Heterogeneity in the Scarring Effects of Displacement

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Abstract:

This paper explores heterogeneity in the scarring effect of displacement, using detailed administrative data from Germany. Among others, I find that relative earnings losses tend to be higher for individuals with low educational attainment, situated near the bottom of the recent earnings distribution, and workers recalled to their previous employer. Motivated by these empirical results, I then propose a model of the labour market that accounts for and explains the heterogeneous scarring effect, as well as its average. In this model, workers face separation shocks that are not directly related to their productivity, interpreted as displacement shocks. The presence of search frictions and human capital ensure the slow recovery process after the initial shock, while the possibility of recall and distinct parameter values by educational attainment generate the heterogeneity as observed in the data. The model is calibrated to data moments generated from the German data, and the calibrated model is used to study and compare the main drivers of the large negative (and heterogeneous) consequences of displacement.

JEL Classifications: E24, J21, J24, J62, J63, J64, J65
Keywords: Unemployment, Displacement, Job Loss, Recall, Job Search, Heterogeneity

*frank.leenders@mail.utoronto.ca, Department of Economics, University of Toronto, Canada. This study uses the LIAB longitudinal model, version 1993-2014, of the Linked-Employer-Employee Data (LIAB) from the IAB, as well as the weakly anonymous Sample of Integrated Labour Market Biographies, or SIAB (Years 1975 - 2017). Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access, under project numbers fdz1774 and fdz1775. DOI (SIAB): 10.5164/IAB.SIAB7517.de.en.v1

1 Introduction

The closure of a large firm or plant results in the destruction of many jobs at once. The workers who lose their job in such events are exposed to a well-documented expected long-term loss in earnings compared to similar workers who did not become unemployed.[1] This paper further explores this scarring effect of displacement.[2] In particular, I use administrative data from Germany to extensively document heterogeneity in this earnings loss. I find that, while the average scarring effect is very similar to that observed in the existing literature (which tends to focus on the U.S.), substantial heterogeneity is visible along the dimensions of recent earnings, education, and ex-post recall status (among others). To be more precise, I find that workers near the bottom of the recent earnings distribution or with a low education level experiencing more severe relative earnings losses, while workers who are recalled to their former employer do better in terms of employment status but suffer from more severe relative earnings losses in the short run. As these observations cannot be explained by the existing models that aim to explain the average scarring effects of displacement, I then propose a search model of the labor market that accounts for both the average scarring effect and this heterogeneity. Such a model can be used to evaluate policy proposals in terms of their efficiency in accounting for the wide variety of earnings paths experienced by different displaced workers.

The prospect of potentially losing one's job is a nightmare scenario for almost every single employed worker. After all, even setting aside all non-monetary factors, a job loss can be thought of as a very negative shock to the worker's income. Furthermore, the subsequent lower (or nonexistent) income is quite likely to persist for at least a few months.[3] Unfortunately, this scenario becomes reality for many workers on a yearly basis. For example, The Bureau of Labor Statistics (2018) reports that between 2015 and 2017 roughly 3 million U.S. workers lost a job in which they had worked for at least 3 years. More recently, the COVID-19 pandemic has caused a large number of U.S. workers to lose their job, with the number of workers claiming unemployment insurance benefits reaching 18.9 million in the week ending May 30th 2020, as reported by Department of Labor (2020).[4] While a single person losing one's job may not have an enormous impact on a

[1] See section 1.1 for a brief overview of the related empirical literature.

[2] Throughout this paper, I will refer to workers losing their job through a mass layoff as displaced worker. For a more precise definition of displacement, as used in the data, see section 2.

[3] Bureau of Labor Statistics (2018) reports that of the workers who lost their job (in which they had at least 3 years of tenure) between 2015 and 2017, only 66% was employed in January 2018.

[4] For comparison, a year earlier the number of workers claiming unemployment insurance benefits was approxi-

country's economy (or even a local economy), the prevalence of job loss is high enough that it is a common theme returning in almost every election cycle anywhere in the developed world, even before the current pandemic. Furthermore, when many workers lose their job at the same time as part of a mass layoff, the media coverage given to these events is often enough to solicit a reaction from a local government, in an attempt to alleviate the negative consequences of job loss for those involved. However, despite governments' best efforts, the earnings losses experienced by workers losing their job as part of a mass layoff are still substantial and long-lasting.

The average effect of displacement on earnings has been documented quite extensively, and in recent years some models have been proposed to explain this average effect (See section 1.1 for a brief overview of this literature). While some of these theoretical models are quite successful in explaining the average scarring effect of displacement, they are not able to capture some of the heterogeneity I observe in the German data. Therefore, I propose a model that can not only explain the average scarring effect, but also generates some of the substantial heterogeneity found in the data. In doing so, I build on some of the insights from the existing models, such as the need for search frictions and human capital (which appreciates during employment and depreciates during unemployment), while also adding elements that enable me to generate and comment on the heterogeneity. In particular, I do so by explicitly allowing workers to wait to be recalled, as well as introducing a fixed worker type (which I interpret as education level). This model, in turn, then allows me to comment on the efficiency of existing (or proposed) policies aimed at alleviating the negative consequences of displacement.

The rest of this paper is organized as follows: After a brief overview of the related literature in the next subsection, section 2 describes the datasets and methodology used to generate the empirical results, which are presented in section 3. Section 4 then presents the model. The quantitative analysis of the model is split into two sections: Section 5 focuses on the calibration of the model. Section 6 then uses the calibrated model to show that it recovers the heterogeneity observed in the data, further studies the long term consequences of displacement, and analyzes a number of simple policy experiments. Finally, Section 7 concludes and provides some directions for potential future research.

mately 1.5 million (Department of Labor, 2020).

1.1 Related Literature

In empirically investigating the long-term consequences of job loss (and mass layoffs in particular), this paper contributes to a large existing literature This literature goes back to Jacobson et al. (1993), who use quarterly administrative data from Pennsylvania to find that displaced workers (defined as workers with a tenure of at least 6 years, who are laid off as part of a mass layoff in 1982 that decreased the firm size by at least 30%) suffer an immediate earnings loss of more than 50% (relative to comparable workers who were not laid off), and still earn roughly 25% less 5 years later. This paper sparked a rich empirical literature, some of which sought to address the criticism that the Jacobson et al. (1993) result was largely caused by a recession and heavy industrialization in Pennsylvania.[5] Subsequent research using data from Connecticut instead (Couch and Placzek, 2010) or using data covering the entire U.S. for a longer time span after the 1982 recession (Von Wachter et al., 2009) found similar results, with observed long-term losses of up to 20% after ten years. Similarly, results from Couch et al. (2011) and Davis and Von Wachter (2011) indicate that while the scarring effect of displacement has a cyclical nature to it, the long-term earnings loss is substantial even when the displacement occurs in good economic conditions. Furthermore, while most of the earlier literature focused on the United States, more recent work has shown that the results also hold in other countries, such as Canada (Bonikowska and Morissette, 2012), Germany (Nedelkoska et al., 2015, and Schmieder et al., 2019), and Portugal (Raposo et al., 2019), while further work focusing on the United States has highlighted the important role of working hours in the short run and wages in the long run for explaining these losses (Lachowska et al., 2020).

Until recently, most of the empirical discussion contained in the existing literature did not consider heterogeneity or only briefly touched upon it. One of the first exceptions to this is Guvenen et al. (2017), who use tax data from the U.S. to document how the scarring effects of job loss differ depending on where the worker is situated in the earnings distribution before being laid off. In recent years, the investigation of heterogeneity has been gaining some more attention. For example, Gulyas and Pytka (2020) uses a machine learning approach to investigate which of the observable variables are most important in causing heterogeneity in the earnings decline after job loss (using administrative data from Austria). In this paper, the documentation of heterogeneity is one of my main focuses. In particular, by using detailed data I am able to document how observable heterogeneity impacts the long-term consequences of displacement (and job loss more generally), thereby substantially enriching the existing observations on this topic.[6]

[5] See Kletzer (1998) for a comprehensive survey of the early literature.

[6] While Guvenen et al. (2017) present some evidence on heterogeneity by previous position on the earnings dis-

One of the elements I observe to be important for the subsequent earnings and employment paths of a displaced worker is whether or not the worker is eventually recalled to their previous employer. The topic of recall has been studied quite extensively, going back to studies such as Feldstein (1976) and Katz (1986). More recently, Nekoei and Weber (2015), as well as Nekoei and Weber (2020) have used detailed administrative data to shed more light on the topic of recall, in particular distinguishing between the expectation of recall and the actual materialization of recall. However, while the literature on the impact of recall on labor market flows is quite sizeable, the existing research generally does not comment on how recalled workers differ from non-recalled workers in terms of their subsequent earnings. In this paper, I contribute to the research on this topic by investigating this dimension specifically.

While the empirical literature on the scarring effects of displacement is quite sizeable, the theoretical analysis of the long-term consequences of displacement has only recently started gaining more attention. After the empirical results were well established, some papers attempted to reconcile the findings with models of the labour market. Among others, Pries (2004) and Davis and Von Wachter (2011) noted that a standard job search model cannot generate the large losses observed in the data, even when expanding it with on-the-job search.[7] Some recent work has attempted to resolve this issue with some success. Jarosch (2015) proposes a model in which firms differ not only in terms of productivity, but also in the separation rate. Combined with the presence of human capital which depreciates during unemployment (and increases while employed), this enables him to reproduce the average earnings loss after displacement, both in the short and in the long run.[8] Krolikowski (2017) is relatively successful in recreating this average effect without the human capital depreciation (though the model is less successful in replicating the losses more than 10 years after displacement), relying on endogenous separation which occurs if the stochastic component of the match productivity falls below a threshold. Huckfeldt (2016) focuses on the cyclicality of the losses and utilizes a model with two occupations (one skill utilizing and one skill neutral) to deliver this cyclicality, as well as observed differences between workers who switch occupations after being displaced and those who stay in their occupation. Finally, Jung and Kuhn (2019) take a different approach by focusing on the lack of mean reversion from the top rather than

tribution, the nature of the data they use does not allow them to look at other observable heterogeneity. Similarly, while Gulyas and Pytka (2020) are able to observe more individual characteristics and exploit this well, the number of characteristics they can consider is still quite limited.

[7] See Pissarides (2000) for an example of such a standard job search model.

[8] Gregory (2020) proposes a very similar model, where firms differ in their learning environment, but does not specifically comment on how that model performs in replicating scarring effects of displacement.

the inability to recover of those falling down the ladder. The resulting model, which relies heavily on the loss of match-specific skills to explain the inability of wages to recover, performs well in replicating the average scarring effect.

While some of these models are successful in explaining the average scarring effect of displacement, they are unable to generate the heterogeneity I observe in the data. For example, as most of these models rely on a job ladder, they predict the earnings loss to be increasing (in absolute value) over the earnings distribution, while the data suggests that it is in fact decreasing over this distribution. By proposing a model that accounts for this heterogeneity in addition to the average scarring effect of displacement, this paper contributes to the theoretical literature, and provides a model that is of particular use to policymakers that aim to alleviate the negative consequences of displacement, but want to do so by specifically targeting workers that are most affected.

One of the key elements in my model is that I explicitly allow for recall, as I find the ex-post recall status to be important when examining earnings losses in the data. There does already exist a rather large body of literature that builds the possibility of recall into a model. Specifically, this strand of literature goes back to early work such as Feldstein (1976), Pissarides (1982), and Katz and Meyer (1990). More recently, recall has been explicitly modeled in Fujita and Moscarini (2017). However, what all these papers have in common is that they focus exclusively on the impact of recall on labor market flows. As such, they do not comment on how workers' earnings are affected by this possibility. Furthermore, the way most existing papers model recall is by considering the current job to be "paused" while the worker is waiting to be recalled. While the worker is waiting to be recalled, they then make the same choices (such as search effort and accepting potential offers) as any other unemployed worker. In my model, this is not quite the case, as I make a sharp distinction between workers waiting to be recalled and other unemployed workers, where workers waiting to be recalled do not search for other jobs, but also do not experience a depreciation of their skills as severe as other unemployed workers.

2 Data and Empirical Methodology

The empirical results in this paper are generated using two administrative datasets from the German Federal Employment Agency's (BA) Institute for Employment Research (IAB). In particular, I use the Linked-Employer-Employee Dataset (LIAB) and the Sample of Integrated Labour Market Biographies (SIAB). While these datasets mostly use data from a common source, and both contain information on the individual as well the (linked) establishment, the two datasets differ slightly in their length and sampling method.[9] The SIAB draws a 2% random sample of the individuals from the Integrated Employment Biographies (IEB), after which the observations are matched with the relevant establishment data. The LIAB, on the other hand, samples 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). In other words, the SIAB samples individuals whereas the LIAB samples establishments. Furthermore, the SIAB covers the period from 1975 to 2017, while the version of the LIAB used in this paper only covers the period from 1993 to 2014. Thus, while the two datasets are quite similar, it is valuable to use both as their respective sampling methods naturally lead to a different sample of (especially) establishments. For example, looking at the summary statistics for establishments in appendix D.2, it becomes clear that SIAB contains a relatively larger sample of large establishments.

Each observation in the original data (for both datasets) represents one spell of employment or non-employment, and is marked by a start and end date. These start and end dates are the dates at which the establishment (or social security administration) submits social security notifications, signalling a changed or ended an employment relation or simply as a yearly notification. Using the establishment ID, as well as the reason for the social security notification, I then construct a yearly and quarterly linked employer-employee dataset, in which the establishment information is used from the establishment at which the individual was employed on the first day of the year/quarter.[10] Further restricting observations to those aged between 25 and 60 leads to a large dataset which nevertheless has some gaps in some workers' time series.[11] These gaps occur because not all forms of employment or non-employment are recorded in the dataset. Among others, individuals are not observed if they are employed for the government, self-employed, or not receiving any social security benefits during nonemployment.[12] When constructing my main dataset, I fill these gaps for observables that can reasonably be interpolated (such as age and location), while leaving key information (such as earnings) missing, thus likely leading to this observation being omitted from estimation procedures. Table 1 summarizes the number of observations and indi-

[9] In the data, an establishment is defined as all locations of a firm within a Kreis (municipality).

[10] If the individual is non-employed at the start of the year/quarter, the information is used for the establishment from which the individual has the highest earning in that period.

[11] Note that for the quarterly dataset I restrict observations to those aged between 30 and 52. This is in line with the empirical literature that uses quarterly datasets, such as Jacobson et al. (1993) and Couch and Placzek (2010).

[12] Other reasons for not observing an individual include working (and moving) abroad.

viduals observed in the original data and the main analysis dataset (both quarterly and yearly). Further summary statistics on both workers and establishments are presented in appendix D.1 and D.2.

	SIAB		LIAB	
Frequency	Yearly	Quarterly	Yearly	Quarterly
Raw observations	66,961,520	66,961,520	53,433,114	53,433,114
Observations (Age restricted)	52,162,319	42,820,711	43,001,421	31,796,168
Main Panel, Observations	24,183,133	79,771,399	25,848,195	76,886,425
Main Panel, Individuals	1,601,849	1,197,965	1,797,764	1,160,841

Table 1: *Number of observations and individuals in the raw dataset and main analysis datasets, using either LIAB or SIAB.*

In order to analyze the consequences of displacement, I first need to be specific on how exactly I define displacement. For the purpose of estimating the specification described below, I define a worker as separated in some period t if this worker no longer works for the same establishment in period $t+1$.[13] Throughout, I drop workers who are trainees, casual workers, or partially retired workers, and further focus in particular on workers whose social security notification indicates that employment at the establishment was ended for a reason that could point to displacement.[14] I then define such a worker as (broadly) displaced if the establishment either closes or experiences a mass layoff.[15] Here, an establishment is defined to experience a mass layoff if the employment at the establishment in the next period is at most 80% of the maximum establishment employment of the prior five years, and the establishment has a net outflow of 20% of its workforce in the displacement year.[16] Finally, a worker is displaced according to the narrow definition if, in addition, the establishment's net inflow in the next five years is not enough to rebound its size to more than 80% of the pre-layoff size.

The empirical results presented in the next section are largely based on the follow-

[13] There is one exception to this rule: I still define a worker as separated if they return to their former establishment more than 31 days after their previous spell ends, and the reason for the end of their previous spell indicates separation. These workers will be defined as separated and subsequently recalled.

[14] This way, I exclude apparent separations that are caused by paternity or maternity leave, disease, or seasonal patterns in employment.

[15] I use an extension file that clarifies the reason for an establishment leaving the sample. In particular, I do not consider an establishment to be closed if a large portion of the workers at the establishment finds employment at a common establishment after the closure. After all, these events point towards a merger or the closure of a firm in one municipality only. See appendix D.2 for more details.

[16] 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 not used for estimation purposes.

ing specifications, which resembles the specification used in Davis and Von Wachter (2011) and Jarosch (2015):

$$e_{it}^{y} = \alpha_i^y + \gamma_t^y + \bar{e}_i^y \lambda_t^y + \beta^y X_{it} + \sum_{k=-5}^{20} \delta_k^y D_{it}^k + u_{it}^y \tag{1}$$

In the equation above, i refers to the individual and t refers to the year (unless indicated otherwise). The dependent variable in this specification, e_{it}, generally refers to the total earnings of individual i in period t (in some estimations I use the employment status instead). The explanatory variables include an individual fixed effect α_i and a time fixed effect γ_t, as well as a quadratic polynomial in age X_{it} and an error term u_{it}. The variable $\bar{e}_i^y$ denotes the average earnings of individual i between years $y-5$ and $y-1$, and I will generally refer to this as recent earnings. When deriving these recent earnings, I condition of the individual having earnings available in the data for at least three of the years between $y-5$ and $y-1$, which must include year $y-1$.[17] The coefficients of interest are a series of coefficients on dummy variables D_{it}^k. These variables equal 1 if individual i was displaced in period $t-k$. As these dummy variables always equal 0 for workers who did not get displaced, the coefficients represent the effect of displacement on earnings (relative to the earnings of non-displaced workers), k periods after displacement. The estimation is done separately for each sample year y.[18] Within each such estimation, only displacements that took place in year y are taken into account, thus implying that the dummy variable D_{it}^k will only equal to 1 if the individual i was displaced in period $t-k$ and this period $t-k$ corresponds to year y. The standard displacement graph then plots the coefficient δ_k over k (where δ_k is a simple average of δ_k^y over base years y), thus revealing an earnings path from 5 periods before to 20 periods after the displacement event.

When estimating the equation discussed above I partially follow the literature by restricting my sample to individuals with a job tenure (in the base year) of at least 6 years (to ensure reasonable attachment to the labor force), and 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). However, in my estimation I combine the data of male and female workers, although I

[17] I also use these recent earnings to generate the recent earnings distribution, which is generated separately for each year, age group, gender, and location. 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).

[18] Note that the similar estimation in Jacobson et al. (1993) and Couch and Placzek (2010) is not done separately by sample year because these papers focused on the effect of displacement in a specific year.

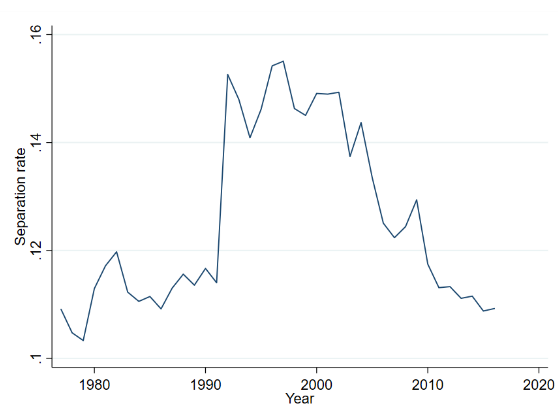
do consider gender as one of the possible dimensions for heterogeneity.

3 Empirical Results

In this section, I present the results generated from the data. In particular, I start by describing the incidence of separation and displacement, and how this differs by a number of observable characteristics of the worker. Then, I present the results for the average scarring effect of separation and displacement on earnings, using the specifications presented in section 2. Finally, I document heterogeneity in the scarring effect of displacement, focusing in particular on the importance of recent earnings, education level, and (ex-post) recall status. All results in this section are generated using the SIAB dataset, unless specifically noted otherwise. However, the same analysis is also done using the LIAB dataset, and these results can be found in appendix D. The conclusions made below hold for either dataset, although the results using the LIAB dataset are often less clear, due to the smaller time period spanned by this dataset.

3.1 The Incidence of Displacement

Before analyzing the detrimental effect displacement can have on a worker's earnings, and how it differs by observable characteristics, it is worth investigating how common a separation or displacement event is. In order to do so, this subsection presents separation and displacement rates for the entire sample as well as several subsets of the sample.



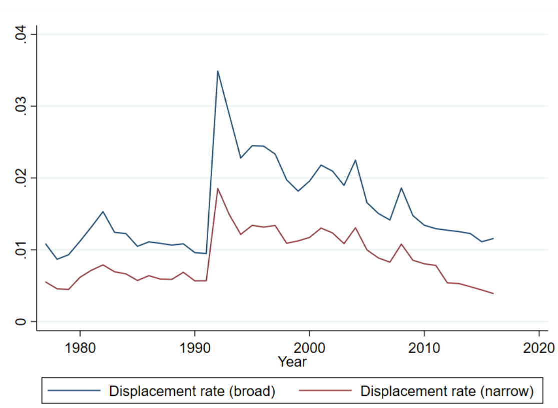


Figure 1: *The incidence of separation (left) and displacement (right) over time.*

First of all, figure 1 displays the separation and displacement rates over time, for the entire sample.

As can be seen in this figure, the separation averages at roughly 12% whereas the displacement rate averages at roughly 0.7 to 1.5% (depending on the definition). All rates display substantial variation over time, and in particular the aftermath of the German reunification is quite clearly visible.[19] While separation and displacement rates tend to peak around recessions, the magnitude of these peaks are relatively small (a look at the period of the Great Recession makes this point very clear).

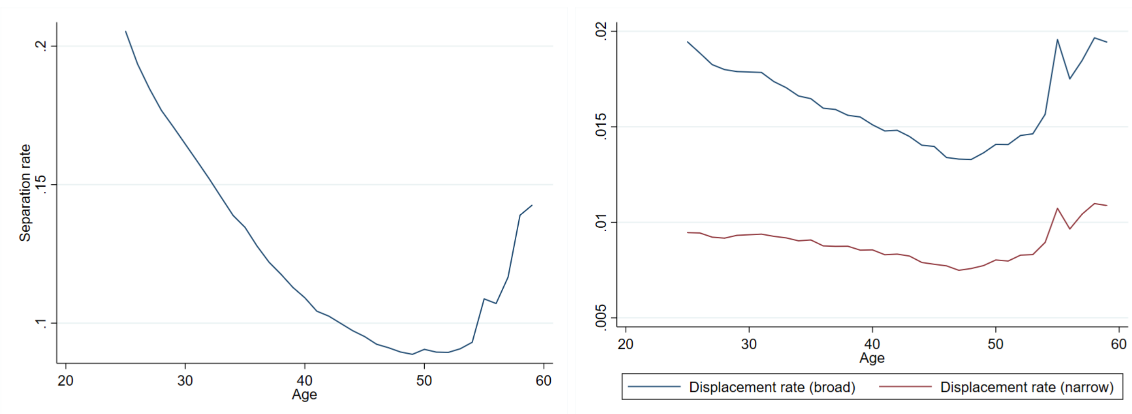


Figure 2: *The incidence of separation (left) and displacement (right) by age.*

In figure 2, the separation and displacement rates are displayed by age of the worker at the time of the event. As can be seen here, the separation rate tends to be higher during early years, but this pattern is not as extreme for the displacement rate, which corresponds to the narrative in the literature (see e.g. Topel and Ward, 1992) that stresses the prevalence of job hopping early in the life cycle.[20] Notably, both the separation and displacement rates increase substantially around the age of 55, which can be explained using the regulations surrounding early (partial) retirement in Germany (ATZ), which can be used by workers aged 55 and above.[21] Finally, it should be noted that while these graphs display the average separation and displacement rates across time, the results generally continue to hold when plotting them over time, as is shown in appendix D.3.5 using data from the LIAB.

[19]Note that workers from East Germany are generally not included in the data before the reunification, so therefore the jump in separation and displacement rates can also partially be explained as a composition effect.

[20]Note that the fact that the peak early in the life cycle (for the separation rate) largely disappears when I impose sample restrictions that I use later in this section, requiring (for example) a tenure of at least 6 years. The corresponding results are shown in appendix D.3.4.

[21]See Berg et al. (2015) for a more extensive description of this policy, implemented in 1996.

Figure 3: *The incidence of separation (left) and broad displacement (right) by gender, over time.*

In figure 3, the separation and (broad) displacement rates over time are plotted separately for male and female workers. While the patterns are more erratic than those seen in figure 1, it can be concluded that until recently the separation rate tended to be higher for female workers, but this was not the case for the displacement rate, thereby implying that female workers do not seem to be disproportionately hit by mass layoffs (conditional on satisfying the sample restrictions as described in section 2). Furthermore, looking at the more recent years, it no longer seems to be the case that female workers face higher separation rates, and displacement rates are now slightly higher for male workers than for female workers.

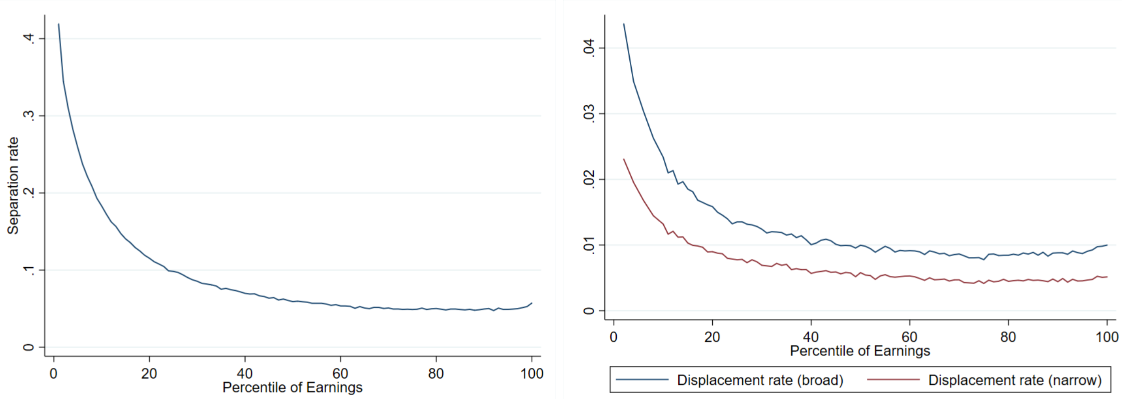


Figure 4: *The incidence of separation (left) and displacement (right) over the earnings distribution.*

As shown in figure 4, the separation and displacement rates in general tends to be higher for individuals located lower on the (recent) earnings distribution. This corresponds with the statement that higher quality matches in terms of productivity also tend to be more stable, as posited in

Jarosch (2015). However, it should be noted that the pattern is not quite monotonic throughout the distribution: above the 80th percentile of the distribution, the displacement rates are slightly increasing again.

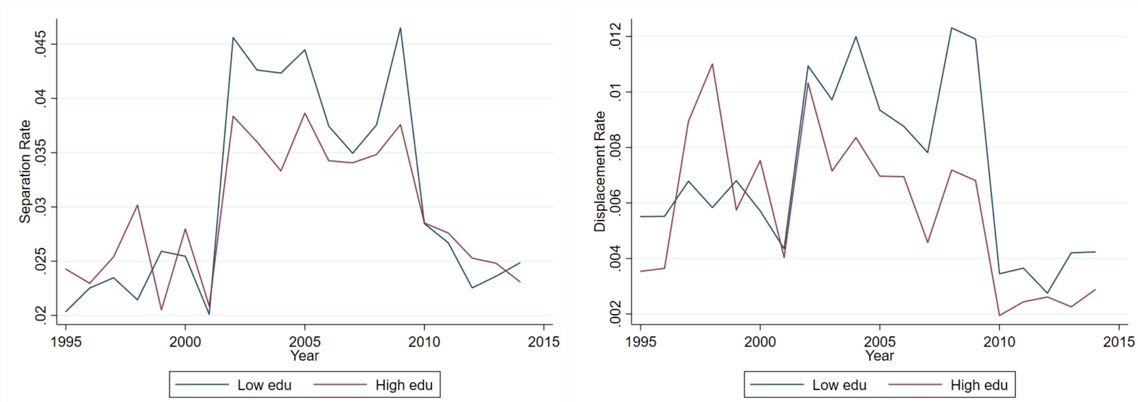


Figure 5: *The incidence of separation (left) and broad displacement (right) by education level, over time, using LIAB and restricting to workers with an establishment tenure of at least 6 years.*

In figure 5, I use a restricted sample of the LIAB to plot the separation and (broad) displacement rates over time by education group, where education level is defined as (1) Non-University or (2) University. As can be seen in the graph, workers with a relatively low education level tend to be more vulnerable to separation or displacement, but this is not always the case. However, with roughly 80% of the workers being categorized in the first group, separations and displacements in any year primarily affect workers with a low education level.

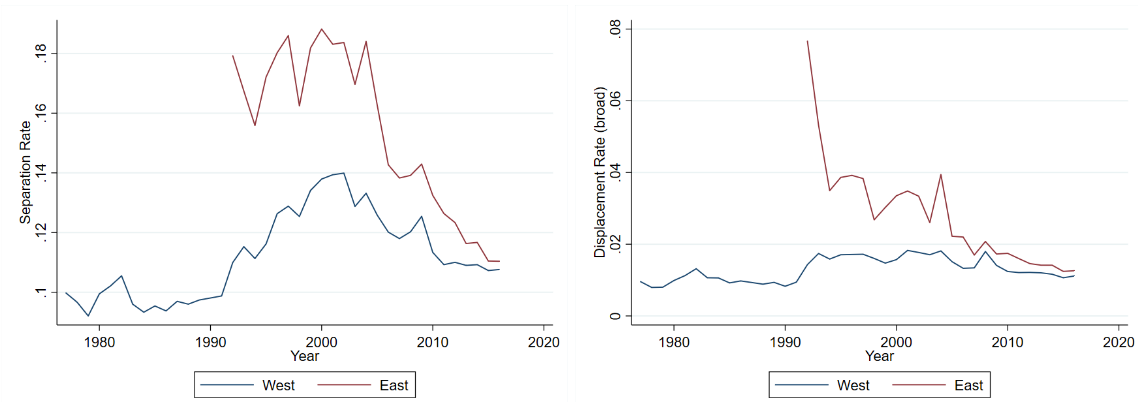


Figure 6: *The incidence of separation (left) and displacement (right) by location.*

Finally, an additional benefit of using data from Germany starting before 1990 is that it allows me to look at a situation specific to Germany: a comparison of the provinces formerly part of West Germany and those formerly part of East Germany. Figure 6 compares the two regions in terms of their separation and (broad) displacement rates. As can be seen in the figure, there is clear convergence between the two regions, but both separation and displacement rates are still higher in Eastern Germany.

While the above analysis has stressed some of the different worker characteristics that are associated with different rates of job loss, it is likely that job loss rates also differ by establishment characteristics such as industry and establishment size. In appendix D.3.3, I further discuss the incidence of separation and displacement along some of these dimension.

3.2 The average scarring effect of job loss

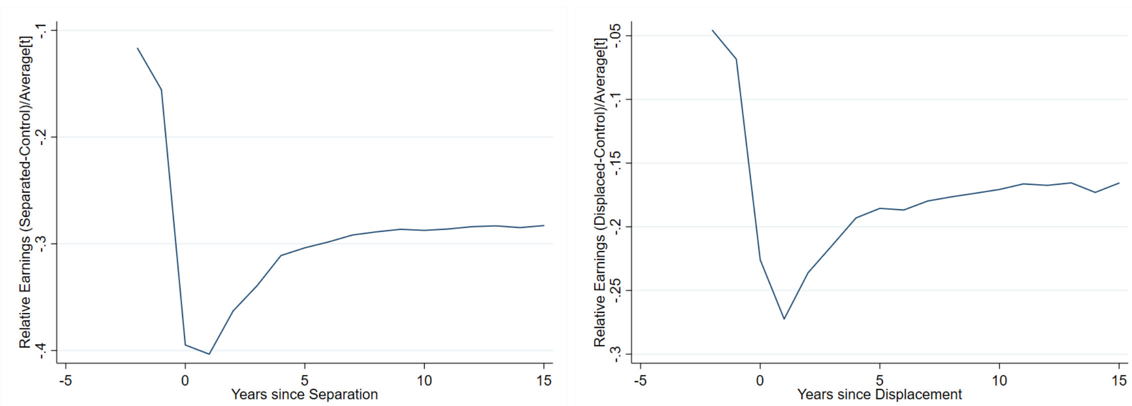


Figure 7: *Raw average difference between earnings of the treatment and control group, defining treatment as either separation (left) or broad displacement (right)*

Having investigated the incidence of job loss across the sample, I will now move towards assessing the effects of this displacement (or separation) on earnings. Before moving to the results of estimating equation (1), however, it is worth looking at the raw earnings differences first. Figure 7 presents these raw earnings differences, where the treatment group is either separated or displacement (using the broad definition). The differences shown in the graphs are generated by calculating the difference between average earnings of the treatment and control (from 2 years before to 15 years after the event), relative to the average earnings of the control group, separately for each base year, and averaging these differences over base years. As can be seen in the figure, the effect of job loss on earnings is quite substantial, and this (raw) effect is worse if one focuses on separation in general rather than displacement. Further, it is worth noting that while there is some recovery over time, earnings are still substantially lower for the treatment group 10 to 15 years after the job loss event.

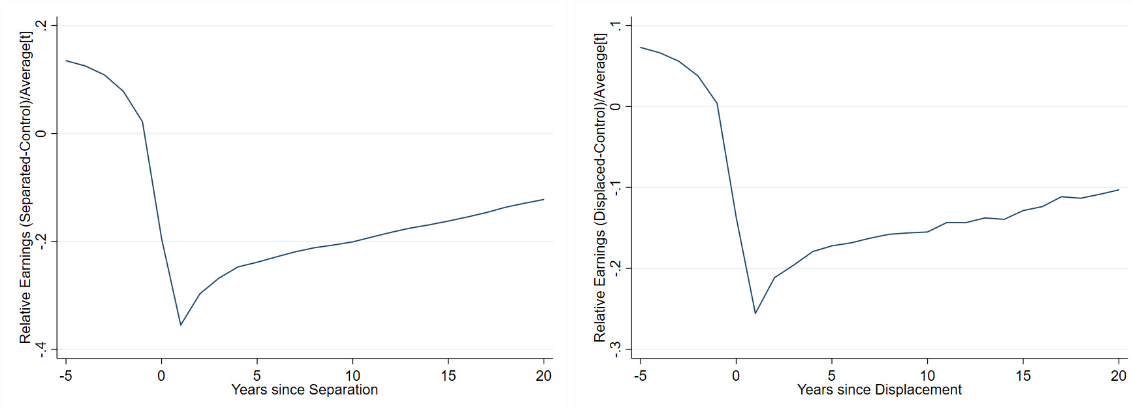


Figure 8: *The effect of separation (left) and broad displacement (right) on earnings, relative to the control group, using estimated coefficients from equation 1.*

Of course, the raw comparison of earnings between separators and non-separators ignores many possible confounding factors, some of which may be unobserved. Therefore, in order to get a better view of the average earnings loss after separation, it is better to control for some other variables that are likely to be important, as done by using the empirical method as described in section 2. Figure 8 shows the results of estimating equation (1), defining the treatment as either separation or (broad) displacement. In particular, it can be seen that in the short-run, workers who are displaced (separated) earn roughly 25% (35%) less on average than a worker in the control group. This earnings loss is shown to be quite persistent, with these displaced (separated) workers still earning 10% (12%) less than workers in the control group 20 years after the job loss took place.[22] These conclusions are in line with what has been observed in the literature, and confirm the large average scarring effect of displacement (and separation) on earnings. As figure 9 shows, the employment status of the displaced and separated workers recovers much faster (though not fully), thus suggesting that a large proportion of the earnings loss may be explained by wages and intensive margin employment choices (working hours).[23]

[22]It should also be noted that the earnings start declining before the job loss actually takes place. This so-called "Ashenfelter's dip" appears in many of my estimates, including those where I restrict workers in the control group to those who were working in the same establishments as the treated workers.

[23]The number of hours worked are not observed in the data beyond an indicator for full-time work, but evidence provided elsewhere in the literature, such as in Lachowska et al. (2020), suggests that it is mostly wages that explain the long-term earnings loss.

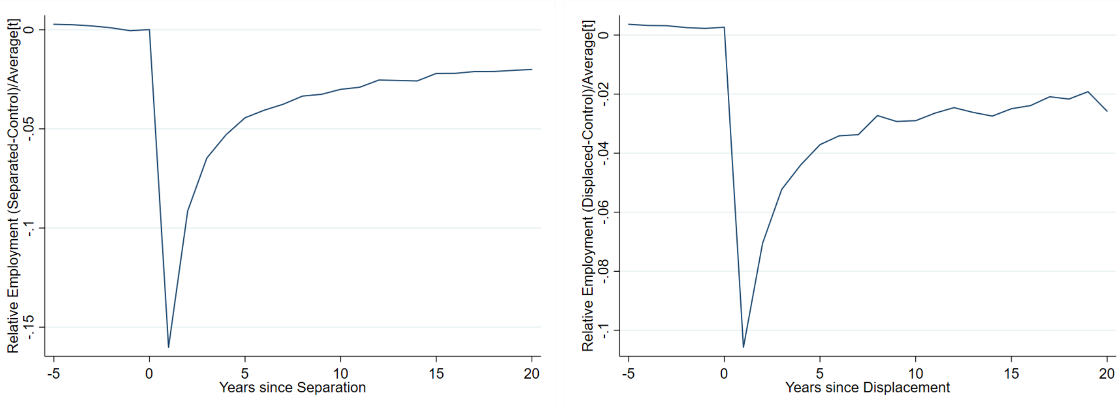


Figure 9: *The effect of separation (left) and broad displacement (right) on employment status, relative to the control group, using estimated coefficients from equation 1.*

3.3 Heterogeneity in the scarring effect of displacement

Unfortunately, the average effects in the previous subsection are not necessarily a good indicator for the earning losses a randomly chosen displaced worker can expect over the next number of years. In order to improve such an indicator, one first needs to have a clearer view of how these average effects differ by a number of observable characteristics of the worker or the establishment they are displaced from. In this subsection, the method I generally use to do this is to split my sample and estimate the empirical specification (1) for a sample in which I restrict all individuals to have a certain characteristic. Comparing the resulting estimation with the average effects in the previous subsection (and with estimates from other subsamples), I can then conclude whether certain characteristics are associated with higher earnings losses, either in the short run (the immediate effect) or in the long run. In this subsection, I will focus on three dimensions in particular, which inform the setup of the model: recent earnings, education level, and ex-post recall status. However, the data allows me to look at many other characteristics of the individual as well as their (former) employer. Results for these other characteristics, and the results of the exercises below using separation rather than displacement, can be found in appendix D.3.2.

3.3.1 Recent Earnings

The first dimension along which I will investigate heterogeneity in the scarring effects of displacement is recent earnings. Arguing that recent earnings may be indicative of other characteristics of the individual (both observable and unobservable), it can be argued that a worker with high recent earnings may experience a very different path (in terms of both earnings and employment) after displacement than a worker with low recent earnings: On the one hand, the worker's high earnings may be indicative of some desirable skill set, and therefore one might expect this worker to be employed faster and not lose as many earnings. On the other hand, if I think about the labour market as a collection of job ladders, the workers with high recent earnings are likely at the top of their ladder, and therefore have further to fall, thus leading to higher earnings losses.

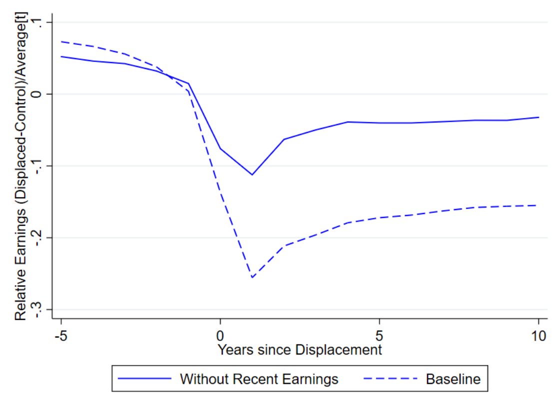


Figure 10: *The effect of (broad) displacement on earnings, relative to the control group, without controlling for recent earnings.*

A first step towards investigating the importance of recent earnings can be made by re-estimating the results in the previous subsection without the control for recent earnings, ($\bar{e}_i^y$ in equation 1). Figure 10 shows how this result compares to the baseline result from figure 8. As can be seen in the figure, not controlling for recent earnings substantially diminishes the estimated effect of displacement on subsequent earnings. The magnitude of the change between the two estimations indicates that taking recent earnings into account is important when estimating this effect.

Motivated by the apparent importance of recent earnings, figure 11 plots the earnings differences over the recent earnings distribution.[24] From this figure, it can be seen that recent earnings does not seem to be very important in expaining subsequent paths of employment status. However, when it comes to the effect of displacement on subsequent earnings, a clear positive gradient is visible. As shown in figure 12, these observations remain true if I omit the sample restriction that requires individuals to have an establishment tenure of at least 6 years. The suggestion that workers with

[24]Note that figures 11 and 12 are not based on the estimation of equation (1). Rather, these graphs show a calculation using raw differences, similar to those done for figure 7.

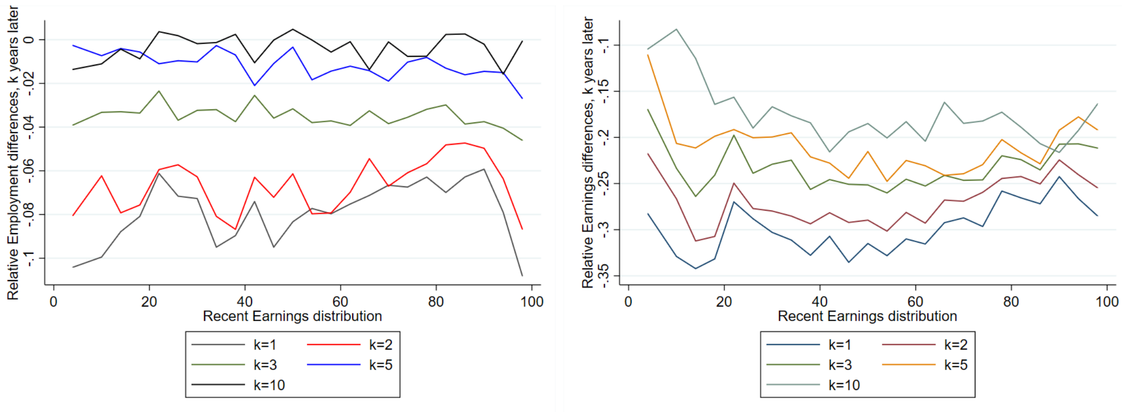


Figure 11: *The raw effect of displacement on employment status (left) and earnings (right), by percentile of recent earnings. Numbers are calculated using the LIAB data, and are relative to workers in the control group in the same percentile of recent earnings. k refers to the number of years that have passed since the displacement event.*

low recent earnings suffer from higher relative earnings losses seemingly contradicts the job ladder view of the labour market, on which most theoretical work on displacement is based. After all, a job ladder would produce higher relative earnings losses for workers at the top of the recent earnings distribution.

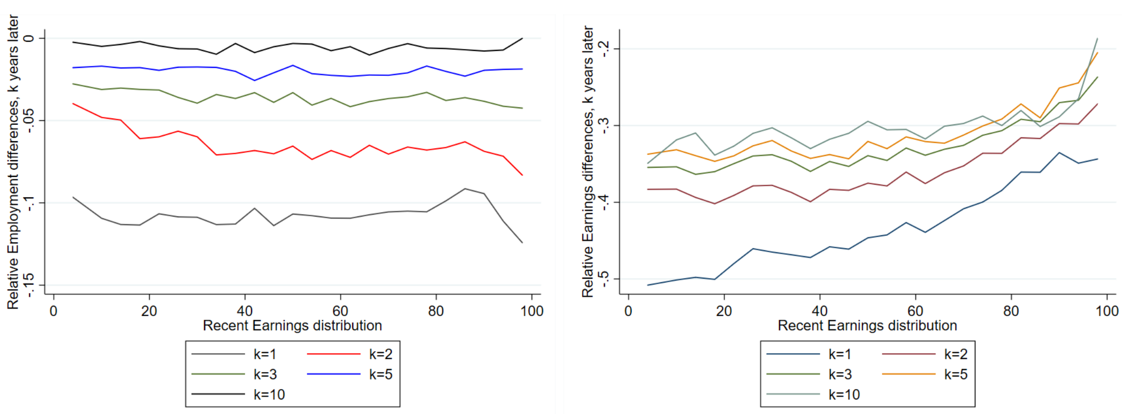


Figure 12: *The effect of displacement on employment status (left) and earnings (right), by percentile of recent earnings and without restrictions on establishment tenure. Numbers are calculated using the LIAB data, and are relative to workers in the control group in the same percentile of recent earnings. k refers to the number of years that have passed since the displacement event.*

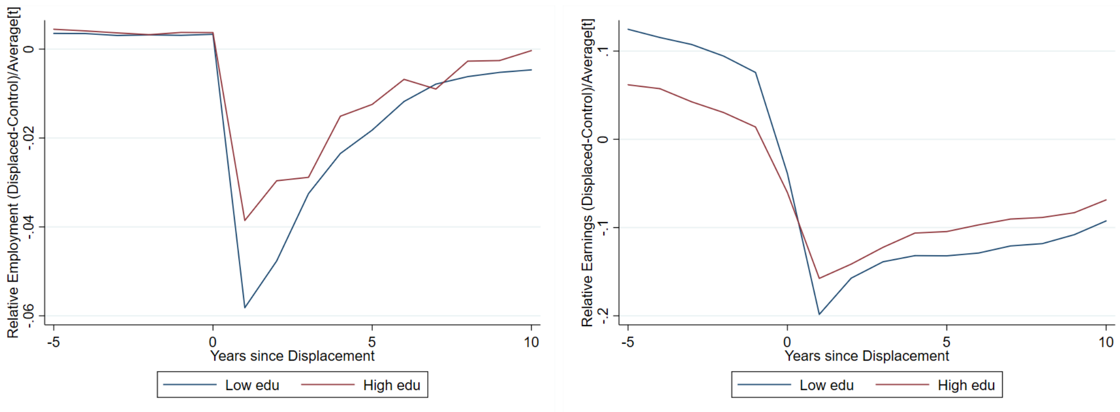


Figure 13: *The effect of displacement on employment (left) and earnings (right), relative to the control group (by education group), using LIAB.*

3.3.2 Education Level

Another factor that one might argue to be important for an individual's earnings loss after displacement is the individuals educational background. In figure 13, I plot the results of the estimation when splitting the sample by education (non-University and University).[25] Comparing the two educational groups, it can be observed that workers with a relatively low education tend to suffer from higher earnings losses, both in the short- and long term. In the short run, this is likely partially driven by a larger initial effect on employment status, which indicates that workers with a high education level find a new job faster (on average).

3.3.3 Recalled Workers

One factor that is generally ignored in the existing literature on the scarring effect of displacement (on earnings) is the possibility of workers being recalled to their former employer. This makes sense for the displacement cases where the establishment closes down, but for displacement in general a non-negligible fraction of workers ends up returning to their former employer.

Figure 14 shows the incidence of recall (within 5 years) after separation and displacement over the recent earnings distribution. Not surprisingly, the incidence of recall is especially high for separation, but even for broad displacement (which notably also includes establishment closures)

[25]Note that I split the sample by education group for both the treatment and control group. In other words, the effects in figure 13 are relative to workers in the same education group. In appendix D.3.2, I show that the results still hold if I don't restrict the control group to have the same education level.

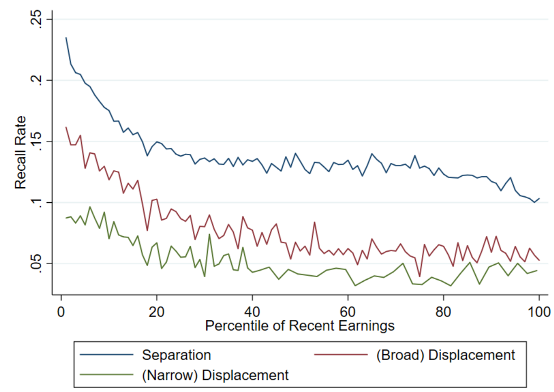


Figure 14: *The incidence of recall within 5 years of separation or displacement, by percentile of the recent earnings distribution.*

the recall rate is consistently above 5% across the recent earnings distribution, and much higher towards the bottom of the distribution. This may seem like a relatively low fraction, but given that workers likely follow a very different path after job loss if they expect to be recalled, it is important to consider these workers separately.

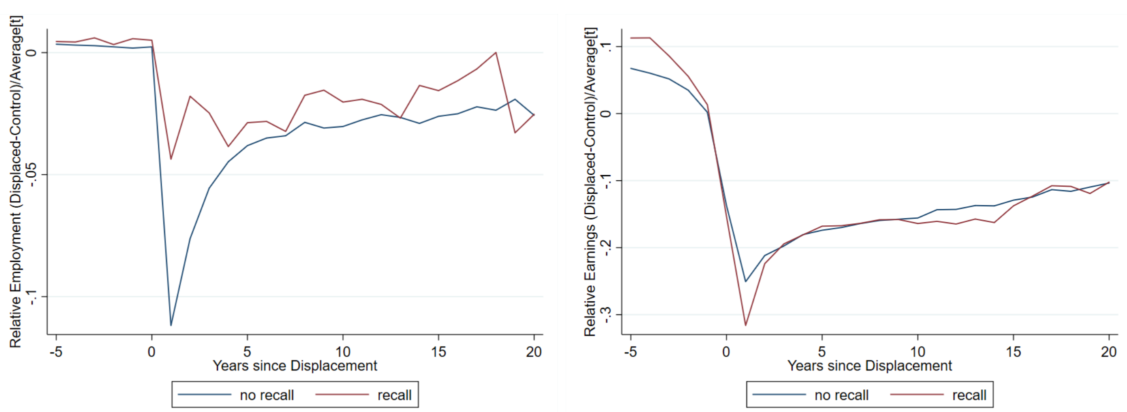


Figure 15: *The effect of separation (left) and broad displacement on earnings relative to the control group, by ex-post recall status (materialization of recall within 5 years).*

In figure 15, I show how the effects of displacement on employment and earnings differs by ex-post recall status.[26] As expected, workers who are recalled tend to be re-employed faster after

[26] As I generally do not observe whether a worker expects to be recalled, I divide workers according to whether or not a recall materializes within 5 years of the job loss. This may not exactly line up with whether a worker expected to be recalled, but given the correlation between the recall rate and the recall expectations (see, for example, Nekoei and Weber, 2015) it serves as a good proxy.

displacement. However, in terms of earnings their loss is more severe in the short run. This result, which is robust to excluding part-time earnings or restricting the sample to certain subsets of the recent earnings distribution (as shown in appendix D.3.2), indicates that recalled workers might suffer more than non-recalled workers in terms of their wage rates. In fact, in combination with the observation that workers near the bottom of the earnings distribution are more likely to be recalled, this may partially explain the observed pattern of earnings loss over the earnings distribution in section 3.3.1.

4 Model

In this section, I propose a search model of the labor market that is aimed at explaining some of the key heterogeneity I observed in section 3. In this discrete-time model, both firms and workers are heterogeneous along two dimensions.[27] Further, the model specifically incorporates the possibility of recall, as a separate state, reflecting my observation that workers who expect to be recalled face a substantially different earnings path.

4.1 Environment

The economy is populated by workers and firms, both of which differ in two dimensions. Firms differ in their productivity y and separation risk δ, which will be summarized using a vector $\theta = [y, \delta]$.[28] Workers differ in their human capital s and type ε, and can be either employed, unemployed, or waiting to be recalled. The type ε is fixed over time, whereas the human capital s can evolve over time. I will interpret the type ε as the worker's education 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. The human capital 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 if unemployed or $\psi_r \psi_u$ when waiting to be recalled). This human capital can therefore be interpreted as being closely related to a worker's market experience.[29]

[27] In particular, the model resembles Jarosch (2015) in that firms are heterogeneous with respect to their productivity and separation rate. However, in contrast to that model, workers are heterogeneous in two dimensions (rather than one), and the possibility of recall is included into the model.

[28] Note that this setup of the firm side of the economy closely resembles Jarosch (2015) and can therefore generate his "job ladder with slippery bottom rungs" if the two dimensions of firm heterogeneity are negatively correlated. However, workers not only differ in their human capital, but also differ in their inherent type α, and my model additionally features a possibility of recall.

[29] The worker's human capital cannot go below s_{min}, so technically the probability ψ_u depends on s: If $s = s_1$, then $\psi_u = 0$. However, in the numerical solution method s_{min} is set sufficiently low such that workers will only reach

4.1.1 Firms

Each firm can hire at most one worker.[30] If a firm is matched to a worker, production takes place according to the log-linear production function $p(s, y) = e^{s+y}$, and the firm pays a wage w to the worker, the determination of which is discussed in subsection 4.1.3. With probability δ, the match faces a separation shock. If this shock materializes, the match is destroyed, and with probability $(1 - \phi^f_\varepsilon)$ the destruction shock is permanent and the worker and firm return to an unmatched and unemployed status. However, with probability ϕ^f_ε the job destruction is potentially only temporary and the worker can choose to wait to be recalled. Upon recall, nevertheless, the productivity of the match is reduced by c^f, such that the recalled match produces $p(s, y') = p(s, y) - c^f$ (where y' is restricted to be in the range of y). The intuition behind the recall penalty is that the firm is likely to incur costs for firing and re-hiring the worker, which it will prefer to earn back (e.g. by lowering the worker's wage).[31] Finally, I assume that firms that are unmatched do not produce anything and also don't face any costs, thus setting the value of an unmatched firm equal to 0.

4.1.2 Workers

Workers are assumed to be infinitely-lived, and unable to transfer resources between periods. Further, their instantaneous utility function is assumed to be logarithmic, and they discount future utility at a rate β. Each worker enters the market as unemployed and with the human capital s_ε. Their education type is determined prior to entering the labor market, corresponding to the sample restriction in the data where I did not consider workers below the age of 25. An unemployed worker meets a firm with probability λ^u_ε, and this firm is drawn from the distribution $G_\varepsilon(\theta)$, where ε shifts the marginal distributions of δ and y (see section 5), thus enabling different types to meet firms with different characteristics on average, but not restricting the range of δ to certain worker types.[32] If the worker meets a firm, the worker decides whether or not to accept the job. If the worker accepts, she becomes employed and receives wage w. If the worker does not accept, or does not receive an offer, the worker receives $b(s)$, which can be interpreted as the instantaneous value of

s_{min} in very rare instances (see appendix A).

[30] Because the firm can only hire one worker, the model does not differentiate between firms, establishments, or jobs. In order to stay consistent with the literature, I will refer to the production entity as a firm, but when making the link with the data these entities can be thought of as establishments.

[31] Instead of explicitly lowering the wage, I chose to lower the productivity of the firm. In practice, this does not affect the wage in any different way, but it avoids the need for introducing another state variable that keeps track of how many times the worker has been recalled.

[32] The parameter that shifts the marginal distribution of y also affects the range of y. In particular, it affects the lower bound of the range, while the upper bound is unaffected.

being unemployed (and is related to the unemployment benefit). It is related to the worker's human capital as I set it equal to a fraction of the lowest possible production a worker could produce in a match: $b(s) = bp(s, y^{min})$. In doing so I try to proxy a setting in which the unemployment benefit depends on the last earned wage, while also not ruling out the scenario where unemployed workers reject some job offers.[33] Finally, it should be noted here that I do not explicitly model how the unemployment benefit is financed, though I will do so when I introduce alternatives in section 6.3. Thus, I essentially assume that the government has exactly enough revenues to pay for the unemployment benefits and obtained this revenues from some outside source.

Naturally, an employed worker faces the same job destruction and recall shocks 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 again drawn from distribution $G_\varepsilon(\theta)$. Upon receiving such an offer, the employed worker can decide to switch to the new firm or to reject the offer. However, before deciding to reject the offer, it can be used to re-bargain with the current employer.

Finally, if a match is temporarily destroyed and the worker is waiting to be recalled, she will receive $b(s)$ (just like the unemployed worker) but will not be searching for a new firm. Rather, she is recalled to her previous match with probability ϕ_ε^r every period, until the recall materializes or until she chooses to forego the option of recall (and thus transitions to a state of unemployment). When the recall materializes, the wage is re-determined as if the worker is using the value of the match with the (same) employer as the outside option, and the productivity of the match (and outside option) declines as described in subsection 4.1.1.[34] While she is waiting to be recalled, the worker's human capital decreases by $\Delta_s(\varepsilon)$ with probability $\psi_r \psi_u$, reflecting that a worker waiting for recall may either experience faster or slower depreciation of human capital. In particular, one could argue that the depreciation is faster because the worker does not have to invest in knowledge needed to match with a new employer. However, it could also be argued that the depreciation is slower, since the worker already knows who she will be employed by in the future, and therefore can keep her job-specific knowledge from depreciating.[35]

[33] In the case where $b = 1$, this unemployment benefit becomes very similar to the one seen in Bagger et al. (2014). In particular, the lower the value of the parameter b is, the lower the value of being unemployed is, and therefore the more job offers will be accepted. In particular, there exists a threshold b, which depends on job offer rates λ_ε^u and λ_ε^e, such that the unemployed worker accepts any job offer as in the model in Bagger et al. (2014).

[34] In appendix C, I show how the main results change if I change the assumption on the outside option used by the worker when coming back from a temporary layoff.

[35] As she is not physically in the workplace, it is likely that she will not be able to increase her knowledge like she would if she were to be employed (as she cannot accumulate any experience in practice).

4.1.3 Wage Setting

In determining the wages, I follow a similar procedure to Bagger et al. (2014). At the time of bargaining the worker and firm agree on a piece-rate $R = e^r$, and the worker receives a wage of $w = Rp(s, y) = e^{r+s+y}$ 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.

When the worker and the firm meet, the piece rate is determined by taking into account the maximum surplus a worker could extract from the match and the maximum surplus that could be extracted from the outside option. In practice, this maximum surplus equals the value function of the worker if the piece-rate R is set equal to 1 (or $r = 0$), and I denote 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, plus a constant fraction of the excess maximum surplus of the impending match. This fraction, κ, is interpreted as the bargaining power of the worker. Denoting the maximum surplus from the outside option by W^{oo}:

$$W_\varepsilon(s, s, \theta, \hat{\theta}) = W^{oo} + \kappa \left(W_\varepsilon^{max}(s, \theta) - W^{oo}\right) \tag{2}$$

Here, it is explicitly taken into account that in general 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 ($\hat{s}$).[36] Note that equation (2) can take three distinct forms. First, if the worker is coming out of unemployment (including temporary unemployment while waiting for a recall), the outside option value W^{oo} equals the value of unemployment, $U_\varepsilon(s)$ and $\hat{\theta} = u$. Then, denoting by x the firm characteristics of the worker's new firm, equation (2) can be rewritten as equation (3).

$$W_\varepsilon(s, s, x, u) = U_\varepsilon(s) + \kappa \left(W_\varepsilon^{max}(s, x) - U_\varepsilon(s)\right) \tag{3}$$

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

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

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 (2) can be rewritten as equation (4). Finally, if the

[36] At the time of bargaining, the human capital "when the worker and firm last bargained" ($\hat{s}$) is set equal to the current human capital (s), so in equations (2) to (5) I set $\hat{s} = s$.

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 (2) can be rewritten as equation (5).

4.2 Timing and Value Functions

To summarize the setup of the model, every model period can be divided into x stages. At the start of the period, in the first stage, the human capital level of the workers is updated. Then, in the second stage, recall materialization, separation, and recall choice takes place.[37] Then, in the third stage, workers who started the period as unemployed or employed (and are still in that state) may receive an offer from a firm, after which they choose to accept or reject it and (re-)bargaining takes place. Finally, at the end of the period, production takes place and wages (and unemployment benefits) are paid out.

Using the above description, I can write out the value functions of the worker and the firm. In particular, I will write out these value functions from the viewpoint of a worker/firm at the end of the period (before the start of the production stage). First, the value of unemployment U for a worker of type ε with human capital s can be written out as follows:

$$\begin{aligned} U_\varepsilon(s) = \ln(b(s)) + \beta \mathbb{E}_{s'|s,u,\varepsilon} \Bigg\{ & \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^u(s')} W_\varepsilon(s', s', x, u) dG_\varepsilon(x) \\ & + \left(1 - \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^u(s')} dG_\varepsilon(x)\right) U_\varepsilon(s') \Bigg\} \end{aligned} \tag{6}$$

Here, the set $\Theta_\varepsilon^u(s)$ is the set of firm characteristics of the firms from whom the worker of type ε would accept an job offer if her current human capital level is s. Using equation (3), this set can be specified as $\Theta_\varepsilon^u(s) = \{x \in [0,1] \times \mathbb{R}_+ : W_\varepsilon^{max}(s,x) \geq U_\varepsilon(s)\}$.

As shown in appendix B, equation (6) can be rewritten in terms of W^{max}, U, and parameters only:

$$U_\varepsilon(s) = \ln(b(s)) + \beta \mathbb{E}_{s'|s,u,\varepsilon} \left\{ \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^u(s')} \kappa \left(W_\varepsilon^{max}(s', x) - U_\varepsilon(s') \right) dG_\varepsilon(x) + U_\varepsilon(s') \right\} \tag{7}$$

[37] In particular, I assume that a worker cannot be recalled in the same period as the layoff, and the worker cannot choose to transition to unemployment until the recall materialization shock ϕ_ε^r is realized, so these three events take place in that specific order.

Similarly, the value of employment W for a worker of type ε with human capital s, matched with a firm of type $\theta = [\delta, y]$, is as specified below:

$$\begin{aligned}W_\varepsilon(s,\hat{s},\theta,\hat{\theta}) = \ln(R_\varepsilon(\hat{s},\theta,\hat{\theta})p(s,y)) + \beta\mathbb{E}_{s'|s,e,\varepsilon}\Bigg\{&\delta\left[\phi^f_\varepsilon \max\left\{F_\varepsilon(s',\theta),U_\varepsilon(s')\right\} + (1-\phi^f_\varepsilon)U_\varepsilon(s')\right] \\ +(1-\delta)\Bigg[\lambda^e_\varepsilon\Bigg(&\int_{x\in\Theta^1_\varepsilon(s',\theta)} W_\varepsilon(s',s',x,\theta)dG_\varepsilon(x) + \int_{x\in\Theta^2_\varepsilon(s',\hat{s},\theta,\hat{\theta})} W_\varepsilon(s',s',\theta,x)dG_\varepsilon(x)\Bigg) \\ +\Bigg(1-\lambda^e_\varepsilon&\int_{x\in\Theta^1_\varepsilon(s',\theta)\cup\Theta^2_\varepsilon(s',\hat{s},\theta,\hat{\theta})} dG_\varepsilon(x)\Bigg) W_\varepsilon(s',\hat{s},\theta,\hat{\theta})\Bigg]\Bigg\} \qquad (8)\end{aligned}$$

Here, I denote by $\hat{s}$ the value of human capital at the time of the most recent bargaining. Similarly, $\hat{\theta} \in \{[0,1]\times\mathbb{R}_+, u\}$ represents the firm characteristics corresponding to the job offer that was used for bargaining.[38] The set $\Theta^1_\varepsilon(s,\theta)$ 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, and $\Theta^2_\varepsilon(s,\hat{s},\theta,\hat{\theta})$ 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 (4) and (5), these sets can be specified as $\Theta^1_\varepsilon(s,\theta) = \{[0,1]\times\mathbb{R}_+ : W^{max}_\varepsilon(s,x) \geq W^{max}_\varepsilon(s,\theta)\}$ and $\Theta^2_\varepsilon(s,\theta) = \{x \in [0,1]\times\mathbb{R}_+ : W^{max}_\varepsilon(s,\theta) > W^{max}_\varepsilon(s,x) \geq W^{max}_\varepsilon(\hat{s},\hat{\theta})\}$.[39] Using equation (8), 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, which is derived in appendix B, no longer depends on the bargaining benchmark, as the outcome of the bargaining (which is the piece-rate) is already known:

$$\begin{aligned}W^{max}_\varepsilon(s,\theta) = \ln(p(s,y)) + \beta\mathbb{E}_{s'|s,e,\varepsilon}\Bigg\{&\delta\left[\phi^f_\varepsilon \max\left\{F_\varepsilon(s',\theta),U_\varepsilon(s')\right\} + (1-\phi^f_\varepsilon)U_\varepsilon(s')\right] \\ +(1-\delta)\Bigg[\lambda^e_\varepsilon&\int_{x\in\Theta^1_\varepsilon(s',\theta)} \kappa\left(W^{max}_\varepsilon(s',x) - W^{max}_\varepsilon(s',\theta)\right)dG_\varepsilon(x) + W^{max}_\varepsilon(s',\theta)\Bigg]\Bigg\} \qquad (9)\end{aligned}$$

The value function F for a worker of type ε with human capital s, waiting to be recalled to a firm of type θ, is as follows:

$$F_\varepsilon(s,\theta) = \ln(b(s)) + \beta\mathbb{E}_{s'|s,r,\varepsilon}\left\{\phi^r_\varepsilon W_\varepsilon(s',s',\theta',\theta') + (1-\phi^r_\varepsilon)\max\left\{F_\varepsilon(s',\theta),U_\varepsilon(s')\right\}\right\} \qquad (10)$$

[38] If a worker comes out of unemployment, she does not have such a job offer to use for bargaining, and uses the value of unemployment instead. I denote this by setting $\hat{\theta} = u$.

[39] 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 $x \in [0,1]\times\mathbb{R}_+$, 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.

Note that since the worker loses her outside option upon separating (even if the separation is temporary), the value function F does not depend on $\hat{s}$ or $\hat{\theta}$. Further, note that $\theta' = [\delta, y']$, where y' is the maximum of y^{min} (the lower bound of the range of y) and y' such that $p(s, y') = p(s, y) - c^f$. Finally, I allow for the depreciation rate of human capital to be different for the worker waiting to be recalled. However, I do not make any assumption on whether the human capital depreciation occurs faster or slower for a worker to be recalled.

Just like value function $U_\varepsilon(s)$, this value function $F_\varepsilon(s, \theta)$ can be rewritten using the bargaining equation (3):

$$F_\varepsilon(s, \theta) = \ln(b) + \beta \mathbb{E}_{s'|s,r,\varepsilon} \left\{ \phi^r_\varepsilon \kappa W^{max}_\varepsilon(s', \theta') + \phi^r_\varepsilon(1 - \kappa) U_\varepsilon(s') + (1 - \phi^r_\varepsilon) F_\varepsilon(s', \theta) \right\} \tag{11}$$

On the firm side, the value function J for a firm of type θ, employing a worker of type ε with human capital s, is as follows:

$$\begin{aligned} J_\varepsilon(s, \hat{s}, \theta, \hat{\theta}) = \left(1 - R_\varepsilon(\hat{s}, \theta, \hat{\theta})\right) p(s, y) + \beta \mathbb{E}_{s'|s,e,\varepsilon} \Bigg\{ (1 - \delta) \Bigg[\lambda^e_\varepsilon \int_{x \in \Theta^2_\varepsilon(s', \hat{s}, \theta, \hat{\theta})} J_\varepsilon(s', s', \theta, x) dG_\varepsilon(x) \\ + \left(1 - \lambda^e_\varepsilon \int_{x \in \Theta^1_\varepsilon(s', \theta) \cup \Theta^2_\varepsilon(s', \hat{s}, \theta, \hat{\theta})} dG_\varepsilon(x)\right) J_\varepsilon(s', \hat{s}, \theta, \hat{\theta}) \Bigg] + \delta \bar{\phi}^f_\varepsilon(s, \theta) J^f_\varepsilon(s', \theta) \Bigg\} \end{aligned} \tag{12}$$

Here, $J^f_\varepsilon(s, \theta)$ is the value for a firm waiting for a recall (the firm analogue of equation 10), and $\bar{\phi}^f_\varepsilon(s, \theta) = \phi^f_\varepsilon \mathbb{1}_{F_\varepsilon(s,\theta) > U_\varepsilon(s)}$, capturing that the worker may choose to forego the option of recall. As mentioned before, the value of an unmatched firm is $V = 0$. Note that because the wage is set using the maximum values that the worker can obtain from the matches, the value functions on the firm side are not needed to solve the model.

Finally, the description of the model above can be used to construct a number of worker flow equations. In particular, 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 $\theta \in [0, 1] \times \mathbb{R}_+$, and benchmark characteristics $\hat{\theta} \in [0, 1] \times \mathbb{R}_+$, 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 $d^f_\varepsilon(s, \hat{s}, \theta, \hat{\theta})$ and $d^f_\varepsilon(s, \hat{s}, \theta, u)$ be the density of such workers waiting to be recalled to such a firm, and let $u_\varepsilon(s)$ be the density of unemployed workers of type ε with human capital s. The flow equations are then as follows:[40]

$$d'_\varepsilon(s,\hat{s},\theta,\hat{\theta}) = (1-\delta)\left(1-\lambda^e_\varepsilon \int_{x\in\Theta^1_\varepsilon(s,\theta)\cup\Theta^2_\varepsilon(s',\hat{s},\theta,\hat{\theta})} dG_\varepsilon(x)\right)\bar{d}_\varepsilon(s,\hat{s},\theta,\hat{\theta})$$
$$+ \mathbb{1}_{s=\hat{s}}\lambda^e_\varepsilon g_\varepsilon(\theta)\left[\int\int\int(1-\hat{\delta})\left(\mathbb{1}_{\theta\in\Theta^1_\varepsilon(s,\hat{\theta})\cup\Theta^2_\varepsilon(s,x,\hat{\theta},y)}\bar{d}_\varepsilon(s,x,\hat{\theta},y)\right)dxdyd\hat{\theta}\right] \tag{13}$$

$$d^{f\prime}_\varepsilon(s,\hat{s},\theta,\hat{\theta}) = (1-\phi^r_\varepsilon)\bar{d}^f_\varepsilon(s,\hat{s},\theta,\hat{\theta}) + \delta\bar{\phi}^f_\varepsilon(s,\theta)\bar{d}_\varepsilon(s,\hat{s},\theta,\hat{\theta}) \tag{14}$$

$$d'_\varepsilon(s,\hat{s},\theta,u) = (1-\delta)\left(1-\lambda^e_\varepsilon \int_{x\in\Theta^1_\varepsilon(s,\theta)\cup\Theta^2_\varepsilon(s',\hat{s},\theta,u)} dG_\varepsilon(x)\right)\bar{d}_\varepsilon(s,\hat{s},\theta,u)$$
$$+ \lambda^u_\varepsilon g_\varepsilon(\theta)\mathbb{1}_{\theta\in\Theta^u_\varepsilon(s)}\bar{u}_\varepsilon(s) + \phi^r_\varepsilon\int\int\left(\mathbb{1}_{\theta'\in\Theta^f_\varepsilon(\theta)}\bar{d}^f_\varepsilon(s,\hat{s},\theta',\hat{\theta})\right)d\theta' d\hat{\theta} \tag{15}$$

$$d^{f\prime}_\varepsilon(s,\hat{s},\theta,u) = (1-\phi^r_\varepsilon)\bar{d}^f_\varepsilon(s,\hat{s},\theta,u) + \delta\bar{\phi}^f_\varepsilon(s,\theta)\bar{d}_\varepsilon(s,\hat{s},\theta,u) \tag{16}$$

$$u'_\varepsilon(s) = \left(1-\lambda^u_\varepsilon\int_{x\in\Theta^u_\varepsilon(s)} dG_\varepsilon(x)\right)\bar{u}_\varepsilon(s) + \int_\theta \delta\left(1-\bar{\phi}^f_\varepsilon(s,\theta)\right)\int_{\hat{s}}\int_{\hat{\theta}}\bar{d}_\varepsilon(s,\hat{s},\theta,\hat{\theta})d\hat{\theta}d\hat{s}d\theta \tag{17}$$

where

$$\bar{d}_\varepsilon(s,\hat{s},\theta,\cdot) = (1-\psi_e)d_\varepsilon(s,\hat{s},\theta,\cdot) + \psi_e d_\varepsilon(s-\Delta_s(\varepsilon),\hat{s},\theta,\cdot)$$
$$\bar{d}^f_\varepsilon(s,\hat{s},\theta,\cdot) = (1-\psi_u)d^f_\varepsilon(s,\hat{s},\theta,\cdot) + \psi_u d^f_\varepsilon(s+\Delta_s(\varepsilon),\hat{s},\theta,\cdot)$$
$$\bar{u}_\varepsilon(s) = (1-\psi_u)u_\varepsilon(s) + \psi_u u_\varepsilon(s+\Delta_s(\varepsilon))$$
$$\Theta^f_\varepsilon(\theta) = \left\{[\delta,y'] \in [0,1]\times\mathbb{R}_+ : y = \max(y^{min}_\varepsilon,\hat{y}); \quad \hat{y} : p(s,\hat{y}) = p(s,y') - c^f\right\}$$

In the steady state, it should hold (for all ε) that $d'_\varepsilon(s,\hat{s},\theta,\hat{\theta}) = d_\varepsilon(s,\hat{s},\theta,\hat{\theta})$ (for $\hat{\theta}\in[0,1]\times\mathbb{R}_+\cup u$), $d^{f\prime}_\varepsilon(s,\hat{s},\theta,\hat{\theta}) = d^f_\varepsilon(s,\hat{s},\theta,\hat{\theta})$ (for $\hat{\theta}\in[0,1]\times\mathbb{R}_+\cup u$), and $u'_\varepsilon(s) = u_\varepsilon(s)$.

4.3 Equilibrium

In this model economy, an equilibrium consists of value functions $U_\varepsilon(s)$, $W_\varepsilon(s,\hat{s},\theta,\hat{\theta})$, $F_\varepsilon(s,\theta)$, $J_\varepsilon(s,\hat{s},\theta,\hat{\theta})$, and a piece-rate function $R_\varepsilon(\hat{s},\theta,\hat{\theta})$, such that, given distribution $G_\varepsilon(\theta)$ and parameters, the value functions $W_\varepsilon(s,\hat{s},\theta,\hat{\theta})$ and $U_\varepsilon(s)$ satisfy equations (3) to (5), the value functions and the piece-rate function satisfy equations (6) to (12), and the distribution of workers across different states evolves according to equations (13) to (17).

4.4 Efficiency

For the purpose of the policy experiments later in this paper, I will now briefly describe the social planner's problem, and how its solution differs from the equilibrium described in the

[40] Note that when I integrate over the last element in d_ε, I include all possible θ as well as u in this integration

previous subsection. For this purpose, I will assume that the social planner maximizes the present discounted utility value of output and transfers. In other words, the planner's instantaneous value of a match equals $u(p(s,y)) = \ln(p(s,y))$ (given the log utility assumption made earlier), whereas the planner's instantaneous value of unemployment equals $u(b(s)) = \ln(b(s))$.[41]

The social planner is subject to the same frictions as the workers and firms in the economy. Taking this into account, one can summarize the social planner's problem with the 3 value functions below, where Y^P denotes the value of a match, U^P denotes the value of unemployment, and F^P denotes the value of a worker waiting to be recalled:

$$Y_\varepsilon^P(s,\theta) = \ln(p(s,y)) + \beta \mathbb{E}_{s'|s,e,\varepsilon} \Bigg\{ \delta \left[(1-\phi_\varepsilon^f) U_\varepsilon^P(s') + \phi_\varepsilon^f \max\{F_\varepsilon^P(s',\theta), U_\varepsilon^P(s')\} \right] \\ + (1-\delta) \left[Y_\varepsilon^P(s',\theta) + \lambda_\varepsilon^e \int_{x \in \Theta_\varepsilon^{1,P}(s',\theta)} \left[Y_\varepsilon^P(s',x) - Y_\varepsilon^P(s',\theta) \right] dG_\varepsilon(x) \right] \Bigg\} \tag{18}$$

$$U_\varepsilon^P(s) = \ln(b) + \beta \mathbb{E}_{s'|s,u,\varepsilon} \left\{ U_\varepsilon^P(s') + \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^{u,P}(s')} \left[Y_\varepsilon^P(s',x) - U_\varepsilon^P(s') \right] dG_\varepsilon(x) \right\} \tag{19}$$

$$F_\varepsilon^P(s,\theta) = \ln(b) + \beta \mathbb{E}_{s'|s,r,\varepsilon} \left\{ \phi_\varepsilon^r Y_\varepsilon^P(s',\theta') + (1-\phi_\varepsilon^r) \max\{F_\varepsilon^P(s',\theta), U_\varepsilon^P(s')\} \right\} \tag{20}$$

Looking at the value functions above, it can be observed that the choice of the social planner can be summarized by the choice between waiting for recall and moving to unemployment, $\max\{F_\varepsilon^P(s',\theta), U_\varepsilon^P(s')\}$, and the two objects $\Theta_\varepsilon^{1,P}(s,\theta)$ and $\Theta_\varepsilon^{u,P}(s)$, which represent the sets of job offers that a worker of type ε with human capital s (who currently works at an establishment with characteristics θ, in the case of $\Theta^{1,P}$) should accept according to the social planner.

When assessing the efficiency properties of the model, I compare the three value functions above (equations 18 to 20) to the corresponding value functions (9), (7), and (11). Comparing those equations, it can be observed that the equations are equivalent iff $\kappa = 1$. In other words, the two objects $\Theta_\varepsilon^{1,P}(s,\theta)$ and $\Theta_\varepsilon^{u,P}(s)$ will be identical to their equivalents $\Theta_\varepsilon^{1}(s,\theta)$ and $\Theta_\varepsilon^{u}(s)$ and the worker will make the same choice about waiting for recall if and only if the worker receives the full value of the match. If this is not the case, the worker will not fully internalize the value of the output produced by the match. Of course, the extent to which this creates inefficiencies depends on the values of κ as well as other parameters. In section 6.2, I will show how different worker and

[41] Note that if I interpret $b(s)$ as (partially) stemming from an unemployment benefit, it has to be acknowledged again that the model is silent on how this benefit is financed. However, I nevertheless choose to include b in the social planner's problem to enhance the comparability of the equilibrium and the social planner's problem. Additionally, including b allows me to avoid issues stemming from attempting to take the natural logarithm of 0.

social planner choices are for the baseline calibration (as laid out in the next section).

5 Calibration

For the purpose of the calibration, I set up the distribution $G_\varepsilon(\theta)$ as a combination of marginal distributions of y and δ, on which I make parametric assumptions. In particular, I assume that the marginal distribution of δ is a Beta distribution with parameters η_δ and $\mu_{\delta,\varepsilon}$, whereas the marginal distribution of y is a Pareto distribution with shape parameters $\mu_{y,\varepsilon}$ and η_y. I then follow Jarosch (2015) in combining the two marginal distributions into the bivariate distribution $G_\varepsilon(\theta)$ using Frank's copula with parameter ρ (which allows for correlation between the two variables). Finally, as alluded to earlier in this paper, I will interpret the worker type ε as the education level. In line with the discussion in section 3, I therefore allow for two worker types.

As table 2 shows, these assumptions lead me to a total of 28 parameters that need to be identified. Of these 28 parameters, I will set 5 parameters exogenously, leaving the remaining 23 parameters to be estimated using the indirect inference method from Gourieroux et al. (1993).[42] In the next two subsections, I describe how I set the 5 exogenous parameters, and which moments I use to identify the remaining 23 parameters. The discussion in these two subsections is summarized in tables 3 and 4, 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.

5.1 Exogenously Set Parameters

As I interpret ε to correspond to the worker's education level, it makes sense to 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 used in section 3, I set the fraction of workers with education levels 1 and 2 to equal 0.79 and 0.21 respectively.

Furthermore, 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

[42] Note that most of the elements of the calibration method are reminiscent of a simulated method of moments approach, which is nested in the indirect inference approach from Gourieroux et al. (1993). However, given the use of an auxiliary regression estimation for one of the moments, it is more appropriate to classify it as the more general indirect inference method.

Par	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
ψ_r	human capital transition, recall
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
λ_ε^u	meeting probabilities, unemployment
λ_ε^e	meeting probabilities, employment
ϕ_ε^f	probability of recall
ϕ_ε^r	recall materialization probability
c^f	production penalty of recall

Table 2: *A summary of all parameters in the model to be set exogenously or to be calibrated.*

Parameter(s)	Value(s)	Source
β	0.98726	5% annual interest rate
s_2	0	normalization
$\Delta_s(1)$	0.1	normalization
ϵ_1	0.79	fraction of workers with education level 1
ϵ_2	0.21	fraction of workers with education level 2

Table 3: *A summary of all exogenously set parameters*

entering the labor 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 ($\Delta_s(1)$). Table 3 summarizes the values of the exogenously set parameters, and the sources used to set these values.

5.2 Calibration Moments

Using that I interpret ε to correspond to education levels, I next identify 33 moments that together identify the values of the 23 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, and I argue that each of these groups are identified by a corresponding group of moments.[43]

[43] Dividing the parameters and moments in groups is an exercise I purely do for exposition purposes. In reality, all parameters directly or indirectly affect all moments, but by dividing the parameters and moments into groups I find

The first set of moments contains information on employment rates and transition rates between employment and non-employment, and these moments are used to calibrate parameters governing the marginal distribution of δ and the job offer rates. 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. Then, to discipline the education-specific first shape parameter of this distribution, I use the average employment rate (by education level). As I show in appendix B.2, a combination of ϕ^r_ε, ϕ^f_ε λ^u_ε, and employment rate uniquely identifies the average separation rate in the population. Since the expected value of a Beta distribution can be calculated using only both shape parameters, a combination of the average separation rate, η_δ, and the recall parameters then allows me to back out limits on $\mu_{\delta,\varepsilon}$. Finally, I use the average job finding rate (by education level) to identify the value of λ^u_ε. Note that job offer rates λ^u_ε are not directly identified, as there may exist combinations of s,δ, and y for which an unemployed worker with human capital s would not accept a job with characteristics δ and y.

The second set of moments is informative about the average wage level (by education level) and its variance. Using that 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 that was not normalized (education level 2). In particular, I use the average educational wage premium for education level 2 (compared to education level 1), both overall and upon labor market entry (identified as a market tenure between 3 and 5 years). As these wage differences are generated primarily by 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 p10-median and p10-p90 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.

The next set of moments focuses on wage growth within and between job spells, thereby helping to identify on-the-job offer rates, human capital transition rates and steps, among others. The specific moments used here include the average quarterly job-to-job transition rate by education, which helps to identify the on-the-job offer rates λ^e_ε, and the net replacement rate in unemployment, which closely relates to the parameter b included in the expression for the instan-

that the main intuition behind the moments is clearer.

taneous value of non-employment $b(s)$.[44] Next, the average yearly wage growth (by education level), conditional on full-year full-time employment, helps to identify the human capital stepsize that was not normalized, $\Delta_s(2)$, and human capital on-the-job transition rate ψ_e, while also providing more information on λ^e_ε (as on-the-job offers may lead to re-bargaining and therefore a wage change). To identify the human capital transition rates during unemployment and while waiting for recall (ψ_u and ψ_r) as well as the penalty associated with recall c^f, I then 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 5 years). Similarly, to identify the human capital transition rates during unemployment and while waiting for recall (ψ_u and ψ_r) as well as the penalty associated with recall c^f, I use the average difference between pre- and post-recall wages, conditional on education level.[45] These last two sets of moments also relate directly to the human capital step-size $\Delta_s(2)$ and therefore aids in its identification.

As the model allows for a choice between unemployment and recall upon separation, the recall probability ϕ^f_ε and the recall materialization probability ϕ^r_ε are likely to be different from the observed recall and recall materialization probabilities. However, given the close relation between the two, I can use the observed probabilities as targets in the calibration. Following the observations made in section 3, I set the targeted recall probabilities equal to 0.1172 and 0.0907 , whereas the targeted recall materialization rates are set to 0.194 and 0.183.

The final group consists of all remaining parameters (κ and ρ), which are identified using information on workers' starting wages and the observed correlation between wages and separation rates. In particular, I use the average wage of a new worker (hired out of unemployment) relative to the average wage to identify the bargaining power κ. Finally, for the identification of the copula parameter ρ, I follow Jarosch (2015) in targeting the regression coefficient γ in the estimation equation (21) below:

$$D^\delta_{i,t} = \alpha_i + \gamma \log(w_{it}) + u_{i,t} \tag{21}$$

In equation (21), the variable $D^\delta_{i,t}$ is a dummy variable that is only filled if the worker i is employed

[44] The net replacement rate is the only moment not derived from the IAB data used in section 3. Rather, I follow Gregory (2020) in taking this moment from OECD (2020).

[45] For the pre- to post-recall wage differential, I chose not to separately estimate the moment by non-employment duration, as the relatively low number of observations in the data with a high non-employment duration made these moments quite noisy. Rather, I condition the estimation of this moment on a non-employment duration of at most 2 years.

in period t and still observed in period $t+1$. It equals 1 if the worker is separated from their job 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, $w_{i,t}$.

5.3 Calibration Results and Model Fit

Description of Moment(s)	**Data**	**Model**	**Parameters**
Average rate of job loss, tenure 1-3.5y	0.0171	0.0162	$\eta_\delta = 0.274$
Average rate of job loss, tenure 3.5-6y	0.0082	0.0122	$\mu_{\delta,1} = 31.21$
Average rate of job loss, tenure 6-9y	0.0049	0.0086	$\mu_{\delta,2} = 46.21$
Average rate of job loss, tenure>9y	0.0022	0.0050	$\lambda_1^u = 0.271$
Average job finding rate	$\{0.2583, 0.2597\}$	$\{0.2585, 0.2512\}$	$\lambda_2^u = 0.377$
Average employment rate	$\{0.9608, 0.9809\}$	$\{0.9599, 0.9715\}$	
p10-p90 ratio of wages	$\{0.3673, 0.4232\}$	$\{0.3521, 0.3928\}$	$\eta_y = 6.789$
p10-median ratio of wages	$\{0.5786, 0.5826\}$	$\{0.5921, 0.6069\}$	$\mu_{y,1} = 1.489$
Educational wage premium (all)	1.4792	1.4774	$\mu_{y,2} = 1.05$
Educational wage premium (entry)	1.632	1.6327	$s_2 = 1.0579$
Job-to-job transition rate	$\{0.0163, 0.0178\}$	$\{0.0145, 0.0108\}$	$\lambda_1^e = 0.0966$
Replacement rate	0.6	0.598	$\lambda_2^e = 0.0723$
Yearly wage growth	$\{0.0457, 0.0511\}$	$\{0.0222, 0.0261\}$	$b = 0.7499$
Pre- to post-layoff wage, duration<0.5y	$\{1.0314, 1.0687\}$	$\{0.997, 0.999\}$	$\Delta_s(2) = 0.1143$
Pre- to post-layoff wage, duration 0.5-1y	$\{0.9792, 1.0182\}$	$\{0.985, 0.997\}$	$c_f = 0.0393$
Pre- to post-layoff wage, duration>1y	$\{0.9656, 0.9591\}$	$\{0.99, 0.974\}$	$\psi_e = 0.0418$
Pre- to post-recall wage, duration<2y	$\{1.0196, 1.0087\}$	$\{1.02, 0.999\}$	$\psi_u = 0.0725$
			$\psi_r = 0.5169$
Recall rate, low education	0.1172	0.1192	$\phi_1^f = 0.4964$
Recall rate, high education	0.0907	0.0974	$\phi_2^f = 0.4784$
Recall materialization, low education	0.194	0.1943	$\phi_1^r = 0.1834$
Recall materialization, high education	0.183	0.1895	$\phi_2^r = 0.1686$
Wage of newly hired worker	0.5775	0.5841	$\kappa = 0.8926$
Coefficient $\hat{\gamma}$ in equation (21)	-0.0063	-0.016	$\rho = -15.317$

Table 4: *A summary of calibration moments, their values in the data and in the calibrated model, and corresponding parameter values*

The moments described above add up to a total of 33 moments used to identify 23 parameters. Further details of the procedure used to estimate these moments can be found in appendix A. Table 4 summarizes the moments and their model counterparts. As can be seen in the table, the model fits the moments quite well. Nevertheless, it can be observed that the model has trouble matching a few moments, in particular the pre-to post-layoff and recall wage differentials and the tenure profile of the separation rate. When it comes to the pre- to post-layoff and recall wage differentials, the problems faced by the model are expected: after all, the model is set up in such a way that a worker would most likely experience a wage drop as a consequence of a non-employment spell. However, the moments that were estimated in the data stress that this is not necessarily the case, estimating a value higher than 1 in several cases.[46]

When looking at the parameter estimates in table 4, a few values stand out. In particular, the estimated value for the worker's bargaining power, κ, is quite high compared to what is usually found in the literature. This is likely to be a consequence of the issues matching the pre- to post-layoff and recall wage differentials, where an increase in κ would lead the post-layoff wage to be less dependent on the outside option, thus alleviating the impact of the loss of negotiation capital upon layoff.
It is also worth noting that the recall rates ϕ_1^f and ϕ_2^f are substantially higher than the observed recall rates in the data and model simulation. This indicates that many workers choose not to wait for recall when offered to do so, and therefore suggests that implementing a choice between waiting for recall and moving to unemployment may be quite important. Similarly, as the recall materialization rates ϕ_1^r and ϕ_2^r do not quite line up with the rates found in the data and model simulation, it can be stated that some workers change their mind after waiting for recall for at least one quarter, and move to unemployment instead. This is all in spite of the fact that waiting for recall seems quite attractive at first sight, with a human capital depreciation rate ($\psi_r\psi_u$) that is about half the depreciation rate in unemployment (ψ_u), and a penalty c^f that is relatively mild.

Moving to the differences between the two education levels, it can be noted that workers with a low education level are less likely to obtain an offer when unemployed ($\lambda_1^u < \lambda_2^u$), but more likely to receive an offer on-the-job ($\lambda_1^e > \lambda_2^e$). Furthermore, compared to the worker with a low education level, a highly educated worker starts with a slightly higher level of human capital $s_2 > 1$ (which is less than one stepsize higher than the starting level of a worker with a low education level), and also experience a slightly bigger change every time they are hit with an appreciation or depreciation shock ($\psi_e, \psi_u, \psi_r\psi_u$), $\Delta_s(2) > 0.1$. When it comes to the firm distributions the workers draw from upon receiving an offer, these are best illustrated in a diagram. Figure 16 visualizes the joint distribution $G_\varepsilon(\theta)$ of the two education groups. For both education groups, 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. When comparing the two distributions, the first thing that can be noted is that the low education level's minimum productivity is higher than that of the high

[46]One possible explanation for the pre- to post-layoff (or recall) wage differentials being higher than one could be that the pre-layoff wage is depressed as a consequence of the aforementioned Ashenfelter's dip. The model does not generate such a dip, and therefore tries to compensate by alleviating the initial earnings drop instead.

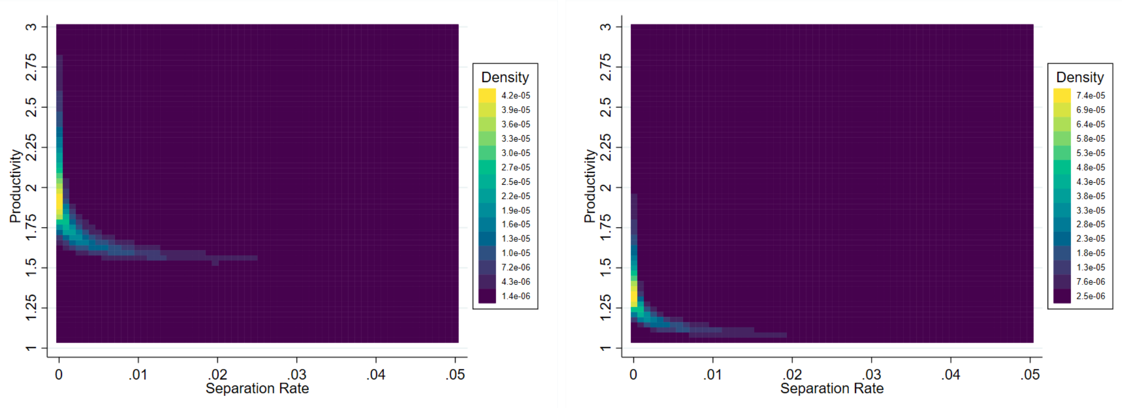


Figure 16: *The joint distribution of firm types faced by workers with a low education level (left) and a high education level (right).*

education level. This is due to $\mu_{y,1} > \mu_{y,2}$, as seen in table 4. However, at the same time the marginal distribution of the separation rate is more right-skewed for the high education level (due to $\mu_{\delta,1} < \mu_{\delta,2}$), thus implying that on average low education workers are more likely to draw a higher separation rate and thus are more likely to be separated once they accept the offer.

6 Simulation Results

In this section, I present the results of the simulation of the model, using the parameters that were calibrated in the previous section. In particular, I will start in subsection 6.1 by comparing the predictions of the model regarding the scarring effects of displacement to the observations I made in the data (in section 3). As none of these patterns were explicitly targeted in the calibration, this can be thought of as a test of the model's performance. Then, in subsection 6.2, I will show how the worker decision in the model compares to that of a social planner as defined in section 4.4. This will lead me to the final subsection, 6.3, in which I use the model to compare a number of policies that have been proposed (and in some cases implemented) to alleviate the scarring effects of displacement.

6.1 Heterogeneity in the scarring effects of displacement

Before moving to the dimensions of heterogeneity highlighted in section 3.3, figure 17 displays the average effect of displacement on employment status and earnings. Just like in section 3.2, the effect is estimated by estimating equation (1), and thus figure 17 can be compared to figure 8 and 9. Making this comparison, it can be seen that while the general average pattern is matched

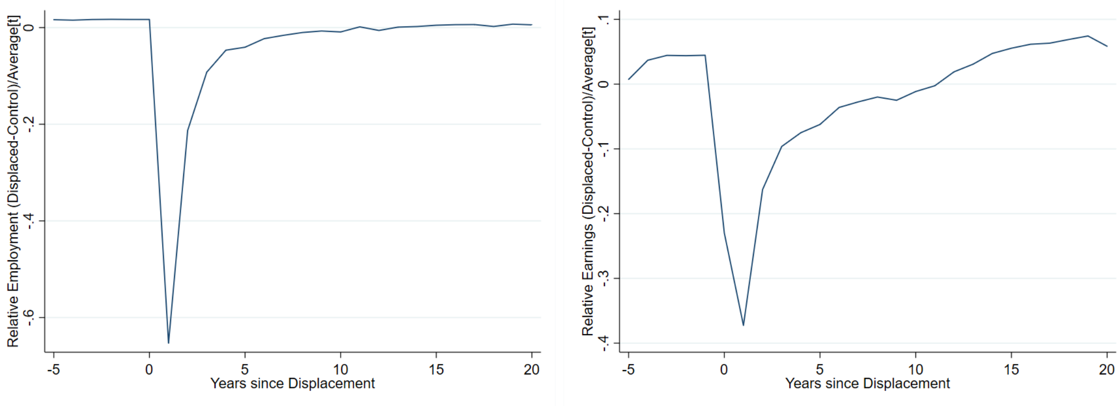


Figure 17: *The effect of displacement on employment (left) and earnings (right), relative to the control group, using model simulation data.*

quite well, the model tends to exaggerate the initial drop, both in employment status and earnings. Furthermore, the model predicts a full recovery of employment status, which I do not see in the data, and therefore also overpredicts the recovery in earnings.

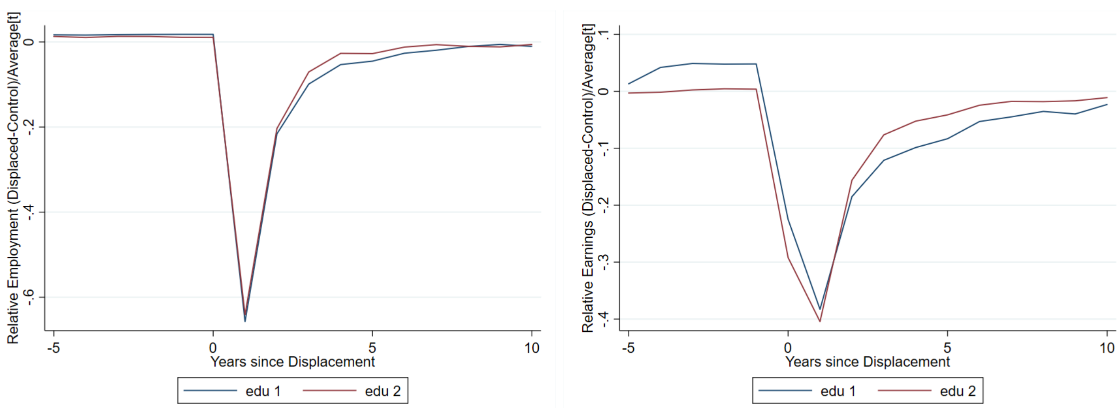


Figure 18: *The effect of displacement on employment (left) and earnings (right), relative to the control group (by education group), using model simulation data.*

Figure 18 shows the predicted effect of displacement on employment status and earnings by education level. Comparing these results to those in figure 13, it can be concluded that the model does not generate differences by education level that are quite as extreme as those seen in section 3.3.2. However, the model does predict that workers with a low education level suffer more in terms of earnings.

In figure 19, I show the estimated effect of displacement on employment and earnings by ex-post recall status. This is therefore the simulation equivalent of figure 15. While the model does

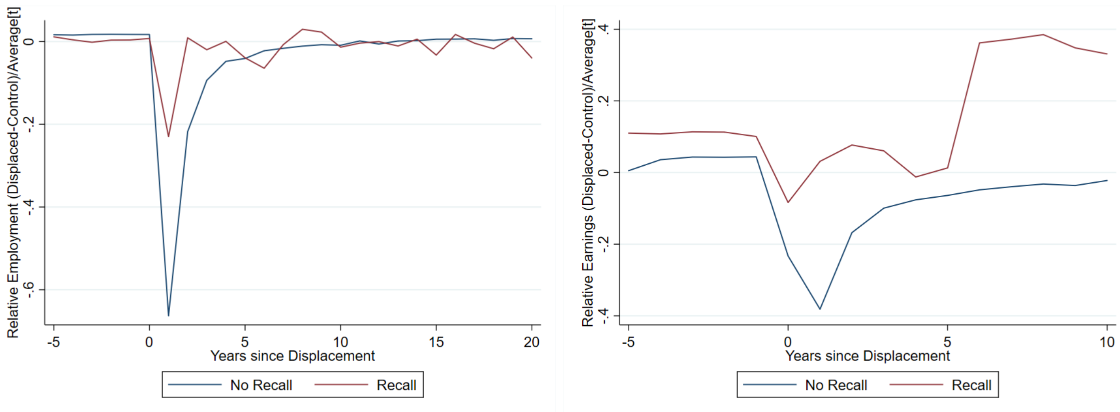


Figure 19: *The effect of separation (left) and broad displacement on earnings relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data.*

not have any issues generating the different effects on employment status that were observed in the data, it has more trouble matching the patterns I observed in the earnings. In fact, it predicts that workers who are recalled are better off, and in the long run even better off than workers who were not displaced. This is likely an artifact of the assumption that workers obtain the full match surplus upon returning to their previous employer, along with the high pre-to post-recall wage differentials observed in the data (and partially matched by the model) as seen in section 4.

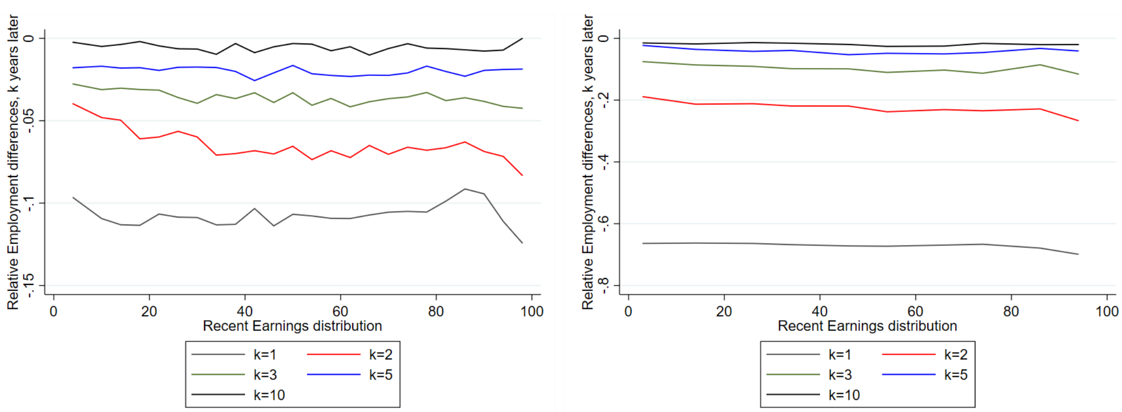


Figure 20: *The effect of displacement on employment status, using LIAB data (left) and model simulation (right), by percentile of recent earnings and without restrictions on establishment tenure. k refers to the number of years that have passed since the displacement event.*

The final main result of section 3.3 focused on the variation by recent earnings. In figure 20, I show how the model performs in replicating this pattern for employment status. Given that I already observed that the model exaggerates the initial response and overestimates the recovery, it is not surprising that I find that the magnitude of the effect is quite different between the data and the model. However, the model does seem to be consistent with the observation that recent earnings do not substantially influence the effect of displacement on subsequent employment status.

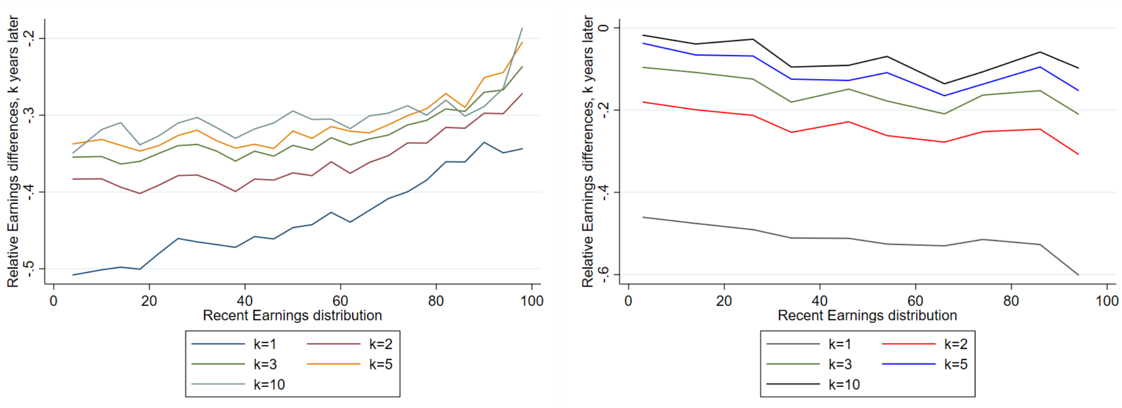


Figure 21: *The effect of displacement on earnings, using LIAB data (left) and model simulation (right), by percentile of recent earnings and without restrictions on establishment tenure. k refers to the number of years that have passed since the displacement event.*

When it comes to the pattern of earnings over the recent earnings distribution, the model is not quite successful. This is especially the case when I plot these patterns without any tenure restrictions, as seen in figure 21. In the data, I observed that the workers near the bottom of the earnings distribution suffered more in terms of their recent earnings, but in the model the forces of the job ladder seem to be too strong, especially in the short run, thus creating a clear downward sloping pattern in the short run and a rough u-shaped pattern in the long run. Restricting the sample to workers with at least 6 years of establishment tenure slightly improves the result, as seen in figure 22, but the model clearly struggles to match this pattern.

In figure 23, I compare the model's performance in matching the pattern over the earnings distribution (as seen in figure 22) to that of alternative specifications of the model.[47] In particular, it can be observed that while the addition of recall and worker types (interpreted as education) do not quite generate the upward sloping pattern observed in the data, these elements do provide a counterweight to the forces of the job ladder, which would generate a strong downward sloping

[47]Note that all versions of the model shown here have been separately calibrated to give them a fair chance in the comparison.

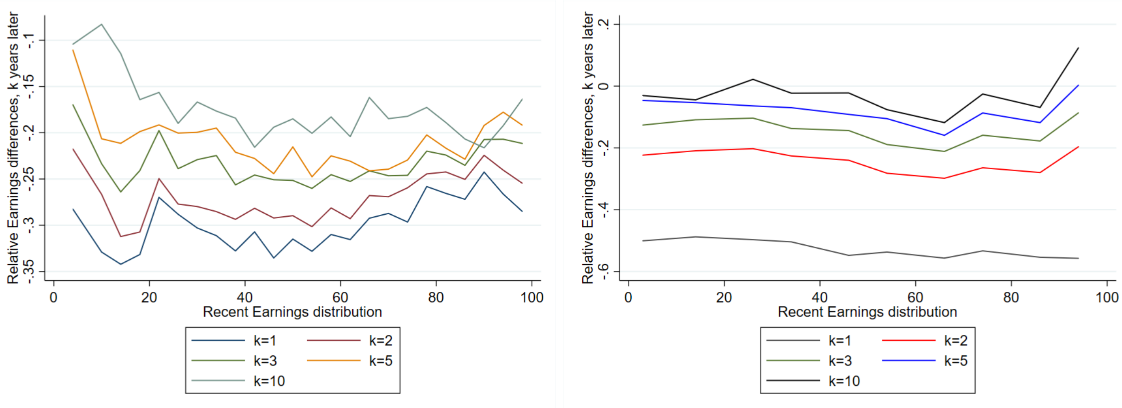


Figure 22: *The effect of displacement on earnings, using LIAB data (left) and model simulation (right), by percentile of recent earnings and with restrictions on establishment tenure. k refers to the number of years that have passed since the displacement event.*

pattern. Given the parameters and moments they are calibrated to match, however, the forces of the job ladder are found to be too strong to be fully alleviated by these extra elements. In ongoing work, I am further investigating what exactly is causing this.

6.2 Efficiency

In this section, I compare the modelled choices of the worker to the choices by the social planner. As shown in section 4.4, the choices of the social planner will be identical to those of a worker if the bargaining power of the worker, κ, equals 1. Given that κ was not calibrated to 1 in section 4, but was calibrated to a rather high value, the expectation would likely be to see slightly different decisions made by a worker and a social planner.

In figure 24, I compare the indifference curves of a worker (in blue) to those of a social planner (in red). The comparison points used for the indifference curves are the highest possible separation rates, so that the differences in slopes are clear. Furthermore, I use the starting value of human capital, so that the comparison is likely to be relevant in a simulation.[48] As can be seen in the figure by comparing the blue and red lines, the social planner's indifference curves are flatter, which indicates that the worker overvalues job security (compared to the social planner). This conclusion is in line with what was found in the existing literature that uses very similar models, such as Jarosch (2015) and Gregory (2020).

In figure 25, I plot the reservation productivities for a worker with a high education level, based

[48] The results for different comparison points yield the same conclusion, and are available upon request.

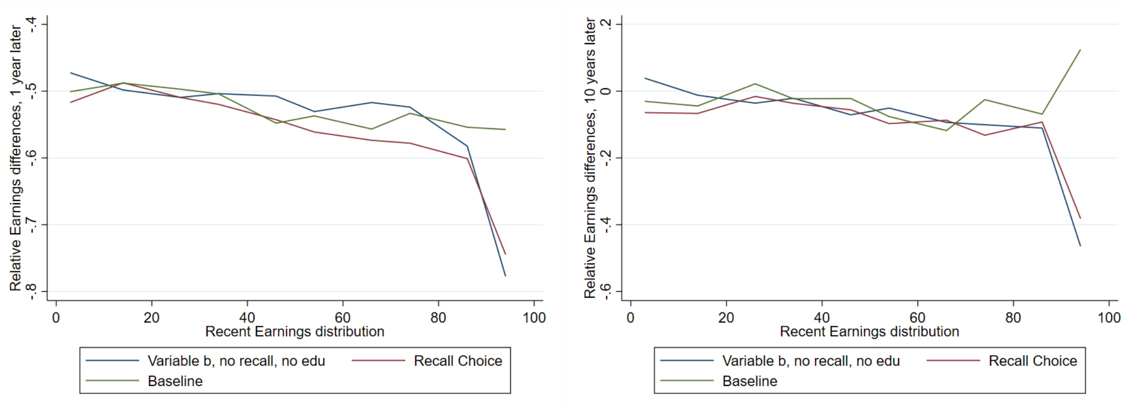


Figure 23: *Decomposition of the effect of displacement on earnings, 1 year (left) and 10 years (right) after displacement, by percentile of recent earnings and with restrictions on establishment tenure, using simulation data for each (separately calibrated) model.*

on choices by the worker (in blue) or social planner (in red). In principle, the graphs show what the minimum productivity of the establishment needs to be, given a certain separation rate, for a worker (at the starting level of human capital) to accept a job offer from this establishment out of unemployment.[49] As can be seen in the figure, the social planner has a consistently higher reservation productivity, indicating that the worker undervalues the matches offered. This is in line with the discussion in section 4.4.

Finally, figure 26 shows the employer characteristics for which the worker and social planner prefer to wait for recall over moving to unemployment when given this option upon separation. It is of particular note here that there exists a band of firm characteristics (displayed in blue) for which the worker prefers to wait for recall, but the social planner prefers to move to unemployment. This result seems counterintuitive given that workers were argued to undervalue matches, but can be explained to be a consequence of the fact that recall materialization rates ϕ^r_ε are lower than offer rates during unemployment rate λ^u_ε. Further more, the assumptions of the model are such that while the worker undervalues the matches coming out of unemployment, she does not undervalue the match retained after recall, as she will obtain the full value of that recalled match. As a result, the worker may choose to wait for recall while the social planner would prefer to move her to unemployment.

[49]The similar figure for the low education level is omitted, as the worker with a low education level accepts any job from unemployment, except for jobs with a low productivity and a very high separation rate. Therefore, this graph only shows reservation productivities for the highest possible separation rate.

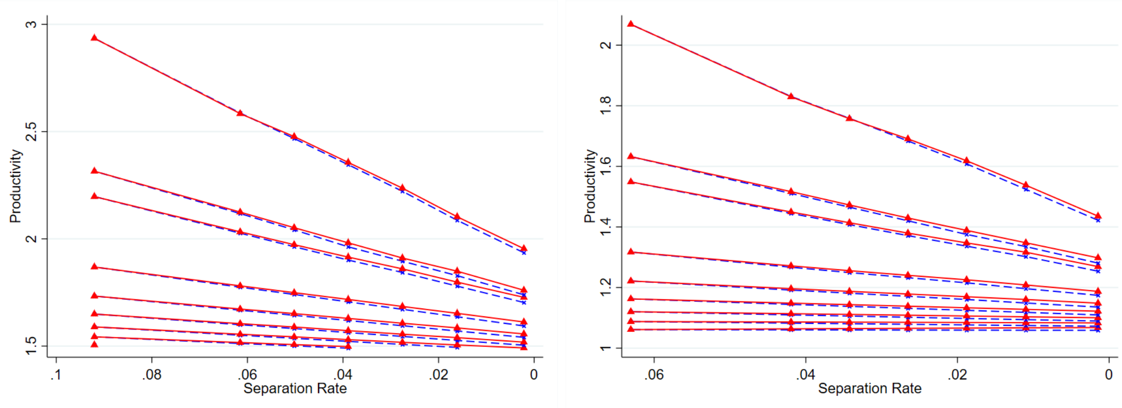


Figure 24: *Indifference curves for the worker (blue) and social planner (red), low education level (left) and a high education level (right). Indifference curves are drawn using as baseline the 9 grid points of the productivity distribution at the highest separation rate, assuming a worker at her starting level of human capital.*

6.3 Policy Experiments

7 Conclusion

In this paper, I study the scarring effect of displacement on earnings and employment along a number of dimensions of observable heterogeneity. Using detailed administrative data from Germany, I find that earnings losses tend to be higher for individuals near the bottom of the recent earnings distribution, as well as for workers with a low education level. Furthermore, I find that while recalled workers do better than non-recalled workers in terms of their employment status after displacement, they suffer more in terms of their earnings in the short run.

As the existing theoretical models cannot account for these observations, I propose a search model of the labour market in which I explicitly allow for recall and distinguish between two worker types, which I interpret as education levels. Further adding a number of elements that have been successful in explaining the average scarring effect of displacement, such as human capital which evolves over time according to the worker's employment status, I find that this model, calibrated to the German data, is able to generate the heterogeneity I observe in the data. This model is then used to study the main drivers of the heterogeneity in the scarring effects of displacement, also focusing on policies that have been suggested in a response to large displacement events.

Based on the results of this paper, one can think of various avenues of future research,

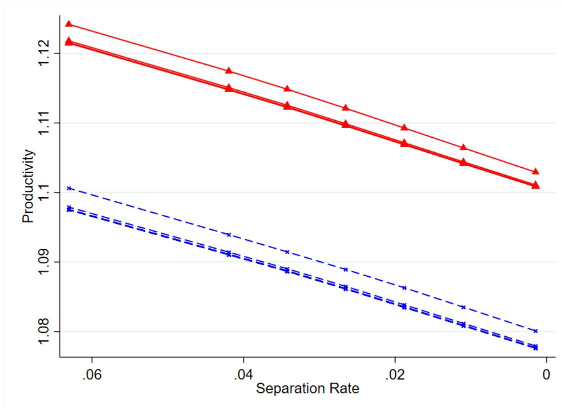


Figure 25: *Reservation productivities for the worker (blue) and social planner (red), given a high education level. The reservation productivities for the low education level are omitted as they are only nonzero for the highest value of the separation rate.*

and I will highlight a few of those possibilities here. First of all, my model focuses in particular on the dimension of ex-post recall status, but given the right data it would be interesting to further look into the differences between recall expectations and recall materialization (as emphasized by Nekoei and Weber, 2015), and its consequences for worker's earning paths after job loss. Furthermore, there are several other dimensions of observable heterogeneity that show promising results and may be key to further improving the understanding of the heterogeneity in the scarring effects of job loss. One particular dimension that comes to mind is that of the industry in which the worker was (formerly) employed. In particular, one may think about what drives workers to switch industries after displacement and how closely this is related to patterns of structural change. Finally, when extending the framework in this paper to one with cyclical variation, and especially when doing so in the context of the German labour market, it will be important to add in the possibility of using short-time employment rather than an explicit layoff when facing an economic downturn.

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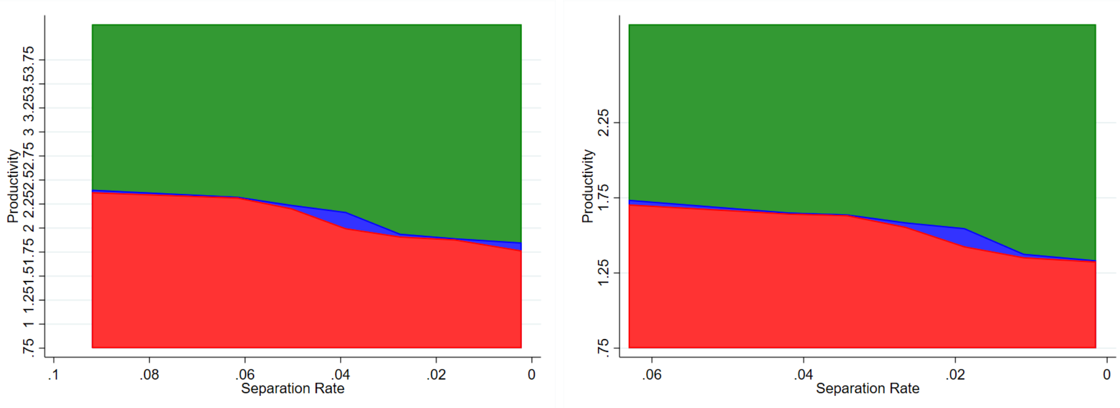

Figure 26: *The recall choice made workers or social planners, given the starting level of human capital and a low education level (left) or a high education level (right). For combinations in green both worker and social planner choose recall, for combinations in red neither chooses recall, and for combinations in blue only the social planner chooses recall.*

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A Numerical Methods

A.1 Solution Method

Due to its size and structure, the model presented in Section 4 is not analytically solvable. Instead, in order to obtain the results in Section 6, I solve the model numerically. The step-by-step procedure followed to obtain the model solution in this paper is described below. It takes as given the values for the parameters.

1. Set up the grid for worker fixed effect ε, using the proportions found in the data (ϵ_1, ϵ_2)

2. Set up the grid for s to solve over. In particular, let the maximum grid point be such that 99.9% of workers would expect to stay below it even if they were employed at all times for 30 years. Remaining grid-points above the middle are set by dividing the max location by 3 and using integer arithmetic, so that the majority of the grid-points is near the middle (where workers will start). A similar approach is used for grid points below the middle, though the gridpoints between the mid and the min are set by dividing the difference by 4 rather than 3. Note that while the number of steps between the grid points is constant, the value of s at those grid points depends on ε through both the stepsize $\Delta_s(\varepsilon)$ and initial value s_ε (which determines the value at the middle point of the grid), so there is a different grid for each ε

3. Set up the grids for y and δ (for each ε). In particular:

   - For y: Divide the unit interval into $N_y - 3$ intervals, and let the midpoint for each of these intervals be i. The first $N_y - 3$ grid-points then correspond to the value of y for which the cdf equals i. The final 3 grid-points correspond to the values of y for which the cdf equals 0.95, 0.99, and 0.999 respectively (noting that the grid-points are subsequently sorted, in case $N_y - 3$ is higher than 20 and therefore the highest of the $N_y - 3$ first grid-points is higher than at least one of the three extra grid-points).

   - For δ: calculating the 1st and 99th percentiles, create equally sized bins to split up the area in between, and setting the grid-point to be $E(\delta)$ within such bin.

4. Set up the cdf of θ (for each ε), using Frank's copula, so that if u_1 is the probability that $y \leq y_1$ and u_2 is the probability that $\delta \leq \delta_1$, then the probability for both these events to be true is

$$G(y_1, \delta_1, \rho) = -\frac{1}{\rho} \ln \left[1 + \frac{\exp(-\rho u_1 - 1) \exp(-\rho u_2 - 1)}{\exp(-\rho) - 1} \right]$$

- Once the joint cdf is calculated using the formula above, the probability matrix for θ can be retrieved,defined on a discrete grid.

5. (From this step, loop over ε) Since equations (25) and (26) only depend on functions W^{max} and U and known functions and parameters, use an iterative loop to solve for functions W^{max} and U. In particular:

   (a) Guess an initial matrix for W^{max} (N_y by N_δ by N_s) and U (1 by N_s).

   (b) Using initial functions W^{max} and U, calculate an updated $U(s)$ for all s and call this $U^*(s)$. For the next step, set the new guess for U as $\hat{U}(s) = \omega_u U^*(s) + (1 - \omega_u)U(s)$ (with some $\omega_u \in (0, 1])$

   (c) Now, using initial guess W^{max} and updated $\hat{U}$, calculate the implied value for value function F. To do this, use its recursive structure (rather than using an iterative loop) to solve directly, thus using the assumption that workers cannot drop below the minimum grid point.

   (d) Using initial guess W^{max}, updated $\hat{U}$, and implied value F, calculate an updated $W^{max}(s, \theta)$ for all combinations of s and θ and call this $W^{max*}(s, \theta)$. For the next step, set the new guess for W^{max} as $\hat{W}^{max}(s, \theta) = \omega_s W^{max*}(s, \theta) + (1 - \omega_s)W^{max}(s, \theta)$ (with some $\omega_s \in (0, 1])$

   (e) Calculate the distance between the initial W^{max} and the updated W^{max}. If this distance is not close enough to zero, return to step b, setting $U = \hat{U}$ and $W^{max} = \hat{W}^{max}$.

   (f) Calculate the distance between the initial U and the updated U. If this distance is not close enough to zero, return to step b, setting $U = \hat{U}$ and $W^{max} = \hat{W}^{max}$.

6. Now that $W^{max}(s, \theta)$ and $U(s)$ are known for all s and θ, and noting that $W^{max}(s, u) = U(s)$, we can use the bargaining condition to calculate $W(s, s, \theta, \hat{\theta}) = W^{max}(s, \hat{\theta}) + \kappa(W^{max}(s, \theta) - W^{max}(s, \hat{\theta}))$. In other words, since we know that at the time of bargaining the extended version of equation 3 holds, but not necessarily if $s \neq \hat{s}$ (note that since s can only go up during employment $s \neq \hat{s}$ implies $s > \hat{s}$), we now know the diagonal elements of $W(s, \hat{s}, \cdot)$ only.

7. Solve for the wage: See section A.2 below.

A.2 Derivation of the wage

To derive the wage (or, to be precise, the piece-rate), I use the value function W (again ignoring the ε):

$$\begin{aligned}
W(s,\hat{s},\theta,\hat{\theta}) = \ln(R(\hat{s},\theta,\hat{\theta})p(s,y)) + \beta\mathbb{E}_{s'|s,e,\varepsilon} \Bigg\{ & \delta\left[\phi_f \max\{F(s',\theta),U(s')\} + (1-\phi_f)U(s')\right] \\
& +(1-\delta)\left[\lambda^e\left(\int_{x\in\Theta^1(s',\theta)} W(s',s',x,\theta)dG(x) + \int_{x\in\Theta^2(s',\hat{s},\theta,\hat{\theta})} W(s',s',\theta,x)dG(x)\right)\right. \\
& \left.\left. + \left(1-\lambda^e\int_{x\in\Theta^1(s',\theta)\cup\Theta^2(s',\hat{s},\theta,\hat{\theta})} dG(x)\right) W(s',\hat{s},\theta,\hat{\theta})\right]\right\}
\end{aligned}$$

Further, note that given a known value for W^{max} and U (for every s and θ), the value $F(s,\theta)$ is known, as shown earlier:

$$F(s,\theta) = \ln(b) + \beta\mathbb{E}_{s'|s,u}\left\{\phi_r W^{max}(s',\theta') + (1-\phi_r)F(s',\theta)\right\}$$

Throughout the derivation that follows, I will therefore denote the value of recall by $\bar{F}$, denoting that since this value is known I will consider it as if it is a constant:

$$\begin{aligned}
W(s,\hat{s},\theta,\hat{\theta}) = \ln(R(\hat{s},\theta,\hat{\theta})p(s,y)) + \beta\mathbb{E}_{s'|s,e,\varepsilon} \Bigg\{ & \delta\left[\phi_f \max\{\bar{F}(s',\theta),U(s')\} + (1-\phi_f)U(s')\right] \\
& +(1-\delta)\left[\lambda^e\left(\int_{x\in\Theta^1(s',\theta)} W(s',s',x,\theta)dG(x) + \int_{x\in\Theta^2(s',\hat{s},\theta,\hat{\theta})} W(s',s',\theta,x)dG(x)\right)\right. \\
& \left.\left. + \left(1-\lambda^e\int_{x\in\Theta^1(s',\theta)\cup\Theta^2(s',\hat{s},\theta,\hat{\theta})} dG(x)\right) W(s',\hat{s},\theta,\hat{\theta})\right]\right\}
\end{aligned}$$

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, $\bar{F}$, and p 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 notation):

$$
\begin{aligned}
C_{s'} &= \beta(1-\delta)\lambda^e \left(\int_{x\in\Theta^1(s',\theta)} W(s',s',x,\theta)dG(x) + \int_{x\in\Theta^2(s',\hat{s},\theta,\hat{\theta})} W(s',s',\theta,x)dG(x) \right) \\
&\quad + \beta\delta(1-\phi_f)U(s') + +\beta\delta\phi_f \max\{\bar{F}(s',\theta), U(s')\} \\
a_{s'} &= \beta(1-\delta)\left(1-\lambda^e \int_{x\in\Theta^1(s',\theta)\cup\Theta^2(s',\hat{s},\theta,\hat{\theta})} dG(x)\right)
\end{aligned}
$$

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

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

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 $\psi_e = 0$.[50] Below, I rewrite the value function using this structure. In what follows, I use $\psi = \psi_e$ (for ease of notation):

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

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

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

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

[50] 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.

(denoting $p_s = p(s, y)$ and $r = \ln(R)$):

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

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

Unfortunately, there is one small complication: the method above is based on the premise that 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 every worker will pass through these grid-points. 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 particular, in practice I 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:

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

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

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 of the model.

A.3 Calibration Method

In this subsection, I will describe in more detail how I estimate the moments used for the calibration of the model (see section 5). 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. This is to avoid biased estimates due to traineeships.[51] With the exception of the yearly wage growth, all moments are estimated using a quarterly data set.

A.3.1 Employment Rate and Transition Rates

As argued in section 5.2, the transition rates of workers between employment and unemployment and between employment at different establishments aids primarily in the identification of the job offer rates, λ_ε^e and λ_ε^u, and the marginal distribution of δ. The estimation of these moments described below.

For the average rate of job loss, I create a variable that is only filled if the worker is employed in the current quarter and still observed in the next quarter. Letting this variable equal 0 if the worker is still employed next quarter and 1 if the worker is unemployed in the next quarter, the moment is then estimated

[51] In principle, workers can be flagged as a trainee in the data, and these observations were omitted when estimating the empirical results, and further do not count towards the measure of market tenure. Thus, this restriction is merely a safety measure to avoid bias arising because certain trainees may not be coded as such.

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. Note that in the model I consider workers that are waiting for a recall to be unemployed for this purpose, reflecting that in the data I do not see whether a worker is waiting to be recalled.

When estimating the job-to-job transition rate, a similar variable is created (and filled under the same conditions). Now, the variable equals 1 if the worker is employed for a different establishment 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. Note that rather than taking the average by establishment tenure, I take the average by education group for this moment.

In order to estimate the average job finding rate, a similar procedure is followed. However, for this moment, only unemployed workers (including those waiting for a recall) are considered, and the variable equals 1 if they are employed in the next quarter, and the average is again taken by education group.

Finally, the estimation of the employment rate in the data is extremely simple, and merely requires a variable that equals 1 if the worker is employed and 0 otherwise. As argued in section 5.2, the employment rate (by education group) can be used to discipline the value of $\mu_{\delta,\varepsilon}$. In particular, I use that if I know the job offer rate λ^u, the average separation rate $\bar{\delta}$, the recall rate ϕ^f, and the recall materialization rate ϕ^r, I can derive the implied employment rate in a steady state, which I then compare to this moment. This also means that if I know all of these parameters except for the average separation rate, and I use the employment rate from the data, I can back out what the average separation rate should be (this is shown in section B.2). Of course, the average separation rate and the expected value from the underlying marginal distribution of δ are not quite the same (as workers with a high value of δ are more likely to be separated), but this average separation rate can still be used to rule out some combinations of η_δ and $\mu_{\delta,\varepsilon}$. In particular, using that the expected value of a Beta distribution with shape parameters μ and η is $\frac{\mu}{\mu+\eta}$, we can rule out any combination of μ and η for which the implied expected value from the distribution is lower than the average separation rate implied by the employment rate.

A.3.2 p10-p90 and p10-median ratios of wages

In order to estimate the p10-p90 and p10-median 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 10th percentile, median, and 90th percentile wage. Once these are retrieved, the p10-p90 and p10-median ratio can be calculated directly.

In the model, the simulation is set up such that workers are ordered by education group, making the separation of individuals by education straightforward. For each education group, I isolate all wages of employed workers.[52] The 10th percentile, median, and 90th 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 10th and 90th percentile. The ratios of interest can then be directly calculated.

A.3.3 Replacement rate, and average wage of new hires

In order to calculate the replacement rate in the model, I need to calculate the average wage and the average unemployment benefit in the simulation. As I track the quarterly wage throughout the entire simulation, this is straightforward to do, and it only requires restricting the sample to employed workers (for the average wage) and non-employed workers (for the average unemployment benefit). Denoting this average wage by $\bar{w}$ and the average unemployment benefit by $\bar{b}$, the replacement rate then equals $\bar{b}/\bar{w}$. As the data counterpart is taken straight from OECD (2020), no further estimation is necessary in the data.

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 is (full-time) employed for the entire quarter, and was unemployed before starting at their current establishment. Calculating the data counterpart of the average wage $\bar{w}$ using 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 in the data, I omit the top and bottom 5% of observations when calculating $\bar{w}_N$ and $\bar{w}$. This is to avoid an extreme influence by some of the outliers I see in the data.

A.3.4 Average educational wage premium, overall and upon entry

In order to estimate the educational wage premium, the same dataset of wages is used as in the previous subsection (though the dataset is separated by education group). In order to estimate the educational wage premium, I estimate the average wage of each education group (again omitting the top and bottom 5%). Denoting this average by $\bar{w}_\varepsilon$, the educational wage premium then equals $\bar{w}_2/\bar{w}_1$. When estimating this educational wage premium upon entry, the same procedure is followed, 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

[52] In the model, a restriction to full-time workers is not necessary, since the model does not allow for part-time work.

years).

A.3.5 Average yearly wage growth

As mentioned earlier, these moments are the only ones for which the yearly dataset is used. In particular, 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.3.6 Recall and Recall materialization rates

In order to estimate the recall rate and the recall materialization rate in the data, I look forward up to 5 years from the point of separation. If the worker's main employing establishment in her first quarter at full employment is the same establishment as the one she was displaced from, I count it as a recall materialization. Further, I record whether or not the recall occurred within 2 years of displacement. From the resulting variable, I then calculate the recall rate as the fraction of displaced workers that are recalled within 5 years. The recall materialization rate is calculated by first obtaining the fraction of recalled workers that were recalled within 2 years. The recall materialization rate is then calculated as the constant materialization rate such that this fraction would indeed be recalled within 2 years.

In the model, it is much easier to detect recalls, as the worker can only have one employer, and I keep track of the state a worker is in for the purpose of the simulation. Beyond that, calculating the recall rate and recall materialization is done using the same method as used in the data.

A.3.7 Pre- to post-layoff wage differentials

In order to calculate the average pre- to post-layoff wage differential, 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 6 subsamples, by education group, and according to unemployment duration (between 1 quarter and 0.5 year, 0.5 to 1 year, and 1 to 5 years). 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 recall is also full-time, the post-layoff wage is equal to the wage in the first full quarter after starting this job, and the wage differential divides the post-layoff wage by the pre-layoff wage. It should be noted that this calculation excludes workers who found a new job immediately or within a quarter, as this is not possible in the model. Further, I exclude workers with an unemployment duration of more than 5 years, due to a low number of observations with a higher duration and to avoid having to correct for unemployment duration when calculating this moment.

In a separate set of moments, I calculate these same wage differentials, restricting the sample to workers who are recalled. In the model, these workers are relatively straightforward to pick out, but in the data this involves looking forward from the moment of separation to see whether the worker will eventually be recalled (as described in the previous subsubsection). Restricting the sample to workers who will be recalled, these moments are nevertheless calculated in the exact same way for each education group (though I do not restrict the sample by nonemployment duration, and instead use all recalled workers with a nonemployment duration of at most 2 years)

A.3.8 Correlation between wages and separation

The final moment to be estimated is the regression coefficient $\hat{\gamma}$ in equation (22):

$$D^{\delta}_{i,t} = \alpha_i + \gamma \log(w_{it}) + u_{i,t} \tag{22}$$

Given the number of individuals in the data (and simulation), this seems like a computationally intensive estimation. However, I can use the fact that the individual fixed effect is constant over time to greatly simplify the estimation, while not throwing out any observations. In particular, I calculate the average 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 (which was 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:

$$D^{\delta}_{i,t} - \bar{D}^{\delta}_{i,t} = \alpha_i - \bar{\alpha}_i + \gamma \log(w_{it}) - \gamma \overline{\log(w_{it})} + u_{i,t} - \bar{u}_{i,t} \tag{23}$$

$$\left(D^{\delta} - \bar{D}^{\delta}\right)_{i,t} = \gamma \left(\log(w) - \overline{\log(w)}\right)_{it} + u_{i,t} \tag{24}$$

As can be seen in equation (24), all elements on both sides of the equation now depend on both i and t, thus allowing for a simple OLS estimation, yielding coefficient $\hat{\gamma}$.

B Additional Derivations

B.1 Derivation of $W^{max}(s, \theta)$ and $U(s)$

Below, I derive the function $W^{max}(s, \theta)$, which is interpreted as the value the worker would derive from a match if they were to receive the entire surplus (i.e. $w(s, \hat{s}, \theta, \hat{\theta}) = p(s, \theta_y)$). In other words, I rewrite equation (8), ignoring all epsilons (since the model can be solved separately for each epsilon), and setting $R(\hat{s}, \theta, \hat{\theta}) = 1$. First, note that we can rewrite the value of waiting for recall, equation (10) in terms of W^{max} and U only:

$$F(s,\theta) = \ln(b(s)) + \beta \mathbb{E}_{s'|s,r} \left\{ \phi^r W(s', s', \theta', \theta') + (1-\phi^r) \max\left\{ F(s', \theta), U(s') \right\} \right\}$$
$$F(s,\theta) = \ln(b(s)) + \beta \mathbb{E}_{s'|s,r} \left\{ \phi^r W^{max}(s', \theta') + (1-\phi^r) \max\left\{ F(s', \theta), U(s') \right\} \right\}$$

Given a guess for W^{max}, one can solve the above equation for the corresponding F, thus essentially eliminating the need for a separate value function. Using this definition (and leaving in F for now), I can now start to rewrite equation (8):

$$\begin{aligned}
W^{max}(s,\theta) = {} & \ln(p(s,y)) + \beta \mathbb{E}_{s'|s,e} \Bigg\{ \delta \left[\phi_f \max\{F(s',\theta), U(s')\} + (1-\phi_f) U(s') \right] \\
& + (1-\delta) \Bigg[\lambda^e \Bigg(\int_{x \in \Theta^1(s',\theta)} W(s', s', x, \theta) dG(x) + \int_{x \in \Theta^2(s', \hat{s}, \theta, \hat{\theta})} W(s', s', \theta, x) dG(x) \Bigg) \\
& + \Bigg(1 - \lambda^e \int_{x \in \Theta^1(s',\theta) \cup \Theta^2(s', \hat{s}, \theta, \hat{\theta})} dG(x) \Bigg) W(s', \hat{s}, \theta, \hat{\theta}) \Bigg] \Bigg\} \\
= {} & \ln(p(s,y)) + \beta \mathbb{E}_{s'|s,e} \Bigg\{ \delta \left[\phi_f \max\{F(s',\theta), U(s')\} + (1-\phi_f) U(s') \right] \\
& + (1-\delta) \Bigg[\lambda^e \int_{x \in \Theta^1(s',\theta)} \Big(W(s', s', x, \theta) - W(s', \hat{s}, \theta, \hat{\theta}) \Big) dG(x) \\
& + \lambda^e \int_{x \in \Theta^2(s', \hat{s}, \theta, \hat{\theta})} \Big(W(s', s', \theta, x) - W(s', \hat{s}, \theta, \hat{\theta}) \Big) dG(x) + W(s', \hat{s}, \theta, \hat{\theta}) \Bigg] \Bigg\}
\end{aligned}$$

To simplify the equation above, use that if the worker gets all the surplus, $W(s', \hat{s}, \theta, \hat{\theta}) = W^{max}(s', \theta)$. Further, note that if the worker already is in the position of receiving all the surplus, there is no more room to re-bargain the piece-rate at the current employer. As such, the re-bargaining set $\Theta^2(s', \hat{s}, \theta, \hat{\theta})$ is an empty set and the corresponding integral cancels out:

$$\begin{aligned}
W^{max}(s,\theta) = {} & \ln(p(s,y)) + \beta \mathbb{E}_{s'|s,e} \Bigg\{ \delta \left[\phi_f \max\{F(s',\theta), U(s')\} + (1-\phi_f) U(s') \right] \\
& + (1-\delta) \Bigg[\lambda^e \int_{x \in \Theta^1(s',\theta)} \Big(W(s', s', x, \theta) - W^{max}(s', \theta) \Big) dG(x) + W^{max}(s', \theta) \Bigg] \Bigg\}
\end{aligned}$$

Finally, to arrive at equation (9), simplify the term inside of the integral by using the bargaining equation $W_\varepsilon(s,s,x,\theta) = W_\varepsilon^{max}(s,\theta) + \kappa\,(W_\varepsilon^{max}(s,x) - W_\varepsilon^{max}(s,\theta))$:

$$
\begin{aligned}
W^{max}(s,\theta) &= \ln(p(s,y)) + \beta\mathbb{E}_{s'|s,e}\Bigg\{\delta\left[\phi_f \max\{F(s',\theta),U(s')\} + (1-\phi_f)U(s')\right] \\
&\quad +(1-\delta)\left[\lambda^e \int_{x\in\Theta^1(s',\theta)} \Big(W^{max}(s',\theta) + \kappa\left(W^{max}(s',x) - W^{max}(s',\theta)\right) - W^{max}(s',\theta)\Big)\, dG(x) \right. \\
&\quad \left. + W^{max}(s',\theta)\right]\Bigg\} \\
&= \ln(p(s,y)) + \beta\mathbb{E}_{s'|s,e}\Bigg\{\delta\left[\phi_f \max\{F(s',\theta),U(s')\} + (1-\phi_f)U(s')\right] \\
&\quad +(1-\delta)\left[\lambda^e \int_{x\in\Theta^1(s',\theta)} \kappa\Big(W^{max}(s',x) - W^{max}(s',\theta)\Big)\, dG(x) + W^{max}(s',\theta)\right]\Bigg\} \qquad (25)
\end{aligned}
$$

In order to solve for both W^{max} and U, I still need to remove the value function W from the value function U, equation (6). To do this, I use the bargaining equation $W_\varepsilon(s,s,x,u) = U_\varepsilon(s) + \kappa\,(W_\varepsilon^{max}(s,x) - U_\varepsilon(s))$

$$
\begin{aligned}
U(s) &= \ln(b(s)) + \beta\mathbb{E}_{s'|s,u}\left\{\lambda^u \int_{x\in\Theta^u(s')} W(s',s',x,u)dG(x) + \left(1 - \lambda^u \int_{x\in\Theta^u(s')} dG(x)\right) U(s')\right\} \\
U(s) &= \ln(b(s)) + \beta\mathbb{E}_{s'|s,u}\left\{\lambda^u \int_{x\in\Theta^u(s')} \Big(W(s',s',x,u) - U(s')\Big)\, dG(x) + U(s')\right\} \\
U(s) &= \ln(b(s)) + \beta\mathbb{E}_{s'|s,u}\left\{\lambda^u \int_{x\in\Theta^u(s')} \kappa\Big(W^{max}(s',x) - U(s')\Big)\, dG(x) + U(s')\right\} \qquad (26)
\end{aligned}
$$

B.2 Derivation of μ_ε^d

In this section, I will show that if I know the job offer rate λ^u, the employment rate E, the recall rate ϕ^f, and the recall materialization rate ϕ^r (all for a certain education group), I can derive the implied average separation rate $\bar{\delta}$ in a steady state (for that same education group), and there is only one such average separation rate (under one condition on the parameter ϕ^r, which is satisfied). This derivation uses a similar logic as the one that is used to derive the steady state unemployment in a simple model where there is no recall (and no heterogeneity in the separation rate).

In the derivation that follows, I will denote by u_1 the fraction of workers that is unemployed (and not waiting to be recalled), whereas u_2 is the fraction of workers that is waiting to be recalled. In a steady state, one can state that the following three equations should hold:

$$
\begin{aligned}
u_1 &= (1-\lambda^u)u_1 + \bar{\delta}(1-\phi^f)(1-u_1-u_2) \\
u_2 &= (1-\phi^r)u_2 + \bar{\delta}\phi^f(1-u_1-u_2) \\
1-u_1-u_2 &= (1-\bar{\delta})(1-u_1-u_2) + \phi^r u_2 + \lambda^u u_1
\end{aligned}
$$

These three equations can be rearranged as follows:

$$u_1 = \frac{\bar{\delta}(1-\phi^f)}{\bar{\delta}(1-\phi^f)+\lambda^u}(1-u_2) \tag{27}$$

$$u_2 = \frac{\bar{\delta}\phi^f}{\bar{\delta}\phi^f+\phi^r}(1-u_1) \tag{28}$$

$$\bar{\delta}(1-u_1-u_2) = \phi^r u_2 + \lambda^u u_1 \tag{29}$$

Now, plug equation (28) into equation (27) to solve for u_1:

$$
\begin{aligned}
u_1 &= \frac{\bar{\delta}(1-\phi^f)}{\bar{\delta}(1-\phi^f)+\lambda^u}\left(1-\frac{\bar{\delta}\phi^f}{\bar{\delta}\phi^f+\phi^r}(1-u_1)\right) \\
u_1 &= \frac{\bar{\delta}(1-\phi^f)}{\bar{\delta}(1-\phi^f)+\lambda^u} - \frac{\bar{\delta}^2\phi^f(1-\phi^f)}{(\bar{\delta}(1-\phi^f)+\lambda^u)(\bar{\delta}\phi^f+\phi^r)}(1-u_1) \\
(\bar{\delta}\phi^f+\phi^r)(\bar{\delta}(1-\phi^f)+\lambda^u)u_1 &= \bar{\delta}^2(1-\phi^f)\phi^f + \bar{\delta}\phi^r(1-\phi^f) - \bar{\delta}^2\phi^f(1-\phi^f) + \bar{\delta}^2\phi^f(1-\phi^f)u_1 \\
\left[\bar{\delta}\lambda^u\phi^f + \phi^r\bar{\delta}(1-\phi^f) + \phi^r\lambda^u\right]u_1 &= \bar{\delta}\phi^r(1-\phi^f)
\end{aligned}
$$

$$u_1 = \frac{\bar{\delta}\phi^r(1-\phi^f)}{\bar{\delta}\lambda^u\phi^f + \phi^r\bar{\delta}(1-\phi^f) + \phi^r\lambda^u} \tag{30}$$

Then, plugging in equation (28) and (30) into equation (29), and using that $E = 1-u_1-u_2$, find a quadratic equation in $\bar{\delta}$:

$$
\begin{aligned}
\bar{\delta}E &= \frac{\bar{\delta}\phi^f\phi^r}{\bar{\delta}\phi^f+\phi^r}\left[\frac{\bar{\delta}\lambda^u\phi^f + \phi^r\bar{\delta}(1-\phi^f) + \phi^r\lambda^u - \bar{\delta}\phi^r(1-\phi^f)}{\bar{\delta}\lambda^u\phi^f + \phi^r\bar{\delta}(1-\phi^f) + \phi^r\lambda^u}\right] + \frac{\lambda^u\bar{\delta}\phi^r(1-\phi^f)}{\bar{\delta}\lambda^u\phi^f + \phi^r\bar{\delta}(1-\phi^f) + \phi^r\lambda^u} \\
\left(\bar{\delta}\phi^f+\phi^r\right)E &= \phi^f\phi^r\left[\frac{\bar{\delta}\lambda^u\phi^f + \phi^r\lambda^u}{\bar{\delta}\lambda^u\phi^f + \phi^r\bar{\delta}(1-\phi^f) + \phi^r\lambda^u}\right] + \frac{\lambda^u\phi^r(1-\phi^f)}{\bar{\delta}\lambda^u\phi^f + \phi^r\bar{\delta}(1-\phi^f) + \phi^r\lambda^u} \\
\left(\bar{\delta}\lambda^u\phi^f + \phi^r\bar{\delta}(1-\phi^f) + \phi^r\lambda^u\right)\left(\bar{\delta}\phi^f+\phi^r\right)E &= \bar{\delta}\lambda^u(\phi^f)^2\phi^r + \phi^f(\phi^r)^2\lambda^u + \lambda^u\phi^r(1-\phi^f) \\
\left((\bar{\delta})^2(\phi^f)^2\lambda^u + \phi^r(\bar{\delta})^2\phi^f(1-\phi^f) + \bar{\delta}\phi^f\phi^r\lambda^u + \phi^r\bar{\delta}\lambda^u\phi^f + (\phi^r)^2\bar{\delta}(1-\phi^f) + (\phi^r)^2\lambda^u\right)E & \\
= \bar{\delta}\lambda^u(\phi^f)^2\phi^r + \phi^f(\phi^r)^2\lambda^u + \lambda^u\phi^r(1-\phi^f) &
\end{aligned}
$$

$$(\bar{\delta})^2\left[(\phi^f)^2\lambda^u E+\phi^r\phi^f E-\phi^r(\phi^f)^2 E\right]+\bar{\delta}\left[\phi^f\phi^r\lambda^u E+\phi^r\lambda^u\phi^f E+(\phi^r)^2 E-(\phi^r)^2\phi^f E-\lambda^u(\phi^f)^2\phi^r\right]$$
$$+(\phi^r)^2\lambda^u E-\phi^f(\phi^r)^2\lambda^u-\lambda^u\phi^r+\lambda^u\phi^r\phi^f=0 \tag{31}$$

This equation can be solved using the quadratic formula. For this purpose define:

$$A=(\phi^f)^2\lambda^u E+\phi^r\phi^f E-\phi^r(\phi^f)^2 E \tag{32}$$
$$B=\phi^f\phi^r\lambda^u E+\phi^r\lambda^u\phi^f E+(\phi^r)^2 E-(\phi^r)^2\phi^f E-\lambda^u(\phi^f)^2\phi^r \tag{33}$$
$$C=(\phi^r)^2\lambda^u E-\phi^f(\phi^r)^2\lambda^u-\lambda^u\phi^r+\lambda^u\phi^r\phi^f \tag{34}$$

Given the information on the parameter bounds, it can be shown that $A>0$ (as all parameters and E are positive and smaller than 1). Similarly, $B>0$ if $\phi^r<E$ (which holds given a reasonable value for ϕ^r such as the one found in section 5.1). Finally, to see that $C<0$, rewrite the expression for C:

$$C=\phi^r\lambda^u\left[\phi^r E-\phi^f\phi^r-1+\phi^f\right]<0 \quad\Leftrightarrow\quad \phi^r E-\phi^f\phi^r-1+\phi^f<0 \quad\Leftrightarrow\quad \phi^r(E-\phi^f)<1-\phi^f$$

Here, the last inequality holds as $0<\phi^r<1$, and $E<1$. Because $C<0$, while $A>0$, the quadratic equation (31) has two real roots. So, potentially there are two values of $\bar{\delta}$ that could solve the system. However, it can be shown that the minimum of the function on the right hand side of equation (31) occurs at $\bar{\delta}=-B/2A$ (this is a minimum as $A>0$), and since it was already shown that equation (31) has two real roots, the value at this minimum must be negative. As both B and A are positive, the minimum of the function must occur at a negative $\bar{\delta}$, thereby indicating that one of the real roots is negative. The other root has to be positive because the discriminant $B^2-4AC>B^2$, so this other root is the only viable solution. So, the solution for the average δ is given by $\bar{\delta}=(2A)^{-1}(-B+\sqrt{B^2-4AC})$, where A, B, and C as in equations (32), (33), and (34). In principle, it is not ruled out that $\bar{\delta}>1$. However, this would simply signal that the chosen combination of parameters (and in particular λ^u, as the others are exogenously set) are implausible and can be ruled out.

C Additional Simulation Results

In this section, I will highlight simulation results of two alternative specifications of the model. Both of these alternative versions differ from the baseline model discussed in the text in their assumption on what the worker's outside option is when being recalled to their previous match. The baseline model assumes the best possible outcome for the worker, where the outside option is the value of the match itself, and therefore the worker retains the full value of the match. In the alternative specifications highlighted here, I assume instead that this outside option is the value of unemployment, or the value of the outside option the worker used prior to displacement. I will refer to these versions as versions A and B respectively.

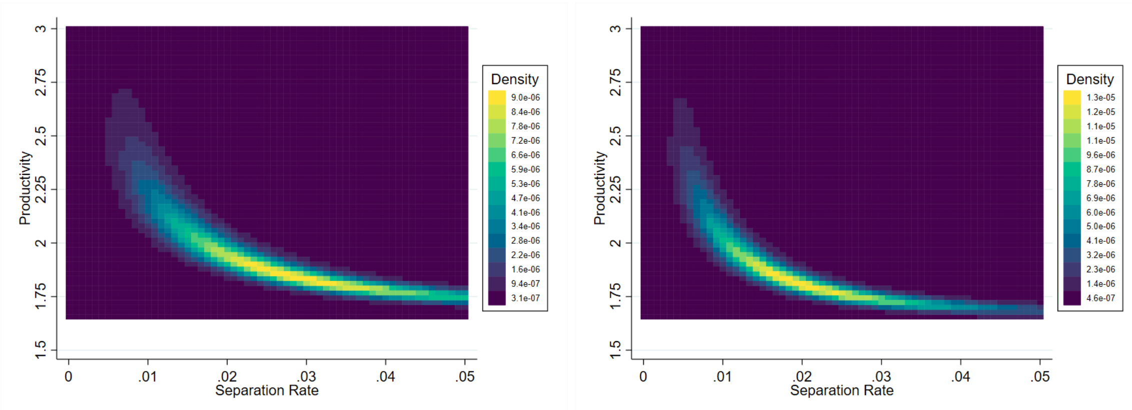

Figure 1: *The joint distribution of firm types faced by workers with a low education level (left) and a high education level (right), using alternative model specification A*

For both of these alternative model specifications, I re-calibrate the model, using the same target moments as in section 4 of the main text. While the purpose of these alternative specifications is to highlight the effect of certain model assumptions on the estimated heterogeneity in the scarring effect of displacement, some alternative specifications also give some different results regarding other figures of the main text. Figure 1 highlights this by showing the joint distribution of firm characteristics under alternative specification A. As can be seen by comparing this figure to the one from the baseline model, figure 16, this alternative specification yields a much less concentrated distribution, especially for the separation rate.

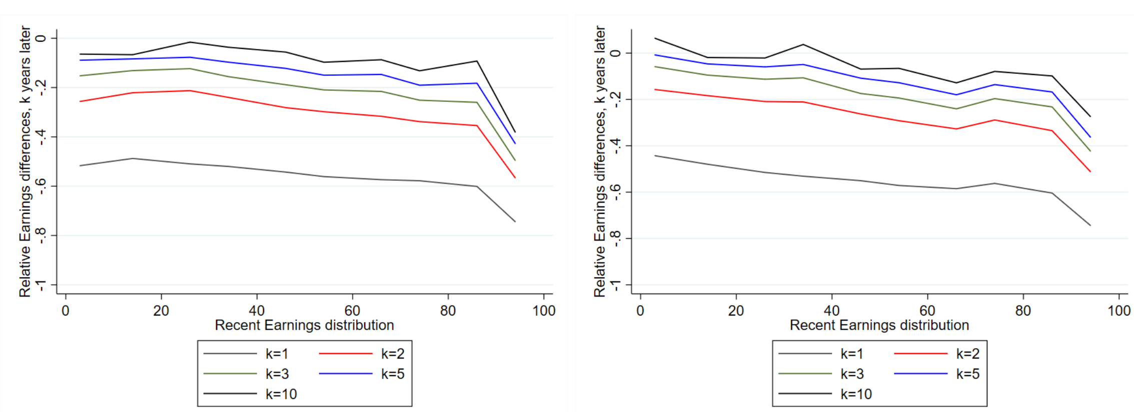

Figure 2: *The effect of displacement on earnings, using alternative specifications A (left) and B (right), by percentile of recent earnings and without restrictions on establishment tenure.* k *refers to the number of years that have passed since the displacement event.*

As figure 2 shows, neither of these alternative model specifications yield any improvement in the pattern of earnings losses after the displacement over the recent earnings distribution. In fact, comparing this figure to the one generated by simulating the baseline model (figure 22 in the main text), the model performs worse than the baseline model, especially near the top of the recent earnings distribution. This is largely due to the fact that in these alternative specifications the option of recall is worse than in the baseline model. As a consequence, the option of recall is less able to provide an effective counterweight to the strong forces of the job ladder in the model.

D Data Appendix

D.1 Individual Summary Statistics

	SIAB		LIAB	
Frequency	Mean	Std.Dev.	Mean	Std.Dev.
Age	41.29	9.897	40.57	9.53
Primeage (aged 35–60)	0.6922	0.462	0.6790	0.467
Gender (female)	0.4634	0.499	0.4037	0.491
Location (east)	0.1897	0.392	0.3647	0.481
Self-employed	0.0059	0.077	0.0021	0.046
Establishment Size	1,143.6	4,606.5	3,529.1	10,668.7
Establishment Tenure (days)	2,222.9	2,260.5	2,678.8	2,769.1
Job Tenure (days)	2,102.5	2,209.4	2,446.1	2,655.0
Yearly earnings (2015 Euros)[53]	17,848.7	15,796.3	23,898.67	15,948.89
Separation	0.1253	0.331	0.1247	0.330
Displacement (broad)	0.016	0.126	0.0224	0.148
Displacement (narrow)	0.0089	0.094	0.0127	0.112

Table D.1: *Summary statistics using the yearly sample, using either LIAB or SIAB.*

Table D.1 presents summary statistics on a number of worker-related variables used in the main analysis. In particular, it presents summary statistics on all important continuous and binary variables (categorical variables are discussed below). A few observations can be made from these summary statistics, include some that were already mentioned in the main text. First, both datasets likely substantially undersample self-employed workers. This is because the structure of the social security is such that self-employed workers would often not be recorded in the administrative data my datasets are based on. Second, female workers and workers residing in West Germany are underrepresented in both the LIAB and SIAB sample. Further, the LIAB has a much larger mean establishment size, which is an artifact of its sampling method (based on sampling establishments rather than individuals), larger mean yearly earnings, and a slightly higher displacement rate (both using the broad and narrow definition).

Figure D.1 shows the fraction of observations accounted for by each major industry and occupation.[54] Looking at how the breakdown of industries and occupations evolves over time, it can be seen that industries and occupations related to manufacturing and construction seem to be declining over time, while

[53] In these yearly earnings, only earnings from employment are taken into account.

[54] The major industries are defined as (1) Agriculture, Fishing, Mining, (2) Manufacturing, Utilities, and Construction, (3) Wholesale and Retail Trade, Hospitality, (4) Business Service Activities, (5) Education, Health, and other Community Services, and (6) Industries not otherwise classified (Public Administration, Private Households, Extra-Territorial).
The major occupations are defined as (1) Agriculture, Forestry, and Horticulture, (2) Manufacturing, Production Technology, and Construction, (3) Personal Services, (4) Business Related Services, and (5) Other Service Occupations.

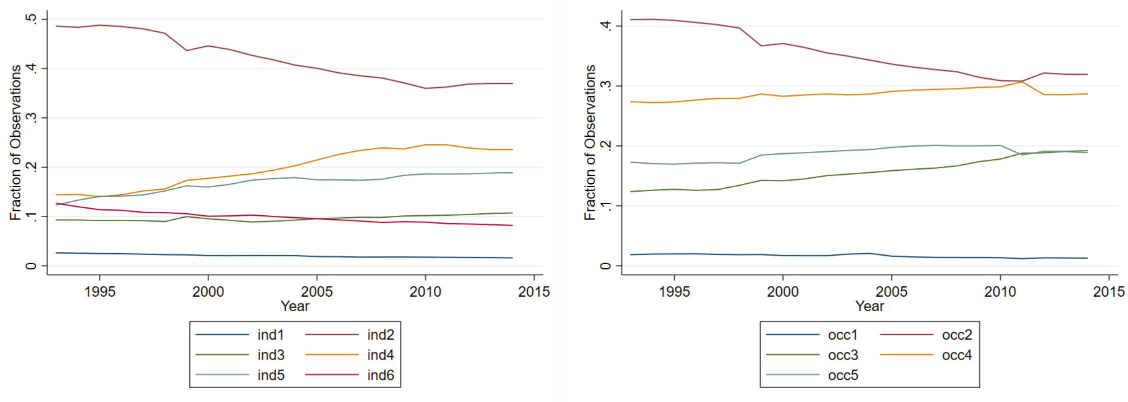

Figure D.1: *The fraction of observations by industry (left) and occupation (right) over time, using LIAB.*

most other industries and occupations are increasing their share of the total over time (with the exception of the "other" industries, category 6, and the occupation and industry related to agriculture). This is used later in this appendix, in section D.3.2, where I compare the scarring effect of separation and displacement by the industry or occupation of origin, comparing the declining industry/occupation with the largest clearly growing industry/occupation.

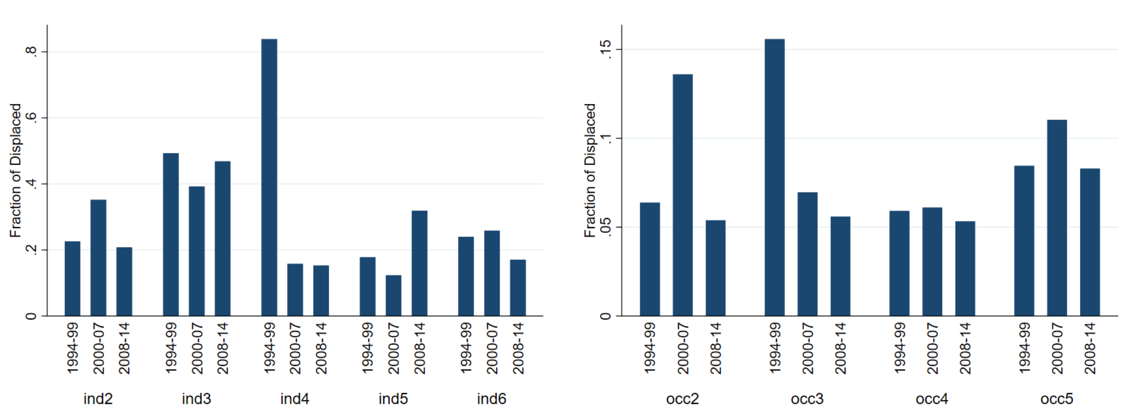

Figure D.2: *The fraction of displaced workers moving industry (left) and occupation (right), using LIAB and by former employing industry/occupation. Industry 1 (Agriculture, Fishing, Mining) and occupation 1 (Agriculture, Forestry, and Horticulture) are not included as the number of underlying observations is not sufficient to yield a reliable estimate.*

As figure D.2 shows, it is not necessarily the case that the workers who switch industry or occupation after being displaced are primarily coming from industries/occupations in decline. After all, while the manufacturing-related industries and occupations do have a slightly higher post-separation mobility rate, they are generally not the industry/occupation associated with the highest mobility rate.

Figure D.3: *The fraction of observations by education (left) and occupational complexity (right) over time, using LIAB.*

Figure D.3 shows the fraction of observations accounted for by each level of education and occupational complexity, measured in the data by the fifth digit of the occupational code.[55] Here, it can be seen that the fraction of highly educated workers is increasing over time, although the increase is generally very gradual. When it comes to occupational complexity, a similar trend can be found. However, as more than 60% of all jobs in any given year is of the second complexity level, and the lowest complexity level is also showing an increasing trend, it is fair to note here that this trend is much less pronounced.

It should be noted that the notion of occupation group and occupational complexity, though seemingly related, represent two distinct features of a job. In particular, it can be argued a worker can potentially move to an occupation within the same occupation group with a higher or lower complexity with relatively low associated costs. In fact, many job changes that one would consider to be promotions would likely show up in the data as a worker moving to a higher complexity level. Therefore, it is not necessarily surprising that I find the occupational complexity moving rate to be higher than the occupational mobility rate: Conditional on broad displacement, the occupational complexity moving rate (in the LIAB) is 11%, whereas the corresponding occupational mobility rate is 7.9%.[56] Furthermore, it can be noted that among the workers that switched occupation groups after (broad) displacement, the occupational complexity moving rate is 52.7%, and among workers that move between complexity levels after (broad) displacement

[55] Contrary to what is done in the main text, I split up the low education into two separate categories here: (1) Without vocational training; Intermediate school leaving certificate or lower, and (2) In-company vocational training; Technical School. The third education level corresponds to ”University”, the high education level in the main text.

[56] Conditional on separation, the occupational complexity moving rate (in the LIAB) is 15.4%, whereas the corresponding occupational mobility rate is 11.1%. Conditional on narrow displacement, the occupational complexity moving rate (in the LIAB) is 9.2%, whereas the corresponding occupational mobility rate is 6.75%.

the occupational mobility rate is 38%.[57] This confirms that while occupational mobility and occupational complexity switching often go together. Even though the correlation is far from perfect, this correlation is strong enough to raise the suspicion that the effects of displacement conditional on switching occupational complexity (see section D.3.2) are largely driven by workers who switch occupational groups.

D.2 Establishments in the Sample

As I classify workers as displaced if the establishment at which they were employed exits (and conditions on the worker are satisfied), it is worth summarizing what the exiting establishments look like. Below, I describe exiting establishments that are included in the SIAB and LIAB, in terms of industry, age, size, and exit type.

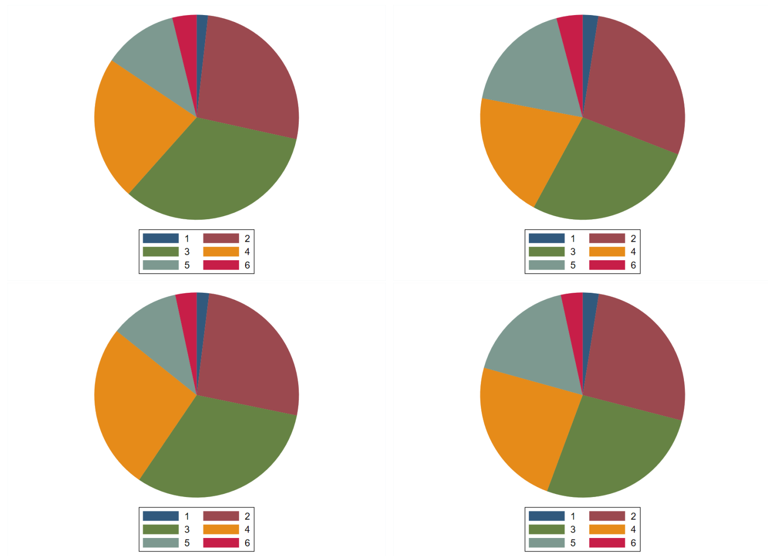

Figure D.4: *Breakdown of exiting establishments (left) and all establishments in the data (right) by major industry*[58]*, using data from the SIAB (top row) and LIAB (bottom row).*

As shown in figure D.4, splitting out the exiting establishments by major industry and comparing this with the breakdown of all establishments in the data by major industry does not reveal any striking

[57] Among the workers that switched occupation groups after separation, the occupational complexity moving rate is 53.8%, and among workers that move between complexity levels after separation the occupational mobility rate is 38.6%. Similarly, among the workers that switched occupation groups after narrow displacement, the occupational complexity moving rate is 52.2%, and among workers that move between complexity levels after narrow displacement the occupational mobility rate is 38.4%

[58] Just like in appendix D.1, major industries include (1) Agriculture, Fishing, Mining, (2) Manufacturing, Utilities, and Construction, (3) Wholesale and Retail Trade, Hospitality, (4) Business Service Activities, (5) Education, Health, and other Community Services, and (6) Industries not otherwise classified (Public Administration, Private Households, Extra-Territorial).

differences. Comparing the two charts, it can be said that industry 3 (Wholesale and Retail Trade, Hospitality) is slightly over-represented in the pool of exiting establishments, whereas industry 5 (Education, Health, and other Community Services) and 6 (Education, Health, and other related services) is slightly under-represented, but the two charts look similar enough to conclude that in general the pool of exiting establishments includes reasonable representation from all major industries.[59]

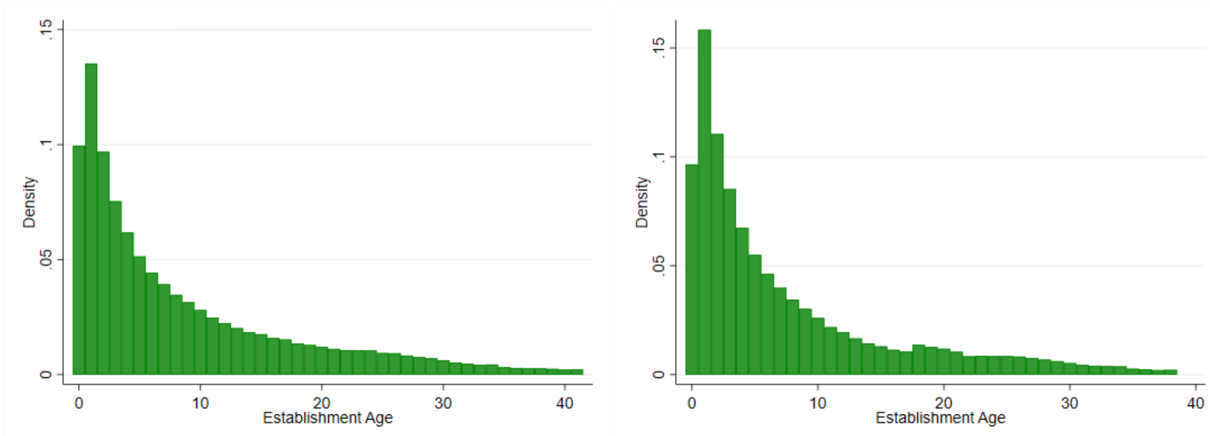

Figure D.5: *The distribution of the exiting establishments in SIAB (left) and LIAB (right) by establishment age.*

Figure D.5 shows how old exiting establishments tend to be when they exit. Not surprisingly, the figure shows that exiting establishment tend to be relatively new. This corresponds to observations made in the literature discussing firm exits (see for example Haltiwanger et al. (2013), who find that age and exits are important when considering the role of small business in accounting for job creation in the U.S.), where the consensus is that young firms tend to have a relatively low survival rate. Similarly, it can be concluded from figure D.6 that the exiting firms are disproportionately small in size, which also corresponds to existing evidence on the topic (discussed in Haltiwanger et al. (2013), among many others). In general, there are relatively few large establishments in the data, and this is true for both SIAB and LIAB. Houwever, note that this doesn't contradict the observation (made in section D.1) that individuals in the LIAB have a much larger mean establishment size, as the sampling method of the LIAB is such that even though not many large establishments are included, all workers employed at these establishments (in the sample period) are included in the dataset.

Since the dataset provides information on what happens to the majority of an establishment's former employees after that establishment exits, it is possible to distinguish between several exit types. Using

[59] The underrepresentation of Manufacturing seems to contradict the notion of automation causing manufacturing firms to lay off many workers, but should not be interpreted as such. After all, an establishment only appears in this chart if it completely exits (rather than laying off many, but not all, workers).

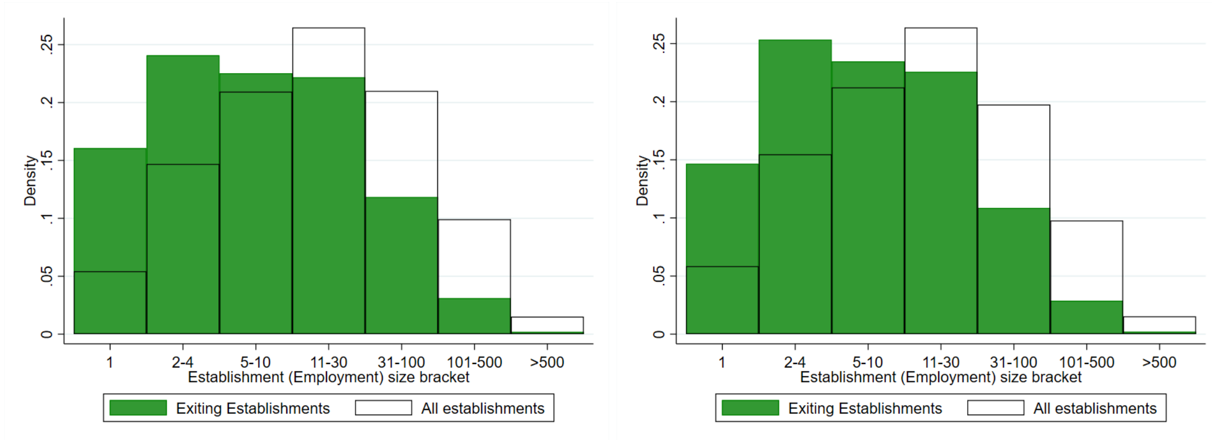

Figure D.6: *The distribution of exiting establishments (green) and all establishments in the data (black) by size group (defined by the number of employees at an establishment), using the SIAB (left) and LIAB (right).*

the definitions from Hethey and Schmieder (2010), I define three exit types. Type A exits are interpreted to be a consequence of an establishment ID change, a takeover, or a spinoff. In practice, this means that the exiting establishment had at least 4 employees, and either at least 80% of the (newly entered) establishment at which the majority of workers are re-employed consists of workers from the exiting establishment, or at least 80% of the workers from the exiting establishment find work at the same (previously existing) establishment but do not make up more than 80% of the employment at their new establishment. An exit is classified as type B (establishment death) if either the exiting establishment had 3 employees or less, or no more than 30% of the former employees of the establishment find employment at the same establishment (and if that establishment is an entrant, the former employees of the exiting establishment do not make up more than 80% of the entering establishment's employment). Finally, an exit is classified as type C if it does not satisfy the conditions for type A and B. These are exits of establishments with at least 4 employees where more than 30% of the former employees finds a job at a common establishment. Further, type C exits do not include cases where that common establishment is an entrant and the former employees make up more than 80% of the entrant's employment, or cases where the common establishment is not an entrant, more than 80% of the exiting establishment's employees is re-employed at that establishment, and these employees make up less than 80% of their common establishment's total employment. Figure D.7 shows how the exiting establishments across all establishment size groups are divided over these three types. Due to the definition of exit types, it mechanically holds that all of the exits of one-person establishments, and the majority of establishments with 2 to 4 employees are classified as type B exits. However, conditioning on establishments having at least 5 employees, it can also be seen that larger exiting establishments are less likely to be classified as exit type B. This may be a consequence of large layoffs often resulting from selling

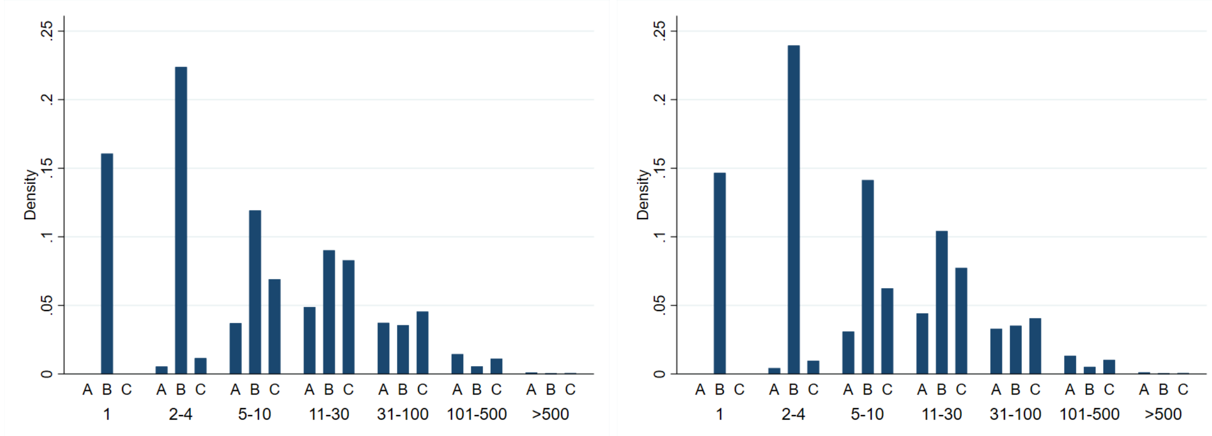

Figure D.7: *The distribution of exiting establishments over exit types A, B, and C (as defined in the text), and size group (defined by the number of employees at an establishment), generated using the SIAB (left) and LIAB (right).*

off parts of the company or establishments making arrangements for laid off workers to gain employment elsewhere before actually laying off the worker.

D.3 Further Empirical Results

D.3.1 The average scarring effect of displacement, using quarterly data

D.3.2 Further heterogeneity in the scarring effect of displacement

As I mentioned in the main text, in section 3.3, the data allows me to look at how the scarring effects of displacement differ along many dimensions of observable heterogeneity. In the main text, I focus on recent earnings, education, and recall, as I argue that these dimensions are particularly important. However, some of the other dimensions also yield interesting results. In this section, I highlight some of the results along some of these other dimensions. Most of this section focuses on (broad) displacement in particular, and uses the SIAB (unless specified otherwise).[60]

Before moving to new dimensions of observable heterogeneity, it is worth exploring some slightly alternative specifications of the results in section 3.3.1 of the main text, where I show how displacement effects differ along the distribution of recent earnings. In figure D.8, I repeat the analysis using separation instead of displacement. The most notable change compared to figure 12 is that the effect on employment status is not entirely flat anymore: it seems like separated workers near the top of the recent earnings distribution suffer slightly more in terms of their relative employment status (in the short run). When it comes to

[60] Results have also been generated for narrow displacement and separation, as well as using the LIAB. These results are omitted here, and are available upon request.

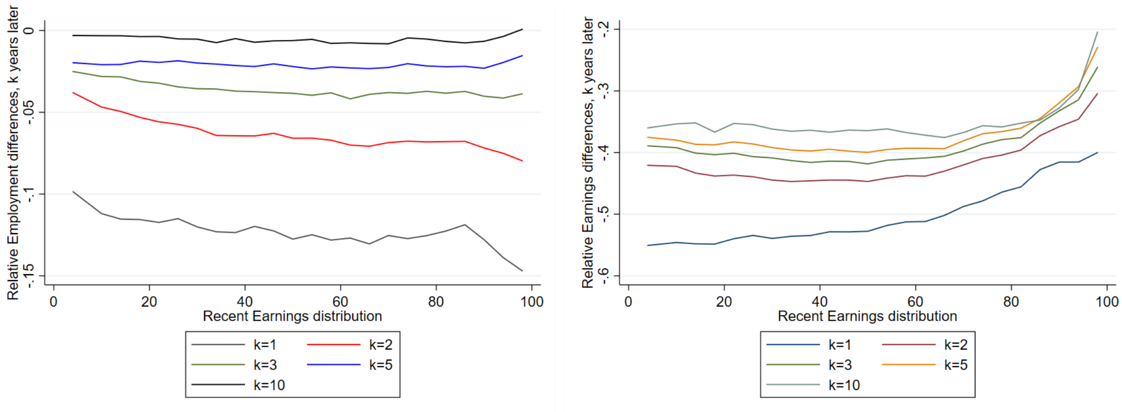

Figure D.8: *The effect of separation on employment status (left) and earnings (right), by percentile of recent earnings and without restrictions on establishment tenure. Numbers are calculated using the LIAB data, and are relative to workers in the control group in the same percentile of recent earnings. k refers to the number of years that have passed since the displacement event.*

earnings, however, the conclusion from the main text remains (if anything, it is strengthened).

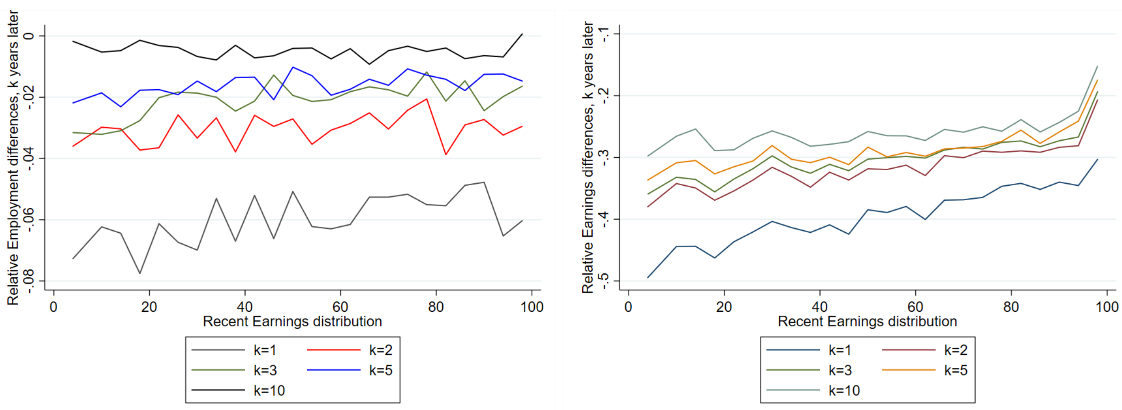

Figure D.9: *The effect of separation on employment status (left) and earnings (right), by percentile of recent earnings, restricting the sample to workers observed in all k. Numbers are calculated using the LIAB data, and are relative to workers in the control group in the same percentile of recent earnings. k refers to the number of years that have passed since the displacement event.*

Similarly, it is worth noting that the result in section 3.3.1 could be influenced by workers being observed for only some years after displacement. However, as figure D.9 shows, restricting the sample to workers observed for all k for which the lines are plotted does not substantially change the conclusion: while recent earnings do not seem to matter much for subsequent employment status, workers near the bottom of the earnings distribution suffer from higher relative earnings losses. Note that comparing figure D.9 with the corresponding figure in the main text (figure 12), it should be pointed out that the upward sloping pattern in the right graph is less pronounced.

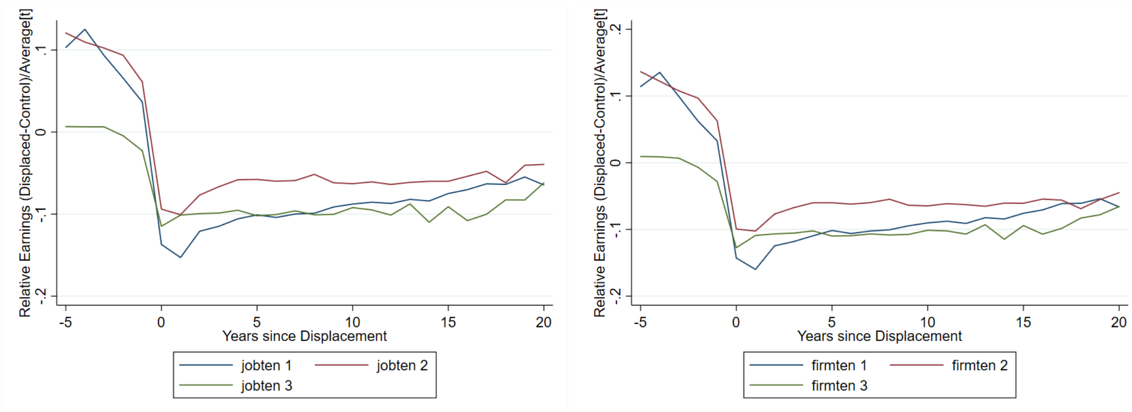

Figure D.10: *The effect of (broad) displacement on earnings relative to the control group, for workers with different pre-event job tenure (left) and establishment (right). Workers are grouped by whether their tenure is 1–5 years (group 1), 5–10 years (group 2), or more than 10 years (group 3)*

Throughout the main text, it has been stressed several times that the tenure of a worker at their (former) job or establishment is likely to substantially affect their likelihood of being displaced. It may also be the case that tenure is indicative of the magnitude of earnings losses a worker should expect after being laid off. This is especially true if one believes that the formation of job-specific or firm-specific human capital plays an important role in explaining earnings differences. Figure D.10 investigates this, by plotting the earnings losses after displacement separately by job and establishment tenure group. Looking at these figures, it can be seen that these tenure groups experience very comparable losses in general.[61] However, a close inspection of the graphs does reveal some subtle differences. In particular, the recovery is slower for workers with higher job or establishment tenure, and for the highest tenure group the recovery is almost nonexistent.

In the main text, in section 3.3.2, it was shown that the worker's education level is a strong indicator of the magnitude of the worker's earnings loss after displacement. Of course, one might argue that an individual's educational background is not necessarily representative of the level of skills their job requires. Therefore, an alternative would be to compare the results by occupational complexity instead. The left panel of figure D.11 shows the results of this alternative comparison. Looking at the figure, there is no clear difference between the groups in terms of their initial earnings loss, and the subsequent trend is

[61] It is of particular note that while I plot the results in one graph, these figures are the result of estimations on three separate samples. In other words, both treatment and control group are restricted to having a certain job or establishment tenure in the base year.

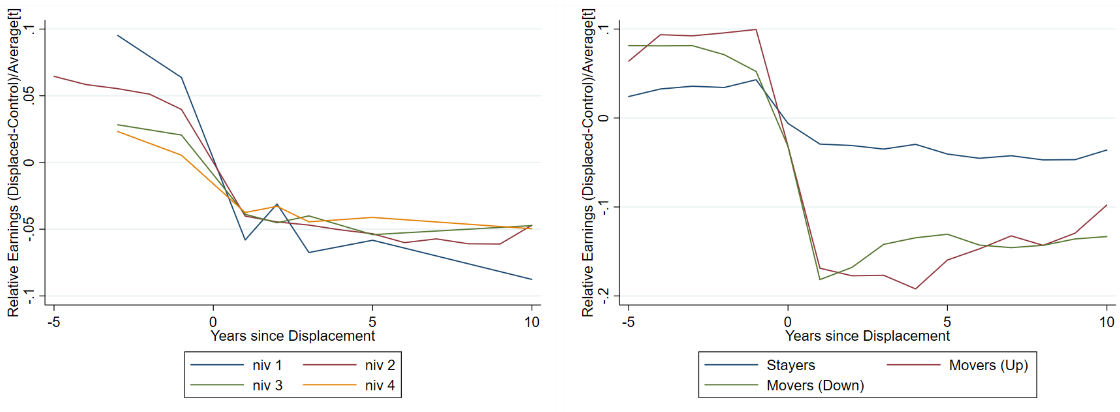

Figure D.11: *The effect of (broad) displacement on earnings, relative to the control group, for workers with different pre-event occupational complexity (left) and for workers switching complexities after displacement (right), using LIAB.*

very comparable between the groups (though the lack of initial recovery is striking), with only the lowest complexity level (representing highly routine jobs) showing a slightly more negative trend. Nevertheless, when considering individuals who switch occupational complexity, in the right panel of figure D.11, a clear difference between switchers and stayers emerges . In fact, whether the individual switches to a more or less complex job does not affect the earnings losses: in either case the average individual suffers a substantial additional initial loss (in addition to the immediate loss suffered by those who do not switch complexity) which is slightly recovered over time as the switchers recover faster than the stayers.

A closely related observable characteristic that might come to mind when discussing how earnings losses

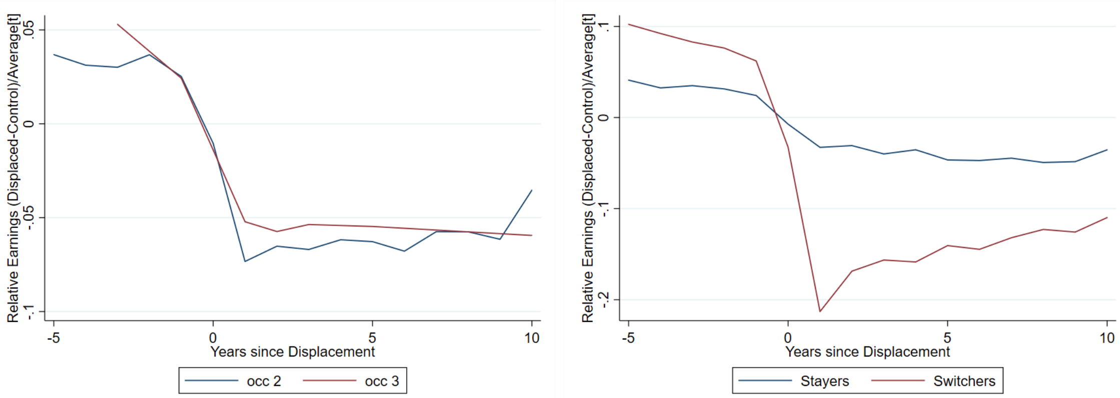

Figure D.12: *The effect of (broad) displacement on earnings, relative to the control group, for workers with occupations 2 and 3 (left) and for workers switching occupations after displacement (right), using LIAB.*

Major occupations used here (left graph) include (2) Manufacturing, Production Technology, and Construction, and (3) Personal Services.

differ between individuals is the occupation in which the worker was employed before being displaced. In the left panel of figure D.12, I show the estimates for the occupation that declined the most during the sample period (occupation 2) and the occupation that grew the most (in terms of employment) over the sample period, occupation 3. As can be seen there, the difference between the declining occupation and the growing occupation is not very sharp. In fact, one could argue that there may not be any long-run difference at all, while the short-run difference is very small. However, when comparing workers who stay in their occupation and those who switch occupations after displacement, as shown in the right panel, a similar difference arises as seen for complexity switchers. Of course, it can not be ruled out that these similarities between occupational switchers and complexity switchers are caused by the two switches often coinciding, as shown in appendix D.1.

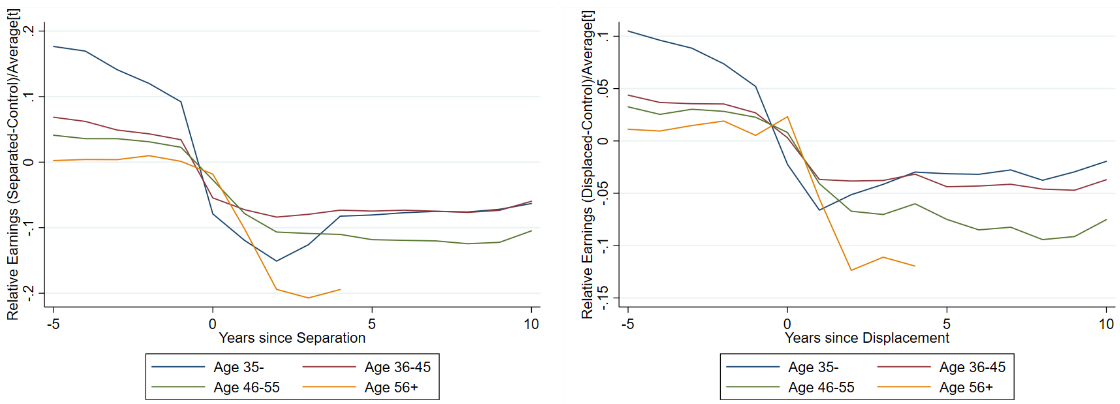

Figure D.13: *The effect of separation (left) and broad displacement on earnings relative to the control group, by age group, using LIAB.*

As it was already observed in the main text (in section 3.1 that younger workers are more likely to be separated and displaced, one might wonder whether they also suffer lower losses. After all, one might argue that it may be easier for a younger worker to adjust their skill set or location as needed when they lose their job. Figure D.13 plots the results of the estimation by age group. Focusing in particular on the long run effects, it can be seen that the earnings loss after either separation or (broad) displacement is indeed much less severe for workers below the age of 45.[62] However, when comparing the two younger groups, there does not seem to be a substantial difference in the long run, while in the short run the youngest workers (aged 35 and below) are worse off.[63]

[62]Note that the workers aged 56 and higher do not have any observations more than 5 years after separation/displacement, because all workers leave the sample when they are older than 60.

[63]Note that interpreting the difference between the two groups this way ignores the fact that the control group is also conditional on the age group. In other words, the control group for the workers in the bottom age group consists of workers in the bottom age group only. Thus, comparing different age groups this way is not fully appropriate as they do not share the same control group.

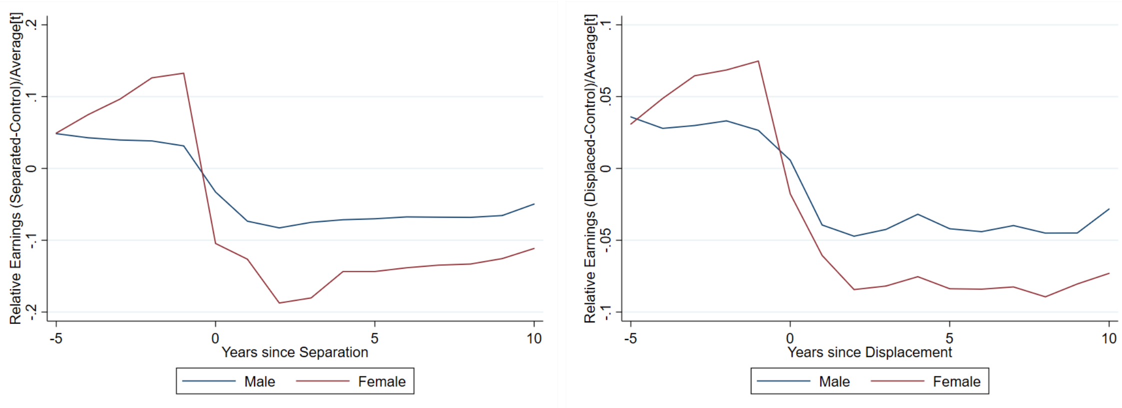

Figure D.14: *The effect of separation (left) and broad displacement on earnings relative to the control group, by gender, using LIAB.*

Figure D.14 displays the results of the estimation by gender. Looking at these graphs, it is clear that female workers experience more severe earnings losses than male workers, even though it was already observed earlier that female workers are not necessarily more likely to lose their job through a mass layoff.

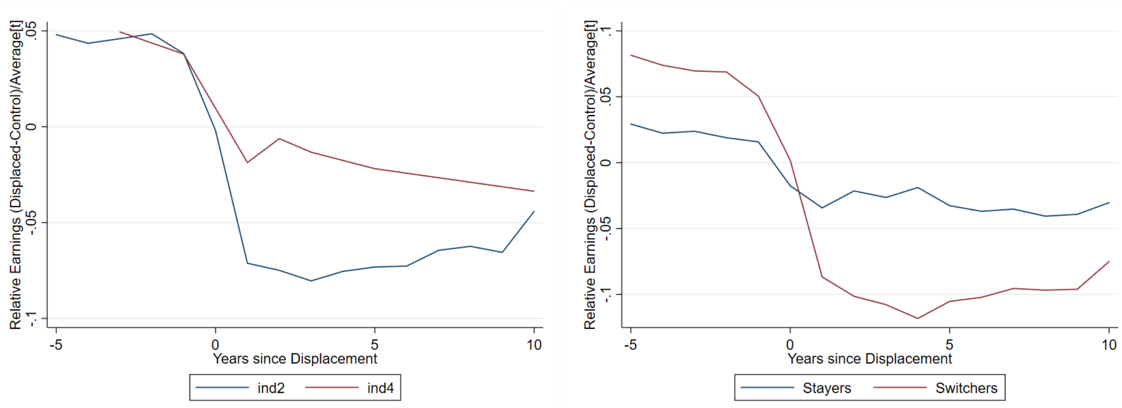

Figure D.15: *The effect of (broad) displacement on earnings, relative to the control group, for workers in industries 2 and 4 (left) and for workers switching industries after displacement (right), using LIAB.*
Major industries used here (left graph) include (2) Manufacturing, and (4) Business Service Activities.

Moving to characteristics of the establishment, the first characteristic that one might think of is the industry in which the establishment operates. In the left panel of figure D.15, I show the estimates for the industry that declined the most during the sample period (industry 2) and the industry that grew the most (in terms of employment) over the sample period, industry 4.[64] When comparing the estimates, it is clear that

[64] In appendix D.2, I show how the fraction of observations by industry changes over time.

workers displaced from the growing industry suffer a much smaller effect, especially in the short run. Part of this difference may be explained by the fact that many workers displaced from a declining industry may choose to switch to a different industry. Indeed, if I compare the average effects for displaced workers who stay in the same industry and those who switched industries after displacement, it is clear that the negative effects are much larger for industry switchers not only initially (which is not necessarily surprising) but also seems to persist in the long run. Nevertheless, the additional negative effect of displacement when also switching occupations (as seen earlier in this section) is much larger than the comparable effect of switching industries, while the difference in the long run is comparable.[65]

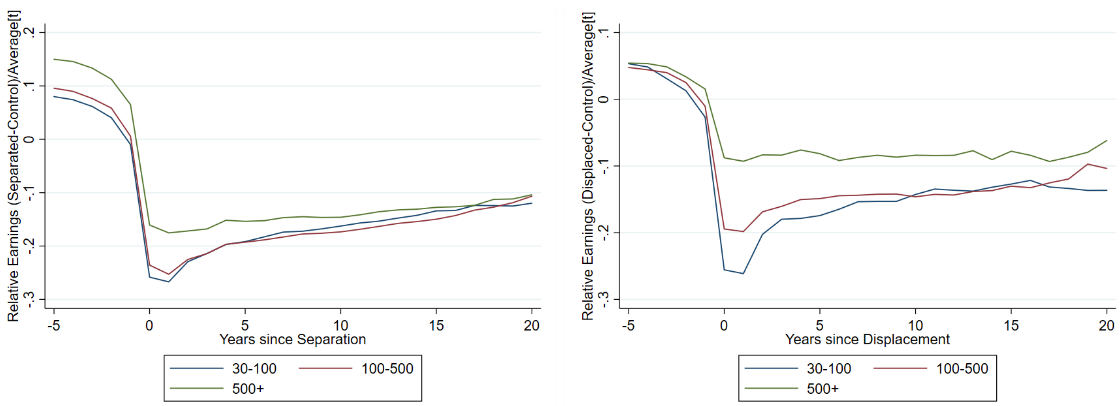

Figure D.16: *The effect of separation (left) and displacement (right) on earnings, by establishment size group*

Another establishment characteristic worth checking is the size of the establishment. In figure D.16 I show the results of the estimation of long-term effects of separation and (broad) displacement, when this estimation is done separately by establishment size group. For this purpose, establishments are grouped into three groups, each of which is represented by one of the lines in these figures. Note that while the lines are plotted in the same figure, the comparison is not entirely clean. After all, the control group also changes between the different groups as I condition both the treatment and control group on the establishment size. Looking at the left panel, which focuses on the effects of separation, it can be concluded that the establishment size does not have a large influence on earnings after separation, especially when comparing the two groups representing the largest establishments. However, when focusing on mass layoffs instead, it can be seen that the size of the establishment seems to make a substantial difference for the estimated effects, especially in the short run. It can be seen that the immediate effects are less severe for workers who were employed in a large establishments. This observation is consistent with the earlier conjecture linking earnings losses to the effort establishments put in to find alternative employment for the workers that are

[65]The large difference in short-run effects can be explained using retraining costs (and time), which may not necessarily be applicable when switching industries as the tasked performed by the worker may be very similar.

laid off. It seems sensible to expect that such efforts are more feasible for large establishments, therefore generating the effect seen in the figure. Furthermore, it should be kept in mind that the threshold for a layoff to be classified as a mass layoff depends on the size of the firm. For example, a layoff of 50 workers at once would be classified as a mass layoff if the establishment initially had 100 workers, but this is no longer the case if the establishment initially had 1000 workers.

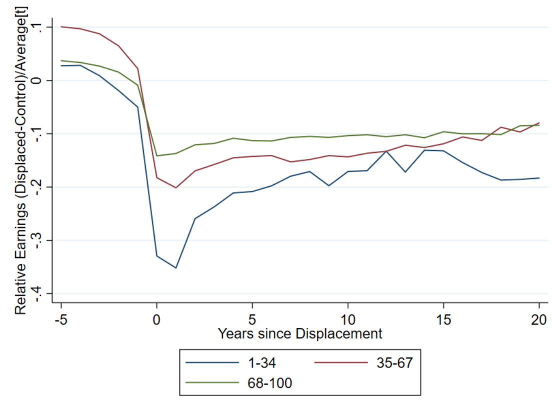

Figure D.17: *The effect of (broad) displacement on earnings, by (grouped) percentile of the median establishment wage*

Finally, as I mentioned that recent earnings can be important in predicting earnings losses after displacement, it seems sensible to analyze whether this may partially be driven by the worker's former employer paying well in general. In figure D.17, I plot the results of the estimation done separately by three groups of establishments, which are formed based on how their median establishment wage compares to that of other establishments. Looking at the results, it can be seen that while the bottom third and the middle third of the distribution experience fairly similar effects, workers at the top third of the distribution face a much less severe initial shock and do not recover over time, so that ten years after displacement their effect is comparable with those in other parts of the distribution. One explanation for this observation could be that the establishments with a high median wage tend to also be the establishments that put in more effort in finding a replacement job for the laid off workers.

One way to further analyze this result is to plot graphs similar to those seen in section 3.3.1, plotting (raw) earnings and employment differences over the establishment wage distribution rather than over time. Of course, this measure is expected to be highly correlated to the recent earnings distribution above, and therefore I would expect the results to be very similar to those in section 3.3.1 of the main text. However, looking at the results in figures D.18, this is not quite the case. In particular, looking at the results for earnings in the right panel, one could still see an upward sloping pattern, but it is much more linear than what was observed for recent earnings. However, one other striking observation can be made from these figures: comparing the low to the high percentiles, it can be seen that the workers previously employed at an establishment with a low median wage tend to do better in terms of employment, which contradicts conjecture that establishments with a high median wage tend to also be the establishments that put in more effort in finding a replacement job for the laid off workers. After all, such workers would then likely suffer from lower losses in terms of their employment status.

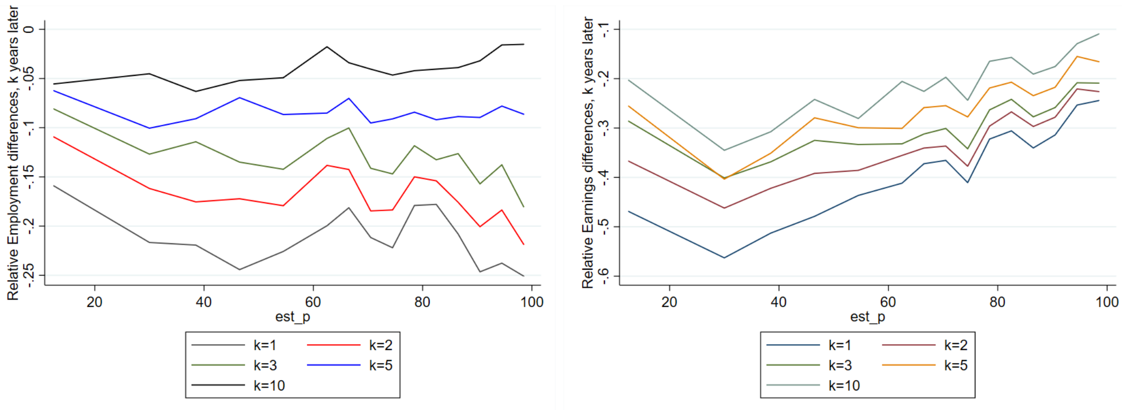

Figure D.18: *The effect of separation (left) and displacement (right) on earnings, by percentile of the median establishment wage*

D.3.3 Further observations on the incidence of displacement

In this subsection, I provide some further observations regarding the incidence of separation and displacement, beyond those that were displayed in section 3.1. In particular, most of this section focuses on the incidence of job loss by establishment characteristics, though I will start by investigating the incidence by some more worker characteristics.

Figure D.19: *The incidence of separation (left) and displacement (right) by age group, with restrictions on worker tenure, using LIAB.*

Figure D.19 plots the separation and (broad) displacement rates by worker age groups over time, thereby complementing the observations from figure 2 (which were averaged across years). Looking at figure D.19, it can be seen that the differences between age groups are quite persistent over time. One exception to this is the 56+ age group, which did not have a higher separation rate than the other age groups until 2002. Similarly, while it can be seen that this age group was experiencing a disproportionately high separation and displacement rate in the the early 2000s, the opposite is the case for the Great Recession, especially when focusing on displacement.

Figure D.20: *The fraction of displacements by education group (left) and occupational complexity (right) over time, with restrictions on worker tenure, using LIAB.*

In figure D.20, the fraction of displacements accounted for by each education and occupational complexity group is plotted over time.[66] These fractions are roughly in line with the fraction of the working population accounted for by each of these groups, which shows that it does not seem to be the case that lower or higher educated workers are more prone to displacement. Nevertheless, since for both of these variables one group accounts for a large portion of all displacements, it is likely that the average scarring effect of displacement, as analyzed in the section 3.2 of the main text, may be largely driven by this group.

A similar pattern can be discovered by plotting the separation and displacement rate by job tenure, as done in figure D.21. Not surprisingly, this figure reveals that the separation and displacement rates are generally higher for workers with a lower job tenure, and a similar conclusion can be reached by looking at establishment tenure instead.[67] As workers with a higher job and establishment tenure are mechanically expected

[66] Occupational complexity is measured by the skill requirement for the job. This is coded into the fifth digit of the occupation code, and can range from “niv 1” (highly routine) to “niv 4” (highly complex).

[67] The figures for establishment tenure are available upon request. They are not included here as they are almost identical to the ones for job tenure.

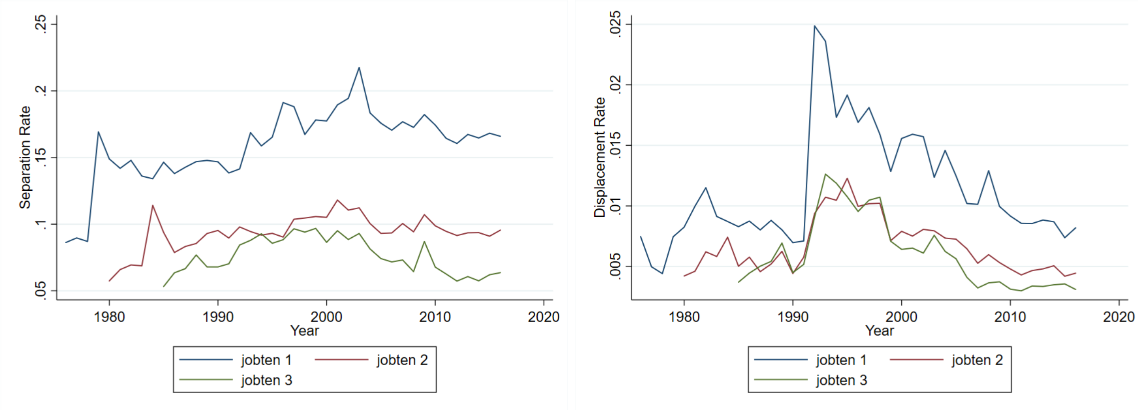

Figure D.21: *The incidence of separation (left) and displacement (right) by job tenure, with restrictions on worker tenure.*

to be older (on average), this figure, combined with figure 2 supports a narrative of separation being more prevalent early in the lifecycle, while also not ruling out an alternative narrative of workers being more likely to be laid off if they have lower tenure (regardless of their age).

While all analysis (of incidence) so far has focused on worker characteristics, it is likely that job loss rates also differ by establishment characteristics such as industry and establishment size. In the remainder of this section, I will focus on some of these establishment characteristics.
The first such characteristic that comes to mind is the industry in which the establishment operates. However, as the left panel of figure D.22 indicates, the incidence of displacement is not consistently higher for certain industries.

Figure D.22: *The incidence of separation by industry (left, using LIAB) and establishment location (right, using SIAB), with restrictions on worker tenure.*

When it comes to the location of the establishment, the pattern is quite similar to the pattern found for worker location in section 3.1. In particular, the differences in displacement rate between establishments in the East and establishments in the West has mostly disappeared in recent years. Furthermore, it is worth noting that (judging by the displacement rate), establishments in the West seemed to be more affected by the Great Recession than establishments in the east.

The left panel of figure D.23 shows the separation rate by establishment size group. As can be seen in this figure, the separation rate tends to be higher for smaller establishments, especially if I remove the restrictions on worker tenure.

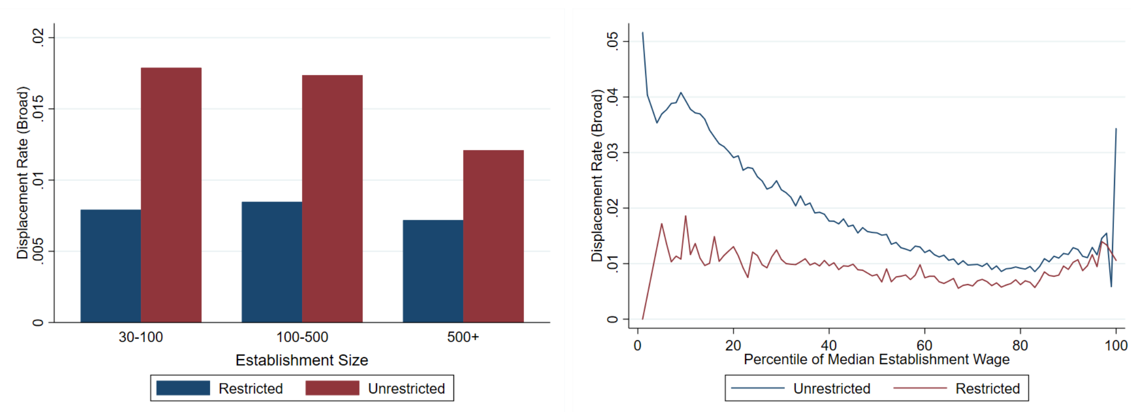

Figure D.23: *The incidence of separation by establishment size (left) and median wage (right), with and without restrictions on worker tenure.*

Finally, the right panel of figure D.23 shows how the separation rate differs according to how high the median establishment wage is. The pattern here is similar to the one seen earlier in figure 4: the separation rate tends to be high especially in establishments that have a low median establishment wage. This resemblance makes sense, as the median establishment wage and an individual's recent earnings are likely to be highly (though not perfectly) correlated.

D.3.4 The incidence of displacement, using a restricted (SIAB) sample

While most results in sections 3.2 and 3.3 are based on a sample that is restricted to workers with a pre-displacement tenure of at least 6 years, this is not the case for most results in section 3.1. In this section, I show that the results from that section continue to hold when using a sample restricted like in sections 3.2 and 3.3.

Before analyzing the detrimental effect displacement can have on a worker's earnings, and how it differs by observable characteristics, it is worth investigating how common a separation or displacement event is. In order to do so, this subsection presents separation and displacement rates for the entire sample as well as several subsets of the sample.

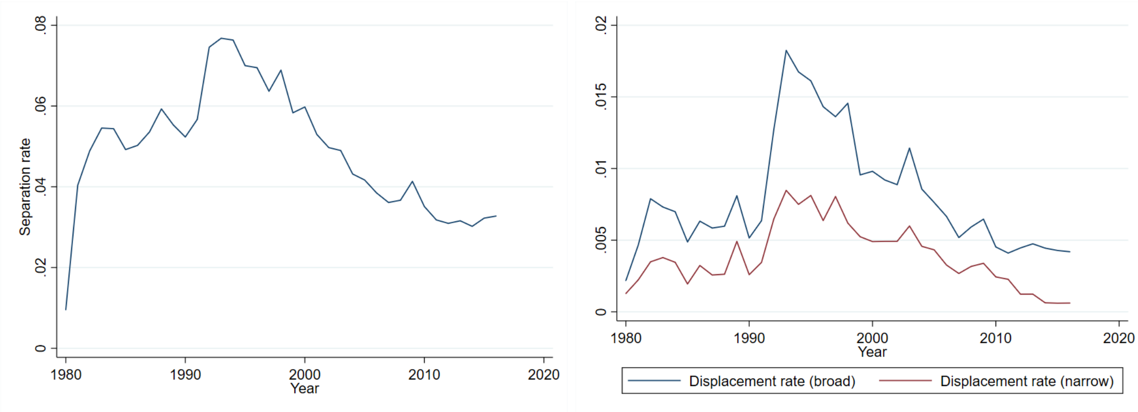

Figure D.24: *The incidence of separation (left) and displacement (right) over time, with restrictions on worker tenure.*

First of all, figure D.24 displays the separation and displacement rates over time, for the entire sample. As can be seen in this figure, the separation averages at roughly 4% for this restricted sample whereas the displacement rate averages at roughly 0.3 to 0.7% (depending on the definition). This is substantially lower than the rates found in the main text for the unrestricted sample, but this is not necessarily surprising given how incidence differs by job tenure (as observed in section D.3.3). Again, the aftermath of the German reunification is quite clearly visible in the graph.

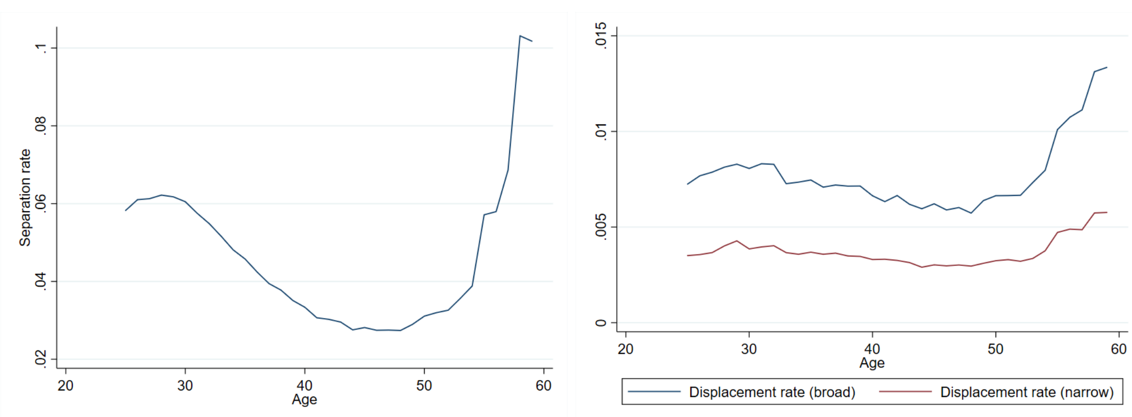

Figure D.25: *The incidence of separation (left) and displacement (right) by age, with restrictions on worker tenure.*

In figure D.25, the separation and displacement rates are displayed by age of the worker at the time of the event. As can be seen here, the pattern where separation and displacement rates tend to be higher during early years largely disappears. This is likely a consequence of the fact that not too many young workers will have reached the threshold of 6 years of job tenure, as they only recently entered into the labor market and furthermore are more likely to be job hopping in early years. As observed in the main text, both the separation and displacement rates increase substantially around the age of 55, likely due regulations surrounding early (partial) retirement in Germany.

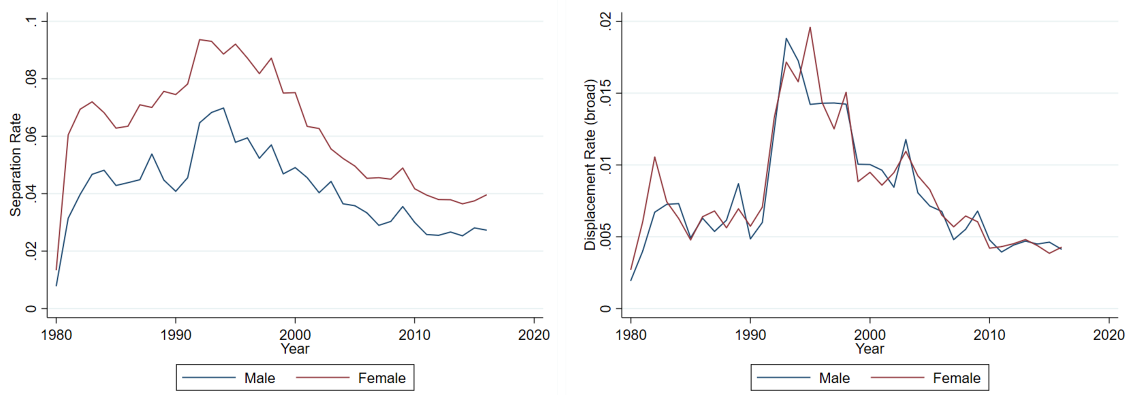

Figure D.26: *The incidence of separation (left) and broad displacement (right) by gender, over time, with restrictions on worker tenure.*

In figure D.26, the separation and (broad) displacement rates over time are plotted separately for male and female workers. From this figure, it can be concluded that unlike in the case without worker tenure restrictions, the separation rate remains higher for female workers in recent years, though one can observe some convergence. For the displacement rate, it remains true that female workers do not seem to be disproportionately hit by mass layoffs.

As shown in figure D.27, the conclusion that the separation and displacement rates in general tend to be higher for individuals located lower on the (recent) earnings distribution continues to hold when worker tenure restrictions are imposed.

Finally, figure D.28 compares the two regions formerly part of East and West Germany in terms of their separation and (broad) displacement rates. As can be seen in the figure, the convergence between the two regions is not as clear as in the main text (especially for the case of separation) when a restriction on worker tenure is imposed. However, it should be noted that this can be partially explained by many workers in Eastern Germany not appearing in the data before the reunification. As these workers do not appear in the data, their tenure could also not be measured, meaning that worker tenure in East Germany would be

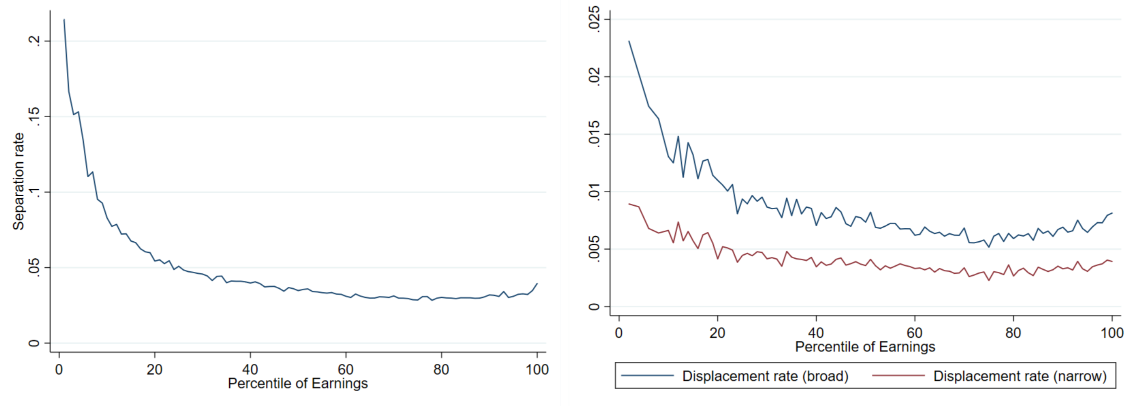

Figure D.27: *The incidence of separation (left) and displacement (right) over the earnings distribution, with restrictions on worker tenure.*

Figure D.28: *The incidence of separation (left) and displacement (right) by location, with restrictions on worker tenure.*

underestimated, especially shortly after the reunification.

D.3.5 The incidence of displacement, using LIAB

In this subsection I repeat the analysis of the incidence of displacement, as seen in section 3.1 in the main text, using data from the LIAB instead of the SIAB.[68]

First of all, figure D.29 displays the separation and displacement rates over time. It can be seen that the average separation and displacement rates are roughly in line with those seen in the main text (though the displacement rates are higher), at 13% and 1.2–2.5% respectively. Just like seen in the main text, all rates

[68] Note that I only repeat the analysis done in the main text in this section. The analysis displayed in sections D.3.3 and D.3.4 is omitted and is available upon request.

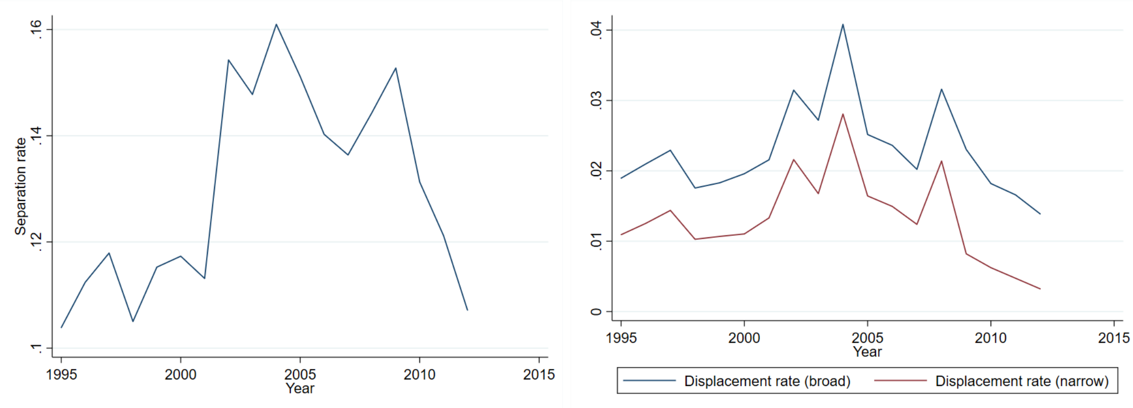

Figure D.29: *The incidence of separation (left) and displacement (right) over time, using LIAB.*

display substantial variation over time, with the peaks generally lining up with recessions in Germany. Because the LIAB sample begins after the German reunification, the jump that was observed around this time in the SIAB is not visible here.

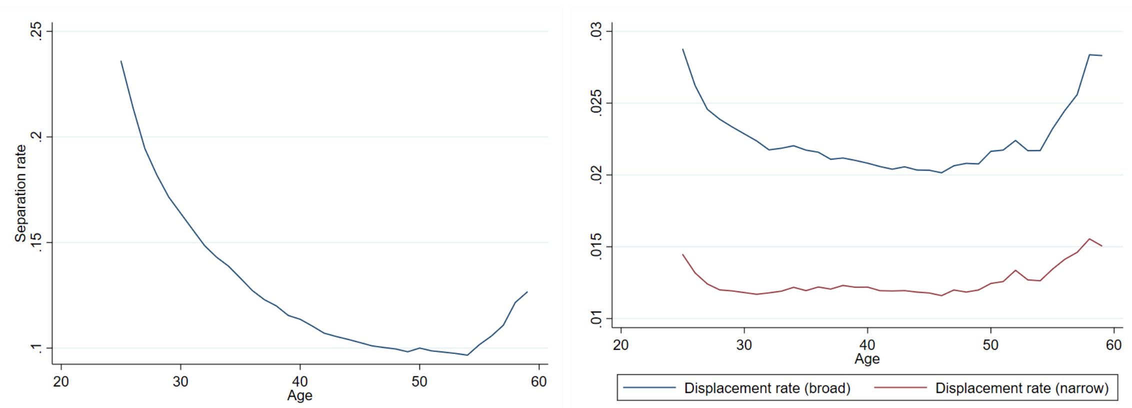

Figure D.30: *The incidence of separation (left) and displacement (right) by age, using LIAB.*

In figure D.30, the separation and displacement rates are displayed by age of the worker at the time of the event. As can be seen here, the separation and displacement rates are slightly higher during early years, like in the main text, and increase substantially around the age of 55.

In figure D.31, the displacement rates over time are plotted separately for male and female workers. Just like in the main text, it can be concluded that while the separation rate tends to be higher for female workers, this is not the case for the displacement rate, thereby implying that female workers do not seem to be disproportionately hit by mass layoffs.

Figure D.31: *The incidence of separation (left) and broad displacement (right) by gender, over time, using LIAB.*

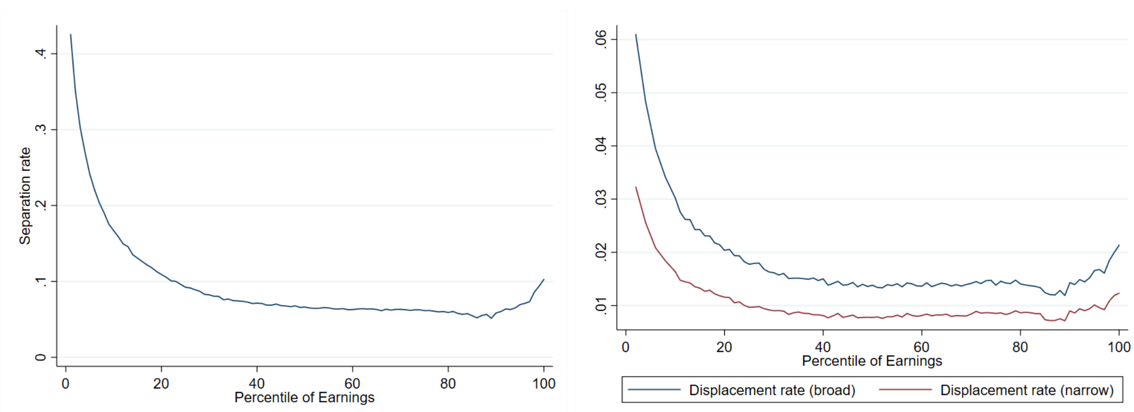

Figure D.32: *The incidence of separation (left) and displacement (right) over the earnings distribution, using LIAB.*

As shown in figure D.32, the separation and displacement rates over the recent earnings distribution display the same pattern as in the SIAB: they tend to be higher for individuals located lower on the (recent) earnings distribution and increase again above the 80th percentile of the distribution.

Finally, figure D.33 compares East and West Germany in terms of their separation and displacement rates. As can be seen in the figure, the separation and displacement rates seem to be converging in recent years.

Figure D.33: *The incidence of separation (left) and displacement (right) by location, using LIAB.*

D.3.6 The average scarring effect of displacement, using LIAB

In this subsection, I repeat the analysis of the average scarring effect of displacement (and separation) as done in section 3.2 of the main text, using the LIAB data instead.

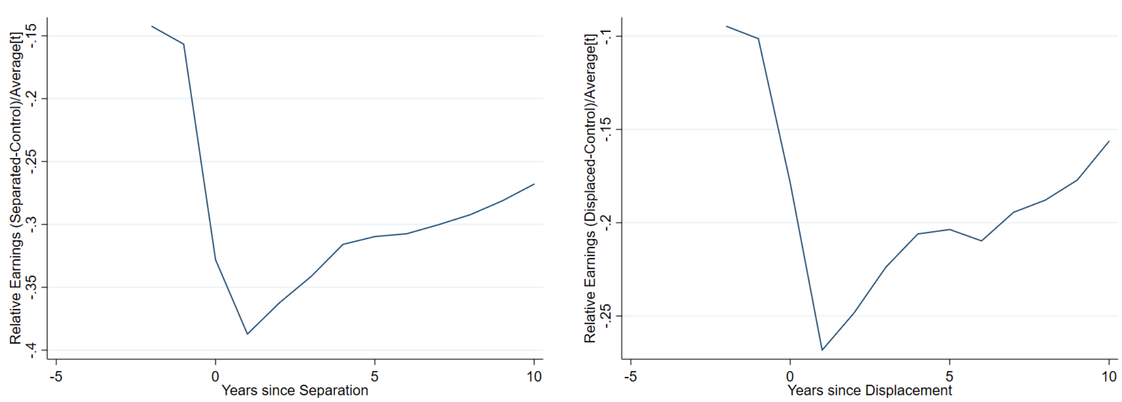

Figure D.34: *Raw average difference between earnings of the treatment and control group, defining treatment as either separation (left) or broad displacement (right), using LIAB.*

First, figure D.34 displays the raw earnings differences after displacement (from 2 years before to 10 years after the event). Just like in the main text (figure 7), the effect of job loss on earnings is quite substantial, and this (raw) effect is worse if one focuses on separation in general rather than displacement. In either case, there is some partial recovery in earnings, but earnings have not fully recovered 10 years after job loss.

Figure D.35 shows the results of estimating equation (1) using the LIAB data, defining the treatment as

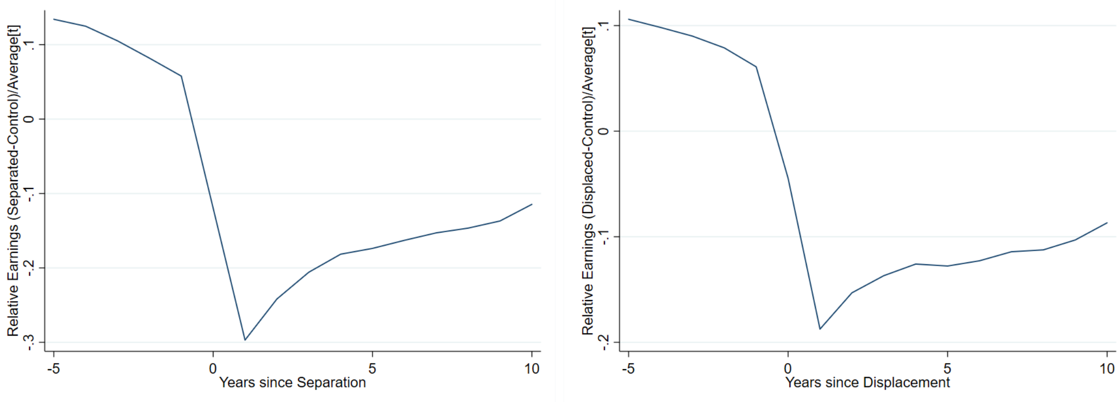

Figure D.35: *The effect of separation (left) and broad displacement (right) on earnings, relative to the control group, using estimated coefficients from equation 1, using LIAB.*

either separation or (broad) displacement.[69] In particular, it can be seen that in the short-run, workers who are displaced (separated) earn roughly 19% (30%) less on average than a worker in the control group. This earnings loss is shown to be quite persistent, with these displaced (separated) workers still earning 9% (11%) less than workers in the control group 10 years after the job loss took place. The same holds when using employment status as the dependent variable, as seen in figure D.36 (which is roughly the equivalent of figure 9).

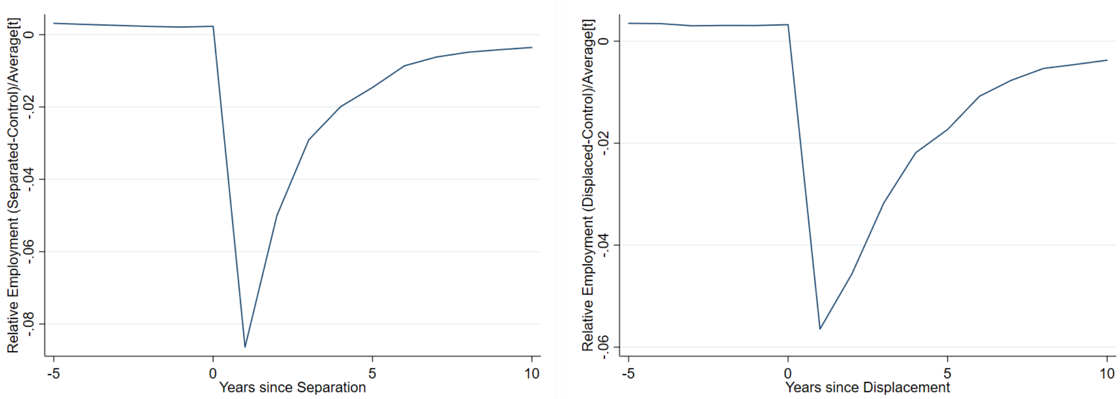

Figure D.36: *The effect of separation (left) and broad displacement (right) on employment status, relative to the control group, using estimated coefficients from equation 1 (with employment status as the dependent variable), using LIAB.*

[69] Figure D.35 is roughly the equivalent of figure 8 in the main text using LIAB data. However, it should be noted that due to the shorter timespan covered by the LIAB, I estimate a slightly altered version of (1), where I estimate the effects of job loss up 10 years (rather than 20 years) after the event.

D.3.7 Heterogeneity in the scarring effect of displacement, using LIAB

In this section, I will use the LIAB to re-affirm the main conclusions from section 3.3 of the main text. As some results in that section already used the LIAB, I will not repeat that analysis. This holds in particular for most of the analysis by recent earnings and education level.

First, figure D.37 re-confirms the importance of controlling for recent earnings ($\bar{e}_i^y$) when estimating equa-

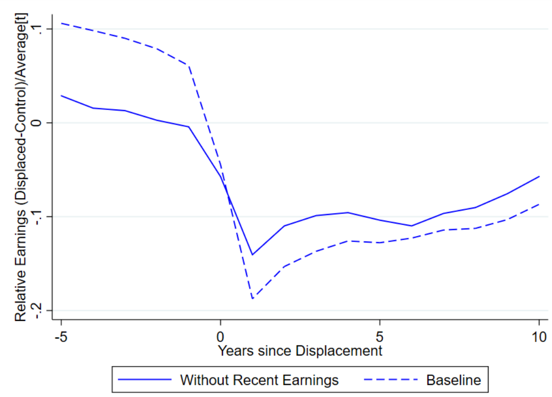

Figure D.37: *The effect of (broad) displacement on earnings, relative to the control group, without controlling for recent earnings.*

tion (1). Just like in the main text (figure 10), it can be seen that not controlling for recent earnings diminishes the estimated effect of displacement on subsequent earnings, thereby indicating that taking recent earnings into account is important when estimating this effect.

Figure D.38: *The incidence of recall within 5 years of separation or displacement, by percentile of the recent earnings distribution.*

When it comes to ex-post recall status, figure D.38 shows that the incidence of recall (within 5 years) is especially high for separation, but even for broad displacement consistently above 5% across the distribution, and much higher towards the bottom of the distribution, in line with the conclusions from figure 14.

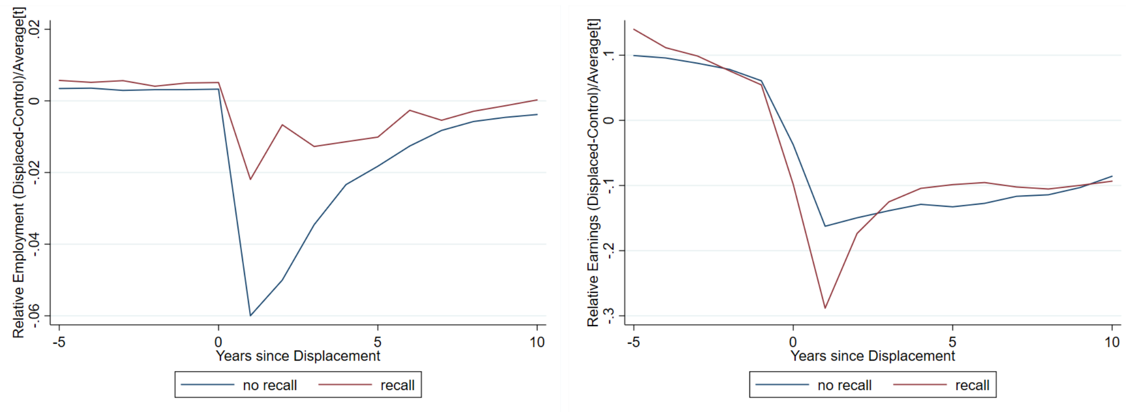

Figure D.39: *The effect of separation (left) and broad displacement on earnings relative to the control group, by ex-post recall status (materialization of recall within 5 years).*

As can be seen in figure D.39, the estimated effects of displacement with and without recall on earnings and employment also roughly lines up with what was found using the SIAB data (figure 15): workers who are recalled tend to be re-employed faster after displacement, but in terms of earnings their loss is more severe in the short run.