Recall and 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. I find that relative earnings losses tend to be higher for individuals who are recalled to their previous employer, even though they are re-employed faster. Furthermore, workers with low educational attainment tend to experience higher relative earnings and employment losses. 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 who are waiting to be recalled are explicitly separated from other unemployed workers. This explicit possibility of recall, and distinct parameter values by educational attainment, generate the heterogeneity as observed in the data, whereas the presence of search frictions and human capital ensure all workers' slow recovery after the initial displacement. 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. The decomposition of the earnings losses by ex-post recall status points towards workers returning to an unstable firm as the most important factor in explaining the larger earnings losses experienced by recalled workers.

JEL Classifications: E24, J21, J24, J62, J63, J64, J65
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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. This paper further explores this scarring effect of displacement.[1] In particular, I use administrative data from Germany to extensively document heterogeneity in this earnings loss along the dimensions of education and ex-post recall status. While the average scarring effect is very similar to that observed in the existing literature (which tends to focus on the U.S.), I find that substantial heterogeneity is visible along these dimensions. To be more precise, I find that while workers who are recalled to their former employer tend to be re-employed faster than their non-recalled counterparts, they suffer from more severe relative earnings losses (in the short run as well as in the long run). Furthermore, I find that workers with a low education level tend to experience more severe relative earnings losses. 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. Using simulation-based counterfactuals, I show that the stability of the next employing establishment following displacement is a major factor in explaining the heterogeneity in long-run scarring effects of displacement, and in particular for how they differ by ex-post recall status. As the model accounts for both the average effects and its heterogeneity, the model can then be used to evaluate policy proposals in terms of their efficiency in accounting for the wide variety of earnings paths experienced by these 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.[2] 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

[1] 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.

[2] 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.

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).[3] While a single person losing one's job may not have an enormous impact on a 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.

In the existing literature, workers who are recalled to their previous employer are generally omitted, especially when using survey data. However, I show in this paper that these recalled workers are important to consider, as they follow a substantially different pattern of earnings and employment after the initial layoff. In fact, I show that workers who are recalled to their former employing establishment do worse in terms of earnings (both in the short and in the long run) as well as days worked per year (in the short run), even though they tend to be re-employed faster.

The estimation of the scarring effects of displacement is not by itself a novel idea: in the past few decades, many papers have tried to identify the scarring effect of job loss on earnings.[4] Most of this literature uses event study frameworks with staggered implementation and uses two-way fixed effects to estimate the effect, and many of these papers are therefore subject to recent criticism of these estimation methods.[5] Before moving on to consider heterogeneity in the scarring effect of displacement, I show that the effects estimated in the existing literature continue to hold when using the method proposed in one of those recent papers, Sun and Abraham (2020).

As mentioned earlier, 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 pro-

[3]For comparison, a year earlier the number of workers claiming unemployment insurance benefits was approximately 1.5 million (Department of Labor, 2020).

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

[5]In section 1.1, I briefly discuss this criticism, as well as some proposed methods to improve the reliability of the estimate.

pose 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 observed in the data. 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). By explicitly allowing workers to wait to be recalled, I can allow these workers to follow a different path while non-employed, thus capturing several possible explanations for the observed severity of the scarring effect of displacement despite recall. In the model, I do this by setting distinct parameters for the worker's human capital depreciation and job finding rates when waiting to be recalled. The calibration confirms that the observations made in the data can partially be explained by assigning a lower human capital depreciation rate and a higher job finding rate to these workers, compared to unemployed workers that are not (or no longer) waiting to be recalled. However, the main factor driving the long-run differences between recalled and non-recalled workers after displacement is the fact that recalled workers return to an unstable firm, and are therefore much more likely to be separated again shortly after being re-employed. The model also allows me to comment on the efficiency of existing (or proposed) policies aimed at alleviating the negative consequences of displacement. These policies explicitly target the dimensions that I find to be important in decomposing the long-term earnings loss of displaced workers.

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.

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 and 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.[6] 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 under 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,[7] 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), finding an especially large role for firm characteristics. In my 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.[8]

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

[7] Examples include Bonikowska and Morissette (2012) for Canada, Hijzen et al. (2010) for the United Kingdom, Deelen et al. (2018) for the Netherlands, Raposo et al. (2019) for Portugal, and Burda and Mertens (2001), Nedelkoska et al. (2015), and Schmieder et al. (2020) for Germany.

[8] While Guvenen et al. (2017) present some evidence on heterogeneity by previous position on the earnings distribution, 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.

While the empirical literature on the long-run effects of displacement (or job loss in general) is quite sizeable, it is worth noting that the majority of existing papers use a very similar method. This method is based on an event-study framework with staggered treatment implementation, and the effects are generally estimated using two-way fixed effects. In some cases, like in Davis and Von Wachter (2011), this estimation is done separately for each year for which displacements are considered in the estimation, and the resulting estimates are averaged afterwards. Some other work, like Flaaen et al. (2019) and Jarosch (2021), stacks the (cohort-specific) samples and estimates the average effect in a single estimation, thus forcing the coefficients to be the same for all of these displacement cohorts, rather than averaging them after the estimation. Both of these methods are subject to the recent criticism of estimating (dynamic) treatment effects using two-way fixed effects specifications, most notably Callaway and Sant'Anna (2020), and Sun and Abraham (2020).[9] In its essence, the issue is that the two-way fixed effects setup as described above does not allow for treatment effect heterogeneity, which is unfortunately quite likely to exist in the case of the long-run effects of job displacement.[10] Furthermore, because of the staggered timing of the treatment, the estimates obtained using two-way fixed effects can be shown to no longer exclusively reflect the effect of displacement in a certain period of interest. Rather, the estimate becomes a weighted average of (cohort-specific) treatment effects for several periods, where the weight can potentially even be negative.[11] Fortunately, both papers also offer a solution. In my paper, I show that the existing results on the long-run effect of displacement on earnings continues to hold even when using this alternative method. In fact, the result becomes stronger, as some of the apparent pre-trends that appear using the "traditional" methods no longer appear when using these proposed methods.

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

[9]There are many other papers highlighting the issues with these estimations, but most of these other papers focus on a setting where the researcher is interested in estimating a single (static) treatment effect, rather than a dynamic treatment effect.

[10]To give an example, it has been shown in the literature that the effects of job loss on earnings are more severe if a worker is laid of during a recession. In other words, it would not be reasonable to assume that the dynamic treatment effect is homogeneous across cohorts, if we define cohorts as groups of workers displaced within the same year.

[11]Both Callaway and Sant'Anna (2020) and Sun and Abraham (2020) contain a more detailed description of the issue, and Sun and Abraham (2020) explicitly derives the decomposition of the two-way fixed effects estimate into cohort-specific estimated treatment effects. See these papers for a more elaborate discussion.

Nekoei and Weber (2020) have used detailed administrative data from Austria to shed more light on the topic of recall, in particular distinguishing between the expectation of recall and the actual materialization of recall. Similarly, studies like Hall and Kudlyak (2020) and Forsythe et al. (2020) have highlighted the unusually large role recalls play in labor market dynamics during the COVID-19 pandemic, especially in the early months. 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 as well.

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.[12] Some recent work has attempted to resolve this issue with some success. Jarosch (2021) 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.[13] 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 (2021) 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. Jung and Kuhn (2019) take a different approach by focusing on the lack of mean reversion from the top rather than 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. Finally, Burdett et al. (2020) propose a model based on wage posting in the tradition of Burdett and Mortensen (1998) and Burdett and Coles (2003). Like

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

[13] 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.

in some other aforementioned models, workers can receive outside offers on the job, but unlike in other models these offers are not visible to the employer and therefore do not trigger a wage change. Nevertheless, through lost accumulation of human capital their model is also able to generate the average scarring effect, as well as scarring effects by education and tenure groups.

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. In particular, as these models do not allow for a worker to be recalled to their former employer (or, rather, only with probability zero), they do not allow for an explanation of the observed differences between recalled and non-recalled workers. 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, and want to do so by specifically targeting workers that are most affected.

One of the key elements of 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).[14] 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 at the same intensity, but also do not experience a depreciation of their skills as severe as other unemployed workers.

[14] In the context of the COVID-19 pandemic, the possibility of recall is also explicitly modeled in Gregory et al. (2020) and Gallant et al. (2020).

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.[15] 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 employment relation, or simply 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.[16] 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. 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

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

[16] 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.

security benefits during nonemployment.[17] When constructing my main dataset, I fill these gaps for variables 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 individuals 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. The raw number of observations and age-restricted observations refer to the number of spells. In the main panel, these spells are collapsed to form yearly (or quarterly) observations.*

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 $t + 1$.[18] 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.[19] I then define such a worker as displaced if the establishment either closes or experiences a mass layoff.[20] 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 establishment's maximum employment over the previous five years, and the establishment has a net outflow of 20% of its workforce in the

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

[18] 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.

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

[20] 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.

displacement year.[21] Finally, in order to determine whether a worker was recalled to their previous establishment, I look ahead at most 5 years after displacement. If the worker's first employing establishment after being displaced is the same as her employing establishment before displacement, I define the worker as recalled.[22]

The empirical results presented in the next section are largely based on the two specifications. The first of these specifications resembles the event study specification used in Davis and Von Wachter (2011):

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

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 $y-1$.[23] 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 $t-k$ (where the dummy variable for $k=-1$ is omitted). 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 maximum number of future periods, K, is either 10 (when using LIAB)

[21] 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.

[22] Note that due to my definition of separation, I will miss unemployment spells of less than 31 days. As workers with such a spell would not be marked as separated, they can also not be defined as displaced (or recalled).

[23] 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).

or 20 (when using SIAB).[24] The estimation is done separately for each sample year y.[25] 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. Furthermore, only observations that correspond to years $y-5$ to $y+K$ are used. To enhance the interpretation of the estimated value, I then divide the estimated coefficient δ_k^y by the control group's average of the dependent variable (usually earnings) in year $y+k$, obtaining relative coefficient $\tilde{\delta}_k^y$. The standard displacement graph then plots the resulting relative coefficient $\tilde{\delta}_k$ over k (where $\tilde{\delta}_k$ is a simple average of $\tilde{\delta}_k^y$ over base years y), thus revealing an earnings path from 5 periods before to K periods after the displacement event.

Recently, a number of papers have stressed the shortcomings of event study settings such as the one described above, in particular stressing that the estimates of δ_k^y may be contaminated by effects from earlier and later periods, as well as by subsequent and prior treatments that are ignored in this specification.[26] In fact, in the specification above individuals who are displaced in years $y+1$ and later, as well as individuals displaced before year y who are re-employed again (and satisfying other sample requirements) are likely to be placed in the control group. While the estimation described above is informative for the purpose of comparing my estimates with those found in previous work, I will therefore also show results based on a specification that takes these issues into account. As the specification (equation 2 below) does not allow for covariates, I will first estimate a trimmed version of specification (1), where the recent earnings and quadratic

[24] I chose a different value for K in the two datasets because setting $K = 20$ means that I require 25 years of data for every y. When using LIAB, this substantially restricts the number of years for which the estimation can be run. An alternative way of dealing with this would be to let K decrease as y increases. This would allow for more estimation years, but also could introduce some bias in the estimates for high values of k if the years with a lower K are also years where the long-run effect of displacement is stronger or weaker.

[25] 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.

[26] See section 1.1 for a brief overview of these papers.

polynomial in age do not appear:[27]

$$e_{it}^{y} = \alpha_i^{y} + \gamma_t^{y} + \sum_{\substack{k=-5 \\ k\neq -1}}^{K} \delta_k^{y} D_{it}^{k} + u_{it}^{y} \tag{1'}$$

In order to take into account potential contamination of the estimate of δ_k^y (and consequentially of the average $\tilde{\delta}_k$), I use the interaction-weighted estimator from Sun and Abraham (2020). In practice, this means that I am estimating the following equation:

$$e_{it} = \alpha_i + \gamma_t + \sum_{C\neq 0} \sum_{\substack{k=-4 \\ k\neq -2}}^{K} \delta_k^{C} D_{it}^{C,k} + u_{it} \tag{2}$$

In the equation above, α_i and γ_t represent the person- and time fixed effects, and u_{it} is an error term. Similarly, the dependent variable, e_{it}, corresponds to earnings (or employment) of individual i in period t, like before. The main difference with equation 1' is that rather than estimating the equation for each base year separately, the above specification is only estimated once. However, the specification allows for a different treatment effect (and different dynamics of this treatment effect) depending on which treatment cohort C the individual belongs to. In my estimation, the definition of the cohort C is equivalent to the base year y in which the individual is displaced, with $C = 0$ corresponding to the cohort of individuals who I do not observe being displaced at all. This "never-treated" group acts as the control group. Furthermore, note that rather than omitting one value of k, I follow Borusyak and Jaravel (2018) in omitting two values of k. This is because generally the relative time indicator D_{it}^{C} can only be identified up to a linear trend, due to collinearity with each other as well as the time fixed effect. In order to allow for anticipation one period ahead, the first period I omit is $k = -2$ (rather than $k = -1$). The second omitted period is the earliest period, $k = -5$ (as reflected by the summation over k starting at $k = -4$). This period is chosen to maximize the distance between the two omitted periods, thereby making the resulting estimate less sensitive to any possible fluctuations (or trend) between these two periods.
Estimation of equation (2) above will yield a set of estimates $\hat{\delta}_k^C$ for all $C \neq 0$ and $k \neq \{-5, -2\}$. These are then be averaged over C, using a weighted average that assigns to each pair (C, k) a

[27] Note that the method proposed in Callaway and Sant'Anna (2020) allows for covariates that do not vary over time, which would allow me to use the person's year of birth (but not age) to come closer to specification (1). This would be especially useful if the covariate in question (year of birth) is expected to influence not only the outcome, but also the probability of being displaced. If the only concern is the effect on the outcome (earnings), this effect would likely be included in the individual fixed effect.

weight equal to the number of observations with (C, k) divided by the number of observations of relative time period k (across cohorts). Since all coefficients δ_k^C are estimated in a single estimation procedure, I can then also form corresponding (pointwise) confidence intervals for the resulting weighted averages $\hat{\delta}_k$.[28]

When estimating the equations 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.

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 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, potentially 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 (as well as subsequent recall) 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.

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

[28] In principle, one could construct confidence intervals for the coefficients that follow from specification (1) or (1') as well. However, in order to do so one would need to make a number of strong assumptions. For example, one would assume that there is no covariance between the estimates of δ_k^y for different values of y.

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

As can be seen in this figure, the separation averages roughly 12% whereas the displacement rate is roughly 1.5% on average. All rates display substantial variation over time, and in particular the aftermath of the German reunification is quite clearly visible.[29] 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).

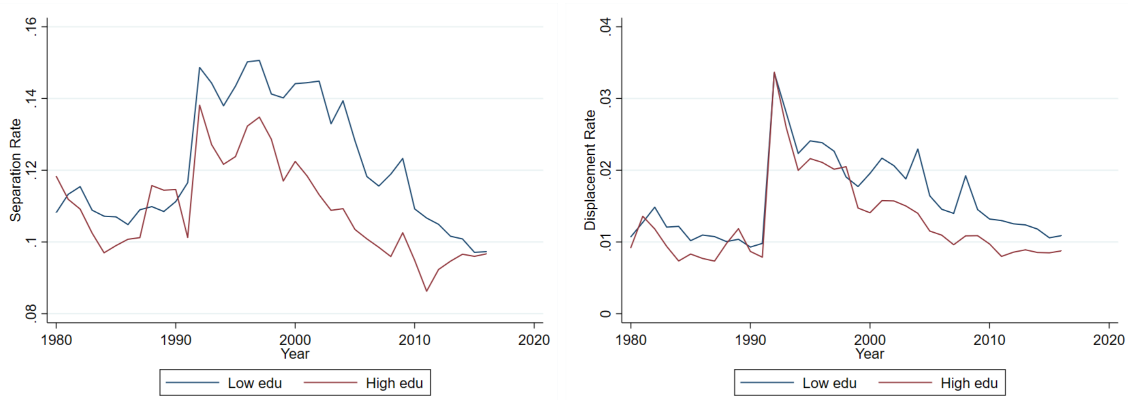


Figure 2: *The incidence of separation (left) and displacement (right) by education level, over time.*

In figure 2, I plot the separation and 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. Furthermore, with roughly 80% of the workers being categorized in the first group, it can be said

[29]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.

that separations and displacements in any year primarily affect workers with a low education level.

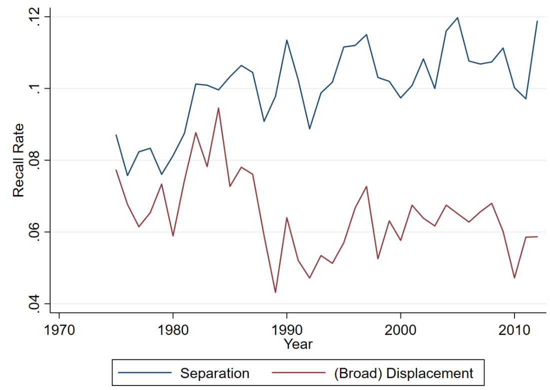


Figure 3: *The incidence of recall within 5 years of separation or displacement (conditional on separation/displacement), over time.*

Next, figure 3 shows the incidence of recall (within 5 years) after separation or displacement. As can be seen in the figure, the recall rate conditional on displacement fluctuates between 4.5% and 7.5% in recent decades. This indicates that generally roughly 6% of the workers who are displaced (notably including workers who are displaced as a consequence of their employing establishment shutting down) return to their previous employer. For separated workers, the incidence of recall is slightly higher, fluctuating between 9% and 12% in recent decades.

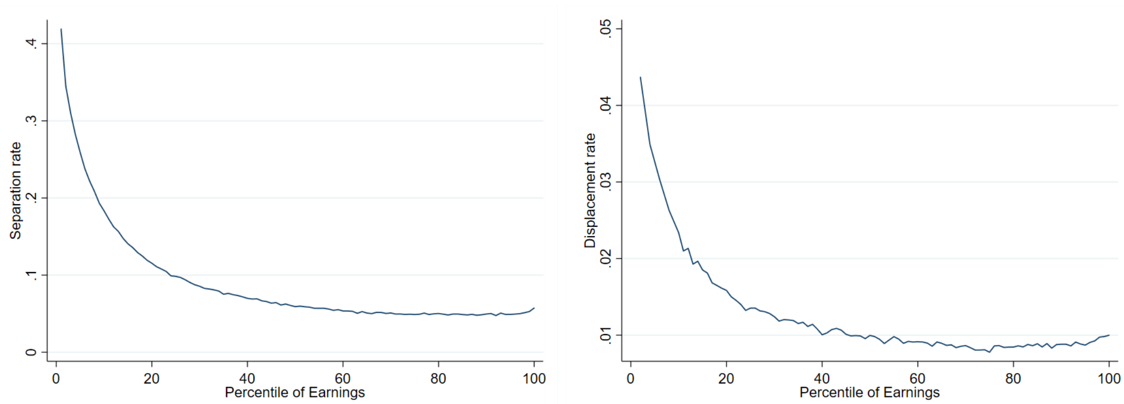


Figure 4: *The incidence of separation (left) and displacement (right) over the earnings distribution.*

As shown in figure 4, the separation and displacement rates in general tend 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 (2021), and therefore seems to support his idea of a job ladder with slippery bottom rungs (which I will use in my model in section 4 as well). However, it should be noted that the pattern in the data is not quite monotonic throughout the distribution: above the 80th percentile of the distribution, the displacement rates are slightly increasing again.

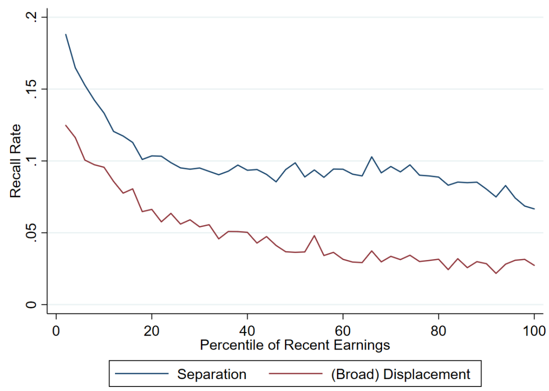
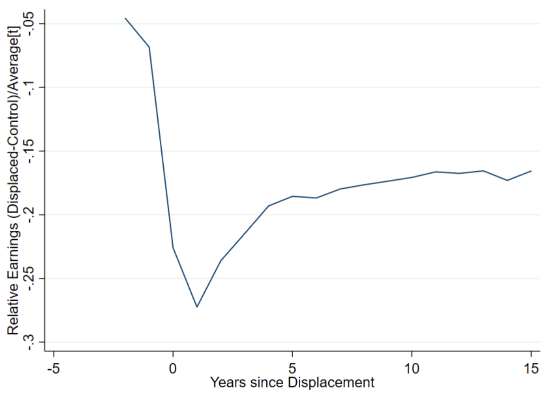


Figure 5: *The incidence of recall within 5 years of separation or displacement, by percentile of the recent earnings distribution.*

Figure 5 shows the incidence of recall (within 5 years) after separation or displacement over the recent earnings distribution. Not surprisingly, the incidence of recall is especially high for separation, but even for displacement (which notably also includes establishment closures) the recall rate is consistently above 2.5% across the recent earnings distribution, and much higher towards the bottom of the distribution. This indicates that while recall is more prevalent for low earning workers, it is not a phenomenon exclusive to these workers. The recall rate itself 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 (as shown in the analysis below), it is important to consider these workers separately.

While the above analysis has stressed some of the different worker characteristics that are associated with different rates of job loss that will appear throughout the remainder of the empirical section as well as in the model, it is likely that job loss rates also differ by other worker characteristics or establishment characteristics. In appendix D.3.1, I further discuss the incidence of separation and displacement along some other dimensions of interest, whereas appendix D.3.2 discusses what happens to the displacement and separation rates if the sample is restricted in the same way as I restrict the sample for the estimation in the next sections and appendix D.3.3 shows incidence rates using the LIAB dataset.

3.2 The average scarring effect of job loss



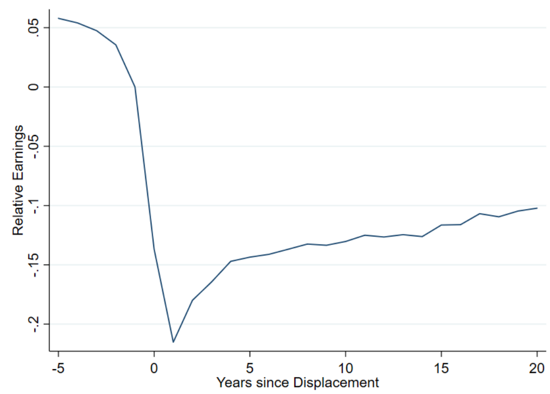


Figure 6: *Raw (left) or regression-based (right, using specification 1) average effect of displacement on earnings, relative to the control group.*

Having investigated the incidence of job loss across the sample, I will now move towards assessing the effects of displacement on earnings.[30] Before moving to the results of estimating equation (1), however, it is worth looking at the raw earnings differences first. The left panel of figure 6 presents these raw earnings differences. The differences shown in the graph 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. Further, it is worth noting that while there is some recovery over time, earnings remain substantially lower for the treatment group 10 to 15 years after the job loss event.

Of course, the raw comparison of earnings between displaced and non-displaced 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 displacement, 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. The right panel of figure 6 shows the results of estimating equation (1), again defining the treatment as displacement. In particular, it can be seen that in the short-run, workers who are

[30]The results presented here focus on displacement only. As shown in appendix D.3.4, the results continue to hold if I focus on separation instead.

displaced lose roughly 20% of their earnings.[31] This earnings loss is shown to be quite persistent, with these displaced workers still earning 10% less 20 years after the job loss took place.[32] These conclusions are in line with what has been observed in the literature, and confirm the large average scarring effect of displacement on earnings. If anything, these conclusions are relatively low compared to what is found in the literature. This could be partially due to some conservative assumptions I make in restricting the sample used in the estimation. In appendix D.3.4, I consider a few alternative estimations in which I relax some of these assumptions, thereby resulting in a slightly larger estimated earnings loss, especially in the short run.

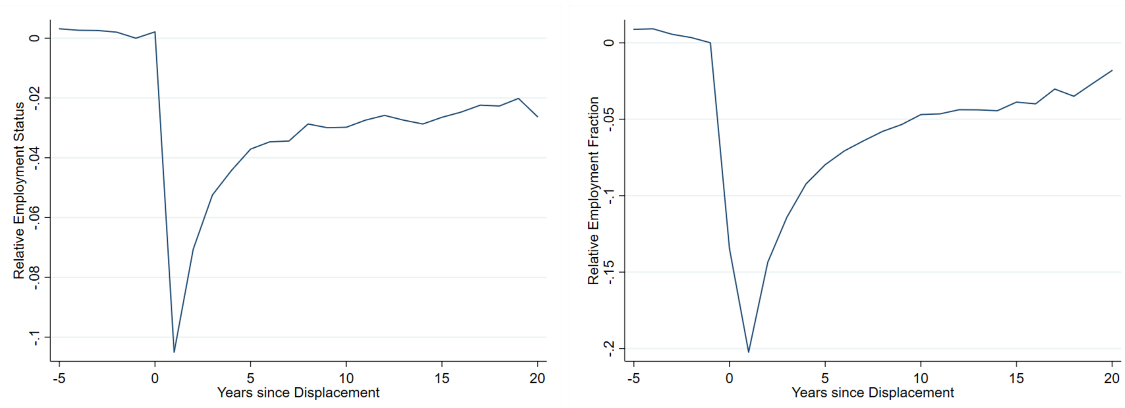


Figure 7: *The effect of displacement on employment status (left) and employment fraction (right), relative to the control group, using estimated coefficients from equation 1.*

As figure 7 shows, the employment status of the displaced workers recovers much faster than earnings (though it does not recover completely), thus suggesting that a large proportion of the earnings loss may be explained by wages and intensive margin employment choices (working hours).[33] In particular, while the likelihood of being employed (at any point in the year) drops by 10% in the year after displacement, this likelihood decrease recovers to roughly 5% after only 3 years, and

[31] To be more precise, the numbers in the graph should be interpreted as earnings loss relative to the expected earnings the worker would have followed if they would not have been displaced (which is based on the trend of the control group). Since this trend is generally positive, the absolute earnings loss is likely larger than indicated in the graph.

[32] It should also be noted that the earnings start declining before the job loss actually takes place. This so-called decline appears in many of my estimates using specification (1), including those where I restrict workers in the control group to those who were working in the same establishments as the treated workers. As pointed out later in this section, some of this could be explained by anticipation, or a so-called "Ashenfelter's dip", but for earlier years this is more likely to be a result of contamination by other cohorts and years.

[33] 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 the long-term earnings loss is mostly explained by wages.

further recovers to roughly 3% in less than 10 years. If I look at the fraction of the year in which the worker is employed, as done in the right panel of figure 7, a similar picture arises, though it should be noted that the effect of displacement here seems stronger and more persistent. This can be explained by the observation that these displaced workers are more likely (than the control group) to be separated from their job in subsequent years as well, as illustrated by Jarosch (2021).

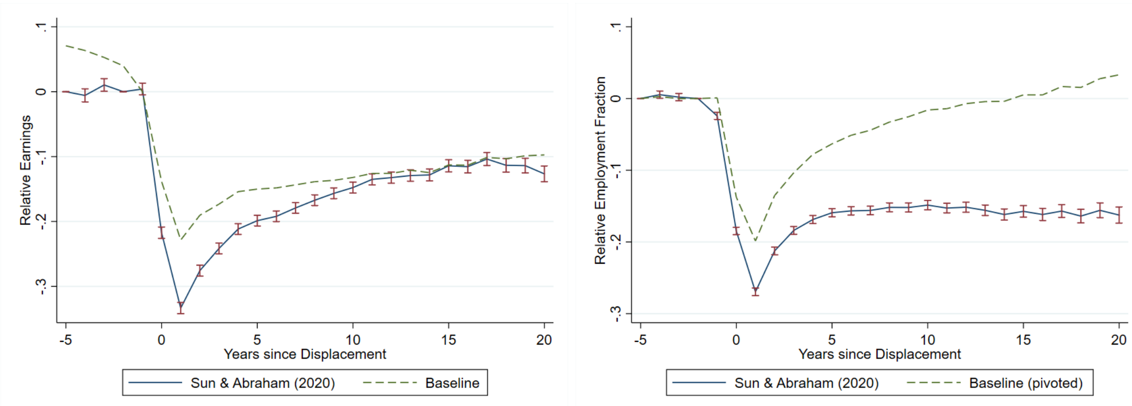


Figure 8: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group, using estimated coefficients from equation 2 (solid) or 1' (dashed). The error bars on the solid line correspond to 95% pointwise confidence intervals*

Finally, figure 8 shows how estimates of the average scarring effect of displacement on earnings and employment (fraction of the year employed) change when instead using the interaction-weighted estimator from Sun and Abraham (2020), as described in section 2. Comparing the estimates using that method to those obtained using equation (1'), included as dashed lines in the figures, reveals that the impact is especially large when it comes to employment. As seen in the right panel of the figure, the estimates of the long-run effect are quite different: while the estimation of equation (1') suggests that employment fully recovers after roughly 15 years, the interaction-weighted estimator reveals that the recovery stagnates after roughly 5 years, and employment remains roughly 15% below that of the control group. This is quite a striking difference, and seems to suggest a larger role for employment in explaining the long-run effects of displacement than traditionally proposed in the literature.

When it comes to earnings, the left panel shows that the differences between the two estimators are mainly visible in the short run and before the event time. Especially the changed estimate in the years prior to displacement is encouraging, as it suggests that the pre-trend that is visible when estimating equations (1) and (1') may not be a genuine pre-trend, but rather an artifact of contamination by other cohorts and time periods, as discussed in section 2.

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) or (2) 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 two dimensions in particular, which inform the setup of the model: 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. In appendix D.3.6, I show that the results presented below are robust to considering some of these other characteristics.[34]

3.3.1 Education Level

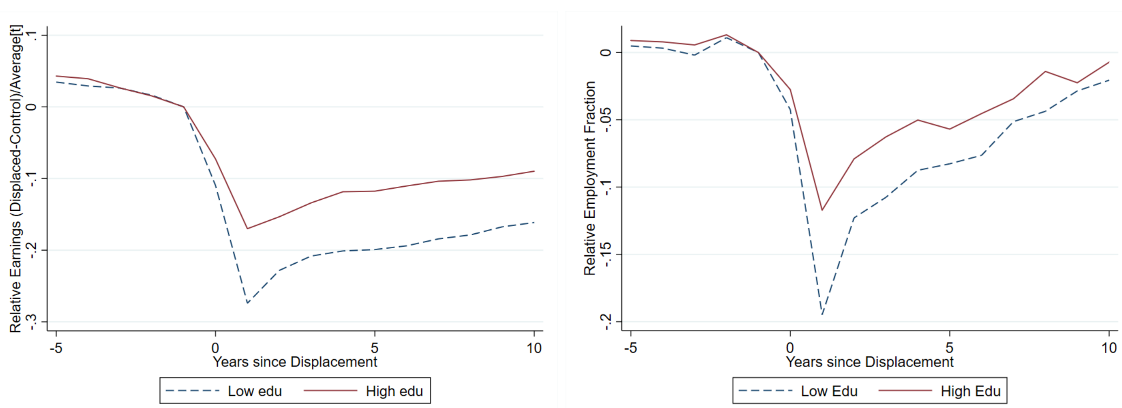


Figure 9: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group (by education group), using LIAB*

One factor that one might argue to be important for an individual's earnings loss after displacement is the individual's educational background. In figure 9, I plot the results of the esti-

[34]For some of these characteristics, I have also generated results similar to the ones presented below. These are omitted (but are available upon request), as they do not inform the remainder of this paper

mation when splitting the sample by education (non-University and University).[35] 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 (and long-run) effect on employment status, which indicates that workers with a high education level find a new job faster (on average). Indeed, comparing the two figures reveals that the recovery in the first few years following displacement is slightly faster for workers with a lower education, although this faster initial recovery only makes a minor difference for the differences between the two education groups in the long run.

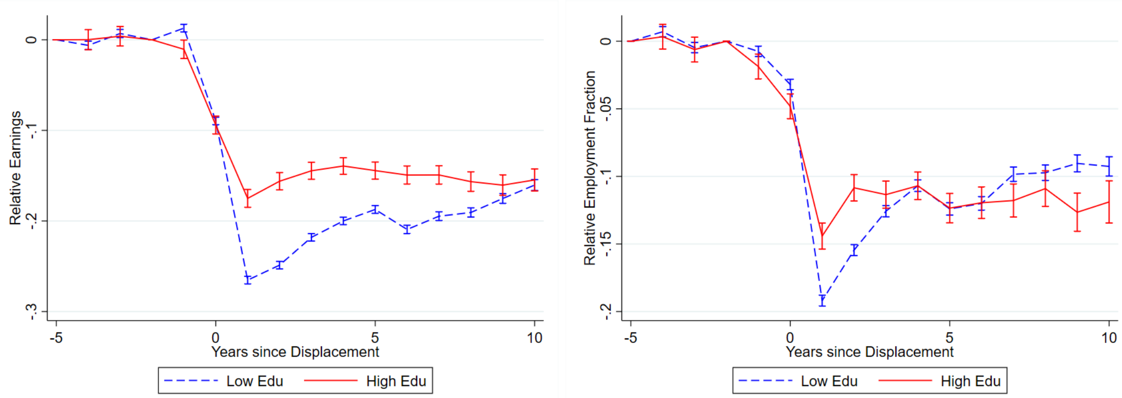


Figure 10: *The effect of displacement on earnings (left) and employment fraction (right) by education level, relative to the control group, using estimated coefficients from equation 2. The error bars correspond to 95% pointwise confidence intervals.*

In figure 10, I show the results obtained by using the interaction-weighted estimator from specification (2) instead. As can be seen, it still holds that the worker with a lower education level experiences higher earnings losses in the short run, but the two groups slowly converge and have roughly equal earnings losses 10 years after the displacement event. In terms of employment, the results are quite different from those in figure 9: while workers with a lower education level still do worse in the short run, they exhibit some recovery over time, while the figure does not reveal much recovery for the highly educated workers. Indeed, 10 years after the displacement event, the worker with the lower education level seems to be doing better in terms of employment.

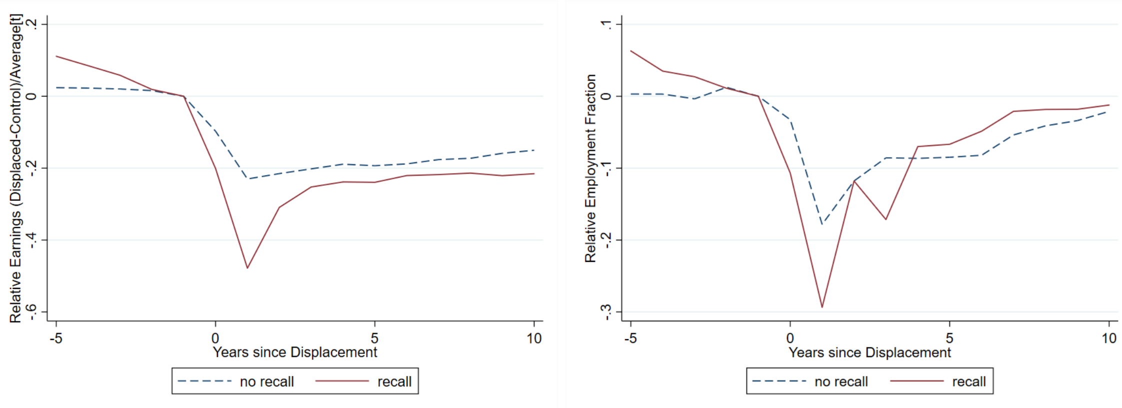


Figure 11: *The effect of displacement on earnings (left) and employment fraction (right) relative to the control group, by ex-post recall status (materialization of recall within 5 years), using estimated coefficients from equation 1 and using data from LIAB.*

3.3.2 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 events where the establishment closes down, but for displacement in general a non-negligible fraction of workers ends up returning to their former employer, as shown in figures 3 and 5. In figure 11, I show how the effects of displacement on employment and earnings differs by ex-post recall status.[36] As can be seen in the figure, workers who are recalled suffer from larger earnings losses, and do worse in the short run when it comes to days employed in the year.[37] As shown in figure 12, this result continues to hold when using the interaction-weighted estimator from specification (2), although the difference between recalled and non-recalled in the short run is slightly smaller and once again the apparent pretrends (especially visible for recalled workers in figure 11) disappear. This result seems quite surprising at first, especially given observations in the literature that recalled workers tend to be re-employed faster.

Figure 13 provides a first step towards an explanation. As can be seen in the figure, recalled workers

[35] Note that I split the sample by education group for both the treatment and control group. In other words, the effects in figure 9 are relative to workers in the same education group. In appendix D.3.6, I show that the results still hold if I don't restrict the control group to have the same education level.

[36] 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.

[37] As shown in appendix D.3.6, recalled workers do better in the short run when considering a binary indicator of employment "at any time during the year".

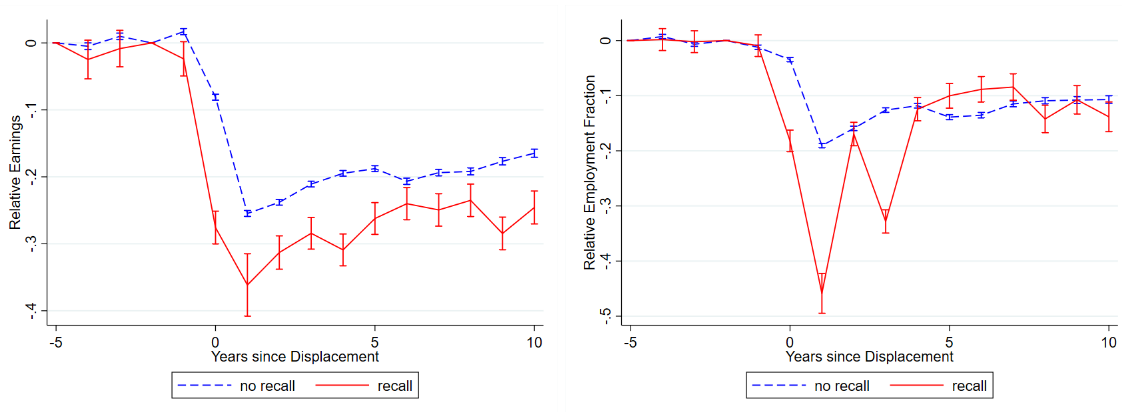


Figure 12: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status, relative to the control group, using estimated coefficients from equation 2 and using data from LIAB. The error bars correspond to 95% pointwise confidence intervals.*

are much more likely to be separated again shortly after being recalled: while non-recalled workers are roughly 18 percentage points more likely to be separated than the control group one year after their initial displacement, recalled workers are more than 30 percentage points more likely to be separated again (compared to the control group). Thus, while recalled workers generally are re-employed faster after their initial displacement, they are also very likely to be separated again shortly, thus leading to less days worked in the year overall. This seems to indicate that workers who are recalled return to an unstable firm, and I will use this insight in the next section to inform the setup of the model. Note that the result strengthens when I allow the estimation to also use workers who are displaced more than once according to my definition (i.e. they are displaced from high-tenure positions more than once), as shown in the right panel of figure 13. This is also the case for the results on earnings and employment fraction, as illustrated in appendix D.3.6.

As the left panel of figure 14 shows, the observation that recalled workers do worse in terms of earnings after displacement holds across the education levels considered earlier. However, it is worth noting that the difference in earnings loss between recalled and non-recalled workers is larger for the high education group. This is primarily because the non-recall group does better for the highly educated workers, consistent with the observations made in figure 9, although it can also be observed that the recall group for highly educated workers does slightly worse. Note that these differences do not arise when looking at the fraction of the years spent in employment, as shown in the right panel of the figure. Here, it can be seen that non-recalled workers with a low education level do slightly worse than their highly educated counterparts, but overall the comparison between recalled and non-recalled workers looks fairly similar for the two education levels.

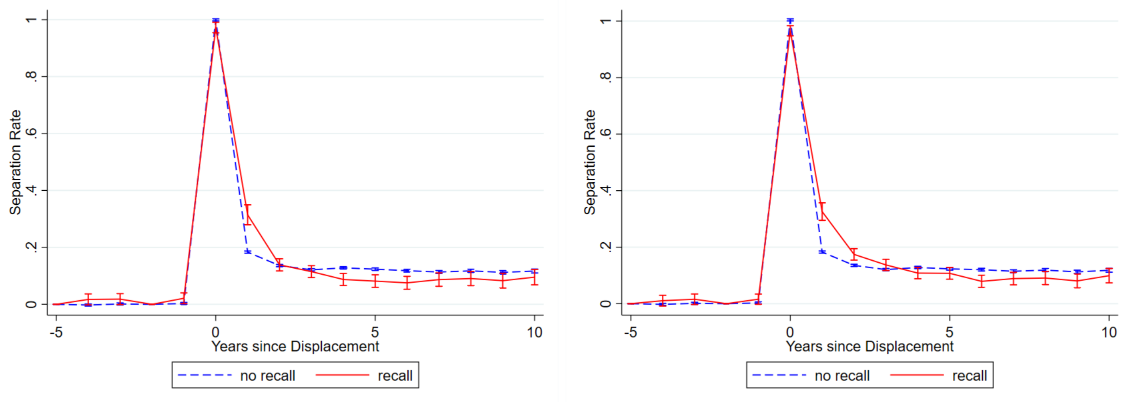


Figure 13: *The effect of displacement on separation rates by ex-post recall status, relative to the control group, using estimated coefficients from equation 2 and using data from LIAB. The error bars correspond to 95% pointwise confidence intervals. Left: estimation allowing for only one displacement per individual; Right: estimation allowing for multiple displacements per individual (classifying the worker according to their first displacement).*

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.[38] Further, the model explicitly features 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 $\theta = [y, \delta]$. 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 proba-

[38] In particular, the model resembles Jarosch (2021) 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 explicitly featured in the model.

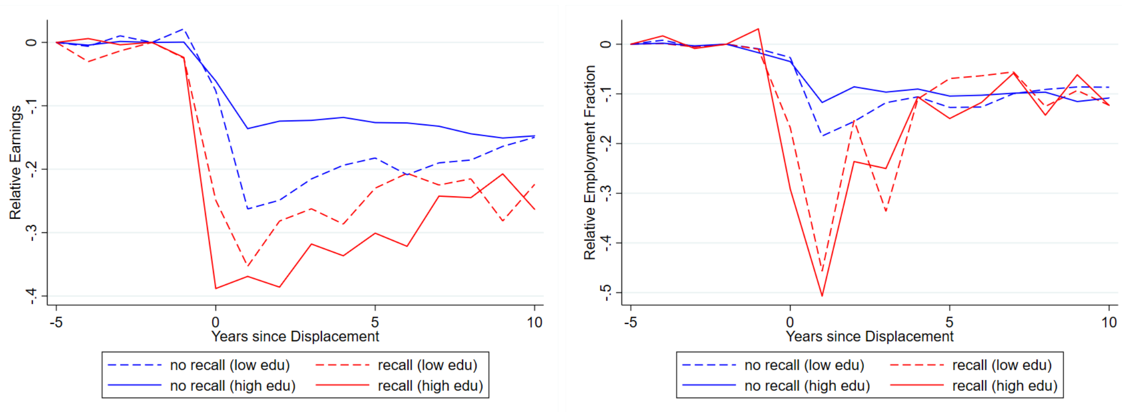


Figure 14: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status and education level, relative to the control group, using estimated coefficients from equation 2 and using data from LIAB. The error bars corresponding to 95% pointwise confidence intervals are omitted and available upon request.*

bility 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.[39]

4.1.1 Firms

Each firm can hire at most one worker.[40] 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 $(1 - \phi_\varepsilon^f)$ the destruction shock is permanent, in which case the worker and firm return to an unmatched and unemployed status. However, with probability ϕ_ε^f the job destruction is potentially only temporary and the worker can choose to wait to be recalled.[41] 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). Furthermore, the separation rate attached to the firm (and therefore to the match) is increased by c^δ. The intuition behind the recall productivity penalty is that the firm is likely to incur costs for firing and re-hiring the worker

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

[40]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.

[41]With probability ϕ_ε^{rg}, this recall takes place in the same model period as the initial displacement.

as well as possible restructuring to survive the circumstances that lead to the layoff in the first place, which it will prefer to earn back (e.g. by lowering the worker's wage).[42] Furthermore, it can be seen in the data that recalled workers are more likely to be separated again within a year of being re-employed, thus reflecting that the worker returns to an unstable firm. The penalty on the separation rate aims to reflect this directly. 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 and/or workers who are still in school. An unemployed worker meets a firm with probability λ^u_ε, and this firm is drawn from the distribution $G_\varepsilon(\theta)$, where ε changes 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.[43] 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 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.[44] 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

[42] 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.

[43] 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.

[44] 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^u_ε and λ^e_ε, such that the unemployed worker accepts any job offer as in the model in Bagger et al. (2014).

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.[45] 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, upon 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). 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.[46] The worker is recalled to her previous match with probability ϕ_ε^r every period. When the recall materializes, the wage is re-determined as if the worker is using the value of unemployment as the outside option, and the firm characteristics change as described in subsection 4.1.1.[47] Furthermore, I allow the worker coming back from recall to face a slightly different wage setting process, as described in the next subsection. If the worker is not recalled, she meets a new employer with probability $\lambda^r\lambda_\varepsilon^u$, where λ^r is expected to be below 1 (but not restricted as such). If the worker meets a new employer, this employer is again drawn from distribution $G_\varepsilon(\theta)$, and the worker can decide whether to accept the offer (leading to a wage w). Finally, if the worker does not get recalled and also does not meet a new firm (or rejects the offer from the new firm), she can decide to give up the wait and move to the state of unemployment.

[45] Additionally, a separated worker who moves into unemployment (regardless of whether this is by choice or not) finds a new job in the same period with probability λ_ε^{rg}.

[46] 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).

[47] The loss of the outside option is a simplifying assumption, but also seems justified by the fact that the worker did not exercise this outside option upon being displaced, so that the firm may no longer consider this outside option to be credible.

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}:

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

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 ($\hat{s}$).[48] Note that equation (3) can take four distinct forms. First, if the worker is coming out of (non-temporary) unemployment, 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 (3) can be rewritten as equation (4).

$$W_\varepsilon(s, s, x, u) = U_\varepsilon(s) + \kappa \left(W_\varepsilon^{max}(s, x) - U_\varepsilon(s)\right) \tag{4}$$
$$W_\varepsilon(s, s, \theta, x) = W_\varepsilon^{max}(s, x) + \kappa \left(W_\varepsilon^{max}(s, \theta) - W_\varepsilon^{max}(s, x)\right) \tag{5}$$
$$W_\varepsilon(s, s, x, \theta) = W_\varepsilon^{max}(s, \theta) + \kappa \left(W_\varepsilon^{max}(s, x) - W_\varepsilon^{max}(s, \theta)\right) \tag{6}$$
$$W_\varepsilon(s, s, \theta, r) = \max\{U_\varepsilon(s), F_\varepsilon(s, \theta)\} + \kappa^r \left(W_\varepsilon^{max}(s, \theta') - \max\{U_\varepsilon(s), F_\varepsilon(s, \theta)\}\right) \tag{7}$$

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

[48] 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 (3) to (6) I set $\hat{s} = s$.

her previous job, $W_\varepsilon^{max}(s,\theta)$, so that equation (3) can be rewritten as equation (5). If the worker is using a job offer from a firm with characteristics x to extract more value from her current employer, the outside option W^{oo} equals the maximum surplus that could have been obtained from this job offer, $W^{max}(s,x)$, and equation (3) can be rewritten as equation (6). Finally, if the worker is being recalled, the determination of the worker's surplus is very similar to that of a worker being hired from unemployment (equation 4), but the recalled worker uses a different bargaining weight κ^r, and uses the maximum of the value of unemployment $U(s)$ and the value of waiting for recall, $F(s,\theta)$, thus reflecting that upon rejecting the offer, the worker can choose to continue waiting for recall or move to unemployment.[49] Furthermore, since the maximum value obtained from the match changed due to the penalties on production and separation rate

4.2 Timing and Value Functions

To summarize the setup of the model, every model period can be divided into 4 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.[50] Then, in the third stage, workers who started the period as unemployed or employed (and are still in that state) or chose to move into unemployment 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:

$$\begin{aligned} U_\varepsilon(s) = \ln(b_\varepsilon(s)) + \beta \mathbb{E}_{s'|s,u,\varepsilon} \Bigg\{ & \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^u(s')} W_\varepsilon(s', s', x, u) dG_\varepsilon(x) \\ & + \left(1 - \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^u(s')} dG_\varepsilon(x)\right) U_\varepsilon(s') \Bigg\} \end{aligned} \tag{8}$$

[49]The value of the recalled worker's bargaining weight, κ^r, is expected to be lower than that of other workers (κ), reflecting that this worker may not be able or willing to find a different employer and thus does not have a very strong bargaining position when entering wage bargaining with the recalling firm. This may strengthen the negative effect of losing the outside offer.

[50]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.

Here, the set $\Theta^u_\varepsilon(s)$ 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 (4), this set can be specified as $\Theta^u_\varepsilon(s) = \{x \in [0,1] \times \mathbb{R}_+ : W^{max}_\varepsilon(s,x) \geq U_\varepsilon(s)\}$.

As shown in appendix B, equation (8) can be rewritten in terms of W^{max}, U, and parameters only:

$$U_\varepsilon(s) = \ln(b_\varepsilon(s)) + \beta \mathbb{E}_{s'|s,u,\varepsilon} \left\{ \lambda^u_\varepsilon \int_{x \in \Theta^u_\varepsilon(s')} \kappa \left(W^{max}_\varepsilon(s',x) - U_\varepsilon(s') \right) dG_\varepsilon(x) + U_\varepsilon(s') \right\} \tag{9}$$

Similarly, the value function F for a worker of type ε with human capital s, waiting to be recalled to a firm of type $\theta = [\delta, y]$, is as follows:

$$\begin{aligned} F_\varepsilon(s,\theta) = \ln(b_\varepsilon(s)) + \beta \mathbb{E}_{s'|s,r,\varepsilon} \Bigg\{ & \phi^r_\varepsilon W_\varepsilon(s',s',\theta',r) + (1-\phi^r_\varepsilon)\lambda^r_\varepsilon \int_{x \in \Theta^r_\varepsilon(s',\theta)} W_\varepsilon(s',s',x,f) dG_\varepsilon(x) \\ & +(1-\phi^r_\varepsilon) \left(1 - \lambda^r_\varepsilon \int_{x \in \Theta^r_\varepsilon(s',\theta)} dG_\varepsilon(x) \right) \max\{F_\varepsilon(s',\theta), U_\varepsilon(s')\} \Bigg\} \end{aligned} \tag{10}$$

Here, $W_\varepsilon(s',s',\theta',r)$ is as defined above, and $W_\varepsilon(s',s',x,f)$ denotes that a worker finding a new job while waiting to be recalled may use either the value of unemployment or the value of waiting for recall as their outside option, thereby also allowing for the set of accepted offers $\Theta^r_\varepsilon(s',\theta)$ to be slightly different from the corresponding set for an unemployed worker ($\Theta^u_\varepsilon(s')$). 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 $\delta' = \delta + c^\delta$ and 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 equations (4) and (7):

$$\begin{aligned} F_\varepsilon(s,\theta) = \ln(b_\varepsilon(s)) + \beta \mathbb{E}_{s'|s,r,\varepsilon} \Bigg\{ & \phi^r_\varepsilon \kappa^r W^{max}_\varepsilon(s',\theta') + \phi^r_\varepsilon(1-\kappa^r) \max\{F_\varepsilon(s',\theta), U_\varepsilon(s')\} \\ & +(1-\phi^r_\varepsilon) \left(\lambda^r \int_{x \in \Theta^r_\varepsilon(s',\theta)} \kappa \left(W^{max}_\varepsilon(s',x) - \max\{F_\varepsilon(s',\theta), U_\varepsilon(s')\} \right) dG_\varepsilon(x) + \max\{F_\varepsilon(s',\theta), U_\varepsilon(s')\} \right) \Bigg\} \end{aligned} \tag{11}$$

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

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

Here, I denote by $\hat{s}$ the value of human capital at the time of the most recent bargaining. Similarly, $\hat{\theta} \in \{[0,1]\times\mathbb{R}_+, u, r, f\}$ represents the firm characteristics corresponding to the job offer that was used for bargaining.[51] 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 (5) and (6), 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 $\Theta^2_\varepsilon(s,\theta) = \{x \in [0,1]\times\mathbb{R}_+ : W^{max}_\varepsilon(s,\theta) > W^{max}_\varepsilon(s,x) \geq W^{max}_\varepsilon(\hat{s},\hat{\theta})\}$.[52] Note that the values $\hat{F}$ and $\hat{U}$ correspond to the value of a newly separated worker who chose to either wait to be recalled or move into unemployment. These values relate to value functions (11) and (9) above as follows:

$$\hat{F}_\varepsilon(s',\theta) = \phi^{rg}_\varepsilon W_\varepsilon(s',s',\theta',r) + (1-\phi^{rg}_\varepsilon)F_\varepsilon(s',\theta) \tag{13}$$

$$\hat{U}_\varepsilon(s') = \lambda^{ug}_\varepsilon \int_{x\in\Theta^u_\varepsilon(s')} W_\varepsilon(s',s',x,u)dG_\varepsilon(x) + \left(1-\lambda^{ug}_\varepsilon\int_{x\in\Theta^u_\varepsilon(s')} dG_\varepsilon(x)\right)U_\varepsilon(s') \tag{14}$$

Using equation (12), 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.3, no longer depends on the bargaining benchmark, as the outcome of the bargaining (which is the piece-rate)

[51] 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 $\hat{\theta} = u$. Similarly, I denote the setting for workers being recalled as $\hat{\theta} = r$ and workers finding a new job while waiting to be recalled as $\hat{\theta} = f$.

[52] 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.

is already known:

$$W_{\varepsilon}^{max}(s,\theta) = \ln(p(s,y)) + \beta \mathbb{E}_{s'|s,e,\varepsilon}\left\{\delta\left[\phi_{\varepsilon}^{f}\max\left\{\hat{F}_{\varepsilon}(s',\theta),\hat{U}_{\varepsilon}(s')\right\} + (1-\phi_{\varepsilon}^{f})\hat{U}_{\varepsilon}(s')\right]\right.$$
$$\left. +(1-\delta)\left[\lambda_{\varepsilon}^{e}\int_{x\in\Theta_{\varepsilon}^{1}(s',\theta)}\kappa\left(W_{\varepsilon}^{max}(s',x) - W_{\varepsilon}^{max}(s',\theta)\right)dG_{\varepsilon}(x) + W_{\varepsilon}^{max}(s',\theta)\right]\right\} \tag{15}$$

On the firm side, one could also set up a value function of a producing firm. However, since the above equations are sufficient to solve the model (for a given set of parameters), these value functions as well as the flow equations are deferred to the appendix (see appendix B.1 and B.2).

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 (4) to (7), the value functions and the piece-rate function satisfy equations (8) to (15) and equation (B.7), and the distribution of workers across different states evolves according to equations (B.10) to (B.15).

4.4 A Social Planner's Problem

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 previous subsection. For this purpose, I will assume that the social planner maximizes the present discounted utility value of output. 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 0.

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:

$$Y_{\varepsilon}^{P}(s,\theta) = \ln(p(s,y)) + \beta \mathbb{E}_{s'|s,e,\varepsilon}\left\{\delta\left[\phi_{\varepsilon}^{f}\max\left\{\hat{F}_{\varepsilon}^{P}(s',\theta),\hat{U}_{\varepsilon}^{P}(s')\right\} + (1-\phi_{\varepsilon}^{f})\hat{U}_{\varepsilon}^{P}(s')\right]\right.$$
$$\left. +(1-\delta)\left[\lambda_{\varepsilon}^{e}\int_{x\in\Theta_{\varepsilon}^{1,P}(s',\theta)}\left(Y_{\varepsilon}^{P}(s',x) - Y_{\varepsilon}^{P}(s',\theta)\right)dG_{\varepsilon}(x) + Y_{\varepsilon}^{P}(s',\theta)\right]\right\} \tag{16}$$

$$U_{\varepsilon}^{P}(s) = \beta \mathbb{E}_{s'|s,u,\varepsilon}\left\{\lambda_{\varepsilon}^{u}\int_{x\in\Theta_{\varepsilon}^{u,P}(s')}\left(Y_{\varepsilon}^{P}(s',x) - U_{\varepsilon}^{P}(s')\right)dG_{\varepsilon}(x) + U_{\varepsilon}^{P}(s')\right\} \tag{17}$$

$$F_\varepsilon^P(s,\theta) = \beta \mathbb{E}_{s'|s,r,\varepsilon} \left\{ (1-\phi_\varepsilon^r) \left(\lambda^r \int_{x\in\Theta_\varepsilon^{r,P}(s',\theta)} \left(Y_\varepsilon^P(s',x) - \max\left\{F_\varepsilon(s',\theta), U_\varepsilon(s')\right\} \right) dG_\varepsilon(x) \right.\right.$$
$$\left.\left. + \max\left\{F_\varepsilon^P(s',\theta), U_\varepsilon^P(s')\right\} \right) + \phi_\varepsilon^r Y_\varepsilon^P(s',\theta') \right\} \tag{18}$$

where

$$\hat{F}_\varepsilon^P(s',\theta) = \phi_\varepsilon^{rg} Y_\varepsilon^P(s',\theta') + (1-\phi_\varepsilon^{rg}) F_\varepsilon^P(s',\theta)$$
$$\hat{U}_\varepsilon^P(s') = \lambda_\varepsilon^{ug} \int_{x\in\Theta_\varepsilon^{u,P}(s')} Y_\varepsilon^P(s',x) dG_\varepsilon(x) + \left(1 - \lambda_\varepsilon^{ug} \int_{x\in\Theta_\varepsilon^{u,P}(s')} dG_\varepsilon(x)\right) U_\varepsilon^P(s')$$

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, $\max\{F_\varepsilon^P(s',\theta), U_\varepsilon^P(s')\}$ ($\max\{\hat{F}_\varepsilon^P(s',\theta), \hat{U}_\varepsilon^P(s')\}$ when coming from employment), and the three objects $\Theta_\varepsilon^{1,P}(s,\theta)$, $\Theta_\varepsilon^{r,P}(s,\theta)$ 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 or recently worked at an establishment with characteristics θ, in the case of $\Theta^{1,P}$ and $\Theta^{r,P}$) should accept according to the social planner.

When assessing the efficiency properties of the model, I compare the three value functions above (equations 16 to 18) to the corresponding value functions (15), (9), and (11). Comparing those equations, it can be observed that the equations are equivalent if $\kappa = \kappa^r = 1$ and $b = 0$. In other words, the objects $\Theta_\varepsilon^{1,P}(s,\theta)$, $\Theta_\varepsilon^{r,P}(s)$and $\Theta_\varepsilon^{u,P}(s)$ will be identical to their equivalents $\Theta_\varepsilon^1(s,\theta)$, $\Theta_\varepsilon^r(s)$ and $\Theta_\varepsilon^u(s)$ and the worker will make the same choice about waiting for recall if the worker receives the full value of the match and furthermore receives no value from being nonemployed. If this is not the case, the worker will not fully internalize the value of the output produced by the match and/or overvalue the nonemployment states. Of course, the extent to which this creates inefficiencies depends on the values of these parameters κ, κ^r, and b, as well as other parameters. In section 6.2, I will show how different worker and 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 $\mu_{\delta,\varepsilon}$, reshaped to the $[0, 0.25]$ interval (rather than $[0, 1]$, whereas the marginal distribution of y is a Pareto distribution with shape parameters $\mu_{y,\varepsilon}$ and η_y. I then follow Jarosch (2021) 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 35 parameters that need to be identified. Of these 35 parameters, I will set 7 parameters exogenously, leaving the remaining 28 parameters to be estimated using the indirect inference method from Gourieroux et al. (1993).[53] In the next two subsections, I describe how I set the 7 exogenous parameters, and which moments I use to identify the remaining 28 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 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 ($\Delta_s(1)$). Finally, I choose to set the probability of being recalled in the same period as being displaced to 0. In other words, I assume that workers who are displaced will not be recalled in the same quarter. This is a fairly strong assumption, made to simplify the estimation of the model. In appendix C, I show how the calibration changes if I allow this probablity to be strictly positive. Table 3 summarizes the values of the exogenously set parameters, and the sources used to set these values.

[53]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.

Parameter	Meaning
β	discount factor
ϵ_ε	distribution of worker types ε
κ	worker's bargaining power
κ_r	worker's bargaining power upon recall
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 relative to non-employment
s_ε	starting value of human capital
$\Delta_s(\varepsilon)$	human capital transition size
$\mu_{\delta,\varepsilon}$	1st shape parameter, marginal distribution of δ
η_δ	2nd shape parameter, marginal distribution of δ
η_y	shape parameter, marginal distribution of y
$\mu_{y,\varepsilon}$	scale parameters, marginal distribution of y
ρ	copula parameter
λ^u_ε	meeting probabilities, unemployed workers
λ^r	relative meeting probability, workers waiting for recall
λ^{ug}_ε	meeting probabilities, newly unemployed workers
λ^e_ε	meeting probabilities, employed workers
ϕ^f_ε	probability of recall
ϕ^r_ε	recall materialization probability
ϕ^{rg}_ε	immediate recall materialization probability
c^f	production penalty of recall
c^δ	stability penalty of recall

Table 2: *A summary of all parameters in the model to be set exogenously or to be calibrated. Note that any notation with a subscript ε represents two parameters: one for each worker type ε.*

5.2 Calibration Moments

Using that I interpret ε to correspond to education levels, I next identify 43 moments that together identify the values of the 28 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 six groups, and I argue that each of these groups are identified by a corresponding group of moments.[54]

The first set of moments contains information on employment rates and transition rates from employment to non-employment, and these moments are used to calibrate parameters governing the marginal distribution of δ and the separation penalty of recall. To identify the second shape parameter of the marginal distribution of δ, η_δ (which is common across education levels), I

[54]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 that the main intuition behind the moments is clearer.

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
ϕ^{rg}_{ε}	0	No recall within a quarter of displacement

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

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 job loss rate (by education level). Finally, the subsequent separation rate after re-employment following a recall or a displacement (including those resulting in recalls) aids in identifying the separation penalty of recall.

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 the model generates these wage differences primarily through differences in productivity y and human capital s, these moments help to identify initial human capital levels for education level 2 (s_1 is normalized to 0) as well as the education-specific scale parameter $\mu_{y,\varepsilon}$ of the marginal distribution of y. The 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 third set of moments provides information regarding job finding probabilities, both on-the-job and from nonemployment. In particular, the job-to-job transition rate upon displacement (by education level) helps to identify the meeting probability for newly unemployed workers ($\lambda^{ug}_{\varepsilon}$), noting that a transition of such a worker to a new job will be observed as a job-to-job transition. The overall quarterly job-to-job transition rate (by education level) therefore also contributes to identifying this parameter, while also informing the value of the on-the-job meeting rate $\lambda^{e}_{\varepsilon}$. Similarly, the average job finding rates (by education level) closely correspond to the job finding rate of unemployed workers, $\lambda^{u}_{\varepsilon}$, while the average education-specific employment rate connects all these different flows into employment (as well as the flows out of unemployment from the first set of moments).

The next set of moments focuses on wage growth within and between job spells, thereby helping to identify human capital transition rates and steps, among others. The specific moments used here include the net replacement rate in unemployment, which closely relates to the parameter b included in the expression for the instantaneous value of non-employment $b(s)$.[55] 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 2 years). As laid out in appendix A.3, this moment closely resembles a difference-in-difference estimation. 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 and non-employment duration (0.25 to 0.5, and 0.5 to 1 year). These last two sets of moments also relate directly to the human capital step-size $\Delta_s(2)$ and therefore aid in their 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. Similarly, I can use information on the fraction of workers waiting for recall who find a new job instead to inform the probability of meeting a new employer, $\lambda^r \lambda^u_\varepsilon$, and in particular the parameter λ^r. [56]

The final group consists of all remaining parameters (κ, κ^r, 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)

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

[56] As explained in appendix A.3, this moment cannot be estimated from my data, so the data equivalent of this moment is based on results in Nekoei and Weber (2015). Analogously, I restrict the estimation in the model to workers waiting to be recalled who are re-employed within a year of displacement.

relative to the average wage to identify the bargaining power κ, and the average wage of a newly recalled worker (relative to the average wage) to identify the bargaining worker of the recalled worker κ^r. Finally, for the identification of the copula parameter ρ, I follow Jarosch (2021) in targeting the regression coefficient γ in the estimation equation (19) below:

$$D^{\delta}_{i,t} = \alpha_i + \gamma \log(w_{it}) + u_{i,t} \tag{19}$$

In equation (19), the variable $D^{\delta}_{i,t}$ is a dummy variable that is only filled if the worker i is employed in period t and still observed in period $t+1$. 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

The moments described above add up to a total of 43 moments used to identify 28 parameters. Further details of the procedure used to estimate these moments can be found in appendix A.3. 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 tenure profile of the separation rate. This could be interpreted as pointing towards the need for a model in which the duration dependence of job finding rates is explicitly modeled, rather than just following from composition effects (as in this model). Similarly, it can be observed that the model tends to exacerbate differences between education levels compared to the data. Given that many of the parameters are already education-specific, one might wonder whether it would be worth splitting some of the remaining parameters into education-specific parameters as well (especially the human capital transition probabilities). I leave this as a robustness exercise.

When looking at the parameter estimates in table 4, and comparing these with closely related models such as those calibrated in Jarosch (2021) and Gregory (2020), it can be seen that the parameters estimated in both models generally yield very comparable estimates.[57] In general, however, it can be said that a few values stand out. In particular, the estimated value for the worker's bargaining power, κ, is quite high. This is not particularly uncommon in models like the one proposed in this paper, and may be a consequence of the calibration attempting to

[57] One major exception to this is the on-the-job meeting probabilities, which are very close to (or equal to) 0 in my calibration. This difference can be explained by the fact that I allow for displaced workers to find a job in the same period as being displaced, and this happens with quite high probability, as indicated by the calibrated values of $\lambda^{ug}_{\varepsilon}$.

Description of Moment(s)	Data	Model	Parameters
Average rate of job loss, tenure 1-3.5y	0.0461	0.049	$\eta_\delta = 3.455$
Average rate of job loss, tenure 3.5-6y	0.0261	0.043	$\mu_{\delta,1} = 12.36$
Average rate of job loss, tenure 6-9y	0.0172	0.038	$\mu_{\delta,2} = 43.22$
Average rate of job loss, tenure>9y	0.0088	0.028	$c^\delta = 0.159$
Average rate of job loss, by education	0.0386	0.048	
	0.03	0.016	
Subsequent separation, displacement	0.1085	0.072	
Subsequent separation, recall	0.2042	0.18	
p75-p25 ratio of wages	1.7299	1.606	$\eta_y = 7.359$
	1.7056	1.739	$\mu_{y,1} = 1.634$
median-p25 ratio of wages	1.313	1.269	$\mu_{y,2} = 1.719$
	1.3088	1.307	$s_2 = 0.426$
Educational wage premium (all)	1.5301	1.552	
Educational wage premium (entry)	1.7144	1.714	
Job-to-job transition rate	0.0377	0.029	$\lambda_1^e = 0$
	0.0352	0.012	$\lambda_2^e = 0.0002$
Job-to-job transition upon displacement	0.6348	0.597	$\lambda_1^{ug} = 0.692$
	0.7558	0.747	$\lambda_2^{ug} = 0.801$
Average job finding rate	0.2583	0.19	$\lambda_1^u = 0.16$
	0.2596	0.227	$\lambda_2^u = 0.213$
Average employment rate	0.8533	0.911	
	0.8689	0.983	
Replacement rate	0.6	0.624	$b = 0.7$
Yearly wage growth	0.0458	0.008	$\Delta_s(2) = 0.19$
	0.0511	0.016	$\psi_e = 0.019$
Pre- to post-layoff wage, duration<0.5y	-0.0503	-0.032	$\psi_u = 0.291$
	0.0183	0.013	$\psi_r = 0.041$
Pre- to post-layoff wage, duration 0.5-1y	-0.1137	-0.136	$c^f = 0.426$
	-0.0599	-0.078	
Pre- to post-layoff wage, duration 1-2y	-0.1857	-0.229	
	-0.1543	-0.145	
Pre- to post-recall wage, duration 0.25-0.5y	-0.022	-0.04	
	-0.0187	-0.034	
Pre- to post-recall wage, duration 0.5-1y	-0.0322	-0.088	
	-0.0484	-0.05	
Recall rate	0.0725	0.097	$\phi_1^f = 0.138$
	0.052	0.048	$\phi_2^f = 0.157$
Recall materialization rate	0.3049	0.297	$\phi_1^r = 0.205$
	0.267	0.272	$\phi_2^r = 0.19$
New job finding rate among furloughed workers	0.2927	0.295	$\lambda^r = 0.762$
Wage of newly hired worker	0.5908	0.57	$\kappa = 0.883$
Wage of newly recalled worker	0.6106	0.681	$\kappa^r = 0.309$
Coefficient $\hat{\gamma}$ in equation (19)	-0.029	-0.029	$\rho = -15.77$

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

match in particular the measures of wage dispersion (the p75-p25 and median-p25 wage ratios) by alleviating the impact of changing outside options.[58] After all, 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 or gain of negotiation capital through on-the-job search. This also makes it more notable that the bargaining weight of a recalled worker is substantially lower, at 0.309, reflecting that omitting this distinction and allocating all workers with the same bargaining weight could lead to a substantial loss of explanatory power. I further explore this as a robustness exercise.

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. As this set of calibrated parameters implies that everyone chooses to wait for recall when offered to do so, this implies that the role of allowing workers to find new jobs despite waiting to be recalled is quite large, despite the meeting probability being only 76.2% of the corresponding meeting probabilities for unemployed workers (as illustrated by the value of λ^r). For a similar reason, it can be seen that 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. In general, it can be observed that the recalled worker is much less likely to lose human capital while waiting to be recalled, with a human capital depreciation rate ($\psi_r \psi_u$) that is only 4% of the depreciation rate in unemployment (ψ_u). However, the recall itself also comes with substantial negative consequences in addition to the aforementioned lower bargaining weight, in the form of a production penalty c^f (that is relatively mild) and a substantial penalty on the separation rate c^δ, which implies that after recall the worker's separation rate increases by almost 16 percentage points.

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, regardless of whether they are unemployed ($\lambda_1^u < \lambda_2^u$), newly unemployed ($\lambda_1^{ug} < \lambda_2^{ug}$), or employed ($\lambda_1^e < \lambda_2^e$). In fact, the on-the-job meeting probability for workers with a low education level is 0, indicating that the model generates all job-to-job transitions through immediate transition after displacement. However, compared to the worker with a low education level, a highly educated worker starts with a much lower level of human capital $s_2 = 0.426 < 1$ (which is more than five low education stepsizes lower than the starting level of a worker with a low education level, which was normalized to 1), although

[58] For comparison, Jarosch (2021) and Gregory (2020), who calibrate models that are fairly similar to the one I propose in this paper, find bargaining weights of 0.96 and 0.66 respectively.

they also experience a bigger change every time they are hit with an appreciation or depreciation shock $(\psi_e, \psi_u, \psi_r\psi_u)$, $\Delta_s(2) = 0.19 > 0.1$. When it comes to the firm distributions the workers

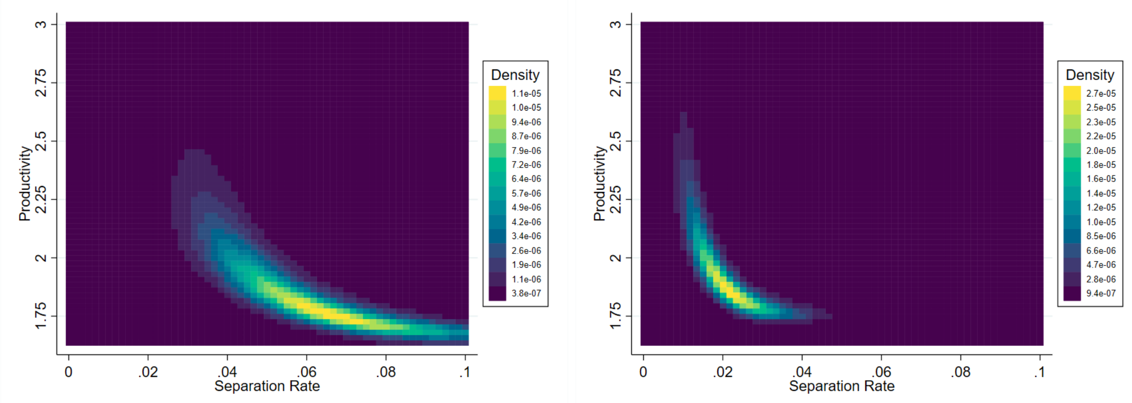


Figure 15: *The joint distribution of firm types faced by workers with a low education level (left) and a high education level (right).*

draw from upon receiving an offer, these are best illustrated in a diagram. Figure 15 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 slightly lower than that of the high 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 much 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

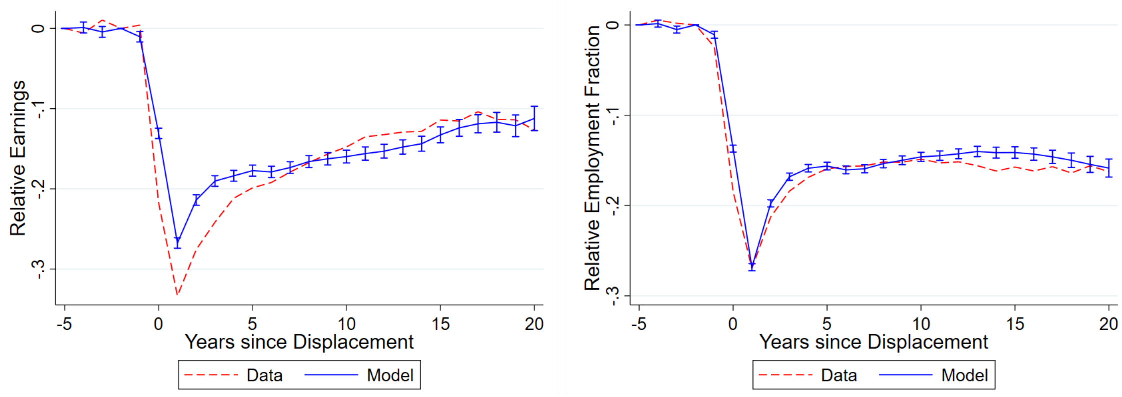


Figure 16: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right), relative to the control group, using model simulation data (solid) and using the data (dashed, corresponding to figure 8).*

Before moving to the dimensions of heterogeneity highlighted in section 3.3, figure 16 displays the average effect of displacement on earnings and employment status (defined as the fraction of the year spent in an employment spell). Just like in section 3.2, the effect is estimated by estimating equation (2), and thus the results can be compared to figure 8. For this purpose, I have included the results from figure 8 in figure 16 as dashed lines. Making this comparison, it can be seen that the average pattern is matched very well. One critical note that can be made here is that the model slightly undershoots the initial drop in earnings and its recovery levels off sooner in the model than in the data. The undershooting of the initial drop could be driven by aggregation in the model, where workers are either not non-employed at all or non-employed for exactly a number of quarters, whereas the data naturally allows for any unemployment duration. It is to be expected that the model will especially miss the lost earnings for workers who have a strictly positive nonemployment duration, but were non-employed for less than a quarter in the data. In the model, these workers are represented by a transition into a new employment spell without going through nonemployment. On the other hand, the model-generated scarring effect on earnings levelling off sooner is likely to be driven by the lack of on-the-job search in the calibrated model (with $\lambda_{\varepsilon}^{e}$ close to or equal to 0).

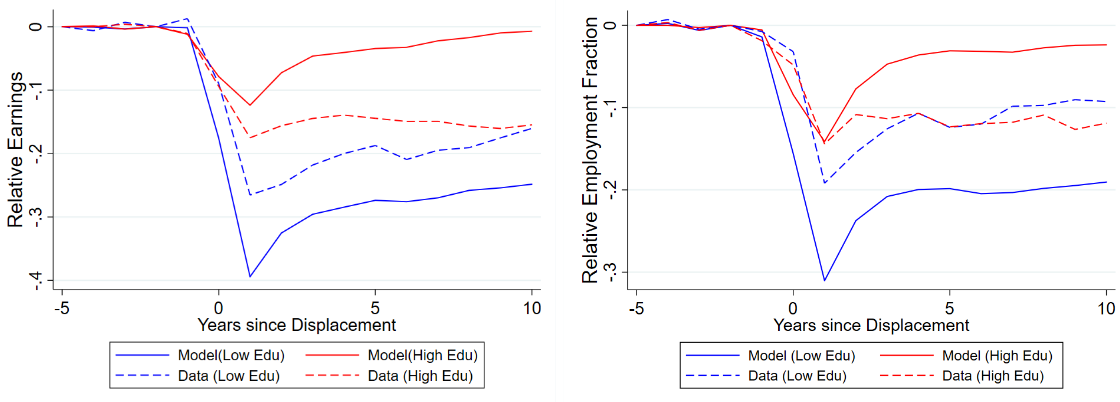


Figure 17: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right), relative to the control group (by education group), using model simulation data (solid) and using the data (dashed, corresponding to figure 10).*

Figure 17 shows the predicted effect of displacement on earnings and employment status (defined as the fraction of the year spent in an employment spell) by education level, compared to the results in figure 10. It can be seen that while the model matches the fact that the workers with a low education level suffer more in terms of earnings, the simulated differences are much more severe than those seen in the data. This reflects the observation in section 5.3 that the model tends to exacerbate differences between education levels compared to the data when it comes to the moments targeted in the calibration. Indeed, when looking at the results for employment fraction in the right panel of 10, it can be seen that while the worker with a low education level recovers faster (like in the data), the initial overshooting of the effect for the low educated worker results in this worker doing worse than the highly educated worker in the long run as well. In other words, the model does not match the observation made in section 3.3.1 that the worker with a low education level only does worse in the short run when it comes to employment fraction.

In figure 18, I show the estimated effect of displacement on earnings and employment fraction (defined as the fraction of the year spent in an employment spell) by ex-post recall status, compared to the results in figure 12. As can be seen from figure 18, the model matches the observation made in section 3.3.2 that recalled workers do worse than non-recalled workers after displacement (in terms of their earnings) in the short and long run, even though the effect on employment is fairly similar in the long run. In particular, while the effect on recalled workers in the short run overshoots the short-run effect found in the data, likely due to my assumption that workers are not recalled in the same quarter as being displaced ($\phi_{\varepsilon}^{rg} = 0$), the long-run gap between

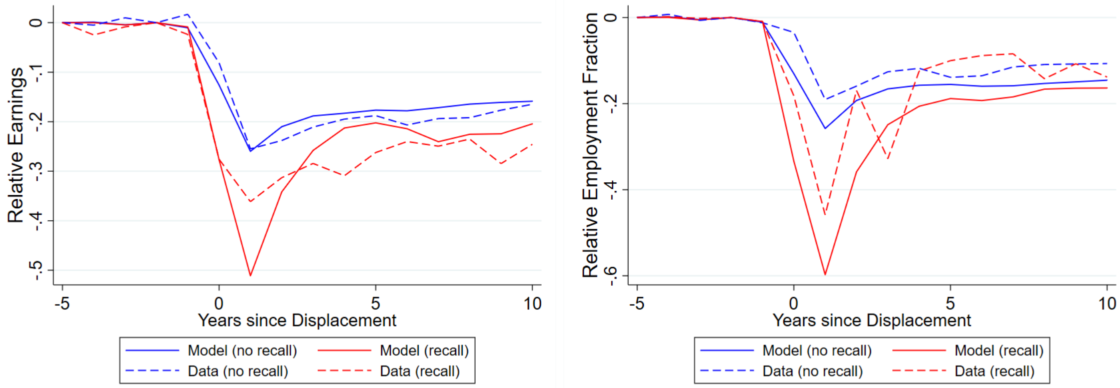


Figure 18: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right) relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data (solid) and using the data (dashed, corresponding to figure 12).*

the scarrings effects for recalled and non-recalled workers is very similar to the gap found in the data. As can be seen in the right panel, this continues to hold when looking at employment fraction instead, even though both groups slightly overshoot the effect estimated from the data.

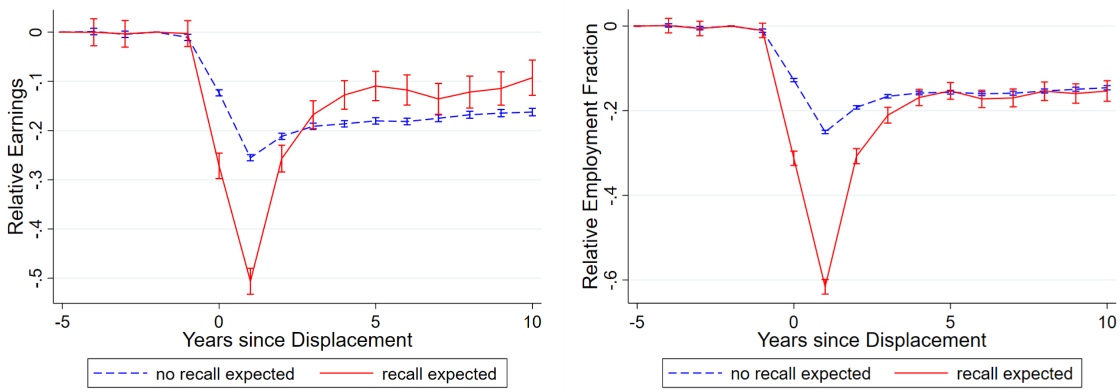


Figure 19: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right) relative to the control group, by post-displacement state, using model simulation data. The red solid line corresponds to workers choosing to wait for a recall, and the blue dashed line corresponds to workers moving into unemployment (not necessarily by choice).*

Given that the model is successful in generating the observed differences between recalled and non-recalled workers after displacement, a natural next question to ask is what is driving these differences. Furthermore, given that recalled workers end up doing worse than non-recalled workers, why would a displaced worker choose to wait for a recall? Figure 19 provides an indication of how one could answer the second question. The figure repeats the estimation from figure 18, but uses worker states immediately after displacement (i.e. whether they are waiting for a recall or not) rather than the ex-post recall status. In other words, figure 19 indicates what the expected earnings path is for someone choosing to wait for a recall (red) and someone moving to unemployment (blue). As can be seen from comparing figure 19 to the solid lines in figure 18, the choice of whether to wait for a recall is not a simple as the ex-post differences between recall and non-recall suggest. In particular, when splitting the sample by post-displacement state rather than ex-post recall status, it can be seen that the worker waiting for recall is expected to do better in the long run, despite being worse off in the short run. The short run difference can be primarily attributed to the 0 probability of moving back into employment in the same period, while a newly unemployed worker meets a new employer with probability $\lambda_{\varepsilon}^{ug}$ (which was shown earlier to be quite high). After this initial period, however, the worker waiting to be recalled has a higher probability of transitioning back to employment than the unemployed worker, and this generates the positive difference in the long run.[59] Given that workers are generally quite patient, as reflected by β, a worker will prefer to wait for a recall. Indeed, under the parameter values resulting from the calibration, all workers choose to wait for recall when given the option.

In figure 20, I fully decompose the differences in estimated post-displacement earnings between recalled and non-recalled workers (as shown in the left panel of figure 18). In particular, I consider all channels through which the worker waiting for a recall is different than an unemployed worker in my model, and switch these channels off one by one in order to generate counterfactual earnings differences. As can be observed from figure 20, I find that the differences between recalled and non-recalled workers are primarily driven by the post-recall firm characteristics. In particular, while the impact of the productivity penalty is very small (and even slightly positive), the negative difference is primarily driven by the worker going back to an unstable firm (as represented in the model by the separation rate penalty c^{δ}. Essentially, the fact that the worker has a much higher probability of being separated again shortly after being re-employed implies that the worker is likely to be set back in her development multiple times, both in terms of human capital and in terms of repeated loss of outside option.[60]

[59] To be specific, a worker with a low education level waiting to be recalled becomes employed in a model period with probability $\phi_1^r + (1 - \phi_1^r)\lambda^r \lambda_1^u = 0.257$, whereas for an unemployed worker this probability equals $\lambda_1^u = 0.16$. Similarly, for a worker with a high education level these probabilities equal 0.321 and 0.213 respectively.

[60] Note that the productivity and separation rate penalty is only applied once, so this penalty does not compound if the worker is separated and recalled a second time.

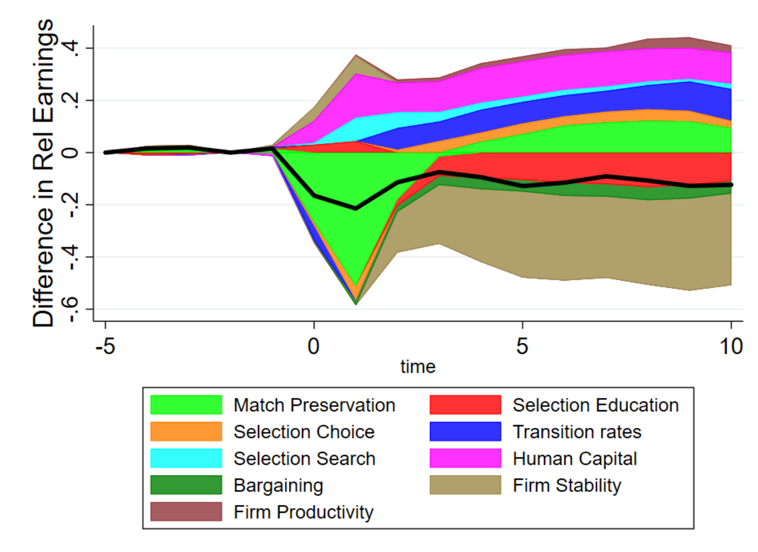


Figure 20: *A decomposition of the difference in the scarring effect of displacement on earnings between (ex-post) recalled and non-recalled workers. The black line represents the total difference, calculated as the difference between the solid red and blue lines in the left panel of figure 18. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals.*

It is further worth noting what the impact is of all the other channels. The selection choice channel reflects the impact of allowing the worker to choose whether or not to wait for recall. As expected, this has a (small) positive impact. Similarly, allowing the worker to search while waiting to be recalled (as indicated by $\lambda^r > 0$) has a small positive impact, denoted "Selection Search" in the figure. While the bargaining power is much lower for a recalled worker, as observed in section 5.3, the negative impact of this difference ("Bargaining") turns out to be quite minor compared to other channels. On the other hand, the finding that the worker waiting to be recalled is much less likely to lose any human capital ("Human Capital") has quite a large positive effect. While the effect of different transition rates is negative in the first period after displacement (due to the worker waiting to be recalled not being able to transition back in the same period as displacement), the effect turns positive shortly after, reflecting the higher transition probabilities of the worker waiting to be recalled after that initial period ("Transition rates"). It is also worth noting that the differences between the two education levels also plays a (negative) role here, although this is likely to be a consequence of lower transition rates from unemployment for the lower educated worker rather than differences by education level for workers waiting to be recalled. Finally, the residual element named "Match preservation", which reflects the difference between the two states if all parameters would be different (and therefore the only difference between the two states is whether they find a new employer or move back to their previous employer), can be observed to be quite large and negative in the short run. This reflects that the displaced workers generally have a worse match than the match they would expect to find when drawing a (random) new employer from the joint distribution $G_{\varepsilon}(\theta)$.

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 powers of the worker (κ and κ^r) equal 1, and the worker receives no benefit from nonemployment ($b = 0$). Given that the calibrated values of these parameters in table 4 do not correspond to these conditions, the expectation would likely be to see slightly different decisions made by a worker and a social planner.

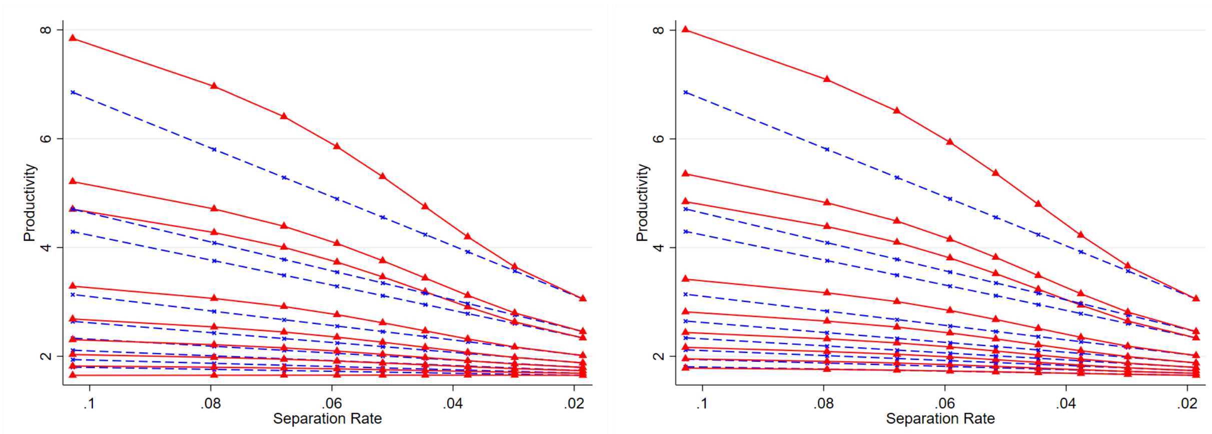


Figure 21: *Indifference curves for the worker (blue) and social planner (red), using the low education level. Indifference curves are drawn using as baseline the 9 grid points of the productivity distribution at the highest separation rate, assuming a worker at her starting level of human capital (right) or 2 steps below the starting level (left).*

In figure 21, 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 lowest possible separation rates, so that the differences in slopes are clear. Furthermore, I use the starting value of human capital and a value slightly below that, so that the comparison is likely to be relevant in a simulation.[61]

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

As can be seen in the figure by comparing the blue and red lines, the social planner's indifference curves do indeed not coincide with the worker indifference curves. However, by inspecting the indifference curves for a given benchmark (which is always the point furthest to the right), it can be seen that it is not always steeper or always flatter. This reflects that there are two main sources for the different decisions here.
First of all, the social planner does not consider any benefits the worker may receive during nonemployment. This is especially important for high values of human capital (since the benefit is increasing in human capital), but in general should lead me to observe flatter steeper indifference curves for the social planner (as they will value job security more). Furthermore, since the social planner internalizes the entire value of the match rather than just a fraction κ, the social planner experience a larger loss from losing the match (even if the social planner would incorporate the nonemployment benefit), which further leads the social planner to value job security more.

In order to see how these differences between social planner and worker play out in their decisions, one can compare the shapes (and levels) of the indifference curves by benchmark productivity, separation rate, and human capital level. First, comparing social planner and worker at different benchmark productivity levels (as indicated by the height of the point furthest to the left), it can be observed that the extend to which the worker undervalues job security (i.e. the blue curve is flatter) increases in the benchmark productivity. This primarily reflects the influence of κ, as the productivity itself does not influence the nonemployment benefit.
Comparing the worker and social planner's choices for different separation rates, it can be observed that the extent to which the worker undervalues job security decreases in the separation rate. This reflects that the social planner loses all value upon separation, whereas the worker only loses part of the value and furthermore receives some replacement value. Indeed, for high values of the separation rate, it can be observed that the worker values job security more than the social planner (this is especially clear in the right panel, for low benchmark productivity).[62]
Finally, comparing the two panels of figure 21, which differ in their human capital level, it can be seen that the social planner's indifference curves are higher for higher levels of human capital, while this is not necessarily the case for the worker. This reflects that from the social planner's point of view, the entire match value is lost upon separation (which is increasing in human cap-

[62] While it might seem strange at first, given the channels discussed, the worker would value job security more, one consideration to make here is that especially if the former job has low productivity, the match after the unemployment spell is likely to be better. This becomes especially attractive if the full benefit of this better match is received (which is the case for the social planner).

ital) without replacement, whereas the worker only loses their own share of the match value and partially replaces this with the benefit during nonemployment (which is also increasing in 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 while recalled workers tend to be re-employed faster than non-recalled workers, they suffer more in terms of their earnings and days employed (in a year). Furthermore, I find that earnings losses tend to be higher for workers with a low education level.

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. In particular, I explain the observation that recalled workers do worse than non-recalled workers after displacement as a combination of a selection and establishment effect. In the model, workers who are waiting to be recalled still search for new jobs as well. If workers get an offer for a new job that dominates the option value of waiting for recall, they will choose to accept this new job. In the data, these workers will be classified as non-recall, and as these workers likely improved their earnings prospects compared to the job they were waiting for, it follows that the non-recalled workers end up doing better than the recalled workers. Furthermore, as established in the data, the recalled workers are more likely to be separated again after returning to employment, reflecting that the workers return to a struggling firm (which can therefore be thought of as a firm with a higher separation rate). This higher separation rate (and, less importantly, lower productivity) plays a large role in explaining the differences between (ex-post) recalled and non-recalled workers in the long run.

Based on the results of this paper, one can think of various avenues of future research, and I will highlight a few of those possibilities here. First of all, this paper 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.[63] 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. Another dimension that may be of potential interest is that of recent or lifetime earnings. As I show in appendix D.3.6, the relative earnings loss after displacement tends to be higher for workers at the bottom of the recent earnings distribution, which seemingly contradicts the idea of the job ladder that most models are based on. A future project could investigate this further, and explain these observations (and their policy implications) using a model. 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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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 between worker types, 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: Divide the unit interval into N_δ equally-sized intervals, and let the lower and upper bound for these intervals be i_{down} and i_{up}. Now, invert these bounds such that B_{down} and B_{up} are the values for δ for which the cdf equals i_{down} and i_{up}. The values of the grid points then equals the expected value of δ, conditional on δ being between B_{down} and B_{up}.

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 (B.16) and (B.17) 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 by 2) and U (1 by N_s).[64]
   (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, first using its recursive structure to solve directly, assuming that a worker waiting to be recalled cannot search for a new job. Then, in a second iteration, add the search option, using the previously calculated F as the possible outside option, and re-calculate F.
   (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. Using the known value for $W^{max}(s, \theta)$ and $U(s)$, calculate the value for F by using the same procedure as in step 5c, but now repeatedly executing the second step until the value for F converges.

7. 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.

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

[64]The fourth dimension of the matrix W^{max} is used to distinguish whether the match carries a separation rate penalty from a previous recall. In the remainder of the description of this solution method I ignore this for notational convenience. In practice, the two 3-dimensional matrices are closely linked together, using only a single matrix for the value of F and U, and further linking through on-the-job search (as an EE transition will lead the worker to transition to a job that does not carry this penalty).

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):

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

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:[65]

$$F(s,\theta) = \ln(b(s)) + \beta\mathbb{E}_{s'|s,r}\Bigg\{\phi^r\kappa^r W^{max}(s',\theta') + \phi^r(1-\kappa^r)\max\{F(s',\theta),U(s')\}$$
$$+(1-\phi^r)\left(\lambda^r\int_{x\in\Theta^r(s',\theta)}\kappa\left(W^{max}(s',x)-\max\left\{F(s',\theta),U(s')\right\}\right)dG(x) + \max\left\{F(s',\theta),U(s')\right\}\right)\Bigg\}$$

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:

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

Further, note that:

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

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 $W(s',\hat{s},\theta,\hat{\theta})$.

[65] To be specific, I solve for the value $F(s,\theta)$ before solving for the wage, as noted in the previous subsection.

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 $\psi_e = 0$.[66] 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:

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

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

The resulting system of equations has $N_s - \hat{s} + 2$ equations and $N_s - \hat{s} + 2$ unknowns and can thus be solved. In order to do so, I set up matrix A and vector B, such that the system is represented as $Ax = B$, where x is a vector containing the unknowns. These matrices will be $N_s - \hat{s} + 2$ by $N_s - \hat{s} + 2$, but take

[66] 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.

an easily generalizeable form. For example, for $\hat{s} = N - 2$, the vectors and matrices will look as follows (denoting $p_s = p(s, y)$ and $r = \ln(R)$):

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

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

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), both in the data and in the model simulation. 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.[67] 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

[67] 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.

employed next quarter and 1 if the worker is unemployed in the next quarter.[68] The job loss rate by tenure is then estimated by taking a simple average over all workers with an establishment tenure of 1 to 3.5 years (i.e. more than exactly 1 year, less than exactly 3.5 years), 3.5 to 6 years, 6 to 9 years, and more than 9 years. Similarly, I take the simple average over all workers with a low and high education level to find the education-specific unconditional rates of job loss. Finally, I take the average over all workers who returned from nonemployment to find the rates of subsequent separation for displaced, and restrict these workers to those who were recalled to find the rate of subsequent separation for recalled workers.

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.[69] In order to construct the moment, I then take the average by education group. Similarly, I calculate the job-to-job transition rate upon displacement (by education group) by following the same procedure, but conditioning the filling of the variable of interest on the worker experiencing a displacement event in the (current) quarter.

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. To compute the moment value, 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. In the model, I do not need to keep track of this explicitly, as employed workers will be marked by having a strictly positive firm productivity y.

A.3.2 p75-p25 and median-p25 ratios of wages

In order to estimate the p75-p25 and median-p25 ratios of wages (by education group) in the data, I restrict the sample to full-time workers only, along with the aforementioned restriction on market tenure. Furthermore, I restrict the observations to those who are (full-time) employed for the entire quarter. In the data,

[68] 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.

[69] An important note to make here is that in the case where a displacement and recall take place within the same quarter, a worker can change firm productivity y while not switching establishments in the model. I account for this by explicitly keeping track of recall events in the simulation.

I can then directly summarize the wage by education group, which will yield the 25th percentile, median, and 75th percentile wage. Once these are retrieved, the p75-p25 and median-p25 ratio can be calculated directly.

In the model, 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.[70] The 25th percentile, median, and 75th percentile wage can then be calculated directly by sorting the resulting vector of wages and taking out the middle observation and the observation at the 25th and 75th percentile. 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 and newly recalled workers. Denoting the average wage of new hires (or new recalls) by $\bar{w}_N$, this moment equals $\bar{w}_N/\bar{w}$. In order to calculate $\bar{w}_N$, I restrict the sample to workers with an establishment tenure of more than a quarter, and less than a year, who are (full-time) employed for the entire quarter, and were unemployed before starting at their current establishment. The average wage of newly recalled workers is calculated in an identical way, restricting the average wage of new hires to those of workers for whom their current establishment is the same as the establishment they worked for prior to their preceding unemployment spell. Calculating the data counterpart of the average wage $\bar{w}$ uses the data equivalent of the procedure outlined above for the replacement rate, again restricting the sample to full-time workers who are employed for the entire quarter. Note that when I estimate this moment 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

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

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 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 that employer's productivity 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.

In order to calculate the new job finding rate for temporarily unemployed workers that are re-employed within a year, I need to keep track of the exact nonemployment state of the worker as well (to disentangle job finding from unemployment and new job finding from temporary unemployment). I do this in the model simulation by assigning workers who are waiting to be recalled a productivity equal to -1 times the productivity of their former employer. I can then calculate the moment of interest by taking all such workers who are re-employed from a state of temporary unemployment (as indicated by the productivity in the period before re-entering employment) and were in that state for at most a year, and calculating the fraction of these workers who moved to a new employer rather than being recalled. As I cannot see in the data whether workers are expecting to be recalled, I base the data equivalent of this model on findings in Nekoei and Weber (2015), who find in their Austrian data that 58% of workers who report to expect being recalled are in fact recalled within a year, while 24% of these workers who are expecting a recall find a new job within a year. Translating this to a new job finding rate conditional on being re-employed from a state of temporary unemployment within a year then yields a data equivalent of 29.27%.

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 16 subsamples: by education group, and according to unemployment duration in quarters (ranging from 1 quarter to 8 quarters). 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 average wage in the first four full quarters after starting this job (conditional on being full-time employed for that entire quarter). The resulting wage differential is the difference between this pre- and post layoff wage. The same procedure is then followed for a control group of non-displaced workers (looking forward the same amount of time as for the corresponding treatment group), after which the moment of interest is the average of the differences in these differences across duration quarters that fall within each group of interest (1 quarter to 0.5 year, 0.5 to 1 year, and 1 to 2 years). Thus, the moment is essentially an average of coefficients of difference-in-difference estimations, where a separate estimation is done for each education level and quarter of nonemployment duration. It should be noted that this calculation excludes workers who found a new job immediately or within a quarter. Further, I exclude workers with an unemployment duration of more than 2 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 (using only workers with a nonemployment duration of 1 to 3 quarters). 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, separately for those with a nonemployment duration of 1 quarter and those with a duration of 2 or 3 quarters.

A.3.8 Correlation between wages and separation

The final moment to be estimated in the baseline calibration is the regression coefficient $\hat{\gamma}$ in equation (A.1):

$$D_{i,t}^{\delta} = \alpha_i + \gamma \log(w_{it}) + u_{i,t} \tag{A.1}$$

In the data, this equation can be estimated using a standard fixed effects estimation. Given the number of individuals in the simulation (and therefore the number of individual fixed effects), however, this is a quite computationally intensive estimation to estimate in each iteration of the calibration. Therefore, I use the fact that the individual fixed effect is constant over time to greatly simplify the estimation, while not 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:

$$D_{i,t}^{\delta} - \bar{D}_{i,t}^{\delta} = \alpha_i - \bar{\alpha}_i + \gamma \log(w_{it}) - \gamma \overline{\log(w_{it})} + u_{i,t} - \bar{u}_{i,t} \tag{A.2}$$

$$\left(D^{\delta} - \bar{D}^{\delta}\right)_{i,t} = \gamma \left(\log(w) - \overline{\log(w)}\right)_{it} + u_{i,t} \tag{A.3}$$

As can be seen in equation (A.3), all elements on both sides of the equation now depend on both i and t, thus allowing for a simple OLS estimation, yielding coefficient $\hat{\gamma}$.

A.3.9 Explicit estimation of the scarring effect of displacement

In some of the alternative calibrations in the appendix of this paper, I estimate the model by directly targeting the scarring effects of displacement by (ex-post) recall status that were estimated in section 3.3.2 of the main text. In other words, I target the outcome of the estimation of the following equation:

$$e_{it} = \alpha_i + \gamma_t + \sum_{C \neq 0} \sum_{\substack{k=-4 \\ k \neq -2}}^{10} \delta_k^C D_{it}^{C,k} + u_{it} \tag{A.4}$$

Given the presence of individual and time fixed effects in equation (A.4), this estimation yields similar issues as those pointed out in the previous subsection. However, the structure of the model and its simulation allow me to make several simplifications. First, note that while different cohorts in the data pick up effects of (among others) differences in economic conditions at the time of displacement, there are no such differences in the model. Therefore, I do not allow for different estimates by cohort in the model equivalent, thus reducing the equation as follows:

$$e_{it} = \alpha_i + \gamma_t + \sum_{\substack{k=-4 \\ k\neq -2}}^{10} \delta_k D_{it}^k + u_{it} \tag{A.5}$$

Then, to get around having to estimate the fixed effects explicitly, I interpret the equation above as a two-way error component model, and use the two-way within transformation from Hansen (2021). In particular, this means that for both the dependent and independent variables in equation (A.5), I calculate $\ddot{X}_{it} = X_{it} - \bar{X}_i - \tilde{X}_t + \bar{X}$, where $\bar{X}$ is the average variable over all individuals and time periods, $\tilde{X}_t$ is the average over individuals within a time period t, and $\bar{X}_i$ is the average over all time periods for an individual i. Using this transformation, the equation to be estimated reduces to the following equation:

$$\ddot{e}_{it} = \sum_{\substack{k=-4 \\ k\neq -2}}^{10} \delta_k \ddot{D}_{it}^k + \ddot{u}_{it} \tag{A.6}$$

The above equation can be estimated fairly easily using OLS, which thus yields the model equivalent of the moments (with one moment for every k). Note that the model estimation is not exactly identical to the data equivalent, because the panel in the simulation is not completely balanced (for example, because I omit simulation data from individuals above the age of 62). Therefore, the targeting of the scarring effect is not as precise as it would be if I were to estimate (A.4) directly, but the transformation does make this (imperfect) targeting feasible, and is therefore allows me to use this for an alternative calibration.

B Model Appendix

B.1 Further Value Functions

As mentioned in section 4, the model can be solved using value functions from the worker side only. However, it could still be valuable to consider what the value function for a (producing) firm looks like. The value function J for a firm of type θ, employing a worker of type ε with human capital s, is as follows:

$$\begin{aligned} J_\varepsilon(s, \hat{s}, \theta, \hat{\theta}) = &\left(1 - R_\varepsilon(\hat{s}, \theta, \hat{\theta})\right) p(s, y) + \beta \mathbb{E}_{s'|s,e,\varepsilon} \left\{ (1-\delta) \left[\lambda_\varepsilon^e \int_{x \in \Theta_\varepsilon^2(s', \hat{s}, \theta, \hat{\theta})} J_\varepsilon(s', s', \theta, x) dG_\varepsilon(x) \right.\right. \\ &\left.\left. + \left(1 - \lambda_\varepsilon^e \int_{x \in \Theta_\varepsilon^1(s', \theta) \cup \Theta_\varepsilon^2(s', \hat{s}, \theta, \hat{\theta})} dG_\varepsilon(x)\right) J_\varepsilon(s', \hat{s}, \theta, \hat{\theta}) \right] + \delta \bar{\phi}_\varepsilon^f(s, \theta) \hat{J}_\varepsilon^f(s', \theta) \right\} \end{aligned} \tag{B.7}$$

Here, $\bar{\phi}_\varepsilon^f(s,\theta) = \phi_\varepsilon^f \mathbb{1}_{F_\varepsilon(s,\theta)>U_\varepsilon(s)}$, capturing that the worker may choose to forego the option of recall. As mentioned before, the value of an unmatched firm is $V = 0$. Finally, $\hat{J}_\varepsilon^f(s,\theta)$ is the value for a firm newly waiting for a recall, which can be decomposed into the separation period-specific part and a general value for a firm waiting for a recall:

$$\hat{J}_\varepsilon^f(s',\theta) = \phi_\varepsilon^{rg} J_\varepsilon(s',s',\theta',r) + (1-\phi_\varepsilon^{rg}) J_\varepsilon^f(s',\theta) \tag{B.8}$$

$$J_\varepsilon^f(s,\theta) = \beta \mathbb{E}_{s'|s,r,\varepsilon} \left\{ \phi_\varepsilon^r J_\varepsilon(s',s',\theta',r) + (1-\phi_\varepsilon^r) \left(1 - \lambda_\varepsilon^r \int_{x\in\Theta_\varepsilon^r(s',\theta)} dG_\varepsilon(x)\right) \mathbb{1}_{F_\varepsilon(s',\theta)>U_\varepsilon(s')} J_\varepsilon^f(s',\theta) \right\} \tag{B.9}$$

B.2 Worker Flows

The description of the model in the main text (section 4) 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 $d_\varepsilon(s,\hat{s},\theta,u)$, $d_\varepsilon(s,\hat{s},\theta,r)$, and $d_\varepsilon(s,\hat{s},\theta,f)$ the equivalents if this worker used unemployment as the outside option at the time of bargaining, was recently recalled to their current job, or found the current job while waiting to be recalled. Further, let $d_\varepsilon^f(s,\theta)$ be the density of workers with current human capital s waiting to be recalled to a firm with characteristics θ, and let $u_\varepsilon(s)$ be the density of unemployed workers of type ε with human capital s. First, define the following densities, defined after human capital accumulation (or depreciation) takes place:

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

The flow equations are then as follows:[71]

$$\begin{aligned} d_\varepsilon'(s,\hat{s},\theta,\hat{\theta}) = {} & (1-\delta)\left(1 - \lambda_\varepsilon^e \int_{x\in\Theta_\varepsilon^1(s,\theta)\cup\Theta_\varepsilon^2(s',\hat{s},\theta,\hat{\theta})} dG_\varepsilon(x)\right) \bar{d}_\varepsilon(s,\hat{s},\theta,\hat{\theta}) \\ & + \mathbb{1}_{s=\hat{s}} \lambda_\varepsilon^e g_\varepsilon(\theta) \left[\iint (1-\hat{\delta}) \left(\mathbb{1}_{\theta\in\Theta_\varepsilon^1(s,\hat{\theta})} \bar{d}_\varepsilon(s,x,\hat{\theta},y)\right) dx dy\right] \\ & + \lambda_\varepsilon^e \left[g_\varepsilon(\hat{\theta}) \iint (1-\hat{\delta}) \left(\mathbb{1}_{\hat{\theta}\in\Theta_\varepsilon^2(s,x,\theta,y)} \bar{d}_\varepsilon(s,x,\theta,y)\right) dx dy\right] \Big\} \end{aligned} \tag{B.10}$$

[71]Note that when I integrate over y in equation (B.10), I include all possible values for $\hat{\theta}$, including u, r, and f, in this integration. The same holds for the integration over $\hat{x}$ in equations (B.11), (B.12), (B.14), and (B.15).

$$d'_\varepsilon(s,\hat{s},\theta,u) = (1-\delta)\left(1-\lambda^e_\varepsilon \int_{x\in\Theta^1_\varepsilon(s,\theta)\cup\Theta^2_\varepsilon(s',\hat{s},\theta,u)} dG_\varepsilon(x)\right)\bar{d}_\varepsilon(s,\hat{s},\theta,u)$$

$$+ g_\varepsilon(\theta)\mathbb{1}_{s=\hat{s}}\mathbb{1}_{\theta\in\Theta^u_\varepsilon(s)}\left(\lambda^u_\varepsilon\bar{u}_\varepsilon(s) + \lambda^{ug}_\varepsilon \iiint \delta(1-\bar{\phi}^f_\varepsilon(s,x))\bar{d}_\varepsilon(s,\tilde{s},x,\hat{x})d\tilde{s}dxd\hat{x}\right) \tag{B.11}$$

$$d'_\varepsilon(s,\hat{s},\theta,r) = (1-\delta)\left(1-\lambda^e_\varepsilon \int_{x\in\Theta^1_\varepsilon(s,\theta)\cup\Theta^2_\varepsilon(s',\hat{s},\theta,r)} dG_\varepsilon(x)\right)\bar{d}_\varepsilon(s,\hat{s},\theta,r)$$

$$+ \int \mathbb{1}_{\theta'\in\Theta^f_\varepsilon(\theta)}\left(\phi^r_\varepsilon\bar{d}^f_\varepsilon(s,\theta') + \bar{\phi}^f_\varepsilon(s,\theta')\phi^{rg}_\varepsilon \iint \bar{d}_\varepsilon(s,\hat{s},\theta',\hat{x})d\hat{s}d\hat{x}\right)d\theta' \tag{B.12}$$

$$d'_\varepsilon(s,\hat{s},\theta,f) = (1-\delta)\left(1-\lambda^e_\varepsilon \int_{x\in\Theta^1_\varepsilon(s,\theta)\cup\Theta^2_\varepsilon(s',\hat{s},\theta,f)} dG_\varepsilon(x)\right)\bar{d}_\varepsilon(s,\hat{s},\theta,f)$$

$$+ \int \mathbb{1}_{\theta\in\Theta^r_\varepsilon(s,x)}(1-\phi^r_\varepsilon)\lambda^r\bar{d}^f_\varepsilon(s,x)dx \tag{B.13}$$

$$d^{f\prime}_\varepsilon(s,\theta) = (1-\phi^r_\varepsilon)\left(1-\lambda^r \int_{x\in\Theta^r_\varepsilon(s,\theta)} dG_\varepsilon(x)\right)\mathbb{1}_{F_\varepsilon(s,\theta)>U_\varepsilon(s)}\bar{d}^f_\varepsilon(s,\theta)$$

$$+ \iint \delta\bar{\phi}^f_\varepsilon(s,\theta)(1-\phi^{rg}_\varepsilon)\bar{d}_\varepsilon(s,\hat{s},\theta,\hat{x})d\hat{s}d\hat{x} \tag{B.14}$$

$$u'_\varepsilon(s) = \left(1-\lambda^u_\varepsilon \int_{x\in\Theta^u_\varepsilon(s)} dG_\varepsilon(x)\right)\bar{u}_\varepsilon(s)$$

$$+ \int \delta(1-\bar{\phi}^f_\varepsilon(s,\theta))\left(1-\lambda^{ug}_\varepsilon \int_{x\in\Theta^u_\varepsilon(s)} dG_\varepsilon(x)\right)\iint \bar{d}_\varepsilon(s,\hat{s},\theta,\hat{x})d\hat{x}d\hat{s}d\theta \tag{B.15}$$

where

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

Alternatively, once could display the flows through a diagram, as is done in figure B.1, although it should be noted that this figure focuses primarily on the transition between the three main states, and ignores the evolution of human capital and the outside option.

B.3 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 (12), 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 one can rewrite the value of waiting for recall, equation (10) in terms of W^{max} and U only. In order to do so, I use the bargaining equations (4) and (7), as mentioned in the main text (in section 4). 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. Furthermore, given that the values for F and U are then known (for a given value of W^{max} and U), I can also directly calculate the corresponding values

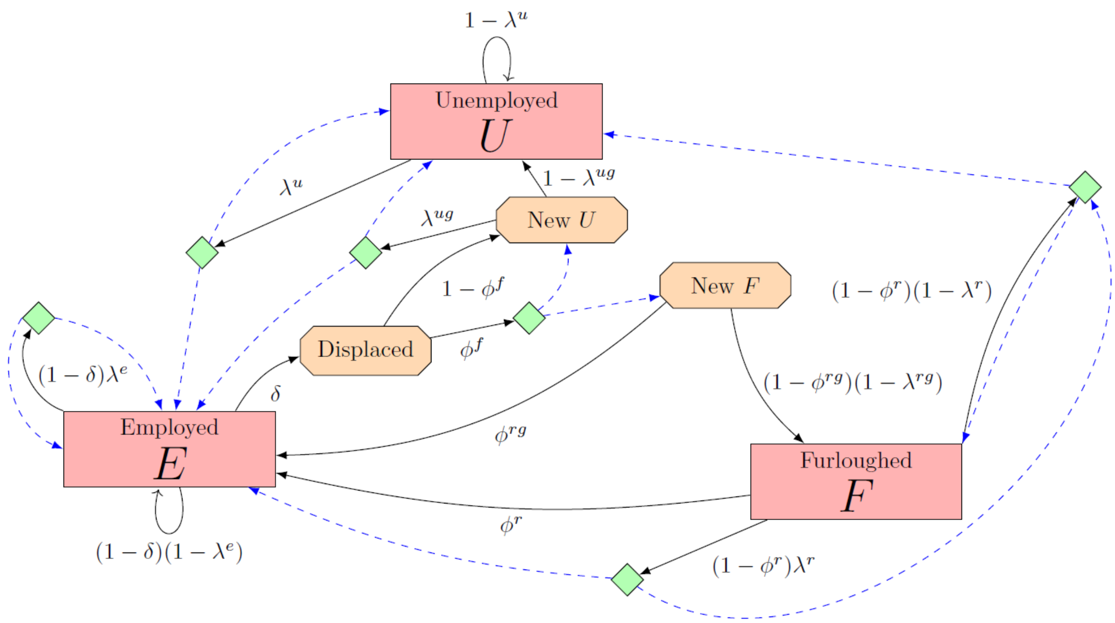


Figure B.1: *A flow chart depicting the flows between the three main states for a worker. Solid arrows depict an exogenous flow, caused by materialization of some probability. Dashed (blue) lines are flows that follow from a decision of the worker, and these decisions are made at decision points (which are denoted by green diamonds).*

for a newly unemployed worker (either temporary or permanent), $\hat{F}(s,\theta)$ and $\hat{U}(s)$.

Using these calculations (and leaving in $\hat{F}$ and $\hat{U}$), I can then start to rewrite equation (12), by plugging in $R(\hat{s},\theta,\hat{\theta})=1$ and rewriting:

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

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:

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

Finally, to arrive at equation (15), simplify the term inside of the integral by using the bargaining equation $W_\varepsilon(s,s,x,\theta) = W_\varepsilon^{max}(s,\theta) + \kappa\,(W_\varepsilon^{max}(s,x) - W_\varepsilon^{max}(s,\theta))$:

$$
\begin{aligned}
W^{max}(s,\theta) = \ln(p(s,y)) + \beta \mathbb{E}_{s'|s,e} \Big\{ & \delta \left[\phi_f \max\{\hat{F}(s',\theta), \hat{U}(s')\} + (1-\phi_f)\hat{U}(s') \right] \\
& +(1-\delta) \Big[\lambda^e \int_{x \in \Theta^1(s',\theta)} \Big(W^{max}(s',\theta) + \kappa \left(W^{max}(s',x) - W^{max}(s',\theta) \right) - W^{max}(s',\theta) \Big) dG(x) \\
& + W^{max}(s',\theta) \Big] \Big\} \\
= \ln(p(s,y)) + \beta \mathbb{E}_{s'|s,e} \Big\{ & \delta \left[\phi_f \max\{\hat{F}(s',\theta), \hat{U}(s')\} + (1-\phi_f)\hat{U}(s') \right] \\
& +(1-\delta) \left[\lambda^e \int_{x \in \Theta^1(s',\theta)} \kappa \Big(W^{max}(s',x) - W^{max}(s',\theta) \Big) dG(x) + W^{max}(s',\theta) \right] \Big\}
\end{aligned} \tag{B.16}
$$

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 (8). To do this, I use the bargaining equation (4):

$$
\begin{aligned}
U(s) &= \ln(b(s)) + \beta \mathbb{E}_{s'|s,u} \left\{ \lambda^u \int_{x \in \Theta^u(s')} W(s',s',x,u) dG(x) + \left(1 - \lambda^u \int_{x \in \Theta^u(s')} dG(x) \right) U(s') \right\} \\
U(s) &= \ln(b(s)) + \beta \mathbb{E}_{s'|s,u} \left\{ \lambda^u \int_{x \in \Theta^u(s')} \Big(W(s',s',x,u) - U(s') \Big) dG(x) + U(s') \right\} \\
U(s) &= \ln(b(s)) + \beta \mathbb{E}_{s'|s,u} \left\{ \lambda^u \int_{x \in \Theta^u(s')} \kappa \Big(W^{max}(s',x) - U(s') \Big) dG(x) + U(s') \right\}
\end{aligned} \tag{B.17}
$$

C Additional Simulation Results

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)[72]	17,848.7	15,796.3	23,898.67	15,948.89
Separation	0.1253	0.331	0.1247	0.330
Displacement	0.016	0.126	0.0224	0.148

Table D.1: *Summary statistics using the yearly sample. The table shows the estimated mean and standard deviation of a number of important variables, using the main sample from either LIAB or SIAB (as defined in section 2, without any of the further restrictions imposed for the estimation).*

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.

Figure D.1 shows the fraction of observations accounted for by each major industry and occupation.[73] Looking at how the breakdown of industries and occupations evolves over time, it can be seen that

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

[73]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

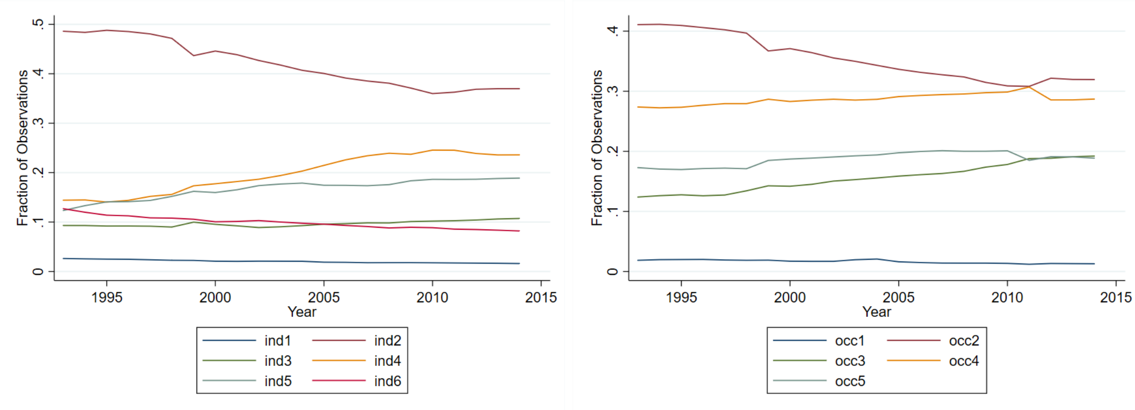


Figure D.1: *The fraction of observations by industry (left) and occupation (right) over time, using LIAB.*

industries and occupations related to manufacturing and construction seem to be declining over time, while 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 could potentially be used to 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.

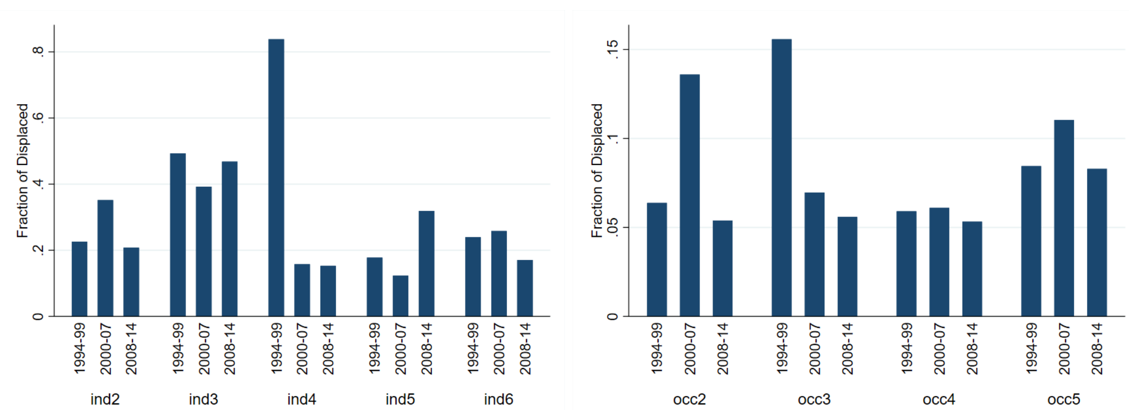


Figure D.2: *The fraction of displaced workers moving industry (left) and occupation (right), using LIAB and by former employing industry/occupation. Industry 1 (Agriculture, Fishing, Mining) and occupation 1 (Agriculture, Forestry, and Horticulture) are not included as the number of underlying observations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

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.

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.

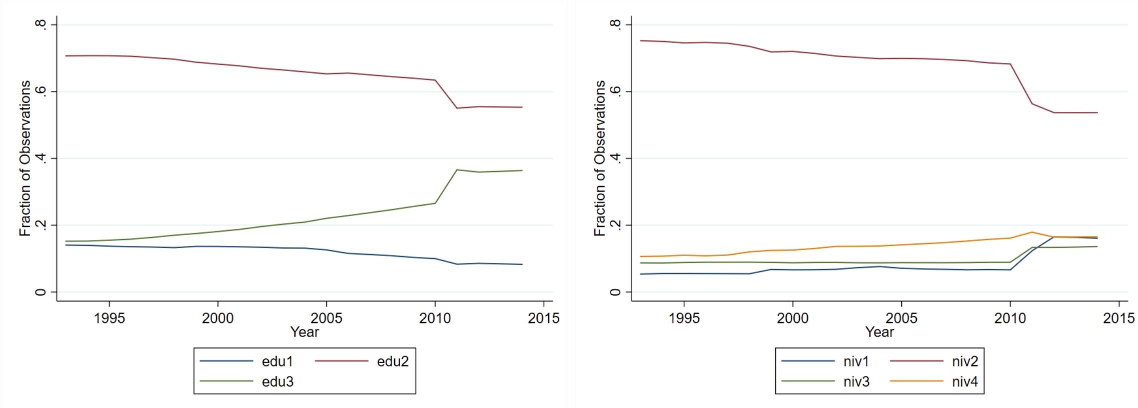


Figure D.3: *The fraction of observations by education (left) and occupational complexity (right) over time, using LIAB.*

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.[74] 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 displacement, the occupational complexity moving rate (in the LIAB) is 11%, whereas the corresponding occupational mobility rate is 7.9%.[75] Furthermore, it can be noted that among the workers

[74]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.

[75]Conditional on separation, the occupational complexity moving rate (in the LIAB) is 15.4%, whereas the corresponding occupational mobility rate is 11.1%.

that switched occupation groups after displacement, the occupational complexity moving rate is 52.7%, and among workers that move between complexity levels after displacement the occupational mobility rate is 38%.[76] This confirms that 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.3.6) 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.

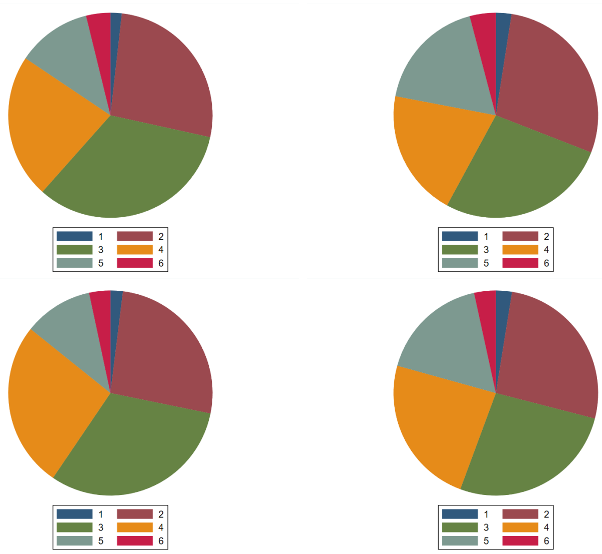


Figure D.4: *Breakdown of exiting establishments (left) and all establishments in the data (right) by major industry*[77]*, using data from the SIAB (top row) and LIAB (bottom row).*

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

[76]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%.

[77]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.[78]

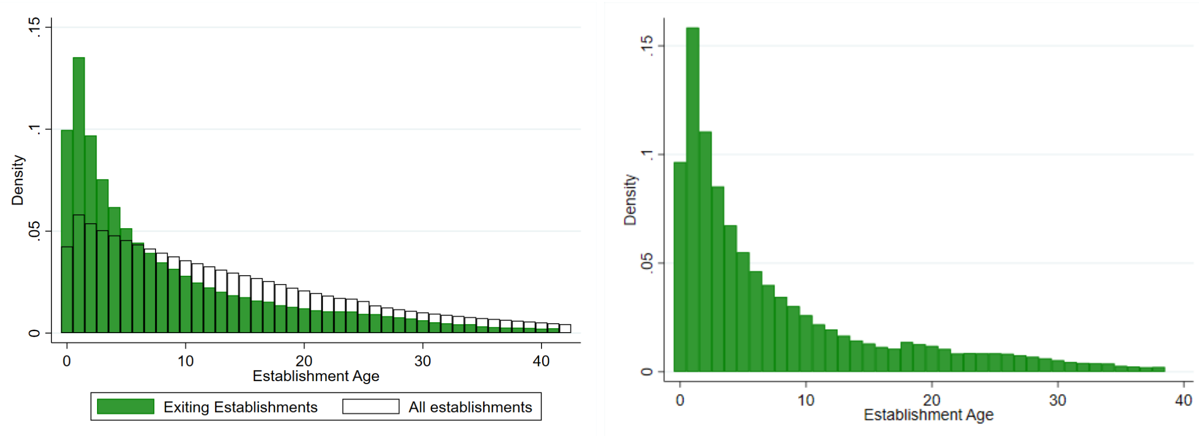


Figure D.5: *The distribution of the exiting establishments in SIAB (left) and LIAB (right) by establishment age.*

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 young. 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

[78]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).

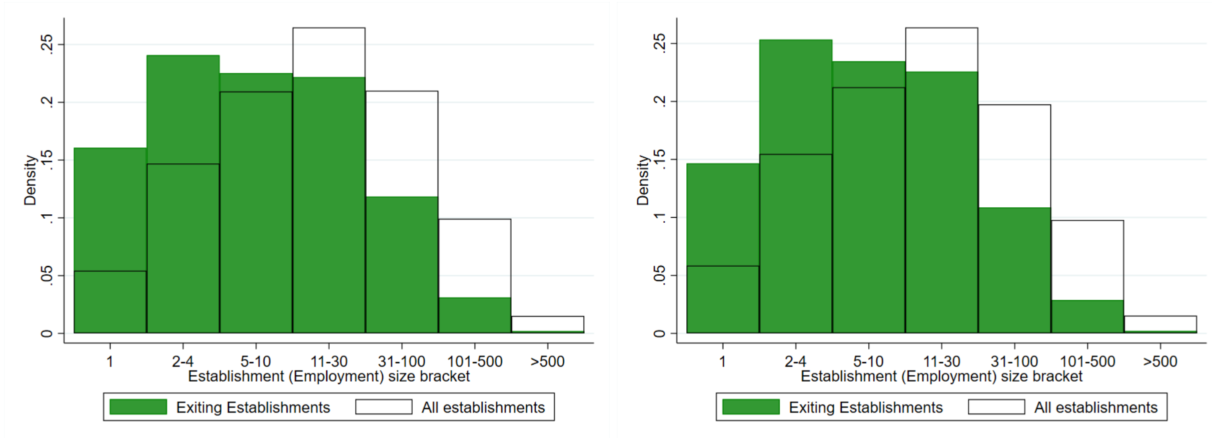


Figure D.6: *The distribution of exiting establishments (green) and all establishments in the data (black) by size group (defined as the number of employees at an establishment), using the SIAB (left) and LIAB (right).*

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

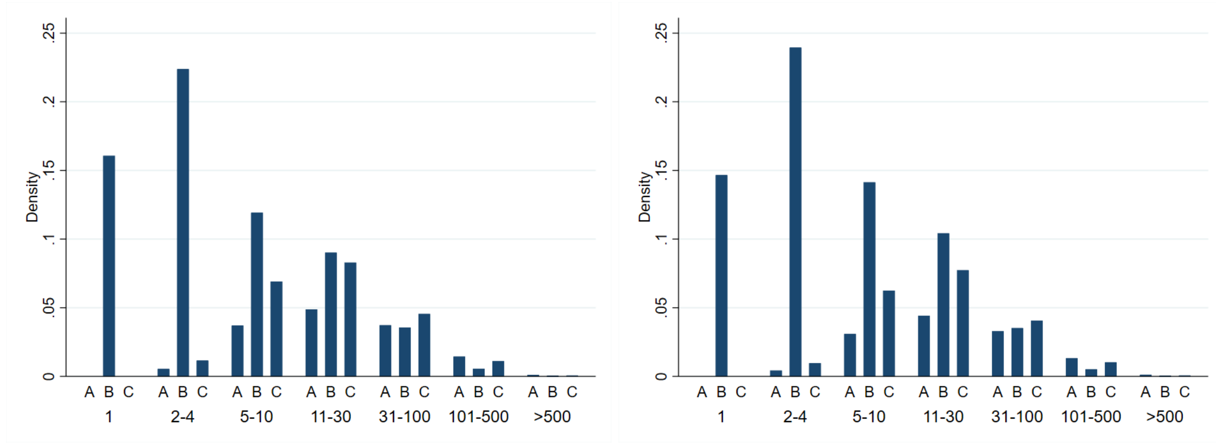


Figure D.7: *The distribution of exiting establishments over exit types A, B, and C (as defined in the text), and size group (defined by the number of employees at an establishment), generated using the SIAB (left) and LIAB (right).*

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 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, this section focuses on the incidence of job loss by worker and establishment characteristics that are not further investigated in the remainder of the paper and do not appear in the model.[79]

In figure D.8, the separation and 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.

In figure D.9, 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

[79]For some of the characteristics discussed in this section I have also investigated differences in the scarring effects of displacement, in a similar way as done in section 3.3. These results are omitted here and available upon request.

Figure D.8: *The incidence of separation (left) and displacement (right) by gender, over time.*

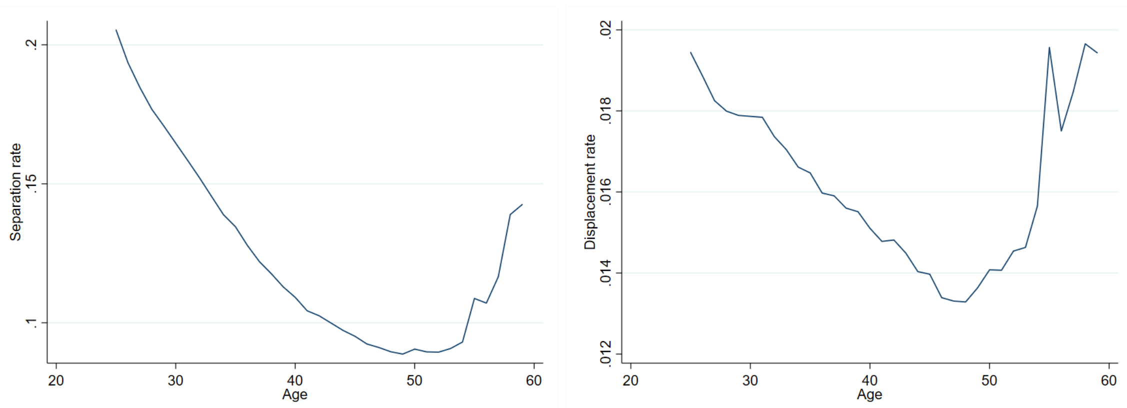


Figure D.9: *The incidence of separation (left) and displacement (right) by age.*

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.[80] 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.[81]

Figure D.10 plots the separation and displacement rates by worker age groups over time, thereby complementing the observations from figure D.9 (which were averaged across years). Looking at figure D.10, 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

[80] Note that the fact that the peak early in the life cycle (for the separation rate) largely disappears when I impose sample restrictions, requiring (for example) a tenure of at least 6 years.

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

Figure D.10: *The incidence of separation (left) and displacement (right) by age group, with restrictions on worker tenure, using LIAB.*

displacement rate in the the early 2000s, the opposite is the case for the Great Recession, especially when focusing on displacement.

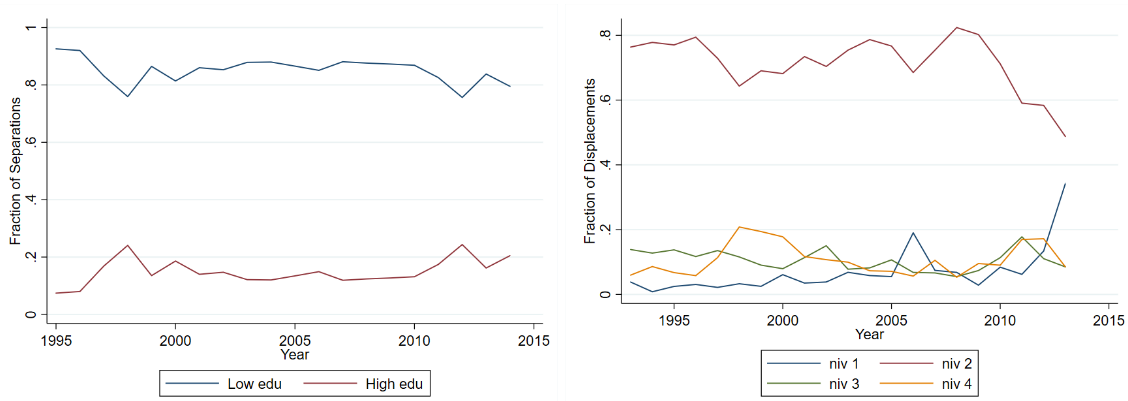


Figure D.11: *The fraction of displacements by education group (left) and occupational complexity (right) over time, with restrictions on worker tenure, using LIAB.*

In figure D.11, the fraction of displacements accounted for by each education and occupational complexity group is plotted over time.[82] 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.

[82] 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).

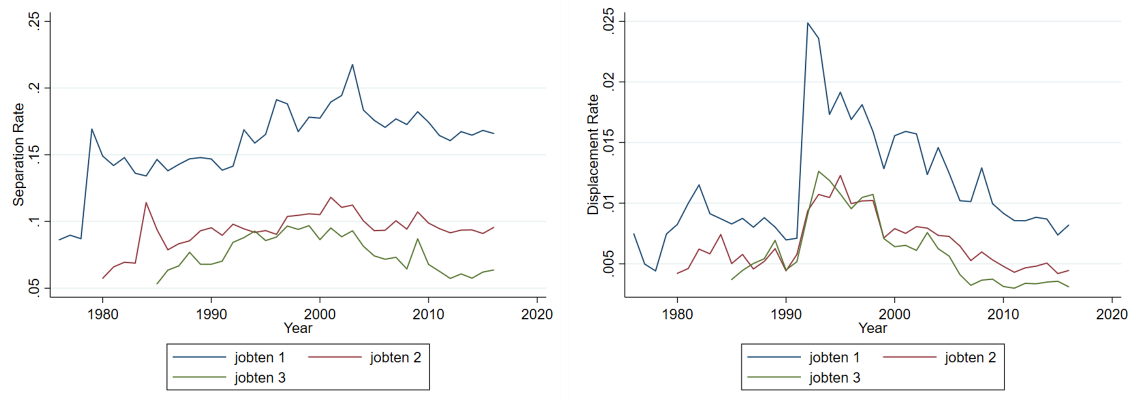


Figure D.12: *The incidence of separation (left) and displacement (right) by job tenure, with restrictions on worker tenure.*

A similar pattern can be discovered by plotting the separation and displacement rate by job tenure, as done in figure D.12. 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.[83] As workers with a higher job and establishment tenure are mechanically expected to be older (on average), this figure, combined with figure D.9 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).

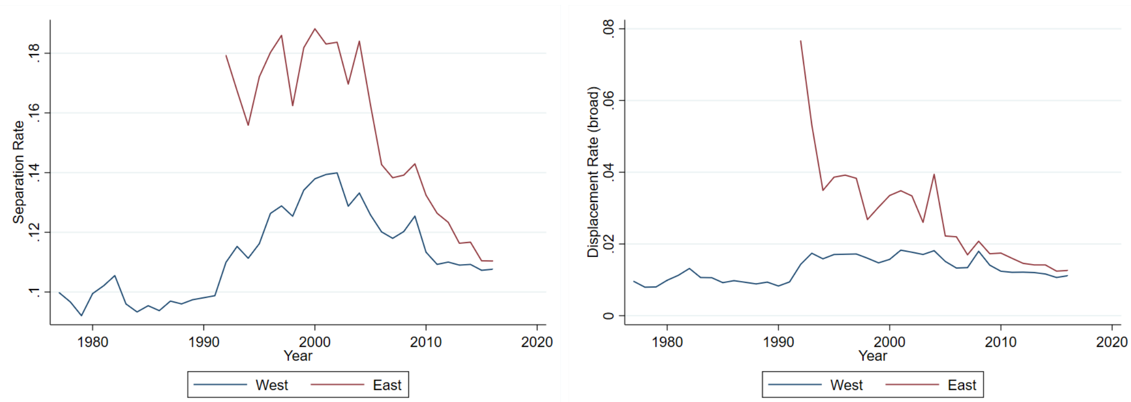


Figure D.13: *The incidence of separation (left) and displacement (right) by location.*

[83]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.

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 D.13 compares the two regions in terms of their separation and 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 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 left panel of figure D.14 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.

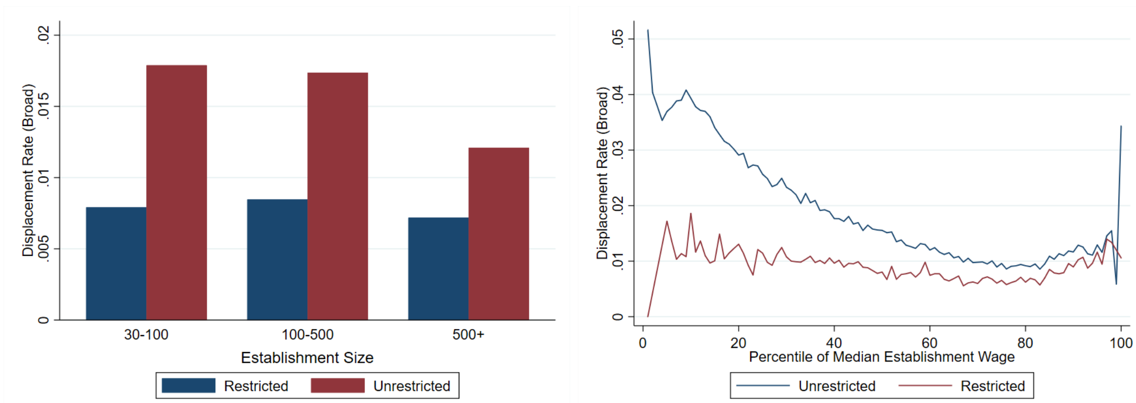


Figure D.14: *The incidence of separation by establishment size (left) and median wage (right), with and without restrictions on worker tenure.*

Finally, the right panel of figure D.14 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.3.2 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.

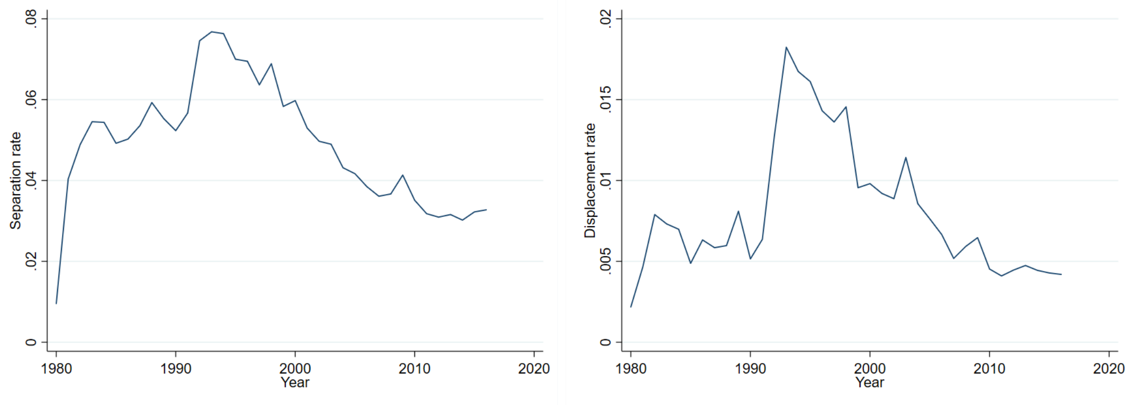


Figure D.15: *The incidence of separation (left) and displacement (right) over time, with restrictions on worker tenure.*

First of all, figure D.15 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 is roughly 0.7% on average. 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.3.1). Again, the aftermath of the German reunification is quite clearly visible in the graph.

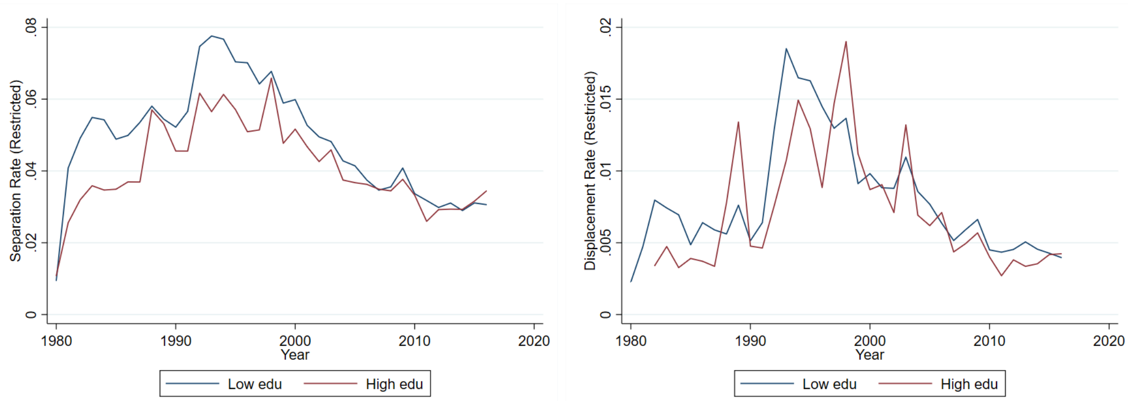


Figure D.16: *The incidence of separation (left) and displacement (right) by education level, over time, with restrictions on worker tenure.*

Figure D.16 displays the restricted separation and displacement rates over time by education level, thus mirroring figure 2 from the main text (which does not impose restrictions on worker tenure). As can be observed by comparing the two figures, imposing restrictions on worker tenure dampens the differences between the low and high educated workers in terms of their separation and displacement rates: while the workers with low educational attainment still have a slightly higher separation and displacement rate on average, the difference is very small.

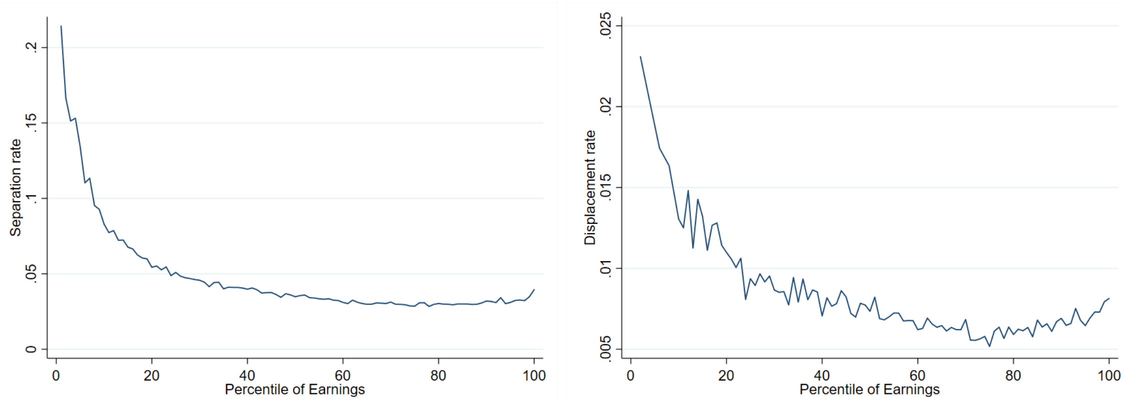


Figure D.17: *The incidence of separation (left) and displacement (right) over the earnings distribution, with restrictions on worker tenure.*

Finally, as shown in figure D.17, 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.

D.3.3 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.[84]

First of all, figure D.18 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 2.5% respectively. Just like seen in the main text, all rates 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.

[84] Note that I only repeat the analysis done in the main text in this section. The analysis displayed in sections D.3.1 and D.3.2 is omitted here and is available upon request.

Figure D.18: *The incidence of separation (left) and displacement (right) over time, using LIAB.*

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

Figure D.19 splits out the incidence rates seen in figure D.18 by education level, furthermore restricting the sample by prior worker tenure. Therefore, it can be seen as the LIAB version of figure D.16. Comparing these two figures reveals that the LIAB seems to suggest much lower displacement and separation rates prior to 2000 than the SIAB. However, when focusing on the years after 2000, the conclusion from the main text as well as section D.3.2 seems to continue to hold: Generally, the workers with low educational attainment are slightly more likely to be displaced and separated, but in recent years the difference between the two groups is negligible when restricting the sample to workers with at least 6 years of prior job tenure.

As shown in figure D.20, 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, when it comes to ex-post recall status, figure D.21 shows that the incidence of recall (within 5

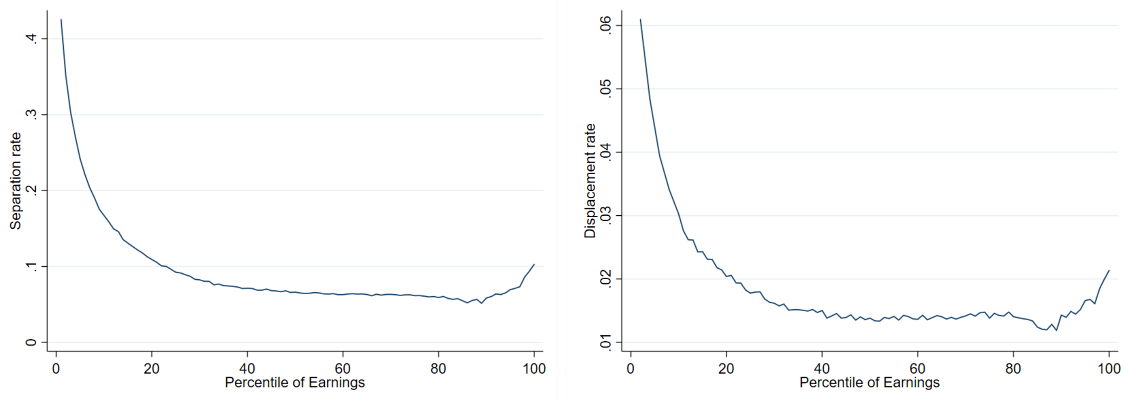


Figure D.20: *The incidence of separation (left) and displacement (right) over the earnings distribution, using LIAB.*

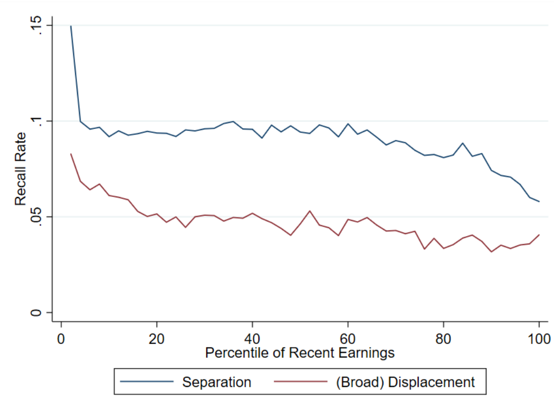


Figure D.21: *The incidence of recall within 5 years of separation or displacement, by percentile of the recent earnings distribution.*

years) is especially high for separation, but even for displacement consistently above 5% across the distribution, and much higher towards the bottom of the distribution, in line with the conclusions from figure 5.

D.3.4 Further observations on the average scarring effect of displacement

In this subsection, I will provide some further results to illustrate the robustness of the results in section 3.2 of the main text.

First, figure D.22 presents the counterpart of figure 6 using separations rather than displacements. As can be seen in the left panel of the figure, the raw effect of separation on earnings is quite substantial, and quite comparable to that seen for displacement in the main text. In particular, the change in relative earnings is fairly similar, thought the initial level is lower than it was for displacement. The right panel of the figure

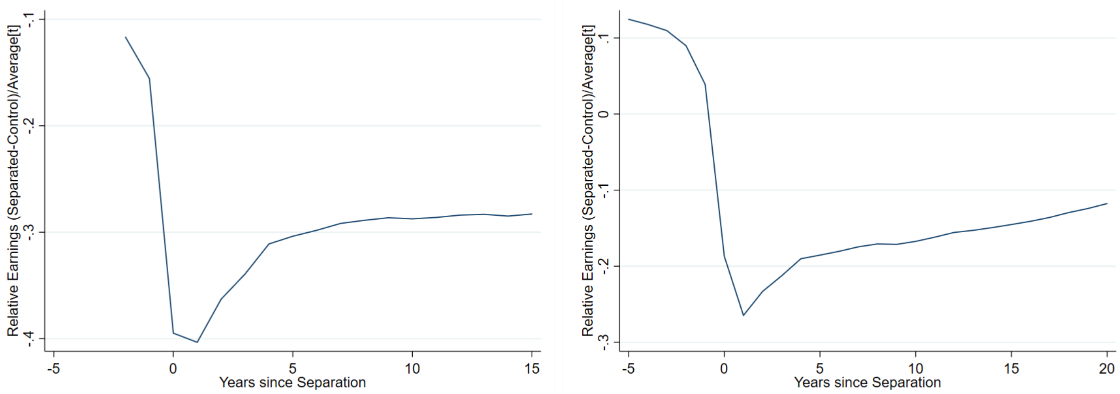


Figure D.22: *Raw (left) or regression-based (right, using specification 1) average effect of displacement on earnings, relative to the control group.*

confirms the similarity between the results for displacement and separation using specification (1): the earnings loss after separation seems to be slightly higher than that for displacement. However, the slightly increased magnitude of the earnings loss as well as the lower initial level in the raw differences can be (partially) attributed to selection of separated workers on their (potential) productivity.

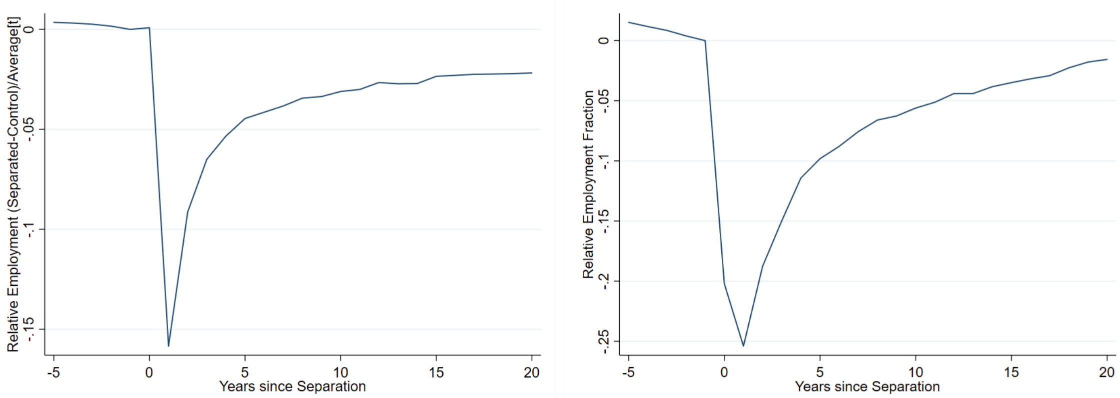


Figure D.23: *The effect of separation on employment status (left) and employment fraction (right), relative to the control group, using estimated coefficients from equation 1.*

As figure D.23 shows, the employment status of the separated workers also follows a similar pattern to that of the displaced workers (as shown in figure 7), with a slightly larger effect in the short run and a slightly faster recovery.

As mentioned in the main text, the conclusions regarding the scarring effect of separation and displacement are in line with the literature, though slightly conservative in some cases. In what follows, I relax some conservative assumptions I make in restricting the sample used in the estimation. First of all, I do not include any observation where the earnings for the individual are missing, arguing that these missing values may not in fact be zero given that there are many possible reasons for the earnings to be missing (including self-employment and employment in the public sector, as indicated in section 2). If I instead include these missing values as zeros in the estimation, the estimated effect (using specification 1) becomes slightly larger, as seen in figure D.24.

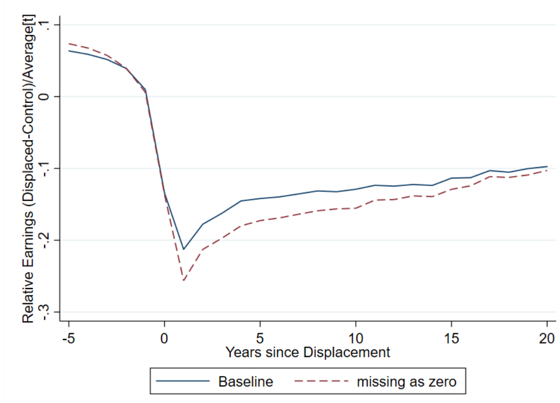


Figure D.24: *The effect of displacement on earnings, relative to the control group, using estimated coefficients from equation 1. The solid line mirrors the estimate from the right panel of figure 6, whereas the dashed line estimates the effect including missing values (interpreted as zero earnings).*

D.3.5 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.

First, figure D.25 displays the raw earnings differences after displacement (from 2 years before to 10 years after the event). Just like in the main text (the left panel of figures 6 and D.22), 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.26 shows the results of estimating equation (1) using the LIAB data, defining the treatment as either separation or displacement.[85] In particular, it can be seen that in the short-run, workers who are displaced

[85]The right panel of figure D.26 is roughly the equivalent of the right panel of figure 6 in the main text which uses SIAB 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. While in principle this should not matter for the estimates, following the argument made in Sun and Abraham (2020) would

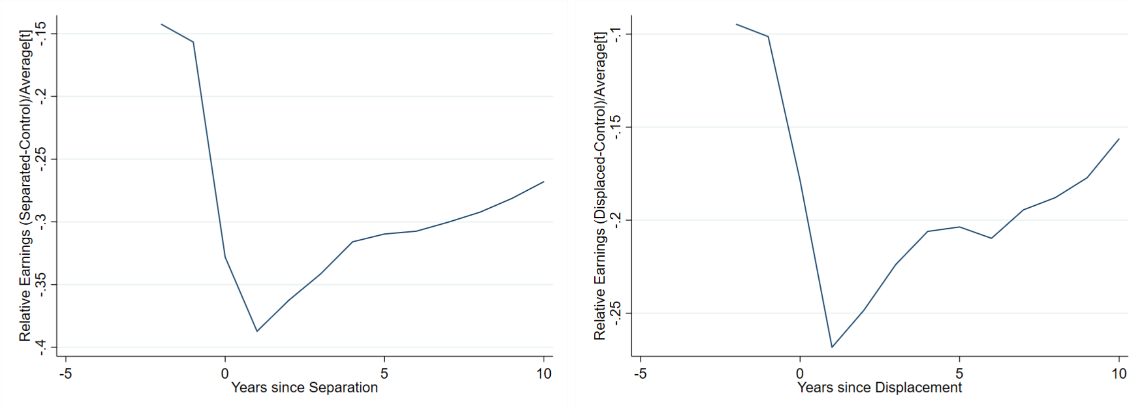


Figure D.25: *Raw average difference between earnings of the treatment and control group, defining treatment as either separation (left) or displacement (right), using LIAB.*

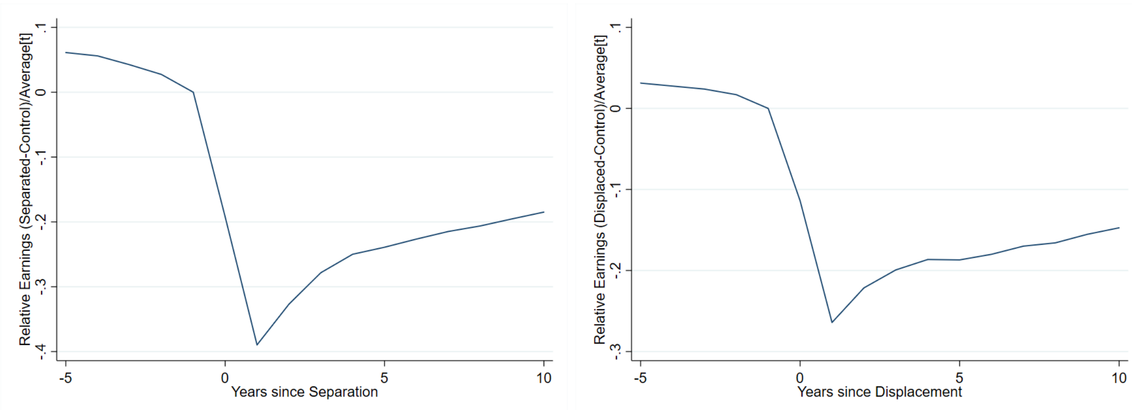


Figure D.26: *The effect of separation (left) and displacement (right) on earnings, relative to the control group, using estimated coefficients from equation 1 and using data from LIAB.*

(separated) earn roughly 25% (37%) 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 14% (18%) less than workers in the control group 10 years after the job loss took place.

Similarly, when using employment status as the dependent variable, as seen in figure D.27 (which is roughly the equivalent of figure 7), the results from the main text continue to hold. Using data from the LIAB instead of the SIAB, I now find that the likelihood of being employed (at any point in the year) drops by 8% (14%) in the year after displacement (separation), this likelihood decreases recovers to roughly 4.5% (5%) after only 3 years, and further recovers to less than 2% (2.5%) by year 8.

suggest that one might find different estimates since omitting observations more than 10 years out would also imply that these observations can no longer contaminate the estimates of the scarring effect less than 10 years after the displacement.

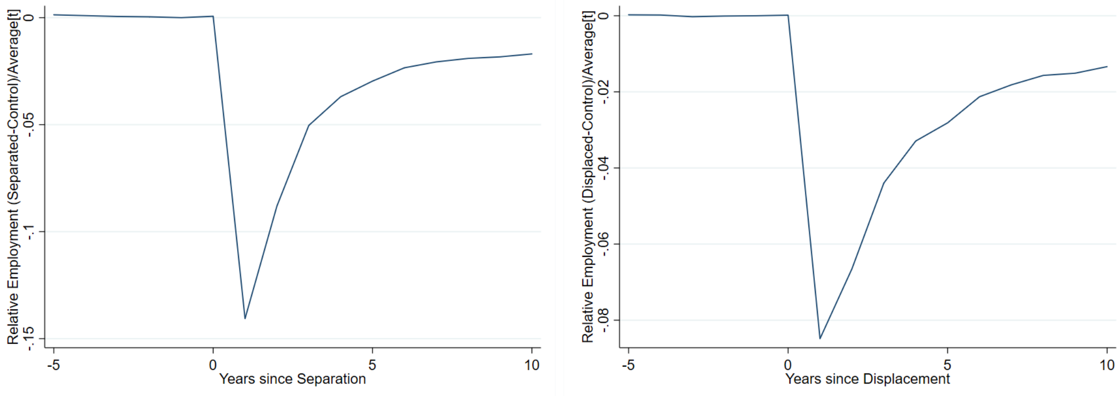


Figure D.27: *The effect of separation (left) and displacement (right) on employment status, relative to the control group, using estimated coefficients from equation 1 and using data from LIAB.*

D.3.6 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 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 the influence of one of these other dimensions (recent earnings) on the results obtained in section 3.3, and present some further results focusing on education and ex-post recall status, thereby highlighting the robustness of the results discussed in section 3.3 of the main text.

The first dimension along which I will further 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 hypothesized 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 much 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.

A first step towards investigating the importance of recent earnings can be made by re-estimating the results in the subsection 3.2 without the control for recent earnings, ($\bar{e}_i^y$ in equation 1). Figure D.28 shows how this result compares to the baseline result from the right panel of figure 6.[86] As can be seen in the figure, not

[86]Note that the estimates in figure D.28 were obtained using an old version of equation (1), where I did not normalize

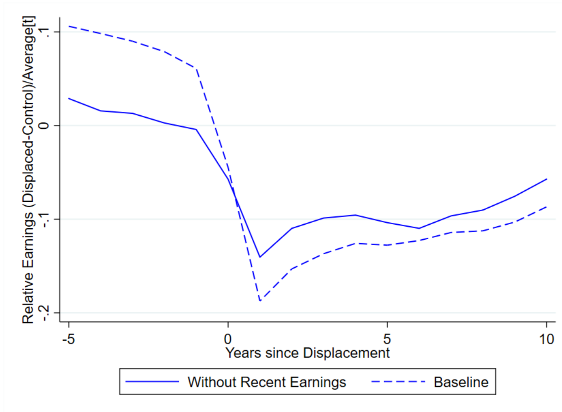


Figure D.28: *The effect of displacement on earnings, relative to the control group, with and without controlling for recent earnings.*

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.

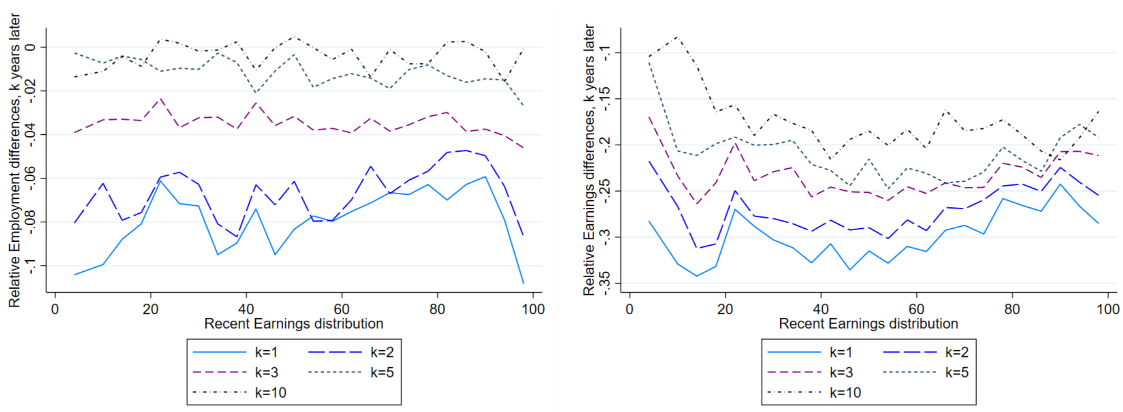


Figure D.29: *The raw effect of displacement on employment status (left) and earnings (right), by percentile of recent earnings. Numbers are calculated using the LIAB data, and are relative to workers in the control group in the same percentile of recent earnings. k refers to the number of years that have passed since the displacement event.*

Motivated by the apparent importance of recent earnings, figure D.29 plots the earnings differences over the recent earnings distribution.[87] From this figure, it can be seen that recent earnings does not seem to be

the coefficient for year $y - 1$ or drop the observations outside of the time interval of interest. Therefore, the dashed line in figure D.28 is in fact slightly different from the right panel of figure 6.

[87]Note that figures D.29 and D.30 are not based on the estimation of equation (1). Rather, these graphs show a calculation using raw differences, similar to those done for the left panel of figure 6.

very important in explaining subsequent paths of employment status. However, when it comes to the effect of displacement on subsequent earnings, a clear positive gradient is visible, especially in the short run and above the 20th percentile. As shown in figure D.30, 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 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. A further investigation of this observation, which may be partially explained by previous (or next) establishment characteristics, is beyond the scope of this paper, but nevertheless seems like a promising avenue for future research.

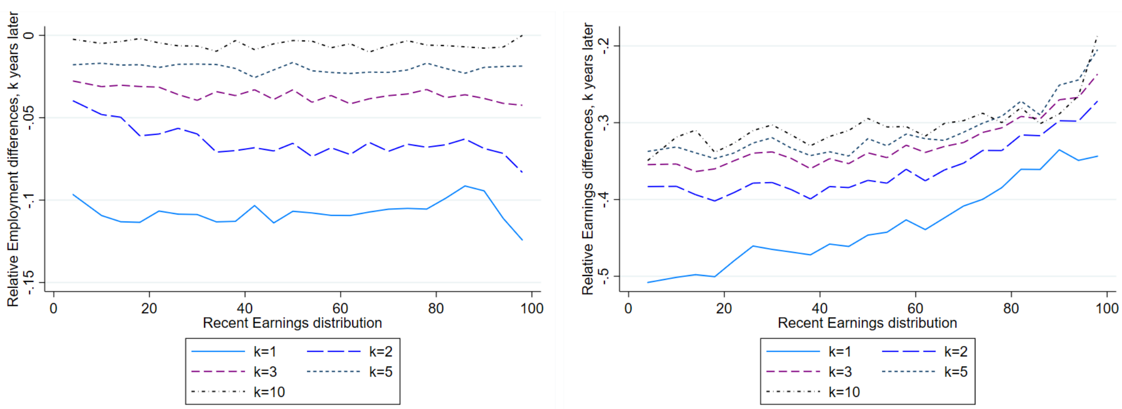


Figure D.30: *The effect of displacement on employment status (left) and earnings (right), by percentile of recent earnings and without restrictions on establishment tenure. Numbers are calculated using the LIAB data, and are relative to workers in the control group in the same percentile of recent earnings.* k *refers to the number of years that have passed since the displacement event.*

In section 3.3.1 of the main text, I show how displacement effects differ by educational attainment. In that section, I found that effects tend to be more severe for workers with a lower education level, especially when it comes to earnings. In figure D.31, I repeat the analysis using specification 1, estimating the effects of separation instead. Comparing figure D.31 to figure 9 in the main text, it can be observed that the effects of separation tend to be worse especially in the short run, and this holds for both education levels. However, the recovery in the subsequent 5 years is faster than the recovery observed after displacement, such that 5 years after the event, the difference between the effects of separation and displacement is much smaller than immediately after the event. When it comes to employment, workers with a low education do worse especially in the short run. In the long run, the different between the two education levels mostly disappears.

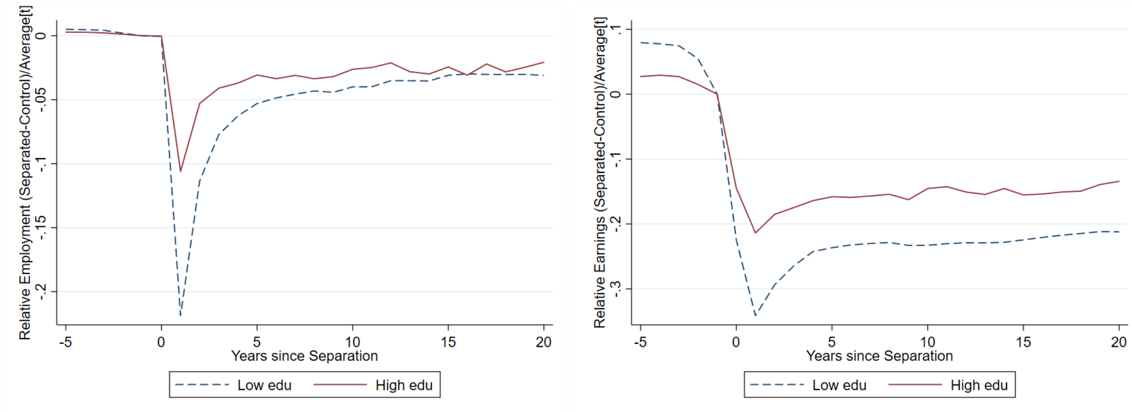


Figure D.31: *The effect of displacement on employment (left) and earnings (right), relative to the control group (by education group).*

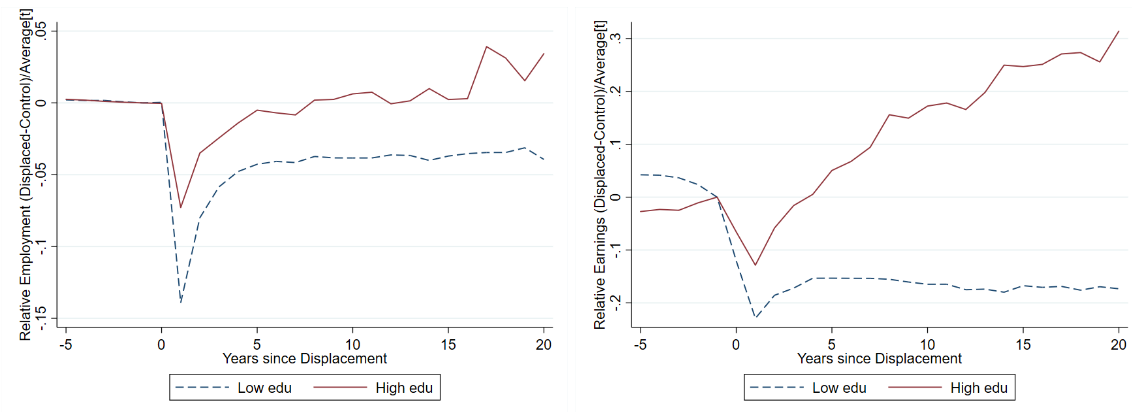


Figure D.32: *The effect of displacement on employment (left) and earnings (right), relative to the control group (by education group), where the control group contains individuals in either education group (rather than individuals from the same education group).*

In figure D.32, I repeat the analysis of the education-specific effect of displacement. However, contrary to the analysis that generated figure 9 in the main text, I now use the same control group for both education groups. That is, the control group contains workers of both education levels. In general, the results from the main text continue to hold. However, it can be noted that in the years following (and preceding) displacement, the relative earnings of the highly educated group grows faster than the relative earnings of the lower educated group. This reflects a trend that will leads the relative earnings difference for the highly educated group of displaced workers to become positive. This does not fully reflect a scarring effect of displacement and is rather an artifact of the treatment group consisting of only highly educated workers, whereas the control group did not select on education. In other words, this figure (and especially the right panel) serves as a reminder that the choice of the correct control group is crucial.

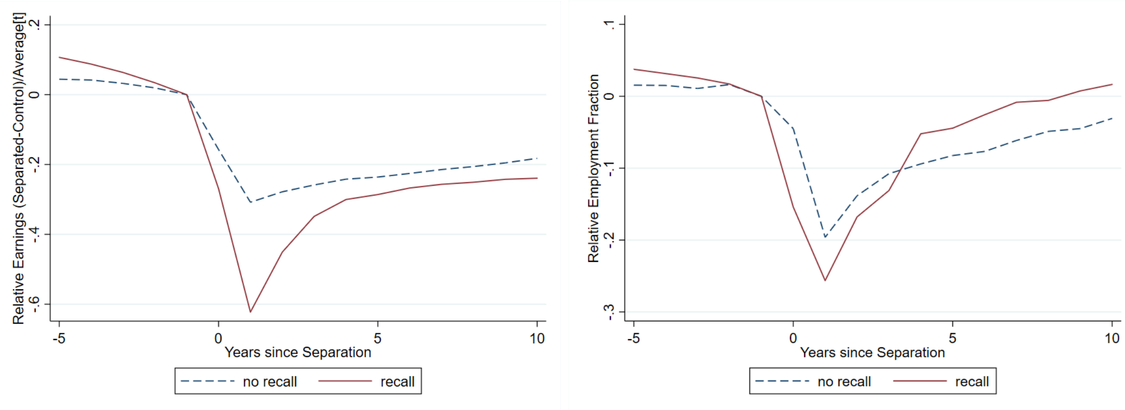


Figure D.33: *The effect of separation on earnings (right) and employment fraction (left) relative to the control group, by ex-post recall status (materialization of recall within 5 years), using specification 1 and using data from LIAB.*

In section 3.3.2 of the main text, I show how displacement effects differ by ex-post recall status. In that section, I found that recalled workers tend to do worse in terms of earnings, and also do worse in terms of employment in the short run. In figure D.33, I repeat the analysis, estimating the effects of separation instead. Comparing figure D.33 to figure 11 in the main text, it can be seen that the effects after separation are more severe than the effects of displacement. However, this is true for both recalled and non-recalled workers, so that the result from the main text continues to hold: recalled workers do better in terms of employment (especially in the short run, although the result here suggests that the difference persists), but suffer more in terms of earnings.

Moving on to the estimation using the interaction-weighted estimator from specification (2), figure D.34 repeats the analysis of figure 12 allowing for workers that experience multiple displacement spells.[88] As can be seen by comparing figure D.34 and figure 12, allowing for multiple displacements slightly strengthens the result as the earnings and employment loss of recalled workers becomes slightly larger in magnitude.

In figure D.35, I repeat the analysis from figure 12 using only employment (and earnings) in full-time jobs, addressing possible concerns of earnings losses being driven by workers transitioning from full-time to part-time jobs after displacement. As can be seen in the figure, the results remain largely intact, with the note that some of the differences in the earnings loss between non-recalled and recalled workers more than 5 years

[88]Recall that in order for a separation to be considered a displacement according to my definition, the workers needs to have a tenure of at least 6 years in the establishment from which they are displaced. As the tenure counter simply resumes counting after returning to a firm, allowing for multiple displacements will primarily affect the group of recalled workers who are displaced again from the same firm.

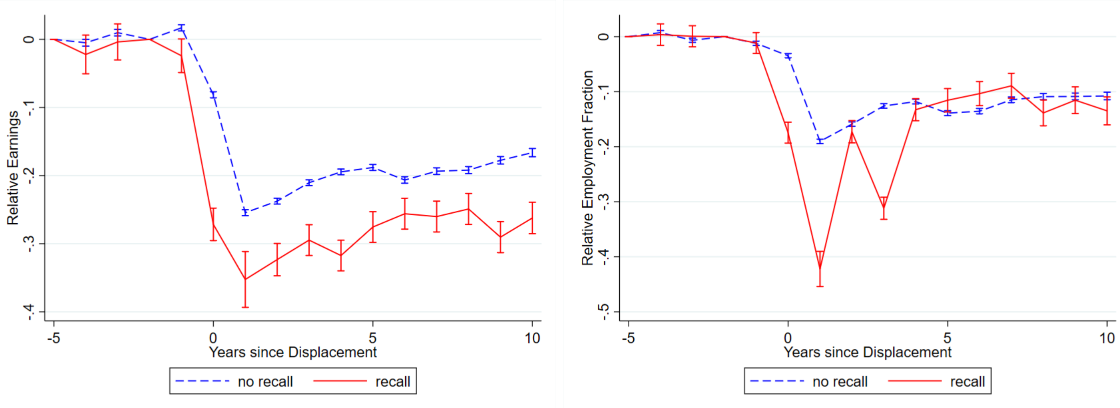
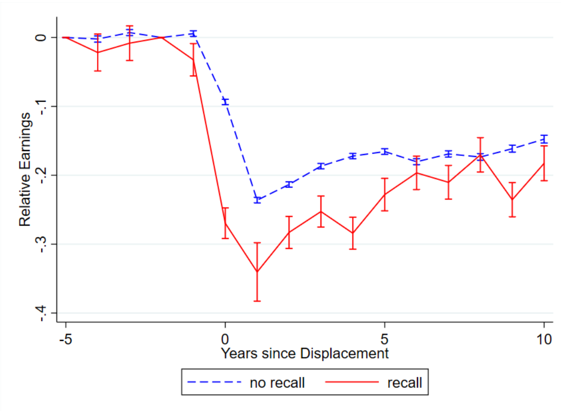


Figure D.34: *The effect of displacement on earnings (right) and employment fraction (left) by ex-post recall status, relative to the control group, using estimated coefficients from equation 2 and using data from LIAB. The error bars correspond to 95% pointwise confidence intervals. Compared to figure 12 in the main text, the estimation here allows for multiple displacements per individual (classifying the worker according to their first displacement).*

after displacement are no longer statistically significant.

Finally, figure D.36 shows that the larger earnings loss experienced by recalled workers cannot be explained solely by a lower wage at the recalling firm. In the figure, I show how the estimation changes when I use only earnings at the recalling firm (for the recall group, leaving the control and non-recall group unchanged). As can be seen in the figure, the short-term earnings loss remains largely the same, but it is no longer the case that the recalled worker also does worse in the long run. This seems to indicate that part of the long-run persistence of the larger earnings losses for recalled workers is driven by subsequent employer changes (possibly after a subsequent separation).



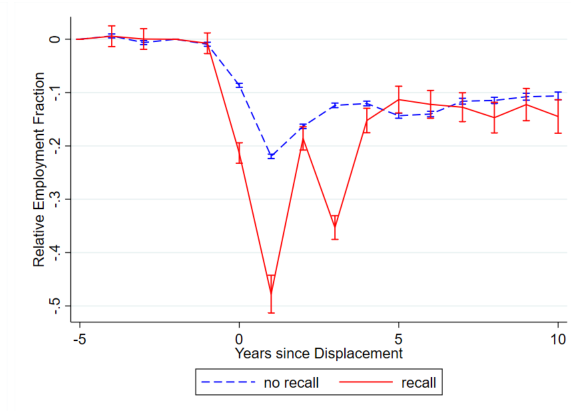


Figure D.35: *The effect of displacement on earnings (right) and employment fraction (left) by ex-post recall status, relative to the control group, using estimated coefficients from equation 2 and using data from LIAB. The error bars correspond to 95% pointwise confidence intervals. Compared to figure 12 in the main text, the estimation here only uses earnings (and employment) from full-time jobs.*

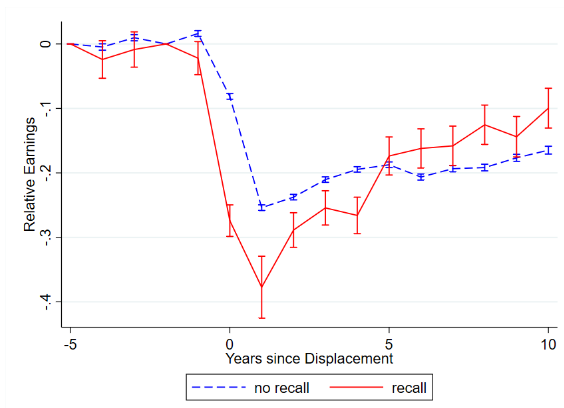


Figure D.36: *The effect of displacement on earnings, by ex-post recall status and relative to the control group, using estimated coefficients from equation 2 and using data from LIAB. The error bars correspond to 95% pointwise confidence intervals. Compared to the left panel of figure 12 in the main text, the estimation here only uses earnings from the firm to which the recalled worker is recalled.*