Job Displacement Scars over the Earnings Distribution

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Abstract:

Workers who are displaced from their job experience a well-documented scarring effect: a large and persistent average earnings loss. However, these average effects mask a substantial amount of heterogeneity along a number of observable dimensions. In this paper, I explore how the scarring effect of job displacement differs by the affected workers' earnings prior to displacement. I use detailed administrative data from Germany to empirically analyze this dimension. I find that earnings losses, relative to pre-displacement earnings, are larger for individuals whose recent earnings situate them at the bottom of the earnings distribution. This seemingly contradicts existing models that can account for the average scarring effect, as these are generally based on the idea of a job ladder, and thus imply that workers at the top of the earnings distribution should suffer from (relatively) larger earnings losses. I then propose a model in which displaced workers do not fall off the ladder completely if they find a new job shortly after being displaced. Rather, the size of their drop is determined by the characteristics of the firm they were laid off from. I show that this framework enables the model to explain the relatively larger earnings losses at the bottom of the earnings distribution.

JEL Classifications: E24, J21, J24, J62, J63, J64, J65
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1 Introduction

On average, workers who lose their job experience a large and persistent earnings loss. The size and persistence of this average earnings loss has been well documented in the literature (see e.g. Jacobson et al., 1993). Naturally, by focusing on the average earnings losses, one ignores the fact that these earnings losses exhibit a substantial amount of heterogeneity: some workers may never find a new job again, whereas other workers may in fact experience an increase in earnings after their displacement. Some of this heterogeneity may be driven by factors that may not be known at the time of the layoff (such as the probability of finding a job vacancy that provides a high quality match for the displaced worker). However, some of the factors driving this heterogeneity may reflect factors that also affected the worker's previous earnings (such as the worker's education level). As a result, one might therefore expect earnings losses after displacement to differ by the worker's earnings history.

In this paper, I study how the long-run effects of job displacement on earnings differ by the affected workers' pre-displacement earnings. These pre-displacement earnings can be thought of as summarizing a set of worker characteristics, but may itself be a dimension of interest as well. After all, differences in earnings losses by pre-displacement earnings could be informative if we are interested in whether job loss tends to increase or decrease income inequality. Furthermore, since existing models that are able to account for average earnings losses will also have tracked the worker's previous earnings, one could think of this as a test for the extent to which these existing models are able to capture heterogeneity in the earnings losses.

Using detailed administrative data from Germany, I show that earnings losses (relative to pre-displacement earnings) are larger for workers with lower pre-displacement earnings. This result can be obtained from plotting the raw data, and remains intact when estimating the earnings losses using an event study framework (estimated using the imputation-based method from Borusyak et al., 2023). This is in line with existing evidence from Guvenen et al. (2017), who come to a similar conclusion in the context of the United States, although they focus on full-year nonemployment instead. Additionally, I show that this gradient in earnings losses is primarily driven by workers who transition to a new job very shortly after losing their job. As such, losses in employment are fairly constant over the earnings distribution.

The result that relative earnings losses are higher for workers with low pre-displacement earnings seemingly contradicts existing models that have been successful in accounting for the average earnings loss after displacement. These models (see the next subsection for a brief overview) generally rely on the idea of a job ladder: over time, workers climb this ladder towards higher productivity (and/or wage) jobs, and if the worker is displaced they lose their place on the ladder and have to start from the bottom again. Following such models, one would expect earnings losses after displacement to be higher (rather than lower) for workers who have high pre-displacement earnings, as these workers would be situated at the top of the job ladder. In other words, these job ladder models would predict the opposite result from the one I document from the data.

In order to reconcile the empirical results with the existing models that can account for the average earnings loss after displacement, I propose a search model of the labor market in which workers climb the job ladder, but do not necessarily lose their position on the ladder if they are displaced. Reflecting the observation that the empirical results were largely driven by workers who transition quickly to their new job, the model allows for workers to draw jobs from a productivity distribution that is truncated from the bottom if they meet with a firm in the same period as the displacement. The extent to which the productivity distribution is truncated is firm-specific, and can therefore be seen as a third firm (or match) characteristic, along with the firm's productivity and stability. While I cannot provide any direct evidence of this in the data, my interpretation of this truncation is that it is the consequence of workers being able to leverage their network to quickly obtain a new job. This could either be through intervention of the displacing firm or through the worker using their personal network. For work empirically investigating this, see Cingano and Rosolia (2012), Bayer et al. (2008), and Eliason et al. (2022), among others. If the worker does not meet with another firm immediately upon displacement, they lose their connection to the firm and can therefore no longer rely on the accompanying network. In such cases, the model dynamics revert back to those of a standard job ladder model.

I calibrate the model using the German administrative data, and show that the model is able to match the observed gradient in post-displacement earnings losses over the pre-displacement earnings distribution. Just like in the data, this result is primarily driven by workers transitioning immediately into a new job. However, in the model's current form, this is exclusively driven by a composition effect, whereas within groups who transition immediately or do not do so, the pattern of earnings losses do not line up with the observations from the data. Ongoing work on this project is working to address this.

The rest of this paper is organized as follows: After briefly reviewing the related literature in the next subsection, Section 2 describes the data and methodology used to generate the empirical results. These empirical results are presented in Section 3. Section 4 then presents the model, after which Section 5 covers the estimation of the model. Section 6 contains the quantitative analysis of the model. In this Section, I show that the model can indeed recover the heterogeneity observed in the data, and discuss the drivers and implications of these observations. Finally, Section 7 concludes.

1.1 Related Literature

By investigating how earnings losses after job displacement vary by pre-displacement earnings, this paper contributes to the extensive literature on job displacement. This literature goes back to the seminal work of Jacobson et al. (1993), who found sizeable and persistent earnings losses among workers displaced in 1982 in Pennsylvania, a result that has since been replicated in many other settings around the world.[1] While most of this work has focused on earnings, there also exists a large amount of work looking at other outcomes, such as Lachowska et al. (2020) who decompose earnings losses into hours and wages, finding a large role in particular for wages in explaining the earnings losses in the long run.

In recent years, this literature has turned towards investigating heterogeneity in post-displacement earnings along many dimensions. One of the first examples of this is Guvenen et al. (2017) who investigate how the earnings consequences of a full-year of nonemployment differ by the worker's pre-separation earnings. As mentioned above, their results seem consistent with the results I obtain from the German data. However, it should be noted that the structure of their data does not allow them to include workers who transition immediately into a new job following a separation. The results in Section 3 indicate that these workers are the main driver of the heterogeneity by recent earnings in the German data, whereas workers who spend time in nonemployment show a much weaker pattern. In that sense, my results are more in line with Fallick et al. (2021), who find an important role for duration of joblessness in explaining earnings consequences regardless of whether or not the worker was displaced, and with Karahan et al. (2022), who find increasing earnings growth over the lifetime earnings distribution especially for job switchers.
A number of recent papers, Gulyas and Pytka (2020) and Athey et al. (2022), have turned to machine learning methods to investigate which dimensions of heterogeneity are most important in explaining earnings losses. Although the methods used by these papers are very different from the

[1] Examples include Von Wachter et al. (2009) for the United States, and Burda and Mertens (2001) for Germany. Furthermore, Bertheau et al. (2022) is able to connect some of this work by providing a comparison between a number of European countries.

method I use in this paper, it is worth pointing out that while Gulyas and Pytka (2020) finds that earnings losses are strongly increasing in firm-specific wage components, thus seemingly contradicting my findings in Section 3, Athey et al. (2022) finds that earnings losses are largest in the bottom parts of the earnings distribution, in line with my findings.

Given the suitability of the German administrative data I use in this paper for estimating earnings losses after displacement, it is not surprising that this is not the first paper that uses this data (or closely related data) to estimate heterogeneity in these post-displacement earnings losses along a number of dimensions. Examples of dimensions investigated in existing work include gender (Illing et al., 2021), firm characteristics (Schmieder et al., 2020), firm wage premiums and employer size (Fackler et al., 2021), ex-post recall status (Leenders, 2022), and age at the time of displacement (Albrecht, 2022).

By proposing a model that reconciles the existing literature with the results found in the empirical section of this paper, I also contribute to the literature that aims to provide a theoretical analysis of the long-term earnings consequences experienced by displaced workers. This strand of the literature is more recent than the aforementioned empirical strand of the literature, with earlier work (such as Davis and Von Wachter, 2011) mainly stressing the inability of standard job search models to generate the large and persistent average earnings losses found in the empirical literature. In recent years, however, a number of models have been proposed that can successfully generate the size and persistence of the earnings loss. The model I propose in Section 4 builds on the model in Jarosch (2021), who proposed a framework in which firms differ in separation rates (as well as productivity), thereby allowing for repeated job losses as observed in the data (see e.g. Stevens (1997)). Other models that have been able to successfully explain average earnings losses generally also include some form of human capital depreciation (with Burdett et al. (2020) stressing this channel in particular) as well as heterogeneous matches in terms of productivity, but stress other factors instead of the aforementioned heterogeneous separation rates. Examples of such factors include stochastic match quality (Krolikowski, 2017), life cycle dynamics and endogenous search effort (Hubmer, 2018), lack of mean reversion among non-displaced workers (Jung and Kuhn, 2019), occupational switching and business cycles (Huckfeldt, 2022), and heterogeneous fixed worker types (Gregory et al., 2021). By building on the model from Jarosch (2021), I abstract from all of these features, although the extension I propose in this paper could also be applied to many of these models.

2 Data and Empirical Methodology

The empirical results presented in the next section are generated using administrative data from the German Federal Employment Agency's (BA) Institute for Employment Research (IAB). In particular, I use the Linked-Employer-Employee Dataset (LIAB, Ruf et al., 2021b). This dataset samples establishments[2] from the Establishment Panel and matches these establishments to individuals employed at these establishments (any time between 2002 and 2012). For all these individuals, the complete individual history is available (from the Integrated Employment Biographies, covering 1975 to 2019). For more information on the construction of this dataset, see Ruf et al. (2021a).

In the original data, each individual observation corresponds to one spell of employment or non-employment, marked by a start and end date, whereas observations at the establishment level are yearly. Using the observed establishment ID of the individual's main employer, I construct a yearly (and quarterly) linked employer-employee dataset.[3] Further restricting observations to those aged between 25 and 60 leads to a large dataset, which is used to generate the empirical results (using the yearly data) and calculate the moment values used in the model estimation (using the quarterly data).[4]

Throughout the empirical sections of this paper, I refer to both separation and displacement. These are two different concepts, with displacement following a stricter definition. In the data, I define a worker as separated in some period t if this worker's employment spell with their establishment ends in period t. This means that the worker either no longer works for the same establishment in period $t+1$ or returned to the establishment after being away for more than 31 days. In doing so, I omit workers who are trainees, casual workers, or partially retired workers. In order to define displacement, I further focus on workers whose social security notification indicates that employment at the establishment ended for a reason that could point to displacement.[5] Further-

[2] An establishment is defined as the combination of all locations of a firm in a municipality.

[3] Generally, the main employer corresponds to the establishment at which the individual was employed on the first day of the year/quarter. If the individual is non-employed at the start of the year/quarter (or employed at multiple establishments), the information is used for the establishment from which the individual has the highest earning in that period.

[4] Gaps occur in the dataset because not all forms of employment or non-employment are recorded. In particular, individuals are generally not observed if they are employed for the government, if they are self-employed, or if they are not receiving any social security benefits during nonemployment. While I can fill these gaps for variables that can reasonably be interpolated (such as age and location), key information such as earnings will remain missing, thus leading to these observations being omitted from estimation procedures.

[5] This way, I exclude apparent separations that are caused by paternity or maternity leave, disease, or seasonal

more, I require that the establishment that the worker separates from either closes or experiences a mass layoff, so that the workers are not necessarily laid off because of their own productivity (which could bias the empirical results) but rather due establishment-wide conditions.[6] I follow the literature by defining a mass layoff as a decrease in the establishment's workforce such that the workforce in the next period is at most 80% of the establishment's maximum workforce over the previous five years, and the establishment has a net outflow of at least 20% of its workforce in the displacement year.[7]

In order to form a measure of how high a worker's pre-displacement earnings are, I construct a recent earnings distribution. In doing so, I largely follow Guvenen et al. (2017). In general, a worker's recent earnings in year y refer to their average earnings between years $y-5$ to $y-1$. To be more specific, this average is formed over all years with admissible observations in that period (conditional on having at least 3 admissible observations to average over, one of which must be from year $y-1$), where an observation is admissible if the worker is aged between 25 and 60, and is not self-employed. The recent earnings distribution is then formed by ranking workers for each combination of year, gender, location, and age group, further restricting the sample to individuals who are not self-employed either 1, 2, 3, 5, or 10 years ahead.[8]

The empirical results presented in the next section are largely based on either raw data comparisons or estimations of an event study framework. The event study results are obtained using the imputation-based estimator proposed in Borusyak et al. (2023). By using this estimator, rather than a standard two-way fixed effects estimator, I can allow for the effect of displacement to differ by the year of displacement. When estimating the average effect of job displacement, one can think of this as estimating the following equation:

$$e_{it} = \alpha_i + \gamma_t + \sum_{C \neq 0} \sum_{k=-1}^{K} \delta_k^C D_{it}^{C,k} + u_{it} \tag{1}$$

patterns in employment.

[6]I use an extension file that clarifies the reason for an establishment leaving the sample. This allows me to avoid including mergers or partial closures (e.g. closure of one location of the firm only), as it allows me to see whether a large portion of the workers at the establishment finds employment at a common establishment after the closure. In doing so, I use the thresholds as proposed in Hethey and Schmieder (2010).

[7]For establishments with up to 20 employees, I use a threshold of 50% for both these conditions. However, as explained later in this section, these mass layoffs are generally not used for estimation purposes.

[8]Here, the two age groups are prime-age (35 to 60) and young (below 35), and the two locations considered are East and West, corresponding to the locations formerly belonging to East and West Germany (with the exception of Berlin, which is classified as East in its entirety).

In Equation (1), the subscript i and t refer to the individual and year, respectively. The outcome variable, e_{it}, will in most cases refer to the individual's yearly earnings (in year t), but may also represent a different outcome, such as the fraction of the year spent in employment. The explanatory variables include and individual and time fixed effect, α_i and γ_t, as well as an error term u_{it}, but the main coefficients of interest (δ_k^C) are embedded within the summation. These coefficients indicate the effect of the indicator variable $D_{it}^{C,k}$, which indicates that the individual i was displaced k periods ago in period t (in other words, they were displaced in period $t-k$), where the year of displacement equals C (referred to as the cohort). The cohort $C = 0$ refers to the group who was never displaced, and this group acts as the control group in the estimation. Furthermore, note that the treatment effect is allowed to take effect one period before displacement, thus allowing for anticipation effects. In order to estimate Equation (1), the imputation-based method calls for first estimating the fixed effects in an estimation where only the never-treated (cohort $C = 0$) and not-yet-treated observations (individuals in a cohort $C \neq 0$, but observed for $k < -1$) are used. The resulting estimated fixed effects can then be used to form the counterfactual outcome, and the difference between this counterfactual outcome and the observed outcome e_{it} is the individual treatment effect. These individual treatment effects are then averaged across all observations with the same combination of C and k to obtain the estimate $\hat{\delta}_k^C$.[9] Finally, in order to enhance the interpretability of the resulting set of estimates $\hat{\delta}_k^C$, I divide them by the average outcome value for the control group in the corresponding year t, and subsequently take a weighted average over cohorts, where the weight is determined by the number of observations for a combination (C, k) relative to the total number of observations for k.[10] The resulting weighted average $\hat{\delta}_k$ can then be plotted over k to generate an event study graph.

$$e_{it} = \alpha_i + \gamma_t + \sum_{C \neq 0} \sum_{p=1}^{P} \sum_{k=-1}^{K} \delta_{k,p}^{C} D_{it}^{C,k,p} + u_{it} \tag{2}$$

When focusing on how the earnings losses after job displacement differ by pre-displacement earnings, I further divide each cohort C into P quantiles, where each quantile covers an equal-sized part of the recent earnings distribution. In practice, this implies that the estimated equation in-

[9] In order to obtain the standard errors that are used to construct confidence intervals, I use the difference between the individual treatment effect and the estimate $\hat{\delta}_k^C$.

[10] An alternative to this method of estimating the relative earnings path is to estimate Equation (1) using log earnings instead. I decided against this, as the data includes many observations with zero earnings, which I would need to omit in order to run this alternative estimation.

cludes an extra sum, as shown in Equation (2) above. Nevertheless, the remainder of the procedure remains the same, such that the result of the procedure is now an event study graph that includes P lines rather than just one. As P increases, the resulting graph becomes increasingly hard to read, which is why I choose to plot the resulting coordinates over p rather than over k, restricting the number of lines to only reflect a select number of leads k rather than the entire horizon $[-1, K]$. In Appendix C.1, I further elaborate on how these graphs are constructed, using a simple example with $P = 3$ for which the regular event study graph (over time) is still reasonably readable.

When estimating the equations discussed above, I follow the literature by restricting my sample to individuals working at an establishment with at least 50 employees (to avoid classifying a job loss as a mass layoff when only a limited amount of workers loses their job) and a pre-displacement establishment tenure of at least 6 years. However, I show in Appendix **??** that the results continue to hold if I only require workers to have at least 1 year of pre-displacement establishment tenure.

3 Empirical Results

In this section, I present the results of the analysis of the German data. In particular, in Subsection 3.1, I describe the incidence of separation, displacement, and job-to-job transitions (upon displacement) over the recent earnings distribution, as well the correlation between the worker's position on the recent earnings distribution and the establishment fixed effect estimated for their employing establishment. Then, in Subsections 3.2 and 3.3, I describe how earnings and employment consequences of displacement differ over the recent earnings distribution and by whether or not the worker immediately transitions into a new job. I investigate this both by looking directly at the raw observations from the data (Subsection 3.2) and by estimating the event study framework discussed in Section 2 (Subsection 3.3). Finally, in Subsection 3.4, I briefly discuss the findings and how they compare to predictions of a simple job ladder model.

3.1 The Incidence of Displacement over the Recent Earnings Distribution

Before moving to the analysis of the average earnings and employment loss experienced by workers situated on different parts of the recent earnings distribution, it is worth highlighting the extent to which the workers at the top and bottom of this distribution are more or less likely to be separated and displaced. In Figure 1, I plot the incidence of separation and displacement over the recent earnings distribution, both for the unrestricted sample and for a restricted sample which only includes workers with a pre-separation establishment tenure of at least 6 years and a pre-separation establishment size of at least 50 workers. As can be seen, the separation and displacement rates are generally declining over the bottom half of the recent earnings distribution, especially so for the unrestricted sample, and remain rather constant throughout the top half of the distribution. This observation of higher separation and displacement rates at the bottom of the distribution seemingly supports the idea of a job ladder with slippery bottom rungs (as proposed in Jarosch, 2021), where lower quality jobs (which are associated with lower earnings) are also subject to higher separation risk.

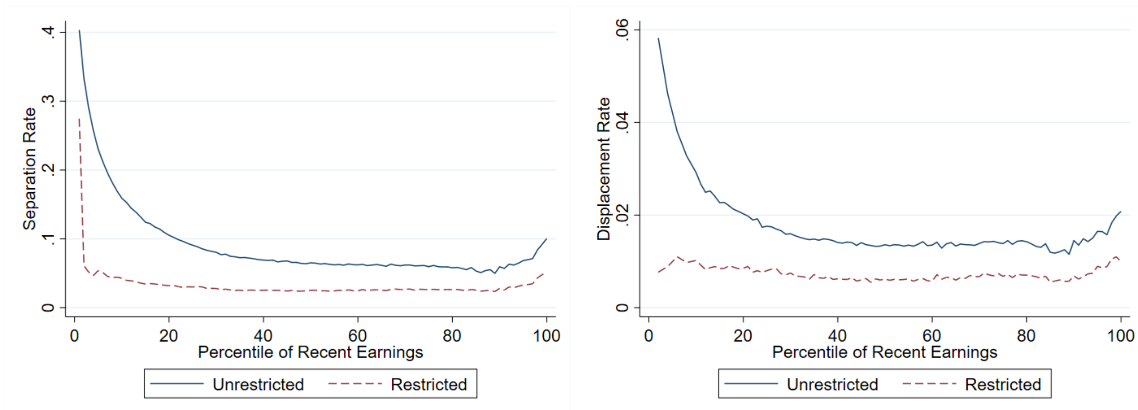

Figure 1: *The incidence of separation (left) and displacement (right) over the recent earnings distribution. The solid line plots the incidence without further restrictions on pre-displacement tenure and establishment size, whereas the dashed line plots the incidence after imposing these restrictions.*

In Figure 2, I show how common it is for displaced workers to transition immediately (within 30 days) to a new job. In other words, the figure shows the job-to-job transition rate (or EE rate) conditional on displacement. Notably, this EE rate is sharply increasing in recent earnings, varying from EE rates of 20% near the bottom to more than 70% near the top of the distribution. Furthermore, the right panel of Figure 2 shows, there is substantial heterogeneity by establishment tenure. In general, the EE rate is lower for workers with lower establishment tenure, and furthermore the EE rate for low-tenured workers exhibits a much lower correlation with the position in the recent earnings distribution than the average EE rate.

3.2 Raw Displacement Scars over the Recent Earnings Distribution

In this subsection, I analyze the average earnings and employment loss after displacement, by percentile of the recent earnings distribution, by calculating these losses directly from

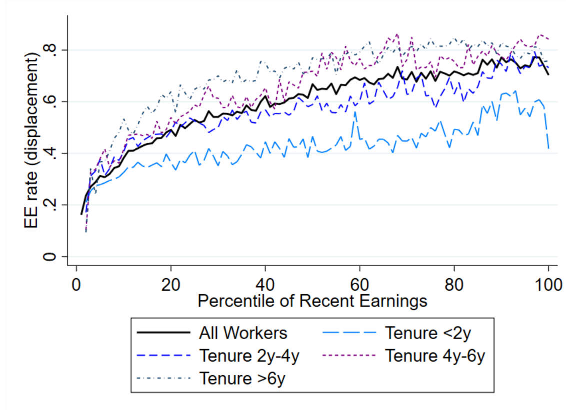

Figure 2: *The incidence of job-to-job transitions upon job displacement, over the recent earnings distribution. The black solid line depicts the overall incidence, whereas the other lines separately plot the incidence for different groups of establishment tenure.*

the data. In other words, the results in these subsection are not based on an estimation, and can therefore be thought of as raw effects instead.

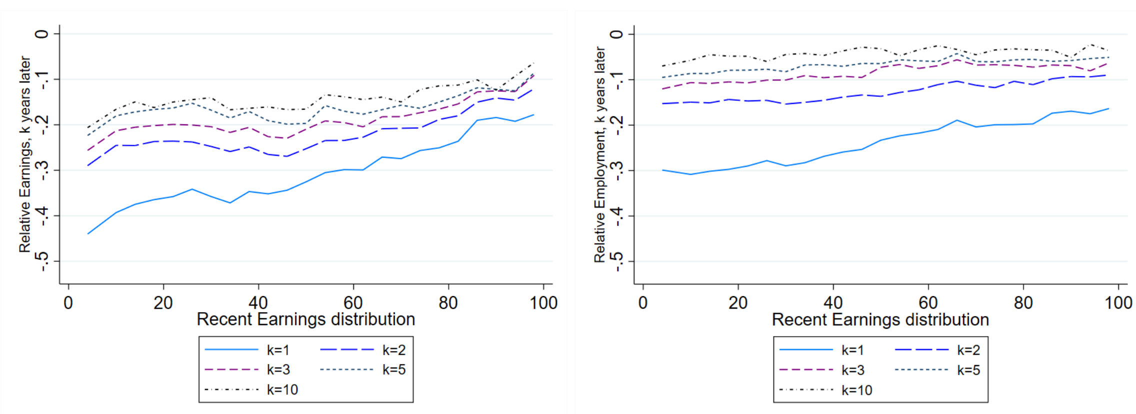

Figure 3: *The effect of displacement on earnings (left) and employment fraction (right), over the recent earnings distribution. The numbers underlying the graphs are calculated directly from the data, and are relative to workers in the control group in the same percentile of the recent earnings distribution. Each line corresponds to a single period, k years after the initial displacement takes place.*

In Figure 3, I show the average loss of earnings and employment (measured as the fraction of the year spent in an employment spell) for all displaced workers, regardless of whether they subsequently spent any time in nonemployment and regardless of their pre-displacement tenure or establishment size.[11] These average losses are constructed by calculating the average earnings for both displaced and non-displaced workers in a certain percentile of the recent earnings distribution, k years after the treatment year, and subsequently averaging the difference between the displaced and non-displaced cohort over treatment years. The resulting average losses are then plotted over the recent earnings distribution, where each line in the figure represents one lead (e.g. the solid light blue line depicts average losses 1 year after the displacement). As can be seen in Figure 3, relative earnings losses are lower for workers with higher recent earnings. This is especially visible in the first few years after displacement. For employment, a similar gradient is visible, but other than in the first year after displacement ($k = 1$) the gradient is not as clear as it is for earnings.

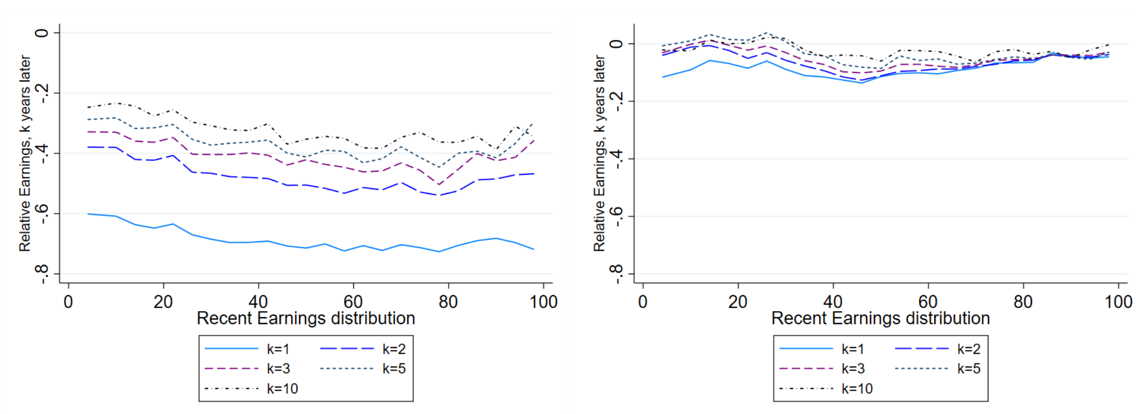

Figure 4: *The effect of displacement on earnings over the recent earnings distribution, for workers who transitioned directly to a new job (right) and workers who did not do so (left). The numbers underlying the graphs are calculated directly from the data, and are relative to workers in the control group in the same percentile of the recent earnings distribution. Each line corresponds to a single period, k years after the initial displacement takes place.*

Naturally, one might expect that some of the average effect shown in Figure 3 may be driven by workers with higher recent earnings moving to a new job more quickly, as indicated by the increasing EE rates in Figure 2. Even if all workers fall off the job ladder upon displacement, this could partially explain the result, as workers with higher recent earnings would then start re-climbing the job ladder faster, even if the initial relative loss of earnings is higher. Therefore, it is worth separating the sample of displaced workers into those making an EE transition and those not making an EE transition. In Figures 4 and 5, I show the resulting four graphs depicting earnings

[11] In Appendix C.2.1, I show how results change when I consider a sample that restricts to individuals with a pre-displacement establishment tenure of at least 6 years and a pre-displacement establishment size of at least 50 workers, in line with the sample restrictions used in Subsection 3.3.

and employment losses over the recent earnings distribution. As can be seen by comparing the two panels of Figure 4, the decreasing relative earnings losses observed in Figure 3 are visible for some workers who make an immediate transition to a new job from a position as well, though the gradient is not as stark as in Figure 3 and the positive gradient only holds in the top half of the recent earnings distribution. For workers who do not make an immediate transition, the pattern (in the left panel of Figure 4) is more in line with what one would expect in a labour market that is characterized by a job ladder. Similarly, the pattern of employment losses, shown in Figure 5, is fairly flat for both groups of displaced workers, especially from $k = 2$ onwards. In other words, while the distinction between displaced workers who do or do not make an EE transition can partially explain the average pattern of earnings and employment losses from Figure 3, it does not seem to provide a complete explanation, especially when it comes to earnings losses experienced by job-to-job switchers.

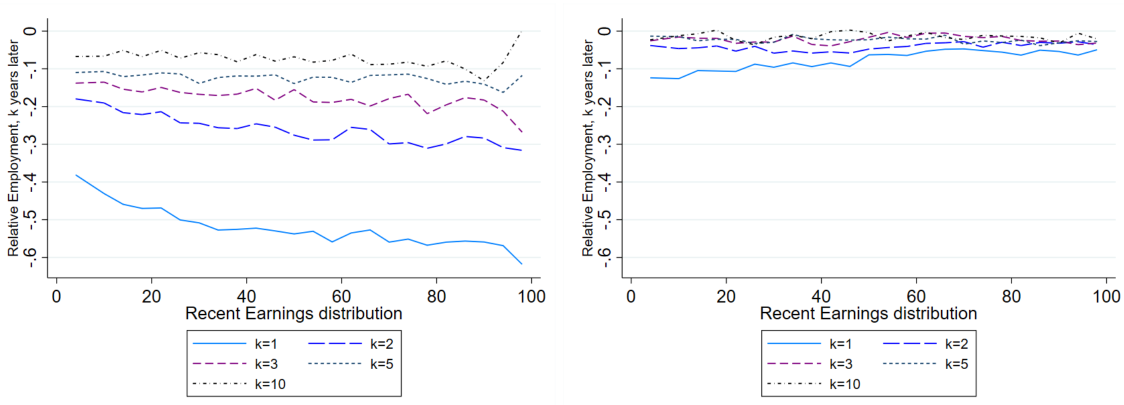

Figure 5: *The effect of displacement on employment fraction over the recent earnings distribution, for workers who transitioned directly to a new job (right) and workers who did not do so (left). The numbers underlying the graphs are calculated directly from the data, and are relative to workers in the control group in the same percentile of the recent earnings distribution. Each line corresponds to a single period, k years after the initial displacement takes place.*

One potential explanation for the observation that relative earnings losses are decreasing in recent earnings, especially when focusing on only job-to-job transitioners, is that workers who are able to quickly transition to a new job may be able to leverage their connections at their previous establishment, and therefore do not completely fall off the job ladder. In this case, one would expect their subsequent earnings growth to be lower. After all, if they are already high up the ladder, their subsequent earnings growth conditional on switching jobs again would be lower (due to having

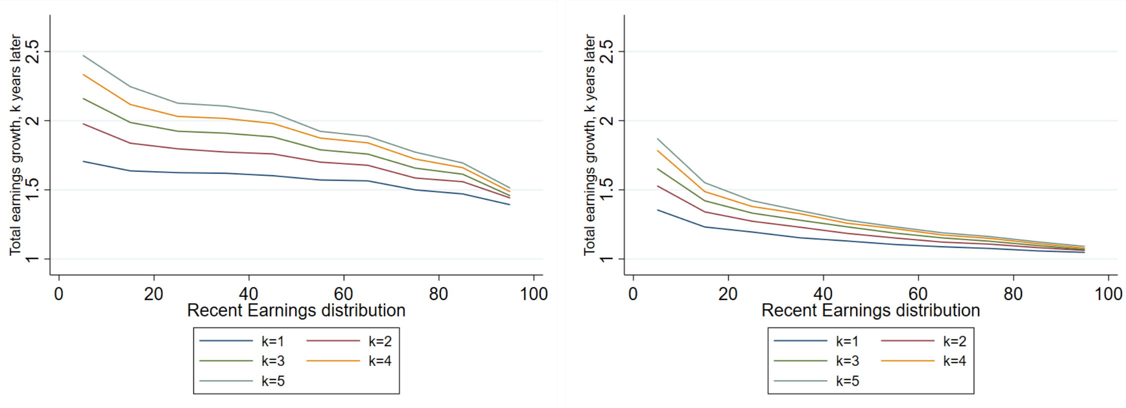

Figure 6: *Earnings Growth in the years after displacement, over the recent earnings distribution, and separately for workers who transitioned directly to a new job (right) and workers who did not do so (left). The numbers underlying the graphs are calculated directly from the data, and are relative to the worker's first post-displacement earnings. Each line corresponds to the average cumulative earnings growth between the first post-displacement earnings and the earnings in year k after displacement for workers in the corresponding decile of (pre-displacement) recent earnings, excluding the top and bottom 5% of workers in terms of growth.*

less room to grow) while the probability of receiving an acceptable offer from another job will also be lower. This seems to be supported by the data, as Figure 6 shows: workers who get displaced from a higher point in the recent earnings distribution tend to have lower earnings growth in the subsequent years. This holds for both workers who make an EE transition and workers who do not, although the effect is stronger for workers who make a direct transition, thus indicating that such a network effect may dissipate over time rather than directly upon entering nonemployment (as I will assume in the model in order to keep the size of the model manageable).

A different way to (indirectly) analyze whether the differences in earnings losses are driven by workers switching to similar jobs (e.g. within their professional network) is to use the so-called AKM individual and establishment fixed effects. These individual and establishment fixed effects are estimated for the LIAB dataset by Card et al. (2013) (and later extended to other periods and an extended sample, see Bellmann et al., 2020), following the estimation strategy originally introduced in Abowd et al. (1999). Notably, this estimation is done for the entire Employee History file, from which the LIAB data (used throughout this section) takes a sample, and separately for five periods: 1985-1992, 1993-1999, 1998-2004, 2003-2010, and 2010-2017. In the analysis below, I assign to each observation the fixed effect corresponding to the individual and their main employer for the specific observation year (where in the case of overlapping periods, I take the fixed effect for which the observation does not fall in the first or final year of the period). In Figure 7, I show how the average percentile of individual and establishment fixed effect differs over the recent earnings distribution. As can be seen in the figure, both individual and establishment fixed effects are generally increasing in recent earnings, and this effect is generally stronger for the individual fixed effect than for the establishment fixed effect. Furthermore, displaced workers generally tend to come from lower percentiles of establishment and individual fixed effects than non-displaced workers with comparable recent earnings.

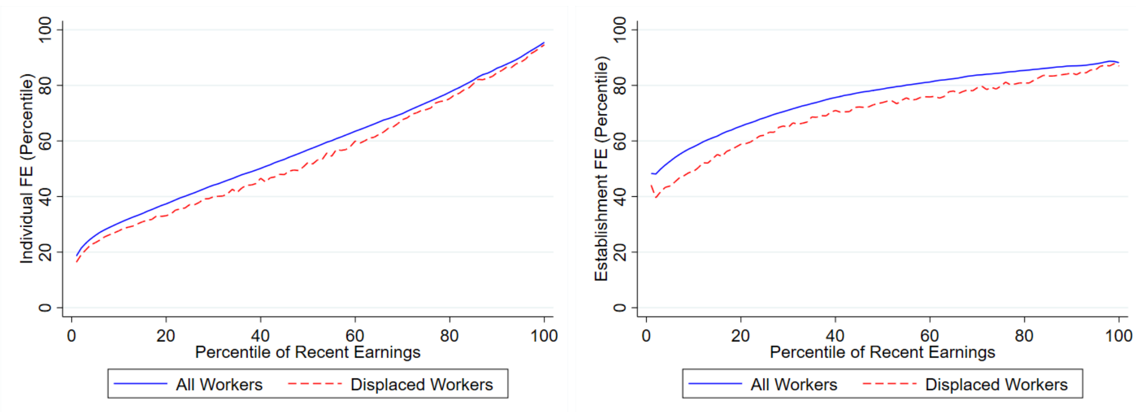

Figure 7: *Average percentile of individual (left) and employing establishment (right) AKM fixed effect, over the recent earnings distribution.*

If it is indeed the case that workers switch to similar-paying establishments after being displaced, one would expect that there is not much change in how the average establishment fixed effect differs over the recent earnings distribution if these are plotted separately for the pre-displacement and (first) post-displacement establishment. In the left panel of Figure 8, I show that this is indeed the case. As the right panel of Figure 8 shows, this is especially true for workers who move to a new job immediately, whereas workers who do not do so tend to move towards the median.

3.3 Regression-Based Displacement Scars by Recent Earnings

The results in the previous subsection were established by directly calculating average earnings from the data. Naturally, calculating average losses in this manner may lead to biased estimates if individuals who are displaced are inherently different from non-displaced workers, or years in which displacement is common coincide with circumstances (such as economic conditions) that lead to different earnings losses. By estimating the earnings losses using the event study

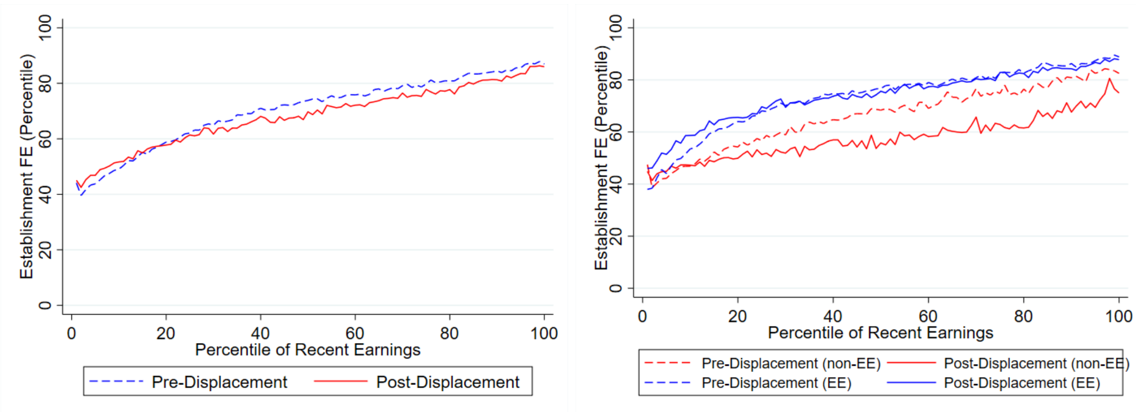

Figure 8: *Average percentile of employing establishment AKM fixed effect among displaced workers over the recent earnings distribution, comparing pre-displacement and post-displacement establishments. The left panel pools all displaced workers, whereas the right panel distinguishes between workers who move to a new job immediately (make an EE transition) and workers who do not do so.*

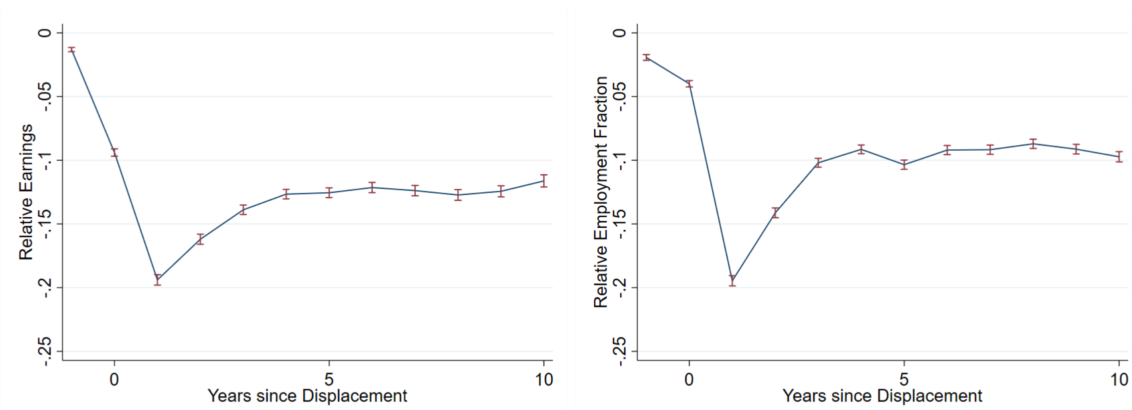

Figure 9: *The effect of displacement on earnings (left) and employment fraction (right), using estimated coefficients from Equation* (1)*. The error bars correspond to 95% pointwise confidence intervals.*

framework discussed in Section 2, I obtain estimates that take into account differences between individuals that are fixed over time (using individual fixed effects) and differences between periods that are fixed across individuals (using time fixed effects). In Figure 9, I show the results of estimating Equation (1) using the imputation-based method from Borusyak et al. (2023). In line with the literature discussed in Section 1.1, the figure shows the estimated earnings losses to be quite large, with an immediate earnings loss of approximately 20%, and very persistent, with displaced workers still earning more than 10% less than the control group 10 years after the displacement. These effects are partially driven by effects on employment, but the estimated effects on employment fraction are consistently less severe than those for earnings after the first year, thus indicating that the employment margin cannot explain all of the earnings losses, and there is an important role for wages as well.

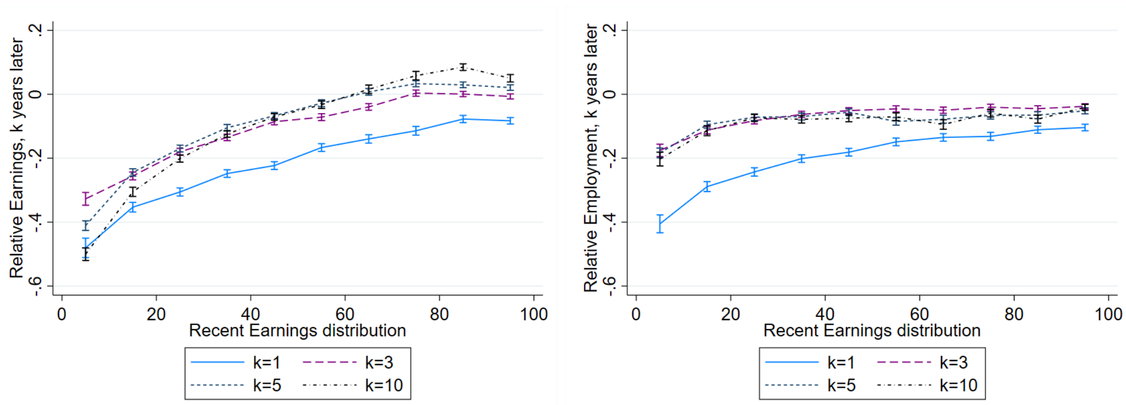

Figure 10: *The effect of displacement on earnings (left) and employment fraction (right) over the recent earnings distribution. The graphs are prepared using estimated coefficients from Equation* (2)*, and error bars correspond to 95% pointwise confidence intervals.*

In the remainder of this subsection, I discuss the results of estimation Equation (2), dividing the recent earnings distribution into $P = 10$ quantiles. Plotting the results of this estimation in an event study graph such as Figure 9 results in a figure with 10 lines, which is fairly difficult to interpret. Therefore, I transform these event study graphs into graphs that resemble the figures from the previous subsection, where I plot the estimated earnings loss for a given post-displacement time k over the recent earnings distribution. For more details on how these graphs are created, please see Appendix C.1, where I construct a similar graph for the case with $P = 3$ quantiles.

In Figure 10, I show the results for the sample where all displaced workers are pooled (analogous to Figure 3). The observed pattern is very similar to that observed in the raw data, although the gradient of the losses over the recent earnings distribution is larger (especially for low values of k and at the bottom of the distribution). Similarly, the observed pattern for employment is similar to that observed in the raw data, with a steeper gradient of employment losses over the recent earnings distribution near the bottom of the distribution, and less recovery after the third post-displacement year ($k = 3$).

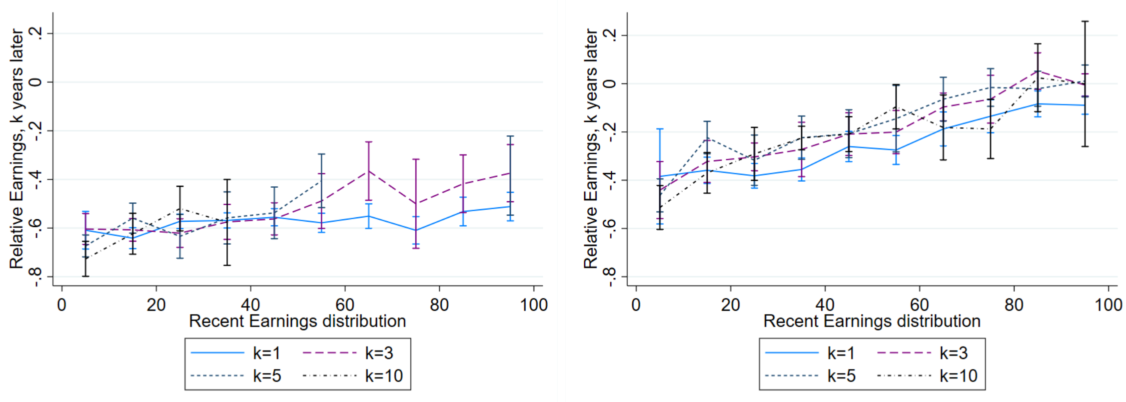

Figure 11: *The effect of displacement on earnings over the recent earnings distribution. The graphs are prepared using estimated coefficients from Equation* (2)*, and error bars correspond to 95% pointwise confidence intervals. The right panel only considers workers who moved to a new job immediately, whereas the left panel only considers workers who did not do so.*

In Figures 11 and 12, I show how results are affected by splitting the sample and estimating Equation (2) separately for workers who make an EE transition upon being displaced versus those who spend some time in nonemployment.[12] As can be observed in the left panel of Figure 11, restricting the sample to workers who spend some time in nonemployment greatly reduces the gradient of the relative earnings loss over the recent earnings distribution. Focusing on workers who make an EE transition instead, a clear upward slope is visible again across the entire recent earnings distribution. As a result, a similar conclusion can be drawn as in the previous subsection: while the incidence of EE switches upon displacement can explain some of the decreasing average relative earning losses over the recent earnings distribution, the pattern remains visible when we focus on

[12]In both Figures 11 and 12, the estimation results for $k = 5$ and $k = 10$ are not omitted for some quantiles of the recent earnings distribution when restricting to workers who spent some time in nonemployment (the left panel in both figures). This is because the the number of observations for combinations of cohort C and these values for k became sufficiently low that the result was no longer reliable enough. As can be seen in Appendix **??**, in which some of the sample restrictions are relaxed, the general pattern for these omitted values tends to closely follow that of the $k = 3$ line.

EE switches only, thus suggesting that another force is needed to fully explain the results from the pooled sample. As shown in Figure 12, however, this is not necessarily the case for employment, where focusing on EE switches (or non-EE switches) leads to a gradient close to zero, thus suggesting that most of the gradient in average employment loss can be explained by the incidence of EE switches upon displacement.

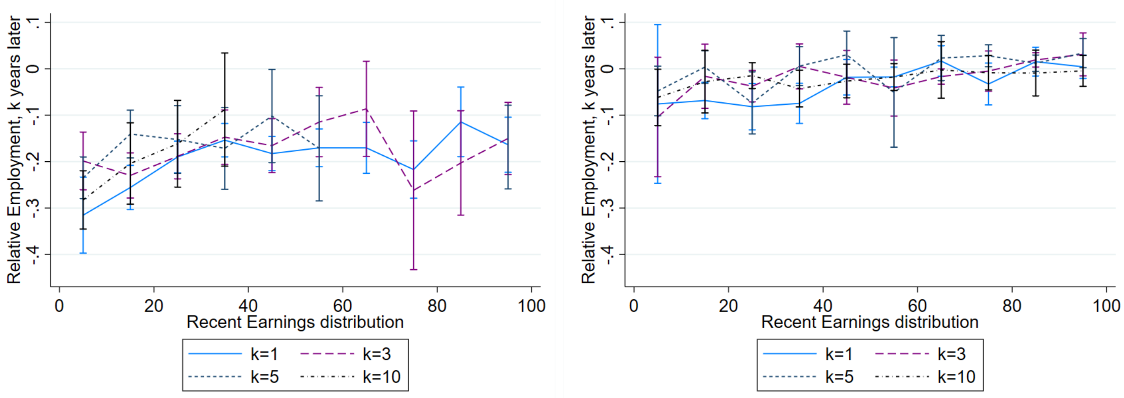

Figure 12: *The effect of displacement on employment fraction over the recent earnings distribution, relative to the control group of never-displaced workers (across the entire distribution). The graphs are prepared using estimated coefficients from Equation* (2)*, and error bars correspond to 95% pointwise confidence intervals. The right panel only considers workers who moved to a new job immediately, whereas the left panel only considers workers who did not do so.*

3.4 Discussion

In the above subsections, I have presented results that indicate that relative earnings losses after displacement tend to be lower for workers higher up the recent earnings distribution, driven primarily by workers who are able to immediately transition to a new job after being displaced. Notably, this seemingly contradicts the predictions of a model based on a job ladder, which generally describes the class of models used to successfully generate the average earnings loss after displacement, such as those briefly discussed in section 1.1. In such models, workers generally increase their earnings over time by making job-to-job transitions to jobs that are "higher on the ladder", where this ladder could be represented by wages directly or indirectly (e.g. through firm productivity). Even without the element of human capital depreciation during nonemployment, these models generate a persistent earnings loss after displacement because workers fall off the ladder when they are separated, and therefore have to start re-climbing the ladder from the bottom.

I show in Appendix B.1 that in a simple job ladder model such as the one briefly described above (and without any additional elements), the relative earnings loss after displacement is higher for workers higher on the recent earnings distribution. This is because all workers return to the same starting point ("the bottom of the ladder"), regardless of the job from which they were separated and regardless of how long they take to find a new job. This contradicts the results from the previous subsections, thus suggesting the need for reconciliation between this empirical evidence and these models that can explain the average earnings loss after displacement. In the next section, I propose a model that can achieve this.

4 Model

In this section, I present a search model of the labour market, with the aim of explaining the observed earnings losses over the recent earnings distribution in section 3.

4.1 Environment

The model is set in discrete time, and the economy is populated by workers and firms, both of which differ in two dimensions. Firms are heterogeneous in their productivity y, separation risk δ, and network strength p, which will be summarized using a vector $\theta = [y, \delta, p]$.[13] Workers differ in their human capital s and type ε, and can be either employed or unemployed. The type ε is fixed over time (and will be interpreted as the education level in the estimation), whereas the human capital s can evolve over time.

4.1.1 Firms

Each firm can hire at most one worker (and can therefore also be thought of as an establishment or a job). If a firm is matched to a worker, production takes place according to the log-linear production function $f(s, y) = e^{s+y}$, and the firm pays a wage w to the worker, the determination of which is discussed in subsection 4.1.3. With (match-specific) probability δ, the match faces a separation shock. If this shock materializes, the worker and firm return to an unmatched and unemployed status. I assume that firms that are unmatched do not produce anything and also don't

[13] The model resembles Jarosch (2021) in that firms are heterogeneous with respect to their productivity and separation rate. Compared to that model, I add a third dimension of firm heterogeneity (which I interpret as network strength), and further allow workers to be heterogeneous according to a fixed type.

face any costs, thus setting the current period value of an unmatched firm equal to 0. As the firm is largely passive in this model, the setup should be thought of as partial and from the viewpoint of the worker.

4.1.2 Workers

Workers are assumed to be infinitely-lived, and unable to transfer resources between periods. Further, their utility function is assumed to be logarithmic, and they discount future utility at a rate β. As mentioned above, workers differ in their human capital s and fixed type ε. I will interpret the fixed worker type ε as the worker's education level when calibrating the model in section 5, but the way it is implemented in the model does not prevent it from being interpreted as some other fixed characteristic like in Gregory et al. (2021). The human capital s increases by $\Delta_s(\varepsilon)$ (with probability ψ_e) when the worker is employed, and decreases by $\Delta_s(\varepsilon)$ when the worker is non-employed (with probability ψ_u).[14]

Each worker enters the market as unemployed and with human capital s_ε. An unemployed worker meets a firm with probability λ_ε^u, and upon meeting the firm draws its characteristics from joint distribution $G_\varepsilon(\theta)$, where ε changes the marginal distributions of δ, y, and p (see section 5). The worker then decides whether or not to accept the job. If the worker accepts, she becomes employed and receives wage w (as discussed in the next subsection). If the worker does not accept, or does not receive an offer, the worker receives $b(s)$, which can be interpreted as the one-period value of being unemployed (and is related to the unemployment benefit). This value is set equal to a fraction of the lowest possible production a worker could produce in a match: $b(s) = bf(s, y_\varepsilon^{min})$. In doing so I proxy a setting in which the unemployment benefit depends on the last earned wage, without having to track an unemployed worker's previous job characteristics.[15] I do not explicitly model how the unemployment benefit is financed.

Naturally, an employed worker faces the same job destruction probability as the firm, and receives the wage w. Additionally, an employed worker meets another firm with probability λ_ε^e, and if she does the offer is drawn from distribution $\hat{G}_\varepsilon(\theta)$. This joint distribution $\hat{G}_\varepsilon(\theta)$ differs from

[14]The worker's human capital cannot go below s_{min}, so technically the probability ψ_u depends on s: If $s = s_{min}$, then $\psi_u = 0$. However, in practice s_{min} is set sufficiently low such that workers will only reach s_{min} in very rare instances (see appendix A).

[15]Note that this setup allows for a scenario where unemployed workers reject some job offers,as in Bagger et al. (2014), who set $b = 1$. In particular, the value of unemployment is decreasing in b, so that if b is high enough the value of unemployment may be higher than the value of accepting a low-value job (e.g. a job where the productivity is close to y_ε^{min}).

the distribution used for offers out of unemployment ($G_\varepsilon(\theta)$), as the worker can leverage the firm's network to obtain better offers. In particular, the adjusted distribution $\hat{G}$ is formed by truncating the marginal distribution of productivity y from below, such that the minimum productivity drawn increased from y_ε^{min} to $\hat{y}_\varepsilon^{min} = (1-p)y_\varepsilon^{min} + p\tilde{y}$, where $\tilde{y}$ is the productivity of the previous job. Given that $p \in [0,1]$ determines how strong the influence of the previous job's productivity is on the productivity (distribution) of the next offer, I interpret p as the firm's network strength.

Upon receiving an offer from another, the employed worker can decide to switch to the new firm or to reject the offer. However, upon deciding to reject the offer, it can be used to re-bargain with the current employer.

Finally, worker who is hit by a job destruction shock finds a new job in the same period with probability λ_ε^{ug}. This can be thought of as a simplified way of capturing that workers may anticipate the impending layoff and may therefore search (and find) a new job before the layoff actually materializes, as pointed out in Simmons (2021). Indeed, a worker receiving an offer in the same period as receiving a job destruction shock draws their new firm from the adjusted joint distribution $\hat{G}_\varepsilon(\theta)$ discussed above, thus still using their (former) employer's network despite the pending separation.

4.1.3 Wage Setting

The wages in the model are set up through piece-rate contracts, following a procedure similar to Bagger et al. (2014). In particular, the worker and firm agree on a piece-rate $R = e^r$ at the time of bargaining, which implies a wage of $w = Rf(s,y) = e^{r+s+y}$. This formula will then determine the wage until either the match is destroyed (because of separation or because the worker switches firms) or until the worker receives an offer that triggers re-bargaining. However, note that the wage itself may still be increasing during that time, as the worker may be accumulating more human capital s.

At the time of bargaining, the piece rate is determined by taking into consideration the maximum surplus a worker could extract from the match and the maximum surplus that could be extracted from the outside option, which can be either unemployment or a different job. The maximum surplus that can be extracted from a match equals the value function of the worker if the piece-rate R is set equal to 1 (or $r = 0$). Going forward, I refer to this value as W^{max}. The piece-rate is set such that the surplus extracted by the worker (W) equals the maximum surplus she could extract from her outside option, W^{oo}, plus a constant fraction of the excess maximum surplus of the pending match. This fraction, κ, is interpreted as the bargaining power of the worker.

$$W_\varepsilon(s, s, \theta, \hat{\theta}) = W^{oo} + \kappa \left(W_\varepsilon^{max}(s, \theta) - W^{oo}\right) \tag{3}$$

Equation (3) explicitly shows that the match value for the worker, W, depends on the value of the firm characteristics θ, the outside option firm characteristics $\hat{\theta}$, and the worker's human capital, both current (s) and when the worker and firm last bargained ($\hat{s}$).[16] Note that equation (3) can take three distinct forms. First, if the worker is coming out of unemployment, the outside option value W^{oo} equals the value of unemployment, $U_\varepsilon(s)$ and $\hat{\theta}$ is set to equal u (with some abuse of notation). Then, denoting by x the firm characteristics of the worker's new firm, equation (3) can be rewritten as equation (4).

$$W_\varepsilon(s, s, x, u) = U_\varepsilon(s) + \kappa \left(W_\varepsilon^{max}(s, x) - U_\varepsilon(s)\right) \tag{4}$$
$$W_\varepsilon(s, s, x, \theta) = W_\varepsilon^{max}(s, \theta) + \kappa \left(W_\varepsilon^{max}(s, x) - W_\varepsilon^{max}(s, \theta)\right) \tag{5}$$
$$W_\varepsilon(s, s, \theta, x) = W_\varepsilon^{max}(s, x) + \kappa \left(W_\varepsilon^{max}(s, \theta) - W_\varepsilon^{max}(s, x)\right) \tag{6}$$

If the worker is moving between two jobs, from a firm with characteristics θ to a firm with characteristics x, the outside option W^{oo} equals the maximum surplus that could have been obtained at her previous job, $W_\varepsilon^{max}(s, \theta)$, so that equation (3) can be rewritten as equation (5). Alternatively, if the worker is using a job offer from a firm with characteristics x to extract more value from her current employer, the outside option W^{oo} equals the maximum surplus that could have been obtained from this job offer, $W^{max}(s, x)$, and equation (3) can be rewritten as equation (6).

4.2 Timing and Value Functions

The setup of the model can be summarized by dividing every model period into 4 stages. At the start of the period, in the first stage, the human capital level of the workers is updated. In the second stage, workers learn of their impending separation. Then, in the third stage, workers may receive an offer from a firm, where the probability of obtaining such an offer (and the distribution of offers) depends on the worker's current state, and information obtained in the first two stages of the period. Workers choose to accept or reject the offer, and (re-)bargaining takes place. Finally, at the end of the period, production takes place and wages (and unemployment benefits) are paid out.

[16]Note that since workers cannot lose human capital during their employment spell, it must be true that $\hat{s} \geq s$.

Using the above description, I can write out the value functions of the worker and the firm. In this section, however, I will only present the worker value functions, since the firm is largely passive in this model and the firm's value functions are not needed to solve the model. The firm's value functions, as well as the worker flow equations, are deferred to appendix B.2. The value functions below represent the worker's value of being in a certain state at the start of the final (production) stage of a period. First, the value of unemployment U for a worker of type ε with human capital s can be written out as follows:

$$\begin{aligned} U_\varepsilon(s) = \ln(b_\varepsilon(s)) + \beta \mathbb{E}_{s'|s,u,\varepsilon} \Bigg\{ & \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^u(s')} W_\varepsilon(s', s', x, u) dG_\varepsilon(x) \\ & + \left(1 - \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^u(s')} dG_\varepsilon(x)\right) U_\varepsilon(s') \Bigg\} \end{aligned} \tag{7}$$

In equation (7), the set $\Theta_\varepsilon^u(s)$ corresponds to the set of firm characteristics from whom the worker of type ε with current human capital level s would accept a job offer. Using equation (4), this set can be specified as $\Theta_\varepsilon^u(s) = \{x \in [0,1]^2 \times \mathbb{R}_+ : W_\varepsilon^{max}(s,x) \geq U_\varepsilon(s)\}$. For the purpose of solving the model, equation (7) can be rewritten in terms of W^{max}, U, and parameters only:

$$U_\varepsilon(s) = \ln(b_\varepsilon(s)) + \beta \mathbb{E}_{s'|s,u,\varepsilon} \left\{ \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^u(s')} \kappa \left(W_\varepsilon^{max}(s', x) - U_\varepsilon(s')\right) dG_\varepsilon(x) + U_\varepsilon(s') \right\} \tag{8}$$

The value of employment W for a worker of type ε with human capital s, matched with a firm of type θ, is as specified below:

$$\begin{aligned} W_\varepsilon(s, \hat{s}, \theta, \hat{\theta}) = \ln(R_\varepsilon(\hat{s}, \theta, \hat{\theta}) f(s, y)) + \beta \mathbb{E}_{s'|s,e,\varepsilon} \Bigg\{ & \delta \hat{U}_\varepsilon(s') \\ + (1-\delta) \Bigg[\lambda_\varepsilon^e \bigg(\int_{x \in \Theta_\varepsilon^1(s', \theta)} & W_\varepsilon(s', s', x, \theta) d\hat{G}_\varepsilon(x) + \int_{x \in \Theta_\varepsilon^2(s', \hat{s}, \theta, \hat{\theta})} W_\varepsilon(s', s', \theta, x) d\hat{G}_\varepsilon(x) \bigg) \\ + \bigg(1 - \lambda_\varepsilon^e \int_{x \in \Theta_\varepsilon^1(s', \theta) \cup \Theta_\varepsilon^2(s', \hat{s}, \theta, \hat{\theta})} & d\hat{G}_\varepsilon(x) \bigg) W_\varepsilon(s', \hat{s}, \theta, \hat{\theta}) \Bigg] \Bigg\} \end{aligned} \tag{9}$$

In equation (9), the set $\Theta_\varepsilon^1(s, \theta)$ is the set of firm characteristics of the firms from whom the worker (of type ε and with human capital s) would accept an job offer if she is currently employed at a firm with characteristics θ. Similarly, $\Theta_\varepsilon^2(s, \hat{s}, \theta, \hat{\theta})$ is the set of firm characteristics of the firms whose offers this worker would use to trigger re-bargaining at her current match. Using equations (5) and (6), these sets can be specified as $\Theta_\varepsilon^1(s, \theta) = \{[0,1]^2 \times \mathbb{R}_+ : W_\varepsilon^{max}(s, x) \geq W_\varepsilon^{max}(s, \theta)\}$

and $\Theta^2_\varepsilon(s,\theta) = \{x \in [0,1]^2 \times \mathbb{R}_+ : W^{max}_\varepsilon(s,\theta) > W^{max}_\varepsilon(s,x) \geq W^{max}_\varepsilon(\hat{s},\hat{\theta})\}$.[17] Finally, the value $\hat{U}$ corresponds to the value of a newly separated worker. This value reflects the possibility of this worker being re-employed in the same period, and therefore relate to value functions (8) and (9) above as follows:

$$\hat{U}_\varepsilon(s') = \lambda^{ug}_\varepsilon \int_{x\in\Theta^u_\varepsilon(s')} W_\varepsilon(s',s',x,u)d\hat{G}_\varepsilon(x) + \left(1 - \lambda^{ug}_\varepsilon \int_{x\in\Theta^u_\varepsilon(s')} d\hat{G}_\varepsilon(x)\right) U_\varepsilon(s') \tag{10}$$

Using equation (9), the value for W^{max} can be deduced for every combination of ε, s and θ, by setting $R_\varepsilon(\hat{s},\theta,\hat{\theta}) = 1$. The resulting expression no longer depends on the bargaining benchmark, as the outcome of the bargaining (which is the piece-rate) is already known:

$$\begin{aligned} W^{max}_\varepsilon(s,\theta) = \ln(f(s,y)) + \beta\mathbb{E}_{s'|s,e,\varepsilon} \Bigg\{ &\delta\hat{U}_\varepsilon(s') \\ +(1-\delta)\left[\lambda^e_\varepsilon \int_{x\in\Theta^1_\varepsilon(s',\theta)} \kappa\left(W^{max}_\varepsilon(s',x) - W^{max}_\varepsilon(s',\theta)\right) d\hat{G}_\varepsilon(x) + W^{max}_\varepsilon(s',\theta)\right]\Bigg\} \end{aligned} \tag{11}$$

4.3 Equilibrium

In this model economy, an equilibrium consists of value functions $U_\varepsilon(s)$, $W_\varepsilon(s,\hat{s},\theta,\hat{\theta})$, $J_\varepsilon(s,\hat{s},\theta,\hat{\theta})$, and a piece-rate function $R_\varepsilon(\hat{s},\theta,\hat{\theta})$, such that, given (unconstrained) distribution $G_\varepsilon(\theta)$ and parameters, the value functions $W_\varepsilon(s,\hat{s},\theta,\hat{\theta})$ and $U_\varepsilon(s)$ satisfy equations (4) to (6), the value functions and the piece-rate function satisfy equations (7) to (11) and equation (B.3), and the distribution of workers across different states evolves according to equations (B.4) to (B.6).

5 Calibration

For the purpose of the calibration, I set up the distribution of firms $G_\varepsilon(\theta)$ as a combination of marginal distributions of productivity y, network strength p separation rate δ, and I make parametric assumptions on these marginal distributions. In particular, I assume that the marginal distribution of δ is a Beta distribution with parameters η_δ and $\mu_{\delta,\varepsilon}$, reshaped to the $[0, 0.25]$ interval (rather than $[0, 1]$). Similarly, the marginal distribution of p follows a Beta distribution, with parameters

[17] Note that the two sets $\Theta^1_\varepsilon(s,\theta)$ and $\Theta^2_\varepsilon(s,\hat{s},\theta,\hat{\theta})$ do not overlap. Further, together they do not cover all possible values of $x \in [0,1]^2 \times \mathbb{R}_+$, revealing the third possible result of receiving an outside offer: if the offer is not good enough for the worker to use to trigger re-bargaining, the worker discards the offer and remains employed under her previously bargained piece-rate.

η_p and $\mu_{p,\varepsilon}$, whereas the marginal distribution of y is a Pareto distribution with scale parameter $\mu_{y,\varepsilon}$ and shape parameter η_y. Following Jarosch (2021), I combine the two marginal distributions of productivity and separation rates into a bivariate distribution using Frank's copula with parameter ρ (thereby allowing for correlation between the two variables). Finally, this bivariate distribution is combined with the marginal distribution of p (assuming independence between p on the one hand and the combination of y and δ on the other hand) to form the (unconstrained) firm distribution $G_\varepsilon(\theta)$. As alluded to earlier, I will interpret the worker type ε as the education level. In line with the level of detail available in the data, I therefore allow for two worker types.[18]

The assumptions laid out above (and in the previous section) result in a total of 27 parameters that need to be estimated. These parameters are summarized in table 1. Of these 27 parameters, I will set 5 parameters outside of the estimation, and I estimate the remaining 22 parameters using the indirect inference method from Gourieroux et al. (1993). In the next two subsections, I describe how I set the 5 exogenous parameters, and which moments I use to identify the remaining 22 parameters. The discussion in these two subsections is summarized in tables 2 and 3, and a more detailed description of the estimation of these moments (both in the data and in the model simulation) can be found in appendix A.1.

5.1 Exogenously Set Parameters

Table 2 summarizes the values of the exogenously set parameters. As I interpret ε to correspond to the worker's education level, which is fixed over time, I exogenously set the distribution of ε so that the fraction of workers in each education group corresponds to the accompanying fractions found in the data. As such, following the definitions of the education groups as consisting of individuals with a non-university and university education respectively, I set the fraction of workers with education levels 1 and 2 to equal 0.7739 and 0.2261 respectively.

As one model period corresponds to one quarter, I set the discount rate $\beta = 0.95^{1/4}$ to reflect an annual interest rate of 5%, and I set $s_1 = 0$ and $\Delta_s(1) = 0.1$ as a normalization, so that the values of human capital coming out of the simulation can be interpreted as relative to the human capital of a worker with education level 1 entering the labour market (s_1), and step-sizes in this human capital can be interpreted as relative to the step-size of a worker with low education

[18] In particular, I distinguish between individuals with and without a university education in the data. In principle, the data allows for more education types, but the distinction between the different types is not clear enough (especially with most workers going through apprenticeships in the earlier years of the data) to be informative for the model.

Parameter	Meaning
β	discount factor
ϵ_ε	distribution of worker types ε
κ	worker's bargaining power
b	unemployment benefit, fraction of minimum production
ψ_e	human capital transition, employment
ψ_u	human capital transition, non-employment
s_ε	starting value of human capital
$\Delta_s(\varepsilon)$	human capital transition size
$\mu_{\delta,\varepsilon}$	1st shape parameter, marginal distribution of δ
η_δ	2nd shape parameter, marginal distribution of δ
η_y	shape parameter, marginal distribution of y
$\mu_{y,\varepsilon}$	scale parameters, marginal distribution of y
ρ	copula parameter
$\mu_{p,\varepsilon}$	1st shape parameter, marginal distribution of p
η_p	2nd shape parameter, marginal distribution of p
λ^u_ε	meeting probabilities, unemployed workers
λ^{ug}_ε	meeting probabilities, newly unemployed workers
λ^e_ε	meeting probabilities, employed workers

Table 1: *A summary of all parameters in the model. Note that any notation with a subscript ε represents two parameters: one for each worker type ε.*

Parameter(s)	Value(s)	Source
β	0.98726	5% annual interest rate
s_1	0	normalization
$\Delta_s(1)$	0.1	normalization
ϵ_1	0.7739	fraction of workers with education level 1
ϵ_2	0.2261	fraction of workers with education level 2

Table 2: *A summary of all exogenously set parameters*

($\Delta_s(1)$).

5.2 Calibration Moments

Using that I interpret ε to correspond to education levels, I next identify 43 moments that together identify the values of the 22 parameters that I calibrate using the indirect inference method from Gourieroux et al. (1993). While the parameters are estimated simultaneously, I divide the parameters into five groups, as the corresponding moments in those groups were chosen with these parameters in particular.

The first set of moments contains a number of transition rates from employment to non-employment, used to estimate parameters governing the marginal distribution of δ. To identify the second shape parameter of the marginal distribution of δ, η_δ (which is common across education levels), I use the average separation rate into non-employment for workers with an establishment tenure of 1-3.5, 3.5-6, 6-9, and 9+ years respectively. To discipline the education-specific first shape parameter of this distribution, $\mu_{\delta,\varepsilon}$, I use the average job loss rates by education level. Finally, the subsequent separation rate after re-employment following a displacement aids in identifying the separation rates for very low tenured workers.

The second set of moments revolves around the distribution of wages in the economy and its link with the job loss rates from the first set of moments. As there is a direct link between production and wages in the model, I use these moments to identify the marginal distribution of firm productivity y, as well as the starting level of human capital for the high education level, s_2. In particular, I use the average educational wage premium for education level 2 (compared to education level 1), both overall and upon labour market entry (identified as a market tenure between 3 and 5 years). As the model generates these wage differences primarily through differences in productivity y and human capital s, these moments help to identify initial human capital levels for education level 2 (s_1 is normalized to 0) as well as the education-specific scale parameter $\mu_{y,\varepsilon}$ of the marginal distribution of y. The median-p25 and p75-p25 ratio of wages (by education level) are then used to complete the identification of the shape parameter η_y and education-specific scale parameter $\mu_{y,\varepsilon}$ of the marginal distribution of y. Finally, for the identification of the copula parameter ρ, I follow Jarosch (2021) in targeting the regression coefficient γ in the estimation equation (12) below:

$$D^{\delta}_{i,t} = \alpha_i + \gamma \log(w_{it}) + u_{i,t} \tag{12}$$

In equation (12), $D^{\delta}_{i,t}$ is a dummy variable that is only filled if the worker i is employed in period t (and still observed in period $t+1$). For these workers, it acts as an indicator of job separation between t and $t+1$. The explanatory variables include an individual fixed effect α_i and the natural logarithm of the worker's wage in period t, $w_{i,t}$.

The third set of moments provides information regarding job finding probabilities, both on-the-job and from nonemployment. In particular, the fraction of job-to-job transitions that followed a displacement helps to identify the meeting probability for newly unemployed workers ($\lambda^{ug}_{\varepsilon}$). After all, such a direct transition of a worker to a new job will be observed as a job-to-job transition. The overall quarterly job-to-job transition rate also contributes to identifying this parameter, while additionally informing the value of the on-the-job meeting rate $\lambda^{e}_{\varepsilon}$. As both types of meetings and subsequent job-to-job transitions are likely to respond to the network strength of a firm (p), and this network strength will be increasingly important for higher recent earnings, I estimate both of these moments separately not only by education level but also by third of the recent earnings distribution. Finally, the average job finding rates closely correspond to the job finding rate of unemployed workers, $\lambda_{\varepsilon}^{u}$, and since the network strength does no longer play a role here in the model, these moments are only estimated by education level (and not by third of the recent earnings distribution).

The next set of moments focuses on wage growth within and between job spells, thereby helping to identify human capital transition rates and stepsizes, among others. The first moment in this set is the net replacement rate in unemployment, which closely relates to the parameter b included in the expression for the instantaneous value of non-employment $b(s)$.[19] The average yearly wage growth (by education level), conditional on full-year full-time employment (in both years), helps to identify the human capital stepsize for highly educated invididuals, $\Delta_s(2)$, and the transition rate of human capital while on the job, ψ_e. To aid in the identification of the human capital transition rates during unemployment (ψ_u), I use the average difference between pre- and post-layoff wages, conditional on education level and non-employment duration (up to 0.5, 0.5 to 1, or 1 to 2 years). As laid out in appendix A.1, this moment closely resembles a difference-in-difference estimation. Finally, I use the average wage of a new worker (hired out of unemployment) relative to the average wage to identify the bargaining power κ.

The final set of moments was chosen with the distribution of network strength in mind. In other words, this final set aids in the identification of parameters η_p, $\mu_{p,1}$ and $\mu_{p,2}$. As the value of p determines how much earnings are potentially gained or lost upon making a job-to-job transition, the set of moments includes a number of differences between wages obtained prior to and after making a job-to-job switch. These are estimated on average (by education level), as well as by education level and third of the recent earnings distribution.

5.3 Calibration Results and Model Fit

The moments described above add up to a total of 44 moments used to identify 22 parameters. Further details of the procedure used to estimate these moments can be found in appendix A.1. In addition, the results from the right panel of figure 3 can be targeted directly. Table 3 summarizes the estimated moment values and their model counterparts for an estimation

[19]The net replacement rate taken directly from OECD (2020) rather than derived from the IAB data used in section 3.

Description of Moment(s)	Data	Model	Parameters
Average rate of job loss, tenure 1-3.5y	0.033	0.0069	$\eta_\delta = 0.44$
Average rate of job loss, tenure 3.5-6y	0.016	0.0083	$\mu_{\delta,1} = 29.7$
Average rate of job loss, tenure 6-9y	0.011	0.008	$\mu_{\delta,2} = 67.2$
Average rate of job loss, tenure>9y	0.005	0.0075	
Average rate of job loss, by education	0.025	0.009	
	0.022	0.004	
Subsequent separation, displacement	0.085	0.01	
p75-p25 ratio of wages	1.79	1.93	$\eta_y = 21.5$
	1.69	1.56	$\mu_{y,1} = 0.244$
median-p25 ratio of wages	1.35	1.35	$\mu_{y,2} = 0.547$
	1.36	1.25	$s_2 = -0.19$
Educational wage premium (all)	1.39	1.53	$\rho = -25.2$
Educational wage premium (entry)	1.42	1.74	
Coefficient $\hat{\gamma}$ in equation (12)	−0.03	0.004	
Job-to-job transition rate, edu 1	0.054	0.007	$\lambda_1^e = 0.003$
(by third of the recent earnings distribution)	0.021	0.006	$\lambda_2^e = 0.002$
	0.014	0.005	$\lambda_1^{ug} = 0.42$
Job-to-job transition rate, edu 2	0.066	0.005	$\lambda_2^{ug} = 0.62$
(by third of the recent earnings distribution)	0.036	0.004	$\lambda_1^u = 0.063$
	0.024	0.004	$\lambda_2^u = 0.292$
Displacement among job-to-job transitions, edu 1	0.501	0.626	
(by third of the recent earnings distribution)	0.449	0.624	
	0.43	0.578	
Displacement among job-to-job transitions, edu 2	0.491	0.588	
(by third of the recent earnings distribution)	0.48	0.628	
	0.47	0.634	
Average job finding rate	0.24	0.053	
	0.253	0.255	
Replacement rate	0.6	0.632	$b = 0.535$
Wage of newly hired worker	0.711	0.644	$\kappa = 0.73$
Yearly wage growth	0.021	0.037	$\Delta_s(2) = 0.074$
	0.025	0.027	$\psi_e = 0.088$
Pre- to post-layoff wage, duration<0.5y	−0.05	−0.056	$\psi_u = 0.199$
	0.016	−0.051	
Pre- to post-layoff wage, duration 0.5-1y	−0.091	−0.116	
	−0.057	−0.085	
Pre- to post-layoff wage, duration 1-2y	−0.11	−0.199	
	−0.126	−0.146	
Pre- to post-EE wage, edu 1	1.055	1.113	$\eta_p = 9.52$
Pre- to post-EE wage, edu 1	1.083	1.05	$\mu_{p,1} = 3.76$
(by third of the recent earnings distribution)	1.026	1.048	$\mu_{p,2} = 1.3$
	1.01	0.991	
Pre- to post-EE wage, edu 2	1.06	1.015	
Pre- to post-EE wage, edu 2	1.14	1.021	
(by third of the recent earnings distribution)	1.086	1.031	
	1.024	0.998	

Table 3: *A summary of calibration moments, their values in the data and in the calibrated model, and corresponding parameter values.*

that targets the pattern of earnings losses over the recent earnings distribution (for $k = 1$ and $k = 5$ years after displacement), in addition to placing limited weight on the aforementioned 44 moments. As can be seen in the table, the resulting estimate generates a decent fit with some of the moments, while others are matched quite poorly. For example, the model does a decent job at matching the wage dispersion moments in the second set of moments, while job separation rates in the first moment set are consistently underestimated.

When looking at the parameter estimates in table 3, and comparing these with closely related models such as those calibrated in Jarosch (2021), it can be seen that the estimated parameter values in table 3 are quite extreme in a number of dimensions. The exception to this observation lies in the value of the bargaining power κ, which takes a reasonable value of 0.73 (and is thus estimated to be further away from 1), as well as in the human capital appreciation and depreciation probabilities ψ_e and ψ_u, which are closer together in the estimation presented in table 3.

Moving to the estimated job offer rates, and differences between the two education levels, it can be noted that workers with a low education level are much less likely to obtain an offer from unemployment ($\lambda_1^u < \lambda_2^u$) or when they are close to entering unemployment ($\lambda_1^{ug} < \lambda_2^{ug}$), but experience a slightly higher on-the-job meeting rate ($\lambda_1^e > \lambda_2^e$). The very low meeting probability for workers with a low education level is especially puzzling, since it results in a much lower average job finding rate in model for this education group than in the data. The on-the-job meeting probability is also generally very low compared to estimated in other work, indicating that the model generates more job-to-job transitions through immediate transition after displacement than observed in the data. This can be seen in table 3, as the model by overshoots the displacement rate among job-to-job switchers, while falling short of the observed overall job-to-job transition rates from the data. Finally, it is worth noting that a highly educated worker starts with a lower level of human capital than a worker with a low education level ($s_2 = -0.19 < 0$), and makes slightly smaller steps every time their human capital level changes ($\Delta_s(2) = 0.074 < 0.1$). As a result, the educational wage premium is primarily driven by differences in the marginal productivity distribution ($\mu_{y,2} > \mu_{y,1}$) rather than by differences in human capital levels.

When it comes to the firm distributions the workers draw from upon receiving an offer, these are best illustrated in a diagram. Figure 13 visualizes the bivariate distribution of firms' productivity and separation rates for the two education groups. For both education groups, the graph illustrates how extreme the estimated distribution is. While the range of the distribution is

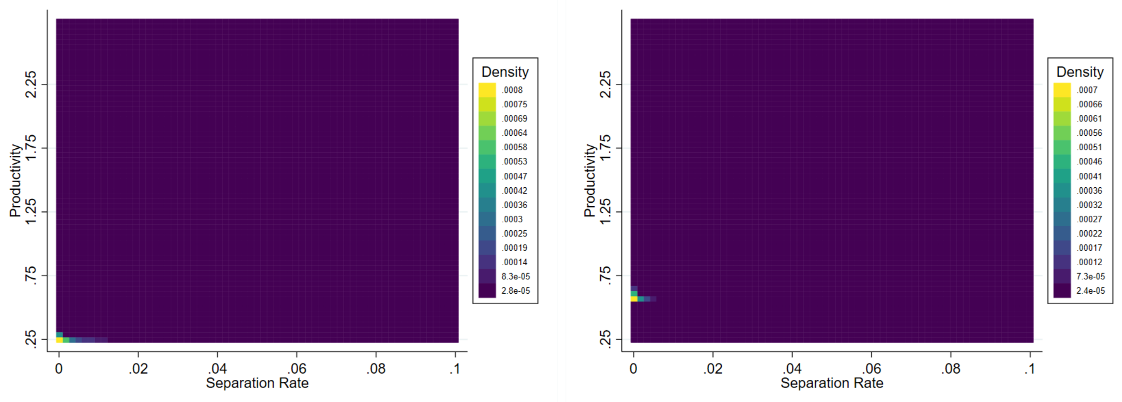

Figure 13: *The joint distribution of productivity and separation risk faced by workers with a low education level (left) and a high education level (right). A lighter colour in this chart corresponds to a higher density.*

reasonable (as illustrated by the upper bounds of the figures), the estimated distributions seem to put an unreasonably large weight on levels of productivity and separation rates that are close to the minimum. As a result of this extremely heavy right skewness, most of the heterogeneity described by the wage dispersion moments in table 3 is driven by differences in human capital levels (and bargaining, to a limited extent), rather than productivity. the bulk of the density is located in the bottom left corner of the graph (which corresponds to low productivity and low separation rates), thus illustrating that both marginal distributions of δ and y are quite heavily right-skewed. The marginal distribution of network strength p, on the other hand, looks much more reasonable, as illustrated in figure 14, with a reasonable spread across possible values, and values closer to 1 for highly educated individuals, indicating higher importance of these network effects for highly educated individuals. Nevertheless, given that the productivity distribution is so strongly right-skewed, these network effects are not likely to have a large effect on outcomes, as the pre-displacement productivities will generally be bunched close together and close to the lower bound μ_y.

6 Simulation Results

In this section, I present results obtained using simulated data from the estimated model, using the parameters that were obtained in the previous section. In particular, I will start in subsection 6.1 by assessing how the model performs in matching the observations from the data (in section 3). Further (future) sections will then decompose these results to investigate what the main driving

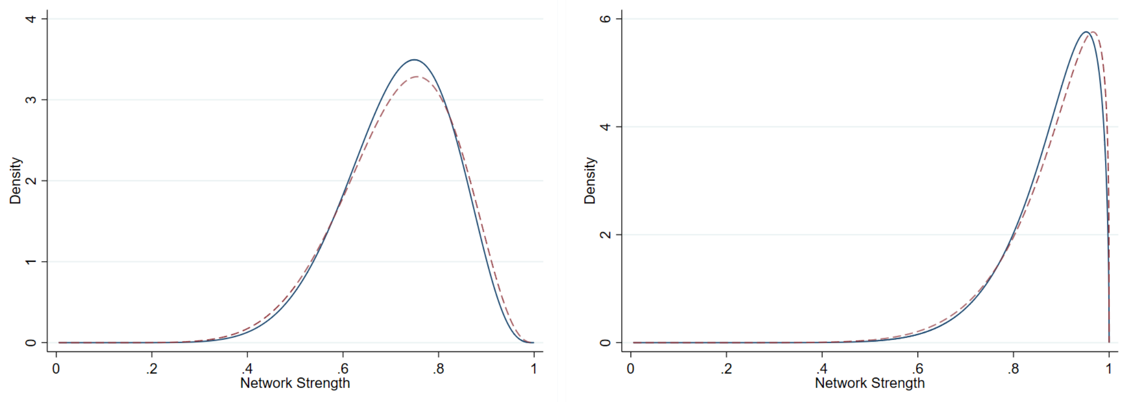

Figure 14: *The marginal distribution of the network strength variable* p *faced by workers with a low education level (left) and a high education level (right). The figures plot the observed distribution of* p *in the simulation sample (solid) as well as the underlying distribution from which workers draw in reality (dashed).*

channels are behind these results, and illustrate the importance of these findings through a number of counterfactual experiements.

6.1 Displacement Scars over the Recent Earnings Distribution

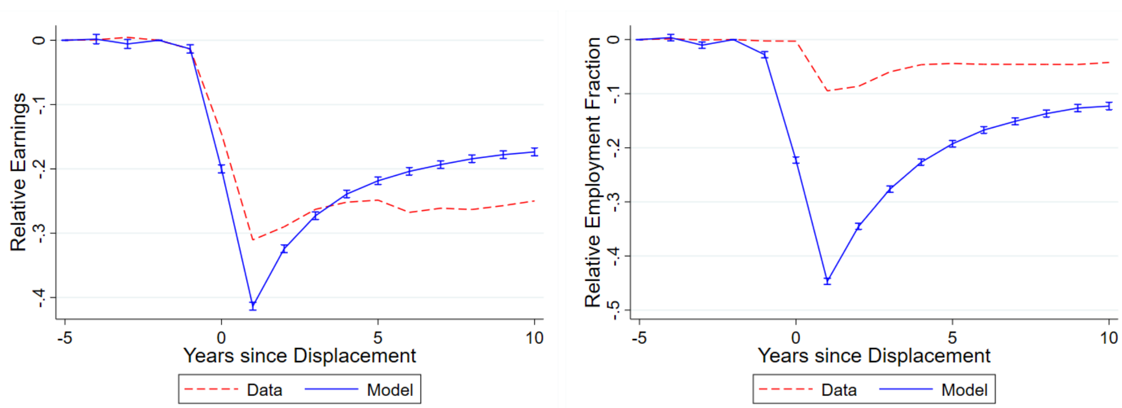

Figure 15: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right), relative to the control group, using model simulation data (solid) and using the data (dashed, corresponding to figure* **??***).*

Before plotting the model-generated earnings losses over the recent earnings distribution, figure 15 provides an indication of the model's ability to match average earnings and employment losses after job displacement. It can be seen that when it comes to earnings losses, the model provides a decent fit, although it initially slightly overshoots the losses and subsequently suggests a recovery that is more rapid than that observed in the data. When it comes to employment fraction, however, the model does not perform very well, and largely overshoots employment losses in the short run and the long run. This is likely a result of the very low job finding rate among workers with a low education level, as highlighted earlier when discussing the results in table 3. For highly educated workers, on the other hand, the model matches the employment loss in the short run, but underperforms in the long run, due to the low job separation rate experienced by highly educated workers in the model (compared to the data).

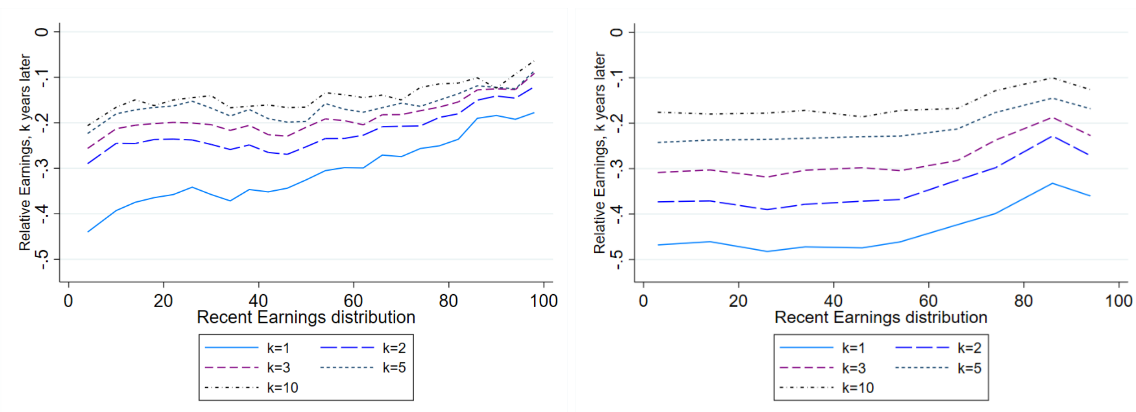

Figure 16: *The effect of displacement on earnings over the recent earnings distribution, using data (left) or model simulations (right). The numbers underlying the graphs are calculated directly from the (simulation) data, and are relative to workers in the control group in the same percentile of the recent earnings distribution. Each line corresponds to a single period, k years after the initial displacement takes place.*

In the right panel of figure 16, I show how earnings losses after job displacement differ by recent earnings in the estimated model. Compared to the corresponding figure from the data (the left panel of figure 3, which is repeated in the left panel of figure 16), it can be seen that the model is able to generate the upward sloping pattern over the recent earnings distribution, as well as the slope of these lines. However, in line with what was observed when discussing the average earnings losses, the recovery over time is generally too fast, as evidenced by the the lines shifting up too much, especially from years 3 onwards.

In figure 17, I show similar results, but using employment rather than earnings. It can be observed in the right panel that the pattern for employment is very similar to the pattern for earnings in the model, thus indicating that employment is the main driver of earnings losses in

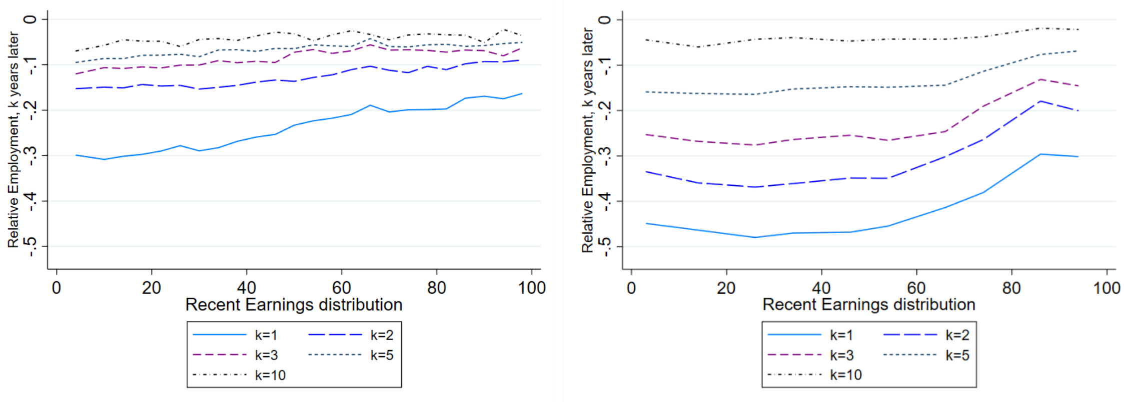

Figure 17: *The effect of displacement on employment fraction over the recent earnings distribution, using data (left) or model simulations (right). The numbers underlying the graphs are calculated directly from the (simulation) data, and are relative to workers in the control group in the same percentile of the recent earnings distribution. Each line corresponds to a single period, k years after the initial displacement takes place.*

the model. Comparing the model with the data, the model once again successfully reproduces an upward slope. However, the magnitude of employment losses is much larger in the model than in the data in the first few years after displacement, in line with the excessively large average employment losses observed above.

In figure 18, I decompose the earnings losses over the recent earnings distribution (as observed in the right panel of figure 16) into figures specific to workers who spend some time in unemployment (left panel) and workers who move to a new job immediately. The pattern observed in figure 18 is quite different from the corresponding pattern observed in the data (in figure 4). In particular, the upward slope remains among workers spending some time in unemployment (although the general magnitude of the losses is matched decently). For workers making an immediate transition, a slight negative slope is observed, although the magnitude of losses is also much lower (and in some cases the workers gains earnings on average). As a result, the model was unable to match the patterns in earnings losses by EE status. This is likely the result of the extremely narrow distribution of firms observed in section 5. In such a narrow distribution, the job ladder forces will be fairly weak. In the absence of a strong job ladder, an upward sloping pattern then results from pre-displacement differences in other characteristics, such as human capital.

While the model is unable to capture the recent earnings gradient is post-displacement earnings losses, it nevertheless points to EE status as an important explanation for the upward

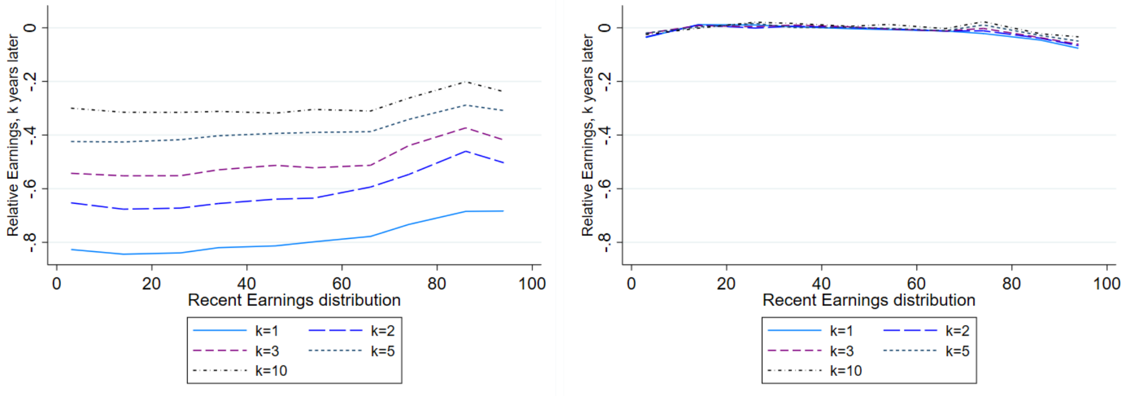

Figure 18: *The effect of displacement on earnings over the recent earnings distribution, for workers who transitioned directly to a new job (right) and workers who did not do so (left). The numbers underlying the graphs are calculated directly using model-simulated data, and are relative to workers in the control group in the same percentile of the recent earnings distribution. Each line corresponds to a single period, k years after the initial displacement takes place.*

slope in figure 16. The upward slope observed in figure 16 is much stronger than in either panel of figure 18, indicating that the model puts a larger weight on differences in composition (within each percentile) between workers who do and do not make an immediately transition. As can be seen in figure 19, the fraction of displaced workers making an immediate transition to a new job is generally increasing in recent earnings. Therefore, the estimated earnings losses for higher percentiles of the recent earnings distribution put a higher weight on the (much smaller) earnings losses for workers who make an immediate transition, thus resulting in a (stronger) upward slope in the right panel of 16.

7 Conclusion

In this paper, I study how the earnings and employment losses experienced by displaced workers differ by these workers' pre-displacement earnings. Using detailed administrative data from Germany, I find that relative earnings losses tend to be lower for workers with higher recent earnings (defined as the average earnings over the 5 years prior to displacement). This pattern is largely driven by workers who make an immediate transition to a new job upon being displaced. The fraction of displaced workers who make such a direct transition is increasing in recent earnings, and workers who make such a transition generally experience lower earnings losses. Furthermore, even

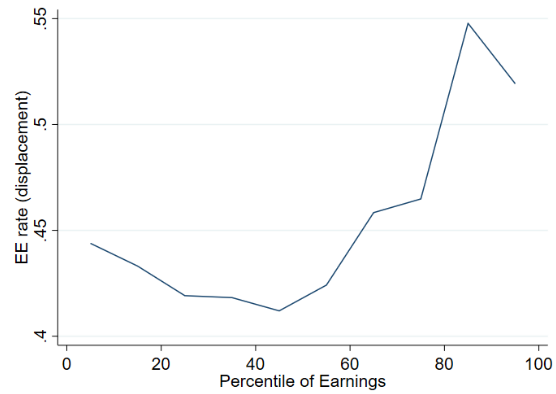

Figure 19: *The incidence of job-to-job transitions upon job displacement in the model simulation, over the recent earnings distribution.*

within the category of workers who make a direct transition, relative earnings losses are decreasing in recent earnings, while for workers who spend some time in unemployment the opposite pattern holds.

I argue that existing models that have been able to replicate the average earnings loss after job displacement are inconsistent with these observations. In particular, these models generally predict that relative earnings losses are increasing with recent earnings, largely driven by the worker falling off the job ladder. In order to reconcile my observations with these models, I develop a search model of the labour market in which I allow workers who make a job-to-job transition to draw from an improved distribution. In particular, the marginal productivity distribution from which they draw their new job is truncated from below, where the truncation point is determined by the job characteristics of their previous job. I interpret this feature as a network effect, where workers are able to leverage their employer's network as long as they are still connected to this employer. Once the worker loses their connection to the employer (i.e. moves into unemployment), they can no longer leverage these connections, and are thus subject to the regular forces of the job ladder.

I estimate the model using moments generated from the German administrative data, and show that the model in its current form is able to replicate the observation that relative earnings losses after displacement are decreasing in recent earnings. In the model simulation, this is purely driven by the increasing fraction of workers making a job-to-job transition. Furthermore, the model simulation indicates that relative earnings losses for workers who spend some time in unemployment is decreasing in recent earnings, whereas workers who make a direct transition are experiencing a slight gain earnings, which is decreasing in recent earnings. This contradicts the observations from the data, and ongoing work in this project is therefore working to address this.

Based on the results of this paper, one can think of various avenues for future research, and I will highlight a few of those possibilities here. First of all, it will be worth further investigating the sources of the differences between workers who spend some limited time in unemployment and those who directly transition to a new job upon being displaced. The channel that operates in the model is interpreted as network strength, but the data is not suitable to provide any evidence of this beyond the use of proxies such as individual and establishment fixed effects or wage and earnings growth experienced after re-employment. Future work could address this, for example by using large scale survey data that provides some information on a worker's (professional or informal) network while also allowing for a replication of the observations provided in this paper.

When it comes to the model, there are also are a number of ways in which one might imagine expanding the analysis presented in this paper. First of all, in the current setup of the model, the effect of the job's network activates immediately upon being hired and disappears immediately upon losing a connection to the firm. In reality, however, one might imagine that it takes time for a worker to establish their connections. In ongoing work, I plan to address this by allowing for the network to stochastically activate (and always being inactive upon hiring). Alternatively, one could think of modeling the activation of the network in a similar way as one models human capital (although that raises the question of how to identify corresponding parameters alongside the human capital accumulation channel), where the job characteristic used in the current setup simply represents the ceiling of the corresponding state variable. Finally, one might imagine that the value of the network depends on the economic conditions at the time of displacement. If the worker is displaced in a boom, it may be much easier to find a suitable job through their network than in a recession, where other firms may also be contracting. Incorporating an element into the model that changes over the business cycle may allow future work to take into account such considerations as well.

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A Numerical Methods

A.1 Derivation of the wage

To derive the wage (or rather the piece-rate), I use value function W (omitting the ε):

$$
\begin{aligned}
W(s,\hat{s},\theta,\hat{\theta}) = \ln(R(\hat{s},\theta,\hat{\theta})f(s,y)) + \beta\mathbb{E}_{s'|s,e}\Bigg\{ & \delta\hat{U}(s') \\
+(1-\delta)\Bigg[\lambda^e\Bigg(&\int_{x\in\Theta^1(s',\theta)} W(s',s',x,\theta)d\hat{G}(x) + \int_{x\in\Theta^2(s',\hat{s},\theta,\hat{\theta})} W(s',s',\theta,x)d\hat{G}(x)\Bigg) \\
+\Bigg(1-\lambda^e\int_{x\in\Theta^1(s',\theta)\cup\Theta^2(s',\hat{s},\theta,\hat{\theta})} d\hat{G}(x)\Bigg)& W(s',\hat{s},\theta,\hat{\theta})\Bigg]\Bigg\}
\end{aligned} \tag{A.1}
$$

Further, note that given a known value for W^{max} and U (for every s and θ), the value $\hat{U}$ can be directly calculated using equation (10). Further, note that:

$$
\begin{aligned}
& x \in \Theta^1(s',\theta) \iff W^{max}(s',x) \geq W^{max}(s',\theta) \\
& x \in \Theta^2(s',\hat{s},\theta,\hat{\theta}) \iff W^{max}(s',\theta) > W^{max}(s',x) \geq W^{max}(\hat{s},\hat{\theta}) \\
& W(s,s,x,\theta) = W^{max}(s,\theta) + \kappa\left(W^{max}(s,x) - W^{max}(s,\theta)\right)
\end{aligned}
$$

Since I know the value of W^{max}, U, and f for a given combination of s and θ, this implies that the only unknowns in the value function are $W(s,\hat{s},\theta,\hat{\theta})$, $R(\hat{s},\theta,\hat{\theta})$, and $W(s',\hat{s},\theta,\hat{\theta})$.

As these are all using the same value for $\hat{s}$, θ and $\hat{\theta}$, this equation can be greatly simplified, by defining the following constants (where the subscript denotes current human capital level s, i.e. the first variable in the value function):

$$
\begin{aligned}
C_{s'} = \beta(1-\delta)\lambda^e & \Bigg(\int_{x\in\Theta^1(s',\theta)} W(s',s',x,\theta)d\hat{G}(x) + \int_{x\in\Theta^2(s',\hat{s},\theta,\hat{\theta})} W(s',s',\theta,x)d\hat{G}(x)\Bigg) \\
& + \beta\delta\hat{U}(s') \\
a_{s'} = \beta(1-\delta) & \Bigg(1-\lambda^e\int_{x\in\Theta^1(s',\theta)\cup\Theta^2(s',\hat{s},\theta,\hat{\theta})} d\hat{G}(x)\Bigg)
\end{aligned}
$$

We can use this notation to rewrite the value function W as follows:

$$
W(s,\hat{s},\theta,\hat{\theta}) = \ln(R(\hat{s},\theta,\hat{\theta})f(s,y)) + \mathbb{E}_{s'|s,e}\left\{C_{s'} + a_{s'}W(s',\hat{s},\theta,\hat{\theta})\right\}
$$

The expression above can be simplified further by using the simple structure of the expectations operator. If the match is formed (as denoted by the subscript e), there are only two options for the future level of s, s': With probability ψ_e, $s' = s+1$ (i.e. the previous level plus 1 stepsize, which may not necessarily be the next grid point) and with probability $1-\psi_e$, $s' = s$. The one exception to this is that if the worker is at the maximum value of s, in which case $\psi_e = 0$.[20] Below, I rewrite the value function using this structure. In what follows, I use $\psi = \psi_e$ (for ease of notation):

$$W(s,\hat{s},\theta,\hat{\theta}) = \ln(R(\hat{s},\theta,\hat{\theta})f(s,y)) + \psi\left\{C_{s+1} + a_{s+1}W(s+1,\hat{s},\theta,\hat{\theta})\right\} + (1-\psi)\left\{C_s + a_s W(s,\hat{s},\theta,\hat{\theta})\right\}$$

In what follows, I will drop the elements $\hat{s}$, $\hat{\theta}$ and θ, so that this equation becomes:

$$\begin{aligned} W_s &= \ln(Rf(s,y)) + \psi\left\{C_{s+1} + a_{s+1}W_{s+1}\right\} + (1-\psi)\left\{C_s + a_s W_s\right\} \\ W_s\left[1-(1-\psi)a_s\right] &= r + \ln(f(s,y)) + \psi\left\{C_{s+1} + a_{s+1}W_{s+1}\right\} + (1-\psi)C_s \end{aligned}$$

This is a system of equations for each value of $\hat{s}$ on the grid. Since $s \geq \hat{s}$, there are (with slight abuse of notation) $N_s - \hat{s} + 1$ equations, one for each $s \geq \hat{s}$, and $N_s - \hat{s} + 2$ unknowns, one for each value W_s and the piecerate R. However, one additional equation can be added, which does not add any unknowns: $W_{\hat{s}} = W^{max}(\hat{s},\hat{\theta}) + \kappa\left(W^{max}(\hat{s},\theta) - W^{max}(\hat{s},\hat{\theta})\right)$

The resulting system of equations has $N_s - \hat{s} + 2$ equations and $N_s - \hat{s} + 2$ unknowns and can thus be solved. In order to do so, I set up matrix A and vector B, such that the system is represented as $Ax = B$, where x is a vector containing the unknowns. These matrices will be $N_s - \hat{s} + 2$ by $N_s - \hat{s} + 2$, but take an easily generalizeable form. For example, for $\hat{s} = N-2$, the vectors and matrices will look as follows (denoting $p_s = p(s,y)$ and $r = \ln(R)$):

$$Ax = \begin{pmatrix} 1-a_N & 0 & 0 & -1 \\ -\psi a_N & 1-(1-\psi)a_{N-1} & 0 & -1 \\ 0 & -\psi a_{N-1} & 1-(1-\psi)a_{N-2} & -1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \cdot \begin{pmatrix} W_N \\ W_{N-1} \\ W_{N-2} \\ r \end{pmatrix}$$

$$B = \begin{pmatrix} C_N + \ln(f_N) \\ \psi C_N + (1-\psi)C_{N-1} + \ln(f_{N-1}) \\ \psi C_{N-1} + (1-\psi)C_{N-2} + \ln(f_{N-2}) \\ W^{max}(\hat{s},\hat{\theta}) + \kappa\left(W^{max}(\hat{s},\theta) - W^{max}(\hat{s},\hat{\theta})\right) \end{pmatrix}$$

Unfortunately, there is one small complication: the method above is based on the assumption that

[20] Note that technically there is no maximum value of s, but I do solve the model on a limited number of grid points for s. Later in this section, I briefly comment on how I reconcile this.

there is a maximum level of human capital. However, given that workers in the model are infinitely-lived, workers could in principle accumulate an infinite amount of human capital if I would run the simulation for an infinite number of periods. Furthermore, as the workers can infinitely accumulate human capital, there are an infinite number of possible values for s and $\hat{s}$.

I get around this issue by using an approximation. In particular, I solve the model (and therefore also the wage) only for a limited number of human capital grid-points, and interpolate and extrapolate the solution for all other grid-points. These grid-points for the solution are heavily concentrated near the lowest possible level, as every worker starts at this low level, and therefore many workers will pass through these grid-points. As mentioned in the previous subsection, I select the maximum grid-point by calculating the grid-point that is achieved only by the top 0.1% of the workers after 30 years.

Of course, solving the model on a limited grid also has consequences for some of the equations discussed above (and explicitly so where I explicitly use the structure of the expectations operator). In practice, I therefore use a slightly adjusted formulation of the matrix A and vector B above. In the matrix A, there are two changes. First in every row except for the first and last row of matrices A and B, I replace ψ by $\psi\frac{\Delta_s}{(N)-(N-1)}$ (for the second row, and similarly for other rows using other values of N), where Δ_s is the actual jump in human capital upon ψ materializing, and N and $N-1$ are the values of s on the Nth and (N-1)st grid-point. This reflects the interpolation between grid points. For the top row, the extrapolation implies that the top left element of A becomes $1-(1+\bar{\psi})a_N$, where $\bar{\psi}=\psi\frac{\Delta_s}{(N)-(N-1)}$. The second element of the first row becomes $\bar{\psi}a_{N-1}$. Finally, the top row of vector B becomes $(1+\bar{\psi})C_N-\bar{\psi}C_{N-1}+\ln(p_N)$. To be explicit, this means that the vectors and matrices will look as follows in practice:

$$A=\begin{pmatrix} 1-\left(1+\psi\frac{\Delta_s}{(N)-(N-1)}\right)a_N & \psi\frac{\Delta_s}{(N)-(N-1)}a_{N-1} & 0 & -1 \\ -\psi\frac{\Delta_s}{(N)-(N-1)}a_N & 1-\left(1-\psi\frac{\Delta_s}{(N)-(N-1)}\right)a_{N-1} & 0 & -1 \\ 0 & -\psi\frac{\Delta_s}{(N-1)-(N-2)}a_{N-1} & 1-\left(1-\psi\frac{\Delta_s}{(N-1)-(N-2)}\right)a_{N-2} & -1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

$$B=\begin{pmatrix} \left(1+\psi\frac{\Delta_s}{(N)-(N-1)}\right)C_N-\psi\frac{\Delta_s}{(N)-(N-1)}C_{N-1}+\ln(f_N) \\ \psi\frac{\Delta_s}{(N)-(N-1)}C_N+\left(1-\psi\frac{\Delta_s}{(N)-(N-1)}\right)C_{N-1}+\ln(f_{N-1}) \\ \psi\frac{\Delta_s}{(N-1)-(N-2)}C_{N-1}+\left(1-\psi\frac{\Delta_s}{(N-1)-(N-2)}\right)C_{N-2}+\ln(f_{N-2}) \\ W^{max}(\hat{s},\hat{\theta})+\kappa\left(W^{max}(\hat{s},\theta)-W^{max}(\hat{s},\hat{\theta})\right) \end{pmatrix}$$

Note that x is still the same as specified above, but using only the value function W on the grid points (along with the piece-rate). The matrix equation $Ax=B$ is then solved for x, using LU decomposition, and the solution will yield the piece-rate $R=e^r$ for this particular value of $\hat{s}$, θ, and $\hat{\theta}$, and solving this system of equations for every combination of $\hat{s}$ (on the grid), θ, and $\hat{\theta}$ (including u) will complete the solution.

In this section, I will describe in more detail the moments used for estimating the model (see section 5) are estimated. When estimating these moments in the data, I restrict the data such that I only consider workers with a market tenure of at least 3 years, to avoid biased estimates due to traineeships. I impose the same restriction in the model simulation, noting that this is done purely in order to preserve consistency between the two estimation methods, as the concerns driving this restriction do not exist in the data. With the exception of the yearly wage growth, all moments discussed below are estimated using the quarterly data set.

A.2 Transition Rates

As argued in section 5.2, the transition rates of workers between employment and unemployment and between employment at different establishments (overall or conditional on impending displacement) were chosen primarily to aid in the identification of the job offer rates, $\lambda_{\varepsilon}^{e}$, $\lambda_{\varepsilon}^{u}$, and $\lambda_{\varepsilon}^{ug}$, and the marginal distribution of δ. The estimation of these moments described below.

In order to estimate the job loss rate, I use a variable which is only filled if the worker is currently employed and still observed in the next period (quarter). Conditional on fulfilling this condition, the variable then acts as an indicator of whether the worker is unemployed in the next quarter. The job loss rates by job tenure are then calculated by taking a simple average over all workers with an establishment tenure of 1 to 3.5 years (i.e. more than exactly 1 year, less than exactly 3.5 years), 3.5 to 6 years, 6 to 9 years, and more than 9 years. Similarly, taking a simple average over all workers with a low and high education level yields the education-specific unconditional rates of job loss. Finally, I take the average over all workers who returned from nonemployment within the last 4 quarters to find the rates of subsequent separation for displaced.

In order to estimate the job-to-job transition rates, I create a similar variable (filled under the same conditions). In this case, the variables acts as an indicator of whether the worker is employed at a different establishment in the next quarter. In the data, this can be tracked using the establishment id number. In the model, the firm productivity y can be used for this. After all, since the marginal distribution of y has a continuous support, the probability that two different establishments in the model have the exact same productivity is negligible (even if the productivity distribution is very concentrated in a small interval), and productivity is assumed to be constant throughout the employment relationship. In order to construct the moment, I take the average by education group and recent earnings percentile group. Similarly, I calculate the job-to-job transition rate upon displacement (by education group and recent earnings group) by following the same procedure, but conditioning the filling of the variable of interest on the worker experiencing a displacement event in the (current) quarter. Note that the recent earnings distribution in the model is formed using the same method as in the data: I construct recent earnings using all observations over the preceding 5 years, whenever available, and condition on at there being at least 3 years observed, including the year preceding displacement (which coincides with the aforementioned condition on market tenure). The resulting recent earnings percentile is then determined by ranking workers within age group only (since there is no meaningful notion of year, gender, or location in the model).

In order to estimate the average job finding rate, a similar procedure is followed. However, for this moment the indicator variable is only filled for currently nonemployed workers who are still observed in the next quarter, and the variable indicates whether these workers are employed in the next quarter. To compute the moment value, the average is taken by education group.

A.3 p75-p25 and median-p25 Ratios of Wages

In order to estimate the p75-p25 and median-p25 ratios of wages (by education group) in the data, I restrict the sample to full-time workers only, along with the aforementioned restriction on market tenure. Furthermore, I restrict the observations to those who are (full-time) employed for the entire quarter. In the data, I can then directly summarize the wage by education group, which will yield the 25th percentile, median, and 75th percentile wage. Once these are retrieved, the p75-p25 and median-p25 ratio can be calculated directly.

In the model, I estimate the moments by isolating all wages of employed workers (since the model does not allow for part-time or part-period work). The 25th percentile, median, and 75th percentile wage can then be calculated directly by sorting the resulting vector of wages and taking out the middle observation and the observation at the 25th and 75th percentile, after which the ratios of interest follow.

A.4 Replacement Rate, and Average Wage of New Hires

In order to calculate the replacement rate in the model, I calculate the average wage and the average unemployment benefit in the simulation, which follows in a straightforward way from simply restricting the sample to employed or unemployed workers. Denoting the resulting average wage by $\bar{w}$ and the average unemployment benefit by $\bar{b}$, the replacement rate then equals $\bar{b}/\bar{w}$. As mentioned in section 5, the data counterpart is taken directly from OECD (2020).

The average wage calculated in order to calculate the replacement rate is also used when calculating the average (relative) wage of new hires. Denoting the average wage of new hires by $\bar{w}_N$, this moment equals $\bar{w}_N/\bar{w}$. In order to calculate $\bar{w}_N$, I restrict the sample to workers with an establishment tenure of more than a quarter, and less than a year, who are (full-time) employed for the entire quarter, and were unemployed before starting at their current establishment. Calculating the data counterpart of the average wage $\bar{w}$ uses the data equivalent of the procedure outlined above for the replacement rate, again restricting the sample to full-time workers who are employed for the entire quarter. Note that when I estimate this moment, I omit the top and bottom 5% of observations when calculating $\bar{w}_N$ and $\bar{w}$. This is to avoid excessive influence by some of the outliers I see in the data.

A.5 Average Educational Wage Premium, Overall and Upon Entry

In order to estimate the educational wage premium, I restrict the sample (in the data and in the model simulation) to employed workers of a given education group. In order to estimate the educational wage premium, I estimate the average wage within each of these samples (again omitting the top and bottom 5%). Denoting this average by $\bar{w}_\varepsilon$, the educational wage premium then equals $\bar{w}_2/\bar{w}_1$. In order to estimate this educational wage premium upon entry, I follow the same procedure, further restricting the sample to workers with a market tenure of 3 to 5 years (i.e. more than exactly 3 years, and less than exactly 6 years).

A.6 Average Yearly Wage Growth

In order to estimate the average yearly wage growth, I restrict the sample in the yearly dataset to workers with a market tenure of at least 3 years who were full-time employed for the entire year as well as the entire next year. For each worker-year combination for which this holds, I then calculate the yearly wage growth as $w_{t+1}/w_t - 1$, after which the average yearly wage growth is a simple average over workers of the same education group (omitting the top and bottom 5%).

A.7 Pre- to Post-layoff Wage Differentials

As mentioned in section 5, the calculation of the average pre- to post-layoff wage differential closely resembles a difference-in-differences estimation procedure. I first identify all individuals who were working full-time at the job from which they were laid off (this is true by definition in the model). The resulting sample is split into 16 subsamples, by education group and unemployment duration in quarters (ranging from 1 quarter to 8 quarters). For all workers in the sample, the pre-layoff wage is then equal to the wage in the quarter before the layoff, provided that the worker worked full-time at this same establishment for this entire previous quarter. Further restricting the sample to workers whose next job after re-employment is also full-time, the post-layoff wage is equal to the average wage in the first four full quarters after starting this job (conditional on being full-time employed for that entire quarter). The resulting wage differential is the difference between this pre- and post layoff wage, and naturally restricts to workers who worked full-time for the entire quarter prior to displacement as well as at least one of the four quarters following re-employment. The same procedure is then followed for a control group of non-displaced workers (looking forward the same amount of time as for the corresponding treatment group), after which the moment of interest is the average of the differences in these differences across duration quarters that fall within each group of interest (1 quarter to 0.5 year, 0.5 to 1 year, and 1 to 2 years). Thus, the moment is essentially an average of coefficients of difference-in-difference estimations, where a separate estimation is done for each education level and quarter of nonemployment duration.

A.8 Correlation between Wages and Separation

The moment estimated to aid in the identification of the copula parameter ρ is n is the regression coefficient $\hat{\gamma}$ in equation (A.2):

$$D^{\delta}_{i,t} = \alpha_i + \gamma \log(w_{it}) + u_{i,t} \tag{A.2}$$

In the data, this equation can in principle be estimated using a standard fixed effects estimation. However, this is quite computationally intensive to do in each iteration of the calibration. Therefore, I use the fact that the individual fixed effect is constant over time to greatly simplify the estimation, while not discarding an excessive number of observations. In particular, I calculate the average log wage for each individual, restricting the calculation in the data to wages in full-quarter full-time employment. Similarly, I calculate the average value of the separation indicator (created earlier to calculate the average rate of job loss) over all the periods for which it is filled. Then, I rewrite the equation by subtracting the average from both sides:

$$D^{\delta}_{i,t} - \bar{D}^{\delta}_{i,t} = \alpha_i - \bar{\alpha}_i + \gamma \log(w_{it}) - \gamma \overline{\log(w_{it})} + u_{i,t} - \bar{u}_{i,t} \tag{A.3}$$

$$\left(D^{\delta} - \bar{D}^{\delta}\right)_{i,t} = \gamma \left(\log(w) - \overline{\log(w)}\right)_{it} + u_{i,t} \tag{A.4}$$

As can be seen in equation (A.4), all elements on both sides of the equation now depend on both i and t, thus allowing for simple OLS estimation both in the simulation and in the data, yielding coefficient $\hat{\gamma}$.

A.9 Average Post-Displacement Earnings Losses by Recent Earnings

In addition to the baseline moments discussed above, one can in principle also directly target the results from the empirical section of the paper. While the estimation of the regression-based results would likely be too computationally intensive to feasibly estimate in each iteration of the estimation, the raw comparisons from section 3.2 are much less intensive to calculate. Indeed, in generating the estimation results presented in sections 5 and 6, I additionally target the raw average earnings losses over the recent earnings distribution displayed in the right panel of figure 3. In particular, I target the observed earnings losses 1 and 5 years after displacement takes place (corresponding to the $k = 1$ and $k = 5$ lines in the figure), arguing that these provide reasonable proxies for the immediate / short-run losses and the persistence of these losses.

In order to estimate the model equivalent of these two lines, I calculate the average (yearly) earnings within each percentile group, 1 and 5 years after displacement, and I do so separately for displaced workers and non-displaced workers (who act as the control group). The corresponding moment value then equals the relative earnings loss of the displaced worker compared to the control worker, measured as the extent to which the displaced worker's average earnings is lower either 1 or 5 years after displacement. In order to avoid results being influenced by the dynamics at the very bottom and top of the earnings distribution, I omit workers in the top and bottom 12 percentiles of the recent earnings distribution, generally grouping all other percentiles in groups of four. Doing this for $k = 1$ and $k = 5$ therefore results in 38 additional moments incorporated into the estimation.

B Model Appendix

B.1 A simple job ladder model

As discussed in section 3.4, a simple job ladder model is not able to generate decreasing relative earnings losses in pre-displacement earnings. In this section, I illustrate this by simulating a job ladder model in the style of Burdett and Mortensen (1998) with four types of firms. In particular, I use the model estimation from Bowlus and Neumann (2006), and show its implications for the cost of job loss over the recent earnings distribution.

In the model, described in some detail in Bowlus et al. (2001) and estimated in Bowlus and Neumann (2006), workers are homogeneous, but firms differ in their productivity. In particular, four firm types are distinguished, and the productivity of a firm of type j is denoted by P_j. The distribution of firms across these four types is represented by γ_j, which denoted the probability that a firm is of type j or lower, and firms are sorted such that a lower type firm has a lower productivity. Workers are characterized by their reservation wage R, and receive a job offer with probability λ_0 when unemployed and with probability λ_1 if employed. If a worker is employed, their match is destroyed with probability δ, the size of which is important especially in relation to the job finding rates, defining $k_0 = \lambda_0/\delta$ and $k_1 = \lambda_1/\delta$. As shown in Bowlus et al. (2001) and Mortensen (1988), the equilibrium distribution of wages in this model is piecewise, $F(w) = \phi_j(w)$, with the highest wage in each segment, $w_{H,j}$, also being the lowest wage in the next segment, $w_{L,j+1}$, and with $w_{L,1} = R$. In particular:

$$\phi_j(w) = \frac{1+k_1}{k_1}\left[1 - \frac{1+k_1(1-\gamma_{j-1})}{1+k_1}\left(\frac{P_j - w}{P_j - w_{L,j}}\right)^{0.5}\right] \quad \text{for } w_{L,j} < w \leq w_{H,j} \tag{B.1}$$

$$w_{H,j} = P_j - (P_j + w_{L,j})\left(\frac{1+k_1(1-\gamma_j)}{1+k_1(1-\gamma_{j-1})}\right)^2 \tag{B.2}$$

For this simulation, I use the estimated parameters from Bowlus and Neumann (2006), which they obtained using data from the NLSY, restricting to fulltime work only. These parameters (and corresponding kink points of the equilibrium wage distribution) are summarized in Table B.1.

Parameter	R	λ_0	λ_1	δ	γ_1	γ_2	γ_3	
Value	115.97	0.0284	0.0077	0.0047	0.524	0.807	0.927	
Parameter	P_1	P_2	P_3	P_4	$w_{H,1}$	$w_{H,2}$	$w_{H,3}$	$w_{H,4}$
Value	296.4	404.64	600.45	2342.97	214.58	300.95	384.77	781.99

Table B.1: *Parameter values used for the simulation of the simple job ladder, obtained from Bowlus and Neumann (2006).*

Figure B.1 shows how earnings losses (left panel) and employment losses (right panel) differ over the recent earnings distribution in the model simulation. The figured is obtained directly from the simulated data, and can thus be thought of as the model equivalent of Figure 3 in the main text. The right panel of Figure B.1 shows that employment losses do not depend on the worker's position in the recent earnings distribution. This is not quite the case in the data (where losses are decreasing in recent earnings in the short run), but given the simple setup of the model one can nevertheless argue that the model simulation does a reasonable job of capturing the data here. However, when it comes to earnings, the pattern implied by the model is opposite to the pattern observed in the data. Indeed, the left panel of Figure B.1 shows the relative earnings loss to be increasing in recent earnings, whereas the left panel of Figure 3 revealed these losses to be decreasing in recent earnings in the data. As such, it can be concluded that a simple job ladder cannot generate the patterns I observe in the data. As the majority of models that have been successful in regenerating the average earnings loss after displacement rely on a job ladder of some form, this suggests that these models will likely imply a similar counterfactual pattern of earnings losses over the recent earnings distribution, thus illustrating the need for a model such as the one I propose in section 4.

B.2 Further Value Functions and Worker Flows

The model presented in section 4 is a partial model in the sense that the firm side of the economy is completely passive. As a result, the model can be solved using value functions from the worker side only. However, the value function for a producing firm can still be defined. In the model described in section 4, the value function J for a firm of type θ, employing a worker of type ε with human capital s, is as

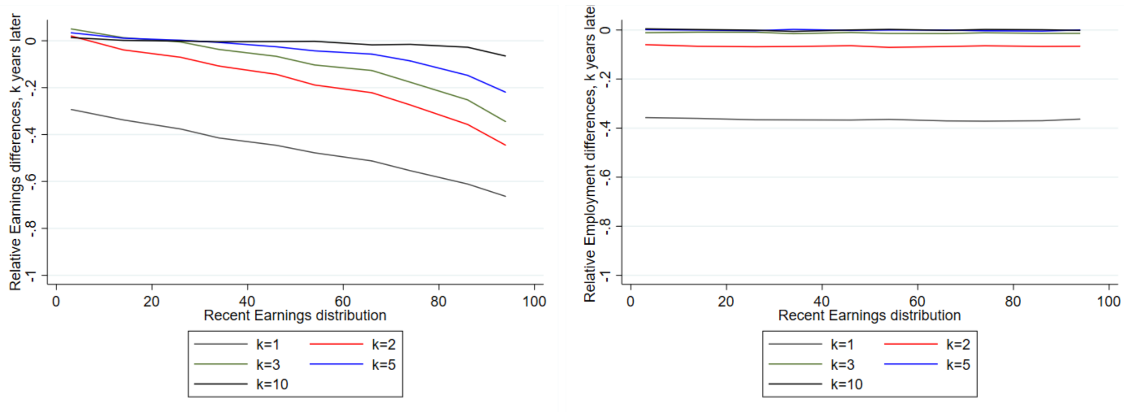

Figure B.1: *The effect of displacement on earnings (left) and employment (right) over the recent earnings distribution, using simulations of the simple job ladder model. The numbers underlying the graphs are calculated directly from the (simulation) data, and are relative to workers in the control group in the same percentile of the recent earnings distribution. Each line corresponds to a single period, k years after the initial displacement takes place.*

follows:

$$J_\varepsilon(s,\hat{s},\theta,\hat{\theta}) = \left(1 - R_\varepsilon(\hat{s},\theta,\hat{\theta})\right) f(s,y) + \beta \mathbb{E}_{s'|s,\varepsilon} \left\{ (1-\delta) \left[\lambda_\varepsilon^e \int_{x \in \Theta_\varepsilon^2(s',\hat{s},\theta,\hat{\theta})} J_\varepsilon(s',s',\theta,x) d\hat{G}_\varepsilon(x) \right.\right.$$
$$\left.\left. + \left(1 - \lambda_\varepsilon^e \int_{x \in \Theta_\varepsilon^1(s',\theta) \cup \Theta_\varepsilon^2(s',\hat{s},\theta,\hat{\theta})} d\hat{G}_\varepsilon(x)\right) J_\varepsilon(s',\hat{s},\theta,\hat{\theta}) \right] \right\} \quad \text{(B.3)}$$

Note that the value of an unmatched firm is $V = 0$, and therefore the scenario of the job being destroyed (either due to the worker making a job-to-job switch or due to the job being hit with the job destruction shock) is not explicitly included in equation (B.3).

The description of the model in the main text (section 4) can also be used to construct a number of worker flow equations. In what follows, denote by $d_\varepsilon(s,\hat{s},\theta,\hat{\theta})$ the density of employed workers of type ε with current human capital s, negotiation benchmark human capital $\hat{s}$, matched to a firm with characteristics $\theta \in [0,1]^2 \times \mathbb{R}_+$, and benchmark characteristics $\hat{\theta} \in [0,1]^2 \times \mathbb{R}_+$, and denote by $d_\varepsilon(s,\hat{s},\theta,u)$ the equivalent if this worker used unemployment as the outside option at the time of bargaining. Further, let $u_\varepsilon(s)$ be the density of unemployed workers of type ε with human capital s. First, define the following densities, defined after human capital accumulation (or depreciation) takes place:

$$\bar{d}_\varepsilon(s,\hat{s},\theta,\cdot) = (1-\psi_e) d_\varepsilon(s,\hat{s},\theta,\cdot) + \psi_e d_\varepsilon(s - \Delta_s(\varepsilon),\hat{s},\theta,\cdot)$$
$$\bar{u}_\varepsilon(s) = (1-\psi_u) u_\varepsilon(s) + \psi_u u_\varepsilon(s + \Delta_s(\varepsilon))$$

In what follows, I denote by $\hat{\delta}$ the separation rate corresponding to a firm with characteristics $\hat{\theta}$. Similarly, the function $\hat{g}_\varepsilon(\theta|x)$ refers to the probability (density) of drawing a firm with characteristics θ when drawing from a truncated distribution informed by firm characteristics x. The flow equations can then be expressed as follows:[21]

$$
\begin{aligned}
d'_\varepsilon(s,\hat{s},\theta,\hat{\theta}) &= (1-\delta)\left(1-\lambda^e_\varepsilon \int_{x\in\Theta^1_\varepsilon(s,\theta)\cup\Theta^2_\varepsilon(s',\hat{s},\theta,\hat{\theta})} d\hat{G}_\varepsilon(x)\right)\bar{d}_\varepsilon(s,\hat{s},\theta,\hat{\theta}) \\
&\quad + \mathbb{1}_{s=\hat{s}}\lambda^e_\varepsilon\left[\iint(1-\hat{\delta})\hat{g}_\varepsilon(\theta|\hat{\theta})\left(\mathbb{1}_{\theta\in\Theta^1_\varepsilon(s,\hat{\theta})}\bar{d}_\varepsilon(s,x,\hat{\theta},y)\right)dxdy\right] \\
&\quad +\lambda^e_\varepsilon\left[\iint(1-\delta)\hat{g}_\varepsilon(\hat{\theta}|\theta)\left(\mathbb{1}_{\hat{\theta}\in\Theta^2_\varepsilon(s,x,\theta,y)}\bar{d}_\varepsilon(s,x,\theta,y)\right)dxdy\right]\Bigg\}
\end{aligned} \tag{B.4}
$$

$$
\begin{aligned}
d'_\varepsilon(s,\hat{s},\theta,u) &= (1-\delta)\left(1-\lambda^e_\varepsilon \int_{x\in\Theta^1_\varepsilon(s,\theta)\cup\Theta^2_\varepsilon(s',\hat{s},\theta,u)} d\hat{G}_\varepsilon(x)\right)\bar{d}_\varepsilon(s,\hat{s},\theta,u) \\
&\quad + \mathbb{1}_{s=\hat{s}}\mathbb{1}_{\theta\in\Theta^u_\varepsilon(s)}\left(g_\varepsilon(\theta)\lambda^u_\varepsilon\bar{u}_\varepsilon(s)+\lambda^{ug}_\varepsilon\iiint\hat{g}_\varepsilon(\theta|x)\delta\bar{d}_\varepsilon(s,\tilde{s},x,\hat{x})d\tilde{s}dxd\hat{x}\right)
\end{aligned} \tag{B.5}
$$

$$
\begin{aligned}
u'_\varepsilon(s) &= \left(1-\lambda^u_\varepsilon\int_{x\in\Theta^u_\varepsilon(s)} dG_\varepsilon(x)\right)\bar{u}_\varepsilon(s) \\
&\quad + \int\delta\left(1-\lambda^{ug}_\varepsilon\int_{x\in\Theta^u_\varepsilon(s)} d\hat{G}_\varepsilon(x)\right)\iint\bar{d}_\varepsilon(s,\hat{s},\theta,\hat{x})d\hat{x}d\hat{s}d\theta
\end{aligned} \tag{B.6}
$$

C Data Appendix

C.1 Construction of the Regression-Based Graphs over the Recent Earnings Distribution

In this section, I provide a more detailed description of how the figures depicting earnings and employment losses in Section 3.3 of the main text are created from the corresponding event study graphs. While the figures in the main text use estimations of Equation (2) with $P = 10$ quantiles, the example I use in this section uses only $P = 3$, for expositional reasons. However, the method explained here extends to the case of $P = 10$ (or the case of employment rather than earnings) in a straightforward way. Additionally, I leave out confidence intervals (which are available upon request) from the figure. These confidence intervals are transferred to the figure over the earnings distribution in the same way as the point estimates, on which the explanation below focuses.

[21] Note that when I integrate over y in equation (B.4), I include all possible values for $\hat{\theta}$, including u, in this integration. The same holds for the integration over $\hat{x}$ in equations (B.5) and (B.6).

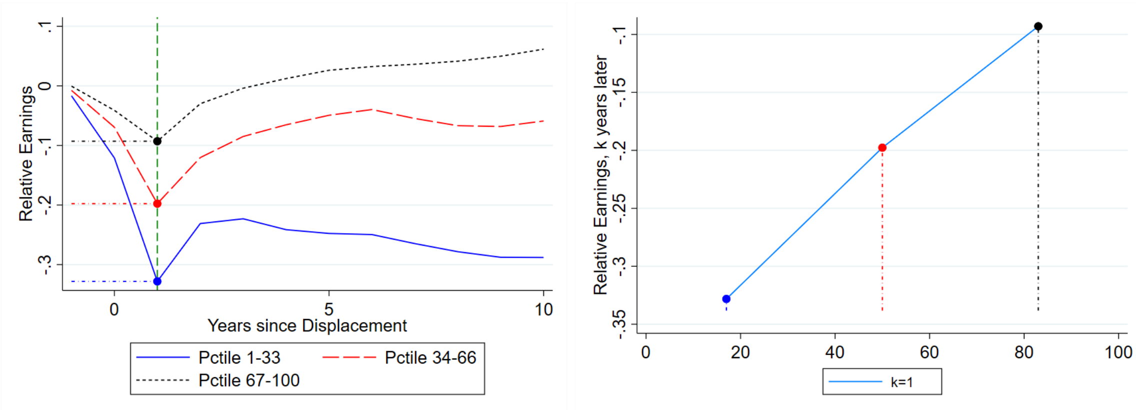

Figure C.1: *Construction of a graph depicting earnings losses over the recent earnings distribution (right) from an event study graph (left). This figure shows the construction of the line for $k = 1$, where the points and levels on the left panel correspond to those on the right panel.*

In Figure C.1, I focus on the construction of the line for $k = 1$, that is, the line that describes how the relative earnings loss 1 year after displacement differs over the recent earnings distribution. In the left panel, the full event study estimation is depicted. In the event study plot, I have highlighted the estimates for 1 year post-displacement for each of the quantiles. In the right panel, each of these estimates corresponds to the point with the same color. For example, in the left panel it can be seen that workers displaced from the highest quantile of the recent earnings distribution earn approximately 9-10% less than the control group (the black data point). In the right panel, this point is plotted at the value for recent earnings percentile corresponding to the mid-point of the quantile (approximately 83, since the quantile covers percentiles 67 to 100). Doing this for each of the three data points in the left panel and connecting the three data points in the right panel reveals the line for $k = 1$.

In Figure C.2, I repeat this procedure, but focus instead on the relative earnings loss 3 years after displacement ($k = 3$), which is used to generate the dashed purple line in the right panel. Notably, the line is decreasing between the first and second quantile, reflecting that in the left panel the red dashed line (corresponding to the second quantile) is now clearly below the blue line (corresponding to the third quantile). Finally, the right panel of Figure C.3 shows the full figure showing the relative earnings losses over the recent earnings distribution, alongside the event study graph (in the left panel), where the vertical lines indicate the periods that were translated into the right panel using the method described above.

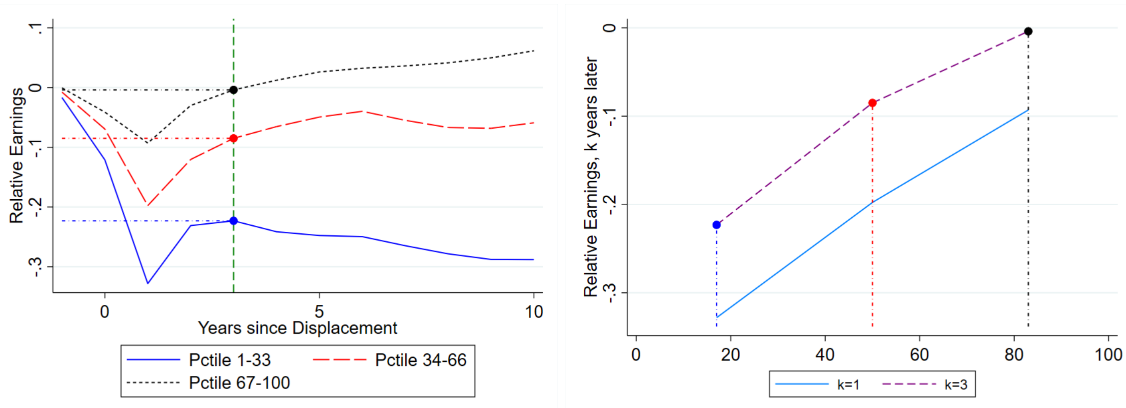

Figure C.2: *Construction of a graph depicting earnings losses over the recent earnings distribution (right) from an event study graph (left). This figure shows the construction of the line for* $k = 3$*, where the points and levels on the left panel correspond to those on the right panel.*

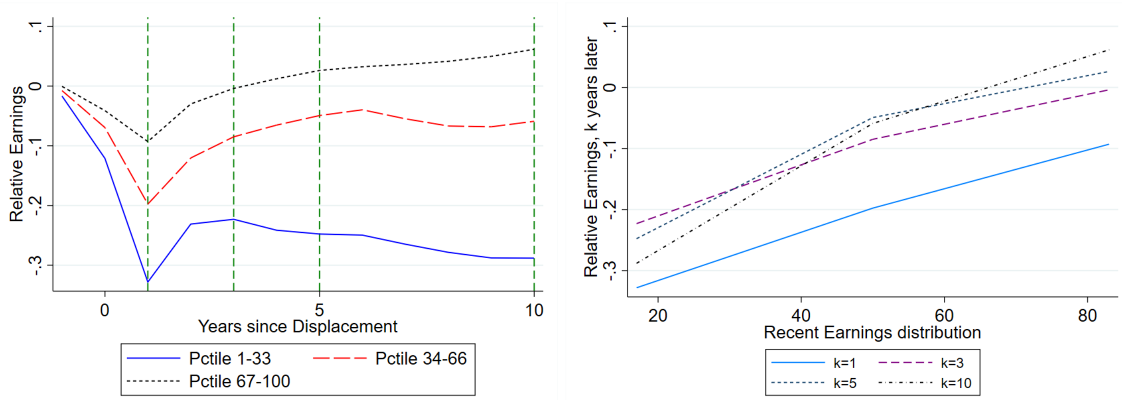

Figure C.3: *Construction of a graph depicting earnings losses over the recent earnings distribution (right) from an event study graph (left). This figure shows the final resulting graphs side by side, where vertical dashed lines in the left panel correspond to the periods for which the lines in the right panel were created.*

C.2 Additional Results from the raw data

C.2.1 Raw Displacement Scars from a restricted sample

As mentioned in Section 3.2 of the main text, the analysis based on raw averages did not impose any restrictions on pre-displacement tenure or establishment size, as is common in the empirical literature examining earnings losses after displacement. In figures C.4, C.5, and C.6, I show how the results are affected by imposing such restrictions.

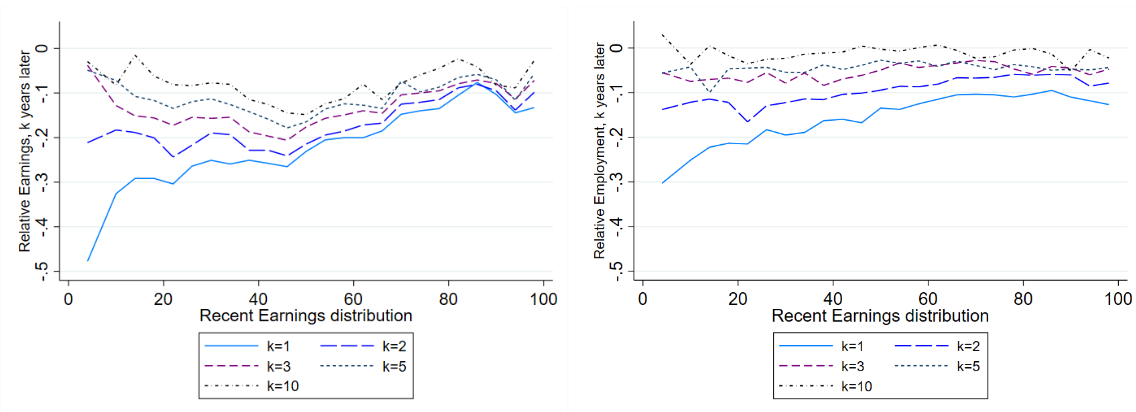

Figure C.4: *The effect of displacement on earnings (left) and employment fraction (right), over the recent earnings distribution, using a sample restricted to workers with 6 years of pre-displacement tenure. The numbers underlying the graphs are calculated directly from the data, and are relative to workers in the control group in the same percentile of the recent earnings distribution. Each line corresponds to a single period, k years after the initial displacement takes place.*

As can be seen by comparing Figure C.4 with it's equivalent from the main text (Figure 3), imposing restrictions on pre-displacement tenure and establishment does not substantially change the results, although the positive gradient is not as clear after the first few post-displacement years. Similarly, splitting out the displaced workers into those who do and do not immediately transition into a new job (as done in Figure C.5 for earnings and Figure C.6 for employment), gives similar but weaker results compared to the main text (Figures 4 and 5).

C.3 Additional Regression-based results

C.3.1 Additional Regression-based results

In this subsection, I present a number of exercises that test the robustness of the result from Figure 10 to splitting the sample in a number of different ways. In particular, I show that the observed decreasing earnings and employment losses over the recent earnings distribution hold across a number of dimensions of

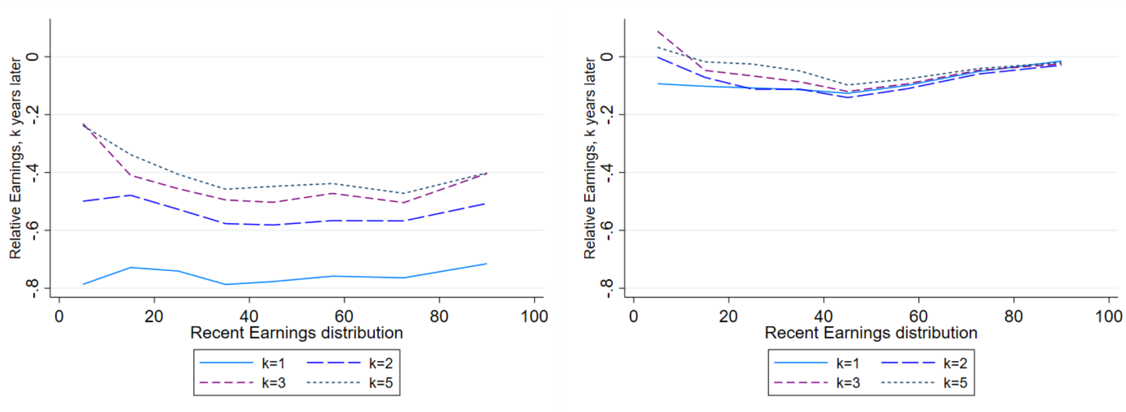

Figure C.5: *The effect of displacement on earnings over the recent earnings distribution, for workers who transitioned directly to a new job (right) and workers who did not do so (left), and using a sample restricted to workers with 6 years of pre-displacement tenure. The numbers underlying the graphs are calculated directly from the data, and are relative to workers in the control group in the same percentile of the recent earnings distribution. Each line corresponds to a single period, k years after the initial displacement takes place.*

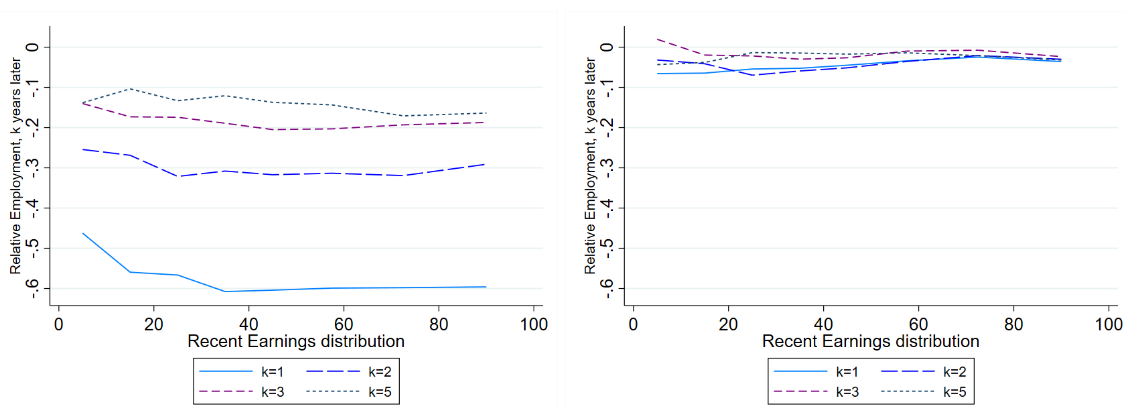

Figure C.6: *The effect of displacement on employment fraction over the recent earnings distribution, for workers who transitioned directly to a new job (right) and workers who did not do so (left), and using a sample restricted to workers with 6 years of pre-displacement tenure. The numbers underlying the graphs are calculated directly from the data, and are relative to workers in the control group in the same percentile of the recent earnings distribution. Each line corresponds to a single period, k years after the initial displacement takes place.*

interest. These dimensions are generally not present in the model proposed in Section 4 (with the exception of education), as the results from the data suggest that these dimensions do not necessarily help explain the result from Figure 10.

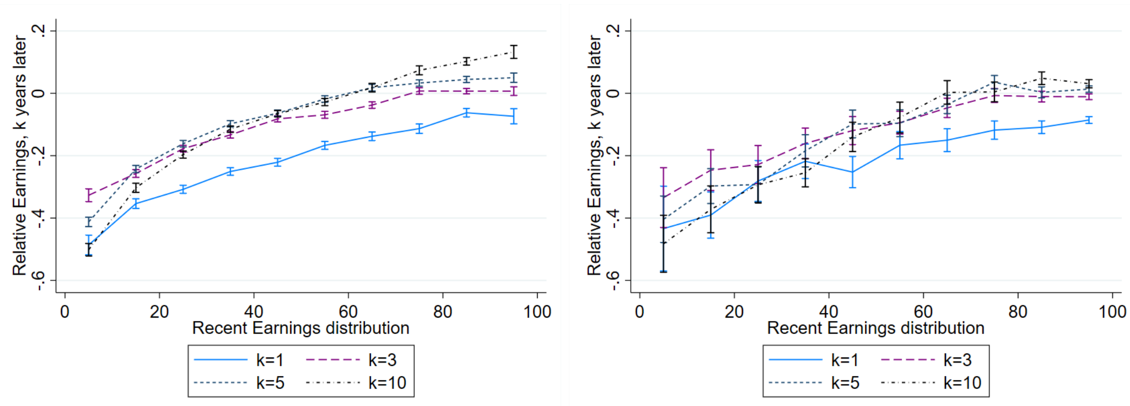

Figure C.7: *The effect of displacement on earnings over the recent earnings distribution, estimated separately for workers with non-university (left) and university (right) education. The graphs are prepared using estimated coefficients from Equation* (2)*, and error bars correspond to 95% pointwise confidence intervals.*

In Figure C.7, I show how the pattern of earnings losses over the recent earnings distribution differs by the worker's education level. Comparing the two panels of Figure C.7 to the left panel of Figure 10, it can be seen that the result does not seem to be heavily dependent on workers' education levels. Indeed, both the magnitude of the losses and it's pattern over the recent earnings distribution are very similar between the two education levels, although it can be seen that the standard errors are generally higher for the high education level (primarily due to a lower number of observations, especially near the bottom of the distribution). A similar conclusion can be drawn for the pattern of employment losses (the corresponding graphs are available upon request).

In Figure C.8, I show the result of estimating earnings losses separately by the worker's gender, which was one of the worker characteristics taken into account when generating the recent earnings distribution. In general, it can be seen in Figure C.8 that the pattern of relative earnings losses does not seem to depend on gender. An exception to this statement arises for female workers in the bottom third of the recent earnings distribution, where earnings losses are not decreasing in recent earnings in the short run ($k = 1$ and $k = 3$). A similar observation can be made when focusing on employment losses instead (the corresponding graphs are available upon request).

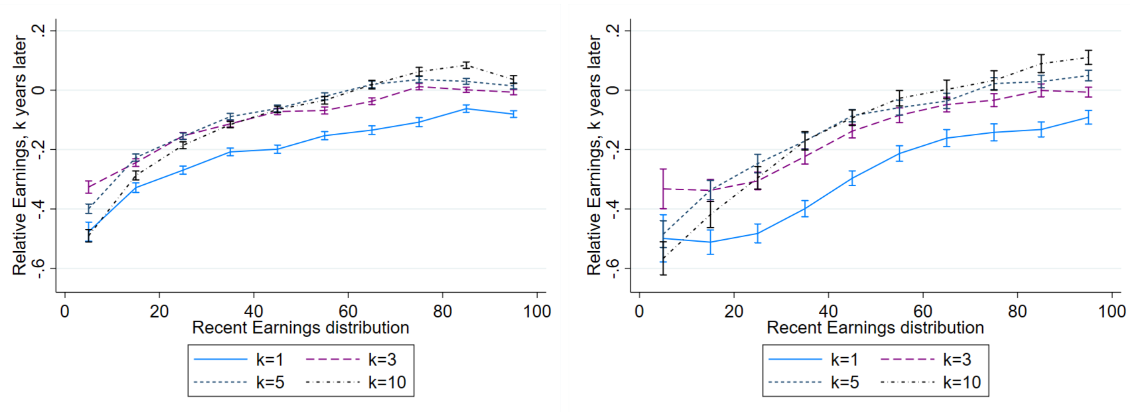

Figure C.8: *The effect of displacement on earnings over the recent earnings distribution, estimated separately for male (left) and female (right) workers. The graphs are prepared using estimated coefficients from Equation* (2)*, and error bars correspond to 95% pointwise confidence intervals.*

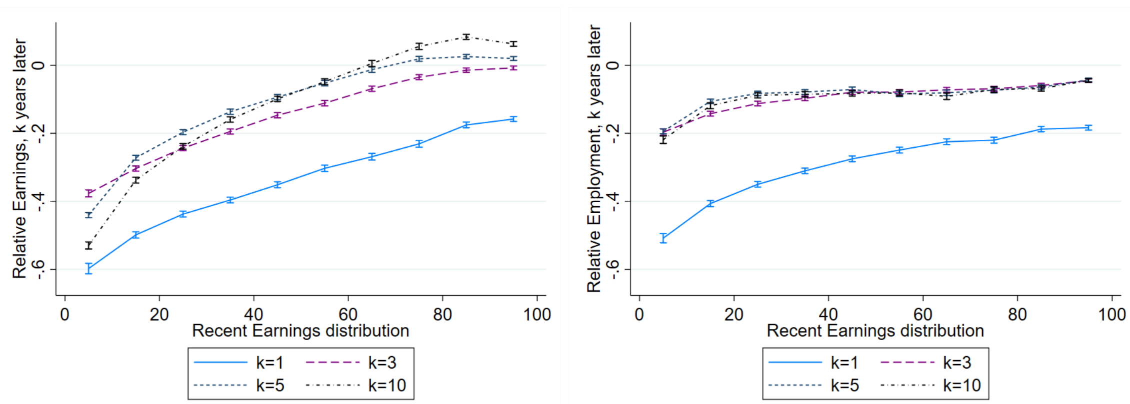

Figure C.9: *The effect of separation on earnings (left) and employment fraction (right) over the recent earnings distribution. The graphs are prepared using estimated coefficients from Equation* (2)*, and error bars correspond to 95% pointwise confidence intervals.*

In order to estimate the results depicted in Figure C.9, I relax the criteria for being considered "treated". In particular, rather than requiring the worker to be displaced, I include all workers who are separated, thus no longer requiring the establishment to be shut down or going through a mass layoff. Notably, this implies that the resulting group of treated individuals may include workers who finished a temporary assignment or who quit their job. Nevertheless, it can be seen by comparing Figures C.9 and 10 that this does not lead to a substantial change in the magnitude of earnings or employment losses, with the exception of the short run ($k = 1$) losses, which are slightly larger under this alternative definition of the treatment. Similarly, using all separations rather than only displacements does not change the patterns of the earnings and employment losses over the recent earnings distribution.

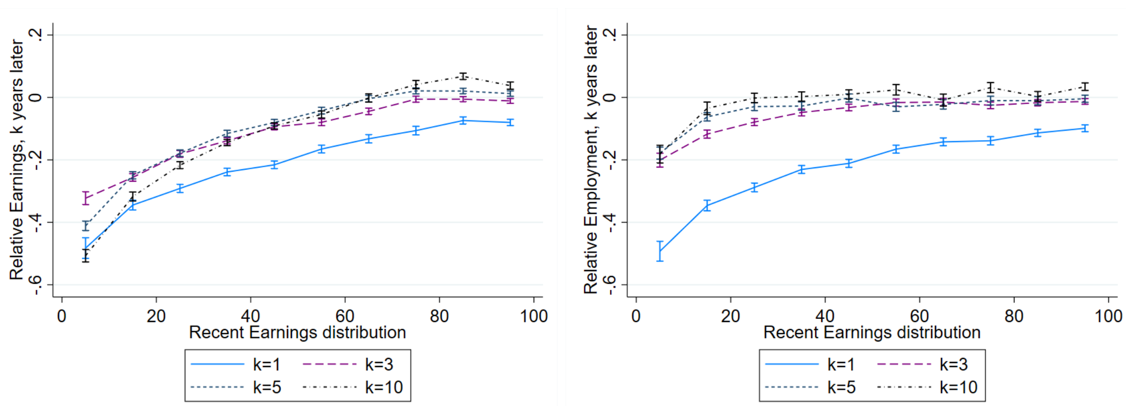

Figure C.10: *The effect of displacement on fulltime earnings (left) and fulltime employment fraction (right) over the recent earnings distribution. The graphs are prepared using estimated coefficients from Equation* (2)*, and error bars correspond to 95% pointwise confidence intervals.*

Finally, Figure C.10 shows how results change when further restricting the observations to only include fulltime employment (and their corresponding earnings). Doing so slightly increases the employment losses in the short run ($k = 1$), but does not seem to affect earnings losses or any of the other employment losses, or their patterns over the earnings distribution.

C.3.2 Regression-based results from a larger sample

The estimation-based results from Section 3.3 were based on a restricted sample, and in particular used the commonly used requirement of 6 years of pre-displacement establishment tenure. In this subsection, I show how the estimation-based results are affected by relaxing this requirement, and imposing a requirement of 1 year of pre-displacement establishment tenure instead.

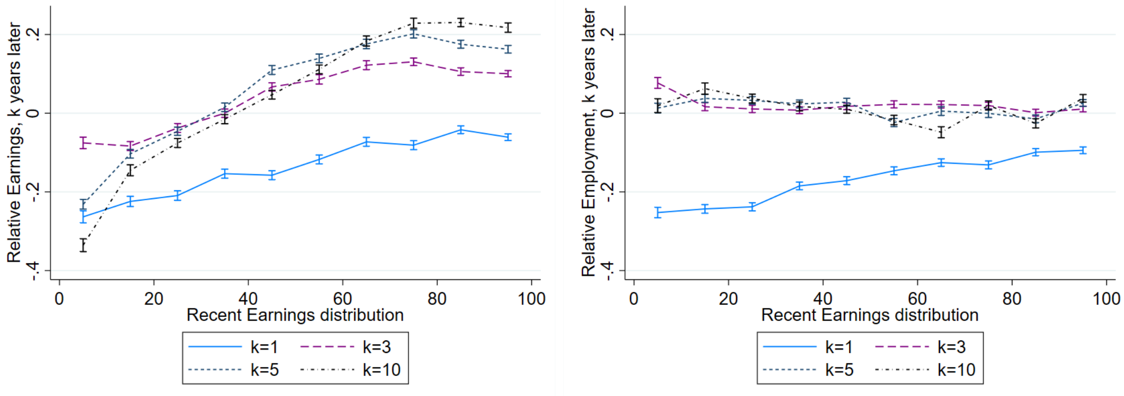

Figure C.11: *The effect of displacement on earnings (left) and employment fraction (right) over the recent earnings distribution, and using a sample restricted to workers with 1 year of pre-displacement tenure. The graphs are prepared using estimated coefficients from Equation* (2)*, and error bars correspond to 95% pointwise confidence intervals.*

First, comparing Figure C.11, which uses the sample that pools workers who do and do not make an immediate transition to a new job, to it's main text equivalent (Figure 10) reveals that relaxing sample restrictions seems to weaken the results for the first year after displacement. After all, the decrease in earnings losses moving from the bottom towards the top of the recent earnings distribution is weaker in Figure C.11 than it was in Figure 10 for $k = 1$. For all other years, results in the left panel of Figure C.11 are similar to those in Figure 10, but shifted up by approximately 0.2, thus implying that average earnings losses decrease by about 20 percentage points when enlarging the sample to additionally include workers with a pre-displacement tenure between 1 and 6 years, so that workers above the median now experience an earnings gain on average from period $k = 3$ onwards. Similarly, employment losses are completely recovered by year $k = 3$, thus leading the corresponding estimates to be around 0 for $k \geq 3$.

It is worth noting that restricting the sample to workers who do or do not spend some time in nonemployment, as done in Figure C.12, reveals the (parallel) decrease in average earnings losses discussed above to be driven primarily by workers who transitioned to a new job immediately. Similarly, Figure C.13 shows that most of the recovery in terms of employment is driven by workers who spend some time in nonemployment (although an increase is also visible among workers making an EE transition at the bottom of the recent earnings distribution). Overall, however, it remains true that while the incidence of EE switches can explain part of the upward slope visible in the left panel Figure 10 (and Figure C.11), it is not by itself a sufficient explanation, as the pattern remains visible when splitting the sample by EE status (especially so for workers making an EE transition).

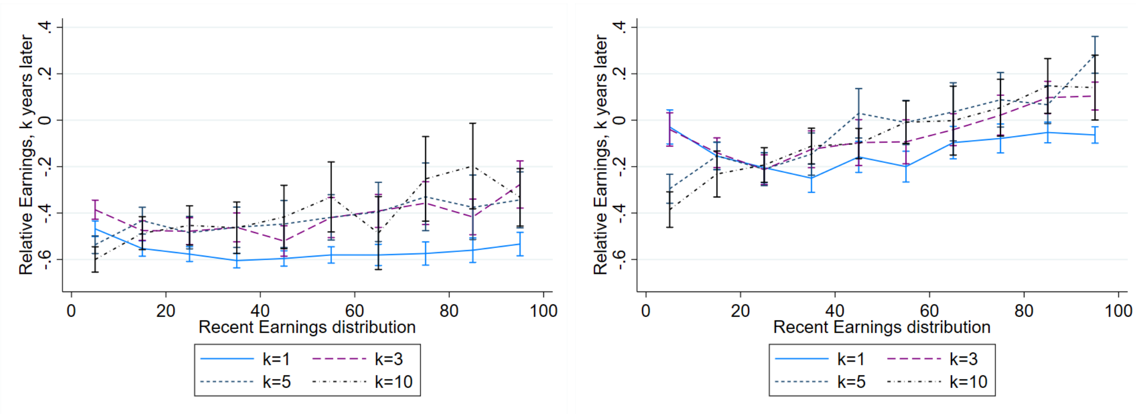

Figure C.12: *The effect of displacement on earnings over the recent earnings distribution, and using a sample restricted to workers with 1 year of pre-displacement tenure. The graphs are prepared using estimated coefficients from Equation* (2)*, and error bars correspond to 95% pointwise confidence intervals. The right panel only considers workers who moved to a new job immediately, whereas the left panel only considers workers who did not do so.*

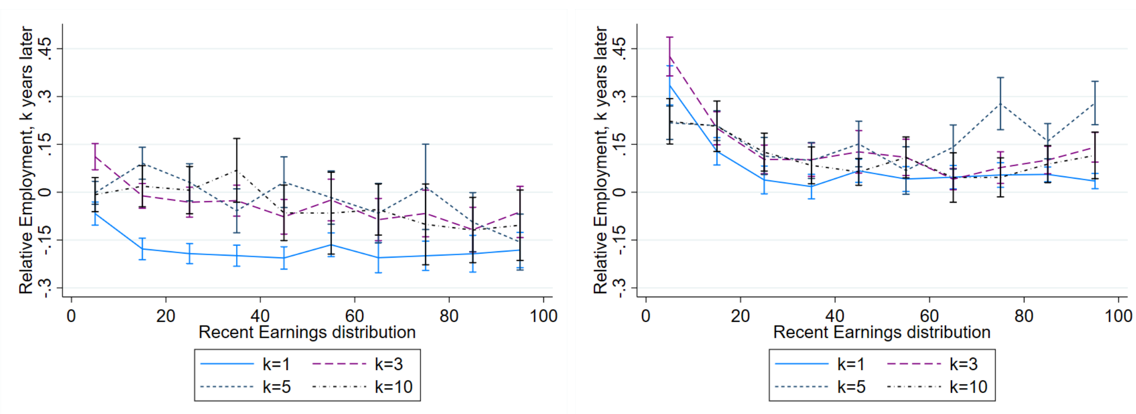

Figure C.13: *The effect of displacement on employment fraction over the recent earnings distribution, and using a sample restricted to workers with 1 year of pre-displacement tenure. The graphs are prepared using estimated coefficients from Equation* (2)*, and error bars correspond to 95% pointwise confidence intervals. The right panel only considers workers who moved to a new job immediately, whereas the left panel only considers workers who did not do so.*

C.3.3 Regression-based results from an alternative estimation method

The main estimation-based results in Section 3.3, as well as the robustness exercises in the previous subsections, were obtained by using the imputation-based method from Borusyak et al. (2023). However, a number of other methods have been proposed to estimate Equations (1) and (2). In this subsection, I show that I obtain similar results when using the interaction-weighted method from Sun and Abraham (2021).

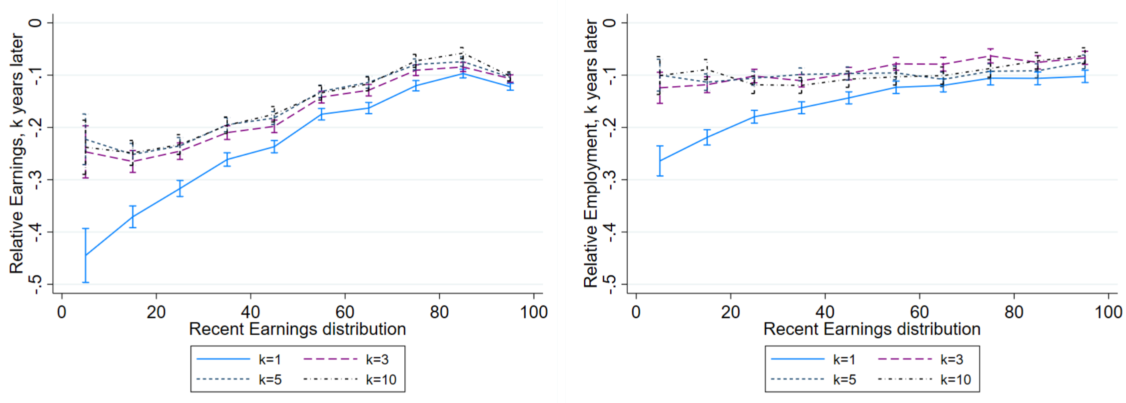

Figure C.14: *The effect of displacement on earnings (left) and employment fraction (right) over the recent earnings distribution, relative to the control group of never-displaced workers (across the entire distribution). The graphs are prepared using estimated coefficients from Equation* (2)*, estimated using the interaction-weighted method from Sun and Abraham (2021), and error bars correspond to 95% pointwise confidence intervals.*

Figure C.14 repeats the estimation from Figure 10 in the main text using the interaction-weighted method. Comparing the two figures reveals results that are very similar, with one minor difference between the increasing earnings losses in recent earnings at the very bottom of the recent earnings distribution in Figure C.14 which was not visible in the main text.

Figures C.15 and C.16 display the results from repeating the estimation depicted in figures 11 and 11 of the main text using the interaction-weighted method instead. In contrast to the results that pool all displaced workers, discussed above, the separate estimations by EE status reveal some sizeable difference in the estimates between the two methods. This is especially true for the earnings losses, which are show much more recovery for non-EE-switchers and much less recovery for EE-switchers when estimated using the interaction-weighted method. For employment, the main differences arise between the left panels of Figure C.16 and 12, where the short-run ($k = 1$) losses are estimated to be much larger across the distribution. Nevertheless, it can be seen that the general patterns of both earnings losses (Figure C.15) and employment losses (Figure C.16) is similar to the pattern observed in the main text.

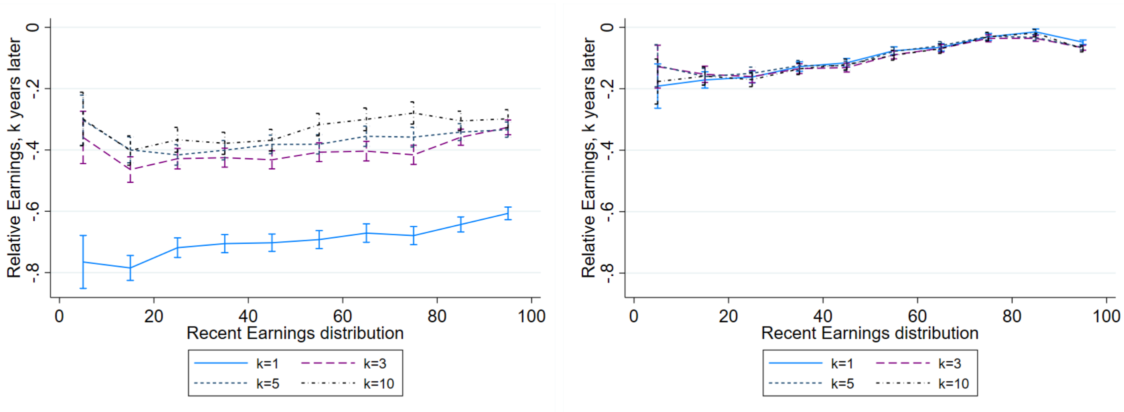

Figure C.15: *The effect of displacement on earnings over the recent earnings distribution, relative to the control group of never-displaced workers (across the entire distribution). The graphs are prepared using estimated coefficients from equation* (2), *estimated using the interaction-weighted method from Sun and Abraham (2021), and error bars correspond to 95% pointwise confidence intervals. The right panel only considers workers who moved to a new job immediately, whereas the left panel only considers workers who did not do so.*

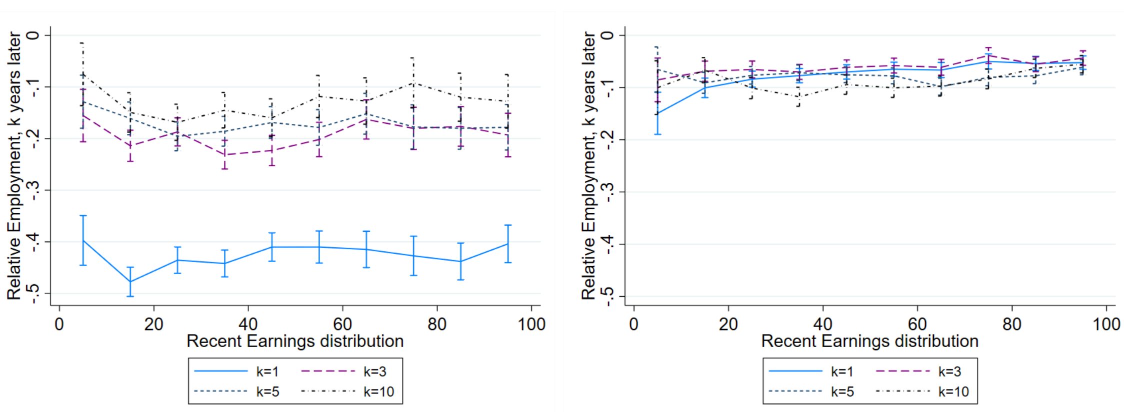

Figure C.16: *The effect of displacement on employment fraction over the recent earnings distribution, relative to the control group of never-displaced workers (across the entire distribution). The graphs are prepared using estimated coefficients from equation* (2), *estimated using the interaction-weighted method from Sun and Abraham (2021), and error bars correspond to 95% pointwise confidence intervals. The right panel only considers workers who moved to a new job immediately, whereas the left panel only considers workers who did not do so.*