

Dauth, Wolfgang; Haller, Peter

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# Loss aversion in the trade-off between wages and commuting distances \*

Wolfgang Dauth †

Peter Haller ‡

University of Wuerzburg, IAB & IZA

Institute for Employment Research (IAB)

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## Abstract

We exploit administrative data on exact commuting distances for a large sample of German employees and study the relation of commuting and wages. We find that it requires 1.5 times as much money in terms of higher wages for job changers to accept an increase of their commute as compared to their willingness to pay for a reduction by the same distance. This provides non-experimental evidence for loss aversion. One third of this can be attributed to sorting of workers into certain firms at various distances and the remainder to a match-specific wage component that workers and firms bargain over.

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

JEL Codes: D90, J31, J64, R12, R40

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†Corresponding author: Department of Economics, University of Wuerzburg, Sanderring 2, 97070 Würzburg, Germany (email: wolfgang.dauth@uni-wuerzburg.de.)

‡Institute for Employment Research (IAB), Regensburger Str. 104, 90478 Nürnberg, Germany (email: peter.haller@iab.de).

# 1 Introduction

Commuting is a necessary evil that allows individuals to choose housing according to their preferences even if it is not located right where the best fitting jobs are – or vice versa. This advantage comes at a cost: Since time spent for commuting is usually neither productive nor recreative, each additional kilometer of commuting reduces an individual’s utility. The standard model of a monocentric city suggests that differences in commuting costs are capitalized in housing prices. In reality, however, neighbors from the same residential area work in different places at different distances from home. The mechanism that determines individual decisions to commute is more complex than merely the tradeoff between commuting costs and housing prices. Before accepting a job offer, individuals consider the bundle of a job’s features, including wage and commuting distance. Thus, at least to some extent, wages and commuting must be compensating differentials. With this paper, we contribute to the literature on the relation between commuting and wages by adding a perspective from behavioral economics: Loss averse individuals value one kilometer of commuting differently when they have to give up wage in order to reduce their commuting distance compared to the wage increase they would demand in order to be willing to commute further. Our study provides non-experimental field evidence for the presence of loss aversion in the context of commuting. In addition, we shed light on the underlying mechanism of how wages react to changes in the commuting distance.

Our empirical analysis uses a novel data set on the employment biographies of German employees with geo-coordinates of the places of residence and work in the years 2000 to 2014 – and the optimal travel route between these places. Focusing on workers who change between jobs allows us to control for individual heterogeneity. Our main finding is that job changers demand a higher wage increase for an additional kilometer of commuting compared to the wage cut they would accept in order to reduce their commuting distance by one kilometer. This indicates that job changers are loss averse. The relation of changes in wages and in commuting distances can be attributed to about one third to workers selecting into plants with different wage setting behaviors at various distances. The remainder of this relation stems from a match-specific wage component that workers and employers bargain over.

The complex individual decision between commuting distances and wages might deviate from standard assumptions about preferences (Thaler, 2018; Thaler, 2016; McFadden, 2001). Since the act of commuting itself is usually not perceived to be pleasant, the commuting distance enters utility as a “bad” (Stutzer and Frey, 2008). If individuals are loss averse, their loss of utility of accepting more of this bad (willingness to accept) is larger than their utility avoiding it (willingness to

pay) (e.g., Kahneman et al., 1991). Empirical studies on loss aversion in various situations typically estimate the willingness to accept to be twice as large as the willingness to pay (Benartzi and Thaler, 1995). However, evidence on loss aversion in the context of commuting so far only stems from experiments. Tversky and Kahneman (1991) find that individuals are loss averse when they are offered a tradeoff between commuting and job pleasantness measured by the amount of social interaction. A later experiment by De Borger and Fosgerau (2008) suggests that loss aversion might also apply if commuting is compensated by money rather than by job satisfaction. They use a survey of actual car drivers presented with hypothetical alternatives to a trip they recently took and estimate the gap between the willingness to pay and willingness to accept for commuting to differ by the factor four. By contrast, our non-experimental field evidence suggests a more moderate difference of about 1.5.

Our work is most closely related to the empirical literature that estimates the marginal willingness to pay for commuting based on various job search models. The literature distinguishes between job seekers who either search for a better job while employed (e.g., Van Ommeren et al., 2000; Van Ommeren and Fosgerau, 2009) or from unemployment (e.g., Van den Berg and Gorter, 1997). Both types of job seekers maximize their utility by simultaneous search on the labor market and on the housing market (see Van Ommeren et al., 1997; Van Ommeren et al., 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 a fixed wage (wage posting) independent of a worker's commuting distance or result from 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 17 Euro for one additional hour of commuting (Van Ommeren and Fosgerau, 2009). For Denmark, Gutiérrez-i-Puigarnau et al. (2016) estimate a household's income elasticity with regard to distance of -0.18. Using survey data from the UK, Manning (2003) detects a semi-elasticity of commuting time and wages of around 0.057 for job movers. Van den Berg and Gorter (1997) also discover a high negative utility from longer commutes for unemployed persons. In addition, Simonsohn (2006) shows that individuals who move to a different city adapt their preferences towards commuting according to the average commuting time at their new location.

The causal interpretation of results from wage regressions in this context is usually hampered by individual heterogeneity and residential sorting. Another strand of the literature employs quasi-experimental strategies to determine the marginal

commuting costs. Mulalic et al. (2014) estimate the individual compensation by the employer by focusing on workers employed at Danish firms that move but continue to exist. They find that each additional kilometer increases the wage by 0.15 percent in the long run. By contrast, for Germany, Heuermann et al. (2017) find that firms compensate their workers only partly for an exogenous change in effective commuting costs caused by a tax reform in the short run.

By and large, there is a consensus in the empirical literature that there is a (causal) positive long-run effect of commuting distance on wages. Nevertheless, there is little agreement on the exact magnitude of this effect. For Germany, in particular, 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 estimate the marginal valuation for an additional kilometer of commuting distance by running wage regressions for job changers. These job changes create variation in both wage and commuting distance while allowing to hold individual characteristics constant. In addition, we use pre-estimated information on the employers' wage-setting to examine the role of workplace heterogeneity in this context.

Our paper contributes to the literature in at least three ways. First, models in urban economics theory do not allow for an asymmetric valuation of positive and negative changes in the commuting distance due to a job transition. While this has also only rarely been discussed in the empirical literature (e.g., Mulalic et al., 2014, p.1101), we do find a significant difference. This finding is in line with a perspective from behavioral economics, where individuals are loss averse against a wage reduction even if it is accompanied by a reduction of the commuting distance. Second, we present a new approach to control for unobserved individual and workplace heterogeneity in the decision to commute using panel data in order to obtain an unbiased estimate of the willingness to pay for commuting. 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 over a period of 14 years.

We find an asymmetric valuation of distance changes. Job changers are willing to pay less for a reduction of their commuting distance compared to what they would demand to accept an increase. The average marginal effect for a reduction of the commuting distance is -0.066 Euros per kilometer. In contrast the effect of a positive distance change is 0.110 Euros, respectively. The coefficient for the overall average semi-elasticity of 0.116 is in line with previous findings (Mulalic et al., 2014; Manning, 2003). After controlling for the plant's wage-setting, the size of the marginal valuation decreases by about one third but the evidence for loss-aversion changes only slightly. This hints that at a large part of the wage compensation for

commuting is a match-specific outcome of some bargaining process.

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 are presented in section 4, and section 5 concludes.

## 2 Theoretical motivation

To motivate our empirical analysis, the following section sketches a theoretical model based on a class of models that are commonly used to analyze job search on the labor market (see Rogerson et al., 2005). Homogenous workers receive a job offer and maximize their (discounted) lifetime utility from choosing between future employment or unemployment. In spatial job search models, this basic framework is extended by adding commuting costs (see, e.g., Rouwendal, 1999; Van Ommeren et al., 2000). 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, 2009). This implies that wages are a function of commuting costs, conditional on the place of residence. Based on these considerations, we assume that an individual  $i$  gains utility  $u_{ij}$  from being employed at firm  $j$ :

$$u_{ij} = u(w_{ij}, z_{ij}, r_{ij}) \quad (2.1)$$

This utility from employment is a function of the wage rate  $w_{ij}$ , the firm's location which determines the distance  $z_{ij}$ , and the housing cost  $r_{ij}$ . In equation (2.1) we only consider realized job matches which were the outcome of a job search with only one job offer.<sup>1</sup> We assume that individuals focus their search effort on the labor market, while keeping the residence constant. This implies that the wage is the only compensating differential for changes in the commuting distance. Since this prohibits search on the housing market, the results can be interpreted only as partial equilibrium. In general equilibrium settings, where residence is not kept constant, one would expect to observe additional adjustment along this margin. However, our results in section 4.4 suggest that this restriction is of minor empirical relevance.<sup>2</sup>

Currently employed workers search for a new job for two reasons: They were either laid off at the previous job and are forced to search, or they have taken up

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<sup>1</sup> In more general search models, this would mean that the job offer rate is zero.

<sup>2</sup> This is the opposite case of the basic monocentric city model, where wages are constant and individuals are fully compensated for commuting costs through the housing market. While this compensation might adhere to similar mechanisms as the wage compensation, we do not pursue this any further in the empirical analysis due to the lack of data.

their current job under incomplete information. With updated information, they now voluntarily search for a new job in order to improve or hold their utility level.

In models with homogeneous rational workers with regard to preferences and mobility patterns, the relation between wages and commuting distance is usually assumed to be linear (e.g., Lucas and Rossi-Hansberg, 2002; Redding and Rossi-Hansberg, 2017). Even without stipulating a certain functional form, the usual assumption is that the indifference curves of trading shorter commuting distances for higher wages are reversible. This implies that individuals are willing to accept an increase of the commuting distance by one kilometer for the same amount of money that they would be willing to pay in order to reduce the distance by one kilometer. This assumption might hold in a cross-sectional setting, but not necessarily in a scenario of individuals changing their jobs.

In this light, we emphasize an aspect from behavioral economics, where the outcome of a job change is not experienced on an absolute scale, but is rather experienced relative to a point of reference (see O’Donoghue and Sprenger, 2018). In such situations, loss averse individuals are far more sensitive to losses (in terms of wages or higher commuting distances) relative to respective gains. To incorporate this behavioral aspect, we alter our initial individual utility function (2.1) and follow O’Donoghue and Sprenger (2018, p.12ff.), who discuss a simple model of reference-dependent preferences in which individuals consider a range of goods  $x_n, n = 1, \dots, N$ . Each good has a reference point  $r_n$  from which individuals evaluate gains and losses. In this setting, prospects of form  $L$  are evaluated according to the following value function:

$$V(L|r) = \sum_{n=1}^N p_n(x_n - r_n), \quad (2.2)$$

where  $p_n$  are probabilities in case the outcome of  $x_n$  is uncertain. We consider individuals who change between two jobs and face changes in their wages  $w_{in}$  and their commuting distances  $z_{in}$  at the new job, denoted by subscript  $n$ . Since we observe realized job changes, rather than the value trade-off before a possible job switch, we set  $p_w = p_z = 1$ . A reasonable reference point is the wage ( $w_{io}$ ) and distance ( $z_{io}$ ) at the previous job  $o$ . The value function proceeds from the reference point as a natural origin, with decreasing absolute marginal utility for gains and losses. Consequently, our value function (2.2) simplifies to equation (2.3).

$$V_{ij}(w, z) = (w_{in} - w_{io}) + (-z_{in} - (-z_{io})) \quad (2.3)$$

Wages enter this function as a good, which means that individuals are better off when they earn a higher wage. The opposite is true for the daily trip to work. Since commuting is usually neither productive nor recreative, it can be regarded as

a “bad” in a sense that utility decreases with the commuting distance (see Stutzer and Frey, 2008). Hence, we observe a gain if the distance decreases ( $z_{in} \leq z_{io}$ ) and a loss if the distance increases ( $z_{in} > z_{io}$ ). If individuals are loss averse, the marginal utility is larger for losses than for gains for each  $x_n$ . Four situations are possible after a job switch in this two-outcome setting:

$$V_{ij}(w, z) = \begin{cases} (w_{in} - w_{io}) + (-z_{in} - (-z_{io})) & \text{if } w_{in} \geq w_{io}, z_{in} \leq z_{io} \quad (\text{I}) \\ (w_{in} - w_{io}) + \lambda(-z_{in} - (-z_{io})) & \text{if } w_{in} \geq w_{io}, z_{in} > z_{io} \quad (\text{II}) \\ \lambda(w_{in} - w_{io}) + (-z_{in} - (-z_{io})) & \text{if } w_{in} < w_{io}, z_{in} \leq z_{io} \quad (\text{III}) \\ \lambda(w_{in} - w_{io}) + \lambda(-z_{in} - (-z_{io})) & \text{if } w_{in} < w_{io}, z_{in} < z_{io} \quad (\text{IV}) \end{cases}$$

In cases (II) to (IV), the individual suffers a loss in terms of either a lower wage, a longer commuting distance, or both. The loss aversion parameter  $\lambda \geq 1$  ensures that the indifference curves will have different slopes in each case even in this simple linear form.<sup>3</sup> To derive the indifference curves, we assume that all agents must have a constant utility level  $\bar{u}$  before and after the job switch. Under this assumption, we can rearrange and simplify each case (I) to (IV). We substitute the “good” with  $\Delta w_i \equiv w_{in} - w_{io}$ , the change in the wage between the old and the new job, as well as the “bad”  $\Delta z_i \equiv z_{in} - z_{io}$ , the change in the commuting distance.

$$V_i(w, z) = \bar{u} \Leftrightarrow \Delta w_i = \begin{cases} \bar{u} + \Delta z_i & \text{if } \Delta w_i \geq 0, \Delta z_i \leq 0 \quad (\text{I}) \\ \bar{u} + \lambda \Delta z_i & \text{if } \Delta w_i \geq 0, \Delta z_i > 0 \quad (\text{II}) \\ \frac{\bar{u}}{\lambda} + \frac{1}{\lambda} \Delta z_i & \text{if } \Delta w_i < 0, \Delta z_i \leq 0 \quad (\text{III}) \\ \frac{\bar{u}}{\lambda} + \Delta z_i & \text{if } \Delta w_i < 0, \Delta z_i < 0 \quad (\text{IV}) \end{cases}$$

We illustrate the different cases in figure 1. Note that the slope of the indifference curve is positive. Workers need to be compensated for an increasing distance by a higher wage in order to maintain a constant utility. The slopes of (II) and (III) differ such that the wage responds more strongly to an increase in the commuting distance than to a decrease of the distance by the same amount. In our empirical analysis, we examine a large sample of realized job switches, where about half of all cases commutes farther away, while the other half commutes less after the switch. This allows us to discriminate the willingness to accept (WTA) to acquire more of the “bad” (commuting) against the willingness to pay (WTP) to avoid the “bad”. The former can be estimated as the wage increase that individuals require

<sup>3</sup> More complex forms with, e.g., diminishing sensitivity are applied in our empirical analysis using quadratic terms.



( $\Delta w_i > 0$ ) to commute longer ( $\Delta z_i > 0$ ), while the latter is how much wage they are prepared to give up ( $\Delta w_i < 0$ ) in order to commute less ( $\Delta z_i < 0$ ). A significant difference between the WTA and the WTP indicates loss aversion (Tversky and Kahneman, 1991). Loss averse individuals will demand a higher wage increase in order to accept an increase of a previously short commuting distance compared to the wage they would give up in order to reduce the distance. Analogously, they would demand a higher reduction of the distance in order to accept a decline of an already achieved wage level compared to the increase in distance they would pay for a wage increase of the same amount.

[FIGURE 1 HERE]

Finally, we are interested in the margin along which wages react to changes in the commuting distance. To discriminate between wage posting by the employers and possible wage bargaining, 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 worker-specific component, a firm-specific component, and a match specific component. The expected log wage is:  $\ln(w_{ij}) = \alpha_i + \psi_{j(i)} + \kappa_{ij}$ .  $\alpha_i$  is the 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.  $\kappa_{ij}$  is a match specific component. When individual outcomes are compared before and after their job change, the worker specific term  $\alpha_i$  cancels out.  $d\psi_{j(i)} \equiv \psi_{n(i)} - \psi_{o(i)}$  is the difference of the firm specific components and  $d\kappa_{ij}$  is the difference of the match specific components of the new and old jobs. For non-negative changes in utility, either  $d\psi_{j(j)}/dz_i$  or  $d\kappa_{ij}/dz_i$  or both must be larger than zero. While we do not know their relative magnitude, holding constant the change in the firm specific wage component will reveal whether the match specific component is important.

## 3 Empirical Approach & Data

### 3.1 Identification Strategy

Next, we take the theoretical considerations laid out in the previous section to the data. In the theory, wage and commuting distance are determined jointly. In the empirical analysis, we think of the following experiment: A worker  $i$  is offered a job at a certain distance  $z_{in}$  from her residence. She decides to accept the offer if the wage  $w_{in}$  is high enough to compensate her for the dis-utility of

commuting, conditional on the other individual and job characteristics. In this case, a regression of the wage on the commuting distance of realized job matches will yield the amount of money that is necessary to compensate a certain increase of the commuting distance.

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

$$\ln(w_{i,n}) = \beta_0 + Z'_{i,n}\beta_z + X'_{i,n}\beta_x + \alpha_i + \varepsilon_{i,n} \quad (3.1)$$

$\ln(w_{i,n})$  is the logarithm of worker  $i$ 's daily wage,  $Z_{i,n}$  is the vector of commuting distance and in some specifications its squared value.  $X_{i,n}$  is the vector of the control variables age, age squared, as well as indicator variables for education (three categories), calendar years, and the municipality of residence. Including municipality fixed effects means that the relation of commuting and wage is identified only by the variation between workers within the same small-scale region.  $\beta_x$  would otherwise capture regional differences that might be correlated with both commuting times and wages, such as the urban wage premium (Glaeser and Maré, 2001).

$\alpha_i$  subsumes all unobserved, time constant individual characteristics that influence the wage. In the first specification, we omit  $\alpha_i$ . In this case,  $\beta_z$  yields a naive estimate of how wages differ with commuting distances for workers with similar observable characteristics. However, this unobserved heterogeneity might be related to both wage and commuting distance. Characteristics that determine an individual's productivity and thus her wage, such as personality, motivation, or family background, might also influence her willingness to commute. Workers might therefore systematically sort into more or less close distances depending on their  $\alpha_i$ , in which case  $\beta_z$  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  $\alpha_i$  is to use the observations before and after the job change and estimate (3.1) in first differences. Our main model is thus:

$$\Delta \ln(w_{i,t}) = \Delta Z'_{i,t}\beta_z + \Delta X'_{i,t}\beta_x + \delta \Delta 1(t = n)_{i,t} + \Delta \varepsilon_{i,t} \quad (3.2)$$

, where  $t = \{o, n\}$ .  $\Delta \ln(w_{i,t})$  measures the difference between the logged wages of the new and the old job and  $\Delta Z_{i,t}$  measures the change in commuting distances and its polynomials.  $\beta_z$  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,  $\Delta 1(t = n)_{i,t}$ . After differencing, this becomes the intercept and can be interpreted as the conditional average wage change for

all job changers.

The model in equation (3.2) does not allow for the slope of the relation of wage changes and changes in the commuting distance to differ between negative and positive distance changes. However, this is exactly what is implied by the presence of loss aversion as depicted in the stylized indifference curve in figure 1. We therefore modify this model to allow for such a change:

$$\begin{aligned} \Delta \ln(w_{i,t}) = & I(\Delta z_{i,t} \geq 0)_i \Delta Z'_{i,t} \beta_z^p + I(\Delta z_{i,t} < 0)_i \Delta Z'_{i,t} \beta_z^n \\ & + \Delta X'_{i,t} \beta_x + \delta \Delta 1(t=0)_{i,t} + \Delta \varepsilon_{i,t} \end{aligned} \quad (3.3)$$

, where  $I(\Delta z_{i,t} \geq 0)_i$  and  $I(\Delta z_{i,t} < 0)_i$  are dummy variables that indicate a positive or negative change in the commuting distance, respectively. In this specification, the parameters  $\beta_z^p$  and  $\beta_z^n$  are allowed to differ for negative and positive distance changes.

## 3.2 Data

**Individual Employment 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 IAB employment history (BeH)<sup>4</sup>. 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 suggested by Card et al. (2013) 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. The BeH offers exact geo-referenced information for the years 2000-2014 and we therefore focus on workers who left their previous job anytime in the years 2000 to 2013. One 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 analysis.

We define job transitions by workers switching to a different establishment identifier. We use the heuristic of Hethey and Schmieder (2010) to discriminate supposedly true job transitions from firm restructuring. If a large share of all workers leaving one plant move to the same new plant, this is likely due to restructuring rather than an actual job switch. We discard all transitions that are

<sup>4</sup> BeH - Beschäftigtenhistorik V10.00.00, Nürnberg 2015

suspect of being due to a spin-off, takeover, ID change, or an unclear case.

**Sampling of Job Changes** 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 missing values are mostly due to problems in the algorithm of string-matching address information to coordinates, e.g., because of spelling errors in the address data, we do not believe this will cause any bias. We also drop people who either worked or lived on one of Germany’s smaller Islands in the North and Baltic Sea that are not connected to the mainland by a bridge or dam, since we believe their commuting habits deviate strongly from people on the mainland. Next, we 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 and earned a wage above the marginal job threshold at the old job. 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 who commuted more than 100 kilometers either to the new or old job. As the distribution of commuting distances is highly right-skewed, this only affects a relatively small number of people (see Dauth and Haller, 2018). Next, we eliminate workers who changed their municipality of residence during the time between one year before or after the job change. Allowing individuals to change workplace and residence simultaneously would require information on housing prices, which we cannot observe at the disaggregated local level. Finally, we restrict the sample to workers who move between jobs within one year. This rules out individuals who had severe difficulties finding a new job after a possibly involuntary separation.<sup>5</sup> For those individuals, the assumption that the utility at the new job needs to be greater or equal to the one at the old job is particularly unlikely to hold. Appendix table A.1 summarizes these restrictions and their effect on the sample size. We discuss how each of those restrictions affects our results in section 4.4.

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,

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<sup>5</sup> In Germany, unemployed people normally receive unemployment insurance benefits of 60% of their previous monthly net income for 12 months according to Social Code III. After 12 months, they only receive means tested benefits at the subsistence level according to Social Code II. In general, unemployed are regarded as harder to integrate once they fall under Social Code II.

this results in a panel with two observations for each individual, one at the old and one at the new job.<sup>6</sup>

**Measurement of Commuting** The BeH offers exact geo-referenced information on the individuals' place of residence and place of work based on the addresses included in the social security information. We use the OpenStreetMap Routing Machine (Huber and Rust, 2016) to calculate the road distance of the optimal car driving route between each pair of residence and workplace addresses. While this procedure provides a credible estimate for the car driving distance, distances might differ for modes of transport. However, the car is by far the most preferred mode for commuting in Germany. According to the German Federal Statistical Office, in 2016 68 percent of all German citizens commuted by car. This share has virtually not changed since 2000 (67 percent).

Despite the physical distance, commuting has a time dimension. One might argue that the dis-utility of commuting is a function of the driving time, not the distance. OpenStreetMap Routing Machine can also be used to estimate the commuting time. This requires to make assumptions on parameters for the average speed on different types of streets, stop times at traffic lights, etc.<sup>7</sup> The estimated driving times are then ideal driving times and can only insufficiently account for rush hours or traffic jams.<sup>8</sup> Since neither the commuting distance nor the estimated commuting time is the ideal proxy for the dis-utility of commuting, we favor the distance for several reasons. First, while we find that even though the driving time does not rise linearly with the distance (see panel A of figure A.1), there is an almost perfect linear relationship of the changes of time and distance between the old and the new job (panel B of figure A.1). Second, the error caused by using the commuting distance cancels out due to first differencing if an individual retains her commuting pattern. In our sample, only 9 percent of urban residents change their commuting pattern from an intra-urban to an urban-rural direction, avoiding the rush hour. Third, actual driving times can partly be endogenous, as people are able to adjust their (flexible) working hours, work in different shifts, or use other modes of transport than the car.

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<sup>6</sup> As a robustness check, we also use the average wage of up to  $k = -5, \dots, 0, \dots, 5$  years before/after taking up the new job, conditional on the worker staying at this job.

<sup>7</sup> 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.

<sup>8</sup> An attempt to capture the real driving time is made by Couture et al. (2018), who rely on survey data to develop a congestion index for certain cities.

## 4 Results

### 4.1 Descriptive Results

Table 1 reports summary statistics for the main variables. The average job changer experiences a wage increase. This is certainly driven by voluntary job changers as incumbent workers are more likely to change between jobs if they can realize a wage increase. On average, the daily wage increases by 5.95 Euros. However, more than 25 percent of the job changers also decide to accept a wage reduction. The mean commuting distance to the old employer is 17.92 kilometers. The average change is 1.97 kilometers, while the median change is only 0.64. Overall, 54 per cent of the 516,480 individuals have a positive distance increase implying the distribution is not skewed towards positive or negative distance changes. Since the 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.

[TABLE 1 HERE]

[FIGURE 2 HERE]

Figure 2 illustrates the distribution of commuting distances to the new job. In order to visualize changes over time, we report separate distributions for jobs that started in 2006 or earlier and in 2007 or later. Qualitatively, both distributions look very similar. Both are positively skewed: The modus is 0-5 km and the frequencies decline for longer distances. This was even stronger in the first half of our observation period. In the second half, frequencies for commuting distances of less than 20 km declined slightly while longer distances became more frequent. This is in line with the common perception that workers need to be increasingly flexible and mobile in order to succeed on the labor market. In addition, this may also reflect rising real estate prices in city centers as well as the improving public transit infrastructure that fostered urban sprawl.

[FIGURE 3 HERE]

The map in figure 3 reports the median commuting distance of residents in each German municipality. Looking at the regional distribution of commuting distances, we observe a distinctive spatial pattern. The labor market regions of Hamburg (North), Berlin(North-East), and Munich (South) are clearly visible in figure 3. Here, residents of the core cities have comparatively short commuting distances that increase in a radial pattern when moving away from the center. In between those centers, there are municipalities with long average distances. The map also shows the marked difference in the spatial scale of municipalities across the different

states. Due to the rather large size of rural municipalities particularly in Hesse, Northrhine-Westphalia, Lower Saxony, and Saxony-Anhalt, extreme values of the median commuting distances are ironed out, which emphasizes the importance of using data at a finer level of aggregation.

## 4.2 Baseline Results

We start by considering only each worker’s first observation at the new job and regress the logarithm of daily wage on both the commuting distance as well as commuting time and observable worker characteristics. In the baseline specification we contrast distance and time to address potential measurement issues discussed in 3.2. The results in table 2 reveal a positive but concave relation of the commuting distance and the log wage that declines with larger distances (columns 1 and 2). This relationship is also reported graphically in figure A.2 in the online appendix. Due to the non-linearity of the relation of commuting distance and log wage, we report average semi-elasticities and marginal effects (in Euros) at the bottom of each results table.<sup>9</sup> 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 a about 0.5 percent higher wage. This conforms to an average marginal effect of around 0.4 Euros per kilometer. The results are very similar when we measure commuting by the estimated car driving time under optimal conditions as reported in columns 3 and 4 of table 2. The wages of individuals who commute approximately one minute longer are about 0.5 percent or 0.4 Euros higher. This is almost exactly the same as the effect found for the commuting distance and reflects that the estimated driving times do not sufficiently account for slow traffic and imply an average velocity of all commuters of around 50 kilometers per hour or 0.8 kilometers per minute. Since we are confident to measure the commuting distance correctly but less so with regard to commuting time, we use the time only as a robustness check.

[TABLE 2 HERE]

These results do not prove that the relationship of commuting distance and wage is actually concave, as the implied functional form might stem exclusively

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<sup>9</sup> The approximate semi-elasticity is the derivative of the regression equation with respect to the commuting distance  $\beta_1 + 2 \cdot \beta_2 \cdot C_i$ , where  $\beta_1$  and  $\beta_2$  are the coefficients of the commuting distance  $C_i$  and its squared value, respectively. We insert the actual distance for each individual and average over all individuals to obtain the average approximate semi-elasticity of the wage with respect to a marginal change in distance in percent. To obtain the average exact marginal effect, we first exponentiate equation 3.1 before deriving it with respect to the distance, which gives  $w_{i,t=-1} \cdot (\beta_1 + 2 \cdot \beta_2 \cdot C_i)$ , the average approximate semi-elasticity multiplied by the wage before the job change. Again, we insert the actual values for  $C_i$  and  $w_{i,t=-1}$  and average over all individuals.

from the logarithmic specification of the dependent variable. To further check the functional form, we therefore first exponentiate equation (3.1) and obtain the second derivative with respect to distance or time, which is small but negative for the average worker. This finding is in line with theoretical models on commuting (e.g., Berliant and Tabuchi, 2018), who assume commuting costs enter an individual’s utility mainly as monetary costs. We illustrate this non-linearity in appendix figure A.2, 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 2. These figures confirm the concave relation of both the log and level wage and the commuting distance.

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 that are unobserved and possibly determine the wage as well, such as ability, preferences, motivation, or family status. Since we observe job changers at both the old and the new job, we run the first-differenced specification described in equation (3.2) and (3.3). As long as these characteristics do not vary during the job transition, this purges all unobserved heterogeneity that might cause omitted variable bias in the OLS model.

In figure 4, we plot the change in log daily wage between the two successive jobs against the change in commuting distance. Like in the cross-section, the relationship between changes in wages and commuting is non-linear, which implies that the semi-elasticity and marginal effect of an increase in commuting by one kilometer or minute is larger for smaller than for larger increases. A little more than half of all job changers move to jobs further away from their home, while the others move to jobs closer by. The resulting figure is the empirical counterpart to the stylized indifference curve from figure 1. Since it is difficult to visually assess differences in the marginal effects, we next turn to the regression results underlying these figures.

[FIGURE 4 HERE]

Table 3 reports the detailed results on the effect of changes in commuting on wage changes. In column (1), we run the baseline specification of equation (3.2). The effect of an additional kilometer of commuting on daily wages drops to about 0.116 percent or 0.09 Euros. To get an estimate of the slopes from figure 4, we interact the distance terms with indicators for a positive or negative change in distance as shown in equation (3.3). Column (2), shows that for the average job changer, the effect of a positive distance change on the daily wage is about 55 percent larger than the effect of a negative change in distance, the difference being



highly statistically significant. The average worker who reduces her commuting distance forgoes about 0.09 percent of her daily wage per reduced kilometer, which is in the same ballpark as the findings from previous studies (e.g., Mulalic et al., 2014). By contrast, the average worker with a positive change in distance earns 0.14 percent more per kilometer. In other words, the willingness to pay for a reduction of their commuting distance is smaller compared to the compensation they demand for an increase by the same distance (willingness to accept). This suggests loss aversion in the spirit of Kahneman et al. (1991). German job changers have loss aversion when trading a shorter commuting distance against a higher wage. They are willing to pay less for a reduction of their commuting distance compared to the compensation they expect for an increase by the same distance.

[TABLE 3 HERE]

While this finding holds for average job changes it is less clear for very small changes of the commuting distance. A comparison of only the coefficients of the level terms reveals neither an economically nor statistically significant difference. In theory, loss aversion is usually represented by a kink of the indifference curve at the individual's reference point. Our field-evidence appears to be less clear cut in this regard. Job changers seem to respond equivalently to small increases and decreases of the commuting distance while their responses differ than they do at larger changes. Apparently, loss aversion is stronger at large than at small stakes, which is well-documented in Rabin and Thaler (2001) and summarized in O'Donoghue and Somerville (2018).

Again, the results are very similar, albeit less pronounced when we measure commuting by the estimated driving time (columns 3 and 4). We also find no evidence for loss aversion at small changes but a significantly stronger effect for larger changes. The magnitude of the coefficients are in the same ballpark. To avoid redundancies we only measure commuting by the distance from now on.

In section A.2 of the online appendix, we examine whether our main result differs between different sub-groups with regard to gender, education, the urban structure of the residence, number of previous jobs and characteristics of the previous workplace. To summarize, we find that loss aversion persists despite various splits of the sample and appears to be particularly strong for women, urban residents, and individuals with either no education or a university degree.

### 4.3 The role of workplace heterogeneity

What exactly is the margin along which wages react to changes in the commuting distance? Our main result can be explained by job changers being able to negotiate a compensation for their increased commuting costs with their new employers (see

Manning, 2011). An alternative explanation would be that workers with increasing commuting distances systematically sort into higher paying firms. Card et al. (2013, henceforth CHK) show that wages of German workers are determined to a substantial part by their workplace establishment, which pays a proportional wage premium or discount to all its workers due to differences in productivity, rent sharing, or collective bargaining compared to other firms. Job seekers might be aware of this and be prepared to commute farther to be able to work at a high paying plant. Or in contrast, abstain from working at such a plant to avoid a longer commuting distance.

Controlling for a plant’s proportional wage premium or discount might mean including a “bad control”: 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. However, a remaining effect of commuting on wages, conditional on the plant premium/discount, could be attributed to a match specific component. This effect would be the result of individual wage bargaining, rather than the firms’ wage setting.

We replicate the analysis of CHK to obtain a measure for the plant specific wage premium/discount. Specifically, we run wage regressions with both worker and plant fixed effects on the full universe of all German workers and plants from the IAB Employee History File (BEH, Version V10.01.00). For each year in our main analysis, we obtain these pre-estimated plant effects using panel data from the previous seven years. These plant effects can only be identified for a set of plants that are interconnected by flows of workers, which covers 87.4 percent of observations in our original sample.<sup>10</sup>

[TABLE 4 HERE]

To make sure our results do not hinge on this restriction to the data, the first column of table 4 repeats the baseline first-differenced regression only for workers who move between plants with valid pre-estimated plant effects. Indeed, the semi-elasticities of wage changes with respect to distance changes decrease by about one third. So apparently, wages react somewhat more strongly to distance changes when workers move between smaller plants. However, the main result, that the relationship between wage and distance changes is asymmetric, still holds. In column 2, we include the pre-estimated plant effects. We refrain from interpreting the magnitude of this coefficient but note that it is positive and highly significant. The  $R^2$  of the model increases by more than two thirds. We are thus confident that this variable does pick up the heterogeneity of plants with regard to wage setting

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<sup>10</sup> See section A.1 of the online appendix for details on how the plant effects are estimated.

behavior. The effects of the commuting distance on wages reduce by one third but remain significantly larger than zero. This indicates that the match specific wage component is important. We conclude that part of the relationship between the commuting distance and wage stems from workers increasing their commuting distances in order to work at plants that pay higher wages. Still, conditional on the plant's wage-setting, there is leeway for individual bargaining in the match specific wage component.

Importantly, 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 smaller amount of money to avoid commuting compared to how much they expect to be rewarded when commuting farther.

Column 3 corroborates these results. Since larger plants also arguably have a different wage setting behavior compared to smaller plants, we replace the pre-estimated firm effects with the logarithm of the plant size. Since this means that we do not lose any observations, we compare those results with column 2 of table 3. Again, the effects of distance changes are sharply reduced, yet stay significant. Workers are willing to commute farther in order to work at larger, better paying firms. However, conditional on the plant wage premium or size, there is still a wage component that asymmetrically reacts to changes in the commuting distance.

#### 4.4 Robustness checks

In section 3, we have explained how we delineated the sample of workers to run our regressions. In table A.5 of the online appendix, we re-estimate our main model on the unrestricted data and then introduce the restrictions step-by-step in order to see how they affect the results. The coefficients estimated from the unrestricted data are comparatively small. The first restriction ensures that workers not only change the establishment id but also to a different location, which barely affects the results. The restriction on individuals with commuting distances below 100 kilometers at both the old and new jobs considerably increases the measured effects. Apparently, the results before were driven by outliers with extremely high distances at either the new and old job. Changes of those extreme distances to or from more normal distances apparently are not reflected in wage differences to the same extent. The other restrictions, namely high job attachment at the old and new job, no simultaneous change of residence, and a rather smooth transition between jobs, do not appear to affect our results in a substantial way. We are thus confident that neither the magnitude of our results, nor the novel finding, that there is loss aversion in the relationship of changes in the commuting distance and wages, hinge on the exact delineation of our sample.

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 into account the price of housing at the individual level, which we are not able to observe. This might introduce selection bias if residence movers react particularly sensitive to changes in commuting distances. However, imposing this restriction in row “no change of residence” of appendix table A.6 only marginally changes the semi-elasticities of wage changes with respect to changes in the commuting distance. If anything, the estimate for the difference between positive and negative changes becomes more conservative. Still, as a robustness check, we focus exclusively on those individuals who simultaneously change both the workplace and the residence, which we have omitted so far, and re-estimate our baseline model in appendix table A.6. Quite remarkably, while the semi-elasticities decline by around a third, we do not find any differences to the main results: The asymmetric effect of changes in the commuting distance on wage changes holds. In section A.3 of the online appendix, we discuss further checks, where we relax some of the assumptions we made to our data and estimation approach that might influence our results.

## 5 Conclusion

The main finding of our study is an asymmetric valuation of positive and negative changes in the commuting distance. Job changers are willing to pay less for a reduction of their commuting distance compared to what they would demand to accept an increase. In other words, the individuals’ willingness to accept (WTA) a longer commuting distance is around 1.5 times as large as the willingness to pay (WTP) for a reduction of the distance. This provides non-experimental evidence for the presence of loss aversion in the spirit of Kahneman et al. (1991). Experimental evidence of De Borger and Fosgerau (2008) find a much larger gap between WTA and WTP of factor four. However, they acknowledge a smaller degree of loss aversion in empirical settings, especially where the reference point is ambiguous.

The presence of loss aversion contradicts the standard theories about rational choice and suggests that people have difficulties to evaluate the complex relation of commuting distance and wage changes after a job switch. The effect on the quality of life that comes with a reduction of commuting distance (e.g., Stutzer and Frey, 2008) is not equally appreciated as the pain of commuting farther. This implies that are fewer job switches of workers to optimize their utility by taking up a job at a different commuting distance (Knetsch, 1989).

Our results emphasize the importance of asymmetric behaviour which seems to be biased towards the status quo. Empirical results about loss aversion in the context of commuting decisions are rather scarce. Simonsohn (2006) documents

that individuals acquire habits with respect to commuting (such as the travel distance). After moving to a different city, they retain those habits and differ from the commuting behavior of natives. Despite the importance of commuting in daily life, the behavioral aspect the economic literature on commuting lacks in non-experimental evidence. Our paper frames the individual commuting decision, in particular the marginal willingness to pay for commuting, into a framework in which this decision is strongly influenced by the individual's behaviour.

The majority of all employees commutes between residence and workplace. This individual behavior provides an important externality: The farther individuals are willing to commute, the larger is the scale of a local labor market. This in turn increases the average productivity of matches between workers and firms (Helsley and Strange, 1990; Petrongolo and Pissarides, 2006). This benefit is recognized by many governments which promote commuting through tax concessions. German taxpayers, for example, are allowed to reduce their taxable income by 0.30 Euros per kilometer of the one-way commuting distance. The fact that we nonetheless find that wages react to changes in the commuting distance proves that the individual costs of commuting—both monetary and non-monetary—are significantly higher than this amount.

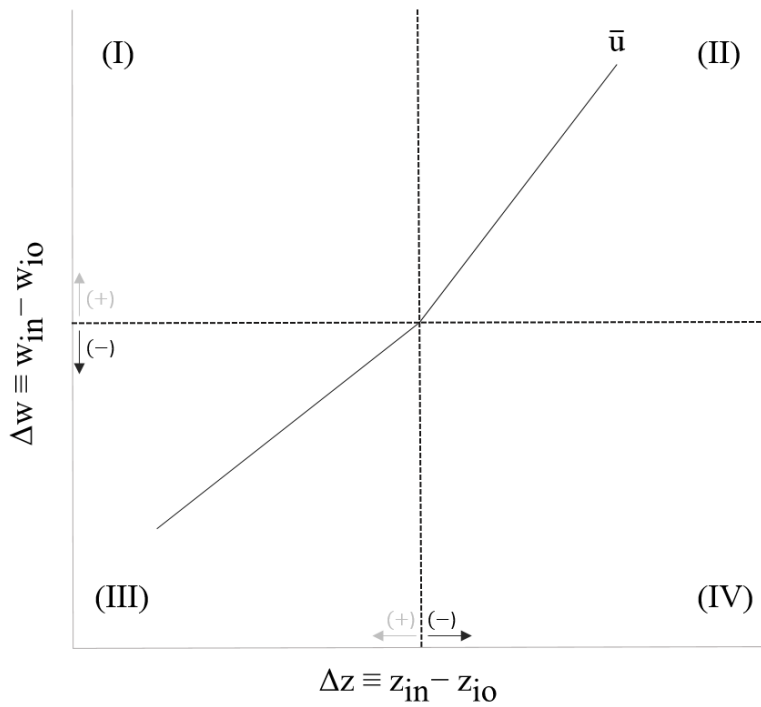
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Notes: The figure depicts four possible situations after a job switch in a two-outcome setting. On the y-axis we find the wage change, on the x-axis the change in commuting distance. Each quadrant alternates with respect to a positive or negative change in either wage or distance. The arrows indicate the “better” or “worse” off direction.

Figure 1: Exemplary indifference curve with loss aversion with one “good” and one “bad”

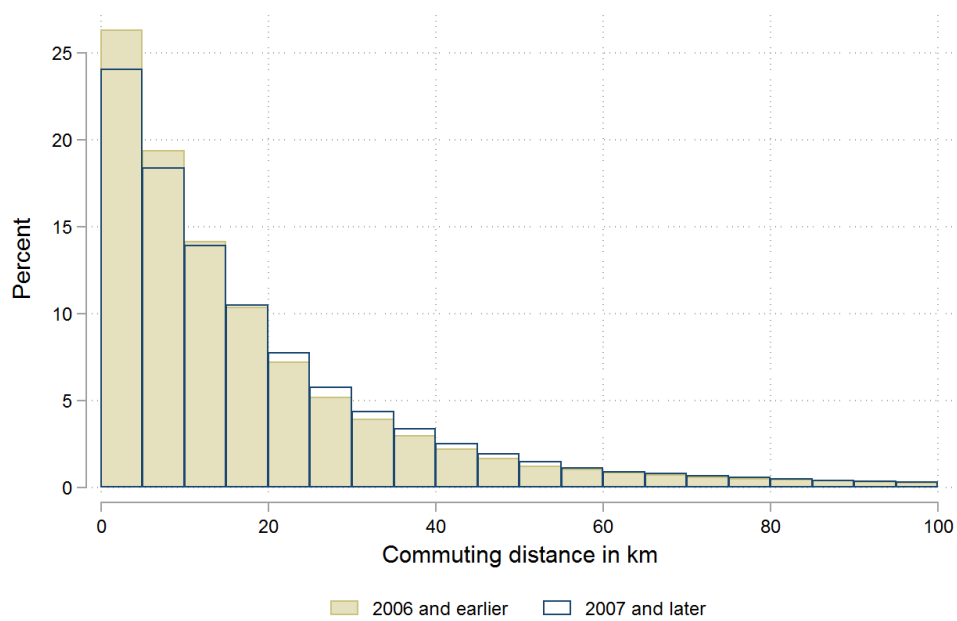
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Notes: The figures report the commuting distance to the new job. For comparison the figures distinguish jobs that started in 2006 or earlier and 2007 or later.

Figure 2: Distribution of initial commuting distances

## Legend

□ Federal state border

0 50 100 150 200 km

Median driving dist.

□ < 15 km

■ 15 - 25 km

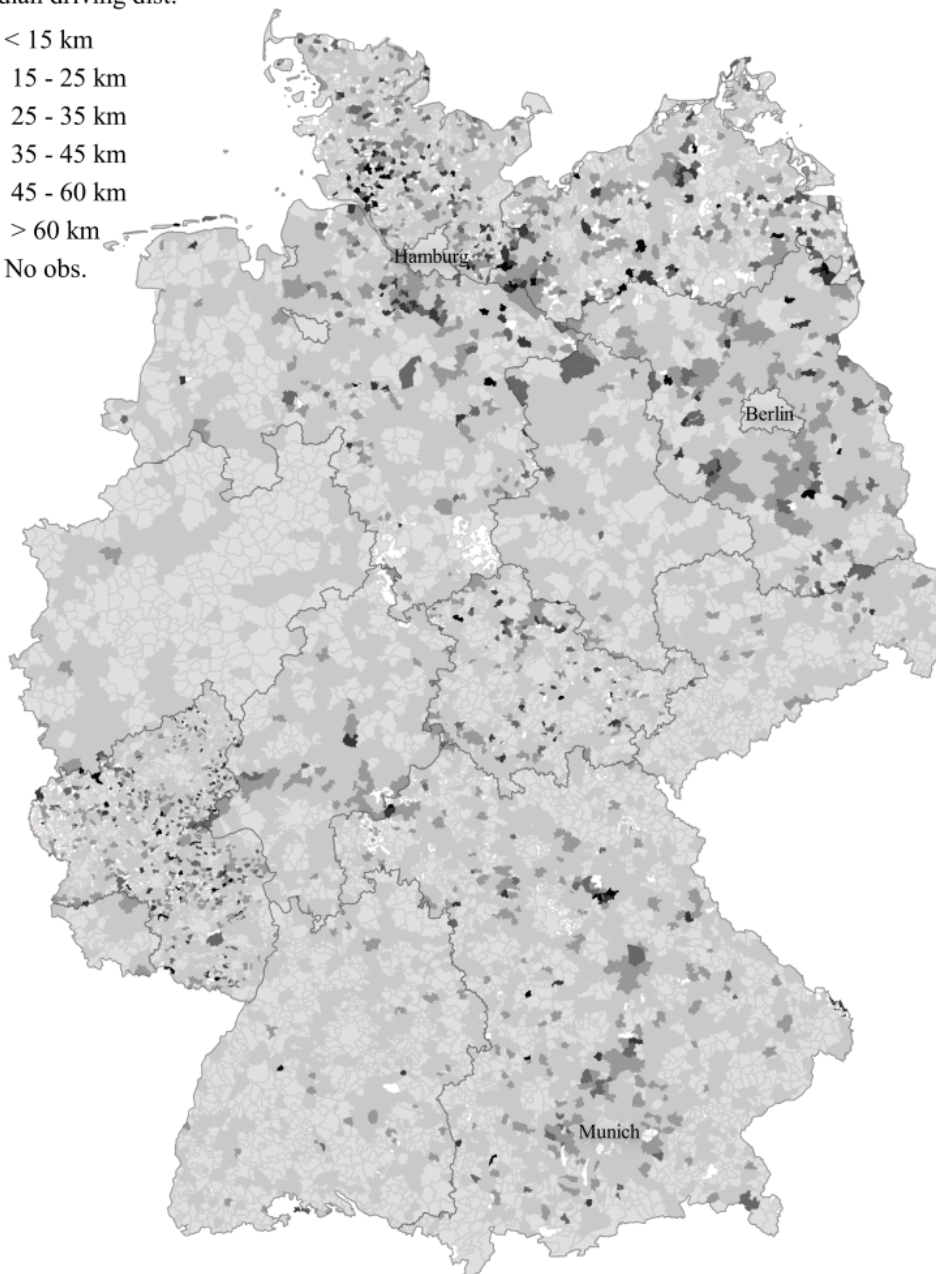
■ 25 - 35 km

■ 35 - 45 km

■ 45 - 60 km

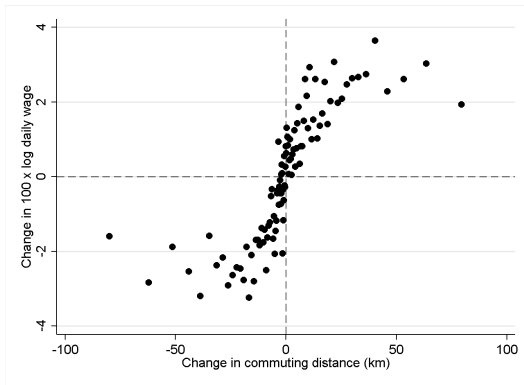
■ > 60 km

□ No obs.

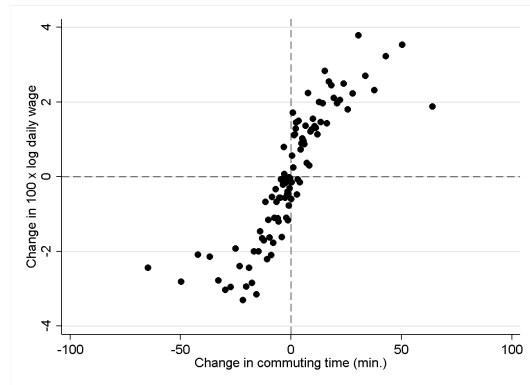


Notes: The map shows the median commuting distance to the new job of all job seekers by municipality of residence in manually chosen distance categories. Municipalities with 'no obs.' emerge due to missing job matches in that region.

Figure 3: Regional distribution of commuting distances



A. log wage and commuting distance



B. log wage and commuting time

Notes: The figures show binned scatterplots of  $100 \times \log(\text{dailywage})$  and commuting distances (Panel A) or time (Panel B), respectively. All variables have been first-differenced and purged from effects of age squared, year of job search, and education. The dots represent the average values of  $100 \times \log(\text{dailywage})$  in 50 percentile categories of the commuting distance.

Figure 4: Changes in commuting and daily wage

Table 1: Summary statistics of main variables

| Variable               | mean    | (std. dev.)                            |
|------------------------|---------|--|
| wage                   | 82.19   | ( 68.35 )<br>[ 43.74 ; 68.59 ; 98.25 ] |
| $\Delta$ wage          | 5.95    | ( 49.21 )<br>[-4.18 ; 3.46 ; 16.65 ]   |
| distance               | 17.92   | ( 18.31 )<br>[4.97 ; 11.97 ; 24.24 ]   |
| $\Delta$ distance      | 1.52    | ( 22.40 )<br>[-6.55 ; 0.42 ; 9.83 ]    |
| dummy: longer distance | 0.54    | ( 0.50 )<br>[0.00 ; 1.00 ; 1.00 ]      |
| observations           | 516,480 |  |

Notes: Means and standard deviations of main variables. 25th, 50th, and 75th percentiles in brackets.

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

| Dependent Variable: 100 x $\log(\text{dailywage})$ |                        |                        |                        |                        |
|--|------------------------|------------------------|------------------------|------------------------|
|  | distance               |                        | time                   |                        |
|  | (1)                    | (2)                    | (3)                    | (4)                    |
| route  | 0.3004***<br>(0.010)   | 0.6714***<br>(0.017)   | 0.3612***<br>(0.012)   | 0.7942***<br>(0.020)   |
| route <sup>2</sup>                                 |                        | -0.0054***<br>(0.000)  |                        | -0.0071***<br>(0.000)  |
| dummy, female=1                                    | -31.4551***<br>(0.854) | -31.2965***<br>(0.850) | -31.4585***<br>(0.857) | -31.3410***<br>(0.853) |
| age  | 8.0481***<br>(0.136)   | 8.0435***<br>(0.135)   | 8.0562***<br>(0.135)   | 8.0489***<br>(0.134)   |
| age squared  | -0.0909***<br>(0.002)  | -0.0908***<br>(0.002)  | -0.0910***<br>(0.002)  | -0.0908***<br>(0.002)  |
| dummy, low skilled=1                               | -39.3458***<br>(0.448) | -39.0659***<br>(0.445) | -39.2991***<br>(0.451) | -39.0569***<br>(0.447) |
| dummy, high skilled=1                              | 44.5697***<br>(0.593)  | 44.6323***<br>(0.596)  | 44.5727***<br>(0.596)  | 44.6197***<br>(0.592)  |
| constant   | 275.6124***<br>(2.656) | 272.4391***<br>(2.698) | 273.9476***<br>(2.654) | 269.9991***<br>(2.710) |
| year dummies                                       | Yes                    | Yes                    | Yes                    | Yes                    |
| N  | 516480                 | 516480                 | 516480                 | 516480                 |
| R <sup>2</sup>                                     | 0.445                  | 0.446                  | 0.445                  | 0.446                  |
| semi elasticity                                    |                        | 0.479***               |                        | 0.524***               |
| marginal effect                                    | 0.247                  | 0.374                  | 0.297                  | 0.408                  |
| curvature of $w(C)$                                |                        | -0.007                 |                        | -0.009                 |

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: Baseline first-differences regressions - Changes in commuting distance or time and daily wages

| Dependent Variable: 100 x $\log(\text{dailywage})$ |                        |                        |                        |                        |
|--|------------------------|------------------------|------------------------|------------------------|
|  | (1)                    | (2)                    | (3)                    | (4)                    |
|  | distance               |                        | time                   |                        |
| route  | 0.1700***<br>(0.007)   |                        | 0.2079***<br>(0.008)   |                        |
| route sq.  | -0.0015***<br>(0.000)  |                        | -0.0021***<br>(0.000)  |                        |
| neg. route change                                  |                        | 0.1697***<br>(0.012)   |                        | 0.2394***<br>(0.014)   |
| neg. route change sq.                              |                        | -0.0016***<br>(0.000)  |                        | -0.0026***<br>(0.000)  |
| pos. route change                                  |                        | 0.1707***<br>(0.012)   |                        | 0.1810***<br>(0.014)   |
| pos. route change sq.                              |                        | -0.0014***<br>(0.000)  |                        | -0.0017***<br>(0.000)  |
| age sq.  | -0.1137***<br>(0.002)  | -0.1137***<br>(0.002)  | -0.1137***<br>(0.002)  | -0.1138***<br>(0.002)  |
| dummy, low skilled=1                               | -44.0427***<br>(0.518) | -44.0502***<br>(0.520) | -44.0431***<br>(0.519) | -44.0663***<br>(0.520) |
| dummy, high skilled=1                              | 4.9161***<br>(0.649)   | 4.9009***<br>(0.643)   | 4.9158***<br>(0.648)   | 4.8921***<br>(0.642)   |
| constant   | 14.1845***<br>(0.254)  | 14.1325***<br>(0.271)  | 14.1794***<br>(0.255)  | 14.2603***<br>(0.273)  |
| year dummies                                       | Yes                    | Yes                    | Yes                    | Yes                    |
| N  | 516,480                | 516,480                | 516,480                | 516,480                |
| R <sup>2</sup>                                     | 0.110                  | 0.110                  | 0.110                  | 0.110                  |
| semi elasticity                                    | 0.116***               |                        | 0.128***               |                        |
| marginal effect                                    | 0.09                   |                        | 0.099                  |                        |
| curvature  | -0.002                 |                        | -0.003                 |                        |
| semi elast. neg. change                            |                        | 0.089***               |                        | 0.105***               |
| semi elast. pos. change                            |                        | 0.138***               |                        | 0.137***               |
| p-value of difference                              |                        | ***                    |                        | **                     |
| marg. eff. neg. change                             |                        | 0.066                  |                        | 0.077                  |
| marg. eff. pos. change                             |                        | 0.11                   |                        | 0.109                  |
| curvature neg. change                              |                        | -0.002                 |                        | -0.004                 |
| curvature pos. change                              |                        | -0.002                 |                        | -0.003                 |

Notes: All models estimated in first differences. Standard errors (clustered by municipality) in parentheses. Levels of significance: \* 10%, \*\* 5%, \*\*\* 1%

Table 4: First-differences regressions - Accounting for firm heterogeneity

| Dependent Variable: $100 \times \Delta \log(\text{dailywage})$ |                        |                        |                        |
|--|------------------------|------------------------|------------------------|
|  | (1)                    | (2)                    | (3)                    |
| distance, neg. change  | 0.1221***<br>(0.012)   | 0.0769***<br>(0.011)   | 0.0977***<br>(0.012)   |
| distance sq., neg. change                                      | -0.0010***<br>(0.000)  | -0.0006***<br>(0.000)  | -0.0011***<br>(0.000)  |
| distance, pos. change  | 0.1138***<br>(0.013)   | 0.0861***<br>(0.012)   | 0.1021***<br>(0.012)   |
| distance sq., pos. change                                      | -0.0009***<br>(0.000)  | -0.0006***<br>(0.000)  | -0.0009***<br>(0.000)  |
| 100 x AKM plant FE   |                        | 0.4912***<br>(0.005)   |                        |
| 100 x ln(plant size)   |                        |                        | 0.0293***<br>(0.001)   |
| age sq.  | -0.1085***<br>(0.002)  | -0.0986***<br>(0.002)  | -0.1125***<br>(0.002)  |
| dummy, low skilled=1   | -43.5943***<br>(0.546) | -44.1357***<br>(0.561) | -43.8608***<br>(0.543) |
| dummy, high skilled=1  | 5.4919***<br>(0.663)   | 4.6895***<br>(0.610)   | 4.4013***<br>(0.650)   |
| constant   | 14.5488***<br>(0.281)  | 12.6299***<br>(0.275)  | 13.3678***<br>(0.292)  |
| Year dummies   | Yes                    | Yes                    | Yes                    |
| N  | 451,202                | 451,202                | 516,480                |
| R <sup>2</sup>   | 0.111                  | 0.191                  | 0.130                  |
| semi elast. neg. change  | 0.068***               | 0.043***               | 0.042***               |
| semi elast. pos. change  | 0.093***               | 0.072***               | 0.081***               |
| p-value of diff.   | **                     | **                     | ***                    |
| marg. eff. neg. change   | 0.054                  | 0.035                  | 0.029                  |
| marg. eff. pos. change   | 0.078                  | 0.062                  | 0.064                  |

Notes: All models estimated in first differences. Further control variables are age sq., calendar year and skill dummies. The CHK plant FE are the coefficients of plant fixed effects obtained from auxiliary regressions of the log wage on worker fixed effects, plant fixed effects, year fixed effects, and education-specific cubic age-profiles, carried out for the 7-year interval prior to the year of the respective observation. Standard errors (clustered by municipality) in parentheses. Levels of significance: \* 10%, \*\* 5%, \*\*\* 1%



# A Online Appendix – Not for Print

## A.1 Accounting for Workplace Heterogeneity

In this section we explain in more detail, how we replicate the analysis by Card et al. (2013, henceforth CHK) to obtain a measure for an employer’s wage posting behavior. Relating to the discussion in section 2, we assume that, conditional on control variables, log wages can be split into three additive components: A worker-specific component, a plant-specific component, and a component that is specific to the match of a certain worker and a certain plant. Assuming that the first component is time invariant, it will be eliminated by first differencing in equation (3.2). Including plant fixed effects in the model would be futile. Since we only have a sample of German workers, we observe only a very small number of workers for most plants, which means that worker and plant effects would be hard to separate. As an alternative, we use the pre-estimated coefficients of plant fixed effects following CHK. In their original paper, CHK estimate regressions models on almost a full sample of the total German workforce for several consecutive seven-year intervals. For each interval, they obtain plant effects which are available to researchers using IAB data and can be merged to the data via a unique establishment identifier. However, we prefer to carry out these regressions on our own to ensure that for each year in our data, plant effects are available that are estimated exclusively using data from previous years. We therefore use the code provided by CHK and data very similar to theirs and estimate 14 regressions. The plant effects obtained from the first regression using data from the years 1993-1999 are then merged to our main data for the year 2000, and so forth.

Including these plant effects comes at the cost that we lose around 12.6 percent of all observations in the estimation sample. The auxiliary regressions require all plants to be interconnected by flows of workers. Prior to the regression, the code by CHK first identifies the largest connected set of plants. All other, mostly small plants must be dropped as their fixed effect would not be quantitatively comparable to those of the largest connected set.

## A.2 Heterogeneous effects by worker characteristics

Commuting patterns vary with the individual’s characteristics (Wang, 2001). We also document differences in commuting patterns to the new employment (see appendix table A.3) and whether the regression results differ between groups of job changers with different characteristics in appendix table A.4.

Men commute around 16 percent farther than women. For instance, household obligations are likely to 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 negative distance changes are more or less equal, the wages of women react more strongly to positive changes. This result is consistent with studies that find female labor supply to be more elastic (Hirsch et al., 2010; Barth and 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 require higher wage rises to accept increases of the commuting distances compared to what they would give up in order to commute less.

Commuting distances clearly increase with education. On average, high-skilled workers commute almost six kilometers farther than low-skilled (42 percent more). The residential location choice of workers highly depends on their educational attainment (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 job seekers is driven mostly by unskilled and high skilled workers, while the asymmetry is much less pronounced for workers with a vocational training. Apparently, loss aversion is particularly strong for workers with no degree or a university degree.

In the same way, individuals differ when living in urban or more rural areas.<sup>11</sup> As expected, rural residents commute 25 percent more. In table A.4 it appears that individuals from rural regions value increases and decreases of the commuting distance equally, while the asymmetry almost exclusively stems from city dwellers. Travel speed is usually higher in rural areas (Wingerter, 2014), which might explain why rural residents require slightly less compensation for an increase of their commuting distance. The biggest difference is that urban residents are willing to give up a lot less wage for a reduction of the distance, which speaks in favor of a stronger loss aversion.

Looking at the number of previous jobs, we find that workers who leave their first job have the strongest loss aversion. Yet, at the same time require a little less compensation for an increase of the commuting distance compared to all other groups. Somewhat contradictory to the age profiles, we find that people commute farther the more often they have changed jobs before. So apparently, commuting is not something that job changers seek to avoid as much as possible as long as they feel sufficiently compensated.

Finally, we distinguish by previous employers' proportional wage premium discussed above and by previous plant size. Here we find that our results mostly

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<sup>11</sup> 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.

stem from small plants with comparatively low wages. Workers from larger and from better paying plants are less averse against losses and also demand a smaller compensation for increases of the distance. This is probably because the latter workers have already maximized their earnings potentials and seldom change jobs any more. If they do, they do so in order to reduce their commuting distance and are willing to pay for this. The regression analysis reveals that higher paying plants and bigger plants attract workers from distant locations.

To summarize, our main finding, the asymmetric effects of changes in the commuting distance driven by loss aversion appears to stem in particular from urban residents with either no education or a university degree.

### A.3 Further Robustness Checks

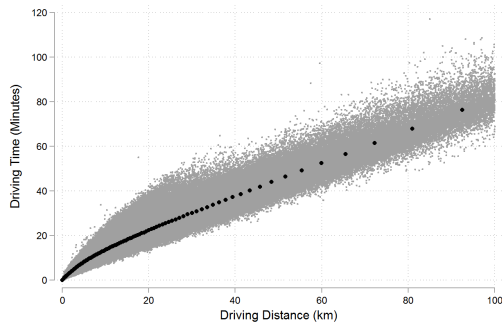
In this section, we discuss some more robustness checks. The results are reported in appendix table A.6. Our identification strategy builds on comparing the difference of daily wages at the end of the previous and the start of the new job. However, when individuals decide on taking up a new job, they might actually consider the earnings difference in the long run rather than the immediate difference at the time of the job change. For example, wages at the previous job could have stagnated prior to a 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 calculate the average daily wage of the old (new) job during the  $T = 2, 3, 4, 5$  years prior to leaving the previous job and after starting the new job, conditional that the observation belongs to the same job as right after/before the move. We then take the change of the average wage as the dependent variable and re-estimate our baseline models. While the magnitude of the main effects increases a little, we still find a significant difference in the wage effect of a positive versus negative change in the commuting distance. This could be due to a steeper wage profile when entering the new job. Another difference is the intercept (not reported in table A.6). The intercept reflects the *ceteris paribus* wage increase due to the job change. It rises from around 14 percent in the baseline specification from table 3 to between 18 (2-year averages) and 24 (5-year averages) percent. 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 workplace address recorded in the administrative data. 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, if a super market chain holds several stores in the same city, it will not be possible to distinguish them in our data. This problem

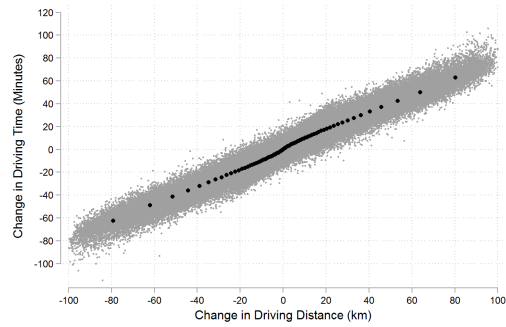
could be aggravated if a firm's employees are mobile across plants, for example in the construction or transport sectors. In both cases, commuting distances of individual workers will not be measured correctly. As a further robustness check, we thus drop those industries where we fear that this issue might be most severe: Construction, transport (on land), temporary agency work, retail trade, financial intermediation, public administration, and defence. Almost a third of all observations are dropped but the results change only marginally in comparison to our baseline results.

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 an intercept which is significantly smaller by 0.85 percentage points. At the same time, the magnitude of the effects of a distance change remain unchanged.

# Appendix Figures and Tables



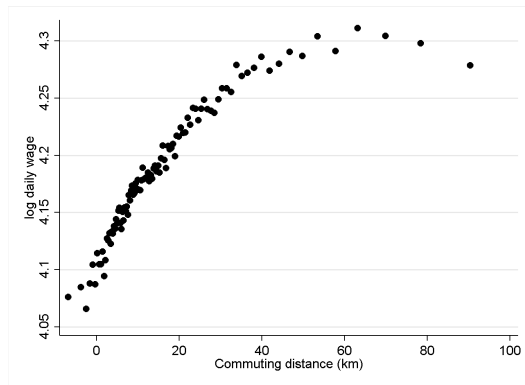
Panel A (time & distance)



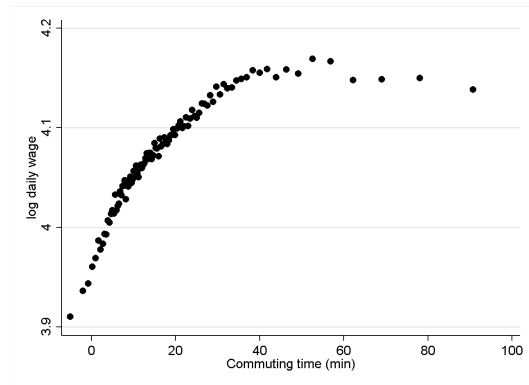
Panel B ( $\Delta$  time &  $\Delta$  distance)

Notes: The figures shows the scatterplots of the relation between commuting time and distance. The bold dots represents binned values. In both panels the vertical axis reports driving time, the horizontal axis driving distance. In panel A, the absolute values are depicted. In panel B, the values are reported in first differences.

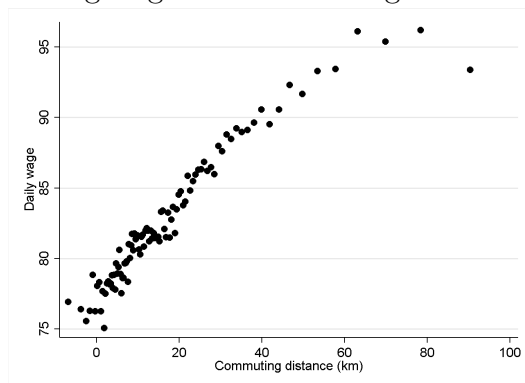
Figure A.1: Commuting time and distance



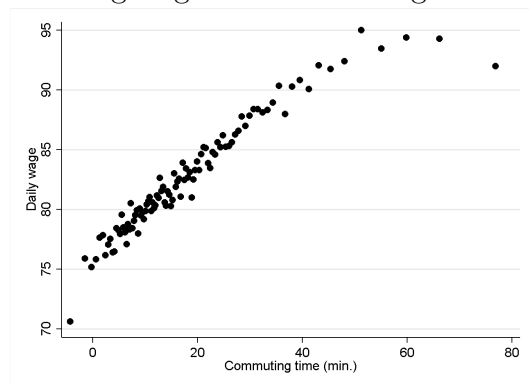
A. log wage and commuting distance



B. log wage and commuting time



C. linear wage and commuting distance



linear wage and commuting time

Notes: The figures show binned scatterplots of the partial relationship of commuting distance (Panels A and C) or time (Panels B and D) and wage. All variables have been purged from the effects of sex, age, age sq., 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/time. In panels A and B, the vertical axis reports residualized values of  $100 \times \log(\text{dailywage})$ . In panels C and D, the vertical axis reports values of the difference between the actual daily wage and its prediction obtained from the logarithmic specification.

Figure A.2: Commuting and daily wage

Table A.1: Summary of sample restrictions

|  | observations | mean                             | (sd)                           | mean                            | (sd)       | mean                         | (sd)                           | mean       | (sd)                         | mean                           | (sd)       | mean                         | (sd)     |
|--|--------------|----------------------------------|--------------------------------|---------------------------------|------------|------------------------------|--------------------------------|------------|------------------------------|--------------------------------|------------|------------------------------|----------|
|  |              | wage                             | Δ wage                         | distance                        | Δ distance | longer dist.                 |                                |            |                              |                                |            |                              |          |
| nonmissing distance  | 1,549,208    | 79.06<br>[38.80 ; 63.63 ; 95.70] | 5.26<br>[-5.82 ; 2.92 ; 17.15] | 42.80<br>[5.22 ; 13.21 ; 30.25] | ( 97.91 )  | 0.46<br>[0.00 ; 0.00 ; 1.00] | 4.80<br>[-6.80 ; 0.00 ; 10.29] | ( 121.21 ) | 0.53<br>[0.00 ; 0.00 ; 1.00] | 5.66<br>[-9.99 ; 0.48 ; 13.99] | ( 130.42 ) | 0.53<br>[0.00 ; 1.00 ; 1.00] | ( 0.50 ) |
| change of workplace coordinates                              | 1,292,615    | 75.82<br>[37.41 ; 60.88 ; 91.40] | 5.33<br>[-7.04 ; 3.45 ; 18.76] | 45.12<br>[5.41 ; 13.73 ; 31.73] | ( 101.29 ) | 0.53<br>[0.00 ; 1.00 ; 1.00] | 5.66<br>[-9.99 ; 0.48 ; 13.99] | ( 130.42 ) | 0.53<br>[0.00 ; 1.00 ; 1.00] | 5.66<br>[-9.99 ; 0.48 ; 13.99] | ( 130.42 ) | 0.53<br>[0.00 ; 1.00 ; 1.00] | ( 0.50 ) |
| < 100km commuting distance                                   | 1,070,295    | 69.83<br>[36.00 ; 58.19 ; 86.17] | 5.03<br>[-6.74 ; 3.32 ; 17.81] | 17.62<br>[4.74 ; 11.61 ; 23.79] | ( 18.31 )  | 0.53<br>[0.00 ; 1.00 ; 1.00] | 1.11<br>[-7.38 ; 0.34 ; 9.78]  | ( 22.91 )  | 0.53<br>[0.00 ; 1.00 ; 1.00] | 1.11<br>[-7.38 ; 0.34 ; 9.78]  | ( 22.91 )  | 0.53<br>[0.00 ; 1.00 ; 1.00] | ( 0.50 ) |
| > 1yr tenure at old job and<br>wage above marginal threshold | 802,491      | 76.95<br>[40.53 ; 63.97 ; 92.60] | 3.67<br>[-7.53 ; 2.53 ; 16.23] | 17.35<br>[4.67 ; 11.41 ; 23.39] | ( 18.07 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | 1.86<br>[-6.67 ; 0.54 ; 10.44] | ( 22.79 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | 1.86<br>[-6.67 ; 0.54 ; 10.44] | ( 22.79 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | ( 0.50 ) |
| > 1yr tenure at new job                                      | 666,501      | 79.47<br>[41.81 ; 66.00 ; 95.38] | 4.82<br>[-6.19 ; 3.11 ; 17.08] | 17.54<br>[4.74 ; 11.58 ; 23.70] | ( 18.20 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | 1.56<br>[-6.86 ; 0.44 ; 10.08] | ( 22.72 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | 1.56<br>[-6.86 ; 0.44 ; 10.08] | ( 22.72 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | ( 0.50 ) |
| no change of residence                                       | 591,185      | 79.62<br>[42.16 ; 66.27 ; 95.58] | 4.34<br>[-6.11 ; 2.85 ; 16.13] | 17.50<br>[4.79 ; 11.59 ; 23.62] | ( 18.09 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | 1.50<br>[-6.59 ; 0.41 ; 9.74]  | ( 22.33 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | 1.50<br>[-6.59 ; 0.41 ; 9.74]  | ( 22.33 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | ( 0.50 ) |
| job change within 1 year                                     | 516,480      | 82.19<br>[43.74 ; 68.59 ; 98.25] | 5.95<br>[-4.18 ; 3.46 ; 16.65] | 17.92<br>[4.97 ; 11.97 ; 24.24] | ( 18.31 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | 1.52<br>[-6.55 ; 0.42 ; 9.83]  | ( 22.40 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | 1.52<br>[-6.55 ; 0.42 ; 9.83]  | ( 22.40 )  | 0.54<br>[0.00 ; 1.00 ; 1.00] | ( 0.50 ) |

Notes: Means and standard deviations of the main variables. 25th, 50th, and 75th percentile in brackets. With each row, an additional restriction is imposed. The bottom row represents the final data on which the baseline regression analyses are carried out.

Table A.2: Summary statistics for control variables

| (N=516,480)             |       |  |
|-------------------------|-------|--|
| Variable                | Mean  | (Std.Dev.)                             |
| dummy, 1 = female       | 0.47  | ( 0.50 )<br>[ 0.00 ; 0.00 ; 1.00 ]     |
| age                     | 36.15 | ( 10.75 )<br>[ 27.00 ; 36.00 ; 44.00 ] |
| dummy, 1 = low skilled  | 0.17  | ( 0.38 )<br>[ 0.00 ; 0.00 ; 0.00 ]     |
| dummy, 1 = med. skilled | 0.69  | ( 0.46 )<br>[ 0.00 ; 1.00 ; 1.00 ]     |
| dummy, 1 = high skilled | 0.14  | ( 0.35 )<br>[ 0.00 ; 0.00 ; 0.00 ]     |
| dummy, 1 = urban        | 0.60  | ( 0.49 )<br>[ 0.00 ; 1.00 ; 1.00 ]     |

Notes: Means and standard deviations of the control variables. 25th, 50th, and 75th percentile in brackets.

Table A.3: Commuting distances by sub-samples

| (N=516,480)                   |                          |           |
|-------------------------------|--------------------------|-----------|
| group                         | mean                     | (sd)      |
| <i>Gender</i>                 |                          |           |
| male                          | 19.40                    | ( 19.19 ) |
|                               | [ 5.60 ; 13.22 ; 26.51 ] |           |
| female                        | 16.22                    | ( 17.11 ) |
|                               | [ 4.36 ; 10.68 ; 21.72 ] |           |
| <i>Age</i>                    |                          |           |
| 1st quartile                  | 16.55                    | ( 16.94 ) |
|                               | [ 4.78 ; 11.25 ; 22.23 ] |           |
| 2nd quartile                  | 18.69                    | ( 18.85 ) |
|                               | [ 5.14 ; 12.47 ; 25.64 ] |           |
| 3rd quartile                  | 18.57                    | ( 18.66 ) |
|                               | [ 5.24 ; 12.58 ; 25.27 ] |           |
| 4th quartile                  | 17.85                    | ( 18.67 ) |
|                               | [ 4.72 ; 11.67 ; 24.05 ] |           |
| <i>Education</i>              |                          |           |
| low skilled                   | 15.58                    | ( 16.95 ) |
|                               | [ 4.15 ; 9.97 ; 20.45 ]  |           |
| medium skilled                | 17.62                    | ( 17.82 ) |
|                               | [ 5.02 ; 12.01 ; 23.82 ] |           |
| high skilled                  | 22.15                    | ( 21.29 ) |
|                               | [ 5.96 ; 15.08 ; 31.77 ] |           |
| <i>Daily wage</i>             |                          |           |
| 1st quartile                  | 14.70                    | ( 16.42 ) |
|                               | [ 3.68 ; 9.34 ; 19.32 ]  |           |
| 2nd quartile                  | 16.13                    | ( 16.71 ) |
|                               | [ 4.52 ; 10.85 ; 21.67 ] |           |
| 3rd quartile                  | 18.08                    | ( 17.94 ) |
|                               | [ 5.34 ; 12.44 ; 24.52 ] |           |
| 4th quartile                  | 22.76                    | ( 20.84 ) |
|                               | [ 7.08 ; 16.22 ; 32.08 ] |           |
| <i>Regional Structure</i>     |                          |           |
| urban                         | 16.26                    | ( 17.66 ) |
|                               | [ 4.30 ; 9.98 ; 21.48 ]  |           |
| rural                         | 20.36                    | ( 18.97 ) |
|                               | [ 6.76 ; 15.00 ; 27.86 ] |           |
| <i>Current job is...</i>      |                          |           |
| 1st job                       | 14.15                    | ( 15.58 ) |
|                               | [ 3.73 ; 9.12 ; 18.59 ]  |           |
| 2nd job                       | 17.70                    | ( 18.25 ) |
|                               | [ 4.81 ; 11.77 ; 23.87 ] |           |
| 3rd job                       | 18.62                    | ( 18.65 ) |
|                               | [ 5.29 ; 12.67 ; 25.42 ] |           |
| ≥4th job                      | 20.08                    | ( 19.37 ) |
|                               | [ 5.99 ; 13.99 ; 27.58 ] |           |
| <i>AKM plant FE</i>           |                          |           |
| missing                       | 11.80                    | ( 13.83 ) |
|                               | [ 2.47 ; 7.38 ; 15.84 ]  |           |
| 1st quartile                  | 16.50                    | ( 17.50 ) |
|                               | [ 4.27 ; 10.74 ; 22.21 ] |           |
| 2nd quartile                  | 17.81                    | ( 18.20 ) |
|                               | [ 5.01 ; 11.89 ; 24.02 ] |           |
| 3rd quartile                  | 18.64                    | ( 18.48 ) |
|                               | [ 5.47 ; 12.71 ; 25.26 ] |           |
| 4th quartile                  | 21.09                    | ( 19.78 ) |
|                               | [ 6.67 ; 14.80 ; 29.05 ] |           |
| <i>Plant size (employees)</i> |                          |           |
| <10                           | 13.98                    | ( 15.34 ) |
|                               | [ 3.43 ; 9.14 ; 18.84 ]  |           |
| 10-49                         | 17.22                    | ( 17.45 ) |
|                               | [ 4.92 ; 11.71 ; 23.28 ] |           |
| 50-99                         | 19.16                    | ( 18.91 ) |
|                               | [ 5.59 ; 13.04 ; 26.09 ] |           |
| 100-499                       | 20.98                    | ( 20.13 ) |
|                               | [ 6.25 ; 14.48 ; 28.94 ] |           |
| ≥500                          | 21.36                    | ( 20.32 ) |
|                               | [ 6.45 ; 14.68 ; 29.57 ] |           |

Notes: Mean and standard deviation of the commuting distance for various groups of workers. 25th, 50th, and 75th percentile in brackets.



Table A.4: Heterogenous effects by sub-samples

| Dependent Variable: $\Delta \log(\text{dailywage})$ |   |                   |                   |            |             |
|---|---|-------------------|-------------------|------------|-------------|
| Group   | Average semi-elasticity<br>(Avg. marginal effects (in Euros)) |                   |                   |            | No. of obs. |
|   | Overall   | Negative          | Positive          | Difference |             |
| <b>Benchmark</b>                                    | 0.12***<br>(0.09)   | 0.09***<br>(0.07) | 0.14***<br>(0.11) | ***        | 516,480     |
| <i>Gender</i>                                       |   |                   |                   |            |             |
| male  | 0.10***<br>(0.09)   | 0.08***<br>(0.07) | 0.11***<br>(0.10) | *          | 275,477     |
| female  | 0.14***<br>(0.09)   | 0.10***<br>(0.06) | 0.18***<br>(0.11) | ***        | 241,003     |
| <i>Education</i>                                    |   |                   |                   |            |             |
| unskilled   | 0.11***<br>(0.05)   | 0.04**<br>(0.02)  | 0.16***<br>(0.08) | ***        | 88,212      |
| medium skilled                                      | 0.12***<br>(0.09)   | 0.11***<br>(0.08) | 0.13***<br>(0.10) | *          | 354,302     |
| high skilled  | 0.10***<br>(0.14)   | 0.05***<br>(0.07) | 0.15***<br>(0.22) | ***        | 73,966      |
| <i>Regional structure</i>                           |   |                   |                   |            |             |
| urban   | 0.11***<br>(0.09)   | 0.07***<br>(0.06) | 0.15***<br>(0.13) | ***        | 307,452     |
| rural   | 0.12***<br>(0.09)   | 0.11***<br>(0.07) | 0.13***<br>(0.09) |            | 209,028     |
| <i>Number of previous jobs</i>                      |   |                   |                   |            |             |
| 1st job   | 0.08***<br>(0.05)   | 0.02<br>(0.01)    | 0.11***<br>(0.08) | ***        | 121,484     |
| 2nd job   | 0.11***<br>(0.09)   | 0.08***<br>(0.06) | 0.13***<br>(0.11) | **         | 111,119     |
| 3rd job   | 0.11***<br>(0.09)   | 0.10***<br>(0.08) | 0.12***<br>(0.10) |            | 90,079      |
| ≥4th job  | 0.12***<br>(0.09)   | 0.10***<br>(0.08) | 0.13***<br>(0.11) | **         | 193,798     |
| <i>AKM plant FE</i>                                 |   |                   |                   |            |             |
| missing   | 0.22***<br>(0.11)   | 0.06**<br>(0.03)  | 0.33***<br>(0.16) | ***        | 45,641      |
| 1st quartile  | 0.13***<br>(0.07)   | 0.06***<br>(0.03) | 0.21***<br>(0.11) | ***        | 117,706     |
| 2nd quartile  | 0.10***<br>(0.07)   | 0.08***<br>(0.05) | 0.13***<br>(0.09) | **         | 117,709     |
| 3rd quartile  | 0.09***<br>(0.07)   | 0.09***<br>(0.07) | 0.06***<br>(0.05) |            | 117,708     |
| 4th quartile  | 0.08***<br>(0.10)   | 0.13***<br>(0.14) | -0.01<br>(0.00)   | ***        | 117,716     |
| <i>Plant size (employees)</i>                       |   |                   |                   |            |             |
| <10   | 0.20***<br>(0.11)   | 0.11***<br>(0.06) | 0.27***<br>(0.16) | ***        | 135,888     |
| 10-49   | 0.11***<br>(0.08)   | 0.09***<br>(0.06) | 0.13***<br>(0.09) | *          | 144,417     |
| 50-99   | 0.08***<br>(0.07)   | 0.08***<br>(0.06) | 0.07***<br>(0.06) |            | 61,814      |
| 100-499   | 0.04***<br>(0.04)   | 0.04***<br>(0.03) | 0.03*<br>(0.03)   |            | 110,897     |
| ≥500  | 0.08***<br>(0.09)   | 0.09***<br>(0.10) | 0.01<br>(0.01)    | **         | 63,464      |

Notes: Semi-elasticities and marginal effects from regressions of the change in log wage on the change in commuting distance analogous to the models reported in table 3. Further control variables are age sq., calendar year and skill dummies. In each block, the data is split into disjunct groups of workers. The top row reports the baseline results. Standard errors (clustered by municipality) in parentheses.

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

Table A.5: Semi-elasticities of wage changes with respect to changes in commuting distances by sample restriction

| Dependent Variable: $\Delta \log(\text{dailywage})$    |   |                   |                   |            |             |
|--|---|-------------------|-------------------|------------|-------------|
| Restriction  | Average semi-elasticity<br>( <i>Avg. marginal effect (in Euros)</i> ) |                   |                   |            | No. of obs. |
|  | Overall   | Negative          | Positive          | Difference |             |
| nonmissing distance<br><b>(Unrestricted)</b>           | 0.03***<br>(0.02)   | 0.02***<br>(0.02) | 0.03***<br>(0.02) | **         | 1,532,223   |
| change of plant coordinates                            | 0.03***<br>(0.02)   | 0.02***<br>(0.01) | 0.03***<br>(0.03) | ***        | 1,278,348   |
| < 100km commuting dist.                                | 0.13***<br>(0.08)   | 0.07***<br>(0.04) | 0.17***<br>(0.12) | ***        | 1,057,839   |
| > 1yr tenure at old job &<br>wage > marginal threshold | 0.15***<br>(0.11)   | 0.12***<br>(0.08) | 0.17***<br>(0.12) | ***        | 802 491     |
| > 1yr tenure at new job                                | 0.15***<br>(0.12)   | 0.12***<br>(0.08) | 0.18***<br>(0.14) | ***        | 666,501     |
| no change of residence                                 | 0.16***<br>(0.12)   | 0.14***<br>(0.10) | 0.17***<br>(0.13) | ***        | 591,185     |
| job change within 1 year<br><b>(Benchmark)</b>         | 0.12***<br>(0.09)   | 0.09***<br>(0.07) | 0.14***<br>(0.11) | ***        | 516,480     |

Notes: Semi-elasticities and marginal effects from regressions of the change in log wage on the change in commuting distance analogous to the models reported in table 3. Further control variables are age sq., calendar year and skill dummies. With each row, an additional restriction is imposed. The bottom row represents the final data on which the baseline regression analyses are carried out. Standard errors (clustered by municipality) in parentheses.  
Levels of significance: \* 10%, \*\* 5%, \*\*\* 1%

Table A.6: Further robustness checks: Semi-elasticities of wage changes with respect to changes in commuting distances

| Dependent Variable: 100 x $\Delta \log(\text{dailywage})$ |   |                   |                   |            |             |
|---|---|-------------------|-------------------|------------|-------------|
| Restriction   | Average semi-elasticity<br>(Avg. marginal effects (in Euros)) |                   |                   |            | No. of obs. |
|   | Overall   | Negative          | Positive          | Difference |             |
| <b>Benchmark</b>  | 0.12***<br>(0.09)   | 0.09***<br>(0.07) | 0.14***<br>(0.11) | ***        | 516,480     |
| residence movers only                                     | 0.10***<br>(0.08)   | 0.06***<br>(0.04) | 0.11***<br>(0.09) | *          | 75,316      |
| 2-year average wage                                       | 0.12***<br>(0.10)   | 0.10***<br>(0.07) | 0.15***<br>(0.12) | ***        | 516,480     |
| 3-year average wage                                       | 0.13***<br>(0.10)   | 0.10***<br>(0.07) | 0.16***<br>(0.13) | ***        | 516,480     |
| 4-year average wage                                       | 0.14***<br>(0.10)   | 0.10***<br>(0.08) | 0.18***<br>(0.14) | ***        | 516,480     |
| 5-year average wage                                       | 0.14***<br>(0.11)   | 0.10***<br>(0.08) | 0.18***<br>(0.14) | ***        | 516,480     |
| exclude industries  | 0.12***<br>(0.10)   | 0.10***<br>(0.07) | 0.15***<br>(0.12) | ***        | 350,415     |
| different intercepts                                      | 0.10***<br>(0.08)   | 0.07***<br>(0.05) | 0.12***<br>(0.09) | ***        | 516,480     |

Notes: Semi-elasticities and marginal effects from regressions of the change in log wage on the change in commuting distance analogous to the models reported in table 3. Further control variables are age sq., calendar year and skill dummies. Standard errors (clustered by municipality) in parentheses. In each row, a different change is made to the benchmark specification. The top row reports the baseline results. Levels of significance: \* 10%, \*\* 5%, \*\*\* 1%