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Yige Duan (Vancouver school of Economics)
Oskar Jost (Institute for Employment Research)
Ramona Jost (Institute for Employment Research)

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

Yige Duan† Oskar Jost‡ Ramona Jost§

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Abstract

We study the long-term impact of job displacement on workers' commuting behavior. Our measures of commuting exploit geo-coordinates of workers' places of residence and places of work, from which we calculate the door-to-door commuting distance and commuting time. Using German employee-employer matched data and an event study design, we identify the causal effect of job loss on workers displaced during a mass layoff. Conditional on finding a new job, workers' commuting distance and commuting time rise sharply after displacement and gradually decline in subsequent years. The recovery is due to employer changes rather than migration, and a larger increase in commuting would mitigate the wage loss due to job displacement. To rationalize our findings, we build an on-the-job search model with heterogeneous firm productivity and commuting distances. Our model predicts a joint recovery of wages and commuting despite a static tradeoff between the two attributes.

Keywords: commuting, mobility, displacement, job search.

JEL code: J3, J6, R23, R41.

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†Vancouver School of Economics, University of British Columbia, yige.duan@ubc.ca.

‡Institute for Employment Research (IAB), oskar.jost@iab.de.

§Institute for Employment Research (IAB), ramona.jost@iab.de.

1 Introduction

Job displacement has profound consequences on individual workers. A large body of literature has documented substantial and persistent earning losses suffered by displaced workers (e.g., Jacobson, LaLonde, and Sullivan, 1993b; Davis and von Wachter, 2011; Bertheau et al., 2021). In particular, the authors attribute the slow recovery from job loss to job search frictions, i.e., displaced workers take time to find a job that pays as much as before. However, less attention has been paid to spatial frictions—the cost of commuting and migration that erodes job opportunities outside displaced workers' local labor markets (Manning and Petrongolo, 2017; Marinescu and Rathelot, 2018). How do spatial frictions affect workers' recovery from job loss? How do workers respond to and trade off multiple job search frictions? These questions are important for developing labor market policies to alleviate the scarring effect of job loss (Bertheau et al., 2021).

In this paper, we investigate the job displacement effect on the commuting behavior of German workers. Our paper makes three major contributions. First, using an event study design, we document a joint recovery of wages and commuting costs. Symmetric to the scarring effect on earnings, job displacement leads to a sharp increase—followed by a gradual decline—in commuting by displaced workers. This symmetry contrasts with the cross-sectional, substituting relationship between wages and commuting, and we use an on-the-job search model to reconcile the static and dynamic patterns.[1] Second, we combine route planning algorithms with geo-coordinate data to precisely measure workers' commuting distance and commuting time. This allows us to overcome bias in the estimation using aggregate distance data, and to distinguish commuting from migration, the latter of which was found to have no mitigating effect on the wage loss of displaced workers (Fackler and Rippe, 2017; Huttunen, Møen, and Salvanes, 2018). Third, we provide empirical evidence that workers could alleviate the wage loss after job displacement by commuting more. As such, policymakers could mitigate the impact of job loss by reducing spatial labor market frictions and workers' commuting costs.

To begin with, we use German social security data to estimate the effects of job displacement on workers' wages and commuting outcomes. Following the seminal event study approach (Jacobson, LaLonde, and Sullivan, 1993b), we compare workers displaced in mass layoffs with a matched group of non-displaced workers exhibiting similar pre-displacement characteristics. To rule out selection into mass layoffs, we control for worker fixed effects and focus on full-time workers at displacing firms. After job displacement,

[1] In cross-sectional data, wages and commuting costs tend to move in the same direction (Le Barbanchon, Rathelot, and Roulet, 2021; Dauth and Haller, 2020). On the contrary, we find an increase in wages accompanied by a decrease in commuting costs in a dynamic setting.

the annual earnings of displaced workers fall by almost half in the short run and gradually recover over subsequent years. Their daily wages exhibit smaller but similarly persistent losses. However, the commuting distance and commuting time of displaced workers both rise by roughly 20 percent after job displacement, and recover steadily afterward. The recovery in commuting is driven by workers switching from distant to nearby firms rather than migrating or relocating their homes.

Prior to our study, many researchers exploited regional-level data (e.g., the shortest distance between two cities) to investigate workers' commuting and migration decisions (Eliasson, Lindgren, and Westerlund, 2003; Fackler and Rippe, 2017; Meekes and Hassink, 2019, 2022). In contract, our unique geo-coordinate data allows us to calculate, for each worker, the exact commuting distance and commuting time along the most likely route between the place of residence and workplace. We emphasize that individual-level commuting data is critical to correctly identify the effects of job displacement. Using our estimates as a benchmark, we show that measuring commutes at the regional level leads to notable bias. The bias either overstates the true effect by omitting within-region commutes, or understates it by misrepresenting commuting patterns across regions. According to our calculation, measuring commutes by German municipalities could inflate the true effect by up to one-fourth.

Next, we investigate whether workers can mitigate the wage losses by increasing commuting or vice versa. Comparing the job loss effects by gender, we find that displaced women's wages drop more than men's but their commuting increases to a lesser extent. This implies women are more willing to accept a lower wage in order to avoid commuting (Le Barbanchon, Rathelot, and Roulet, 2021; Illing, Schmieder, and Trenkle, 2021; Meekes and Hassink, 2022). At the individual level, we find workers with a greater estimated wage loss tend to have a smaller increase in commuting. Therefore, we conclude that commuting attenuates the wage losses of displaced workers.

The above results suggest that displaced workers experience declining commuting costs and increasing wages in the years following their job loss. This contrasts with the static tradeoff between wages and commuting, where workers compensate for longer commuting distances by asking for higher wages. To reconcile the countervailing forces, we develop a Burdett-Mortensen on-the-job search model (Burdett and Mortensen, 1998) with heterogeneous firm productivity and commuting distances. Our model is able to capture both the static and the dynamic relationship between wages and commuting.

In static settings, workers trade off the two attributes and are willing to sacrifice higher wages for less commuting. Since both outcomes are associated with the joint match surplus, we use the latter to establish a preference order among jobs, and claim that worker prefer jobs at higher surplus levels. Using the first jobs taken on by displaced workers, we graphically identify the set of jobs that create a positive surplus. Dynamically, however, on-the-job search allows workers to gradually improve their job opportunities by bargaining for higher wages or moving to more proximate firms. We prove that workers accept a job offer only if it creates a higher match surplus than the current level, and the expected productivity (commuting distance) is higher (lower) conditional on a higher surplus. As is shown by the event study estimates, after the initial job separation, the average productivity of new employers increases over time, and the average commuting cost declines. More generally, our model is able to characterize the dynamics of the optimal search effort and workers' tradeoff between multiple job characteristics.

Our study delivers several insights for policymakers. First, it sheds light on the value of transportation infrastructure in the labor market. Studies have found that better transport facilities allow workers to access job opportunities more easily (Asher and Novosad, 2020; Brooks and Donovan, 2020). We argue this will particularly benefit unemployed workers, who incur more substantial commuting costs in job search. Our findings also point to the benefits of commuting subsidies (Franklin, 2018; Moreno-Monroy and Posada, 2018), which directly lowers the cost of commuting and has been adopted in several European countries.[2] Temporary commuting subsidies would in particular help displaced workers recover from job loss. Finally, the growing popularity of working from home (Barrero, Bloom, and Davis, 2021), which substantially reduces the commuting cost of remote-job workers, would attenuate the negative employment shocks caused by the Covid-19 pandemic.

1.1 Related Literature

Our paper contributes to a long literature on earning losses due to unemployment (Jacobson, LaLonde, and Sullivan, 1993b; Stevens, 1997; Couch and Placzek, 2010; Davis and von Wachter, 2011; Flaaen, Shapiro, and Sorkin, 2019; Schmieder, von Wachter, and Heining, 2020; Bertheau et al., 2021). Prior to our study, Eliasson, Lindgren, and Westerlund (2003) and Meekes and Hassink (2019) investigate how job loss impacts cross-regional commuting, while Fackler and Rippe (2017) focus on the effect on migration. Our research differs from their work in three ways. First, we examine commuters both within and across regions and distinguish between commuting and migration. Since one-third of commutes take place within administrative regions, focusing on cross-regional mobility

[2]For example, Austria, Denmark, Germany, and Sweden subsidize commuting via income tax deductions, and France via tax-free reimbursements.

is likely to overestimate the displacement effect on commuting. Second, we demonstrate that the recovery of commuting behavior is driven by workers changing firms rather than relocation. This confirms Huttunen, Møen, and Salvanes's (2018) claim that migration by displaced workers is mainly driven by non-economic factors. Third, commuting is not only costly, but also moderates the wage loss from job displacement. Therefore, our study depicts a more complete picture of the consequences of job loss.

Next, our study is related to the theoretical literature on job search. To rationalize the long-term behavior of displaced workers, we develop a job search model in the spirit of Burdett and Mortensen (1998) and Postel-Vinay and Robin (2002a,b). Our model extends Jacobson, LaLonde, and Sullivan (1993a) and Le Barbanchon, Rathelot, and Roulet (2021) to allow for on-the-job search, and to study the long term impacts of job loss. Our model is also related to Jarosch (2021), in which jobs differ in both productivity and security. However, we demonstrate that the joint recovery of wages and commuting is driven by workers' tradeoffs rather than a correlation between the two attributes.

Finally, we contribute to the literature on spatial labor markets, specifically on how mobility costs affect people's location choices. Analyzing job application data in the U.K. and the U.S., Manning and Petrongolo (2017) and Marinescu and Rathelot (2018) find that job seekers are discouraged from applying for distant jobs. This suggests an aversion to commuting or migration. Another strand of literature directly estimates the costs of relocation (Kennan and Walker, 2011; Schmutz and Sidibé, 2019; Ransom, 2021) and the cost of commuting (Van den Berg and Gorter, 1997; Mulalic, Van Ommeren, and Pilegaard, 2014; Dauth and Haller, 2020; Jost, 2020). We complement their work by showing that the willingness to commute varies with workers' employment status: Unemployed workers have the strongest incentive to commute; but as workers recover from job loss, they exhibit a greater preference for jobs in the proximity of their homes. Moreover, we exploit granular and precise commuting data to distinguish between commuting and migration, and our findings reveal that they play different roles in job search by displaced workers.

The rest of the paper is organized as follows. Section 2 discusses the data and empirical methods. Section 3 presents the estimation results and robustness checks. Section 4 examines whether workers could mitigate the wage loss from job displacement by increasing commuting. Section 5 introduces a job search model to rationalize the empirical findings. Finally, Section 6 concludes.

2 Data and Empirical Methods

2.1 Data

Our study exploits two administrative data sets provided by the Institute for Employment Research in Germany: The Integrated Employment Biographies (IEB) and the Establishment History Panel (BHP). Our IEB data cover a representative sample of German workers subject to social security, and contain information on each individual's age, gender, educational attainment, employment history, and receipt of unemployment benefits. However, the data do not include civil servants and the self-employed. Meanwhile, the BHP provides information on all establishments in Germany, e.g., their industry classification (2008 edition) and number of employees on June 30 each year.

A unique feature of our data is the additional information on the place of residence and place of work in the form of geo-coordinates. Combining the granular location data with road network data from OpenStreetMap.org (Huber and Rust, 2016; Dauth and Haller, 2020; Jost, 2020), we calculate the door-to-door commuting distance and commuting time by car for all employed workers. We argue that the driving distance and driving time are representative measures of commuting costs, as 68 percent of German commuters drive to work (Destatis, 2017). Using Google Maps data, we also validate that driving distances are highly correlated with distances via other means of transportation. However, since the driving time is calculated using estimated driving speeds in ideal road and traffic conditions, it likely underestimates the true driving time, e.g., where traffic is heavy or parking takes time (Dauth and Haller, 2020). To alleviate this bias, we estimate the effect of job displacement on the within-individual, percentage change of commuting time, and show that the estimates using driving distance and driving time are closely aligned.

As in Schmieder, von Wachter, and Heining (2020) and Illing, Schmieder, and Trenkle (2021), we consider workers of both genders aged from 20 to 54. The sample period spans from 2000 to 2017, as the location information is only available from 2000 onwards. Following the data preparation guide by Dauth and Eppelsheimer (2020), we transform the employment spells from the IEB into a worker-year panel. For each year, we calculate the worker's total earnings, number of days in full-time, part-time, and mini jobs[3], the main employer as of June 30, commuting time and distance to the main employer, and average daily wage paid by the main employer. If a worker has multiple employers on June 30, we choose the one with the highest daily wage as the main employer. In addition,

[3]Mini jobs are a form of marginal employment in Germany with a monthly income of 450 euros or less. (Tazhitdinova, 2020; Illing, Schmieder, and Trenkle, 2021)

we winsorize daily wages below 20 euros, impute wages that are top-coded due to the social security threshold (Card, Heining, and Kline, 2013), and impute missing education variables (Fitzenberger, Osikominu, and Völter, 2005). Finally, we exclude workers whose maximum commuting distance exceeds 100 kilometers, as they are unlikely to commute on a daily basis (Dauth and Haller, 2020).

On the establishment side, we consider mass layoffs as the source of involuntary job displacement (Blien, Dauth, and Roth, 2021; Burdett, Carrillo-Tudela, and Coles, 2020; Fackler, Mueller, and Stegmaier, 2021; Jarosch, 2021). An establishment is said to have a mass layoff in calendar year τ if (i) it has at least 20 workers on June 30 of year τ; (ii) the number of workers decreases by at least 30 percent from June 30 of year τ to June 30 of year $\tau + 1$; and (iii) the number of workers on June 30 of year τ is not higher than 130 percent of that on June 30 of year $\tau - 1$. After merging with the worker-level data, we identify 25,699 mass layoff events. The average layoff establishment has 121 employees, 60 percent of whom are laid off. Hereafter, we will use "firm" and "establishment" interchangeably.

To further distinguish mass layoffs from voluntary job-to-job transition, firm reorganizations, and outsourcing (Goldschmidt and Schmieder, 2017), we follow the literature and impose additional restrictions on the displaced workers. A worker is displaced in year τ if he (i) leaves the displacing firm between years τ and $\tau + 1$; (ii) receives unemployment benefits for at least 30 days between June 30 of year τ and that of year $\tau + 1$ (Burdett, Carrillo-Tudela, and Coles, 2020; Jarosch, 2021); (iii) has worked full-time at the displacing firm for at least three years before the mass layoff (Fackler, Mueller, and Stegmaier, 2021). Furthermore, if a worker experiences multiple mass layoffs during our sample period, only the first time is considered for analysis.

It is worth noting that the BHP only identifies mass layoffs between June 30 of two consecutive years. As such, a worker could be displaced either in the second half of our defined year of displacement or in the first half of the following year. Due to this discrepancy, we expect mass layoffs to have a partial but immediate impact on workers' annual total earnings. However, this does not affect the wage rate or commuting in the same year, as they are measured on June 30, the earliest possible day of mass layoffs.

2.2 Identification Strategy

To identify the effect of mass layoffs on workers' earnings, wages, and commuting behavior, we exploit the seminal event study approach by Jacobson, LaLonde, and Sullivan (1993b). Specifically, let ML_i indicate if worker i experiences a mass layoff and $\tau(i)$ be the mass layoff year. The outcome of interest Y_{it}, for worker i in year t, is determined by

$$Y_{it} = \sum_{\substack{k=-4,\\ k\neq -1}}^{11} \left[\alpha_k I\{t = \tau(i) + k\} + \beta_k I\{t = \tau(i) + k\} ML_i\right] + X_{it}'\boldsymbol{\gamma} + \phi_i + \psi_t + \epsilon_{it}. \tag{1}$$

In (1), α_k captures the outcome of non-displaced workers in the k-th year after ($-k$-th year before) the mass layoff relative to the year immediately before $(\tau(i) - 1)$. For displaced workers, this is captured by $\alpha_k + \beta_k$. As such, β_k represents the partial effect of job displacement on Y_{it} in the k-th year after ($-k$-th year before) the mass layoff. In addition, X_{it} controls for time-varying worker characteristics, i.e., a cubic polynomial of age. Other time-invariant characteristics, such as gender and education, are absorbed by the worker fixed effect ϕ_i. In addition, ψ_t represents the calendar-year fixed effect and u_{it} is the error term.

We also estimate the average displacement effect over the entire post-displacement period. The estimates are obtained by a difference-in-differences (DID) regression:

$$\begin{aligned} Y_{it} = &\sum_{k=-4}^{-2} \left[\alpha_k I\{t = \tau(i) + k\} + \beta_k I\{t = \tau(i) + k\} ML_i\right] \\ &+ \alpha^* I\{t \geq \tau(i)\} + \beta^* I\{t \geq \tau(i)\} ML_i + X_{it}'\boldsymbol{\gamma} + \phi_i + \psi_t + \epsilon_{it}, \end{aligned} \tag{2}$$

where β_{-4} to β_{-2} still capture the pretrend but β^* now represents a weighted average of β_k for all $k \geq 0$, i.e., the average of the year-by-year displacement effects. Other components of (2) remain the same as in (1).

To identify the causal effect of job displacement on workers' outcomes, we rely on the unconfoundedness assumption—that mass layoff incidences are not correlated with workers' characteristics relevant to their labor market outcomes. This assumption could be violated if less productive workers or workers with unstable employment relationships face higher risks of being displaced in a mass layoff, as it is more difficult for them to find new jobs. As discussed earlier, we alleviate this concern by including worker fixed effects in the regression, and focusing on workers who had worked at the displacing firm for at least three years before the mass layoff. In Section 3.3, we perform additional robustness checks to validate our estimates.

2.3 Coarsened Exact Matching

To identify the fully dynamic effects of job displacement, we also need a control group of workers who are not displaced but have comparable characteristics to those of the displaced workers (Krolikowski, 2018; Borusyak, Jaravel, and Spiess, 2021). Thus, we employ coarsened exact matching (CEM, Iacus, King, and Porro, 2012) as described below.

To begin with, we select a pool of non-displaced workers eligible for CEM using the same restrictions as for displaced workers. For each worker displaced in year τ, we identify workers who were not displaced in that year, had been employed full-time and not changed employers in the three years before τ (Krolikowski, 2018; Blien, Dauth, and Roth, 2021; Meekes and Hassink, 2019). Next, we match the displaced and non-displaced workers using their characteristics in the year before displacement. The matching variables are selected following Schmieder, von Wachter, and Heining (2020). We use exact matching on gender, educational attainment, one-digit industrial sector, and western versus eastern Germany. We also use coarsened matching on age, firm tenure, firm size, and annual earnings. The procedure yields a matched sample comprising 18,190 displaced workers and 273,142 non-displaced workers.

Table 1 reveals that displaced and non-displaced workers have balanced characteristics after CEM. In both groups, roughly one-fourth of the matched workers are female, and the average age prior to mass layoffs is 41 years old. The majority of those workers have vocational training (77 percent) and live in western Germany (83 percent). At the time of the mass layoff, an average worker has 15 years of total work experience and eight years of experience with the current employer; moreover, the average worker earns 100 euros per day and drives 15 kilometers (14 minutes) one-way between home and work. In comparison, Stutzer and Frey (2007) and Giménez-Nadal, Molina, and Velilla (2022) report the average one-way driving time for all German workers to be 21-22 minutes. Besides, Appendix A, Figure A1 reports the event study estimates using the regular (full-time or part-time) employment indicator as the dependent variable. We find no pre-trend in workers' employment status. Hence, the matching procedure yields balanced pre-displacement characteristics.

Finally, we use the matched worker sample to construct the worker-year panel for analysis. Each worker is tracked for a maximum of four years before and 11 years after displacement, and is observed in the year when he is in regular employment on June 30. In total, the panel comprises 3,213,415 yearly observations from the 291,332 matched workers. Table A1 reports summary statistics for the worker-year panel.

3 Results

We estimate model (1) using ordinary least squares (OLS). Table 2 reports estimates of all β_k and Figure 1 plots the estimates with 95 percent confidence intervals. In Table 3, we also present the DID estimates. All standard errors are clustered by workers.

First of all, we estimate the effect of job displacement on log daily wages and log annual earnings. From Table 2 and Figure 1, (a)-(b), we draw two major conclusions. First, workers' daily wage and annual earnings drop significantly upon job displacement. From the year before displacement to the year afterwards, the average daily wage of displaced workers falls by 19.6 percent, and the average annual earnings drop by 43.2 percent. The larger effect on earnings is due to the reduced number of days worked by the displaced workers. Second, both outcomes gradually recover over subsequent years. Ten years after displacement, earnings and wages are roughly 17 percent lower than their pre-displacement levels. In addition, the DID estimates in Table 3 reveal that a displaced worker's average earnings decrease by 20 percent and her wage by 25 percent over all post-displacement years. These estimates are consistent with previous studies using the same data (Burdett, Carrillo-Tudela, and Coles, 2020; Jarosch, 2021).

Next, we estimate the effect of job displacement on workers' commuting behavior. In Table 2 and Figure 1, (c)-(d), workers' commuting distance and commuting time both increase significantly upon job displacement and gradually decline in subsequent years. Relative to the year before displacement, the average displaced worker commutes a 21.8 percent longer distance and 18.7 percent longer time in the year after displacement (conditional on having found a new regular job). Ten years after displacement, the average commuting distance and commuting time have both recovered by one-half, but still exceed the pre-displacement level by 9.9 and 8 percent, respectively. According to the DID estimates in Table 3, the long-run increases in commuting distance and commuting time amount to 15.7 and 13.3 percent, respectively.

Using a simple back-of-the-envelope analysis, we calculate the pecuniary value of the increased commuting for displaced workers. According to government statistics (Stutzer and Frey, 2007; Destatis, 2018), the average hourly wage in Germany is 20 euros and the average commuting time is 0.7 hours a day. As such, job displacement increases the commuting time of an average German worker by $0.7 \times 0.187 = 0.131$ hours per day or $0.131 \times 250 = 32.75$ hours in the first year after displacement. This is equivalent to $32.75 \times 20 = 655$ euros of opportunity cost in annual earnings. Repeating this exercise for all post-displacement years, we find the long-run opportunity cost of increased commuting time to be 4,820 euros, or 3,955 euros in present value (assuming a discount factor of 0.95).

3.1 Mechanism

What explains the dynamics of commuting after job displacement? To reduce commuting between home and workplace, workers can either switch to an employer closer to their homes or move their homes closer to the employer. To determine which drives the recovery of commuting, we estimate model (1) using the indicators of firm change and relocation as the dependent variable, respectively. Firm changes are identified from changes in the firm identifier, and relocation from changes in the place of residence (at the geo-coordinate level). In the latter case, we also exploit the home location of unemployed workers. In Figure 2 and Table 4, firm changes and relocation both increase in the first few years after job displacement, but the increase in relocation is of a much smaller magnitude and does not persist in subsequent years. Therefore, the long-term recovery of commuting is mostly driven by firm changes. This validates Huttunen, Møen, and Salvanes's (2018) argument that relocation of displaced workers is driven by non-economic factors and commuting is a more effective response to job displacement than migration.

3.2 The Value of Granularity

A major advantage of our study is due to the granular commuting data. For each individual worker, we know the driving distance between their exact place of residence and place of work alone the most likely routes. In comparison, existing research on commuting often identifies workers and firms at the geographic regional level and calculates the average distance across regions (Eliasson, Lindgren, and Westerlund, 2003; Fackler and Rippe, 2017; Meekes and Hassink, 2019, 2022). In this subsection, we compare our estimates with those using regional-level distances and illustrate the value of having granular commuting data.

We argue that measuring distances at the regional level is associated with three types of errors. First, it omits all commutes within regions. This causes a censoring problem where within-region commuters are assumed not to commute at all. Second, the distance travelled by individual workers rarely coincide with the distance between two regional centers, which is often used to define cross-region distances. Especially if cross-regional commuters are more likely to live and work near regional borders, their commuting distances will be overestimated at the regional level. Third, if the distance between two regions is measured along the geodesic (the shortest path between two geo-coordinates), it will underestimate the actual distance travelled along the roads.

To quantify the severity of (each of) the errors, we generate several commuting measures by municipality, the lowest level of administrative areas in Germany.[4] Then we compare the estimates of model (1) using these measures as the outcome variable. The resulting estimates are reported in Table 5 and visualized in Figure 3.

In Table 5, column (a), we force the log distance of within-municipality commutes to zero and leave distances across municipalities unchanged. This is to shutdown commutes within municipalities. Compared with Table 2, column (c), the results overestimate the effect of job displacement on commuting by 16.8 to 32.3 percent. Averaged across all post-displacement years, the bias amounts to roughly one-fourth of the true effect. The sign of the bias suggests that, although displaced workers increase commuting relative to non-displaced workers, many of the commutes still occur within municipalities.

Next, we calculate the driving distance between municipality centers using OpenStreetMaps.org and substitute this for the driving distances along each individual's route. Hence, all workers commuting from municipality A to B are assumed to travel the same distance. As shown In Table 5, column (b), the increase in commuting is still overestimated, but to a lesser extent. Furthermore, we replace the driving distance between municipalities by the geodesic between municipality centers. As geodesics ignore geographic variations in the commuting routes across municipalities, the resulting estimates are further driven down to an average of 7.5 percent, and a maximum of 14.4 percent each year (Table 5, column (c)).

To summarize, the use of aggregated commuting data yields significantly overestimated effects of job loss. The overall bias consists of two countervailing biases: the omission of within-municipality commutes leads to overestimation, and the aggregation of cross-municipality commuting causes underestimation. It is worth noting that the largest bias occurs in the first few years after job displacement, when the increase in commuting is also the greatest. In Figure A2, we obtain robust results by performing the same decomposition for commuting by districts *Kreis*, a more aggregated and commonly studies level of regions in Germany (Schmidtlein, Seth, and Vom Berge, 2020).

3.3 Additional Estimates and Robustness Checks

To conclude this section, we estimate the effect of job loss on other outcomes following existing research, and present various robustness checks regarding our main results.

Effect on Firm Wage Premiums. Related to the job displacement effect on wages, Fackler, Mueller, and Stegmaier (2021) argue that a major component of the wage losses

[4]Germany has 11,014 municipalities in 2020. An average municipality has a population of 7,557.7 and an area of 32.47 square kilometers.

is due to workers moving to low-paying firms. Similarly, we estimate the impact of job loss on firm-specific wage premiums, measured by Card, Heining, and Kline's (2013) estimates of firm fixed effects. As shown in Figure A3 and Table A2, part (a), we find a negative and persistent impact of job displacement on the firm fixed effects, and the effect magnitude corresponds to half of the estimated wage loss.

Effect on Job Types. Next, job displacement could affect wages and commuting via workers' choice of flexible or regular jobs (Meekes and Hassink, 2022). In particular, displaced workers take part-time or mini jobs as stepping stones back to full-time employment. In Figure A3 and Table A2, parts (b)-(d), we estimate the effect of job loss on workers' labor supply in mini, part-time, and full-time jobs, measured by the number of days worked in each job type. Immediately after displacement, workers first take up part-time and mini jobs, in which their labor supply increases sharply. Four years after displacement, full-time jobs start to catch up and labor supply in other types levels off or starts to decline. With worker fixed effects, these effects are driven by within-worker adjustment of labor supply rather than changes in worker composition.

Attrition. In contrast to the seminal event study design (Jacobson, LaLonde, and Sullivan, 1993b), our estimation focuses on an unbalanced panel where workers are employed in regular jobs. Thus, attrition could arise if the worker (i) is employed in a mini job or temporarily unemployed; (ii) becomes a civil servant or self-employed; (iii) goes back to school for vocational or advanced education; or (iv) goes abroad or leaves the workforce. Referring to the unemployment registration data, we find the majority (70 percent) of missing observations are accounted for by unemployment. To rule out attrition bias, we estimate model (1) on a subsample of workers without *any* attrition. Specifically, we focus on displaced workers who find another regular job in two years and remains in employment until the seventh year after the mass layoff, and estimate their displacement effects up to seven years. The estimates in Figure A4 are consistent with the main results.

Recalls. Our estimates are not driven by recalled workers, who account for 10 to 20 percent of all displaced workers (Leenders, 2021; Jost, 2022). For these workers, commuting distance recovers to the pre-displacement level mechanically. In Figure A5, we exclude workers recalled by the displacing firms and reestimate model (1). The estimated effects on all outcomes are slightly larger but robust.

Alternative Sample Restriction. In Figure A6, we exclude worker-years in which the main job on June 30 is part-time. There is little change in the estimates.

Alternative Estimation Method. Finally, we examine robustness to dynamic treatment effects and treatment effect heterogeneity using the imputation method proposed by Borusyak, Jaravel, and Spiess (2021). As shown in Figure A7, the results are in line with the original estimates using two-way fixed effects.

4 Does Commuting Mitigate the Wage Loss?

The above estimates suggest that, on average, job displacement lowers the wage of displaced workers and increases their commuting costs. However, the average displacement effects might conceal sizeable heterogeneity across workers. On one hand, workers could mitigate the wage losses by bearing higher commuting costs, leading to a positive correlation between the two outcomes. On one hand, due to different labor market conditions or job search effort, some workers may experience, relative to other workers, a greater wage loss as well as a larger increase in commuting. In what follows, we find empirical evidence for both mechanisms.

To investigate the mitigating effect, we modify model (2) and assume worker-specific average displacement effects. Then we formulate a random coefficient model

$$\begin{aligned} Y_{it} = &\sum_{k=-4}^{-2} \left[\alpha_k I\{t=\tau(i)+k\} + \beta_k I\{t=\tau(i)+k\} ML_i\right] \\ &+ \alpha^*_{Yi} I\{t \geq \tau(i)\} + \beta^*_{Yi} I\{t \geq \tau(i)\} ML_i + X'_{it}\gamma + \phi_i + \psi_t + \epsilon_{it}, \quad Y = W, C \end{aligned} \tag{3}$$

where β^*_{Wi} and β^*_{Ci} represent the job displacement effect on worker i's wage and commuting distance, respectively. Then we calculate the correlation between β^*_{Wi} and β^*_{Ci}. Following Verdier (2020), we estimate a fully saturated model with an interaction between $I\{t \geq \tau(i)\} ML_i$ and all worker indicators. The resulting coefficients identify the displacement effect on each displaced worker i. We find the correlation coefficient between $\hat{\beta}^*_{Wi}$ and $\hat{\beta}^*_{Ci}$ to be 0.084, which is positive and statistically significant.[5] We interpret the correlation as the mitigating effect among displaced workers: They can attenuate their wage losses from job displacement by accepting a larger increase in commuting distance.

Moreover, we apply the mitigating effect to compare the job displacement effects between male and female workers. Existing studies show that after losing a job, women suffer from a greater wage penalty, but increase commuting less than men (Illing, Schmieder,

[5]These figures provide a lower bound of the true correlation. Since each worker is observed a maximum of 16 times, each individual displace effect is estimated with potentially large noise. Thus, the variances of both $\hat{\beta}_{Wi}$ and $\hat{\beta}_{Ci}$ will overstate the true variances of displacement effects (Kline, Saggio, and Sølvsten, 2020). However, the covariance is consistently estimated if the estimation errors in $\hat{\beta}^*_{Wi}$ and $\hat{\beta}^*_{Ci}$ from different equations are uncorrelated. In total, the correlation coefficient Cov$(\beta^*_{Wi}, \beta^*_{Ci})/[\text{Var}(\beta^*_{Wi})\text{Var}(\beta^*_{Ci})]^{1/2}$ is underestimated.

and Trenkle, 2021; Le Barbanchon, Rathelot, and Roulet, 2021; Meekes and Hassink, 2022). This is illustrated in Figure 4, where women's post-displacement earnings and wages are both lower than men's by almost 10 percentage points. Meanwhile, women's commuting distance and commuting time are lower than men's, especially from the fifth year after displacement. Estimating the random coefficient model separately, we find robust positive correlations of 0.079 for men and 0.097 for women. As such, we argue that women's commuting decisions are more sensitive to the wage loss after job displacement.

In Appendix A, we conduct more split-sample analysis. In Figures A8-A9, we estimate model (1) for workers below and above the sample-medium age upon mass layoff (43 years old) and residing in urban and rural areas, respectively. In Figures A10-A11, we compare the effects on high-wage and low-wage workers and displacement from high-wage and low-wage firms (Card, Heining, and Kline, 2013). However, we do not find any significant difference in the job displacement effects on commuting. As such, we cannot rule out the other effect that wages and commuting are negatively correlated, i,e., workers who experience a greater wage loss also increase commuting to a larger extent.

To summarize, we find two possible ways in which wages and commuting are correlated after job loss. If displaced workers face different local labor market conditions, some will generally find a job more easily than others, and experience a smaller wage loss associated with less increase in commuting. In contrast, taking external job opportunities as given, displaced workers will trade off wage losses with longer commuting. This gives rise to a positive correlation between the two outcomes.

5 A Job Search Model

In this section, we develop a discrete-time job search model to rationalize the findings above. Readers are referred to Appendix B for proof.

5.1 Setup

Consider a continuum of infinitely-lived workers and firms in a linear city $\mathbf{R}_+$. All workers are ex ante homogeneous and located at the origin. Following the empirical findings, we assume they do not move home. In contrast, firms are ex ante heterogeneous in productivity and locations. Thus, we denote a firm-type by $\theta = (y, r)$, where $y \in [\underline{y}, \bar{y}] \subset \mathbf{R}_{++}$ is the productivity and r is the distance between the firm and the origin. In what follows, we assume y and r are independent, such that the joint distribution F_θ is the product of marginal distributions F_y and F_r.

In every period of unemployment, a worker receives unemployment benefits z and a job offer with probability λ_0. When employed at firm θ, he earns a flow wage $w(\theta, \hat{\theta})$, incurs a commuting cost $c(r)$, and receives an job offer with probability λ_1. In particular, $w(\theta, \hat{\theta})$ depends on the current firm type θ and the worker's best outside option $\hat{\theta}$; $c(r)$ strictly increases in r; and $c(0) = 0$. Throughout this section, we assume all workers receive job offers from an exogenous distribution F_θ.[6] All jobs dissolve with probability δ per period.

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

$$S(\theta) = \max\{0, W(\theta, \hat{\theta}) - U + J(\theta, \hat{\theta})\}, \tag{4}$$

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

Wages are determined by Nash bargaining. With on-the-job search, bargaining takes the form of sequential auctions (Cahuc, Postel-Vinay, and Robin, 2006; Postel-Vinay and Robin, 2002a,b). When an unemployed worker meets a firm of type θ, the worker bargains for an exogenous share $\alpha \in [0, 1]$ of the joint surplus:

$$W(\theta, u) - U = \alpha S(\theta). \tag{5}$$

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

$$W(\theta_2, \theta_1) - U = S(\theta_1) + \alpha(S(\theta_2) - S(\theta_1)). \tag{6}$$

If $S(\hat{\theta}) < S(\theta_2) < S(\theta_1)$, the old firm retains the worker at a higher wage to match the better outside option θ_2. The renegotiated wage satisfies

$$W(\theta_1, \theta_2) - U = S(\theta_2) + \alpha(S(\theta_1) - S(\theta_2)). \tag{7}$$

[6] As discussed in Section 2, the average number of workers displaced in a mass layoff is negligible relative to the size of a local labor market. Therefore, mass layoffs are unlikely to have general equilibrium effects on the job offer distribution or labor market tightness (Flemming, 2020).

Finally, if $S(\theta_2) \leq S(\hat{\theta})$, the worker remains at the old firm at the current wage. In what follows, we use $M_1(\theta_1)$ to represent the set of offers that incur a move to the new firm, and $M_2(\theta_1, \theta_2)$ for those leading to wage renegotiation within the old firm. The corresponding probability measures are $p_1(\theta_1)$ and $p_2(\theta_1, \theta_2)$, respectively.

Now we pin down the value functions U, W, and J. They are respectively given by

$$U = z + \beta \left\{ \lambda_0 \int_{M_1(u)} W(x, u) dF_\theta(x) + (1 - \lambda_0 p_1(u)) U \right\}, \tag{8}$$

$$\begin{aligned} W(\theta, \hat{\theta}) = & w(\theta, \hat{\theta}) - c(r) + \beta \left\{ \delta U + (1-\delta)[1 - \lambda_1 (p_1(\theta) + p_2(\theta, \hat{\theta})] W(\theta, \hat{\theta}) \right. \\ & \left. + (1-\delta)\lambda_1 \left[\int_{M_1(\theta)} W(x, \theta) dF_\theta(x) + \int_{M_2(\theta, \hat{\theta})} W(\theta, x) dF_\theta(x) \right] \right\}, \end{aligned} \tag{9}$$

and

$$J(\theta, \hat{\theta}) = y - w(\theta, \hat{\theta}) + \tilde{\beta} \left\{ \lambda_1 \int_{M_2(\theta, \hat{\theta})} J(\theta, x) dF_\theta(x) + [1 - \lambda_1 (p_1(\theta) + p_2(\theta, \hat{\theta})] J(\theta, \hat{\theta}) \right\}, \tag{10}$$

where $\tilde{\beta} = \beta(1 - \delta)$.

5.2 Dynamics of Surplus, Commuting, and Wage

To investigate the dynamics of wage and commuting costs after job displacement, we associate both outcomes with the job match surplus. Plugging the value functions (8)-(10) and wage bargaining rules (5)-(7) into (4), we obtain the following equation regarding the surplus function:

$$S(\theta) = \frac{y - c(r) - z}{1 - \tilde{\beta}} + \frac{\alpha \tilde{\beta} \lambda_1}{1 - \tilde{\beta}} \int [S(x) - S(\theta)]^+ dF_\theta(x) - \frac{\alpha \beta \lambda_0}{1 - \tilde{\beta}} \int [S(x)]^+ dF_\theta(x). \tag{11}$$

Given the exogenous parameters, the job characteristics $\theta = (y, r)$ uniquely pin down the value of $S(\theta)$. As shown in Appendix B, Lemma 2, the surplus level increases in the firm's productivity y but decreases in the commuting distance r. At the same surplus level, workers' commuting costs $c(r)$ must be compensated one-to-one by the firm's increased productivity.

Motivated by this observation, we define *isosurplus curves* on the job space $[\underline{y}, \bar{y}] \times \mathbf{R}_+$. Figure 5 plots three isosurplus curves assuming the commuting cost is linear in distance. All jobs (y, r) on the same curve yield the same surplus, and the curve on a higher position represents a greater surplus level.

Proposition 1. *Suppose a worker is exogenously displaced in period* 0 *and does not experience another separation by period* T*. The worker's total matched surplus* $S(\theta)$ *and their surplus share* $W(\theta, \hat{\theta}) - U$ *are both non-decreasing in* t *for* $0 \leq t \leq T$*.*

Proposition 1 states that voluntary job transitions will never reduce a worker's surplus level. Next, we associate the recovery of surplus with the dynamics of productivity, commuting, and wages.

Proposition 2. *Let* $\mathbf{E}[y|s]$ *and* $\mathbf{E}[r|s]$ *be, respectively, the expected productivity and expected distance of a firm that generates match surplus* s*. Also, define* $F_c(\cdot) = F_r(c^{-1}(\cdot))$*. If*
(i) F_y *and* F_c *are twice differentiable with density functions* f_y *and* f_c*, respectively;*
(ii) f_y *and* f_c *are log-concave;*
then $\mathbf{E}[y|s]$ *increases in* s *and* $\mathbf{E}[r|s]$ *decreases in* s*.*

Therefore, workers with a higher job match surplus, in expectation, are matched to more productive and more proximate firms. This is obvious when y and r are uniformly distributed: In Figure 5, the conditional expectation is given by the midpoint of the iso-surplus curve. Proposition 2 extends this result to general distributions, provided the density functions are not too volatile or skewed.

Combining the two propositions, we can characterize the recovery of displaced workers over time. After a worker is displaced, the expected productivity of the new employers increases over time, and the expected commuting distance decreases over time. This process will continue until he is displaced again. As Jarosch (2021) points out, if α is high, i.e., the worker gets a large share of the joint surplus, the expected wage will also increase over time.[7]

In Appendix C, we consider two extensions of the model: (i) endogenous search effort and (ii) firm-specific separation rates. In the first extension, we show that displaced workers search for jobs less intensively over time. However, this declining search effort is driven by recovery of surplus, so it differs from the effect of exhausting unemployment benefits. In the second case, workers move from less to more secure jobs as they recover from job loss. This provides another explanation for our findings in Section 3.3—that workers view job security as an independent job attribute and on-the-job search allows them to move from less to more secure jobs.

[7]As Jarosch (2021) explains, when α is small, workers at more productive firms may accept a lower wage in exchange for greater wage growth potential.

5.3 Empirical Validation

According to Proposition 1, displaced workers will accept a job offer only if it yields a positive surplus, i.e., lies above the zero-surplus curve. To empirically validate this claim, we plot the distribution of first jobs accepted by displaced workers. Figure 6, panel (a) depicts the productivity y and commuting distance r of first jobs accepted by a displaced worker, where productivity is proxied by firm fixed effects (Card, Heining, and Kline, 2013). As distance increases, the distribution of firm productivity shifts up, and the likelihood of observing a low productivity firms diminishes. In particular, most of the points lie above a hypothetical, upward sloping curve as implied by the zero-surplus curve. This pattern becomes more pronounced in panel (b), where we replace the firm fixed effects by log wages. The implied lower bound represents an upward-sloping indifference curve between wages and commuting. The slope of the indifference curve measures the worker's willingness to pay (WTP) for commuting.

The patterns in Figure 6 align our dynamic model with the static ones found in Dauth and Haller (2020) and Le Barbanchon, Rathelot, and Roulet (2021). Using the same data as ours, Dauth and Haller (2020) estimate the WTP for commuting to be 0.06 for an average German worker. Combining survey data with actual job acceptance in France, Le Barbanchon, Rathelot, and Roulet (2021) directly identify the slope of the indifference curve and study gender gaps in the valuation for commuting. Our model differs from theirs by considering on-the-job search and the shift in indifference curves themselves. With on-the-job search, workers increase wages and reduce commuting at the same time, yielding the opposite relationship between wages and commuting with respect to the static case.

6 Conclusion

In this paper, we investigate the adjustment of commuting behavior by displaced workers. Using an event study approach, we estimate the short-term and long-term impact of being displaced during mass layoffs on the worker's earnings, wages, and commuting costs. Consistent with existing studies, we find a large and persistent loss in earnings and wages after job displacement. In contrast, we show that displaced workers commute longer distances after displacement, and their commuting patterns gradually recover to the pre-displacement level in subsequent years. Further analysis reveals that the recovery of commuting is driven by workers moving to proximate firms rather than migration or relocation. Besides, we provide evidence that workers attenuate the wage loss after job displacement by increasing commuting, or vice versa.

The declining commuting and increasing wage of post-displacement workers contrasts with their static relationship, where longer commuting distances are compensated for by higher wages. To reconcile the countervailing forces, we build a job search model with heterogeneous firm productivity and commuting costs. We show that on-the-job search plays an important role. With on-the-job search, workers can increase their job match surplus by moving from less to more productive firms and moving from distant to proximate firms. Whereas conditional on a fixed surplus level, they make a tradeoff between higher wages and shorter commuting, leading to the opposite correlation. Using data on the first jobs taken by displaced workers, we validate that workers rarely take up jobs with both low pay and high commuting costs.

A large literature has documented the profound consequences of job loss on individual workers. We contribute to the literature by demonstrating the multi-dimensional nature of the impacts of job loss. Not only do displaced workers experience a negative shock on wages and earnings, but they also face increased commuting costs to find new jobs. In addition, displaced workers may suffer from poorer job match quality, job security, etc. Hence, it would be interesting for future researchers to consider the effect of job loss on other outcome dimensions and evaluate the welfare loss of displaced workers (e.g., Meekes and Hassink, 2022). Our multi-dimensional model in Appendix C.2 provides a feasible starting point.

For policymakers, our paper sheds light on the value of employment assistance programs. Except for cash benefits and skill training, measures to reduce job search frictions would also assist unemployed workers. Future research could examine whether commuting subsidies, online job boards, or working-from-home options facilitate the return to employment by displaced workers, and whether they accelerate the recovery from job loss (Franklin, 2018; Paetzold, 2019; Gürtzgen et al., 2021). It would also be valuable to study how job search frictions impact the effectiveness of employment assistance programs.

Finally, our study highlights the importance of granular commuting data for studying individuals' responses to job loss. In other research areas, we see a similar value of measuring commuting at the individual level. For example, studies of job search, labor market frictions, monopsony, and social networks all emphasize individuals' commuting decisions. Hence, we also expect oppotunites for multidisciplinary research between economics and geographical science.

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Tables and Figures

Table 1: Coarsened Exact Matching: Results

Variable	Unit	Displaced	Non-Displaced
Female	Indicator	0.285	0.264
		(0.452)	(0.441)
Age	Year	40.53	40.95
		(8.082)	(7.994)
High school or less	Indicator	0.178	0.177
		(0.383)	(0.382)
Vocational training	Indicator	0.765	0.771
		(0.424)	(0.420)
University or above	Indicator	0.048	0.043
		(0.213)	(0.204)
Eastern Germany	Indicator	0.177	0.170
		(0.381)	(0.376)
Work experience	Year	14.77	15.52
		(7.575)	(7.714)
Firm tenure	Year	8.336	8.924
		(6.391)	(6.718)
Firm size	Count	224.9	218.3
		(760.8)	(784.0)
Daily wage	Euro	99.78	101.7
		(48.23)	(49.91)
Commuting distance	Kilometer	15.36	14.63
		(15.93)	(15.07)
Commuting time	Minute	14.98	14.37
		(12.95)	(12.42)
Workers		18,190	273,142

Note: The table reports means and standard deviations (in parentheses) of displaced workers and matched non-displaced workers in the year before mass layoff. The sample is obtained using exact matching on gender, education qualification, one-digit industrial sector, and indicator of eastern Germany, and coarsened matching on age, firm tenure, firm size, and average daily wage in 2015 real prices.

Table 2: Effects of Job Displacement on Wages and Commuting: Event Study Estimates

	(a) Daily wage (log)	(b) Annual earnings (log)	(c) Commuting distance (log)	(d) Commuting time (log)
β_{-4}	0.014***	0.013***	-0.009	-0.006
	(0.002)	(0.002)	(0.008)	(0.006)
β_{-3}	0.009***	0.008***	-0.005	-0.002
	(0.002)	(0.002)	(0.005)	(0.004)
β_{-2}	0.007***	0.010***	-0.003	-0.002
	(0.001)	(0.001)	(0.003)	(0.003)
β_0	-0.013***	-0.132***	-0.006**	-0.005*
	(0.002)	(0.002)	(0.003)	(0.003)
β_1	-0.196***	-0.432***	0.218***	0.187***
	(0.004)	(0.006)	(0.016)	(0.014)
β_2	-0.230***	-0.334***	0.206***	0.177***
	(0.004)	(0.005)	(0.014)	(0.012)
β_3	-0.230***	-0.281***	0.176***	0.152***
	(0.004)	(0.005)	(0.014)	(0.012)
β_4	-0.217***	-0.248***	0.172***	0.147***
	(0.004)	(0.005)	(0.015)	(0.012)
β_5	-0.204***	-0.228***	0.158***	0.135***
	(0.004)	(0.005)	(0.015)	(0.013)
β_6	-0.191***	-0.209***	0.145***	0.122***
	(0.005)	(0.005)	(0.016)	(0.013)
β_7	-0.185***	-0.198***	0.135***	0.113***
	(0.005)	(0.005)	(0.016)	(0.014)
β_8	-0.181***	-0.188***	0.122***	0.100***
	(0.005)	(0.006)	(0.017)	(0.014)
β_9	-0.172***	-0.183***	0.110***	0.091***
	(0.005)	(0.006)	(0.018)	(0.015)
β_{10}	-0.164***	-0.174***	0.099***	0.080***
	(0.006)	(0.006)	(0.019)	(0.016)
β_{11}	-0.156***	-0.160***	0.088***	0.073***
	(0.006)	(0.007)	(0.020)	(0.017)
Observations	3,213,415	3,213,415	3,213,415	3,213,415
Workers	291,332	291,332	291,332	291,332
R^2	0.055	0.194	0.005	0.005

Notes: Each column represents estimates of model (1) with the dependent variable in the column title. Samples comprise a yearly panel of workers with regular jobs on June 30 of the year. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors in parentheses clustered by workers. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 3: Effects of Job Displacement on Wages and Commuting: DID Estimates

	(a) Daily wage (log)	(b) Annual earnings (log)	(c) Commuting distance (log)	(d) Commuting time (log)
β_{-4}	0.014***	0.015***	-0.010	-0.007
	(0.002)	(0.002)	(0.008)	(0.006)
β_{-3}	0.009***	0.008***	-0.005	-0.002
	(0.002)	(0.002)	(0.005)	(0.004)
β_{-2}	0.008***	0.010***	-0.003	-0.002
	(0.001)	(0.001)	(0.003)	(0.003)
β_0	-0.013***	-0.132***	-0.006**	-0.005*
	(0.002)	(0.002)	(0.003)	(0.003)
β^*	-0.200***	-0.250***	0.157***	0.133***
	(0.004)	(0.004)	(0.013)	(0.011)
Observations	3,213,415	3,213,415	3,213,415	3,213,415
Workers	291,332	291,332	291,332	291,332
R^2	0.194	0.055	0.005	0.005

Notes: Each column represents estimates of model (2) with the dependent variable in the column title. Samples comprise a yearly panel of workers with regular jobs on June 30 of the year. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors in parentheses clustered by workers. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 4: Effects of Job Displacement on Worker Mobility

	(a) Relocation	(b) Firm change
β_{-4}	0.010**	0.002**
	(0.004)	(0.001)
β_{-3}	0.004	0.014***
	(0.004)	(0.003)
β_{-2}	-0.001	0.007**
	(0.004)	(0.003)
β_{0}	0.009**	0.000
	(0.004)	(0.000)
β_{1}	0.049***	0.852***
	(0.006)	(0.006)
β_{2}	0.053***	0.596***
	(0.005)	(0.006)
β_{3}	0.023***	0.298***
	(0.004)	(0.006)
β_{4}	0.019***	0.198***
	(0.004)	(0.005)
β_{5}	0.021***	0.145***
	(0.005)	(0.005)
β_{6}	0.016***	0.116***
	(0.005)	(0.005)
β_{7}	0.014***	0.095***
	(0.005)	(0.005)
β_{8}	0.019***	0.075***
	(0.005)	(0.005)
β_{9}	0.011**	0.066***
	(0.005)	(0.006)
β_{10}	0.014**	0.061***
	(0.005)	(0.006)
β_{11}	0.006	0.049***
	(0.005)	(0.006)
Observations	3,213,415	3,213,415
Workers	291,332	291,332
R^2	0.010	0.059

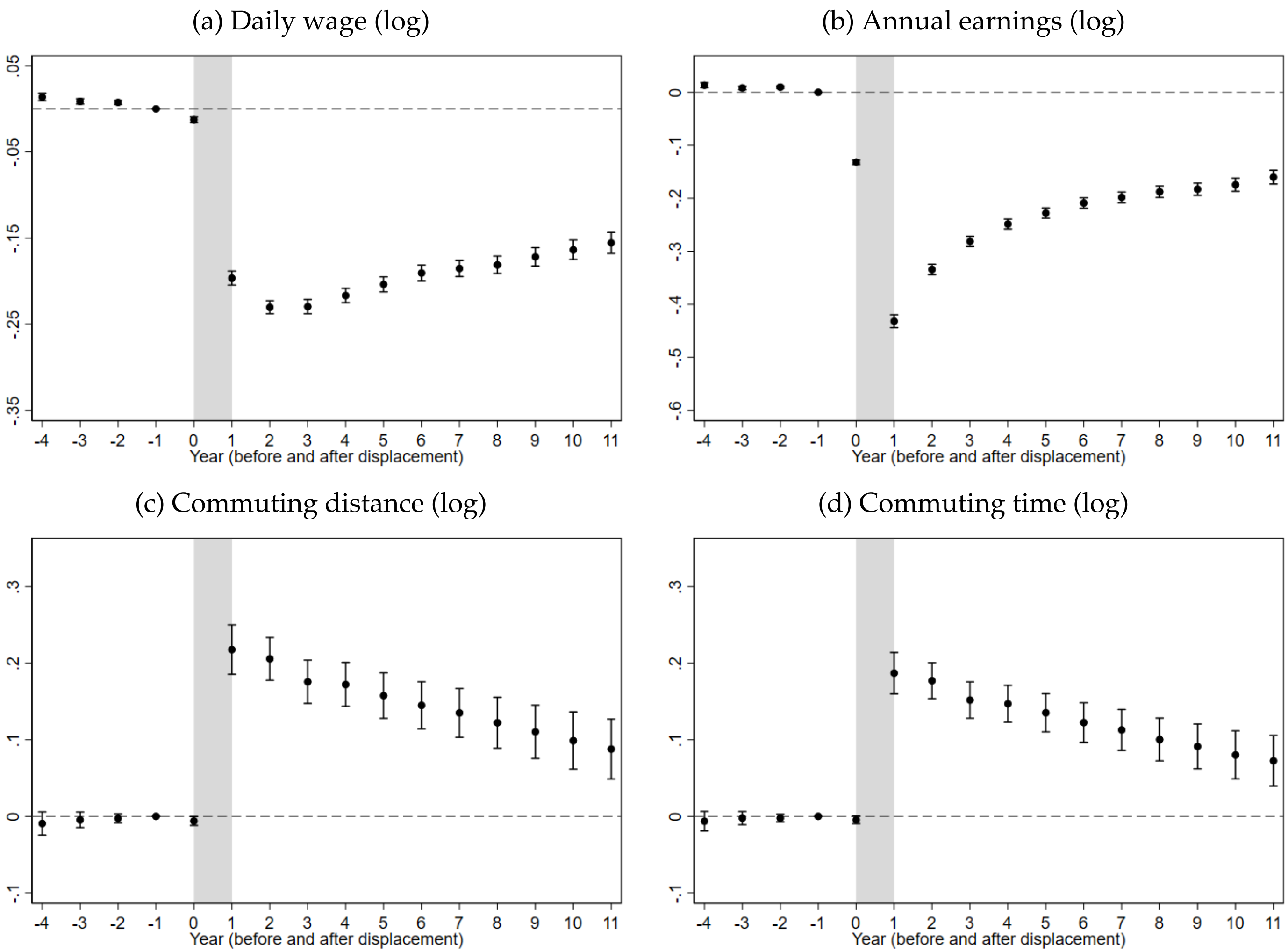
Notes: Each column presents estimates of model (1) with the dependent variable in the column title. Samples comprise a yearly panel of workers with regular jobs on June 30 of the year. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors in parentheses clustered by workers. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Table 5: Granular versus Coarse Commuting Distances

	(a) No commute within municipality	(b) Single route btw. municipalities	(c) Geodesic btw. municipalities
β_{-4}	-0.014	-0.014	-0.015
	(0.010)	(0.009)	(0.010)
β_{-3}	-0.003	-0.004	-0.005
	(0.006)	(0.006)	(0.006)
β_{-2}	-0.000	-0.001	-0.001
	(0.004)	(0.003)	(0.004)
β_0	-0.007**	-0.006*	-0.006*
	(0.004)	(0.003)	(0.004)
β_1	0.268***	0.244***	0.256***
	(0.021)	(0.020)	(0.021)
β_2	0.257***	0.232***	0.245***
	(0.018)	(0.017)	(0.018)
β_3	0.228***	0.201***	0.213***
	(0.018)	(0.017)	(0.018)
β_4	0.209***	0.183***	0.194***
	(0.019)	(0.017)	(0.018)
β_5	0.194***	0.168***	0.179***
	(0.019)	(0.018)	(0.019)
β_6	0.175***	0.151***	0.162***
	(0.020)	(0.019)	(0.020)
β_7	0.158***	0.135***	0.146***
	(0.021)	(0.019)	(0.020)
β_8	0.152***	0.128***	0.137***
	(0.022)	(0.020)	(0.021)
β_9	0.140***	0.119***	0.127***
	(0.023)	(0.021)	(0.023)
β_{10}	0.131***	0.111***	0.117***
	(0.024)	(0.023)	(0.024)
β_{11}	0.109***	0.090***	0.096***
	(0.026)	(0.024)	(0.025)
Observations	3,213,415	3,204,807	3,204,807
Workers	291,332	290,747	290,747
R^2	0.005	0.005	0.005

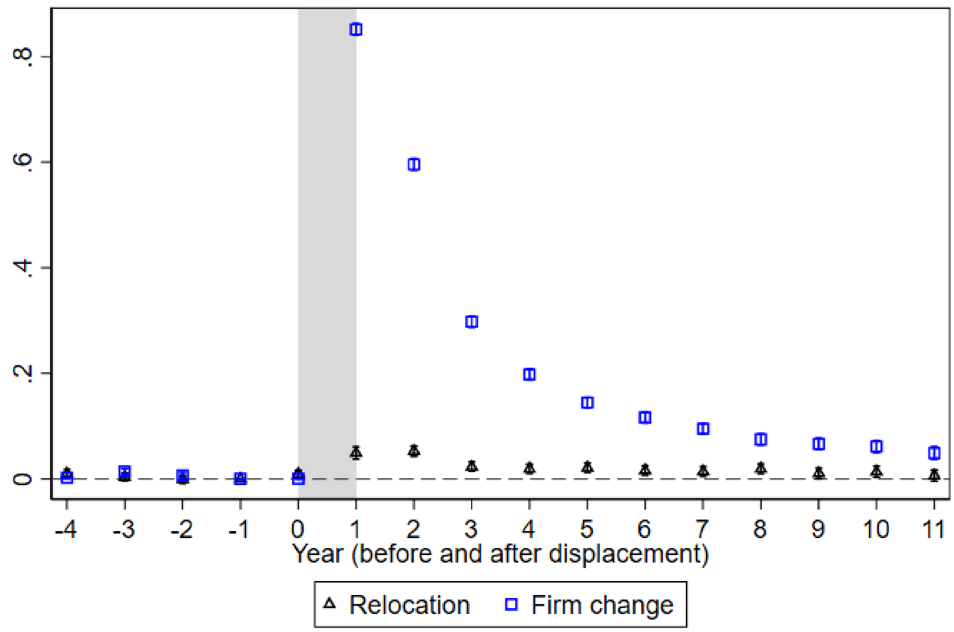
Notes: Each column presents estimates of model (1) using the following distance measures as the dependent variable. Column (a): driving distance between geo-coordinates of an individual's residence and workplace, but zero log distance assumed for commutes within municipalities; Column (b): distance for commutes from one municipality to another replaced by driving distance between municipality centers; Column (c): driving distance between municipalities replaced by geodesic between municipality centers. Samples comprise a yearly panel of workers with regular jobs on June 30 of the year. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors in parentheses clustered by workers. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Figure 1: Effects of Job Displacement on Wages and Commuting



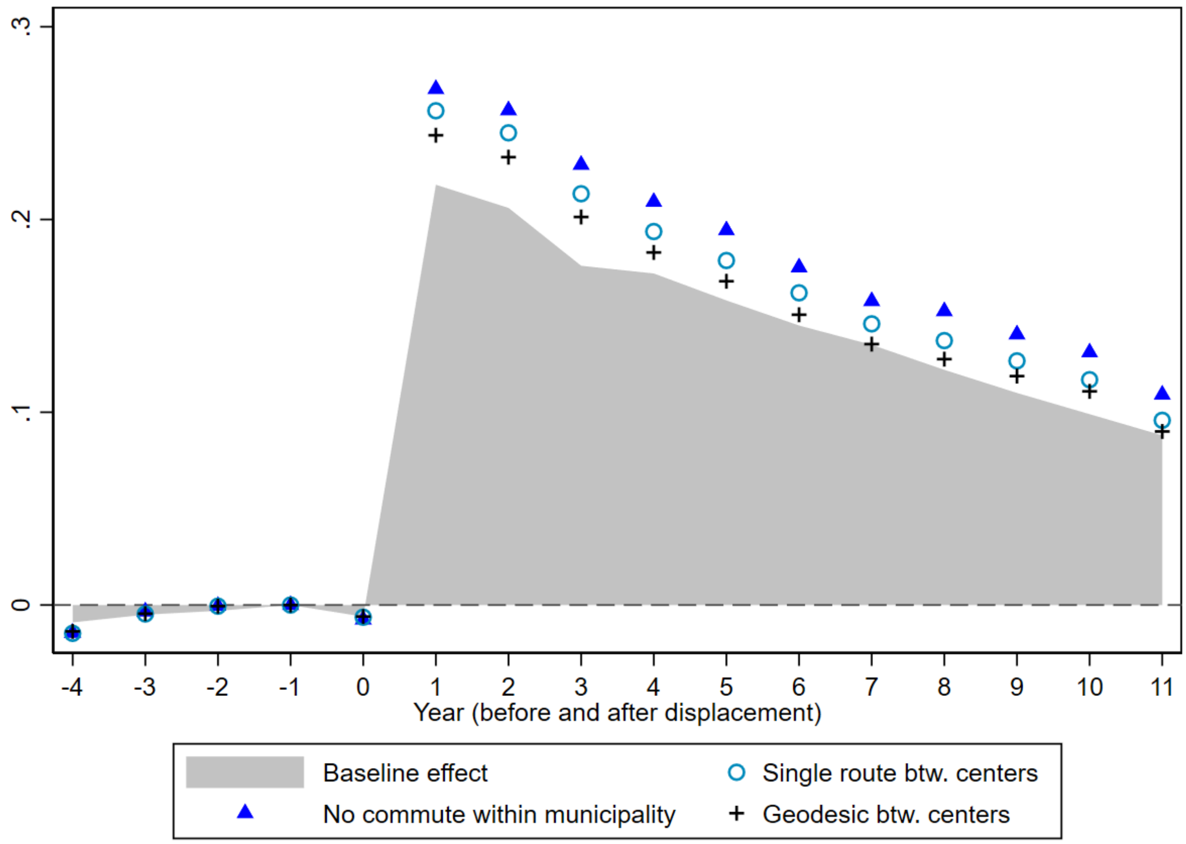
Notes: Each plot depicts estimates of model (1) with the dependent variable in the subtitle. Samples comprise a yearly panel of workers with regular jobs on June 30 of the year. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure 2: Effects of Job Displacement on Worker Mobility



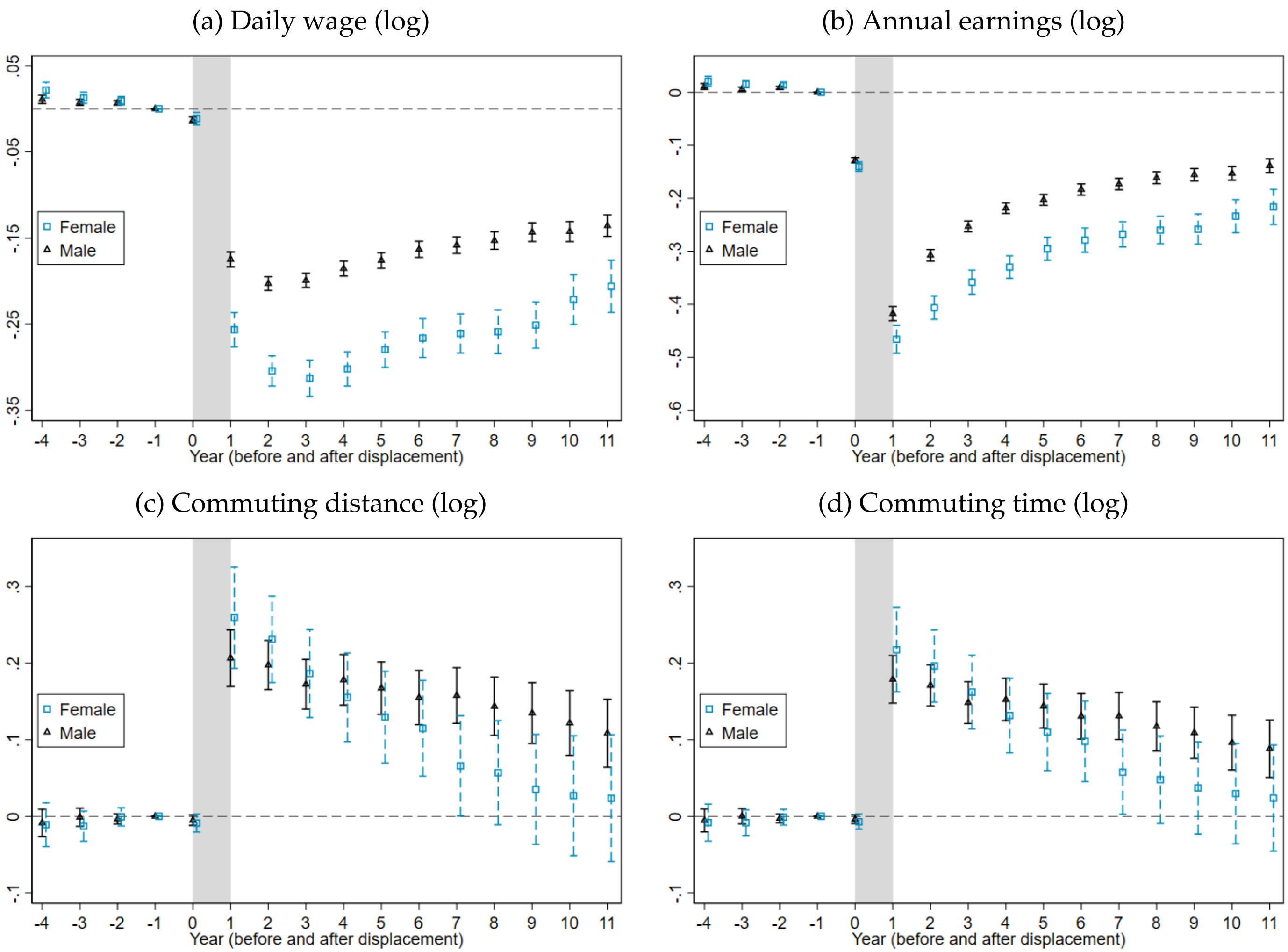
Notes: The figure depicts estimates of model (1) with indicators of relocation and firm change as the dependent variable. Samples comprise a yearly panel of workers with regular jobs on June 30 of the year. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure 3: Individual- and Municipality-Level Commuting Distances



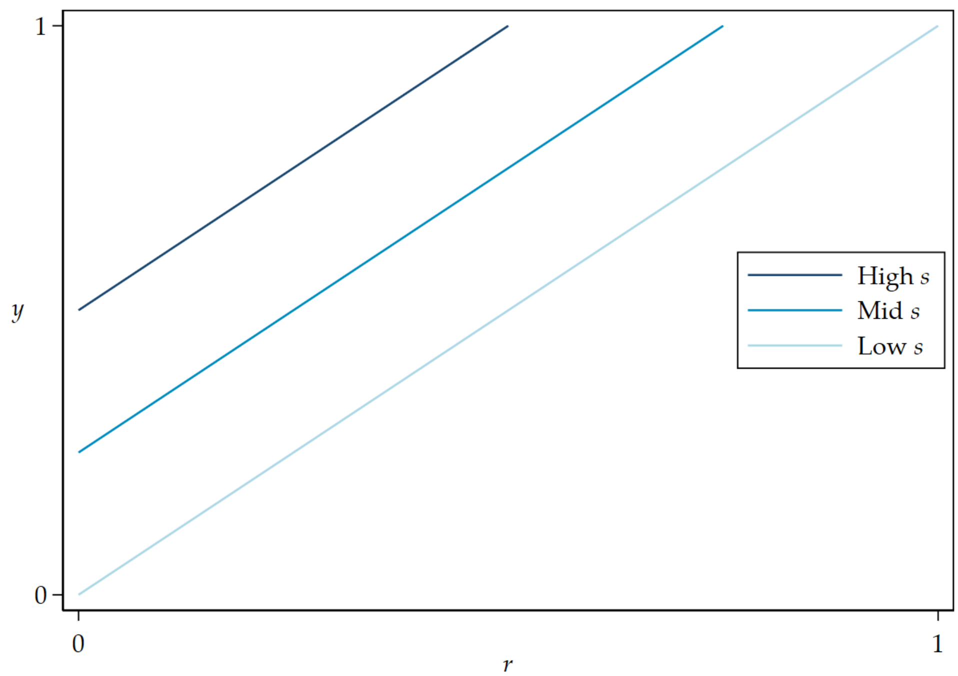
Notes: The figure depicts estimates of model (1) using various distance measures as the dependent variable. The gray area represents the driving distance between geo-coordinates of an individual's residence and workplace (the baseline); the blue triangles assume zero log distance for commutes within municipalities; the red circles further calculate the distance for all commutes from one municipality to another by the driving distance between municipality centers; the black stars further replace driving distances between municipalities by geodesics between municipality centers. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure 4: Effect Heterogeneity by Gender



Notes: Each plot depicts estimates of model (1) with the dependent variable in the subtitle. Samples comprise a yearly panel of workers with regular jobs on June 30 of the year. The blue and red markers represent male and female workers, respectively. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

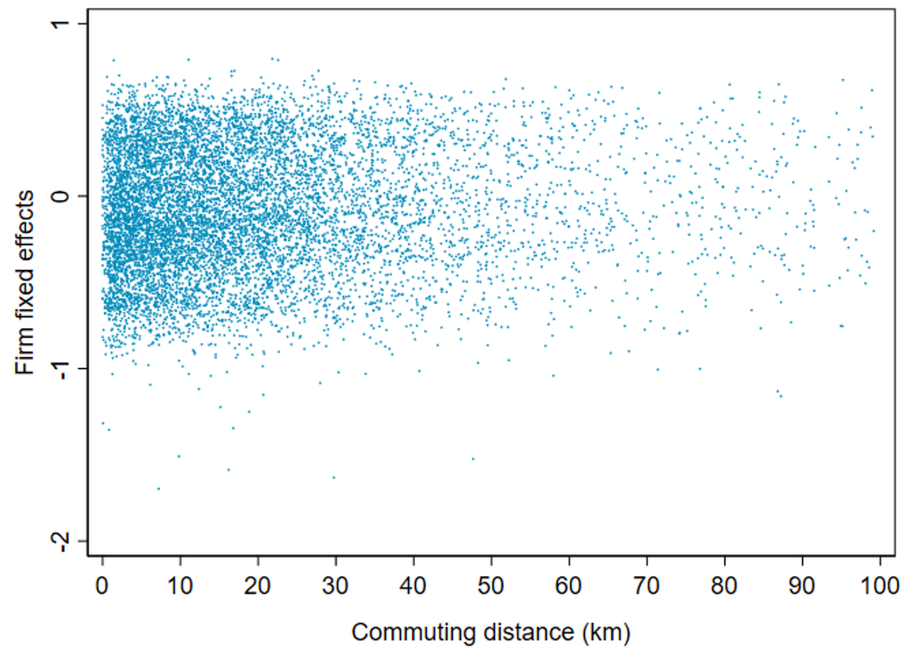
Figure 5: Isosurplus Curves with $c(r) = r$



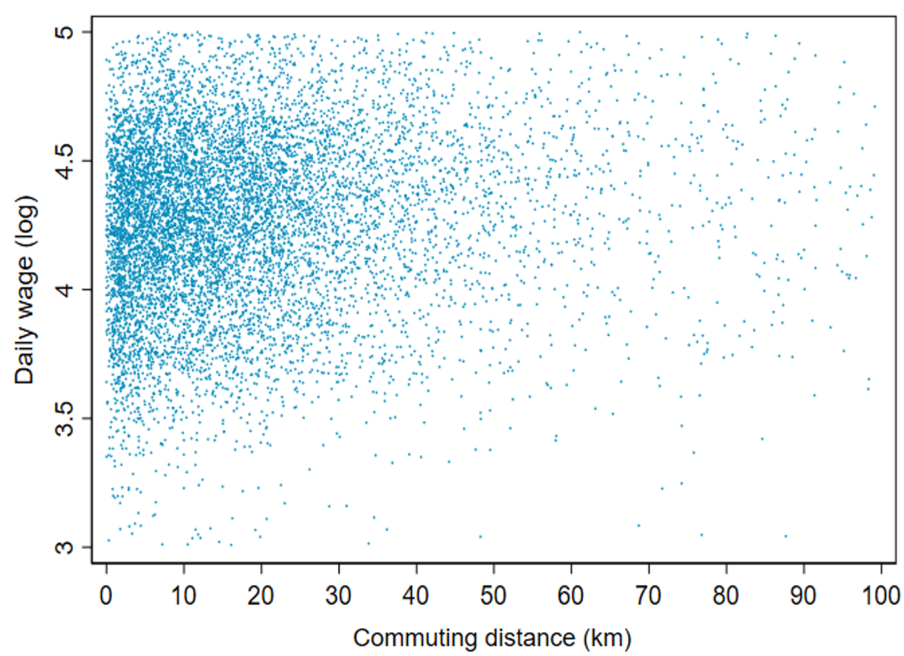
Notes: This figure depicts three isosurplus curves under the assumption $c(r) = r$. The support of productivity y and distance r are given by $[\underline{y}, \bar{y}] = [0, 1]$ and $\mathbf{R}_+$, respectively.

Figure 6: First Jobs after Displacement

(a) Productivity and Distance



(b) Wage and Distance



Notes: Sample comprises all first jobs accepted by displaced workers. Panel (a) plots Card, Heining, and Kline's (2013) estimated firm fixed effects and commuting distances; Panel (b) plots average daily wages and commuting distances (jobs with log daily wage above 5 are not shown).

Appendix

A Additional Tables and Figures

Table A1: Summary Statistics

Variables	Unit	Mean	S.D.	Min.	Max.
Female	Indicator	0.103	0.304	0	1
Age	Year	43.08	7.353	20	54
High school or less	Indicator	0.097	0.296	0	1
Vocational training	Indicator	0.883	0.322	0	1
University or above	Indicator	0.019	0.137	0	1
Eastern Germany	Indicator	0.074	0.261	0	1
Work experience	Year	19.64	7.651	0.003	39
Firm tenure	Year	13.06	8.290	0.003	39
Firm size	Count	313.2	1,309	0	57,420
Full-time job	Indicator	0.988	0.111	0	1
Daily wage	Euro	111.9	42.55	0.011	1,369
Annual earnings	Euro	36,662	11,619	3.650	311,510
Commuting distance	Kilometer	13.66	13.62	0.003	100.0
Commuting time	Minute	13.51	11.31	0.017	104.5
Firm change	Indicator	0.054	0.225	0	1
Relocation	Indicator	0.069	0.253	0	1
Observations		3,213,415			
Workers		291,332			

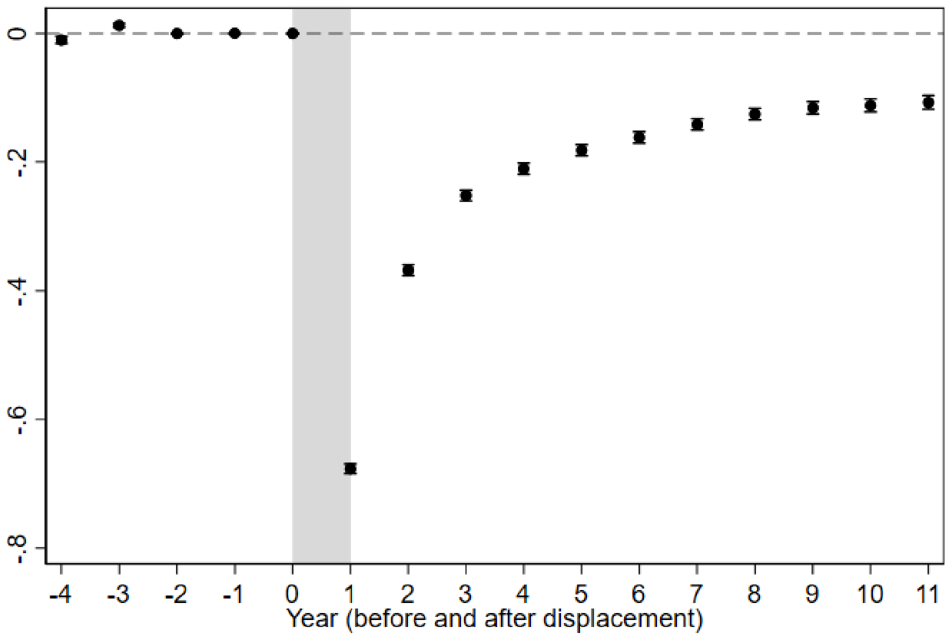
Note: The sample comprises a yearly panel of displaced workers and matched non-displaced workers using CEM. Earnings and wages are in 2015 real prices.

Table A2: Effects of Job Displacement on Other Outcomes

	(a) Firm wage premiums	(b) Days in full-time jobs	(c) Days in part-time jobs	(d) Days in mini jobs
β_{-4}	-0.010***	0.436	-2.136***	0.231
	(0.001)	(0.317)	(0.388)	(0.905)
β_{-3}	-0.005***	-0.820***	-1.787***	4.948***
	(0.001)	(0.139)	(0.152)	(0.493)
β_{-2}	-0.003***	-0.073	-0.04	0.773***
	0.000	(0.052)	(0.033)	(0.230)
β_0	0.006***	0.858***	0.428***	-34.427***
	0.000	(0.089)	(0.066)	(0.490)
β_1	-0.101***	11.548***	3.523***	-207.022***
	(0.003)	(0.422)	(0.402)	(1.133)
β_2	-0.118***	15.399***	12.458***	-134.668***
	(0.002)	(0.589)	(0.704)	(1.478)
β_3	-0.111***	15.886***	15.500***	-95.378***
	(0.002)	(0.667)	(0.867)	(1.510)
β_4	-0.105***	16.117***	16.775***	-81.861***
	(0.003)	(0.740)	(0.974)	(1.578)
β_5	-0.100***	14.059***	17.907***	-74.692***
	(0.003)	(0.749)	(1.071)	(1.623)
β_6	-0.092***	13.459***	17.088***	-68.135***
	(0.003)	(0.783)	(1.149)	(1.684)
β_7	-0.082***	12.849***	16.999***	-64.001***
	(0.003)	(0.813)	(1.242)	(1.741)
β_8	-0.083***	11.727***	16.295***	-57.321***
	(0.003)	(0.857)	(1.386)	(1.850)
β_9	-0.077***	10.925***	18.234***	-56.583***
	(0.003)	(0.902)	(1.531)	(1.984)
β_{10}	-0.074***	10.202***	17.444***	-56.766***
	(0.003)	(0.954)	(1.676)	(2.124)
β_{11}	-0.069***	11.188***	17.130***	-54.336***
	(0.003)	(1.035)	(1.794)	(2.247)
Observations	3,209,856	3,335,347	3,335,347	3,335,347
Workers	291,329	291,922	291,922	291,922
R^2	0.918	0.012	0.043	0.097

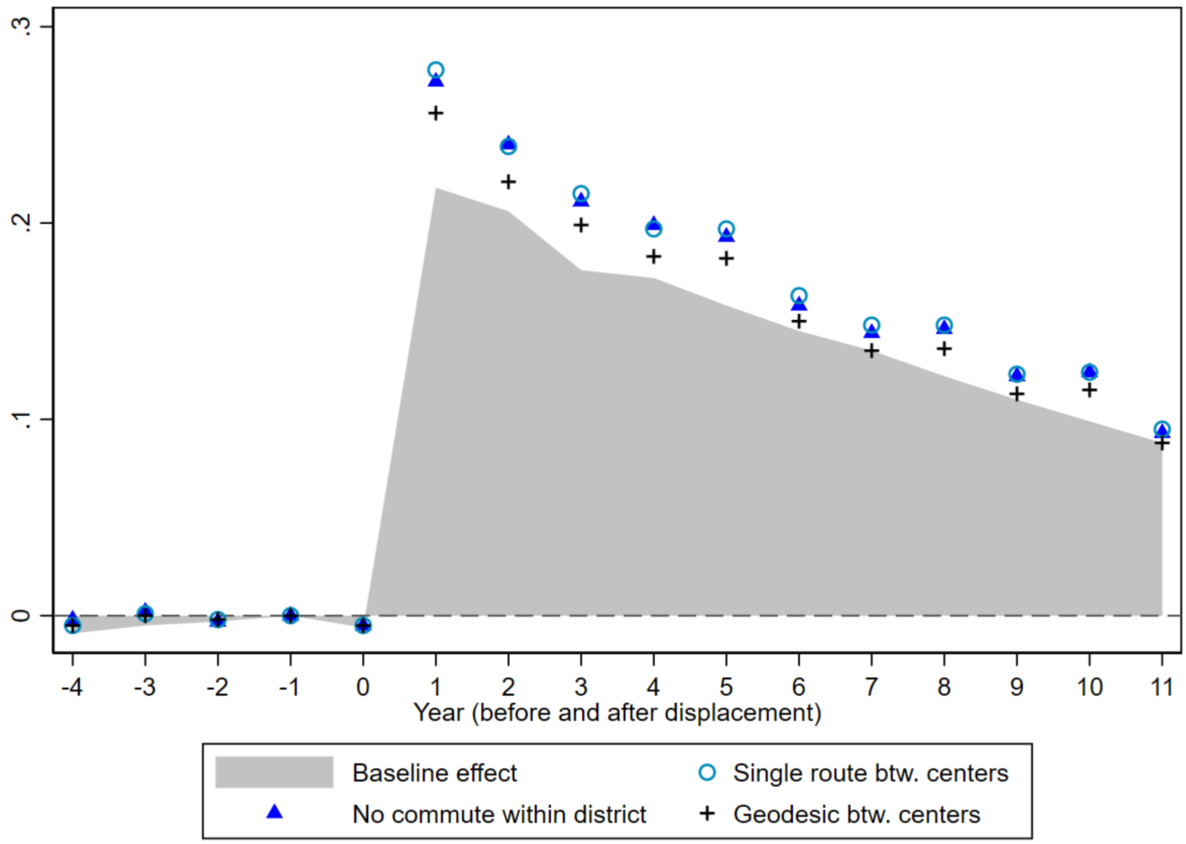
Notes: Each column represents estimates of model (1) with the dependent variable in the column title. Samples comprise a yearly panel of workers with regular jobs on June 30 of the year (column (a)) or a complete yearly panel of workers (columns (b)-(d)). All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors in parentheses clustered by workers. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

Figure A1: Mass Layoffs and Regular Employment



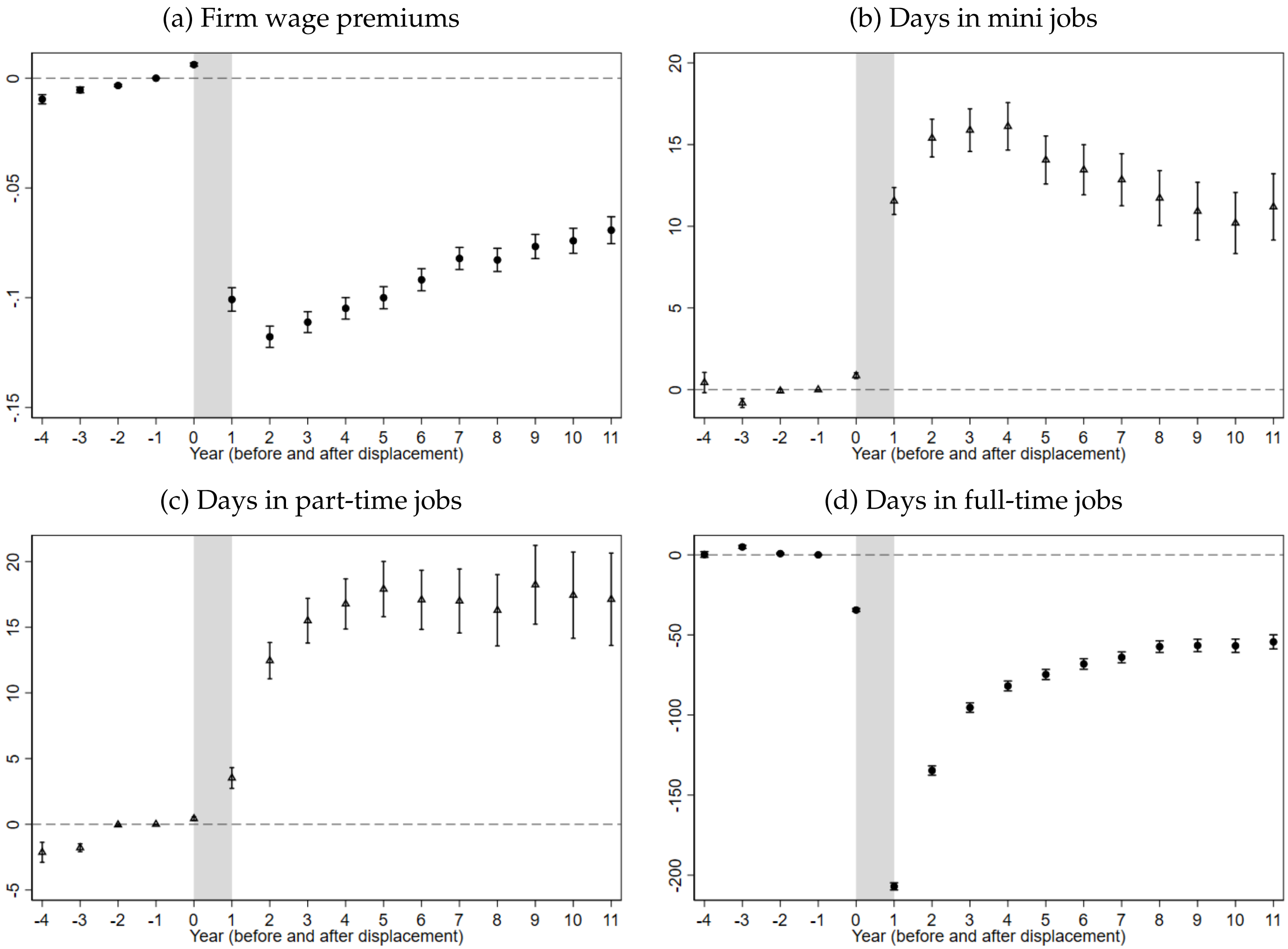
Notes: The figure depicts estimates of model (1) with the probability of having regular employment as the dependent variable. The sample comprises a complete yearly panel of workers. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure A2: Individual- and District-Level Commuting Distances



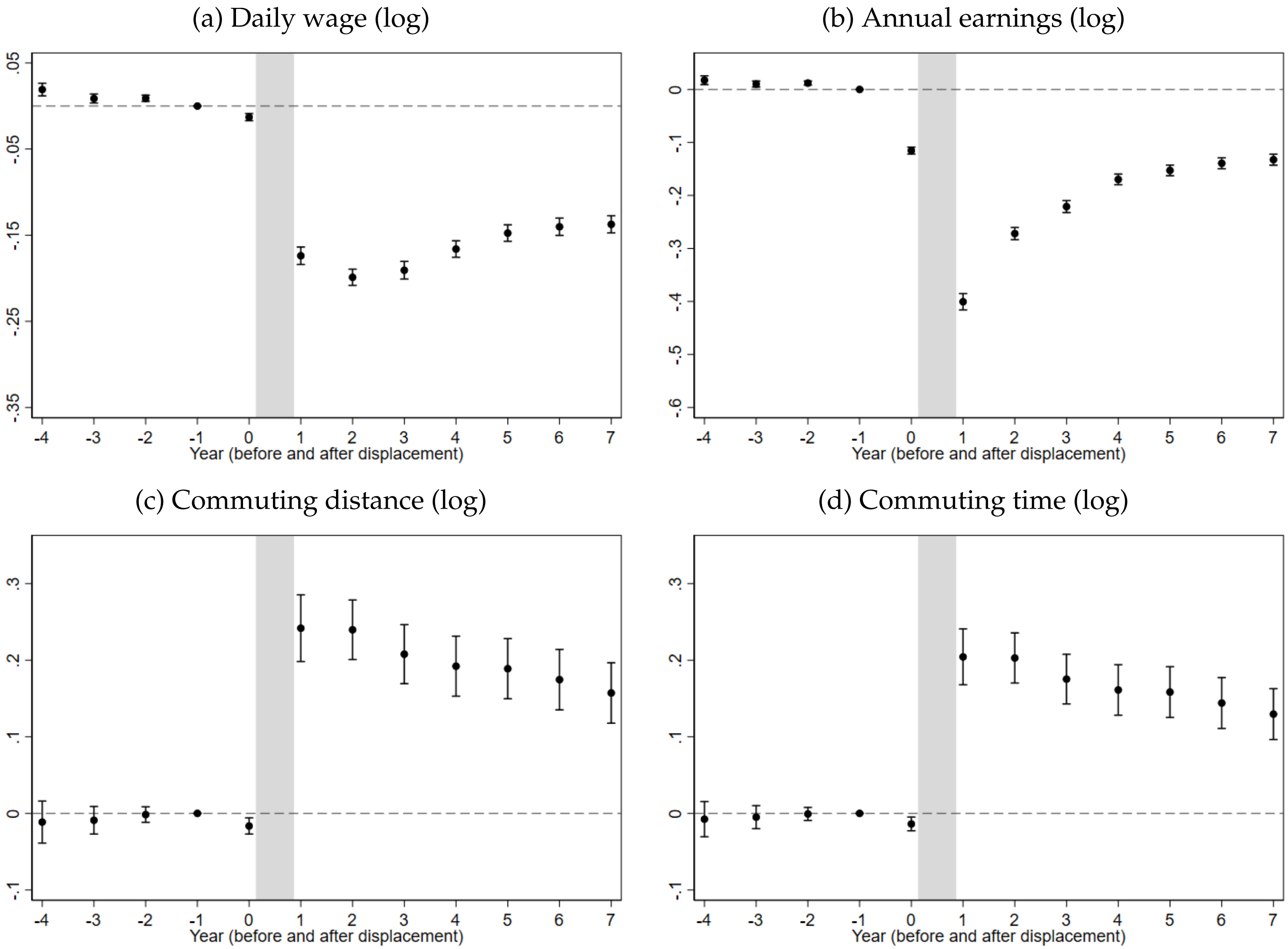
Notes: The figure depicts estimates of model (1) using various distance measures as the dependent variable. The gray area represents the driving distance between geo-coordinates of an individual's residence and workplace (the baseline); the blue triangles assume zero log distance for commutes within districts; the red circles further calculate the distance for all commutes from one district to another by the driving distance between district centers; the black stars further replace driving distances between districts by geodesics between district centers. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure A3: Effects of Job Displacement on Other Outcomes



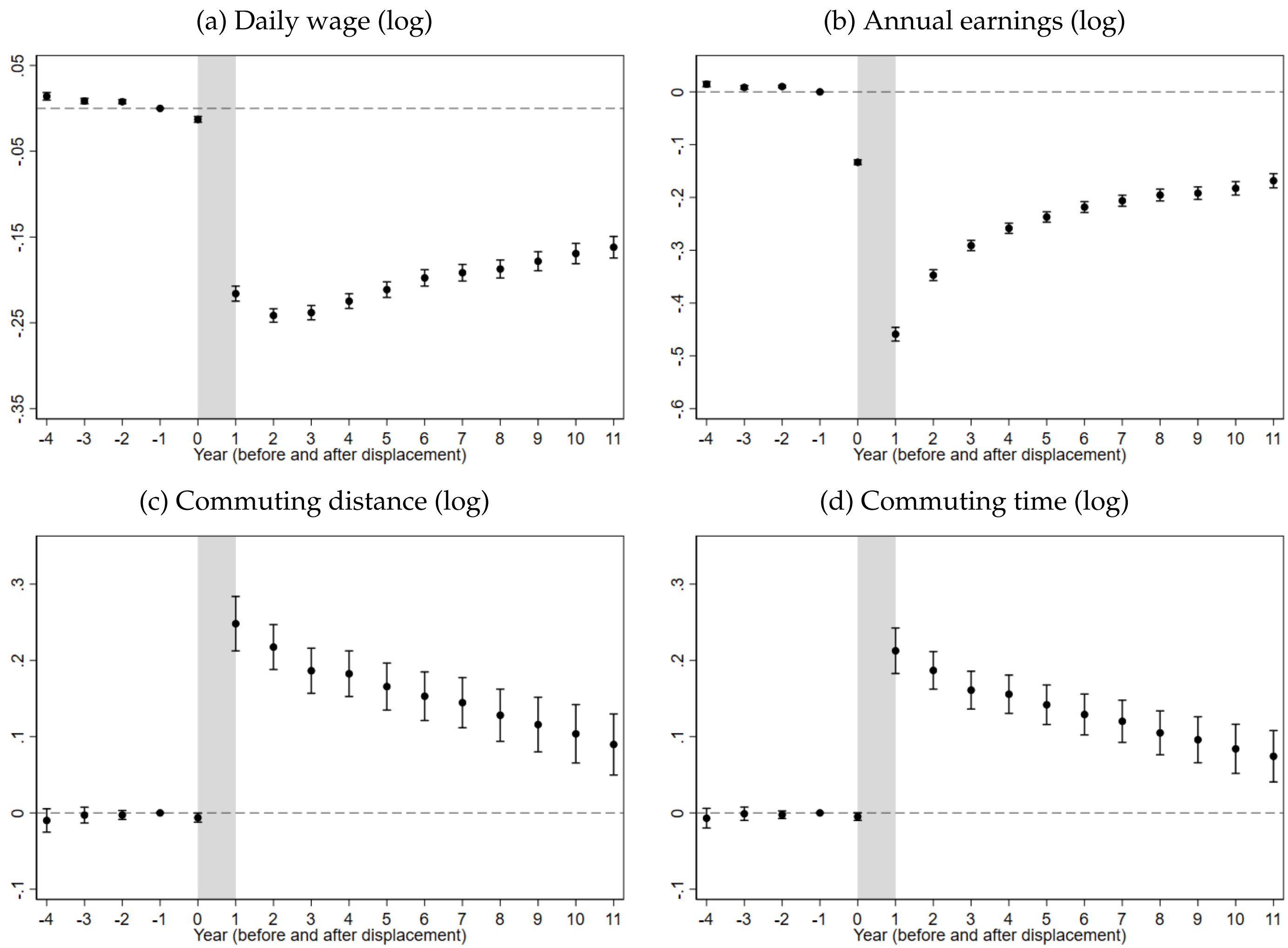
Notes: Each plot depicts estimates of model (1) with the dependent variable in the subtitle. In panel (a), firm wage premiums are measured by Card, Heining, and Kline's (2013) estimated firm fixed effects. Samples comprise a yearly panel of workers with regular jobs on June 30 (panel (a)) and a complete yearly panel or workers (panels (b)-(d)). The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure A4: Robustness to Attrition



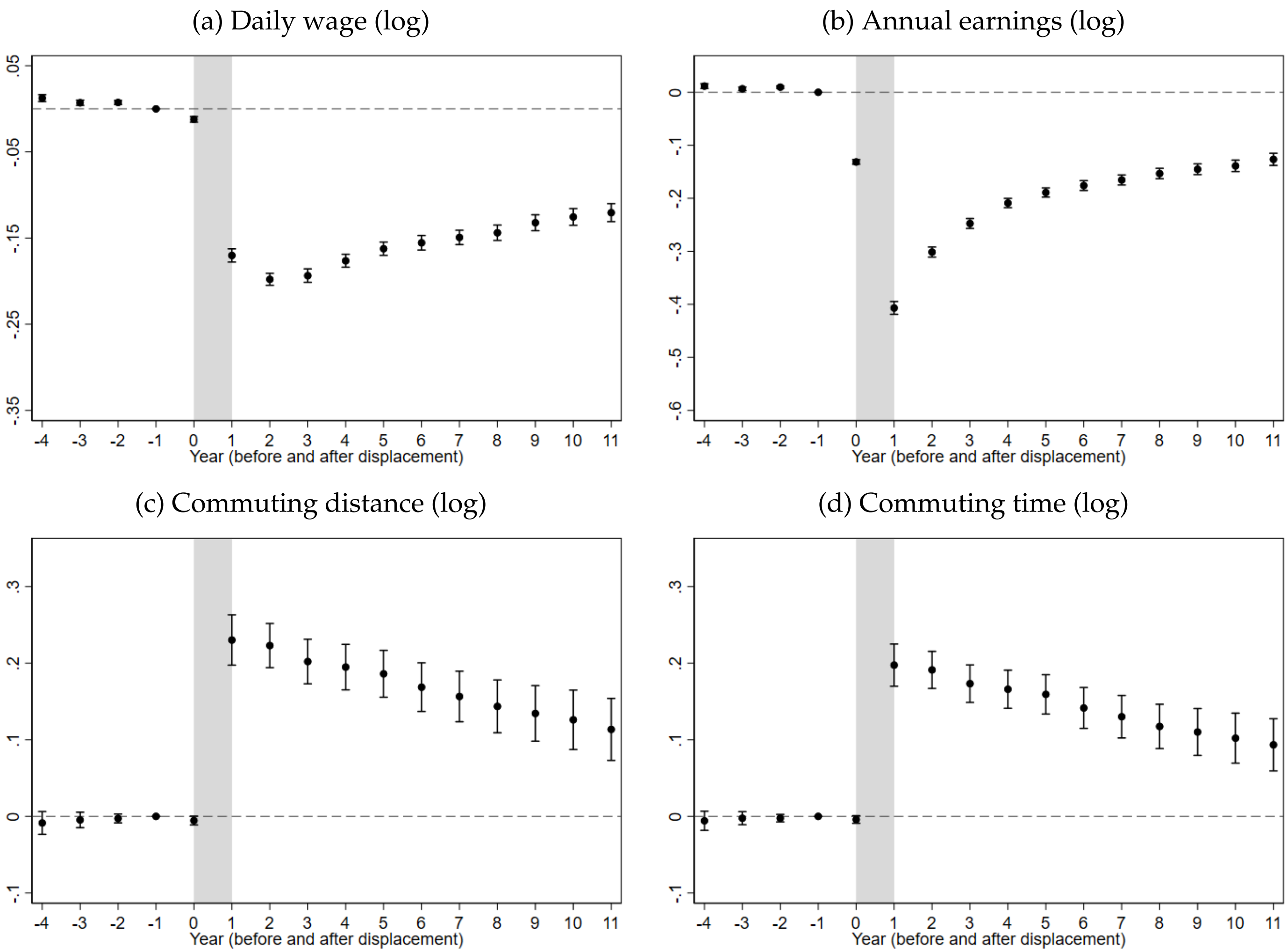
Notes: Each plot depicts estimates of model (1) with the dependent variable in the subtitle. Samples comprise a yearly panel of workers with regular jobs on June 30 from the second to the seventh year after displacement. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure A5: Robustness to Recalls



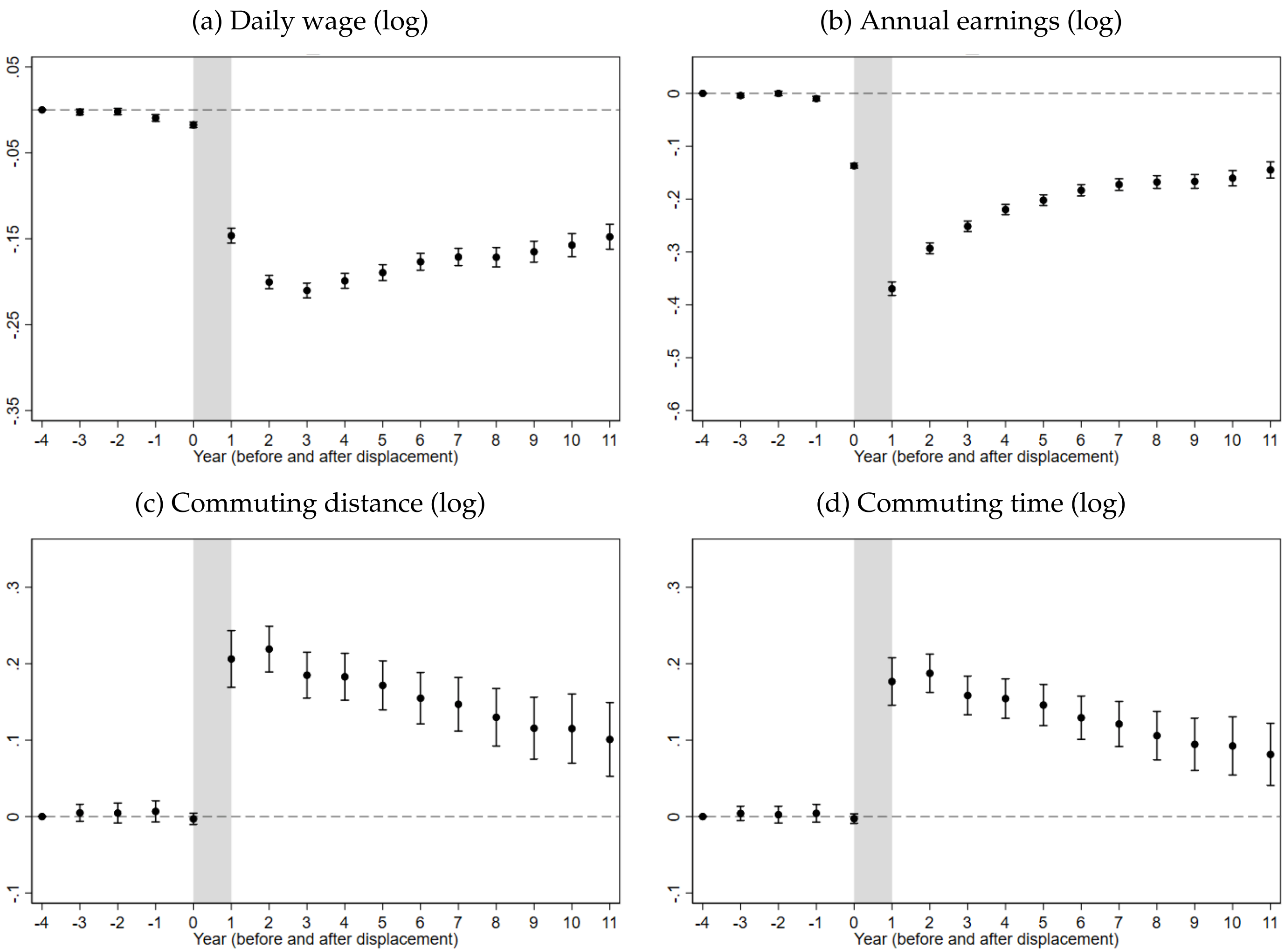
Notes: Each plot depicts estimates of model (1) with the dependent variable in the subtitle. Samples comprise a yearly panel of workers with regular jobs on June 30, excluding displaced workers recalled by their pre-displacement firms. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure A6: Robustness to Excluding Part-Time Jobs



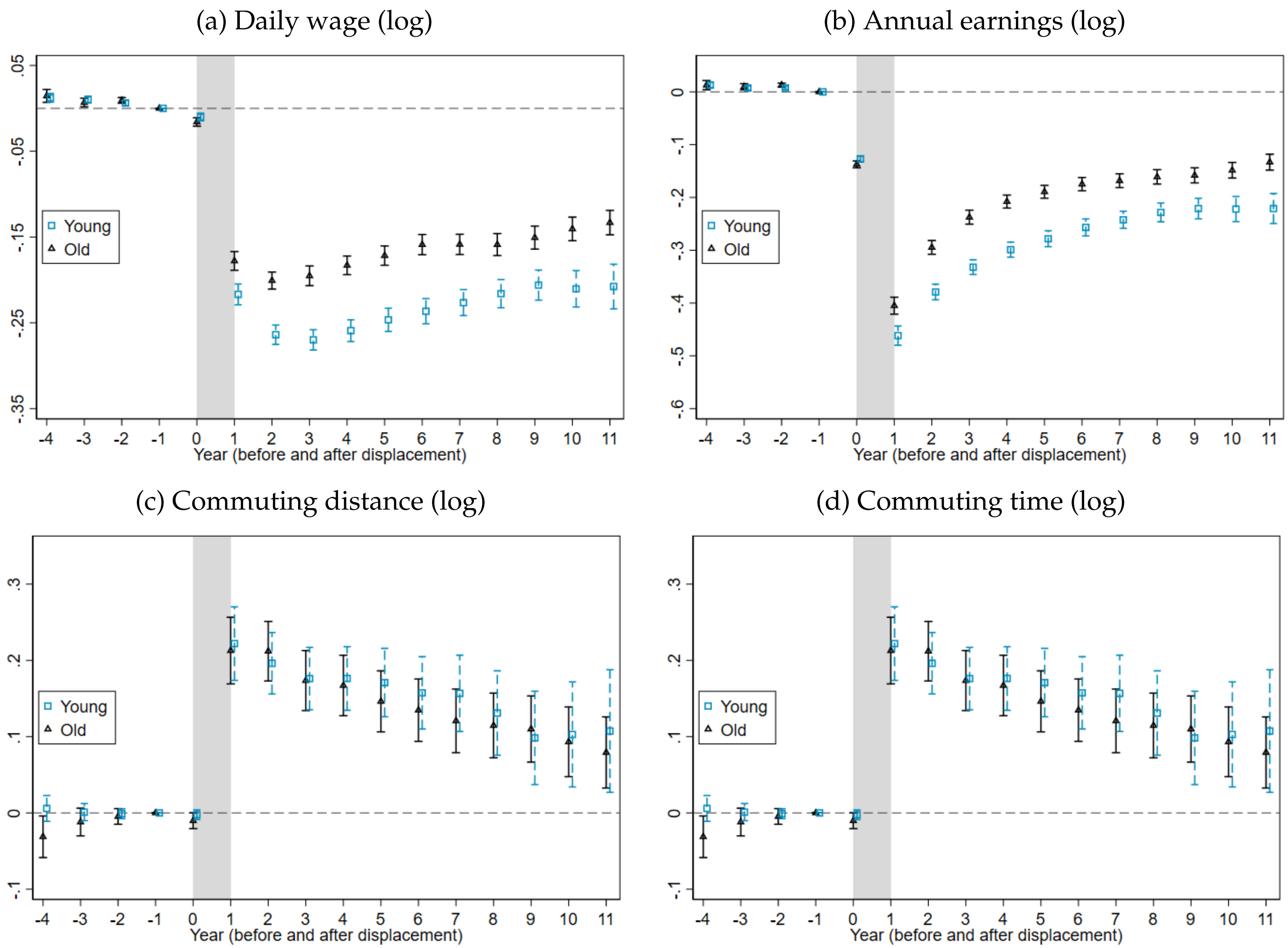
Notes: Each plot depicts estimates of model (1) with the dependent variable in the subtitle. Samples comprise a yearly panel of workers with regular jobs on June 30, limited to full-time jobs. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure A7: Robustness to Alternative Estimation Method



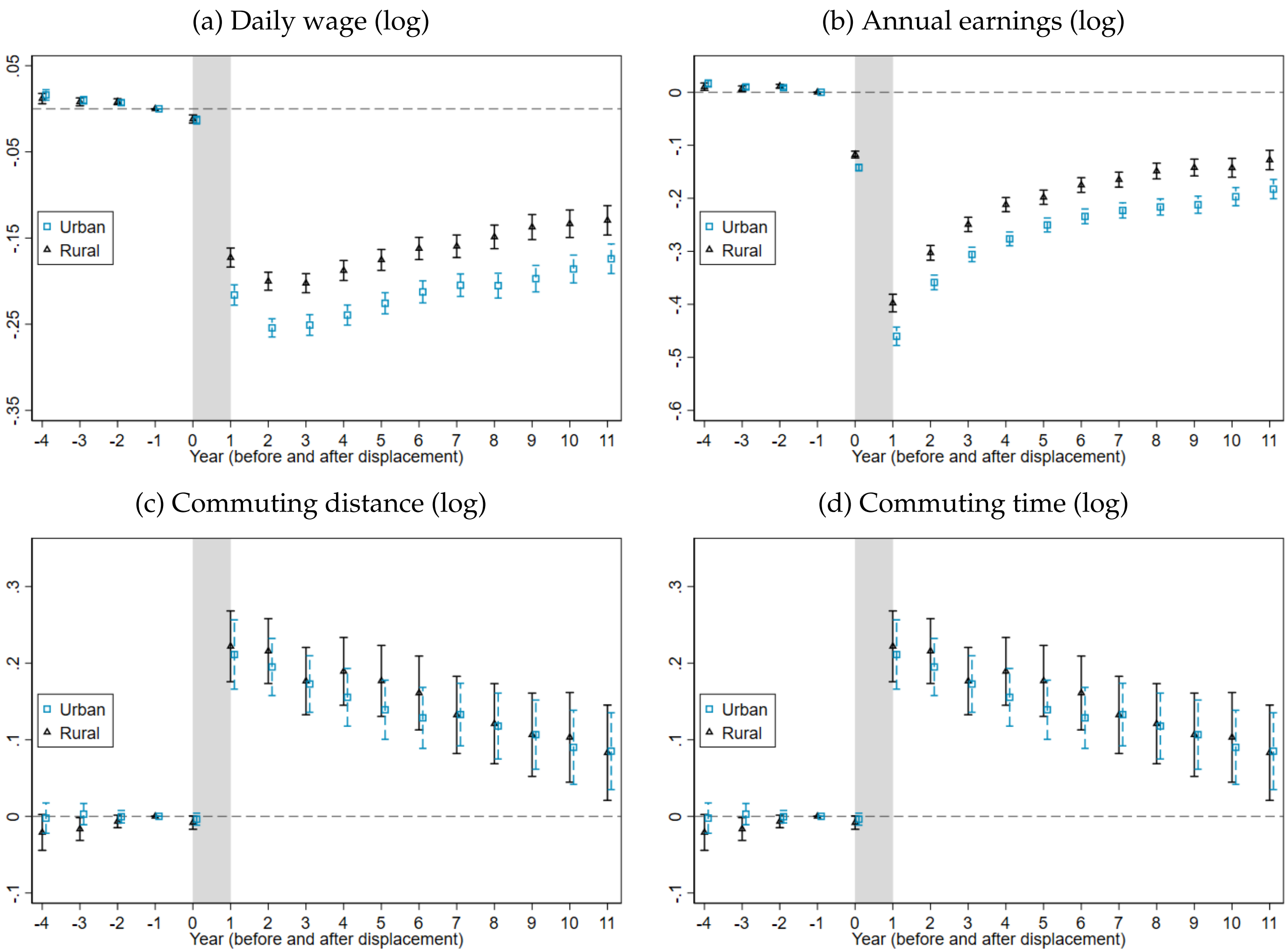
Notes: Each plot depicts estimates of model (1) with the dependent variable in the subtitle, using the imputation method of Borusyak, Jaravel, and Spiess (2021). Samples comprise a yearly panel of workers with regular jobs on June 30. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure A8: Effect Heterogeneity by Age



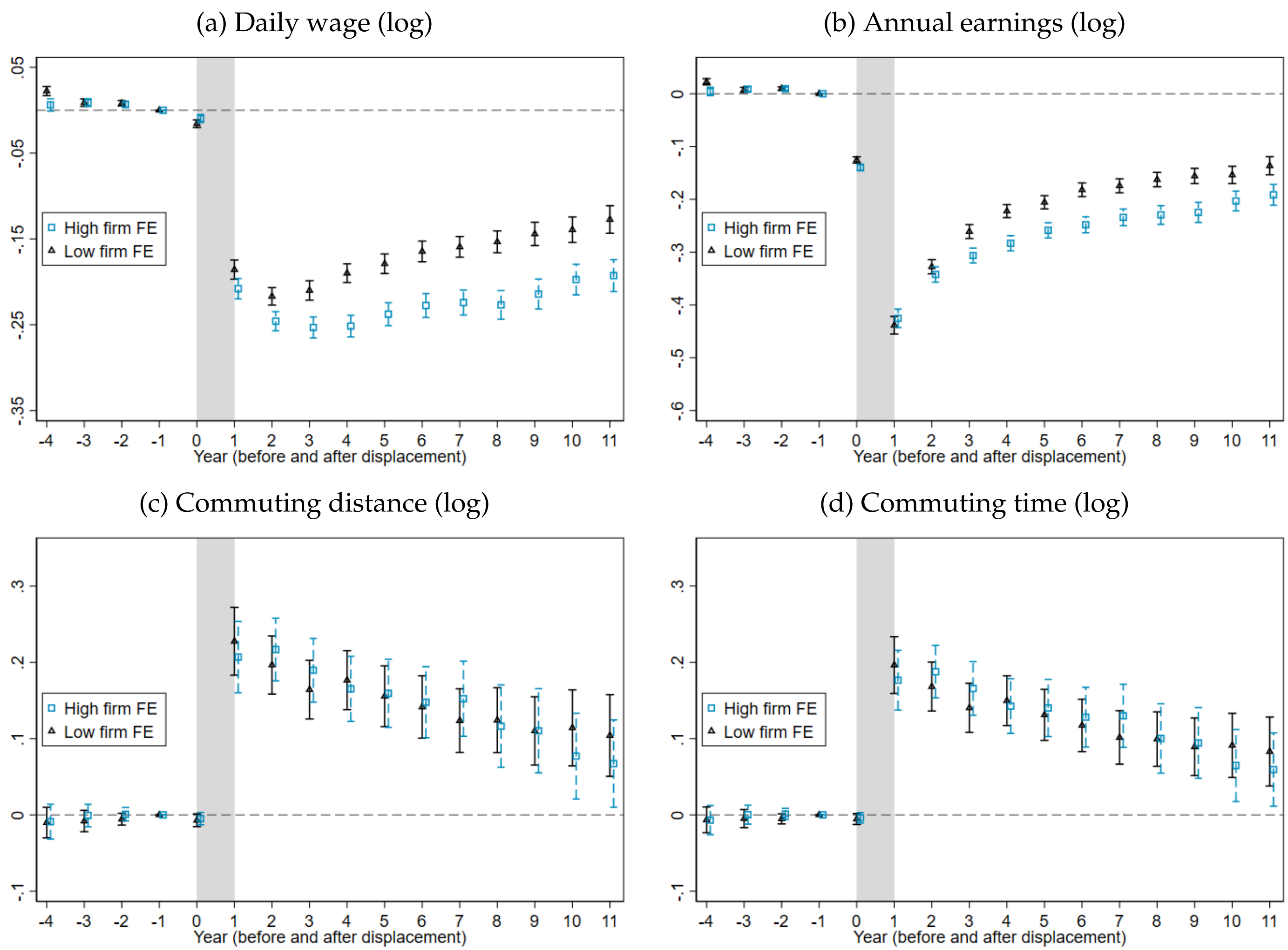
Notes: Each plot depicts estimates of model (1) with the dependent variable in the subtitle. Samples comprise a yearly panel of workers with regular jobs on June 30. The black and red markers represent workers under and over the age of 43 the displacement year, respectively. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure A9: Effect Heterogeneity by Urban and Rural Residence



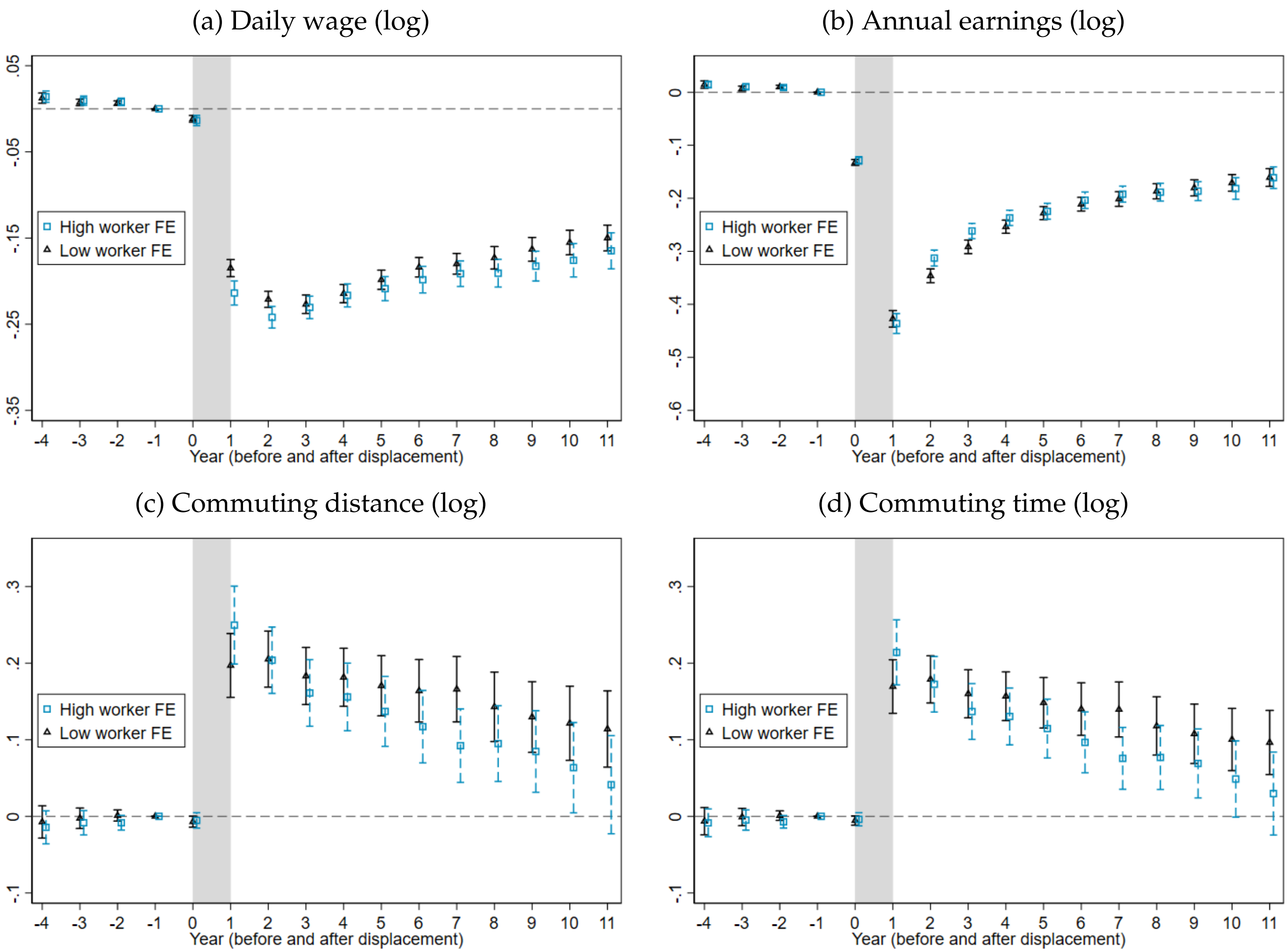
Notes: Each plot depicts estimates of model (1) with the dependent variable in the subtitle. Samples comprise a yearly panel of workers with regular jobs on June 30. The black and red markers represent workers living in urban and rural districts (*Kreise*) in the displacement year, respectively. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure A10: Effect Heterogeneity by Displacing Firms' Fixed Effects



Notes: Each plot depicts estimates of model (1) with the dependent variable in the subtitle. Samples comprise a yearly panel of workers with regular jobs on June 30. The black and red markers represent workers displaced from firms whose estimated fixed effects (Card, Heining, and Kline, 2013) are below and above the sample median, respectively. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

Figure A11: Effect Heterogeneity by Worker Fixed Effects



Notes: Each plot depicts estimates of model (1) with the dependent variable in the subtitle. Samples comprise a yearly panel of workers with regular jobs on June 30. The black and red markers represent workers whose estimated fixed effects (Card, Heining, and Kline, 2013) are below and above the sample median, respectively. The shaded area indicates the displacement year, and each dot/bar represents the point estimate/95 percent CI of β_k. All estimates control for a polynomial of age, worker fixed effects, calendar year fixed effects, and year relative to displacement fixed effects. Robust standard errors clustered by workers.

B Proof

B.1 Proof for Proposition 1

When a worker is unemployed, his total surplus $S(0)$ and surplus share $W(0,0) - U$ are both zero and cannot decrease further. When he is employed at firm type θ with outside option $\hat{\theta}$, in the next period he either moves to a new firm, renegotiates a higher wage at the current firm, or stays at the current wage. In the first two cases, his share of surplus increases according to either (6) and (7), and the total surplus either increases or stays the same. In the last case, the total surplus and the share remain unchanged. The monotonicity of $W(\theta, \hat{\theta}) - U$ follows immediately.

B.2 Proof for Proposition 2

Since the joint surplus s increases over time, it suffices to prove that the expected commuting distance declines, and the expected productivity increases in s.

Lemma 1. *The surplus function S strictly increases in y and strictly decreases in r.*

Proof. See Jarosch (2021). □

Lemma 2. *The surplus function S is continuous and linear in y and $c(r)$ with opposite slopes.*

Proof. Prove by contradiction. Suppose S is linear in y and $c(r)$ with opposite slopes, such that $y_1 - c(d_1) = y_2 - c(d_2)$, but $S(y_1, r_1) \neq S(y_2, r_2)$. Then (11) implies

$$S(y_1, r_1) - S(y_2, r_2) = \frac{\eta \lambda_1 (1 + \alpha)}{1 - \eta} \int \left\{ [S(x) - S(y_1, r_1)]^+ - [S(x) - S(y_2, r_2)]^+ \right\} dF_\theta(x), \tag{B.1}$$

which is not possible because the two sides have different signs. Continuity can be proved in an analogous way. □

As a result, we can express the surplus function as $S(y, r) = a(y - c(r) + b)$ for some constants $a > 0$ and b. Let $L_s = \{(y, r) : S(y, r) = s, r \geq 0\}$ denote the isosurplus curve corresponding to the surplus level s. To circumvent the unknown function c, we define $\tilde{L}_s = \{(y, c) : S(y, c) = s, c \geq 0\}$, the isomorphism of L_s in the space of (y, c). Along this curve, we have $c = y - s/a + b$.

The expectation of y conditional on s is given by

$$\mathbf{E}[y|s] = \int_{\tilde{L}_s} y dF(y, c|s), \tag{B.2}$$

where $F(y, c|s)$ is the conditional distribution of (y, c) given $\tilde{L}_s$. By independence of y and $c(r)$, the density function is

$$f(y, c|s) = \frac{f_y(y) f_c(c)}{\int_{\tilde{L}_s} dF(y, c|s)} = \frac{f_y(y) f_c\left(y - \frac{s}{a} + b\right)}{\int_{y_s}^{\bar{y}} f_y(y) f_c\left(y - \frac{s}{a} + b\right) \sqrt{2} dy}. \tag{B.3}$$

where $y_s = s/a - b$ is the intercept of $\tilde{L}_s$ on the (y, c)-plane.

Plug (B.3) into (B.2),

$$\mathbf{E}[y|s] = \frac{\int_{y_s}^{\bar{y}} y f_y(y) f_c\left(y - \frac{s}{a} + b\right) dy}{\int_{y_s}^{\bar{y}} f_y(y) f_c\left(y - \frac{s}{a} + b\right) dy} \equiv \frac{Y_1}{Y_2}. \tag{B.4}$$

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

$$Y_1' = -\frac{1}{a} \int_{y_s}^{\bar{y}} y f_y(y) f_c'\left(y - \frac{s}{a} + b\right) dy - \frac{1}{a} y_s f_y(y_s) f_c(0) \tag{B.5}$$

$$Y_2' = -\frac{1}{a} \int_{y_s}^{\bar{y}} f_y(y) f_c'\left(y - \frac{s}{a} + b\right) dy - \frac{1}{a} f_y(y_s) f_c(0) \tag{B.6}$$

Note that

$$f_y(y_s) f_c(0) \left[\int_{y_s}^{\bar{y}} (y - y_s) f_y(y) f_c\left(y - \frac{s}{a} + b\right) dy\right] > 0, \tag{B.7}$$

$$\frac{\int_{y_s}^{\bar{y}} y f_y(y) f_c'\left(y - \frac{s}{a} + b\right) dy}{\int_{y_s}^{\bar{y}} f_y(y) f_c\left(y - \frac{s}{a} + b\right) dy} = \mathbf{E}\left[y \frac{f_c'(c)}{f_c(c)} \middle| s \right], \tag{B.8}$$

$$\frac{\int_{y_s}^{\bar{y}} f_y(y) f_c'\left(y - \frac{s}{a} + b\right) dy}{\int_{y_s}^{\bar{y}} f_y(y) f_c\left(y - \frac{s}{a} + b\right) dy} = \mathbf{E}\left[\frac{f_c'(c)}{f_c(c)} \middle| s \right], \tag{B.9}$$

and, because y and $f'_c(c)/f_c(c)$ are negatively correlated on $\tilde{L}_s$,

$$\mathrm{Cov}\left(y, \frac{f'_c(c)}{f_c(c)}\bigg| s\right) = \mathbf{E}\left[y\frac{f'_c(c)}{f_c(c)}\bigg| s\right] - \mathbf{E}\left[\frac{f'_c(c)}{f_c(c)}\bigg| s\right]\mathbf{E}\left[y|\, s\right] < 0. \tag{B.10}$$

Combining (B.7)-(B.10), we can find

$$\frac{\partial \mathbf{E}[y|s]}{\partial s} = \frac{Y_1'Y_2 - Y_2'Y_1}{Y_2^2} > 0, \tag{B.11}$$

Analogously, the expectation of r conditional on s is given by

$$\mathbf{E}[r|s] = \int_{\tilde{L}_s} \mathbf{c}(c)dF(y, c|s), \tag{B.12}$$

where $\mathbf{c}(\cdot) = c^{-1}(\cdot)$. As before, rewrite

$$\mathbf{E}[r|s] = \frac{\int_0^{\bar{c}_s} \mathbf{c}(c) f_y\left(c + \frac{s}{a} - b\right) f_c(c)dc}{\int_0^{\bar{c}_s} f_y\left(c + \frac{s}{a} - b\right) f_c(c)dc} \equiv \frac{R_1}{R_2}. \tag{B.13}$$

where $\bar{c}_s = (\bar{y} - s/a + b)$.

The derivatives of R_1 and R_2 with respect to s are, respectively,

$$R_1' = -\frac{1}{a}\mathbf{c}(\bar{c}_s)f_y(\bar{y})f_c(\bar{c}_s) + \frac{1}{a}\int_0^{\bar{c}_s} \mathbf{c}(c)f_y'\left(c + \frac{s}{a} - b\right) f_c(c)dc, \tag{B.14}$$

$$R_2' = -\frac{1}{a}f_y(\bar{y})f_c(\bar{c}_s) + \frac{1}{a}\int_0^{\bar{c}_s} f_y'\left(c + \frac{s}{a} - b\right) f_c(c)dc, \tag{B.15}$$

Since $\mathbf{c}(c) - \mathbf{c}(\bar{c}_s) < 0$,

$$f_y(\bar{y})f_c(\bar{c}_s)\int_0^{\bar{c}_s} (\mathbf{c}(c) - \mathbf{c}(\bar{c}_s))f_y\left(c + \frac{s}{a} - b\right) f_c(c)dc < 0 \tag{B.16}$$

Following the previous steps,

$$\frac{\int_0^{\bar{c}_s} \mathbf{c}(c)f_y'\left(c + \frac{s}{a} - b\right) f_c(c)dc}{\int_0^{\bar{c}_s} f_y\left(c + \frac{s}{a} - b\right) f_c(c)dc} = \mathbf{E}\left[\mathbf{c}(c)\frac{f_y'(y)}{f_y(y)}\bigg| s\right], \tag{B.17}$$

$$\frac{\int_0^{\bar{c}_s} f_y'\left(c+\frac{s}{a}-b\right) f_c(c)dc}{\int_0^{\bar{c}_s} f_y\left(c+\frac{s}{a}-b\right) f_c(c)dc} = \mathbf{E}\left[\left.\frac{f_y'(y)}{f_y(y)}\right| s\right]. \tag{B.18}$$

$$\text{Cov}\left(\mathbf{c}(c), \left.\frac{f_y'(y)}{f_y(y)}\right| s\right) < 0. \tag{B.19}$$

Combining (B.16)-(B.19), we can find

$$\frac{\partial \mathbf{E}[r|s]}{\partial s} = \frac{R_1' R_2 - R_2' R_1}{R_2^2} < 0. \tag{B.20}$$

C Model Extensions

C.1 Endogenous Job Search Effort

In this subsection, we extend our model to allow for endogenous search effort. Suppose the worker pays a search cost $h(R)$ to receive job offers from his neighboring locations $[0, R]$, where $h(R)$ is increasing and convex in the radius R. The increasing cost of search with respect to distance has been established in the empirical literature (Manning and Petrongolo, 2017; Marinescu and Rathelot, 2018). For traceability, we assume y and r are independent.

With the search cost, the value functions of unemployed and employed workers become

$$\begin{aligned} U = \max_R \Big\{ & z - h(R) + \beta \Big[\lambda_0 \int_0^R \int_{c(r)-b}^{\bar{y}} W(y, r, y_0, 0) dF_y(y) dF_r(r) \\ & + (1 - \lambda_0 p_1(u)) U \Big] \Big\}, \end{aligned} \tag{C.1}$$

$$\begin{aligned} W(y, r, \hat{y}, \hat{r}) = \max_R \Big\{ & w(y, r, \hat{y}, \hat{r}) - c(r) - h(R) + \beta \delta U \\ & + \beta(1-\delta)\lambda_1 \int_0^R \int_{c(r') + \frac{S(y,r)}{a} - b}^{\bar{y}} W(y', r', y, r) dF_y(y') dF_r(r') \\ & + \beta(1-\delta)\lambda_1 \int_0^R \int_{c(r') + \frac{S(\hat{y},\hat{r})}{a} - b}^{c(r') + \frac{S(y,r)}{a} - b} W(y, r, y', r') dF_y(y') dF_r(r') \\ & + \beta(1-\delta) \left(1 - \lambda_1 \int_0^R \int_{c(r') + \frac{S(\hat{y},\hat{r})}{a} - b}^{\bar{y}} dF_y(y') dF_r(r') \right) W(y, r, \hat{y}, \hat{r}) \Big\}. \end{aligned} \tag{C.2}$$

In either case, the optimal search radius R^* satisfies

$$h'(R^*; u) = \beta \lambda_0 \int_{c(R^*)-b}^{\bar{y}} W(y, R^*, y_0, 0) dF_y(y). \tag{C.3}$$

$$\begin{aligned} h'(R^*; y, r, \hat{y}, \hat{r}) = & \beta(1-\delta)\lambda_1 \Big\{ \int_{c(R^*) + \frac{S(y,r)}{a} - b}^{\bar{y}} \left[W(y', R^*, y, r) - W(y, r, \hat{y}, \hat{r}) \right] dF_y(y') \\ & + \int_{c(R^*) + \frac{S(\hat{y},\hat{r})}{a} - b}^{c(R^*) + \frac{S(y,r)}{a} - b} \left[W(y, r, y', R^*) - W(y, r, \hat{y}, \hat{r}) \right] dF_y(y') \Big\}. \end{aligned} \tag{C.4}$$

Note that $h'(R)$ is the increasing marginal cost of search, and the right-hand side (RHS) of (C.3) and (C.4) are the present-value marginal payoffs from search. Since $W(y, r, \hat{y}, \hat{r})$ decreases in r and $\hat{r}$, the RHS diminishes in R, so R^* is unique.

A natural question that arises here is whether the optimal search radius decreases during the recovery from displacement. To answer this question, we use (6)-(7) to rewrite the RHS of (C.4) as $\beta(1-\delta)\lambda_1$ times

$$\alpha \int_{c(R^*)+\frac{S(y,r)}{a}-b}^{\bar{y}} [S(y',R^*) - S(y,r)]dF_y(y') + (1-\alpha)\int_{c(R^*)+\frac{S(\hat{y},\hat{r})}{a}-b}^{\bar{y}} [S(y,r) - S(\hat{y},\hat{r})]dF_y(y') \tag{C.5}$$

Note that (C.5) decreases in $S(\hat{y},\hat{r})$. Therefore, a greater outside option lowers the marginal payoff from search, thereby reducing the optimal search radius.[8]

Proposition 3. *The optimal search radius R^**
(i) decreases in $S(\hat{y},\hat{r})$;
(ii) decreases in $S(y,r)$ if α is sufficiently large.

Proof. Examine the partial derivatives of (C.5) with respect to $S(\hat{y},\hat{r})$ and $S(y,r)$. □

The first part of Proposition 3 suggests that, following a wage renegotiation with the current employer, a worker will optimally reduce his search radius because $S(\hat{y},\hat{r})$ increases while $S(y,r)$ remains unchanged. However, the second part implies that if the worker moves to another firm, the search radius unambiguously decreases only if the worker appropriates a large share α of the additional surplus.

C.2 Heterogeneous Job Security

In the second extension, we consider heterogeneous job separation rates. Assume δ is firm-specific and distributed in the support $(0,1)$. With slight abuse of notation, we let $\theta = (y,r,\delta)$ include the separation rate as a third attribute of the firm. Rearranging (11) yields

$$y = c(r) + \delta G(S(\theta)) + H(S(\theta)). \tag{C.6}$$

where

$$G(s) = \beta\left[s + \lambda_1(1+\alpha)\int [S(x)-s]^+ dF_\theta(x)\right], \tag{C.7}$$

$$H(s) = s - \beta\left[s + \lambda_1(1+\alpha)\int [S(x)-s]^+ dF_\theta(x) + \lambda_0 \int [S(x)]^+ dF_\theta(x)\right]. \tag{C.8}$$

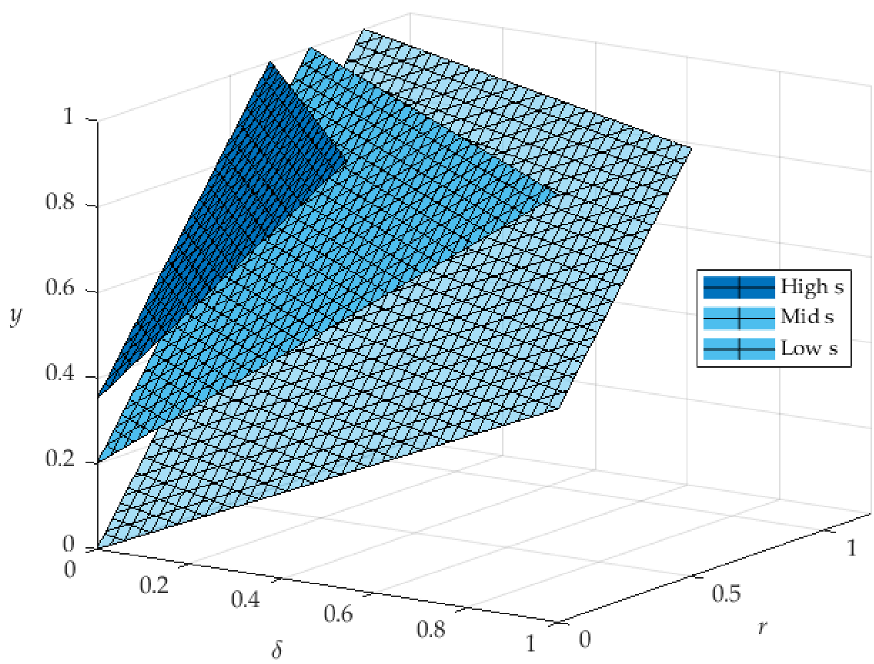
As such, y, δ, and $c(r)$ are linearly dependent given surplus level $S(\theta)$. It is easy to verify that S strictly decreases in δ and both G and H increase in s.

[8] Guglielminetti et al. (2019) suggest the exhaustion of unemployment benefits as a countervailing force driving up the search radius over time. However, this effect is muted once the worker finds a job after displacement.

Analogous to (11), (C.6) defines an *isosurplus surface* on the three-dimensional job space $[\underline{y}, \bar{y}] \times \mathbf{R}_+ \times (0,1)$. As depicted in Figure C1, a higher surface indicates a higher surplus; besides, the maximum job separation rate and maximum distance both decrease in the surplus level. By a similar argument to Proposition 2, workers enjoy increased job security as they recover from job loss.

The above results differ from Jarosch (2021) in that we assume firm productivity and separation rate are independent. As such, their joint recovery is explicitly driven by workers' tradeoffs rather than mechanical correlation between the two attributes. It is worth noting that our framework can be generalized to incorporate multiple firm attributes.

Figure C1: Isosurplus Surfaces with $c(r) = r$



Notes: This figure depicts three isosurplus surfaces under the assumption $c(r) = r$. The support of productivity y, distance r, and separation rate δ are given by $[\underline{y}, \bar{y}] = [0, 1]$, $\mathbf{R}_+$, and $(0, 1)$, respectively.