from the exclusion of industries with a smaller share of high-skilled workers, e.g. construction and temporary agency work. Despite this difference our main findings remain robust.

A crucial assumption in our analysis is that individuals only change their workplace but not their residence. We ensure this by restricting our sample to individuals who do not move across municipalities. 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 22,500 and 9,200, respectively. The change in the marginal effects is very small for both groups of job seekers. We can infer, a stronger assumption regarding the residence location leaves our findings almost unchanged.

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 show a significant smaller intercept, i.e. 0.59 percentage points for voluntary and 1.88 percentage points for involuntary job changers. However, the effects of the magnitude of the distance change remain virtually unchanged.

4.3.3 Heterogeneous effects

Obviously, commuting patterns vary with characteristics of individuals. We document the different commuting patterns in appendix table A.3. We see that men commute around 17 to 24 percent further than women. There is also an age pattern: Younger (than the median age) workers have 6 to 12 percent shorter commutes than older workers. Commuting distances clearly increase with education. High-skilled workers commute six kilometers more than low-skilled, i.e. 47 to 53 percent more. In the same way individuals differ when living in urban or more rural areas.[10] As expected rural residents commute 45 to 51 percent more. We re-estimate our benchmark specification for each of those groups to see if the variation in the distance leads to different valuations of the commuting distance.

The results of the regressions for individual groups are summarized in table 6. In general it appears that the groups value positive and negative distance changes differently is more robust for voluntary job changers.

Comparing male and female job changers, we find higher elasticities for women than for men. While the effects of positive distance changes are about in the same ballpark, the wages of women react even more strongly to negative changes than for men. Both differences are more pronounced for voluntary than for involuntary job seekers. These results are consistent with studies that find female labor supply to be more elastic for women than for men. (e.g. Hirsch/Schank/Schnabel, 2010; Barth/Dale-Olsen, 2009).

For younger job seekers, the elasticity of a reduction in commuting distance is larger than for elder workers. This also transfers into a higher absolute valuation. In case of a voluntary job change, young and old want to improve their career prospects and therefore the valuation pattern appears to be similar. The desire to reduce the commuting distance is slightly higher for younger workers. In case of involuntary job search, the pattern changes. Younger workers value a reduction even higher, but the wage increases less with distance. Older workers do not value positive and negative distance changes differently. This is plausible since the loss of job tenure is much more severe for older workers.[11]

[10] 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.

[11] Although, younger workers should not change their job too often in their early career (see Light/McGarry, 1998)

Table 6: Heterogenous effects by sub-samples

Dependent Variable: $\Delta log(dailywage)$

Group	Average semi-elasticity				Average marginal effects (in Euros)			No. of obs.
	Overall	Positive	Negative	Difference	Overall	Positive	Negative	
			Voluntary job change					
Benchmark	0.148***	0.082***	0.236***	***	0.149	0.082	0.239	159,446
Gender								
Male	0.136***	0.079***	0.218***	***	0.147	0.085	0.234	109,226
Female	0.169***	0.083***	0.274***	***	0.147	0.072	0.238	50,220
Age								
Young	0.184***	0.102***	0.295***	***	0.158	0.087	0.256	74,537
Old	0.111***	0.062***	0.178***	***	0.127	0.071	0.203	84,909
Skill								
Unskilled	0.094**	0.135***	-0.052	**	0.069	0.098	-0.039	5,710
Skilled	0.154***	0.080***	0.253***	***	0.134	0.069	0.218	117,850
High-skilled	0.139***	0.082***	0.228***	***	0.210	0.126	0.342	35,886
Regional structure								
Urban	0.192***	0.144***	0.228***		0.205	0.148	0.248	53,242
Rural	0.128***	0.059***	0.234***	***	0.125	0.058	0.227	106,204
			Involuntary job change					
Benchmark	0.142***	0.077***	0.250***	**	0.109	0.059	0.194	59,983
Gender								
Male	0.115***	0.069***	0.185***		0.093	0.056	0.151	38,886
Female	0.196***	0.096***	0.381***	**	0.135	0.065	0.267	21,097
Age								
Young	0.151***	0.061**	0.328***	**	0.107	0.043	0.234	29,649
Old	0.135***	0.094***	0.175***		0.112	0.077	0.147	30,334
Skill								
Unskilled	0.035	0.175*	-0.274	**	0.019	0.096	-0.157	2,340
Skilled	0.158***	0.096***	0.226***	*	0.110	0.066	0.159	47,067
High-skilled	0.119***	0.039	0.327***	*	0.135	0.047	0.372	10,576
Regional structure								
Urban	0.205***	0.118**	0.342***		0.167	0.094	0.282	19,718
Rural	0.123**	0.071***	0.213***	**	0.092	0.052	0.160	40,265

Notes: Semi-elasticities and marginal effects from first difference regressions of wage regressions analogous to the ones reported in table 3. Further control variables are age^2, calendar year and skill dummies. Standard errors (clustered by municipality) in parentheses. Source: Own calculations.
Levels of significance: * 1%, ** 5%, *** 10%

When splitting the sample by educational attainment, we find that unskilled workers have the highest valuation of commuting costs when changing into a job further away, but exhibit no significant valuation of distance when changing to a closer job. They are willing to commute more if the wage increases, but are not willing to give up income for a shorter commute. For voluntary job changes, medium- and high-skilled workers reveal almost the same elasticities to positive and negative distance changes, respectively. However, the similarity between medium- and high-skilled individuals disappears for involuntary job changers. While the elasticities of medium-skilled workers remain similar to the general population, high-skilled only value a reduction of the commuting distance. This is in line with previous evidence that richer households prefer to live closer to their workplace (see Gutiérrez-i Puigarnau/Mulalic/van Ommeren, 2016). Since higher education is highly correlated with wealth, this can be an explanation for the consistently high valuation of commuting distance reductions.

Another interesting finding is that city dwellers value positive distance changes higher than their rural counterparts. Though economically meaningful, the difference between the valuations of positive and negative distance changes for urban workers is not statistically significant any more. An increase of the commuting distance is presumably more painful in a city compared to the same increase in an rural area, where the largest part of commuting is likely to take place on country roads. Rural residents do value an increase or decrease differently in both job change scenarios: They value a reduction higher than an increase.

5 Conclusion

We analyze the valuation of commuting distances of individuals who are changing between two jobs. 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.

We present a novel approach to measure the willingness to pay for commuting. Our identification comes from the effect of a change of commuting distance on the change of the daily wage. We can hence control for unobserved heterogeneity that would otherwise simultaneously affect both variables.

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 dis-utility of commuting. All other things equal, when changing to a new job, people are willing to give up a part of their daily wage to be able to spend less time commuting. In the opposite case, they are not in the position to capitalize a higher commuting distance in higher wages to the same extent. The largest part of a wage increase due to a longer commuting distance is due to sorting into a better paying firm and only to a small degree due to individual bargaining.

Our results stem from a rather small time window, where German georeferenced 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.

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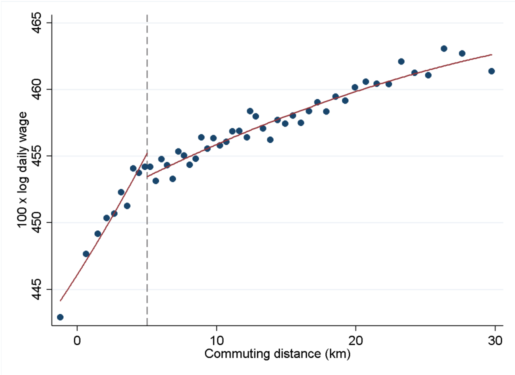
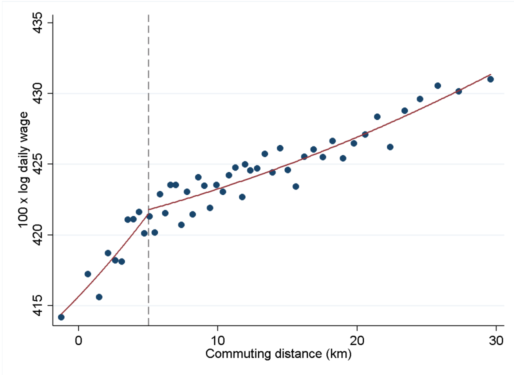
Appendix

A Appendix Figures and Tables



Voluntary job change



Involuntary job change

Notes: The figures show binned scatterplots of 100 x $log(dailywage)$ and commuting distances. Both variables have been purged from effects of sex, age, year of job search, education, and municipality of residence. The dots represent the average values of 100 x $log(dailywage)$ in 50 percentile categories of the commuting distance. Source: Own calculations.

Figure A.1: Commuting distance and daily wage

Table A.1: Summary of sample restrictions

	Voluntary job change	Involuntary job change
All	327,584	179,876
Nonmissing distance	281,789	141,441
No change of residence	252,789	138,770
Change of workplace coordinates	218,448	90,448
$>$ 1 year tenure new job	208,693	73,361
$>$ 1 year tenure old job	184,982	66,846
$<$ 100 km commuting distance	160,407	60,090
No extreme wages	159,446	59,983

Source: Own calculations.

Table A.2: Summary statistics for control variables

Variable	Mean	Std.Dev.	25th Perce.	Median	75th Perce.
Voluntary job change (N=159,446)					
Female	0.315	0.465	-	-	-
Age	37.796	9.563	30	37	45
Low skilled	0.050	0.218	-	-	-
Medium skilled	0.748	0.434	-	-	-
High skilled	0.202	0.402	-	-	-
Urban	0.334	0.472	-	-	-
Involuntary job change (N=59,983)					
Female	0.352	0.478	-	-	-
Age	38.634	10.143	30	39	46
Low skilled	0.063	0.243	-	-	-
Medium skilled	0.788	0.409	-	-	-
High skilled	0.150	0.357	-	-	-
Urban	0.329	0.470	-	-	-

Source: Own calculations.

Table A.3: Commuting distances by worker groups

Group	Mean	Std.Dev.	25th Perce.	Median	75th Perce.
Voluntary job change (N=159,446)					
Male	23.454	20.904	7.774	17.212	32.731
Female	19.632	18.662	6.251	13.795	26.786
Young	20.947	19.369	6.724	15.062	28.921
Old	23.665	21.179	7.807	17.192	33.070
Low skilled	19.025	18.863	5.840	12.826	25.318
Medium skilled	21.409	19.626	7.082	15.505	29.407
High skilled	25.527	22.253	8.003	18.858	36.642
Urban	18.151	18.533	5.826	11.521	23.173
Rural	24.305	20.832	8.662	18.734	33.842
Involuntary job change (N=59,983)					
Male	20.669	19.251	6.624	14.916	28.443
Female	17.971	17.321	5.613	12.708	24.524
Young	19.105	18.101	5.947	13.674	26.128
Old	20.390	19.187	6.539	14.582	27.736
Low skilled	16.027	17.037	4.490	10.904	20.963
Medium skilled	19.082	17.921	6.175	13.820	25.883
High skilled	23.376	21.421	6.915	16.594	33.293
Urban	16.114	16.997	5.212	10.235	20.163
Rural	21.486	19.148	7.233	16.498	29.634

Source: Own calculations.

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Editorial staff
Ricardo Martinez Moya, Jutta Palm-Nowak

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Renate Martin

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For further inquiries contact the authors:

Wolfgang Dauth
Phone +49.911.179 8417
E-mail wolfgang.dauth@uni-wuerzburg.de

Peter Haller
Phone +49.911.179 5704
E-mail Peter.Haller@iab.de