

Recall and the Scarring Effects of Job Displacement

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Job Market Paper

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Abstract:

Workers who lose their job in mass layoffs experience a well-documented scarring effect: a large and persistent earnings loss on average. However, these effects abstract from the fact that many workers who lose their job end up returning to their previous employer (i.e. they are recalled) rather than finding a new job. In this paper, I explore how the scarring effect of job displacement differs by whether or not workers are recalled to their previous employer. I use detailed administrative data from Germany to document these differences. I then develop a job search model that can explain these heterogeneous effects, as well as the average scarring effect. The data show that earnings losses are larger for individuals who are recalled to their previous employer than for workers who move to a new job, even though recalled workers are re-employed faster. I find that this difference in earnings loss is driven by employment in the short run and by wages in the long run. Using the calibrated model, I show that an important factor in explaining recalled workers' larger long-term losses is that these workers are more likely to experience repeated job loss.

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

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1 Introduction

Workers who lose their job are exposed to a well-documented expected large and persistent loss in earnings compared to similar workers who did not lose their job (see e.g. Jacobson et al., 1993).¹ The literature that has documented this “scarring” effect of job loss generally focuses on workers who are displaced permanently from a firm.² However, it has also been documented that a large fraction of workers who lose their job will return to their former employer rather than move to a new employer.³ This group of recalled workers is quite sizeable, accounting for up to 50% of all workers losing their job and up to 10% of displaced workers. Therefore, understanding how (and why) their pattern of earnings and employment after the initial job loss differs from the pattern uncovered for other displaced workers is important in gathering a more complete understanding of the long-run effects of job loss.

In this paper, I explore the long-run effects of displacement, estimating and explaining the effects separately for workers who returned to their previous employer and those who did not. In particular, I document heterogeneity in this earnings loss along this dimension of ex-post recall status, finding that recalled workers suffer from larger earnings losses after displacement than non-recalled workers. In order to explain this, I develop a job search model of the labour market. In this model, I explicitly distinguish between workers who are expecting a recall and workers who do not. This allows these two groups to differ during their nonemployment spell (as well as afterwards), in terms of transition rates and human capital depreciation rates (among others). The model, calibrated to the data, explains the larger earnings loss experienced by recalled workers, and points to subsequent separations as the main explanation of this result. Human capital depreciation, on the other hand, works in the other direction. In particular, human capital depreciation only plays a minor role in explaining the long-run earnings differences for recalled workers, while its role in explaining such differences is large for non-recalled workers. This, in turn, suggests that while alleviating a worker’s human capital depreciation during nonemployment may be successful in bringing down the long-term earnings losses for non-recalled workers, it will not be very effective

¹In section 1.1 I briefly discuss this literature.

²Throughout this paper, I will refer to workers losing their job through a mass layoff as displaced worker. For a more precise definition of displacement (which I use in the data), which closely corresponds to the definition used in the literature, see section 2.

³For example, Fujita and Moscarini (2017) found that this holds for over 40% of employed workers who move into unemployment upon losing their job (in the United States). In the context of Germany, findings from Mavromaras and Rudolph (1998) imply a similar (slightly lower) figure. In section 3.1, I show that I find recall rates ranging from 30 to 50% in my data (before conditioning on displacement).

in alleviating recalled workers' earnings losses.

In order to document the scarring effects of displacement by ex-post recall status, I use detailed administrative data from Germany. This data allows me to reliably identify individuals who are recalled to their former employing establishment, and therefore allows me to separate the treatment group of displaced workers into a recalled and non-recalled group, where the recall group accounts for close to 10% of the sample of displaced workers. By separating these two groups, I can then separately estimate the scarring effect of displacement, rather than restricting the sample to omit recalls.⁴

To estimate the scarring effects of displacement, I use recently proposed methods that aim to provide a reliable estimate of the dynamic treatment effects by accounting for treatment effect heterogeneity (by cohort).⁵ In particular, the main results in the empirical section of the paper are generated using the interaction-weighted estimator from Sun and Abraham (2020). These results are contrasted with the results obtained using a “standard” two-way fixed effects (TWFE) approach, which the recent event study literature proved to be subject to (unwarranted) contamination across cohorts and observation years. This comparison reveals that using these two different methods will yield a different implied decomposition of the (average) earnings effect into employment and wages: whereas the standard TWFE approach suggests that the long-run earnings losses are primarily driven by lower wages, the results obtained using the interaction-weighted estimator suggest that wages almost fully recover and the long-run earnings losses are driven by a persistent loss in employment fraction (defined as the fraction of the year spent in an employment spell).

As can be observed in figure 1, separately estimating the long-run effect of displacement on earnings for displaced workers who are either recalled or not recalled to their former employer reveals that recalled workers suffer from a larger earnings loss than non-recalled workers (relative to the control group of never displaced workers), both in the short run and in the long run. This is despite the recalled worker generally finding re-employment faster than the non-recalled worker. Moreover, estimating the effect on the employment fraction reveals that this larger earnings loss is driven by employment in the short run, but by wages in the long run. In particular, I find that a

⁴In the existing literature, recalled workers are often omitted from the sample. For example, Lachowska et al. (2020) focused on “permanent separations”, and Schmieder et al. (2020) omitted any worker who returns to work for the same employer in the first 10 years after displacement.

⁵In section 1.1, I briefly discuss the issue that these papers seek to avoid, as well as some of the proposed methods to improve the reliability of the estimate.

recalled worker is 6 to 10 percentage points more likely than a non-recalled worker to be separated from their job again in the first few years following the initial displacement.

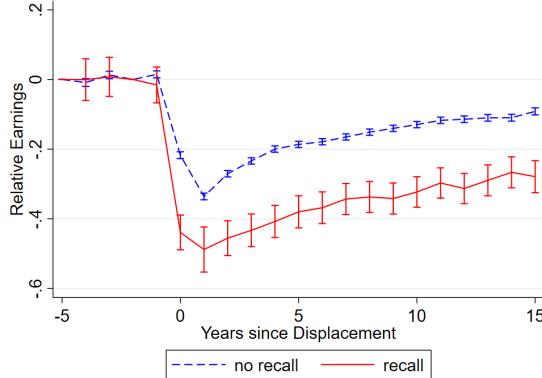


Figure 1: *The estimated effect of displacement on earnings by recall status (observed ex-post), relative to the control group of never-displaced workers, generated using the interaction-weighted estimator from Sun and Abraham (2020). The error bars correspond to 95% pointwise confidence intervals. The details of the estimation procedure are described in sections 2 and 3.3 of the paper.*

I then develop a job search model of the labour market that is able to explain the larger earnings losses experienced by recalled workers, while still fitting the average scarring effect of displacement as achieved by some existing models. In order to do so, I use two of the elements from these existing models. The first of these elements is human capital, which appreciates during employment and depreciates during unemployment.⁶ The second element is heterogeneity of firms by both productivity and separation rate, thus generating a job ladder with slippery bottom rungs, as proposed in Jarosch (2021). I also add elements that enable me to generate and comment on the heterogeneity observed in the data. In particular, I introduce a fixed worker type (which I interpret as the education level), and explicitly distinguish between workers who are expecting to be recalled and workers who are not (interpreting them as two different states). By explicitly assuming workers who expect to be recalled to be in a different state from those who do not expect a recall, I can allow these workers to follow a different path while non-employed. Thereby, I can capture several possible explanations for the observed severity of the scarring effect of displacement for recalled workers. Among others, I do this by setting distinct parameters for the worker's human capital

⁶This element is commonly used across several existing papers, such as Huckfeldt (2021), Jung and Kuhn (2019), Jarosch (2021), and Burdett et al. (2020).

depreciation and job finding rates while nonemployed, and allowing for the recalled worker to return to a more unstable and less productive job.⁷

The model is calibrated to moments generated from the German data.⁸ Counterfactual simulations generated from the calibrated model show that the empirical results can partially be explained by assigning a lower human capital depreciation rate and a higher job finding rate to these workers,⁹ compared to unemployed workers that are not (or no longer) expecting to be recalled. In particular, this implies that while human capital depreciation may be important to explain the long-run earnings loss for non-recalled workers, this is not the case for recalled workers (who experience a probability of human capital depreciation close to 0 during their initial nonemployment spell).

Finally, I use counterfactual simulations to decompose the observed difference in earnings loss after displacement between recalled and non-recalled workers. This decomposition reveals that the differences in the long run are primarily driven by the instability of the job to which the worker is recalled. In other words, I explain the larger long-term earnings loss through compounding the scarring effect of several job loss events. This compounding effect is more likely to occur for the recalled worker, who (as confirmed in the data) is more likely to be separated again in the first few years after the initial displacement, thereby generating the larger earnings loss for the recalled worker (compared to the non-recalled worker) as estimated from the data.

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 data 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, and studies the drivers and implications of these observations. Finally, Section 7 concludes and provides some directions for potential future research.

⁷While the assumption that jobs become more unstable after a recall is motivated directly by my observations in the data, the assumption on lower productivity is not directly observed in the data. Here, I argue that jobs may be less productive because firms may have had to cut down on their capacity in order to survive the events leading up to the initial layoff.

⁸In particular, I do not directly target the estimation results from the empirical section, but use a number of moments that more directly inform the parameter values (through an indirect inference method) and then check whether the resulting set of parameter values can successfully match the empirical results.

⁹The higher job finding rate for workers expecting to be recalled is a combination of the recall (materialization) rate and the new job finding rate. The new job finding rate itself is found to be roughly 25% lower than the new job finding rate for workers not expecting a recall.

1.1 Related Literature

In empirically investigating the impact of recalls on the long-term consequences of job loss (and mass layoffs in particular), this paper contributes to a substantial existing literature. This literature goes back to Jacobson et al. (1993), who used quarterly administrative data from Pennsylvania and find that workers who were displaced in 1982 suffered an immediate earnings loss of more than 50% (relative to comparable workers who were not laid off), and still earned 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.¹⁰ 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,¹¹ 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).

By focusing on ex-post recall status (and education), this paper enriches the literature investigating heterogeneity in the scarring effects of displacement. Until recently, most of the empirical discussion contained in the existing displacement literature abstracted from heterogeneity or only briefly touched upon it. One of the first exceptions to this is Guvenen et al. (2017), who used 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) used a machine learning approach to investigate which of the observable variables are most important in explaining heterogeneity in the earnings decline after job loss (using administrative data from Austria), finding an especially large role for firm characteristics.

Aside from contributing to the investigation of heterogeneity in the scarring effects of displacement, this paper also contributes to the existing displacement literature by analyzing the impact of using recently proposed methods that aim to correct for treatment effect heterogeneity (by cohort). The majority of existing papers use a very similar method, based on an event-study framework with staggered treatment implementation, and the effects are generally estimated us-

¹⁰See Kletzer (1998) for a comprehensive survey of the early literature. Examples of later papers that addressed this issue include Couch and Placzek (2010) and Von Wachter et al. (2009).

¹¹Examples 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.

ing two-way fixed effects. In some cases, like in Davis and Von Wachter (2011), this is done separately for each year for which displacements are considered, and the resulting estimates are averaged afterwards. Some other work, like Flaaen et al. (2019) and Jarosch (2021), stacked 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 afterwards. 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), Sun and Abraham (2020), and Borusyak et al. (2021).¹² 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.¹³ 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.¹⁴ Fortunately, all three papers also offer a solution that aims to avoid this contamination of the estimated dynamic treatment effects by observations from other cohorts and time periods. Throughout the empirical section, I will primarily use the method from Sun and Abraham (2020), which is further discussed in section 2. I show how results on the long-run effect of displacement on earnings obtained using this method differ from those obtained using the “traditional” methods. As a robustness exercise, I also show that similar results can be obtained using the method from Borusyak et al. (2021) instead.

A final contribution of the empirical section of this paper is to the growing literature analyzing the incidence and consequences of recalls, to which I contribute by examining subsequent earnings and employment outcomes of recalled workers. The topic of recall has been studied quite extensively, going back to studies such as Feldstein (1976) and Katz (1986). More recently,

¹²There are many other papers highlighting the issues with these estimations, generally focusing on a setting where the researcher is interested in estimating a single (static) treatment effect, rather than a dynamic treatment effect.

¹³To 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 off during a recession (see Davis and Von Wachter, 2011, for example). 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.

¹⁴Both Callaway and Sant'Anna (2020) and Sun and Abraham (2020) contain a more detailed description of the issue, and Sun and Abraham (2020) explicitly derived the decomposition of the two-way fixed effects estimate into cohort-specific estimated treatment effects. See these papers for a more elaborate discussion. The issue is also briefly discussed in Borusyak et al. (2021), who also discuss other issues such as the collinearity between the set of treatment leads and lags and the time fixed effects in the standard two-way fixed effects setup.

Nekoei and Weber (2015), as well as 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.

The model section of this paper contributes to the literature providing theoretical analysis of the long-term consequences of displacement, in particular by distinguishing between recalled and non-recalled workers. 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.¹⁵ Some recent work has attempted to resolve this issue with some success. The paper closest to mine in terms of the developed model is Jarosch (2021), who proposed a model in which firms differ not only in terms of productivity, but also in the separation rate, thereby allowing for workers to experience several subsequent displacements after the initial one (as observed earlier by Stevens, 1997). This, combined with the presence of human capital which depreciates during unemployment (and increases while employed), enables him to reproduce the average earnings loss after displacement, both in the short and in the long run. Other models that have been successful in replicating the average earnings loss after displacement include Krolikowski (2017), Huckfeldt (2021), Jung and Kuhn (2019), Burdett et al. (2020), and Gregory et al. (2021).¹⁶

Finally, I contribute to the theoretical analysis of recalls by explicitly distinguishing between nonemployed workers expecting a recall and nonemployed workers not expecting a recall.

¹⁵See Pissarides (2000) for an example of such a standard job search model.

¹⁶The result in Huckfeldt (2021) that workers who switch occupations suffer from larger losses than workers who stay in their former occupation may seem to contradict my result that recalled workers do worse than non-recalled workers, but this is not quite the case. In particular, for workers to be considered recalled in my setting, they do not necessarily have to return in the same occupation. Indeed, throughout the paper I do not explicitly consider occupational switching after displacement, which can therefore be considered as one of the dimensions of heterogeneity that are still masked by some of my estimated effects (including those by ex-post recall status).

In my model, these two workers are in a separate state, thereby allowing for these workers to follow different paths in all outcome variables of interest (both during and after nonemployment). 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).¹⁷ 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 unemployed. Until the recall materializes, 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 expecting to be recalled and other unemployed workers, where workers expecting a recall 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.

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.¹⁸ 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.

¹⁷In 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).

¹⁸In the data, an establishment is defined as all locations of a firm within a Kreis (municipality).

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 (especially of 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, which either act as a yearly notification or signal a changed or ended employment relation. Using the establishment ID, as well as the observed 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.¹⁹ 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 security benefits during nonemployment.²⁰ 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 leading to these observations 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).²¹ Further summary statistics on both workers and establishments are presented in appendix D.1 and D.2.

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's employment spell with their establishment ends in period t . This means that the worker either no longer works for the same establishment in period $t + 1$ or returned to the establishment after being away for more than 31 days. Throughout, I drop workers who are trainees, casual workers, or partially retired workers,

¹⁹If the individual is non-employed at the start of the year/quarter (or employed at multiple establishments), the information is used for the establishment from which the individual has the highest earning in that period.

²⁰Other reasons for not observing an individual include working (and moving) abroad.

²¹Note that the results discussed in the empirical section of the paper are based on the yearly dataset only. In contrast, the quarterly dataset is the primary source used to calculate the moments that I use to calibrate the model.

| Frequency | SIAB | | LIAB | |
|-------------------------------|------------|------------|------------|------------|
| | Yearly | Quarterly | Yearly | Quarterly |
| Raw observations | 66,961,520 | 66,961,520 | 53,433,114 | 53,433,114 |
| Observations (Age restricted) | 52,162,319 | 52,162,319 | 43,001,421 | 43,001,421 |
| 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.*

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.²² I then define such a worker as displaced if the establishment either closes or experiences a mass layoff.²³ Following the literature, 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 at least 20% of its workforce in the displacement year.²⁴ 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.²⁵

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 that was estimated

²²This way, I exclude apparent separations that are caused by paternity or maternity leave, disease, or seasonal patterns in employment.

²³I 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.

²⁴For establishments with up to 20 employees, I use a threshold of 50% for both these conditions. However, as explained later in this section, these mass layoffs are generally not used for estimation purposes.

²⁵Note 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). Furthermore, a worker who is displaced from a closing establishment will always be in the non-recalled group of displaced workers. As I show in section 3.1, however, excluding these workers does not substantially alter the recall rate. Indeed, as I show in appendix D.3.6, excluding workers whose establishment closes from the estimation altogether does not change the results.

in Davis and Von Wachter (2011):

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

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} refers to the outcome variable of interest for individual i in period t . In most cases, this outcome variable is the individuals yearly earnings or the fraction of the year the individual spent in an employment relationship. Other outcome variables considered include the (yearly) job loss rate and the (yearly) average daily wage. 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 $y - 1$.²⁶ 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) or 20 (when using SIAB).²⁷ The estimation is done separately for each sample year y .²⁸ 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 vari-

²⁶I 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).

²⁷I 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.

²⁸Note 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.

able (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 the 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.²⁹

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.³⁰ 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 satisfy 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 primarily focus on 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 polynomial in age do not appear:³¹

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

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:

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

²⁹An alternative to this method of estimating the relative earnings path is to estimate equation (1) using log earnings instead. I decided against this, as the data includes many observations with zero earnings, which I would need to omit in order to run this alternative estimation.

³⁰See section 1.1 for a brief overview of these papers.

³¹Note 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.

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 the value of the outcome variable of interest for 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 still 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.³² Furthermore, note that rather than omitting one value of k , I follow the discussion in Borusyak et al. (2021) by omitting two values of k . This is because generally the set of relative time indicators D_{it}^C is collinear with itself as well as with 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.³³

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 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 $\hat{\delta}_k^C$ are estimated in a single estimation procedure, I can then also form corresponding (pointwise) confidence intervals for the resulting weighted averages $\hat{\delta}_k$.³⁴

When estimating the equations discussed above I partially follow the literature by restricting my sample to individuals with an establishment tenure (prior to displacement, if applicable) 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. In appendix D, I show how the results presented below are affected

³²In appendix D, I show how results are affected by instead using the “last-treated” group as the control group.

³³Note that Borusyak et al. (2021) also propose an alternative estimation themselves. I show in appendix D.3.6 that using their method yields the same results as using the interaction-weighted estimator from Sun and Abraham (2020).

³⁴In 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 $\hat{\delta}_k^y$ for different values of y .

when changing one of these restrictions.

3 Empirical Results

In this section, I present the results generated from the data. In particular, I start by describing the incidence of separation, displacement, and subsequent recall, 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. 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 sometimes less convincing, potentially due to the smaller time period spanned by this dataset and its different sampling method.

3.1 The Incidence of Displacement and Recall

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, displacement, and recall rates for the entire sample as well as several subsets of the sample.³⁵

First of all, figure 2 displays the separation and displacement rates 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 in 1990 is quite clearly visible.³⁶ While separation and displacement rates tend to peak around recessions, the magnitude of these peaks are relatively small. For example, it can be seen that during the Great Recession, the separation and displacement rates increased but still remained below pre-2005 levels.

³⁵All graphs in this subsection are generated using the complete sample. In other words, the restrictions on pre-displacement establishment tenure and establishment size used to generate the restricted sample used for estimating equations (1) to (2) are not applied here.

³⁶Note 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. In appendix D.3.1, I show the separation and displacement rates over time for East and West Germany separately.

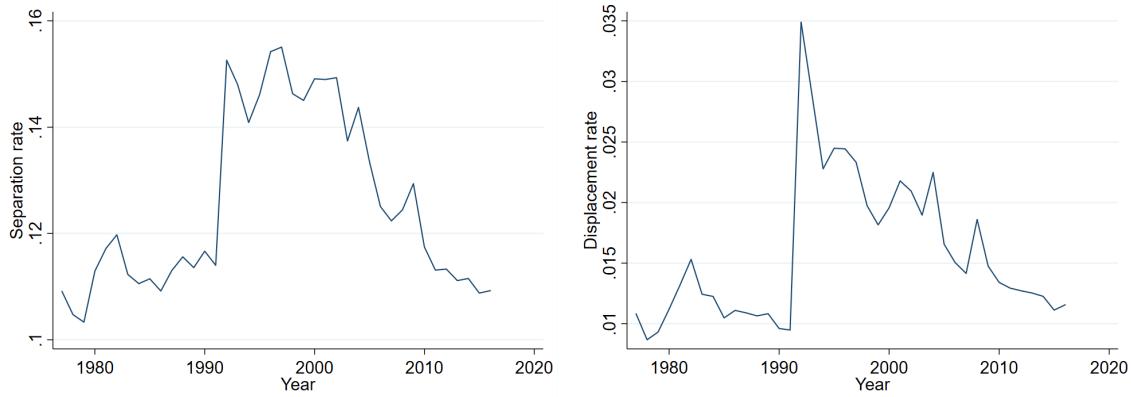


Figure 2: *The incidence of separation (left) and displacement (right) over time.*

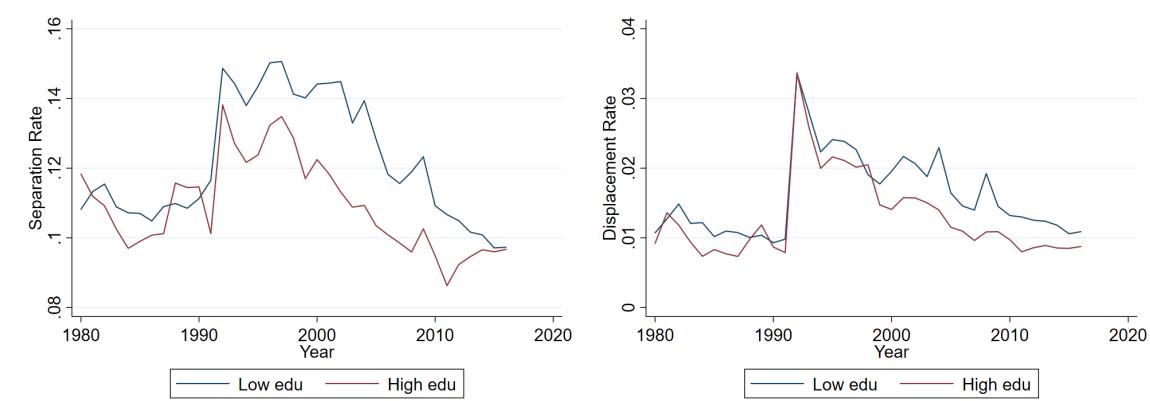


Figure 3: *The incidence of separation (left) and displacement (right) by education level, over time.*

In figure 3, I plot the separation and displacement rates over time by education group, where education level is defined as (1) Non-University (low) or (2) University (high). As can be seen in the graph, workers with a relatively low education level tend to be more vulnerable to separation and displacement. Furthermore, with roughly 80% of the workers being categorized in the first group, the overall fluctuations of the separation and displacement rates observed in figure 2 primarily follow those of workers with a low education level.

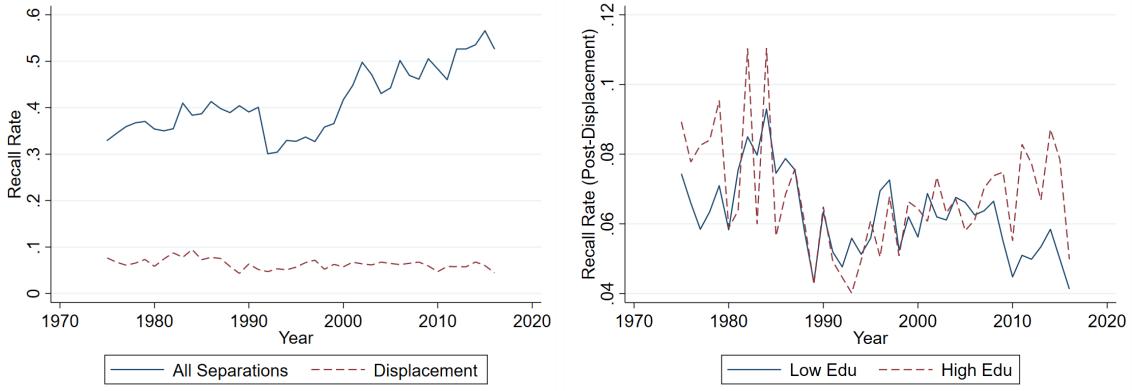


Figure 4: *Left: The incidence of recall within 5 years of job loss over time, unconditionally and conditional on displacement. Right: The incidence of recall within 5 years of job loss, conditional on displacement, over time and by education level.*

Next, figure 4 shows the incidence of recall (within 5 years), unconditionally or conditional on displacement. As can be seen in the figure, the unconditional incidence of recall is fairly high, and takes values between 30% and 55%, in line with observations from existing papers such as Fujita and Moscarini (2017) and Mavromaras and Rudolph (1998). The recall rate conditional on displacement is much lower, and fluctuates between 4.5% and 7% 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. As can be seen in the right panel of figure 4, the recall rates (conditional on displacement) are fairly similar for the two education levels.

As shown in figure 5, 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

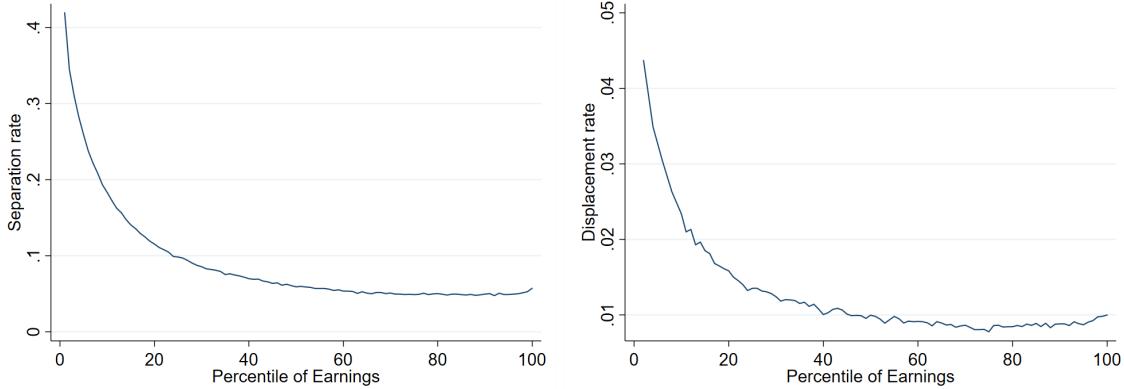


Figure 5: *The incidence of separation (left) and displacement (right) over the earnings distribution.*

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.

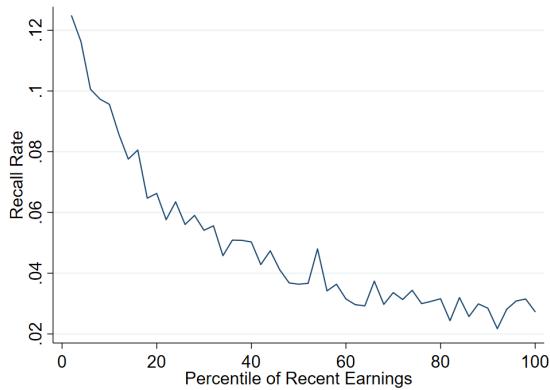


Figure 6: *The incidence of recall within 5 years of displacement, by percentile of the recent earnings distribution.*

Figure 6 shows the incidence of recall (within 5 years) after displacement, over the recent earnings distribution. As can be seen in the figure, the recall rate (conditional on displacement) 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 highlighted 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, separation, and recall 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

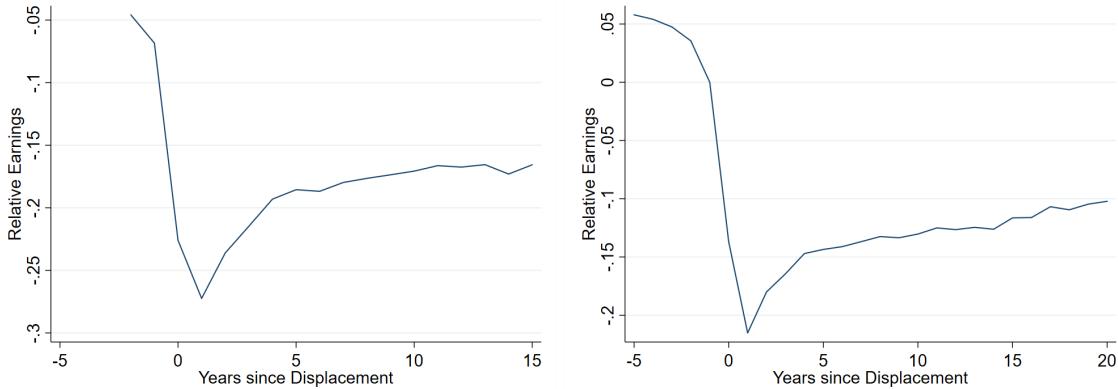


Figure 7: Raw (left) or regression-based (right, using specification 1) average effect of displacement on earnings, relative to the control group.

Having investigated the incidence of job loss across the sample, I will now move towards assessing the effects of displacement on earnings.³⁷ Before moving to the results of estimating equations (1) and (2), however, it is worth looking at the raw earnings losses first. The left panel of figure 7 presents these raw earnings losses. 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

³⁷The 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.

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. The right panel of figure 7 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 displaced lose roughly 20% of their earnings.³⁸ 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.³⁹ These conclusions are in line with what has been observed in the literature, and confirm the observation of a large average scarring effect of displacement on earnings (though what I find here is on the lower end of the estimates found in existing work).

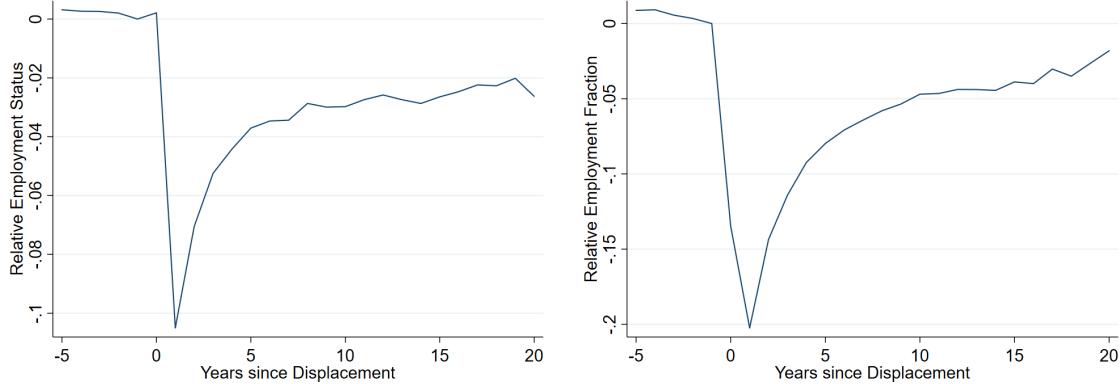


Figure 8: *The effect of displacement on employment status (left) and employment fraction (right), relative to the control group, using estimated coefficients from equation (1).*

As the left panel of figure 8 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

³⁸To 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.

³⁹It 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.

choices (working hours).⁴⁰ In particular, while the likelihood of being employed (at any point in the year) drops by 10% in the year after displacement, the decrease recovers to roughly 5% after only 3 years, and 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 8, a similar picture arises, though it should be noted that the effect of displacement on employment fraction is estimated to be stronger and more persistent than the effect on employment status. One potential explanation of this is that these displaced workers are more likely (than the control group) to be separated from their job in subsequent years, as illustrated by Jarosch (2021). If such a subsequent nonemployment spell is less than a year in duration, it would count towards the employment fraction but not toward the employment status (as the worker would still be employed at some point in the year).

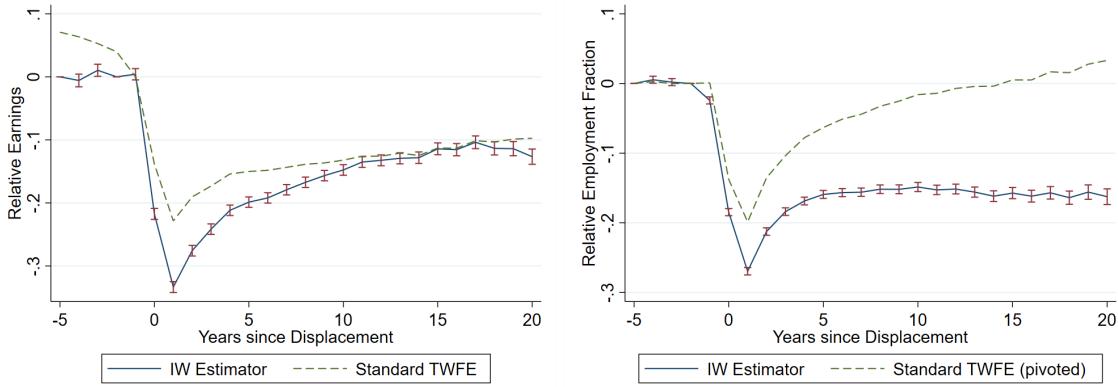


Figure 9: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group, using estimated coefficients from equation (2) (solid) or (1') (dashed). The error bars on the solid line correspond to 95% pointwise confidence intervals*

Finally, figure 9 shows how estimates of the average scarring effect of displacement on earnings and employment (fraction of the year employed) change when using the interaction-weighted estimator from Sun and Abraham (2020), as described in section 2, instead.⁴¹ 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

⁴⁰The 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.

⁴¹In appendix D.3.4, I show that the results are similar when using the alternative method from Borusyak et al. (2021).

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.⁴²

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, 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.

3.3.1 Education Level

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 10, I plot the results of estimating equation (1) when splitting the sample by education (non-University and University).⁴³ Comparing the two educational groups, it can be observed that workers with a relatively low education tend to suffer from higher earnings losses, both in the short- and long term. In the short run, this is likely partially driven by a larger initial effect on employment fraction, which suggests that workers with a high

⁴²In fact, comparing the left and right panel of figure 9 suggests that the effect of displacement on (daily) wages completely dissipates after 10-15 years. This can be confirmed by using this daily wage itself as the dependent variable, as shown in appendix D.3.4. This seemingly contradicts Lachowska et al. (2020), but it should be noted that the wages used in that paper are not necessarily comparable to the “daily wages” considered in this exercise (see appendix D.3.4).

⁴³Note that I split the sample by education group for both the treatment and control group. In other words, the effects in figure 10 are relative to workers in the same education group. In appendix D.3.6, I show how the results change if I don't restrict the control group to have the same education level.

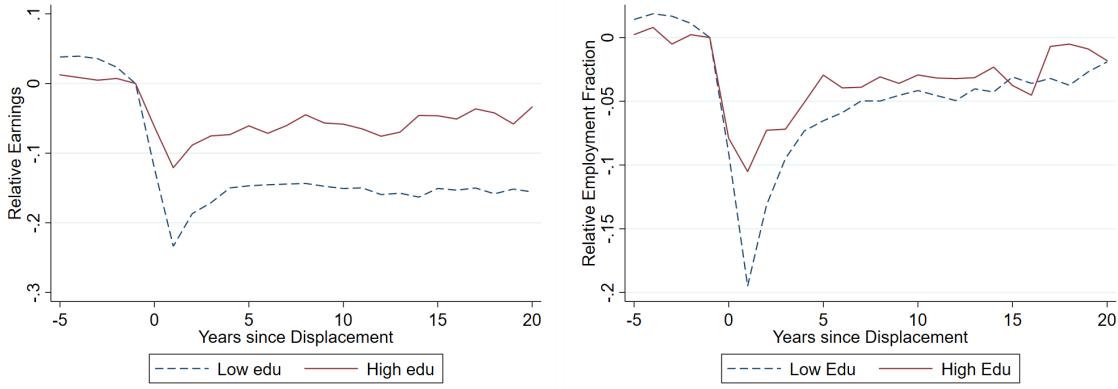


Figure 10: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group (by education group), using estimated coefficients from equation (1).*

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.⁴⁴

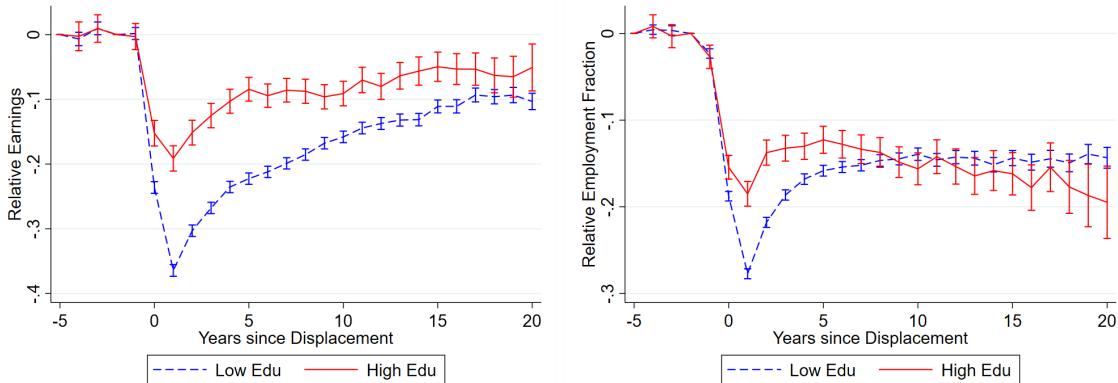


Figure 11: *The effect of displacement on earnings (left) and employment fraction (right) by education level, relative to the control group, using estimated coefficients from equation (2). The error bars correspond to 95% pointwise confidence intervals.*

In figure 11, 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

⁴⁴The result that workers with a lower education level suffer from larger earnings losses is consistent with what has been found in other work using similar data, such as Schmieder et al. (2020) and Burdett et al. (2020). Note that Burdett et al. (2020) split the sample into three education groups, and my “low education” group can be thought of as a combination of their “low” and “medium” education groups.

experiences higher earnings losses in the short run, but the two groups slowly converge and have roughly equal earnings losses 20 years after the displacement event. Furthermore, the magnitude of the losses is generally larger in figure 11 than in figure 10. In terms of employment, the results are quite different from those in figure 10, although the comparison between the two education groups is similar: 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 (especially more than 5 years after the event). Indeed, 20 years after the displacement event, the worker with the lower education level seems to be doing better in terms of employment.

3.3.2 Recalled Workers

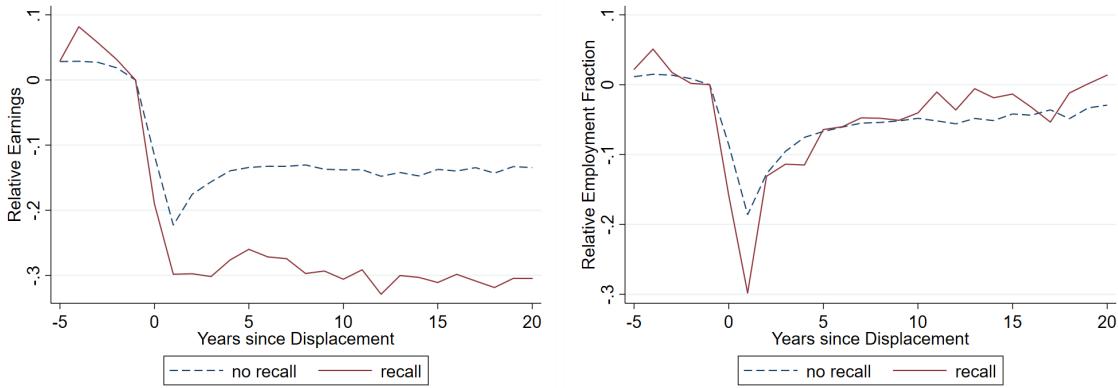


Figure 12: *The effect of displacement on earnings (left) and employment fraction (right) relative to the control group, by ex-post recall status (materialization of recall within 5 years), using estimated coefficients from equation (1).*

One factor that is generally abstracted from 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 (small portion of) displacement events where the establishment closes down, but for displacement in general a fairly sizeable fraction of workers ends up returning to their former employer, as shown in figures 4 and 6. In figure 12, I show how the effects of displacement on employment and earnings differs by ex-post recall status.⁴⁵ As can be seen in the figure, workers who are recalled suffer from larger earnings losses (both in the short and in the long run), and do

⁴⁵As I 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 e.g. Nekoei and Weber, 2015) it serves as a good proxy.

worse in the short run when it comes to days employed in the year, compared to the non-recalled (but still displaced) worker.⁴⁶ As shown in figure 13, this result also appears when using the interaction-weighted estimator from specification (2), although the difference between recalled and non-recalled is slightly smaller in the short run and larger in the long run, and once again the apparent pretrends (especially visible for recalled workers in figure 12) disappear. At the same time, the recalled worker tends to be re-employed faster (not visible in the graph), which may seem to generate a contradiction.

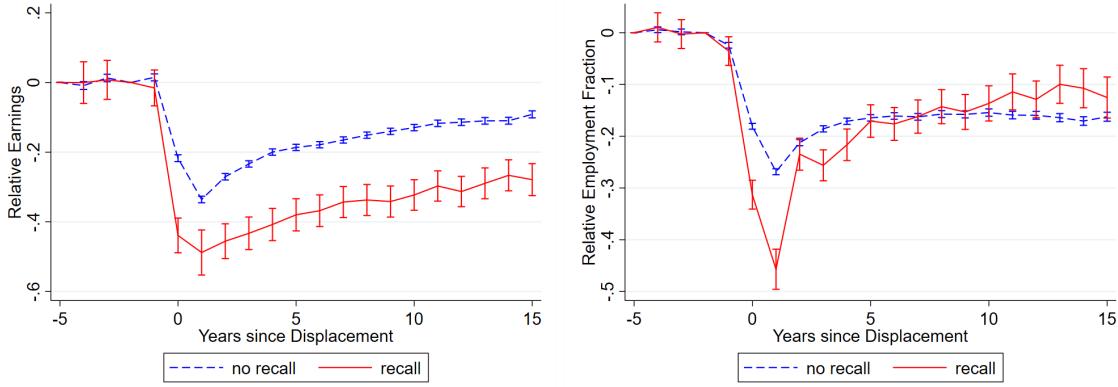


Figure 13: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status, relative to the control group, using estimated coefficients from equation (2). The error bars correspond to 95% pointwise confidence intervals.*

Figure 14 provides a first step towards an explanation. As can be seen in the figure, recalled workers are much more likely to be separated again shortly after being recalled: while non-recalled workers are roughly 14 percentage points more likely to be separated than the control group one year after their initial displacement (and 11 percentage points two and three years after displacement), recalled workers are more than 18 percentage points more likely to be separated again (compared to the control group) in the first three years after displacement. 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 job, 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

⁴⁶As 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”.

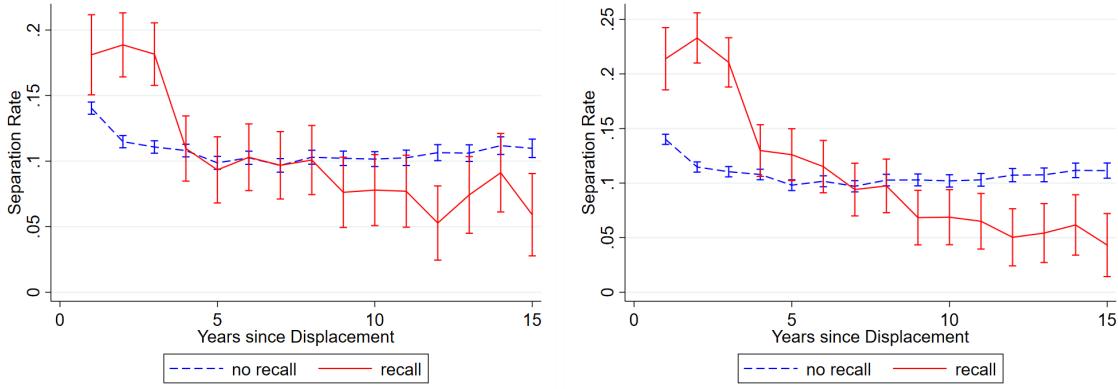


Figure 14: *The effect of displacement on separation rates by ex-post recall status, relative to the control group, using estimated coefficients from equation (2). The error bars correspond to 95% pointwise confidence intervals. Left: estimation allowing for only one displacement per individual; Right: estimation allowing for multiple displacements per individual (classifying the worker according to their first displacement). Only results from period $k = 1$ onwards are displayed here. The full graphs (starting from $k = -5$) are included in appendix D.3.6.*

figure 14. This is also the case for the results on earnings and employment fraction, as illustrated in appendix D.3.6. Additionally, I show in appendix D.3.6 that this result generally continues to hold when the data is further restricted along observable dimensions such as traditionally seasonal industries, gender, and age group.

As the left panel of figure 15 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 more volatile for the high education group. This is primarily because the highly educated recall group is fairly small in the SIAB. These differences also arise when looking at the fraction of the years spent in employment, as shown in the right panel of the figure. Nevertheless, 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.

4 Model

In this section, I develop a search model of the labor market, with the aim of explaining some of the key heterogeneity I observed in section 3. In this discrete-time model, both firms and workers

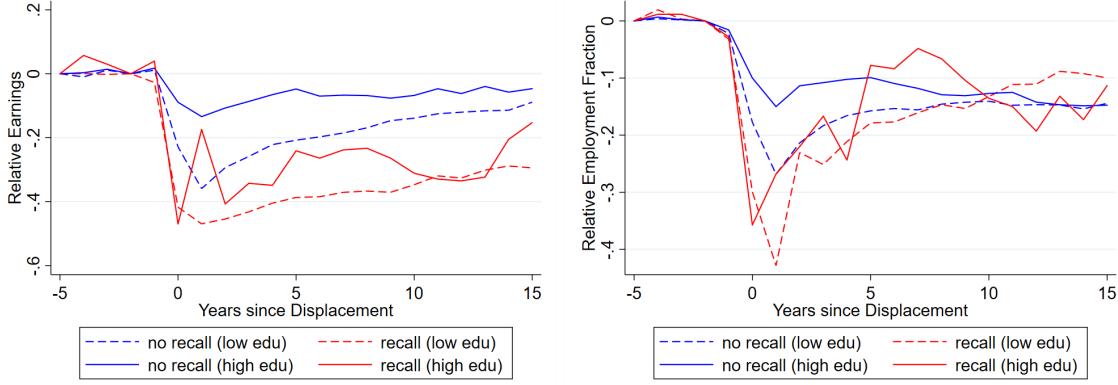


Figure 15: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status and education level, relative to the control group, using estimated coefficients from equation (2). The error bars corresponding to 95% pointwise confidence intervals are omitted and available upon request.*

are heterogeneous along two dimensions.⁴⁷ 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. By allowing workers who are expecting a recall to be in a different state, I can account for differences between workers who are expecting or not expecting a recall, both after their nonemployment spell and during their nonemployment spell.

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 nonemployed while expecting to be recalled. The type ε is fixed over time, whereas the human capital s can evolve over time. I will interpret the type ε as the worker's education when calibrating the model in section 5, but the way it is implemented in the model does not prevent it from being interpreted as some other fixed characteristic. The human capital increases by $\Delta_s(\varepsilon)$ (with probability ψ_e) when the worker is employed, and decreases by $\Delta_s(\varepsilon)$ when the worker is non-employed (with probability ψ_u if unemployed or $\psi_r\psi_u$ when expecting a recall). This human capital can therefore be interpreted as being closely related to a worker's market experience.⁴⁸

⁴⁷In 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 as well (rather than one), and the possibility of recall is explicitly featured in the model.

⁴⁸The worker's human capital cannot go below s_{min} , so technically the probability ψ_u depends on s : If $s = s_{min}$, then $\psi_u = 0$. However, in practice s_{min} is set sufficiently low such that workers will only reach s_{min} in very rare

4.1.1 Firms

Each firm can hire at most one worker.⁴⁹ 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 (match-specific) 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 potentially be recalled.⁵⁰ 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 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).⁵¹ 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 (see figure 14), thus reflecting that the worker returns to an unstable job. 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 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_ε^u , and this firm is drawn from the distri-

instances (see appendix A).

⁴⁹Because 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.

⁵⁰With probability ϕ_ε^{rg} , this recall takes place in the same model period as the initial displacement.

⁵¹Instead 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.

bution $G_\varepsilon(\theta)$, 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.⁵² 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 value of being unemployed (and is related to the unemployment benefit). It is a function of 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.⁵³ Finally, it should be noted here that I do not explicitly model how the unemployment benefit is financed, though I can do so when I introduce counterfactual policies such as those suggested in section 6.3. Thus, I essentially assume that the government has exactly enough revenues to pay for the unemployment benefits and obtained this revenues from some outside source.

Naturally, an employed worker faces the same job destruction and recall shocks as the firm, and receives the wage w . Additionally, an employed worker meets another firm with probability λ_ε^e , and if she does the offer is again drawn from distribution $G_\varepsilon(\theta)$. Upon receiving such an offer, the employed worker can decide to switch to the new firm or to reject the offer. However, 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 expecting to be recalled, she will receive $b(s)$ (just like the regular unemployed worker). While she is nonemployed and expecting a recall, the worker's human capital decreases by $\Delta_s(\varepsilon)$ with probability $\psi_r\psi_u$, reflecting that a worker expecting a 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.⁵⁴ The worker is re-

⁵² Additionally, a separated worker who moves into regular unemployment (regardless of whether this is by choice or not) finds a new job in the same period with probability λ_ε^{ug} .

⁵³In the case where $b = 1$, this unemployment benefit is very similar to the one seen in Bagger et al. (2014). In particular, the lower the value of the parameter b is, the lower the value of being unemployed is, and therefore the more job offers will be accepted. In particular, there exists a threshold b , which depends on job offer rates λ_ε^u and λ_ε^e , such that the unemployed worker accepts any job offer, as in the model in Bagger et al. (2014).

⁵⁴As 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).

called 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 nonemployment as the outside option, and the firm characteristics change as described in subsection 4.1.1.⁵⁵ 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 in a period, 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 move to the regular state of unemployment, thus giving up the potential recall.

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 using 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 pending match. This fraction, κ , is interpreted as the bargaining power of the worker. Denoting the maximum surplus from the outside option by W^{oo} :

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

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

⁵⁵The loss of the outside option is a simplifying assumption, but is justified by the fact that the worker did not exercise this outside option upon being displaced, so that the firm may no longer consider the threat of leaving to accept this outside offer to be credible.

human capital, both current (s) and when the worker and firm last bargained (\hat{s}).⁵⁶ Note that equation (3) can take four distinct forms. First, if the worker is coming out of (regular) 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).

$$W_\varepsilon(s, s, x, u) = U_\varepsilon(s) + \kappa (W_\varepsilon^{max}(s, x) - U_\varepsilon(s)) \quad (4)$$

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

$$W_\varepsilon(s, s, x, \theta) = W_\varepsilon^{max}(s, \theta) + \kappa (W_\varepsilon^{max}(s, x) - W_\varepsilon^{max}(s, \theta)) \quad (6)$$

$$W_\varepsilon(s, s, \theta, r) = \max\{U_\varepsilon(s), T_\varepsilon(s, \theta)\} + \kappa^r (W_\varepsilon^{max}(s, \theta') - \max\{U_\varepsilon(s), T_\varepsilon(s, \theta)\}) \quad (7)$$

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 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, $W_\varepsilon^{max}(s, x)$, 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 nonemployment while expecting a recall, $T(s, \theta)$, thus reflecting that upon rejecting the offer, the worker can choose to give up the potential recall and move to regular unemployment.⁵⁷ Furthermore, since the maximum value obtained from the match changed due to the penalties on production and separation rate, the firm characteristic that is relevant for the determination of the maximal surplus obtained from the recall is not quite the same as the previous characteristic (as denoted by using θ' rather than θ).

⁵⁶At 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 $\hat{s} = s$.

⁵⁷The 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.

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.⁵⁸ 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 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:

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

Here, the set $\Theta_\varepsilon^u(s)$ is the set of firm characteristics of the firms from whom the worker of type ε would accept an job offer if her current human capital level is s . Using equation (4), this set can be specified as $\Theta_\varepsilon^u(s) = \{x \in [0, 1] \times \mathbb{R}_+ : W_\varepsilon^{max}(s, x) \geq U_\varepsilon(s)\}$.

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

$$U_\varepsilon(s) = \ln(b_\varepsilon(s)) + \beta \mathbb{E}_{s'|s,u,\varepsilon} \left\{ \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^u(s')} \kappa \left(W_\varepsilon^{max}(s', x) - U_\varepsilon(s') \right) dG_\varepsilon(x) + U_\varepsilon(s') \right\} \quad (9)$$

Similarly, the value function T for a worker of type ε with human capital s , expecting to be recalled to a job of (former) type $\theta = [\delta, y]$, is as follows:

$$T_\varepsilon(s, \theta) = \ln(b_\varepsilon(s)) + \beta \mathbb{E}_{s',r,\varepsilon} \left\{ \phi_\varepsilon^r W_\varepsilon(s', s', \theta', r) + (1 - \phi_\varepsilon^r) \lambda^r \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^r(s', \theta)} W_\varepsilon(s', s', x, f) dG_\varepsilon(x) \right. \\ \left. + (1 - \phi_\varepsilon^r) \left(1 - \lambda^r \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^r(s', \theta)} dG_\varepsilon(x) \right) \max\{T_\varepsilon(s', \theta), U_\varepsilon(s')\} \right\} \quad (10)$$

⁵⁸In particular, I assume that the worker cannot choose to transition to unemployment until the recall materialization shock ϕ_ε^r is realized, so these two events take place in that specific order.

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 expecting to be recalled may use either the value of unemployment or the value of nonemployment while expecting a recall as their outside option, thereby also allowing for the set of accepted offers $\Theta_\varepsilon^r(s', \theta)$ to be slightly different from the corresponding set for an unemployed worker ($\Theta_\varepsilon^u(s')$). Note that since the worker loses her outside option upon separating (even if the separation is temporary), the value function T 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 expecting to be recalled. However, I do not make any assumption on whether the human capital depreciation occurs faster or slower for a worker expecting a recall.

Just like value function $U_\varepsilon(s)$, this value function $T_\varepsilon(s, \theta)$ can be rewritten using the bargaining equations (4) and (7):

$$T_\varepsilon(s, \theta) = \ln(b_\varepsilon(s)) + \beta \mathbb{E}_{s'|s, r, \varepsilon} \left\{ \phi_\varepsilon^r \kappa^r W_\varepsilon^{\max}(s', \theta') + \phi_\varepsilon^r (1 - \kappa^r) \max\{T_\varepsilon(s', \theta), U_\varepsilon(s')\} \right. \\ \left. + (1 - \phi_\varepsilon^r) \left(\lambda^r \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^r(s', \theta)} \kappa \left(W_\varepsilon^{\max}(s', x) - \max\{T_\varepsilon(s', \theta), U_\varepsilon(s')\} \right) dG_\varepsilon(x) + \max\{T_\varepsilon(s', \theta), U_\varepsilon(s')\} \right) \right\} \quad (11)$$

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:

$$W_\varepsilon(s, \hat{s}, \theta, \hat{\theta}) = \ln(R_\varepsilon(\hat{s}, \theta, \hat{\theta})p(s, y)) + \beta \mathbb{E}_{s'|s, e, \varepsilon} \left\{ \delta \left[\phi_\varepsilon^f \max \left\{ \hat{T}_\varepsilon(s', \theta), \hat{U}_\varepsilon(s') \right\} + (1 - \phi_\varepsilon^f) \hat{U}_\varepsilon(s') \right] \right. \\ \left. + (1 - \delta) \left[\lambda_\varepsilon^e \left(\int_{x \in \Theta_\varepsilon^1(s', \theta)} W_\varepsilon(s', s', x, \theta) dG_\varepsilon(x) + \int_{x \in \Theta_\varepsilon^2(s', \hat{s}, \theta, \hat{\theta})} W_\varepsilon(s', s', \theta, x) dG_\varepsilon(x) \right) \right. \right. \\ \left. \left. + \left(1 - \lambda_\varepsilon^e \int_{x \in \Theta_\varepsilon^1(s', \theta) \cup \Theta_\varepsilon^2(s', \hat{s}, \theta, \hat{\theta})} dG_\varepsilon(x) \right) W_\varepsilon(s', \hat{s}, \theta, \hat{\theta}) \right] \right\} \quad (12)$$

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.⁵⁹ The set $\Theta_\varepsilon^1(s, \theta)$ is the set of firm characteristics of the firms from whom the worker (of type ε and with human capital s) would accept an job offer if she is currently employed

⁵⁹If 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. With some abuse of notation, 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 expecting a recall as $\hat{\theta} = f$.

at a firm with characteristics θ , and $\Theta_\varepsilon^2(s, \hat{s}, \theta, \hat{\theta})$ is the set of firm characteristics of the firms whose offers this worker would use to trigger re-bargaining at her current match. Using equations (5) and (6), these sets can be specified as $\Theta_\varepsilon^1(s, \theta) = \{[0, 1] \times \mathbb{R}_+ : W_\varepsilon^{max}(s, x) \geq W_\varepsilon^{max}(s, \theta)\}$ and $\Theta_\varepsilon^2(s, \theta) = \{x \in [0, 1] \times \mathbb{R}_+ : W_\varepsilon^{max}(s, \theta) > W_\varepsilon^{max}(s, x) \geq W_\varepsilon^{max}(\hat{s}, \hat{\theta})\}$.⁶⁰ Note that the values \hat{T} and \hat{U} correspond to the value of a newly separated worker who chose to either potentially be recalled or move into unemployment. These values relate to value functions (11) and (9) above as follows:

$$\hat{T}_\varepsilon(s', \theta) = \phi_\varepsilon^{rg} W_\varepsilon(s', s', \theta', r) + (1 - \phi_\varepsilon^{rg}) T_\varepsilon(s', \theta) \quad (13)$$

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

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) is already known:

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

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 $U_\varepsilon(s)$, $W_\varepsilon(s, \hat{s}, \theta, \hat{\theta})$, $T_\varepsilon(s, \theta)$, $J_\varepsilon(s, \hat{s}, \theta, \hat{\theta})$, 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.1), and the distribution of

⁶⁰Note that the two sets $\Theta_\varepsilon^1(s, \theta)$ and $\Theta_\varepsilon^2(s, \hat{s}, \theta, \hat{\theta})$ 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.

workers across different states evolves according to equations (B.4) to (B.9).

5 Calibration

For the purpose of the calibration, I set up the distribution of firms $G_\varepsilon(\theta)$ as a combination of marginal distributions of productivity y and separation rate δ , and I make parametric assumptions on these marginal distributions. In particular, I assume that the marginal distribution of δ is a Beta distribution with parameters η_δ and $\mu_{\delta,\varepsilon}$, reshaped to the $[0, 0.25]$ interval (rather than $[0, 1]$), whereas the marginal distribution of y is a Pareto distribution with scale parameter $\mu_{y,\varepsilon}$ and shape parameter 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 (thereby allowing 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).⁶¹ 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%,

⁶¹Note 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_ε^u | meeting probabilities, unemployed workers |
| λ^r | relative meeting probability, workers expecting a recall |
| λ_ε^{ug} | meeting probabilities, newly unemployed workers |
| λ_ε^e | meeting probabilities, employed workers |
| ϕ_ε^f | probability of recall |
| ϕ_ε^r | recall materialization probability |
| ϕ_ε^{rg} | 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 .

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. Table 3 summarizes the values of the exogenously set parameters, and the sources used to set these values.

5.2 Calibration Moments

Using that I interpret ε to correspond to education levels, I next identify 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

| Parameter(s) | Value(s) | Source |
|-------------------------|----------|--|
| β | 0.98726 | 5% annual interest rate |
| s_1 | 0 | normalization |
| $\Delta_s(1)$ | 0.1 | normalization |
| ϵ_1 | 0.79 | fraction of workers with education level 1 |
| ϵ_2 | 0.21 | fraction of workers with education level 2 |
| ϕ_ε^{rg} | 0 | No recall within a quarter of displacement |

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

group of moments.⁶²

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 c^δ . To identify the second shape parameter of the marginal distribution of δ , η_δ (which is common across education levels), I use the average separation rate into non-employment for workers with an establishment tenure of 1-3.5, 3.5-6, 6-9, and 9+ years respectively. 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, s_2 (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 median-p25 and p75-p25 ratio of wages (by education level) are then used to complete the identification of the shape parameter η_y and education-specific scale parameter $\mu_{y,\varepsilon}$ of the marginal distribution of y .

⁶²Dividing 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 dividing the parameters and moments into groups clarifies the main considerations leading to the choice of certain moments.

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 ($\lambda_{\varepsilon}^{ug}$). Note that such a direct transition of a worker to a new job will be observed as a job-to-job transition. The overall quarterly job-to-job transition rate (by education level) therefore also contributes to identifying this parameter, while also informing the value of the on-the-job meeting rate λ_{ε}^e . Similarly, the average job finding rates (by education level) closely correspond to the job finding rate of unemployed workers, λ_{ε}^u , 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 stepsizes, 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 $b(s)$.⁶³ 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_{ε}^e (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 expecting a recall (ψ_u and ψ_r) as well as the production 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 expecting a recall (ψ_u and ψ_r), as well as the production 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 its identification.

As the model allows for a choice between unemployment and potential recall upon separation, the recall probability ϕ_{ε}^f and the recall materialization probability ϕ_{ε}^r are likely to be different from the observed recall and recall materialization probabilities. However, given the close

⁶³The net replacement rate is not derived from the IAB data used in section 3. Rather, I follow Gregory (2021) in taking this moment from OECD (2020).

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 expecting a recall who find a new job instead to inform the probability of meeting a new employer, $\lambda^r \lambda_\varepsilon^u$, and in particular the parameter λ^r .

⁶⁴

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) 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 power 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 (16) below:

$$D_{i,t}^\delta = \alpha_i + \gamma \log(w_{it}) + u_{i,t} \quad (16)$$

In equation (16), the variable $D_{i,t}^\delta$ 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 estimated moment values 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, an example being 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

⁶⁴As 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 expecting to be recalled who are re-employed within a year of displacement.

| Description of Moment(s) | Data | Model | Parameters |
|--|--------------------|------------------|--|
| Average rate of job loss, tenure 1-3.5y | 0.0461 | 0.049 | $\eta_\delta = 3.455$ $\mu_{\delta,1} = 12.36$ $\mu_{\delta,2} = 43.22$ $c^\delta = 0.159$ |
| Average rate of job loss, tenure 3.5-6y | 0.0261 | 0.043 | |
| Average rate of job loss, tenure 6-9y | 0.0172 | 0.038 | |
| Average rate of job loss, tenure >9y | 0.0088 | 0.028 | |
| Average rate of job loss, by education | 0.0386 0.03 | 0.048 0.016 | |
| Subsequent separation, displacement | 0.1085 | 0.072 | |
| Subsequent separation, recall | 0.2042 | 0.18 | |
| p75-p25 ratio of wages | 1.7299 1.7056 | 1.606 1.739 | $\eta_y = 7.359$ $\mu_{y,1} = 1.634$ $\mu_{y,2} = 1.719$ $s_2 = 0.426$ |
| median-p25 ratio of wages | 1.313 1.3088 | 1.269 1.307 | |
| Educational wage premium (all) | 1.5301 | 1.552 | |
| Educational wage premium (entry) | 1.7144 | 1.714 | |
| Job-to-job transition rate | 0.0377 0.0352 | 0.029 0.012 | |
| Job-to-job transition upon displacement | 0.6348 0.7558 | 0.597 0.747 | $\lambda_1^e = 0$ $\lambda_2^e = 0.0002$ $\lambda_1^{ug} = 0.692$ $\lambda_2^{ug} = 0.801$ $\lambda_1^u = 0.16$ $\lambda_2^u = 0.213$ |
| Average job finding rate | 0.2583 0.2596 | 0.19 0.227 | |
| Average employment rate | 0.8533 0.8689 | 0.911 0.983 | |
| Replacement rate | 0.6 | 0.624 | |
| Yearly wage growth | 0.0458 0.0511 | 0.008 0.016 | $b = 0.7$ $\Delta_s(2) = 0.19$ $\psi_e = 0.019$ $\psi_u = 0.291$ $\psi_r = 0.041$ $c^f = 0.426$ |
| Pre- to post-layoff wage, duration < 0.5y | -0.0503 0.0183 | -0.032 0.013 | |
| Pre- to post-layoff wage, duration 0.5-1y | -0.1137 -0.0599 | -0.136 -0.078 | |
| Pre- to post-layoff wage, duration 1-2y | -0.1857 -0.1543 | -0.229 -0.145 | |
| Pre- to post-recall wage, duration 0.25-0.5y | -0.022 -0.0187 | -0.04 -0.034 | |
| Pre- to post-recall wage, duration 0.5-1y | -0.0322 -0.0484 | -0.088 -0.05 | |
| Recall rate | 0.0725 0.052 | 0.097 0.048 | |
| Recall materialization rate | 0.3049 0.267 | 0.297 0.272 | |
| New job finding rate, workers expecting a recall | 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 (16) | -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

transition probabilities).

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 (2021), it can be seen that the parameters estimated in both models generally yield very comparable estimates.⁶⁵ 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 match in particular the measures of wage dispersion (the p75-p25 and median-p25 wage ratios) by alleviating the impact of changing outside options.⁶⁶ After all, an increase in κ would lead the 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.

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 in favour of a potential recall when offered to do so, this implies that the role of allowing workers to find new jobs despite expecting 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 a nonemployed worker is much less likely to lose human capital while expecting 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)⁶⁷ and a substantial penalty on the separation rate c^δ , which implies that after recall the worker's separation rate increases by almost

⁶⁵One 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 λ_ε^{ug} .

⁶⁶For comparison, Jarosch (2021) and Gregory (2021), 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.

⁶⁷For context, note that the value of the lowest possible value of production for a worker of education level 1 with the starting level of human capital, $p(s_1, y^{min})$ equals $e^{0+1.634} \approx 5.12$

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. Furthermore, compared to the worker with a low education level, a highly educated worker starts with a much lower level of human capital $s_2 = 0.426 > 0$ (which is more than five low education stepsizes higher than the starting level of a worker with a low education level, which was normalized to 1), while 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 draw

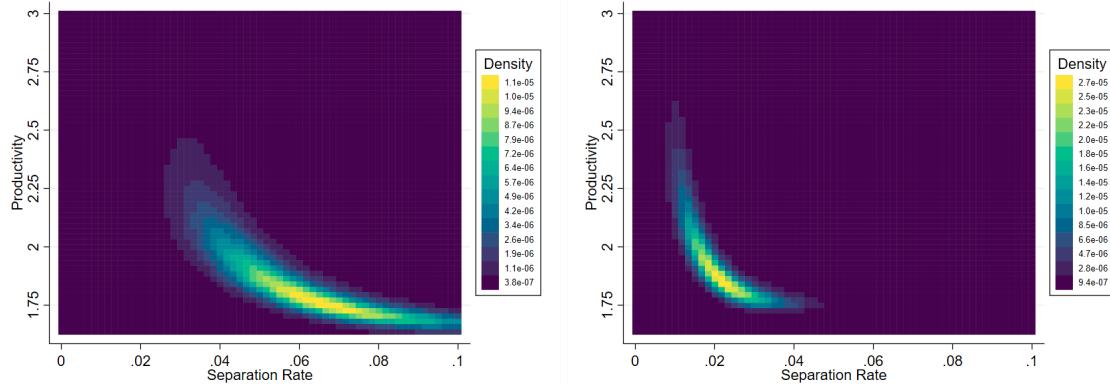


Figure 16: *The joint distribution of firm types faced by workers with a low education level (left) and a high education level (right).*

from upon receiving an offer, these are best illustrated in a diagram. Figure 16 visualizes the joint distribution of firms $G_\varepsilon(\theta)$ for 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. Furthermore, 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 in achieving its aim. Then, in subsection 6.2, I use the model to illustrate the importance of taking into account the possibility of recall, by simulating a temporary shutdown of 50% of the economy. Finally, in subsection 6.3, I use the model to comment on 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

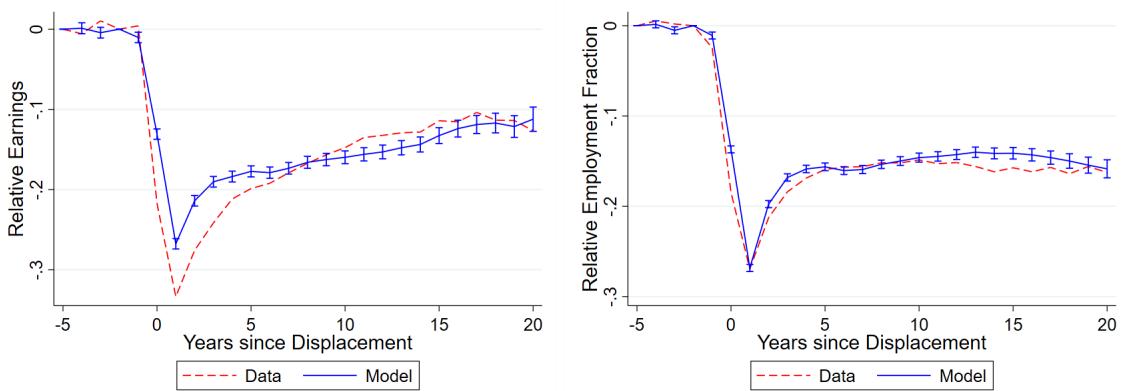


Figure 17: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right), relative to the control group, using model simulation data (solid) and using the data (dashed, corresponding to figure 9).*

Before moving to the dimensions of heterogeneity highlighted in section 3.3, figure 17 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 9. For this purpose, I have included the results from figure 9 in figure 17 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 λ_ε^e close to or equal to 0).

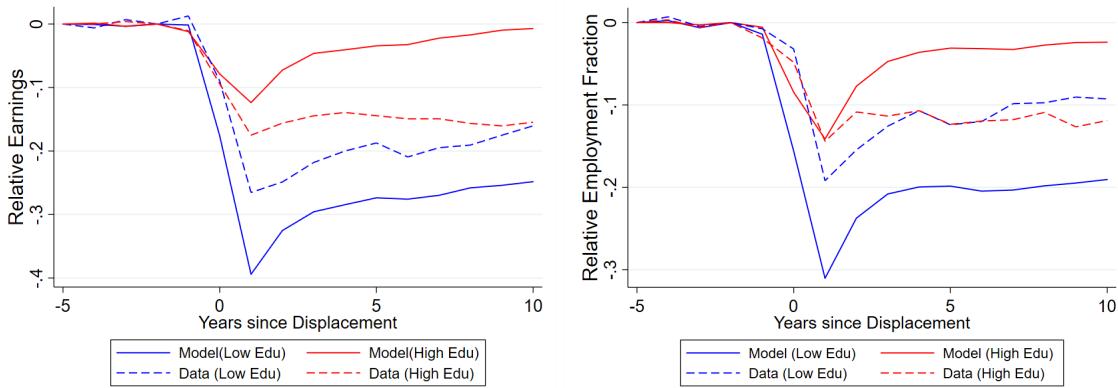


Figure 18: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right), relative to the control group (by education group), using model simulation data (solid) and using the data (dashed, corresponding to figure D.51).*

Figure 18 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 D.51. 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 figure 18, 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.

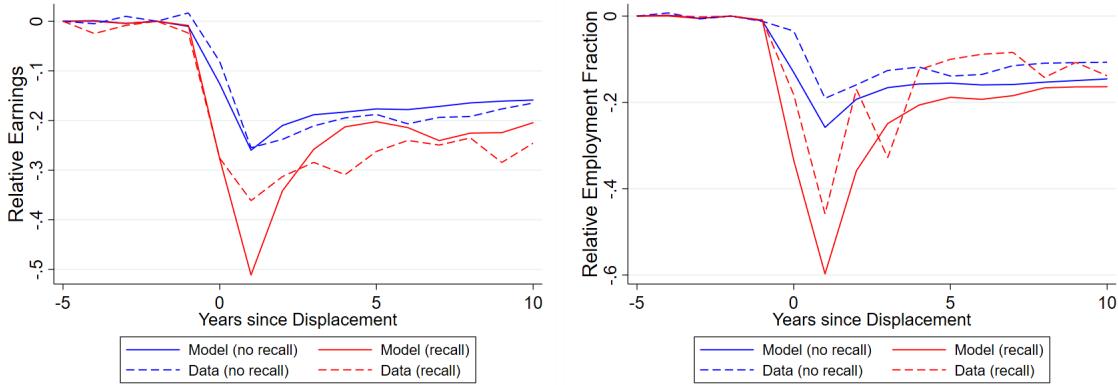


Figure 19: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right) relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data (solid) and using the data (dashed, corresponding to figure D.54).*

In figure 19, 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 D.54. As can be seen from figure 19, 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, potentially 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 the scarring 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.

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. In particular, given that recalled workers end up doing worse than non-recalled workers, why would a displaced worker choose a potential recall? Figure 20 provides an indication of how one could answer the second question. The figure repeats the estimation from figure 19, but uses worker states immediately after displacement (i.e. whether they expecting a recall or not) rather than the ex-post recall status. In other words, figure 20 indicates what the expected earnings

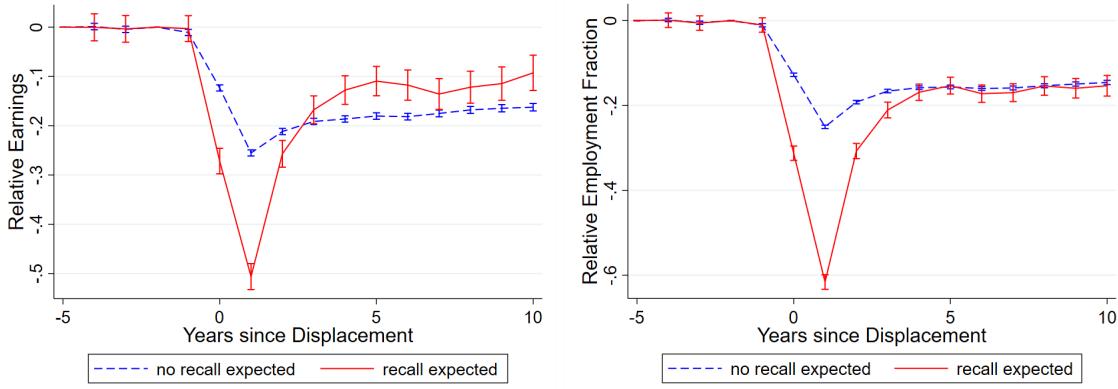


Figure 20: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right) relative to the control group, by post-displacement state, using model simulation data. The red solid line corresponds to workers expecting a recall, and the blue dashed line corresponds to workers moving into unemployment (not necessarily by choice).*

path is for someone choosing for a potential recall (red) and someone moving to unemployment (blue). As can be seen from comparing figure 20 to the solid lines in figure 19, the choice of whether to accept a potential recall is not as 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 expecting a 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 expecting 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.⁶⁸ Given that workers are generally quite patient, as reflected by β , a worker will prefer to move into the nonemployment state with a potential for a recall. Indeed, under the parameter values resulting from the calibration, all workers choose for a potential recall when given the option.

In figure 21, I fully decompose the differences in estimated post-displacement earnings between recalled and non-recalled workers (as shown in the left panel of figure 19). In particular, I consider all channels (discussed below) through which the ex-post recalled worker is (potentially)

⁶⁸To be specific, a worker with a low education level expecting 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.

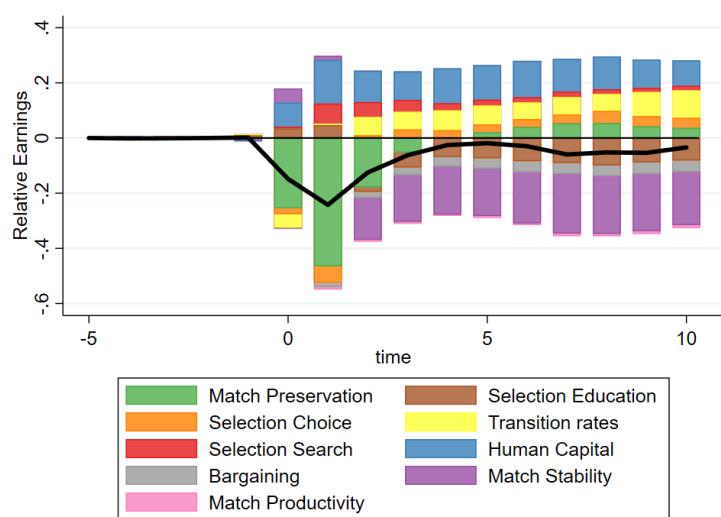


Figure 21: *A decomposition of the difference in the scarring effect of displacement on earnings between (ex-post) recalled and non-recalled workers. The black line represents the total difference, calculated as the difference between the solid red and blue lines in the left panel of figure 19. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals. Corresponding numerical values for selected time periods (0, 1, 3, 5, and 10 years after displacement) can be found in the appendix in table C.1.*

different than a non-recalled worker in my model, and switch these channels off one by one in order to generate counterfactual earnings differences between recalled and non-recalled workers. As can be observed from figure 21, I find that the differences between recalled and non-recalled workers are primarily driven by the post-recall match characteristics. In particular, while the impact of the productivity penalty c^f is very small (and even slightly positive), the negative difference is primarily driven by the worker going back to an unstable job (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.⁶⁹

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 between the regular unemployment state and the state of nonemployment while expecting a recall. As expected, this has a

⁶⁹Note 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.

(small) positive impact. Similarly, allowing the worker to search while expecting 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 expecting 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 expecting a recall 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 expecting a recall 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 (“Selection Education”), 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 expecting to be recalled. Finally, the residual element named “Match preservation”, which reflects the difference between the two states if all parameters would be the same (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 are negatively selected towards workers who are in a worse match (in terms of productivity and separation rate) than the match they would expect to find when drawing a (random) new employer from the joint distribution $G_\varepsilon(\theta)$.

While the discussion above focuses on the decomposition of the (difference in) earnings losses for recalled and non-recalled workers, the setup of the model and the fact that it is able to match the difference in employment fraction as well (as shown in figure 19) also allows me to further decompose earnings losses into employment and wage components. In figure 22, I use the results from figure 19 to decompose the earnings loss into employment and wages. Corresponding to my findings in the data (in section 3.3.2), I find that the short-term difference is entirely driven by the employment margin. In fact, the wage margin goes in the opposite direction, suggesting that conditional on employment the recalled workers earn more.

In figure 23, I further decompose the wage and employment differences into the same 9 channels used for the earnings decomposition above. As can be seen in the left panel, the observed positive difference in the short term for wages is primarily explained by the human capital margin. This reflects that the worker expecting a recall barely loses any human capital at all, while

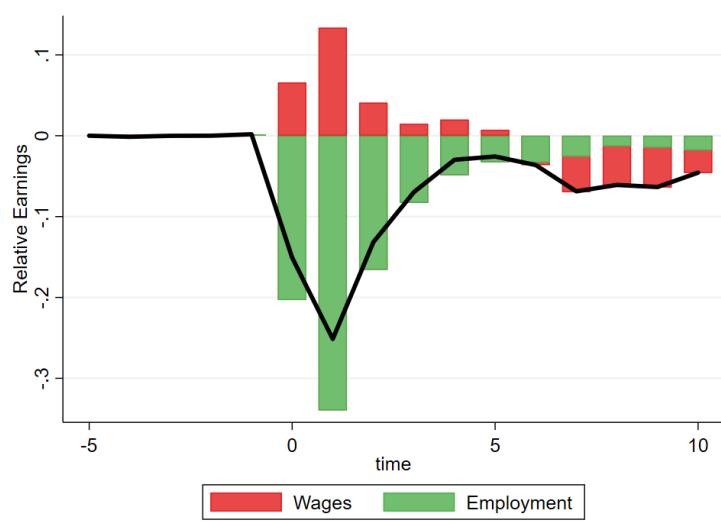


Figure 22: *A decomposition of the difference in the scarring effect of displacement on earnings between (ex-post) recalled and non-recalled workers, into earnings and employment. The black line represents the total difference, calculated as the difference between the solid red and blue lines in the left panel of figure 19. The decomposition is generated by using the estimation for employment (the difference between the solid red and blue lines in the right panel of figure 19), and backing out the effect on wages as a residual.*

the general unemployed worker faces a substantial loss of human capital. As a result, it can be concluded that if the human capital depreciation would be the only channel at work, the recalled worker would return to their job with the same wage as before, whereas the non-recalled worker would lose some wage due to human capital depreciation, thus generating the positive difference as depicted in the left panel of figure 23. In the long run, this positive difference is increasingly offset by the negative influence of the higher separation rate faced by the recall worker, thus eventually leading to a negative wage difference.

In the right panel of figure 23, it can be seen that this human capital channel does not play a substantial role when it comes to employment. For employment, the main drivers are related to the higher separation rate faced by the recalled worker. In principle, the fact that the separation rate faced by the recalled worker is higher than the separation rate faced by the non-recalled worker can be attributed to two channels. First, as stressed before, the recalled worker returns to a job that has a higher separation rate than it had before the layoff. This is due to the penalty on the separation rate, and this channel is represented in the figure by the “Match Stability” elements. The second channel playing a role here is the fact that displaced workers in general come from matches of

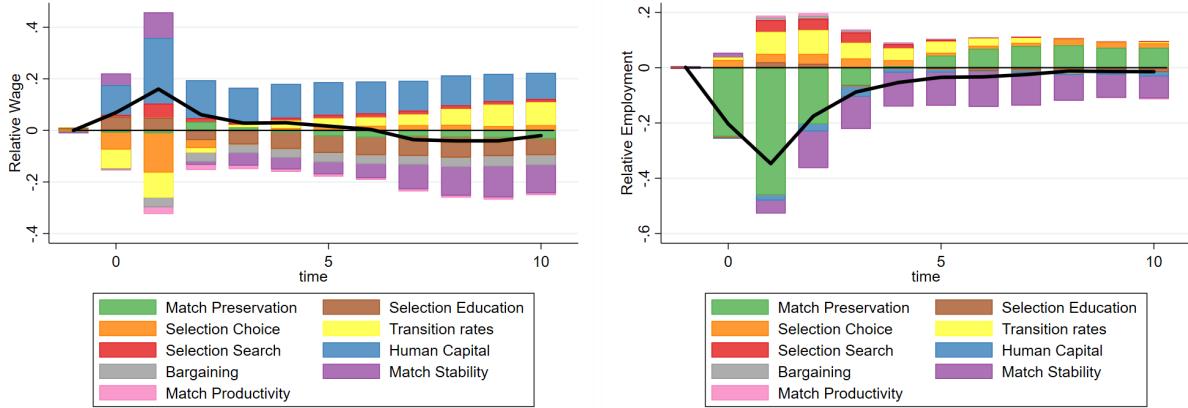


Figure 23: *A decomposition of the difference in the scarring effect of displacement on wages (left) and employment (right) between (ex-post) recalled and non-recalled workers. The black line represents the total difference, as depicted in figure 22. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals. Corresponding numerical values for selected time periods (0, 1, 3, 5, and 10 years after displacement) can be found in the appendix in tables C.3 and C.2.*

lower quality than the average match quality in the economy. In other words, the displaced worker tends to come from a match with a lower productivity and higher separation rate than the average. This also means that even without the additional penalty on the separation rate, the recalled worker would still be more likely to be separated again compared to the non-recalled worker (who on average will draw a lower separation rate when finding a new job). This is important especially in the short run, and is reflected by the ‘‘Match preservation’’ channel in the decomposition.

6.2 A Shutdown Simulation

In this section, I use the calibrated model to simulate a temporary shutdown of the model economy. Using this simulation, and comparing its implied worker recovery patterns to the baseline simulation, I then highlight the importance of explicitly taking into account that workers may expect a potential return to their previous employer after the shutdown ends.

In order to simulate the temporary shutdown of the economy, I simulate the model twice, using the same realizations of random variables in both simulations so that I can directly calculate the effect of the shutdown on an individual level. I randomly select 50% of the workers, who (unexpectedly) move into nonemployment at the start of the shutdown.⁷⁰ The worker stays in this state

⁷⁰Since the workers do not interact, the size of the shutdown does not affect the results of the simulation. In the baseline simulation shown in this section, the shutdown occurs in the 15th quarter of the simulation. In appendix C.2 I show that the timing (and duration) of the shutdown does not substantially affect results.

of nonemployment for 4 quarters, after which the economy starts to re-open again. After reopening, I (initially) assume that the probability of moving back into employment is higher than usual for two quarters, after which the economy resumes operating as it did before the shutdown.⁷¹

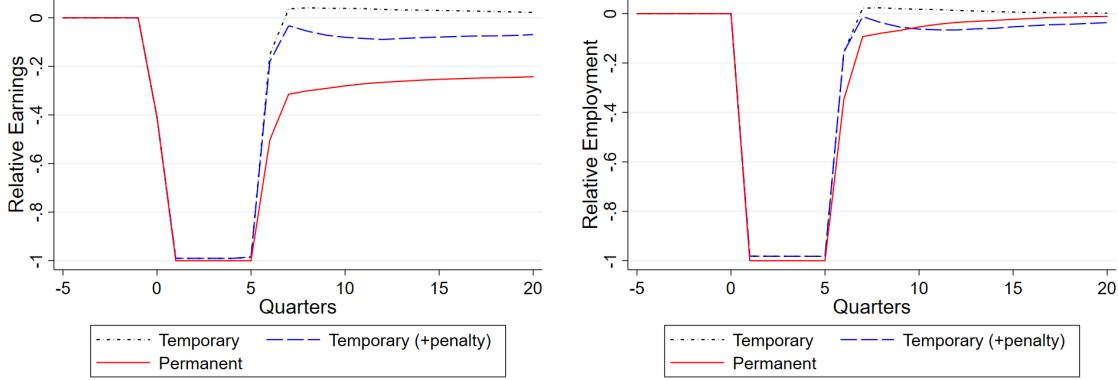


Figure 24: *The effect of a temporary shutdown on the earnings and employment status of affected workers. During the shutdown, workers are assumed to be either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (black, short-dashed).*

In figure 24, I show how the effect of the shutdown on earnings and employment of the affected worker depends on the type of nonemployment experienced by the affected worker. In the left panel, it can be seen that the worker who moves into the temporary unemployment state (expecting a recall) rather than the permanent (“regular”) unemployment state is able to recover much faster, regardless of whether the recall penalties c^δ and c^f are imposed or not.⁷² As shown in the right panel, this is not necessarily the case when looking at employment, in which a worker forced into temporary unemployment may be worse off in the long run if the recall comes with the usual penalties. As figure 25 shows, these conclusions on the shutdown’s effect on earnings and employment continue to hold when focusing only on workers with a high education level.⁷³

In figure 26, I show the importance of the assumed transition probabilities in the peri-

⁷¹To be specific, I assume that this higher transition probability equals the average of 1 and the “usual” transition probability. In appendix C.2, I show that the conclusions are very similar if I assume that the transition rates return to the usual rates immediately after the shutdown ends.

⁷²Given that the shutdown occurs randomly, one could argue that the recall penalties may not be as large as in the baseline model. After all, it may no longer be the case that the worker returns to an unstable job if the reason for the shutdown was in no way related to the job itself (as I’m assuming here by randomly selecting the affected matches).

⁷³In appendix C.2, I show that these conclusions also hold when focusing only on workers with a low education level instead.

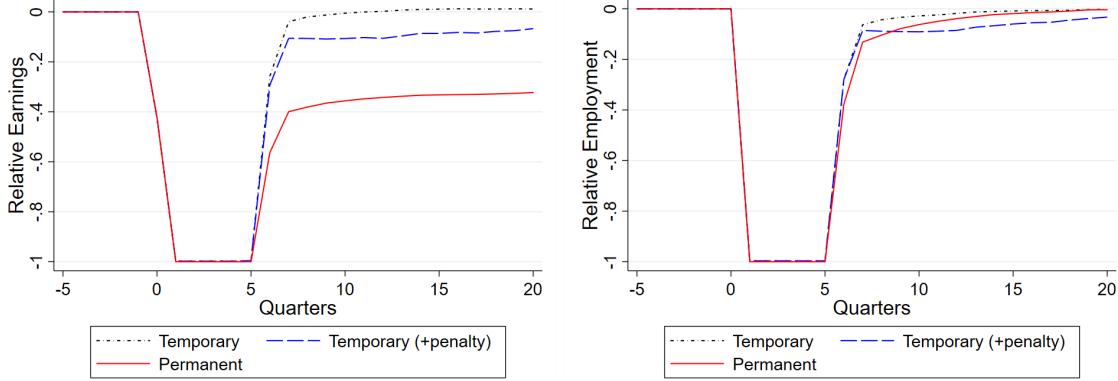


Figure 25: *The effect of a temporary shutdown on the earnings and employment status of affected workers with a high education level. During the shutdown, workers are assumed to be either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (black, short-dashed).*

ods immediately following the lifting of the shutdown (assuming that workers were temporarily unemployed without the associated penalties). As can be seen in the left panel of the figure, assuming an immediate transition back to the worker’s former employer slightly improves the worker’s outcome compared to the baseline “faster” transition (which corresponds to the simulation illustrated in figure 24), which in turn substantially improves the recovery compared to a simulation in which I assume the transition rates to return to the rates in the baseline economy immediately after the shutdown ends. Notably, in the two simulations with higher transition probabilities, the recovery initially overshoots the counterfactual outcome (in which the worker did not experience the shutdown). This is primarily due to workers returning to a job they would have lost in the counterfactual simulation, and as can be seen in the figure this is gradually corrected over time.

Overall, this simulation exercise serves to emphasize two points. First of all, contrary to what the figures in section 3.3 may suggest, being recalled by their former employer may not necessarily be bad for the worker’s outcomes. Indeed, as stressed in the previous section, a substantial part of the apparent negative effect of recall is caused by selection: the workers that are recalled in reality tend to be matched to an employer with lower productivity and higher separation rate. If separation would occur at the same probability across all matches, as assumed in this simulation exercise, the prospect of recall may be better than the prospect of permanent unemployment, as the lost matches are of higher productivity (on average) than they are in the baseline model.

Secondly, the large difference between the recovery paths under temporary and perma-

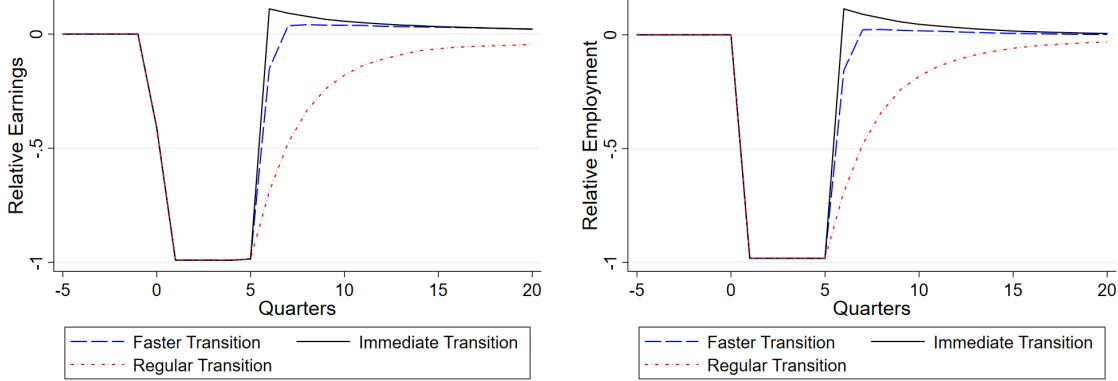


Figure 26: *The effect of a temporary shutdown on the earnings and employment status of affected workers. During the shutdown, workers are assumed to be in the temporary unemployment state without the associated penalties. After the shutdown, workers transition back to employment either immediately (blue, dashed), at a faster rate than usual (black, solid), or at the usual rate (red, short-dashed).*

ment unemployment serves to re-emphasize the importance of explicitly including the possibility of recall in a model of the labour market, especially in a situation where workers are likely to return to their previous employer. Using a “standard” model of the labour market, in which this possibility is not included, would likely lead to an overestimation of the negative effects of the shutdown on the affected workers, and therefore potentially to policies that target to alleviate more losses than actually experienced by the worker.

6.3 Policy Implications

Throughout this paper, I have illustrated that workers who return to their employer after being laid off tend to do worse in terms of earnings than their non-recalled (but still laid off) counterparts. In the previous subsections, I have illustrated that this can be explained using the model I developed in section 4. Given that I have highlighted the importance of accounting for these two sets of workers (recalled and non-recalled) in a model, this might leave one wondering about the policy implications of this result. Unfortunately, the setup of the model is such that it is not necessarily informative to think of a social planner. After all, the model stresses the viewpoint of the worker, and thereby abstracts from other elements that a social planner may wish to take into account.⁷⁴ Nevertheless, a number of lessons can still be drawn from the results in the previous subsections, and in this discussion I highlight some of these lessons.

⁷⁴Two prominent examples of such elements include the firm choosing who to (potentially) recall, as well as the potential congestion externalities in the labour market (which I abstract from by setting exogenous offer arrival rates).

The decomposition of the differences (between recalled and non-recalled workers) in earnings loss after displacement in section 6.1 highlighted the depreciation of human capital as a channel that works in favour of the recalled worker. Indeed, as pointed out in section 4, the probability of human capital depreciation for a worker expecting a recall is very close to zero ($\psi_r \psi_u = 0.012$), so while a regular unemployed worker loses some of their human capital in 29.1% of the periods they spend in unemployment, this is only 1.2% for the worker expecting a recall. As shown in appendix C.3, this implies that while human capital depreciation accounts for a large portion of long-run earnings losses for the non-recalled worker (18.9% in year $k = 10$ after displacement), it only plays a minor role in explaining the long-run earnings losses for a recalled worker (0.9 – 2.5% in year $k = 10$ after displacement).⁷⁵ This is in contrast with the decomposition of the average scarring effect of displacement, which largely follows the non-recalled worker and therefore yields a large role for human capital depreciation, in line with what the existing literature has found. Naturally, a response to the decomposition of the average scarring effect of displacement might be to suggest a policy that would help the nonemployed worker prevent human capital depreciation. However, as this depreciation plays a minor role for the recalled worker, this would not help the recalled worker. Indeed, as I show in appendix C.3, an unintended consequence of such a policy would be that it increases the gap between recalled and non-recalled workers. In other words, given that the recalled worker tends to do worse, such a policy would not help the workers that have been shown to suffer the most from displacement.

Finally, while the model in this paper was calibrated to data from Germany, it is worth exploring how results might change when using data from a labor market that is associated with less generous unemployment benefits, such as the United States. As a final simulation exercise, in appendix C.3, I re-calibrate the nonemployment benefit parameter b to the United States equivalent of the replacement rate, keeping all other model parameters constant at their values calibrated using the German data. Given that the replacement rate in the US is lower than in Germany (0.45 versus 0.6), I find a lower value of b (0.52 instead of 0.7). In order to keep the government budget balanced, I also calibrate a proportional subsidy ($-\tau = 0.0114$) on output such that the costs of this subsidy equals the savings generated by lowering b . As I show in appendix C.3, the resulting counterfactual simulation shows a widened gap between recalled and non-recalled

⁷⁵These numbers only include the depreciation during nonemployment, and do not account for the increasing human capital of the non-displaced (control) worker. Including this channel as well leads to human capital accounting for 14.2% and 35.8% of the earnings losses of recalled and non-recalled workers respectively (in year $k = 10$ after displacement).

workers compared to the baseline model. In other words, if the unemployment benefit were to be the only difference between the two countries, I would expect the recalled worker in the United States to do even worse than his counterpart in Germany. Given the availability of appropriate data to fully calibrate a US version of the model, it would be interesting to see whether this prediction holds up. I leave this as an exercise for future work.

7 Conclusion

In this paper, I study the scarring effect of displacement on earnings and employment, focusing in particular on how these effects differ by whether workers are recalled to their previous employer. 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. In the short run, this is driven by the recalled workers losing more days of employment (per year), due to a higher probability of subsequent job loss. In the long run, however, the difference between the recalled and non-recalled workers is driven by recalled workers experiencing a larger negative effect on wages (even though recalled workers do better than non-recalled workers in this dimension in the short run). 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 develop a search model of the labour market in which I explicitly allow for recall by dividing newly nonemployed workers into two separate states, according to whether or not the workers are expecting to be recalled. Furthermore, I distinguish between two fixed worker types, which I interpret as education levels. Further adding 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.

I then use the calibrated model to study the main drivers of the heterogeneity in the scarring effects of displacement. In particular, I explain the observation that recalled workers do worse than non-recalled workers after displacement as a combination of a selection and job stability effect. In the model, there is a negative correlation between the separation rate and the job productivity (which is directly related to the wage). Because of this negative correlation, the jobs that workers are displaced from are less productive and less stable than the average job in the

economy. This implies that if workers return to such a job, they return to a job with a relatively low productivity and low stability, whereas workers moving to a new job will draw from the overall distribution of jobs and find a more productive and more stable job on average. This selection into displacement translates into the observation that recalled workers do worse than non-recalled workers in the short run. Furthermore, the 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 as well, as a subsequent separation sets back the worker in their path of recovery, especially if such a subsequent separation no longer comes with (the expectation of) a future recall.

When decomposing the long-run effect of displacement on earnings for recalled and non-recalled workers separately, I find that whereas human capital depreciation plays a large role for non-recalled workers, its role for recalled workers is much smaller. This implies that a policy designed to dampen the depreciation of human capital (traditionally identified as one of the key drivers of the long-run effects of displacement on earnings) will likely be much less effective for recalled workers, thus further widening the long-run gap between recalled and non-recalled workers. For a recalled worker, a more beneficial policy might be one that aids the rehiring firm after the recall takes place, thus reducing the probability that the worker will be displaced again shortly after being rehired.

Based on the results of this paper, one can think of various avenues for future research, and I will highlight a few of those possibilities here. First of all, 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.⁷⁶ Furthermore, there are several other dimensions of observable heterogeneity that show promising results and may be key to further improving the understanding of the heterogeneity in the scarring effects of job loss. One particular dimension that comes to mind is that of the industry in which the worker was (formerly) employed. In particular, one may think about what drives workers to switch industries after displacement and how closely this is related to patterns of structural change. Finally, when extending the framework in this paper to one with cyclical variation, and especially when doing so in the context of the German labour market, it will be important to

⁷⁶As highlighted in section 6.1, I can use my model to generate a simulation-based analysis of this dimension, but I cannot verify this analysis in the data since I do not observe recall expectations in the data.

explicitly add in the possibility of using short-time employment rather than an explicit layoff when facing an economic downturn. This will be particularly important given the wide usage of short-time employment policies throughout Europe during the Covid-19 pandemic.

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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 all 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 (over which the model will be solved). 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 $y \leq y_1$ and $\delta \leq \delta_1$ to hold 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.10) and (B.11) 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:
- Guess an initial matrix for W^{max} (N_y by N_δ by N_s by 2) and U (1 by N_s).⁷⁷
 - Using initial guesses 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 $\omega_u \in (0, 1]$)
 - Now, using initial guess W^{max} and updated \hat{U} , calculate the implied value for value function T . To do this, first using its recursive structure to solve directly, assuming that a worker expecting to be recalled cannot search for a new job. Then, in a second iteration, add the search option, using the previously calculated T as the possible outside option, and re-calculate T .
 - Using initial guess W^{max} , updated \hat{U} , and implied value T , 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 $\omega_s \in (0, 1]$)
 - 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 $W^{max} = \hat{W}^{max}$.
 - 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 calculated value for $W^{max}(s, \theta)$ and $U(s)$, calculate the value for T by using the same procedure as in step 5c, but now repeatedly executing the second step until the value for T 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.

⁷⁷The 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 T 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 rather the piece-rate), I use value function W (again omitting the ε):

$$W(s, \hat{s}, \theta, \hat{\theta}) = \ln(R(\hat{s}, \theta, \hat{\theta})p(s, y)) + \beta \mathbb{E}_{s'|s,e,\varepsilon} \left\{ \delta \left[\phi_f \max\{\hat{T}(s', \theta), \hat{U}(s')\} + (1 - \phi_f) \hat{U}(s') \right] \right. \\ \left. + (1 - \delta) \left[\lambda^e \left(\int_{x \in \Theta^1(s', \theta)} W(s', s', x, \theta) dG(x) + \int_{x \in \Theta^2(s', \hat{s}, \theta, \hat{\theta})} W(s', s', \theta, x) dG(x) \right) \right. \right. \\ \left. \left. + \left(1 - \lambda^e \int_{x \in \Theta^1(s', \theta) \cup \Theta^2(s', \hat{s}, \theta, \hat{\theta})} dG(x) \right) W(s', \hat{s}, \theta, \hat{\theta}) \right] \right\}$$

Further, note that given a known value for W^{max} and U (for every s and θ), the value $T(s, \theta)$ is known:⁷⁸

$$T(s, \theta) = \ln(b(s)) + \beta \mathbb{E}_{s'|s,r} \left\{ \phi^r \kappa^r W^{max}(s', \theta') + \phi^r (1 - \kappa^r) \max\{T(s', \theta), U(s')\} \right. \\ \left. + (1 - \phi^r) \left(\lambda^r \int_{x \in \Theta^r(s', \theta)} \kappa \left(W^{max}(s', x) - \max\{T(s', \theta), U(s')\} \right) dG(x) + \max\{T(s', \theta), U(s')\} \right) \right\}$$

Similarly, for given values W^{max} and U , and T , the values \hat{U} and \hat{T} can be directly calculated using equations (13) and (14). Throughout the derivation, I will therefore denote the value of a newly nonemployed worker expecting a recall by \bar{T} , denoting that since this value is known I consider it to be a constant:

$$W(s, \hat{s}, \theta, \hat{\theta}) = \ln(R(\hat{s}, \theta, \hat{\theta})p(s, y)) + \beta \mathbb{E}_{s'|s,e,\varepsilon} \left\{ \delta \left[\phi_f \max\{\bar{T}(s', \theta), \hat{U}(s')\} + (1 - \phi_f) \hat{U}(s') \right] \right. \\ \left. + (1 - \delta) \left[\lambda^e \left(\int_{x \in \Theta^1(s', \theta)} W(s', s', x, \theta) dG(x) + \int_{x \in \Theta^2(s', \hat{s}, \theta, \hat{\theta})} W(s', s', \theta, x) dG(x) \right) \right. \right. \\ \left. \left. + \left(1 - \lambda^e \int_{x \in \Theta^1(s', \theta) \cup \Theta^2(s', \hat{s}, \theta, \hat{\theta})} dG(x) \right) W(s', \hat{s}, \theta, \hat{\theta}) \right] \right\}$$

Further, note that:

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

⁷⁸To be specific, I solve for the value $T(s, \theta)$ before solving for the wage, as noted in the previous subsection.

Since I know the value of W^{max} , U , \bar{T} , and p for a given combination of s and θ , this implies that the only unknowns in the value function are $W(s, \hat{s}, \theta, \hat{\theta})$, $R(\hat{s}, \theta, \hat{\theta})$, and $W(s', \hat{s}, \theta, \hat{\theta})$.

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

$$C_{s'} = \beta(1 - \delta)\lambda^e \left(\int_{x \in \Theta^1(s', \theta)} W(s', s', x, \theta) dG(x) + \int_{x \in \Theta^2(s', \hat{s}, \theta, \hat{\theta})} W(s', s', \theta, x) dG(x) \right) \\ + \beta\delta(1 - \phi_f)\hat{U}(s') + \beta\delta\phi_f \max\{\bar{T}(s', \theta), \hat{U}(s')\}$$

$$a_{s'} = \beta(1 - \delta) \left(1 - \lambda^e \int_{x \in \Theta^1(s', \theta) \cup \Theta^2(s', \hat{s}, \theta, \hat{\theta})} dG(x) \right)$$

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 $\psi_e = 0$.⁷⁹ Below, I rewrite the value function using this structure. In what follows, I use $\psi = \psi_e$ (for ease of notation):

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

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

$$W_s = \ln(Rp(s, y)) + \psi \{ C_{s+1} + a_{s+1} W_{s+1} \} + (1 - \psi) \{ C_s + a_s W_s \}$$

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

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

⁷⁹Note 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.

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

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

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

Unfortunately, there is one small complication: the method above is based on the assumption 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. As mentioned in the previous subsection, I select the maximum grid-point by calculating the grid-point that is achieved only by the top 0.1% of the workers after 30 years.

Of course, solving the model on a limited grid also has consequences for some of the equations discussed above (and explicitly so where I explicitly use the structure of the expectations operator). In practice, I therefore use a slightly adjusted formulation of the matrix A and vector B above. In the matrix A , there are two changes. First in every row except for the first and last row of matrices A and B , I replace ψ by $\psi \frac{\Delta_s}{(N)-(N-1)}$ (for the second row, and similarly for other rows using other values of N), where Δ_s is the actual jump in human capital upon ψ materializing, and N and $N - 1$ are the values of s on the N th 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.

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.⁸⁰ With the exception of the yearly wage growth, all moments are estimated using the 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. I set this variable to 0 if the worker is still employed next quarter and 1 if the worker is unemployed in the next quarter.⁸¹ The job loss rate by tenure

⁸⁰In 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.

⁸¹Note that in the model I consider workers that are expecting a recall to be unemployed for this purpose, reflecting that in the data I do not see whether a worker is expecting to be recalled.

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 take the average over all workers who returned from nonemployment through a recall 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.⁸² 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 nonemployed workers (including those expecting 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 taken by education group.

Finally, the estimation of the employment rate in the data is fairly simple, and merely requires the average of a variable that equals the fraction of the quarter the worker spent in an employment relation. In the model, I do not need to keep track of this explicitly, as employed workers will always be employed for the full quarter, which will be marked by having a strictly positive firm productivity y . In other words, the value of this fraction in the model will always be either 0 or 1.

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, I can then directly summarize the wage by education group, which will yield the 25th percentile, median,

⁸²An 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.

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.⁸³ 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 directly 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 premium, I estimate the average wage of each education group (again omitting the top and bottom 5%).

⁸³In the model, a restriction to full-time workers is not necessary, since the model does not allow for part-time work.

Denoting this average by \bar{w}_ε , 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 quarterly 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 expecting 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 re-employment is also full-time, the post-layoff wage is equal to the average wage in the first four full quarters after starting this job (conditional on being full-time employed for that entire quarter). The resulting wage differential is the difference between this pre- and post layoff wage. 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 in the data (especially for the high education level).

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):

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

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 log wage for each individual, restricting the calculation in the data to wages in full-quarter full-time employment. Similarly, I calculate the average value of the separation indicator (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:

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

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

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 an alternative calibration of the model, I could 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:

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

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:

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

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 $\ddot{X}_{it} = X_{it} - \bar{X}_i - \bar{X}_t + \bar{X}$, where \bar{X} is the average variable over all individuals and time periods, \bar{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:

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

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:

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

Here, $\bar{\phi}_\varepsilon^f(s, \theta) = \phi_\varepsilon^f \mathbb{1}_{T_\varepsilon(s, \theta) > U_\varepsilon(s)}$, 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 expecting to recall, which can be decomposed into the separation period-specific part and a general value for a firm expecting to recall:

$$\hat{J}_\varepsilon^f(s', \theta) = \phi_\varepsilon^{rg} J_\varepsilon(s', s', \theta', r) + (1 - \phi_\varepsilon^{rg}) J_\varepsilon^f(s', \theta) \quad (\text{B.2})$$

$$J_\varepsilon^f(s, \theta) = \beta \mathbb{E}_{s' | s, r, \varepsilon} \left\{ \phi_\varepsilon^r J_\varepsilon(s', s', \theta', r) + (1 - \phi_\varepsilon^r) \left(1 - \lambda_\varepsilon^r \int_{x \in \Theta_\varepsilon^r(s', \theta)} dG_\varepsilon(x) \right) \mathbb{1}_{T_\varepsilon(s', \theta) > U_\varepsilon(s')} J_\varepsilon^f(s', \theta) \right\} \quad (\text{B.3})$$

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 expecting to be recalled. Further, let $d_\varepsilon^f(s, \theta)$ be the density of workers with current human capital s expecting to be recalled to a firm with (pre-recall) 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:

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

The flow equations are then as follows:⁸⁴

$$\begin{aligned} d'_\varepsilon(s, \hat{s}, \theta, \hat{\theta}) &= (1 - \delta) \left(1 - \lambda_\varepsilon^e \int_{x \in \Theta_\varepsilon^1(s, \theta) \cup \Theta_\varepsilon^2(s', \hat{s}, \theta, \hat{\theta})} dG_\varepsilon(x) \right) \bar{d}_\varepsilon(s, \hat{s}, \theta, \hat{\theta}) \\ &\quad + \mathbb{1}_{s=\hat{s}} \lambda_\varepsilon^e g_\varepsilon(\theta) \left[\iint (1 - \hat{\delta}) \left(\mathbb{1}_{\theta \in \Theta_\varepsilon^1(s, \hat{\theta})} \bar{d}_\varepsilon(s, x, \hat{\theta}, y) \right) dx dy \right] \\ &\quad + \lambda_\varepsilon^e \left[g_\varepsilon(\hat{\theta}) \iint (1 - \hat{\delta}) \left(\mathbb{1}_{\hat{\theta} \in \Theta_\varepsilon^2(s, x, \theta, y)} \bar{d}_\varepsilon(s, x, \theta, y) \right) dx dy \right] \} \end{aligned} \quad (\text{B.4})$$

⁸⁴Note that when I integrate over y in equation (B.4), 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.5), (B.6), (B.8), and (B.9).

$$d'_\varepsilon(s, \hat{s}, \theta, u) = (1 - \delta) \left(1 - \lambda_\varepsilon^e \int_{x \in \Theta_\varepsilon^1(s, \theta) \cup \Theta_\varepsilon^2(s', \hat{s}, \theta, u)} dG_\varepsilon(x) \right) \bar{d}_\varepsilon(s, \hat{s}, \theta, u) \\ + g_\varepsilon(\theta) \mathbb{1}_{s=\hat{s}} \mathbb{1}_{\theta \in \Theta_\varepsilon^u(s)} \left(\lambda_\varepsilon^u \bar{u}_\varepsilon(s) + \lambda_\varepsilon^{ug} \iint \delta(1 - \bar{\phi}_\varepsilon^f(s, x)) \bar{d}_\varepsilon(s, \tilde{s}, x, \hat{x}) d\tilde{s} dx d\hat{x} \right) \quad (\text{B.5})$$

$$d'_\varepsilon(s, \hat{s}, \theta, r) = (1 - \delta) \left(1 - \lambda_\varepsilon^e \int_{x \in \Theta_\varepsilon^1(s, \theta) \cup \Theta_\varepsilon^2(s', \hat{s}, \theta, r)} dG_\varepsilon(x) \right) \bar{d}_\varepsilon(s, \hat{s}, \theta, r) \\ + \int \mathbb{1}_{\theta' \in \Theta_\varepsilon^f(\theta)} \left(\phi_\varepsilon^r \bar{d}_\varepsilon^f(s, \theta') + \bar{\phi}_\varepsilon^f(s, \theta') \phi_\varepsilon^{rg} \iint \bar{d}_\varepsilon(s, \hat{s}, \theta', \hat{x}) d\hat{s} d\hat{x} \right) d\theta' \quad (\text{B.6})$$

$$d'_\varepsilon(s, \hat{s}, \theta, f) = (1 - \delta) \left(1 - \lambda_\varepsilon^e \int_{x \in \Theta_\varepsilon^1(s, \theta) \cup \Theta_\varepsilon^2(s', \hat{s}, \theta, f)} dG_\varepsilon(x) \right) \bar{d}_\varepsilon(s, \hat{s}, \theta, f) \\ + \int \mathbb{1}_{\theta \in \Theta_\varepsilon^r(s, x)} (1 - \phi_\varepsilon^r) \lambda^r \bar{d}_\varepsilon^f(s, x) dx \quad (\text{B.7})$$

$$d_\varepsilon^{f'}(s, \theta) = (1 - \phi_\varepsilon^r) \left(1 - \lambda^r \int_{x \in \Theta_\varepsilon^r(s, \theta)} dG_\varepsilon(x) \right) \mathbb{1}_{F_\varepsilon(s, \theta) > U_\varepsilon(s)} \bar{d}_\varepsilon^f(s, \theta) \\ + \iint \delta \bar{\phi}_\varepsilon^f(s, \theta) (1 - \phi_\varepsilon^{rg}) \bar{d}_\varepsilon(s, \hat{s}, \theta, \hat{x}) d\hat{s} d\hat{x} \quad (\text{B.8})$$

$$u'_\varepsilon(s) = \left(1 - \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^u(s)} dG_\varepsilon(x) \right) \bar{u}_\varepsilon(s) \\ + \int \delta(1 - \bar{\phi}_\varepsilon^f(s, \theta)) \left(1 - \lambda_\varepsilon^{ug} \int_{x \in \Theta_\varepsilon^u(s)} dG_\varepsilon(x) \right) \iint \bar{d}_\varepsilon(s, \hat{s}, \theta, \hat{x}) d\hat{x} d\hat{s} d\theta \quad (\text{B.9})$$

where

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

Alternatively, one 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 abstracts from 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 the fixed worker types (since the model can be solved separately for each type ε), and setting $R(\hat{s}, \theta, \hat{\theta}) = 1$. First, note that one can rewrite the value of expecting a recall, equation (10) in terms of W^{max} and U only. In order to do so, I use the bargaining equations (4) and (7), leading to equation (11), mentioned in the main text (in section 4). Given a guess for W^{max} , one can solve the above equation (11) for the corresponding T , thus essentially eliminating the need for a separate value function. Furthermore, given that the values for T and U are then known (for a given value of W^{max} and U), I can

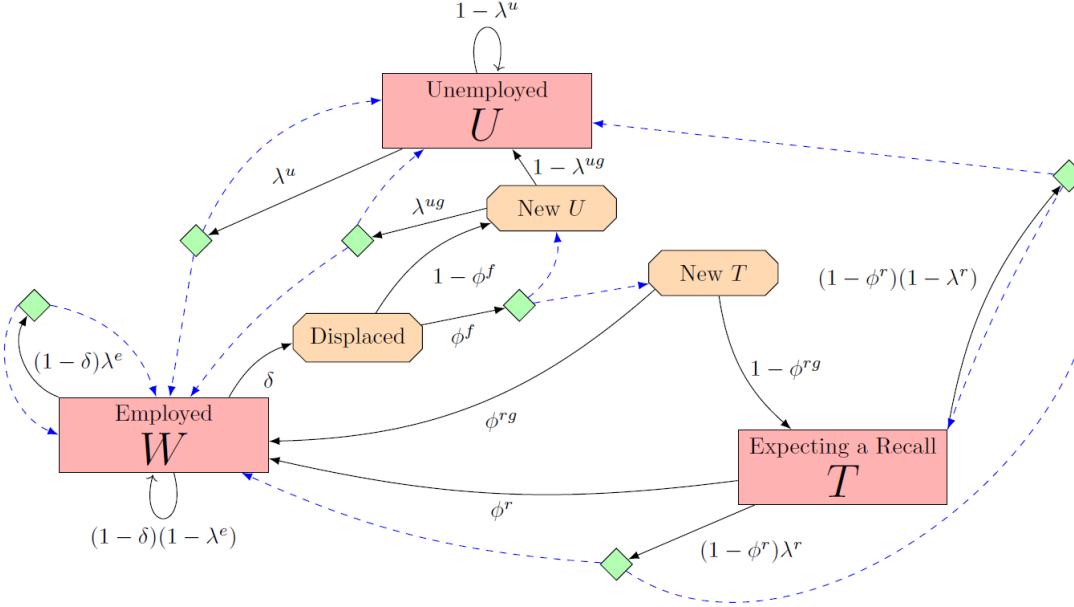


Figure B.1: A flow chart depicting the flows between the three main states for a worker. Solid arrows depict an exogenous flow, caused by materialization of some probability. Dashed (blue) lines are flows that follow from a decision of the worker, and these decisions are made at decision points (which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

also directly calculate the corresponding values for a newly nonemployed worker (either expecting a recall or not expecting a recall), $\hat{T}(s, \theta)$ and $\hat{U}(s)$.

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

$$\begin{aligned}
W^{max}(s, \theta) &= \ln(p(s, y)) + \beta \mathbb{E}_{s'|s, e} \left\{ \delta \left[\phi_f \max\{\hat{T}(s', \theta), \hat{U}(s')\} + (1 - \phi_f) \hat{U}(s') \right] \right. \\
&\quad + (1 - \delta) \left[\lambda^e \left(\int_{x \in \Theta^1(s', \theta)} W(s', s', x, \theta) dG(x) + \int_{x \in \Theta^2(s', \hat{s}, \theta, \hat{\theta})} W(s', s', \theta, x) dG(x) \right) \right. \\
&\quad \left. \left. + \left(1 - \lambda^e \int_{x \in \Theta^1(s', \theta) \cup \Theta^2(s', \hat{s}, \theta, \hat{\theta})} dG(x) \right) W(s', \hat{s}, \theta, \hat{\theta}) \right] \right\} \\
&= \ln(p(s, y)) + \beta \mathbb{E}_{s'|s, e} \left\{ \delta \left[\phi_f \max\{\hat{T}(s', \theta), \hat{U}(s')\} + (1 - \phi_f) \hat{U}(s') \right] \right. \\
&\quad + (1 - \delta) \left[\lambda^e \int_{x \in \Theta^1(s', \theta)} (W(s', s', x, \theta) - W(s', \hat{s}, \theta, \hat{\theta})) dG(x) \right. \\
&\quad \left. \left. + \lambda^e \int_{x \in \Theta^2(s', \hat{s}, \theta, \hat{\theta})} (W(s', s', \theta, x) - W(s', \hat{s}, \theta, \hat{\theta})) dG(x) + W(s', \hat{s}, \theta, \hat{\theta}) \right] \right\}
\end{aligned}$$

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:

$$W^{max}(s, \theta) = \ln(p(s, y)) + \beta \mathbb{E}_{s'|s,e} \left\{ \delta \left[\phi_f \max\{\hat{T}(s', \theta), \hat{U}(s')\} + (1 - \phi_f)\hat{U}(s') \right] \right. \\ \left. + (1 - \delta) \left[\lambda^e \int_{x \in \Theta^1(s', \theta)} (W(s', s', x, \theta) - W^{max}(s', \theta)) dG(x) + W^{max}(s', \theta) \right] \right\}$$

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

$$W^{max}(s, \theta) = \ln(p(s, y)) + \beta \mathbb{E}_{s'|s,e} \left\{ \delta \left[\phi_f \max\{\hat{T}(s', \theta), \hat{U}(s')\} + (1 - \phi_f)\hat{U}(s') \right] \right. \\ \left. + (1 - \delta) \left[\lambda^e \int_{x \in \Theta^1(s', \theta)} (W^{max}(s', \theta) + \kappa (W^{max}(s', x) - W^{max}(s', \theta)) - W^{max}(s', \theta)) dG(x) \right. \right. \\ \left. \left. + W^{max}(s', \theta) \right] \right\} \\ = \ln(p(s, y)) + \beta \mathbb{E}_{s'|s,e} \left\{ \delta \left[\phi_f \max\{\hat{T}(s', \theta), \hat{U}(s')\} + (1 - \phi_f)\hat{U}(s') \right] \right. \\ \left. + (1 - \delta) \left[\lambda^e \int_{x \in \Theta^1(s', \theta)} \kappa (W^{max}(s', x) - W^{max}(s', \theta)) dG(x) + W^{max}(s', \theta) \right] \right\} \quad (\text{B.10})$$

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):

$$U(s) = \ln(b(s)) + \beta \mathbb{E}_{s'|s,u} \left\{ \lambda^u \int_{x \in \Theta^u(s')} W(s', s', x, u) dG(x) + \left(1 - \lambda^u \int_{x \in \Theta^u(s')} dG(x) \right) U(s') \right\} \\ U(s) = \ln(b(s)) + \beta \mathbb{E}_{s'|s,u} \left\{ \lambda^u \int_{x \in \Theta^u(s')} (W(s', s', x, u) - U(s')) dG(x) + U(s') \right\} \\ U(s) = \ln(b(s)) + \beta \mathbb{E}_{s'|s,u} \left\{ \lambda^u \int_{x \in \Theta^u(s')} \kappa (W^{max}(s', x) - U(s')) dG(x) + U(s') \right\} \quad (\text{B.11})$$

C Additional Simulation Results

C.1 Further Decomposition Results

In the main text, in section 6.1, I used the calibrated model to decompose the difference in the scarring effects of displacement (on earnings, employment, and wages) between recalled and non-recalled workers into the channels through which the two groups are potentially different according to the model. In tables C.1 (earnings), C.2 (employment), and C.3 I show the numerical values used to construct a selection of the bars in the corresponding figures 21 and 22.

| Channel | $k = 0$ | $k = 1$ | $k = 3$ | $k = 5$ | $k = 10$ |
|----------------------------|---------|---------|---------|---------|----------|
| Match Productivity Penalty | -0.002 | -0.009 | -0.007 | -0.007 | -0.011 |
| Match Stability Penalty | 0.051 | 0.015 | -0.169 | -0.172 | -0.193 |
| Bargaining | -0.003 | -0.016 | -0.028 | -0.037 | -0.041 |
| Human Capital | 0.087 | 0.158 | 0.103 | 0.125 | 0.092 |
| Selection Search | 0.006 | 0.073 | 0.043 | 0.022 | 0.017 |
| Transition Rates | -0.048 | 0.005 | 0.064 | 0.068 | 0.1 |
| Selection Choice | -0.022 | -0.059 | 0.031 | 0.029 | 0.037 |
| Selection Education | 0.034 | 0.047 | -0.054 | -0.073 | -0.081 |
| Match Preservation | -0.254 | -0.465 | -0.053 | 0.021 | 0.036 |
| Total | -0.148 | -0.242 | -0.062 | -0.019 | -0.034 |

Table C.1: *Summary of the decomposition of the difference in the scarring effect of displacement on earnings between (ex-post) recalled and non-recalled workers. The total difference is calculated as the difference between the solid red and blue lines in the left panel of figure 19. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals. The numbers reflect the contribution of each channel to the difference in the scarring effect of displacement on earnings, k years after displacement, and reflect the corresponding decomposition depicted in figure 21*

In these tables, I separate the differential effects on earnings, employment, and wages (denoted “Total”) into the 9 channels that could potentially drive these differences in the model. For clarification purposes, I will discuss here again how these channels are incorporated into the model that was presented in section 4 of the main text.

The first two channels listed in the tables correspond directly to the two penalty parameters c^f (“Match Productivity Penalty”) and c^δ (Match Stability Penalty). In other words, the contribution of these channels is calculated by setting these parameters to zero instead of their calibrated value. Next, the “Bargaining” channel corresponds to the difference between bargaining power κ and κ^r . This contribution is therefore calculated by setting κ^r to the same value as the calibrated value for κ . Similarly, the “Human Capital” channel corresponds directly to the difference between human capital depreciation rates ψ_u and $\psi_r \psi_u$, and is therefore calculated by setting $\psi_r = 1$.

| Channel | $k = 0$ | $k = 1$ | $k = 3$ | $k = 5$ | $k = 10$ |
|----------------------------|---------|---------|---------|---------|----------|
| Match Productivity Penalty | 0 | 0.007 | 0.005 | 0.002 | -0.004 |
| Match Stability Penalty | 0.015 | -0.047 | -0.116 | -0.12 | -0.079 |
| Bargaining | 0.001 | 0.009 | 0.006 | 0.002 | 0.001 |
| Human Capital | -0.003 | -0.021 | -0.037 | -0.012 | -0.016 |
| Selection Search | 0.001 | 0.043 | 0.038 | 0.006 | 0.003 |
| Transition Rates | 0.009 | 0.079 | 0.056 | 0.041 | 0.004 |
| Selection Choice | 0.028 | 0.03 | 0.033 | 0.01 | 0.017 |
| Selection Education | -0.005 | 0.02 | -0.004 | -0.006 | -0.016 |
| Match Preservation | -0.248 | -0.46 | -0.064 | 0.044 | 0.072 |
| Total | -0.203 | -0.347 | -0.088 | -0.035 | -0.014 |

Table C.2: *Summary of the decomposition of the difference in the scarring effect of displacement on employment fraction between (ex-post) recalled and non-recalled workers. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals. The numbers reflect the contribution of each channel to the difference in the scarring effect of displacement on employment fraction, k years after displacement, and reflect the corresponding decomposition depicted in figure 23*

As mentioned in the main text, a worker expecting to be recalled generally transitions back into employment faster than other unemployed workers. In order to calculate the impact of these “Transition Rates”, I set the transition rates from the two states equal by setting $\phi_\varepsilon^r = \lambda_\varepsilon^u$, and $\phi_\varepsilon^{rg} = \lambda_\varepsilon^{ug}$. In other words, the recall materialization rates are set equal to the job finding rates of the general unemployed worker.⁸⁵

Finally, the model contains four explicit selection channels, which can be referred to as selection into displacement, selection into recall expectation, selection out of recall expectation, and selection by education. The last of these channels corresponds to “Selection Education” in the tables and figures, and is calculated by setting all education-specific parameters equal to their value for education level 1. The selection into recall expectation, “Selection Choice”, refers to the worker being able to choose whether or not move into the state of expecting a recall upon being offered as such (which happens at rate ϕ_ε^f). In order to calculate the contribution of this channel, I remove this choice, thus forcing a worker into the recall expectation state with probability ϕ_ε^f . The selection out of recall expectation, “Selection Search”, is incorporated into the model by allowing the worker expecting a recall to search for a new job, which arrives at a rate $\lambda^r \lambda_\varepsilon^u$. In order to calculate the contribution of this channel, I shut down this model element by setting $\lambda^r = 0$. Finally, the selection into displacement, “Match Preservation”, refers to the fact that (in the model) displaced workers are coming from jobs with lower productivity and higher separation rates, due to the negative correlation between those two job characteristics. The pure contribution of this final

⁸⁵Note that I shut down this “Transition Rates” channel after shutting down the “Selection Search” channel, so at this point I already have $\lambda^r = 0$.

channel is calculated as a residual. After all, if all other channels are shut down, the only difference between the two states that remains is that the workers expecting a recall move back to their previous job, whereas the workers not expecting a recall draw a new job from the distribution $G_\varepsilon(\theta)$ (which at this point of the decomposition no longer depends on ε).

| Channel | $k = 0$ | $k = 1$ | $k = 3$ | $k = 5$ | $k = 10$ |
|----------------------------|---------|---------|---------|---------|----------|
| Match Productivity Penalty | -0.003 | -0.027 | -0.013 | -0.009 | -0.008 |
| Match Stability Penalty | 0.045 | 0.1 | -0.048 | -0.046 | -0.108 |
| Bargaining | -0.005 | -0.037 | -0.033 | -0.037 | -0.039 |
| Human Capital | 0.116 | 0.254 | 0.136 | 0.126 | 0.102 |
| Selection Search | 0.007 | 0.055 | 0.006 | 0.014 | 0.013 |
| Transition Rates | -0.073 | -0.097 | 0.01 | 0.028 | 0.089 |
| Selection Choice | -0.067 | -0.153 | -0.001 | 0.019 | 0.02 |
| Selection Education | 0.053 | 0.049 | -0.054 | -0.065 | -0.063 |
| Match Preservation | -0.008 | -0.01 | 0.01 | -0.022 | -0.033 |
| Total | 0.069 | 0.16 | 0.028 | 0.016 | -0.02 |

Table C.3: *Summary of the decomposition of the difference in the scarring effect of displacement on wages between (ex-post) recalled and non-recalled workers. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals. The numbers reflect the contribution of each channel to the difference in the scarring effect of displacement on wages, k years after displacement, and reflect the corresponding decomposition depicted in figure 23*

C.2 A Shutdown Simulation

In section 6.2, I showed the importance of taking into account the possibility of recall using a simulation of a temporary shutdown of 50% of the economy, taking place in quarter 15 of the simulation and lasting for 4 quarters. In the main text, I used the results from a simulation in which I assume that transition rates back into employment are higher than usual in the first two quarters after the shutdown ends. However, as can be seen in figure C.1, the results continue to hold if I assume that transition rates immediately go back to normal, although in this case the effects on employment are slightly more distinct between the temporary and permanently unemployed workers. Furthermore, I showed in the main text that the results continue to hold when focusing on workers with a high education level only. As can be seen in figure C.2, this remains true when focusing on the low education level only. In fact, the results for the low education level closely mirror those of the full simulation shown in figure 24.

In the main text, I also highlighted that the stark difference between temporary and permanent unemployment as a result of the shutdown does not necessarily hold for employment status. As can be seen

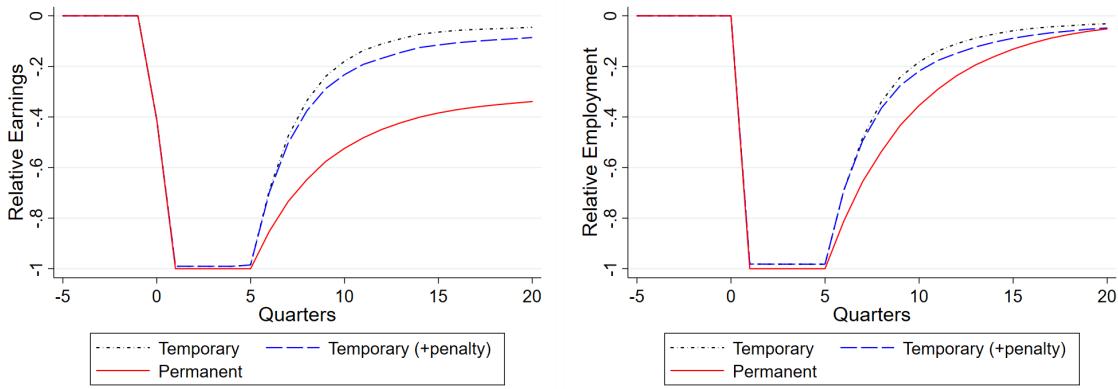


Figure C.1: *The effect of a temporary shutdown on the earnings and employment status of affected workers, without imposing two quarters of subsequent faster transitions. During the shutdown, workers are assumed to be either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (black, short-dashed).*

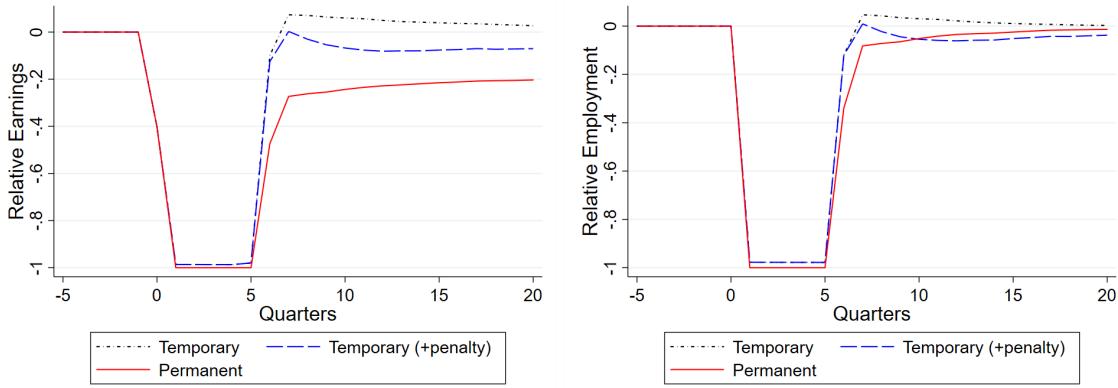


Figure C.2: *The effect of a temporary shutdown on the earnings and employment status of affected workers with a low education level. During the shutdown, workers are assumed to be either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (black, short-dashed).*

in the left panel of figure C.3, the result similarly does not necessarily hold when focusing on the productivity of the worker. This productivity, calculated as the value of the production function (and thus taking into account both firm and worker productivity), follows a fairly similar pattern to that of the employment status (as seen in figure 24 in the main text).

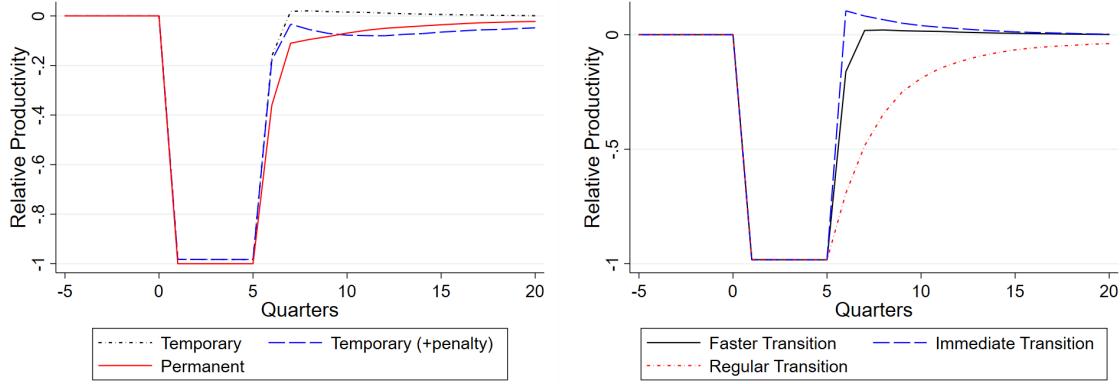


Figure C.3: The effect of a temporary shutdown on the productivity of affected workers. Left panel: during the shutdown, workers are assumed to be either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (black, short-dashed), and after the shutdown workers transition back to employment at a faster rate than usual. Right panel: during the shutdown workers are assumed to be in the temporary unemployment state without the associated penalties, and after the shutdown workers transition back to employment either immediately (blue, dashed), at a faster rate than usual (black, solid), or at the usual rate (red, short-dashed).

In figure C.4, I show that the results discussed in the main text do not depend on the timing of the shutdown. Letting the shutdown take place in quarter 55 or 105 leads to slightly worse recovery paths for the affected worker, primarily due to the average worker being in a more stable match at that time and therefore the counterfactual simulation being less likely to include a separation for the affected worker. However, as can be seen in the figure, the difference is fairly small and therefore does not alter any of the aforementioned results.

Finally, I show in figure C.5 that the results are similarly not majorly affected by the length of the shutdown (aside from the periods of the shutdown itself). As can be seen in the left panel of figure C.5, a longer shutdown slightly worsens the affected workers' earnings in subsequent periods. This is due to the human capital depreciation during the shutdown. However, as the depreciation probability in the temporary unemployment state is fairly small (as shown in section 4 of the main text), the difference is small and it does not affect the main results of the simulation exercise.

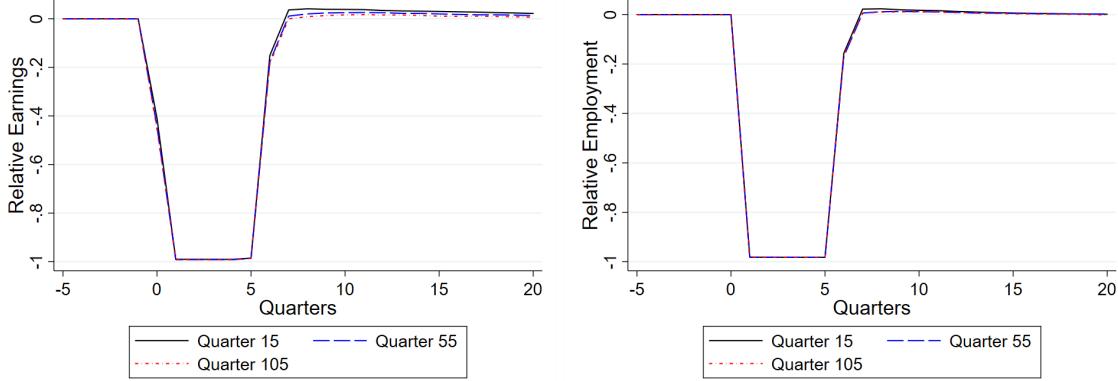


Figure C.4: *The effect of a temporary shutdown on the earnings and employment status of affected workers. During the shutdown, workers are assumed to be either in the temporary unemployment state without the associated penalties, and after the shutdown workers transition back to employment at a faster rate than usual. The shutdown starts in either period 15 (black, solid), period 55 (blue, dashed), or period 105 (red, short-dashed) of the simulation.*

C.3 Policy Implications

In section 6.3, I briefly discussed two counterfactual exercises that illustrate the policy relevance of the findings in this paper. In this subsection, I provide some of the underlying details (and illustrations).

First of all, figure C.6 and accompanying tables C.4 and C.5 illustrate my statement in section 6.3 that while human capital depreciation accounts for a large portion of long-run earnings losses for the non-recalled worker, it only plays a minor role in explaining the long-run earnings losses for a recalled worker. This is clearly visible in the figure, where the human capital depreciation elements are represented by the pink and dark green areas.

As can be observed in the figure, the human capital depreciation for workers expecting a recall (in pink) is barely visible at all, even for the group of recalled workers, due to the fact that this depreciation rate is so close to zero. Similarly, because the recalled worker does not lose their match, the match loss element is essentially zero for them. As a result, the bulk (more than 85%) of the earnings losses experienced by the recalled worker is explained by “Frictions”, which encompasses losses that occur because the worker spends time in nonemployment (anything other than human capital loss).

Indeed, as can be seen in figure C.7, the decomposition of the average scarring effect of displacement looks fairly similar to the decomposition for non-recalled workers only, reflecting that the group of

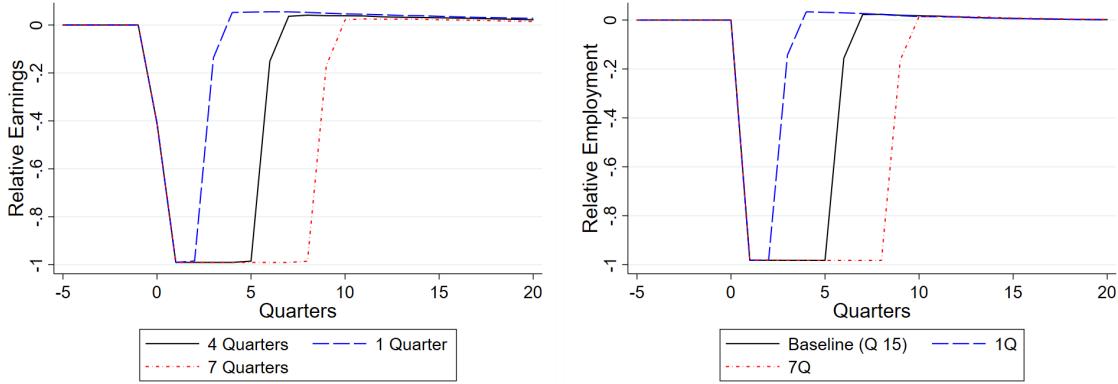


Figure C.5: *The effect of a temporary shutdown on the earnings and employment status of affected workers. During the shutdown, workers are assumed to be either in the temporary unemployment state without the associated penalties, and after the shutdown workers transition back to employment at a faster rate than usual. The shutdown lasts for either 1 period (blue, dashed), 4 periods (black, solid), or 7 periods (red, short-dashed) of the simulation.*

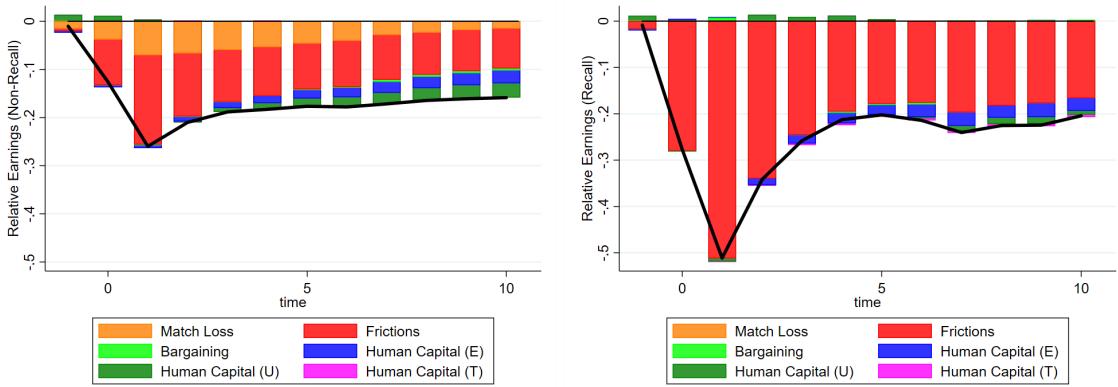


Figure C.6: *A decomposition of the scarring effect of displacement on earnings for (ex-post) non-recalled workers (left) and recalled workers (right). The black line represents the total earnings loss, and corresponds to the solid blue and red lines in the left panel of figure 19. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals. Corresponding numerical values for selected time periods (0, 1, 3, 5, and 10 years after displacement) can be found in the appendix in tables C.4 and C.5.*

| Channel | $k = 0$ | $k = 1$ | $k = 3$ | $k = 5$ | $k = 10$ |
|-------------------|---------|---------|---------|---------|----------|
| Match Loss | 0 | 0 | 0 | 0 | 0 |
| Bargaining | 0.001 | 0.007 | 0 | -0.002 | 0.003 |
| Frictions | -0.28 | -0.512 | -0.246 | -0.178 | -0.166 |
| Human Capital (U) | 0.004 | 0.009 | 0.009 | 0.004 | 0.003 |
| Human Capital (T) | 0 | -0.001 | -0.003 | -0.004 | -0.005 |
| Human Capital (E) | 0.004 | 0.001 | -0.018 | -0.021 | -0.027 |
| Total | -0.279 | -0.511 | -0.258 | -0.202 | -0.204 |

Table C.4: *Summary of the decomposition of the difference in the scarring effect of displacement on earnings for (ex-post) recalled workers. The total difference corresponds to the solid red line in the left panel of figure 19. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals. The numbers reflect the contribution of each channel to the difference in the scarring effect of displacement on earnings, k years after displacement, and reflect the corresponding decomposition depicted in figure C.6*

| Channel | $k = 0$ | $k = 1$ | $k = 3$ | $k = 5$ | $k = 10$ |
|-------------------|---------|---------|---------|---------|----------|
| Match Loss | -0.038 | -0.071 | -0.059 | -0.046 | -0.015 |
| Bargaining | 0 | -0.002 | 0 | -0.001 | -0.004 |
| Frictions | -0.095 | -0.186 | -0.108 | -0.095 | -0.083 |
| Human Capital (U) | 0.011 | 0.003 | -0.008 | -0.016 | -0.03 |
| Human Capital (T) | 0 | 0 | 0 | 0 | 0 |
| Human Capital (E) | -0.004 | -0.006 | -0.012 | -0.018 | -0.027 |
| Total | -0.126 | -0.26 | -0.188 | -0.177 | -0.159 |

Table C.5: *Summary of the decomposition of the difference in the scarring effect of displacement on earnings for (ex-post) non-recalled workers. The total difference corresponds to the solid blue line in the left panel of figure 19. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals. The numbers reflect the contribution of each channel to the difference in the scarring effect of displacement on earnings, k years after displacement, and reflect the corresponding decomposition depicted in figure C.6*

non-recalled workers is much larger than the group of recalled workers.

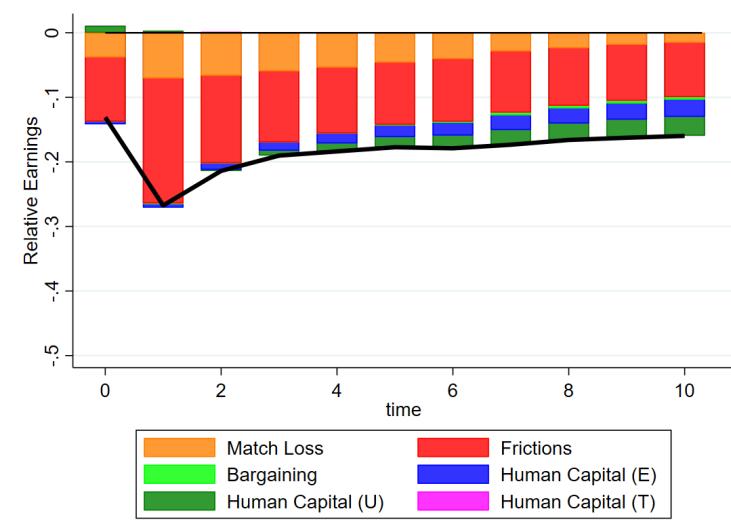


Figure C.7: A decomposition of the average scarring effect of displacement on earnings. The black line represents the total earnings loss, and corresponds to the solid line in the left panel of figure 17. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals.

Since the decomposition of the average scarring effect of displacement (on earnings) points towards human capital depreciation as one of the major reasons for the large losses in the long run, it is natural to expect that a policy aimed at helping displaced workers may be targeted at bringing down the depreciation rate of human capital for nonemployed workers. In figure C.8, I consider the extreme case where human capital depreciation is zero (i.e. $\psi_u = 0$, and therefore also $\psi_r \psi_u = 0$). As can be seen in the figure, such a policy would help the non-recalled worker more than the recalled worker. This is especially true in the first few years, where the recalled worker's outcome does not improve at all. After more than 5 years, the policy also starts to aid the recalled worker, who at that point will be experiencing their subsequent separations. As these subsequent separations are potentially without the expectation of recall, the recalled worker will at that point also be exposed to the higher human capital depreciation rate faced by the workers not expecting a recall, thus explaining why bringing down the depreciation rate to zero helps the recalled worker somewhat (but not as much as the non-recalled worker).

Finally, the last paragraph of section 6.3 discussed how the difference between recalled and non-recalled workers would change if I were to calibrate the nonemployment benefit fraction b to the US replacement rate rather than the German replacement rate. As mentioned in the main text, such an exercise

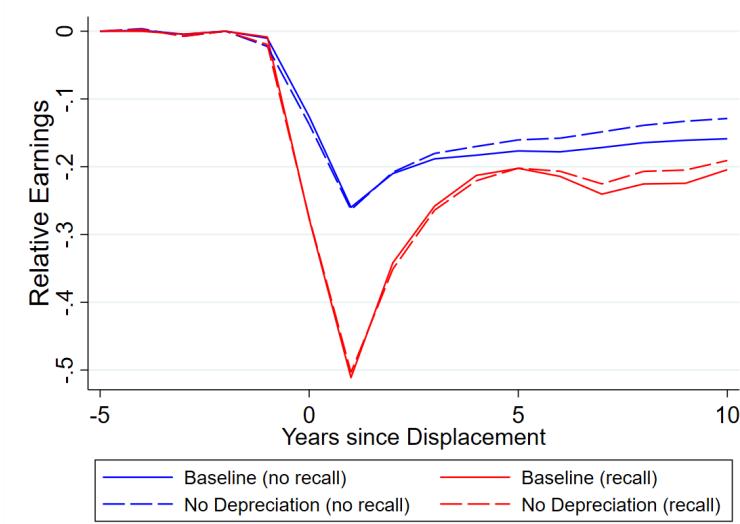


Figure C.8: *The effect of displacement on earnings relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data from the baseline model (solid, corresponding to figure 19) and a counterfactual in which nonemployed workers do not lose human capital during nonemployment ($\psi_u = \psi_r \psi_u = 0$, dashed).*

yields a value of $b = 0.52$ (rather than $b = 0.7$ as found in section 4 using the German replacement rate). In order to account for the fact that with a lower nonemployment benefit, the government will also have lower expenses, I additionally calibrate a proportional subsidy on the output, such that the total cost faced by the government stays the same. As mentioned in the main text, the resulting value of $-\tau = 0.0114$ is fairly mild.

In figure C.9, I compare the results of estimating the scarring effect of displacement (on earnings) by ex-post recall status for this alternative parametrization of the model (with and without the proportional subsidy) to those obtained in the baseline specification. As can be seen in the figure, the non-recalled workers face very similar earnings losses, but the recalled worker now suffers from much larger earnings losses. As indicated by the difference between the dashed and dotted lines, the addition of the proportional subsidy does not change this result. Therefore, I conclude that conditional on all other parameters being the same in both economies, I would expect the seemingly negative effect of recall to be much stronger in an economy with less generous nonemployment benefits.

Given that the nonemployment benefit plays a large role in determining the value of both states of nonemployment, one potential reason for this disparity in the effects of lowering b on recalled and non-recalled workers could be that the value of nonemployment is more important in determining the next wage for recalled workers (compared to non-recalled workers), because they re-bargain their wage using a bar-

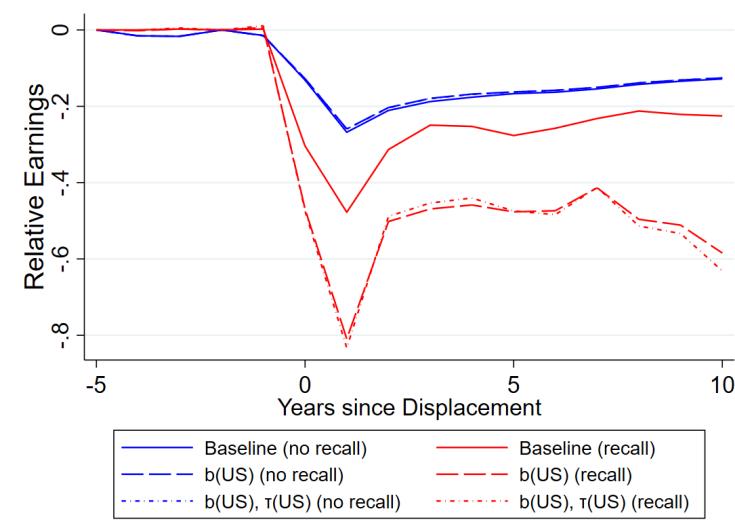


Figure C.9: *The effect of displacement on earnings relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data from the baseline model (solid, corresponding to figure 19) and alternative parametrizations with a lower value of b (dashed) or a lower value of b and a proportional output subsidy (dotted), where the lower value of b is calibrated to match the US replacement rate.*

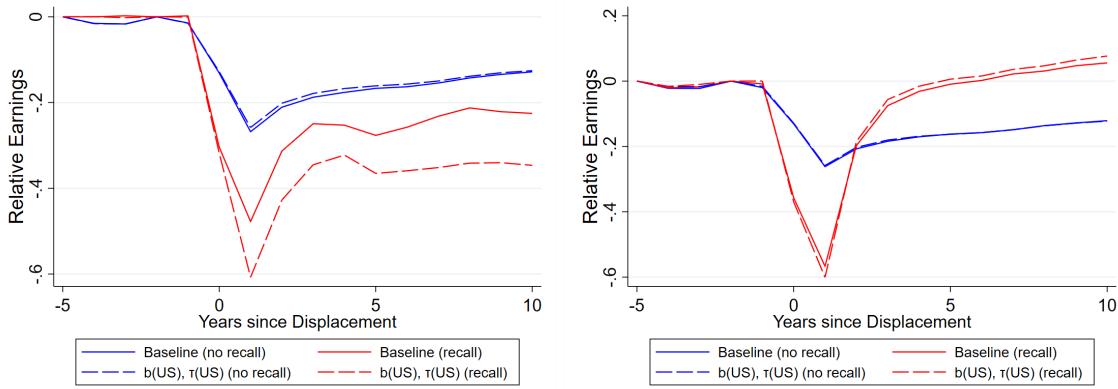


Figure C.10: *The effect of displacement on earnings relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data from the baseline model (solid) and alternative parametrizations with a lower value of b and a proportional output subsidy (dotted), where the lower value of b is calibrated to match the US replacement rate. The figures are generated using model versions with either $\kappa^r = \kappa$ (left) or $c^\delta = 0$ (right).*

gaining power of $\kappa^r = 0.309$ rather than $\kappa = 0.883$. However, the left panel of figure C.10 shows that this does not fully explain the disparity. If I set the value of κ^r equal to the calibrated value of κ , the lower value of b still impacts the recalled worker much more than the non-recalled worker. Rather, the larger impact is driven by the fact that the recalled worker is much more likely to lose their job again. Therefore, the recalled worker is exposed to the lower value of b multiple times. If I disable the separation rate penalty c^δ (by setting it to 0), the large difference no longer arises, as shown in the right panel of figure C.10.

D Data Appendix

D.1 Individual Summary Statistics

| Frequency | SIAB | | LIAB | |
|--|----------|----------|-----------|-----------|
| | 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) ⁸⁶ | 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, including 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 system 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.⁸⁷ Looking at how the breakdown of industries and occupations evolves over time, it can be seen that

⁸⁶In these yearly earnings, only earnings from employment are taken into account.

⁸⁷The major industries are defined as (1) Agriculture, Fishing, Mining, (2) Manufacturing, Utilities, and Construction, (3) Wholesale and Retail Trade, Hospitality, (4) Business Service Activities, (5) Education, Health, and other Community Services, and (6) Industries not otherwise classified (Public Administration, Private Households, Extra-Territorial).

The major occupations are defined as (1) Agriculture, Forestry, and Horticulture, (2) Manufacturing, Production Technology, and Construction, (3) Personal Services, (4) Business Related Services, and (5) Other Service Occupations.

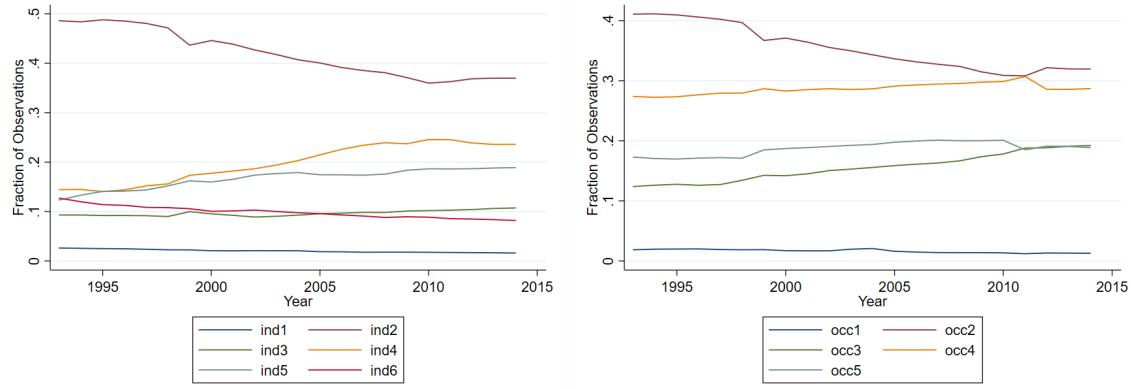


Figure D.1: *The fraction of observations by industry (left) and occupation (right) over time, using LIAB. The labels corresponding to the industry and occupation numbers can be found in footnote 87.*

industries and occupations related to manufacturing and construction (industry and occupation 2) 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 in future work, comparing the scarring effect of separation and displacement by the industry or occupation of origin, and comparing the declining industry/occupation with the largest clearly growing industry/occupation.

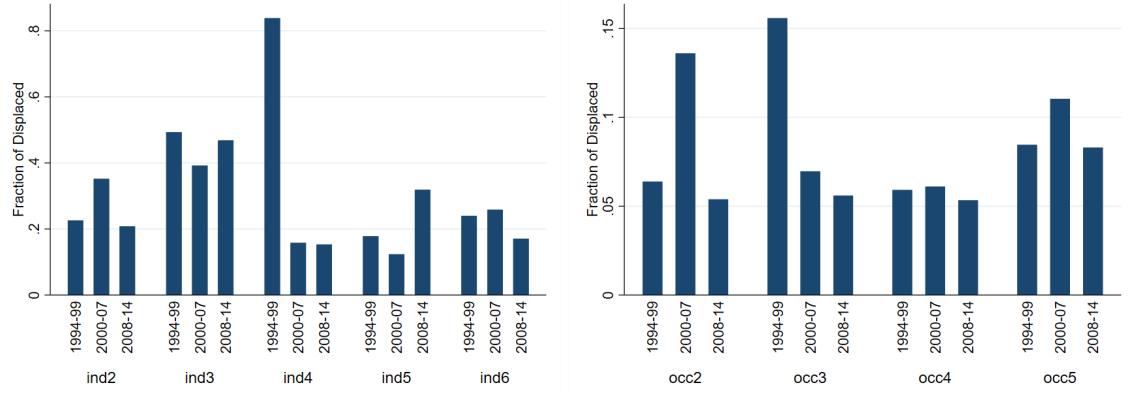


Figure D.2: *The fraction of displaced workers moving industry (left) and occupation (right), using LIAB and by former employing industry/occupation. Industry 1 (Agriculture, Fishing, Mining) and occupation 1 (Agriculture, Forestry, and Horticulture) are not included as the number of underlying observations is not high enough to yield a reliable estimate. The labels corresponding to the industry and occupation numbers can be found in footnote 87.*

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 (industry and occupation category 2) do have a slightly higher post-separation mobility rate, they are generally not the industry/occupation associated with the highest mobility rate.

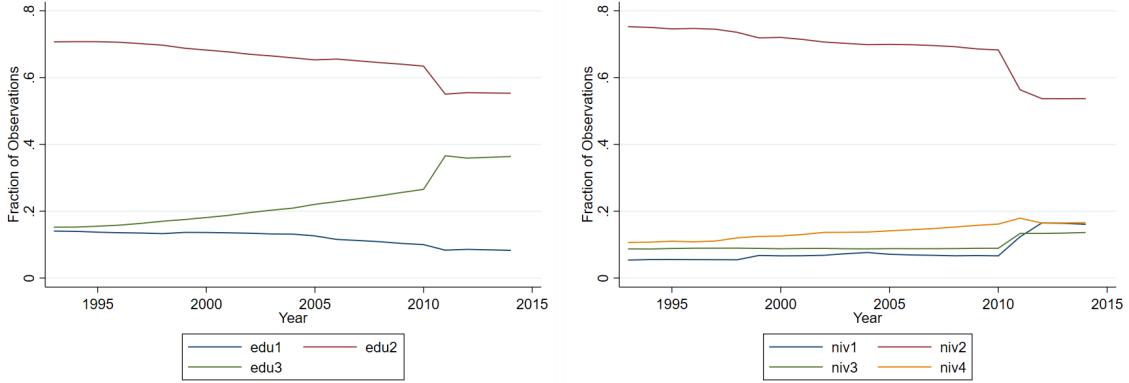


Figure D.3: *The fraction of observations by education (left) and occupational complexity (right) over time, using LIAB.*

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.⁸⁸ Here, it can be seen that the fraction of highly educated workers is increasing over time, although the increase is generally very gradual (prior to 2010). 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 seems natural to 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

⁸⁸Contrary 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.

occupational mobility rate is 7.9%.⁸⁹ Furthermore, it can be noted that among the workers 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%.⁹⁰ This suggests that occupational mobility and occupational complexity switching often go together.

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 these 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.

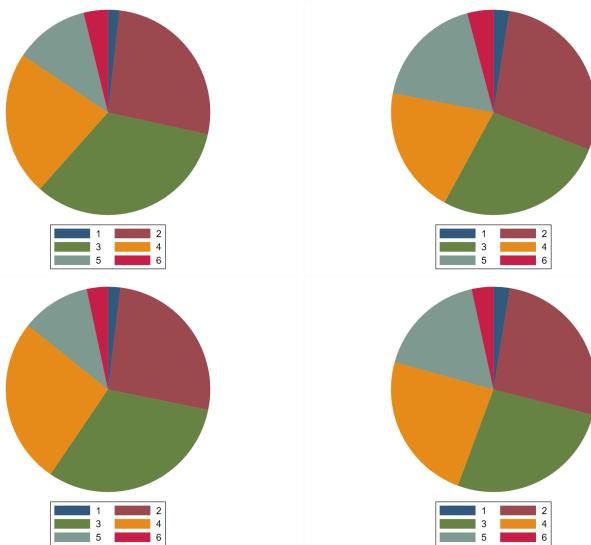


Figure D.4: *Breakdown of exiting establishments (left) and all establishments in the data (right) by major industry⁹¹*, using data from the SIAB (top row) and LIAB (bottom row).

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

⁸⁹Conditional on separation, the occupational complexity moving rate (in the LIAB) is 15.4%, whereas the corresponding occupational mobility rate is 11.1%.

⁹⁰Among 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%.

⁹¹Just 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 industries 5 (Education, Health, and other Community Services) and 6 (Education, Health, and other related services) are 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.⁹²

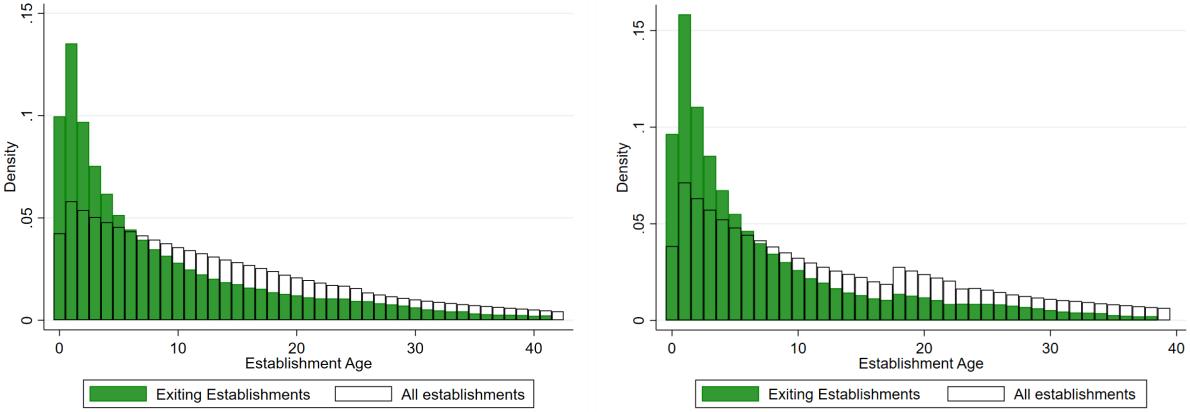


Figure D.5: *The distribution of the exiting establishments in SIAB (left) and LIAB (right) by establishment age.*

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. However, note that this does not 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 an establishment exits, it is possible to distinguish between several exit types. Using

⁹²The 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).

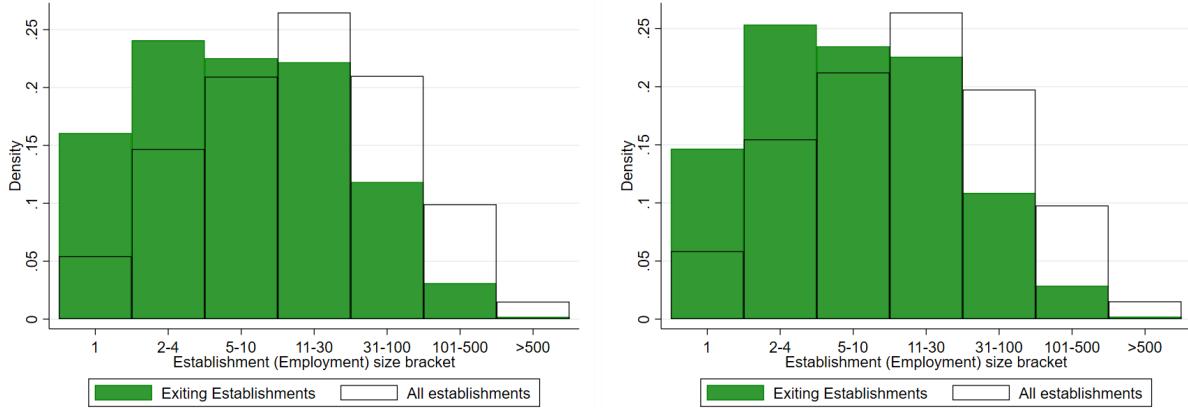


Figure D.6: *The distribution of exiting establishments (green) and all establishments in the data (black) by size group (defined as the number of employees at an establishment), using the SIAB (left) and LIAB (right).*

the definitions from Hethay 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. Therefore, these are exiting establishments with at least 4 employees where more than 30% of the former employees find 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

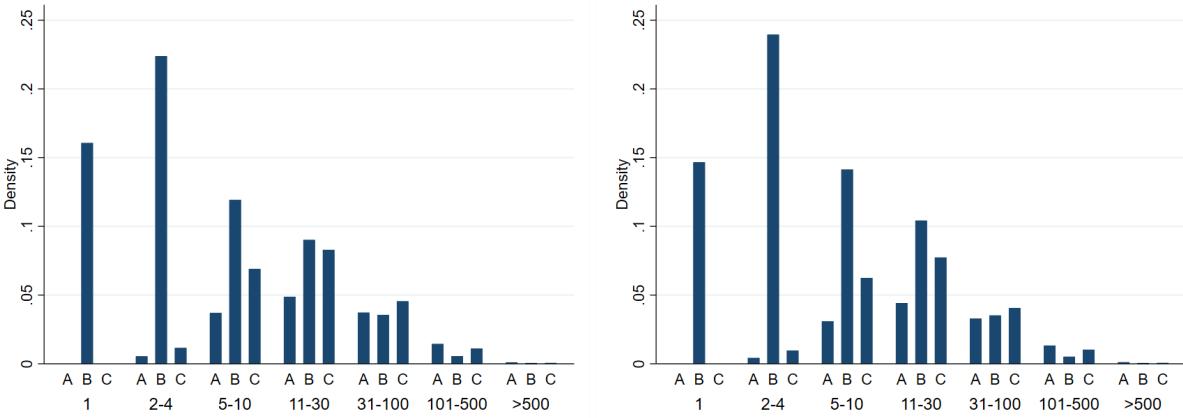


Figure D.7: *The distribution of exiting establishments over exit types A, B, and C (as defined in the text), and size group (defined by the number of employees at an establishment), generated using the SIAB (left) and LIAB (right).*

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

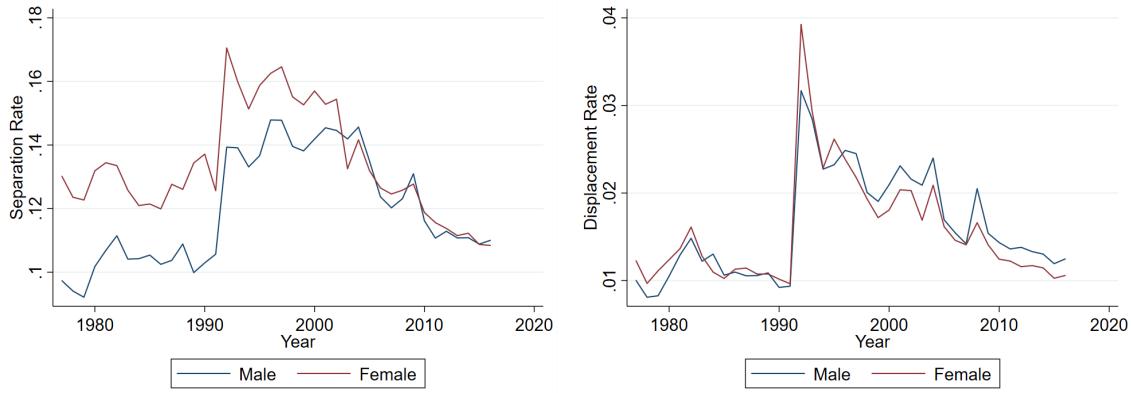


Figure D.8: *The incidence of separation (left) and displacement (right) by gender, over time.*

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 2, 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 (as defined in section 2). Furthermore, looking at the more recent years, it no longer seems to be the case that female workers face higher separation rates, and displacement rates are now slightly higher for male workers than for female workers.

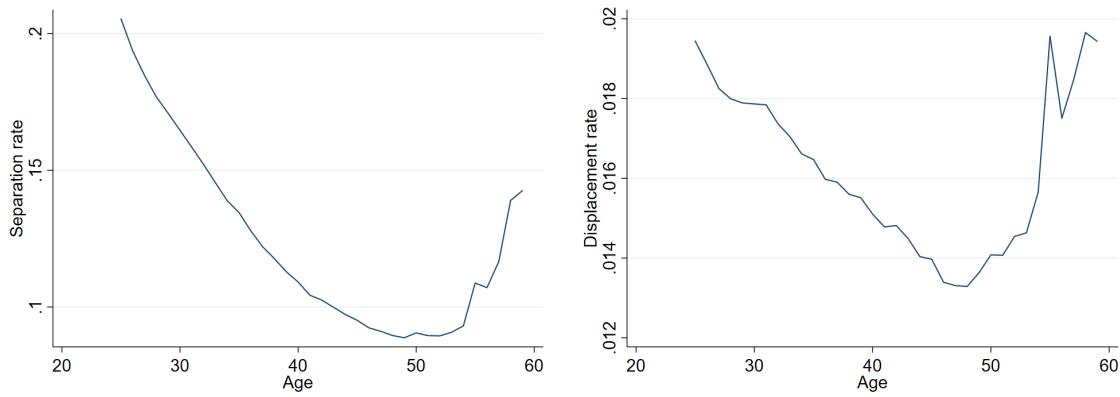


Figure D.9: *The incidence of separation (left) and displacement (right) by age.*

In figure D.9, the separation and displacement rates are displayed by age of the worker at the time of the job loss event. As can be seen here, the separation rate tends to be higher during early years, but this pattern is not as extreme for the displacement rate, which corresponds to the narrative in the literature (see e.g. Topel and Ward, 1992) that stresses the prevalence of job hopping early in the life cycle.⁹³ 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.⁹⁴

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

⁹³Note 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.

⁹⁴See Berg et al. (2015) for a more extensive description of this policy, implemented in 1996.

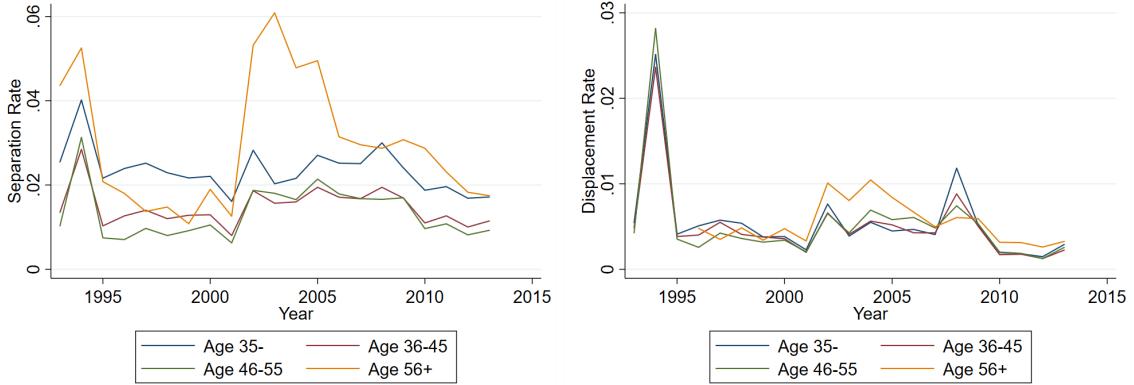


Figure D.10: *The incidence of separation (left) and displacement (right) by age group, using LIAB.*

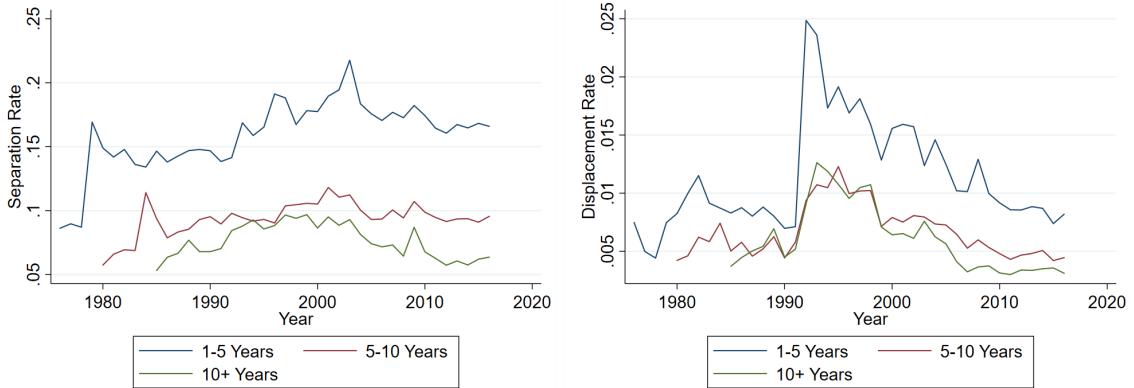


Figure D.11: *The incidence of separation (left) and displacement (right) by job tenure.*

A similar pattern can be discovered by plotting the separation and displacement rate by job tenure, as done in figure D.11.⁹⁵ As one might expect, 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.⁹⁶ 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).

⁹⁵Note that job (or establishment) tenure in the data is measured from the start of the data in 1975. As such, it is not possible for a person to have more than 5 (10) years of tenure in the data until 1980 (1985), as is reflected by the lines for these higher tenure groups starting from that year.

⁹⁶The figures for establishment tenure are available upon request. They are not included here as they are very similar to the ones for job tenure.

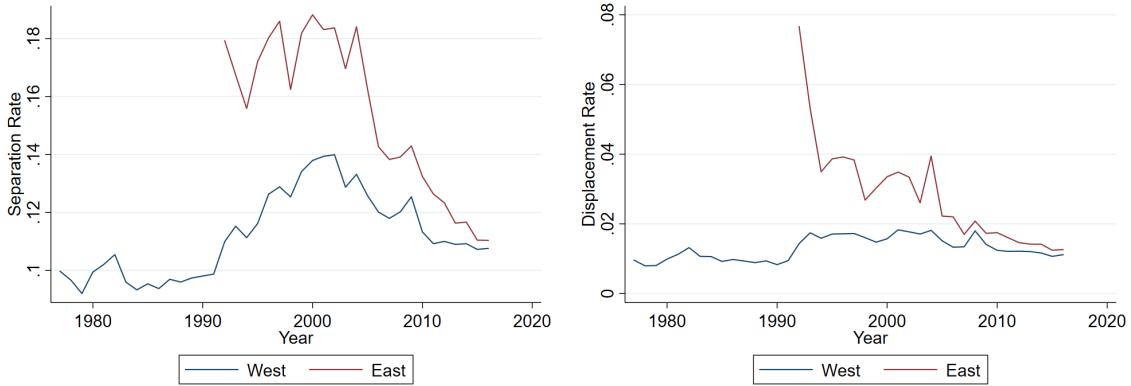


Figure D.12: *The incidence of separation (left) and displacement (right) by location.*

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.12 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.

It is likely that job loss rates also differ by establishment characteristics such as establishment size. The left panel of figure D.13 shows the displacement rate by establishment size group. As can be seen in this figure, the displacement rate tends to be higher for smaller establishments, especially if I remove the restrictions on worker tenure.

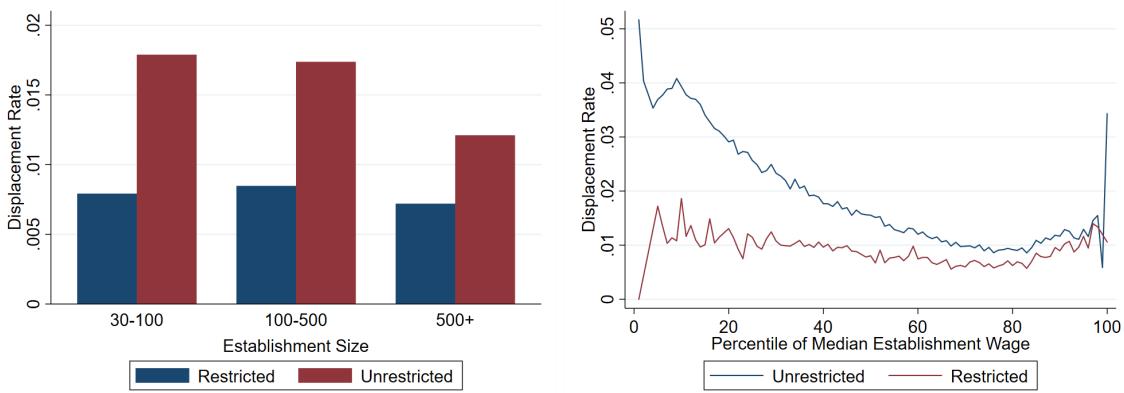


Figure D.13: *The incidence of displacement by establishment size (left) and median wage (right), with and without restrictions on worker tenure.*

The right panel of figure D.13 shows how the displacement rate differs according to how high the median establishment wage is. The pattern here is similar to the one seen earlier in figure 5: the displacement 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.

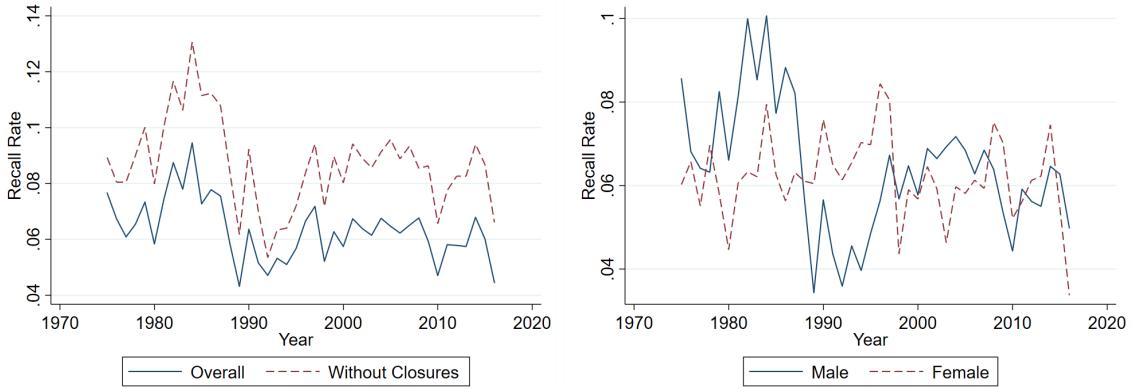


Figure D.14: Left: The incidence of recall within 5 years of job loss over time, conditional on displacement, with and without including establishment closures in the definition of a displacement. Right: The incidence of recall within 5 years of job loss, conditional on displacement, over time and by gender.

The left panel of figure D.14 shows how the incidence of recall (within 5 years), conditional on displacement, changes if establishment closures are excluded from the definition of a mass layoff. As workers who are laid off from a closing establishment can not be recalled, these closures mechanically drive down the recall rate. Indeed, as can be observed in the figure, excluding these establishment closures leads to an increase in the recall rate of approximately 2 percentage points (from an average of 6% to an average of 8%).

Finally, the right panel of figure D.14 shows that recall rates are fairly similar for male and female workers, although the recall rate for male workers does appear to be slightly more volatile.

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.

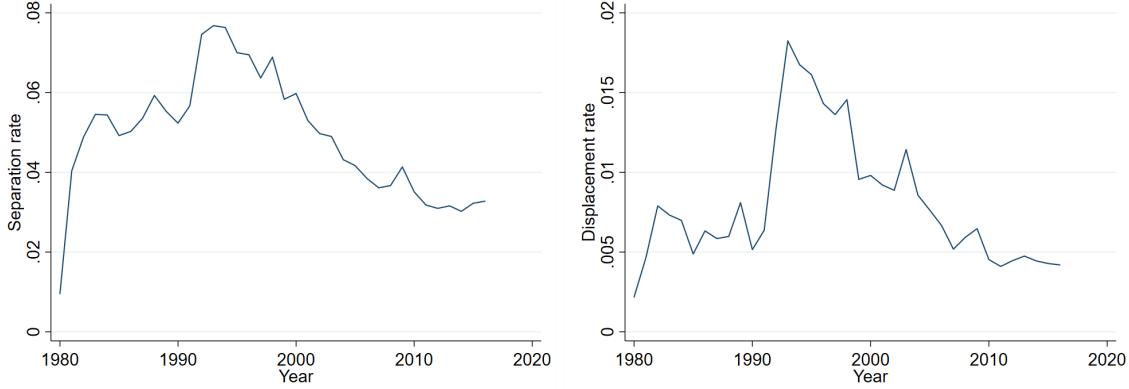


Figure D.15: *The incidence of separation (left) and displacement (right) over time, with restrictions on worker tenure.*

First of all, figure D.15 displays the separation and displacement rates over time, for the (tenure-)restricted sample. As can be seen in this figure, the separation rate 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, reflecting how incidence differs by job tenure (as observed in section D.3.1). As before, the aftermath of the German reunification is quite clearly visible in the graph.

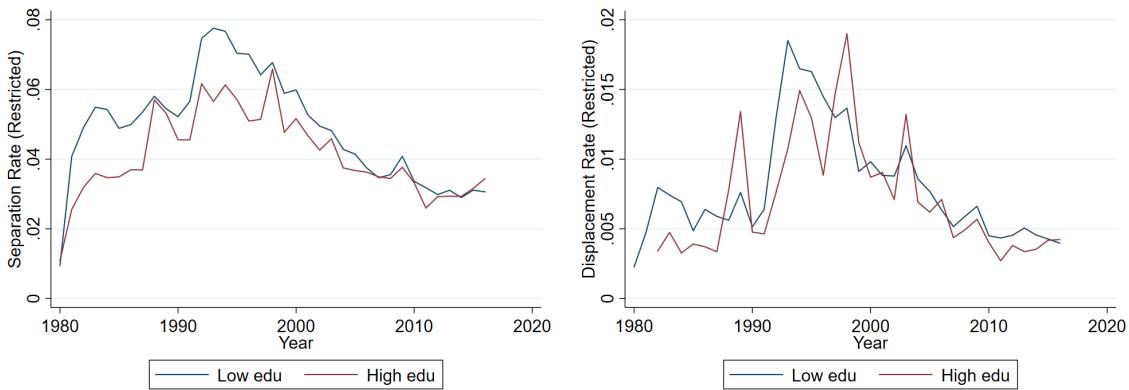


Figure D.16: *The incidence of separation (left) and displacement (right) by education level, over time, with restrictions on worker tenure.*

Figure D.16 displays the restricted separation and displacement rates over time by education level, thus mirroring figure 3 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.

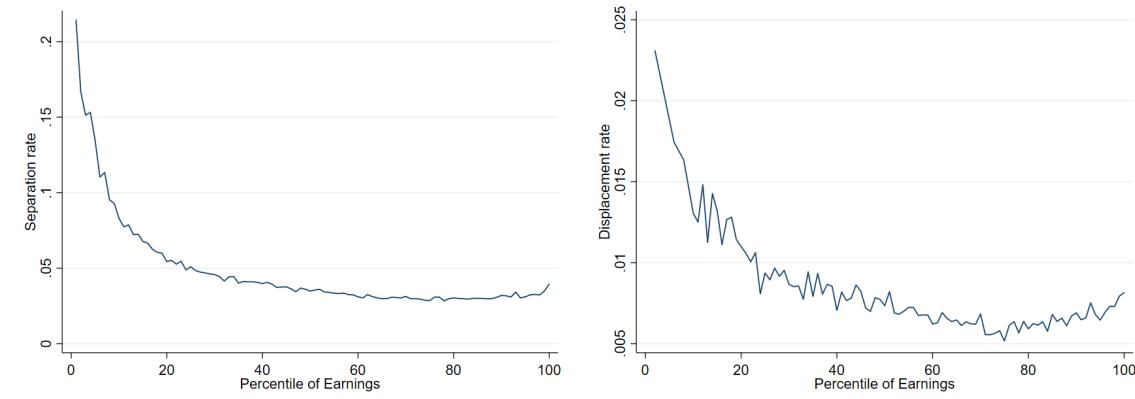


Figure D.17: *The incidence of separation (left) and displacement (right) over the earnings distribution, with restrictions on worker tenure.*

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.

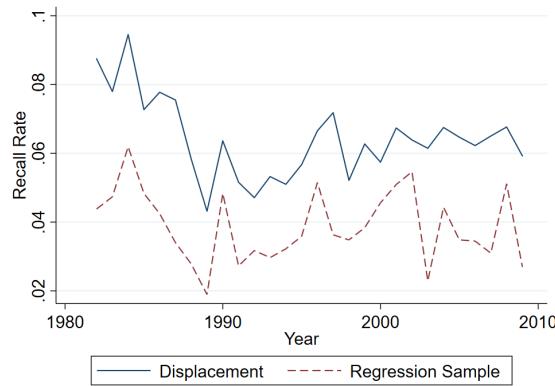


Figure D.18: *The incidence of recall within 5 years of job loss over time, conditional on displacement, with and without further sample restrictions (as imposed for regression estimation).*

Finally, figure D.18 shows how the incidence of recall (within 5 years), conditional on displacement, changes when I impose the further sample restrictions for the purpose of the regression estimations in section 3.2 and 3.3. In particular, this means that I require the worker to have at least 6 years of establishment tenure prior to displacement and I require the establishment to contain at least 50 workers (prior to displace-

ment). As can be seen in the figure, this further decreases the recall rate to an average of approximately 4%.

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.⁹⁷



Figure D.19: *The incidence of separation (left) and displacement (right) over time, using LIAB.*

First of all, figure D.19 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 in the early 1990s in the SIAB is not visible here.

Figure D.20 splits out the incidence rates seen in figure D.19 by education level. Therefore, it can be seen as the LIAB version of figure 3. 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.

⁹⁷Note 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.

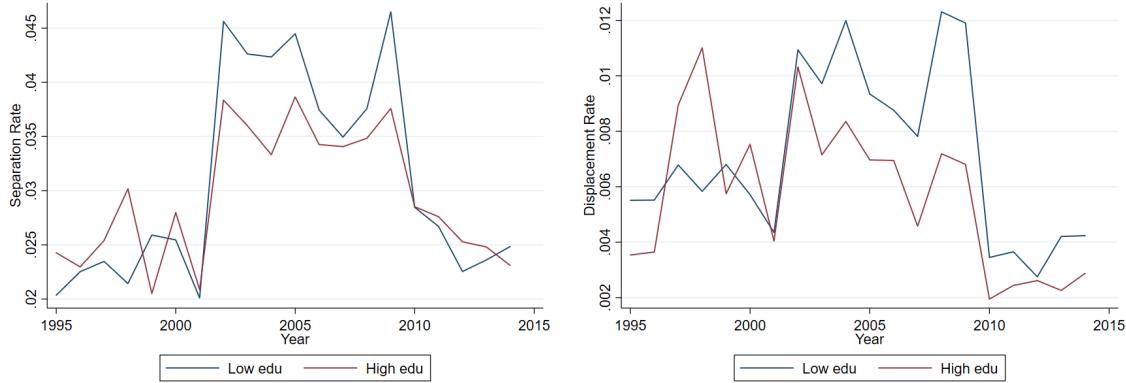


Figure D.20: *The incidence of separation (left) and displacement (right) by education level, over time, using LIAB.*

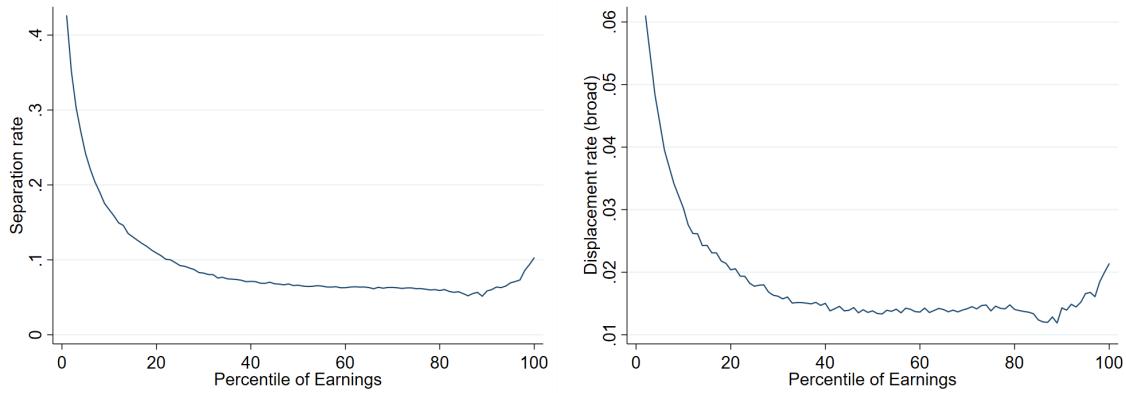


Figure D.21: *The incidence of separation (left) and displacement (right) over the earnings distribution, using LIAB.*

As shown in figure D.21, 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.22 shows that the incidence of recall (within 5 years) is especially high for separation, but even for displacement consistently above 3.5% across the distribution, and much higher towards the bottom of the distribution, in line with the conclusions from figure 6.

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.

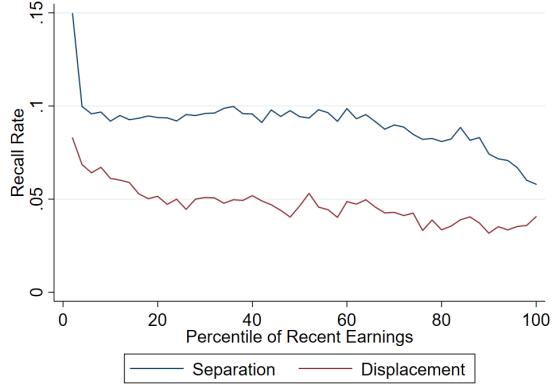


Figure D.22: *The incidence of recall within 5 years of separation or displacement, by percentile of the recent earnings distribution.*

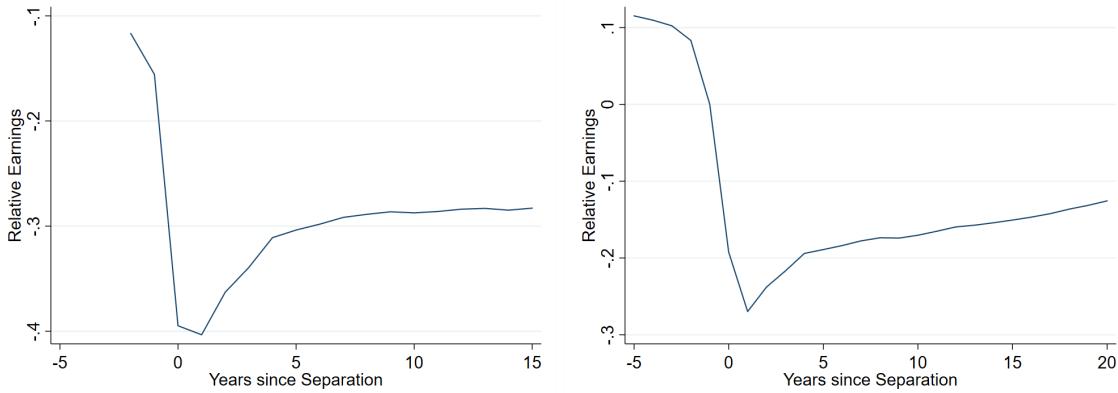


Figure D.23: *Raw (left) or regression-based (right, using specification 1) average effect of separation on earnings, relative to the control group.*

First, figure D.23 presents the counterpart of figure 7 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 the estimated effects of displacement seen in the main text. In particular, the change in relative earnings is fairly similar, though the initial level is lower than it was for displacement. The right panel of the figure 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, which was the main reason for focusing on displacements instead.

As figure D.24 shows, the employment status of the separated workers also follows a similar pattern to that of the displaced workers (as shown in figure 8), with a slightly larger effect in the short run

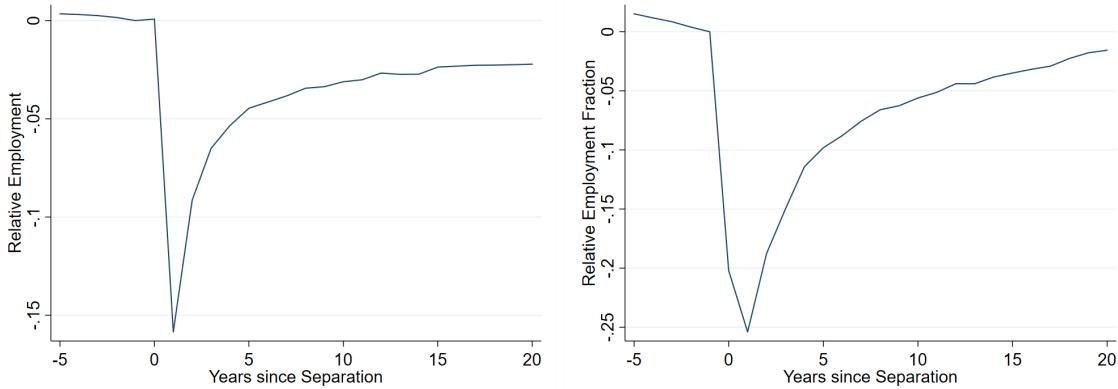


Figure D.24: *The effect of separation on employment status (left) and employment fraction (right), relative to the control group, using estimated coefficients from equation 1.*

and a slightly faster recovery.

As mentioned in the main text, the conclusions regarding the scarring effect of displacement are in line with the literature, though slightly conservative in some cases. In what follows, I change some of the restrictions on the sample used in obtaining the estimation results in the main text, to show how sensitive results are to these restrictions. First of all, I did not include any observation where the earnings for the individual are missing when creating my estimation sample used in the main text. I chose not to include these observations, as 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.25.

Second of all, the estimation of the interaction-weighted estimator (described in section 2 and summarized by equation (2)) only allows for an individual to be assigned to a single cohort. In the estimation discussed in the main text, I accounted for this by excluding any individual that experienced multiple displacements. An alternative method would be to assign these individuals to the cohort corresponding to their first observed displacement. The estimation results using this alternative sampling method can be seen in figure D.26, where the original result (as seen in the main text) is included for the reader's convenience. Comparing the two lines in figure D.26, it can be observed that including individuals who experience multiple displacements leads to a slightly larger estimate of the scarring effect of displacement (in the long run). However, the difference is very small and almost indistinguishable on the graph, and the difference between the point estimates is not statistically significant, thus showing that the decision to omit individuals who experience multiple displacements does not seem to affect the result.

As I mention in section 3.2, the estimated scarring effects of displacement on earnings and employment fraction seem to suggest that the daily wage of the displaced worker recovers relatively quickly. In

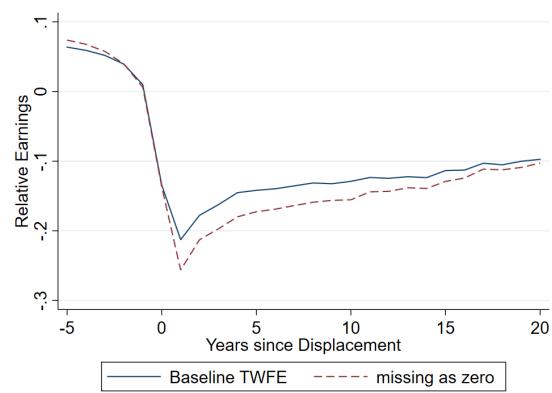


Figure D.25: *The effect of displacement on earnings, relative to the control group, using estimated coefficients from equation 1. The solid line mirrors the estimate from the right panel of figure 7, whereas the dashed line estimates the effect including missing values (interpreted as zero earnings).*

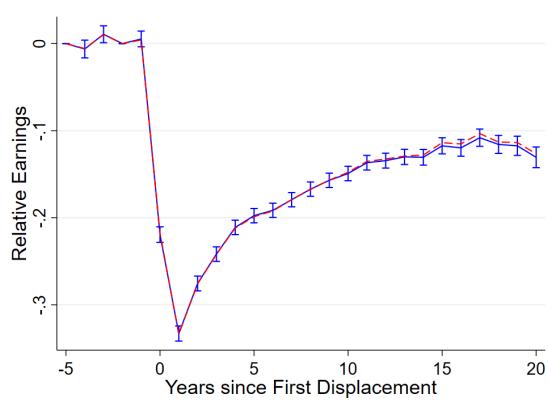


Figure D.26: *The effect of displacement on earnings, relative to the control group, using estimated coefficients from equation 2, and using either the main sample (dashed, red), or using a sample that additionally includes individuals who experience multiple displacements (solid, blue).*

figure D.27, I confirm this hypothesis by showing the results of estimating equation 2 using the (daily) wage as the dependent variable. As can be seen in the left panel, using the full sample gives rather inconclusive results when it comes to daily wages, likely due to some workers earning very high daily wages in the data.⁹⁸ If I instead omit the top and bottom 5% of the observed wages, the result becomes much clearer, as seen in the right panel. Here it can be seen that it is indeed the case that the effect of displacement on daily wages is estimated to fully disappear within roughly 10 years.

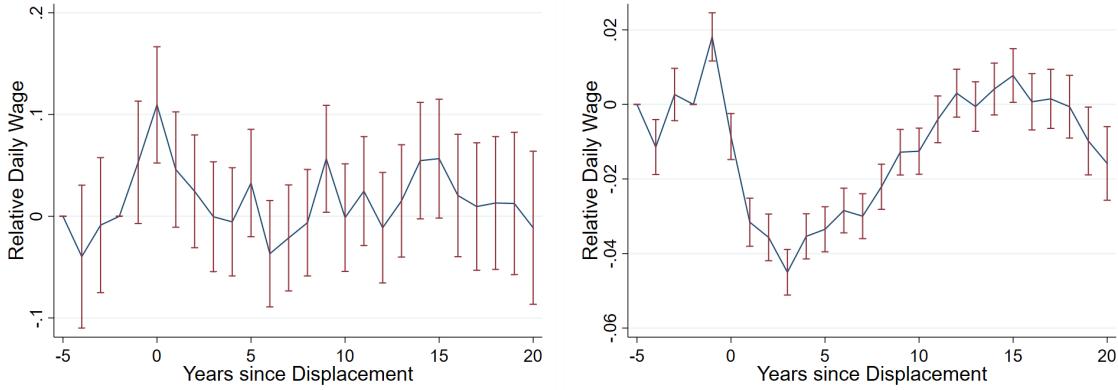


Figure D.27: *The effect of displacement on daily wages, relative to the control group, using estimated coefficients from equation 2, and using either the full sample (left), or using a sample that excludes the top and bottom 5% of the daily wages (right).*

The richness of the data allows me estimate the scarring effect of displacement for several subsamples. In the main text, I already stressed the difference by educational attainment and ex-post recall status. Some other dimensions that are often investigated are that of the worker's gender and age, as well as the economic conditions at the time of displacement.

In figure D.28, I show how the estimated scarring effect of displacement changes depending on the economic conditions at the time of displacement. For this estimation, I divide the cohorts used in the estimation of equation (2) into two groups, according to the unemployment rate at the time of displacement. Notably, the results for earnings (in the left panel) are very similar to the results found by Davis and Von Wachter (2011), who use data from the United States. Just like in that paper, I find that workers who are displaced during booms experience a lower earnings loss than workers who were displaced during recessions. As can be seen in the right panel, the difference in the effect on employment fraction is much smaller.

In figure D.29, I show how the results differ by the worker's gender. As can be seen in the left panel, the results suggest that female workers suffer from much larger earnings losses after displacement

⁹⁸In the original data, these observations are censored, and I use a program from the FDZ at the IAB to impute values for these wages. Omitting the top 5% of daily wages leads to me omitting many of these imputed values, thereby also likely yielding a more reliable estimate.

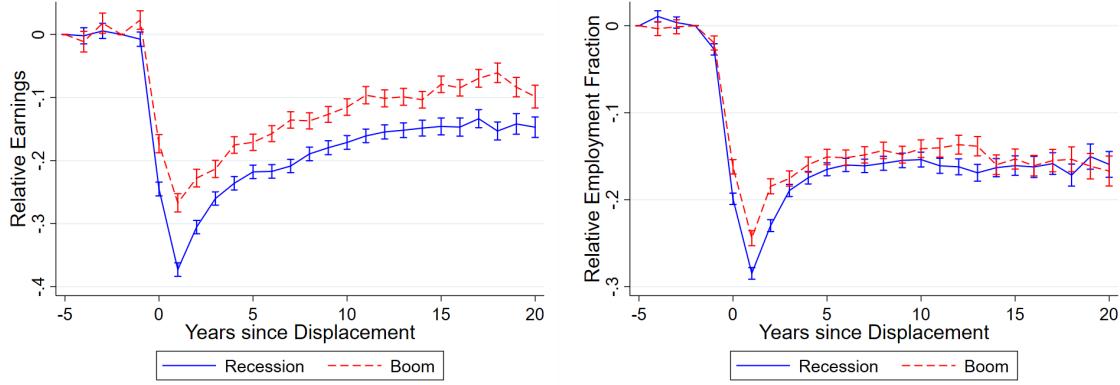


Figure D.28: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group, using estimated coefficients from equation 1, and averaging the resulting coefficients separately by economic conditions at the time of displacement.*

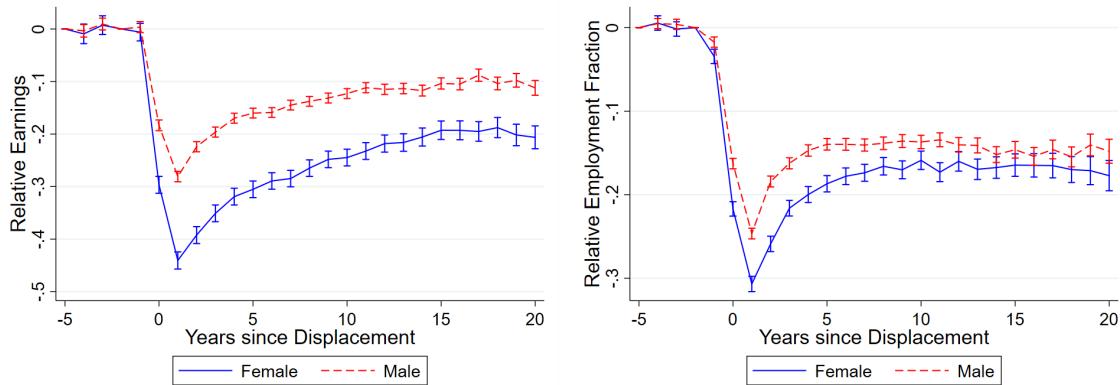


Figure D.29: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group, using estimated coefficients from equation 1, estimated separately for male and female workers.*

than male workers. Nevertheless, the general shape of the earnings loss graph is very similar between the two subsamples. Again, the difference is much smaller when looking at the effect on employment fraction, as shown in the right panel of figure D.29.

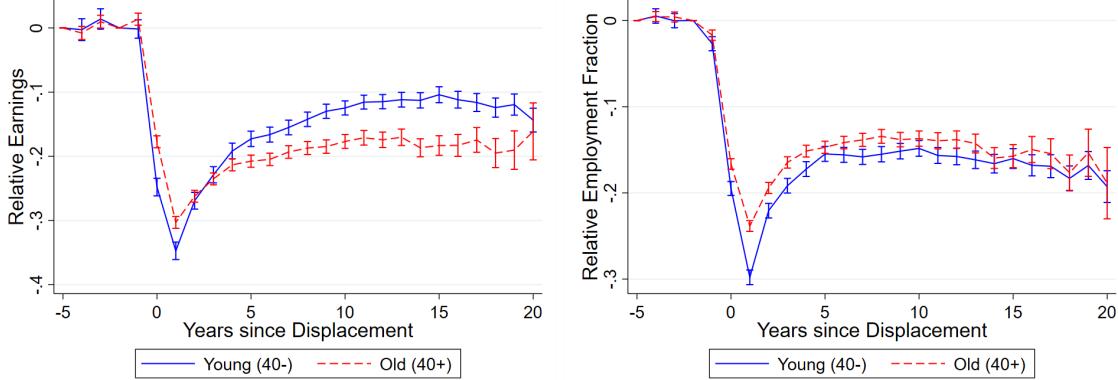


Figure D.30: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group, using estimated coefficients from equation 1, estimated separately for workers who are “young” (below 40) or “old” (40 or older) at the time of displacement.*

Figure D.30 plots the results of estimating equation 2 separately by age groups. For the purpose of this estimation, I split the sample by age at the time of displacement, where the “young” sample includes those aged below 40 at the time of displacement, and the “old” cohort includes workers aged 40 or higher at the time of displacement. For the control group, a similar restriction is put in place to ensure that they cover a similar age span. This means that for the estimation on the “young” sample, control observations with an age above 50 are omitted, whereas for the estimation on the “old” sample I omit control observations for workers aged below 35. As can be observed in figure D.30, the young workers tend to experience a slightly larger effect on both earnings and employment fraction upon impact. However, where the difference between young and old for the effect on employment fraction is fairly constant over time, the young workers recover much faster than the old workers in terms of their earnings.

Finally, when discussing the interaction-weighted estimator from Sun and Abraham (2020) in section 2, I mentioned that it is not the only estimator that aims to correct for contamination of the coefficients estimated a two-way fixed effects model such as equation (1) by other time periods and other cohorts. An alternative method is proposed in Borusyak et al. (2021), and I have estimated the main results from sections 3.2 and 3.3 using this alternative method as well.

The method proposed in Borusyak et al. (2021) proceeds in three steps. In the first step, the method aims to directly estimate the counterfactual implicitly used in a difference-in-differences estimation procedure. This is done by estimating a standard two-way fixed effects model (without the leads and lags for treatment) on all not-yet-treated and never-treated workers in the sample. Following the notation in section

2, this means that I estimate the following equation:

$$e_{it} = \alpha_i + \gamma_t + u_{it} \quad (\text{D.1})$$

The estimates of the individual and time fixed effects in equation (D.1) are then used to estimate the untreated (counterfactual) outcome for all treated observations as well. In other words, the estimated counterfactual outcome combines the estimated individual fixed effect (estimated using the individual's observations before treatment) and the estimated time fixed effect (estimated using other individuals, who were not treated at the time period of interest).

In the second step, these counterfactual untreated outcomes are compared to the (observed) treated outcome to form an estimate of the individual- and time-specific treatment effect (which is thus the difference between the estimated untreated outcome from step 1 and the observed outcome). In the third and final step, the target aggregation is then estimated using a weighted average of the individual and time-specific estimated treatment effects from step 2.

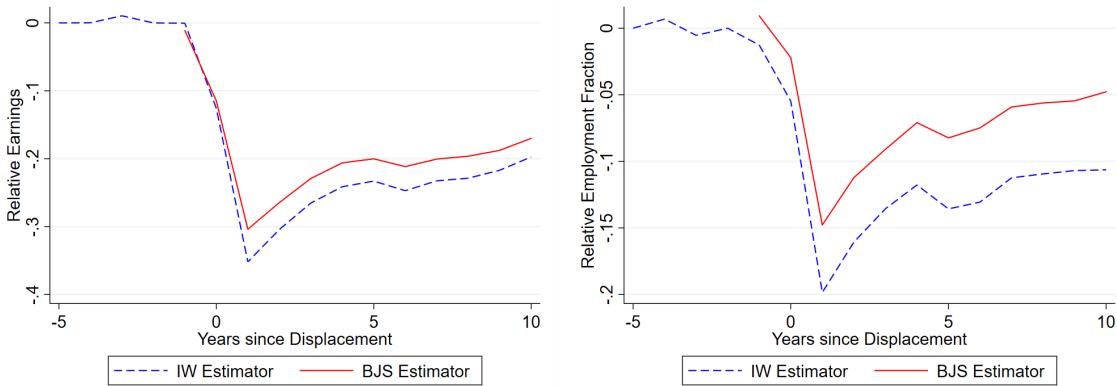


Figure D.31: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group, using estimated coefficients from either equation 1 (blue) or the three-step method from Borusyak et al. (2021) (red), and using data from LIAB.*

In figure D.31, I show how the estimated scarring effect of displacement differs by the used method. As can be seen in the figure, the results for the two methods are very similar, noting that the three-step method from Borusyak et al. (2021) yields slightly smaller earnings and employment losses. This is especially true for employment, indicating that the contrast between the standard two-way fixed effects estimation and these alternative methods (as shown in figure 9 for the interaction-weighted estimator) would have been slightly weaker if I had used the the three-step method from Borusyak et al. (2021) instead.

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.

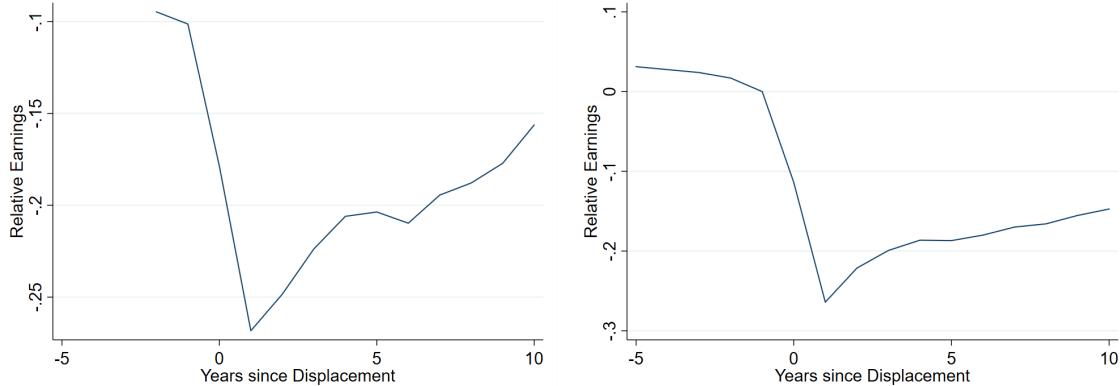


Figure D.32: *Raw (left) or regression-based (right, using specification 1) average effect of displacement on earnings, relative to the control group, and using data from LIAB.*

First, the left panel of figure D.32 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 7), the effect of job loss on earnings is quite substantial. There is some partial recovery in earnings, but earnings have not fully recovered 10 years after job loss.

The right panel of figure D.32 shows the results of estimating equation (1) using the LIAB dataset.⁹⁹ In particular, consistent with the findings in the main text, it can be seen that in the short-run, workers who are displaced earn roughly 25% less on average than a worker in the control group. This earnings loss is shown to be quite persistent, with these displaced workers still earning 14% 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.33 (which is roughly the equivalent of figure 8), 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

⁹⁹The right panel of figure D.32 is roughly the equivalent of the right panel of figure 7 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 to 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 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.

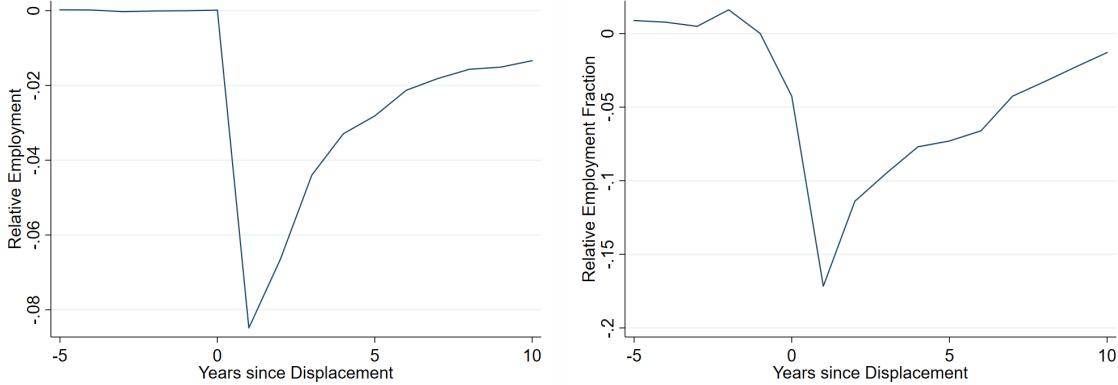


Figure D.33: *The effect of displacement on employment status (left) and employment fraction (right), relative to the control group, using estimated coefficients from equation 1 (left) and 1' (right) and using data from LIAB.*

by 8% in the year after displacement, this likelihood decreases recovers to roughly 4.5% after only 3 years, and further recovers to less than 2% by year 8. Similarly, in terms of the fraction of the years spent in employment, I find in the LIAB that this is roughly 17% lower in the short run (for displaced workers, compared to the control group), but almost fully recovers in 10 years.

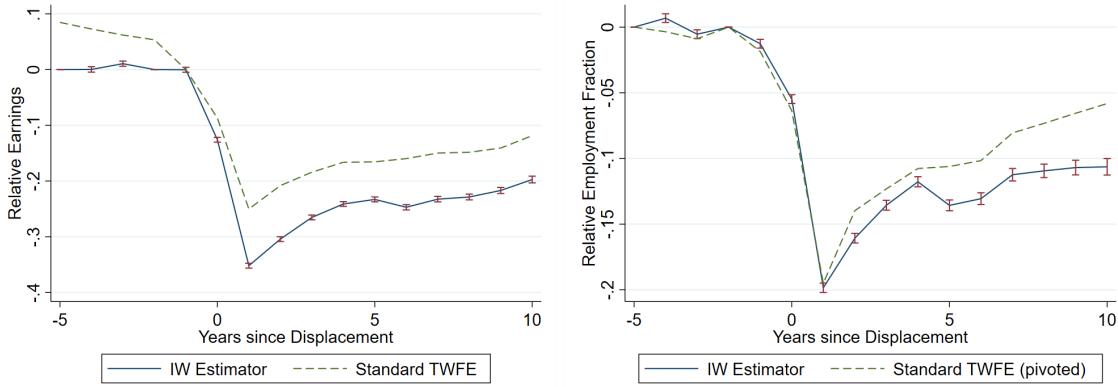


Figure D.34: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group, using estimated coefficients from equation (2) (solid) or (1') (dashed) and using data from LIAB. The error bars on the solid line correspond to 95% pointwise confidence intervals*

Finally, I show in figure D.34 that the estimates of the average scarring effect of displacement (on earnings and employment fraction) change in a similar way as seen in the main text (figure 9) when using the interaction-weighted estimator from Sun and Abraham (2020). When it comes to employment fraction (in

the right panel), the interaction-weighted estimator reveals stagnation in the recovery after 5 years, even if the long-run effect estimated from the LIAB is slightly smaller than estimated from the SIAB (roughly 10% rather than roughly 15%). Comparing the estimates from the interaction-weighted estimator and a standard two-way fixed effects approach for earnings (in the left panel), it can be seen that the difference is slightly larger in the LIAB than in the SIAB. Where the effect in the SIAB was mainly visible in the short run and before the event time, the difference in the LIAB persists over time, thus suggesting larger earnings losses both in the short run and in the long run.

D.3.6 Further Heterogeneity in the Scarring Effect of Displacement

In the main text, in section 3.3, I showed that the scarring effect of displacement on both earnings and (in the short run) employment tends to be worse for workers with a lower education level and for workers who are recalled to their previous employer. In this section, I highlight the robustness of the results discussed in section 3.3 of the main text, by showing how these results change when conditioning the sample on some other observable variable, or when using alternative estimation methods.

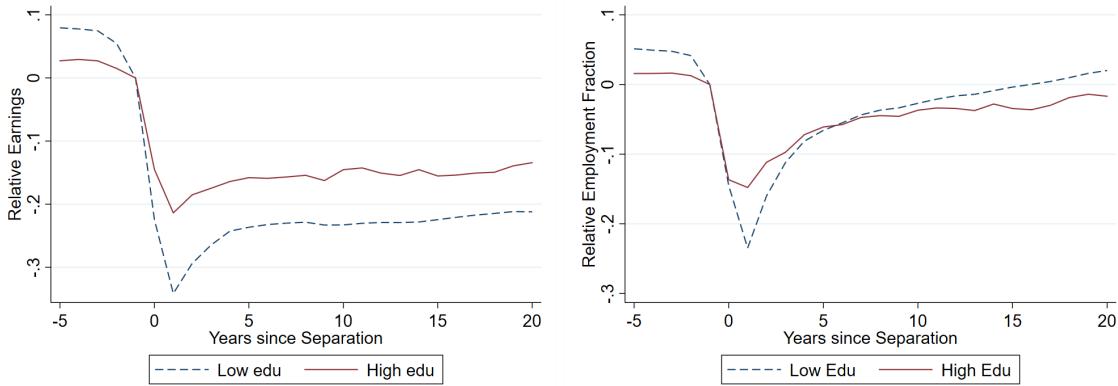


Figure D.35: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group (by education group).*

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.35, I repeat the analysis using specification 1, estimating the effects of separation instead. Comparing figure D.35 to figure 10 in the main text, it can be observed that the effects of separation tend to be worse than the effects of displacement in the short run, and this holds for both education levels. However, the recovery in the first 5 years after separation 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 employ-

ment, workers with a low education suffer from a larger loss in the short run. In the long run, however, the difference between the two education levels mostly disappears.

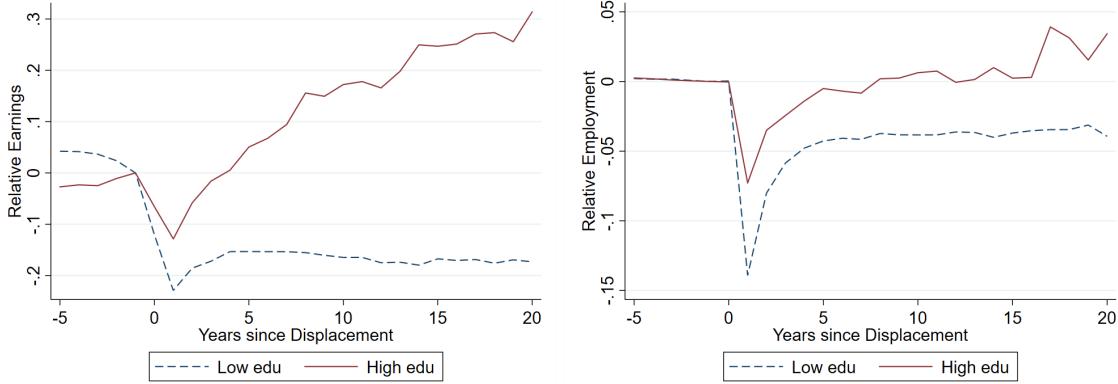


Figure D.36: *The effect of displacement on earnings (left) and employment status (right), relative to the control group (by education group), where the control group contains individuals in either education group (rather than individuals from the same education group).*

In figure D.36, I repeat the analysis of the education-specific effect of displacement. However, contrary to the analysis that generated figure 10 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 eventually leads the relative earnings difference for the highly educated group of displaced workers (compared to the control group) to become positive. This does not fully reflect a scarring effect of displacement. Rather, it is an artifact of the treatment group consisting of only highly educated workers, whereas the control group also includes workers with a low education level. In other words, this figure (and especially the left panel) serves as a reminder that the choice of the correct control group is crucial.

In figure 11 in the main text, I show results obtained using the interaction-weighted estimator from Sun and Abraham (2020), which is one of the proposed alternatives to the “standard” two-way fixed effects estimator commonly used. However, as mentioned in section 1.1, several of these alternative estimators have been proposed. In figure D.37, I show how the results from the interaction-weighted estimator differ from those obtained using the three-step estimation method from Borusyak et al. (2021), outlined in appendix D.3.4. As can be seen in the figure, using this method yields very comparable results, though the resulting estimates are not quite identical. In particular, the three-step method yields smaller estimates of the

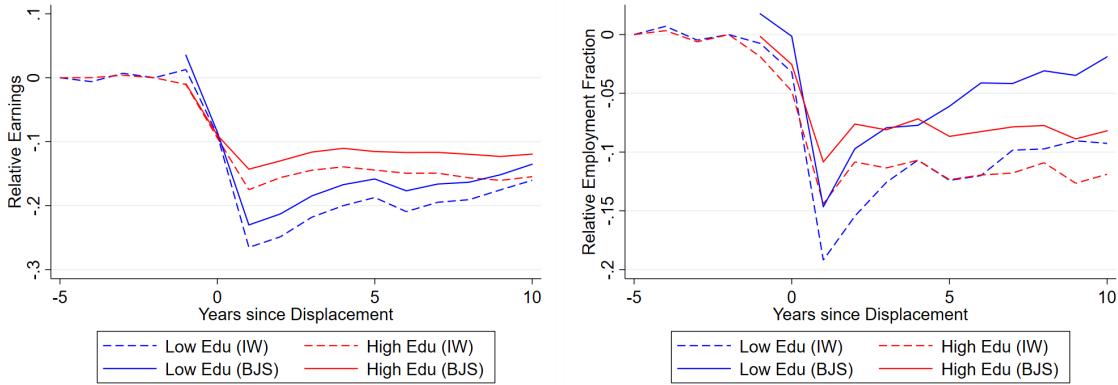


Figure D.37: *The effect of displacement on earnings (left) and employment fraction (right) by education level, relative to the control group, using either estimated coefficients from equation 2 (dashed) or estimated coefficients from the three-step method in Borusyak et al. (2021) (solid) and using data from LIAB.*

scarring effect for both education groups, but the difference between the two groups is consistent between the two methods.

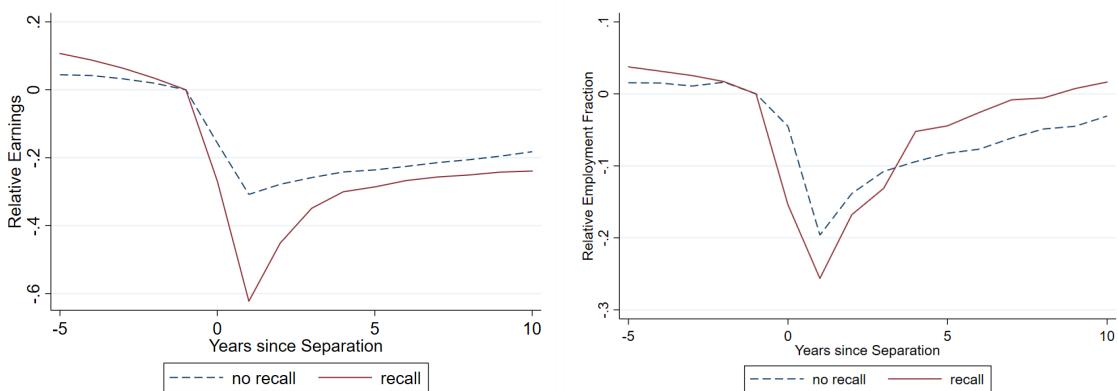


Figure D.38: *The effect of separation on earnings (left) and employment fraction (right) relative to the control group, by ex-post recall status (materialization of recall within 5 years), using specification (1) and using data from LIAB.*

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 than non-recalled (but displaced) workers in terms of earnings, and do worse in terms of employment in the short run. In the remainder of this section I will examine the robustness of these findings.¹⁰⁰ In figure D.38, I repeat the analysis, estimating the effects

¹⁰⁰Note that in some cases I use the LIAB instead of the SIAB. The LIAB equivalents of the results in section 3.3.2 can be found in appendix D.3.7.

of separation instead. Comparing figure D.38 to figure 12 in the main text (or figure D.53 in appendix D.3.7), 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: compared to non-recalled workers, recalled workers do worse in terms of employment in the short run only, but suffer more in terms of earnings in the short run and the long run.

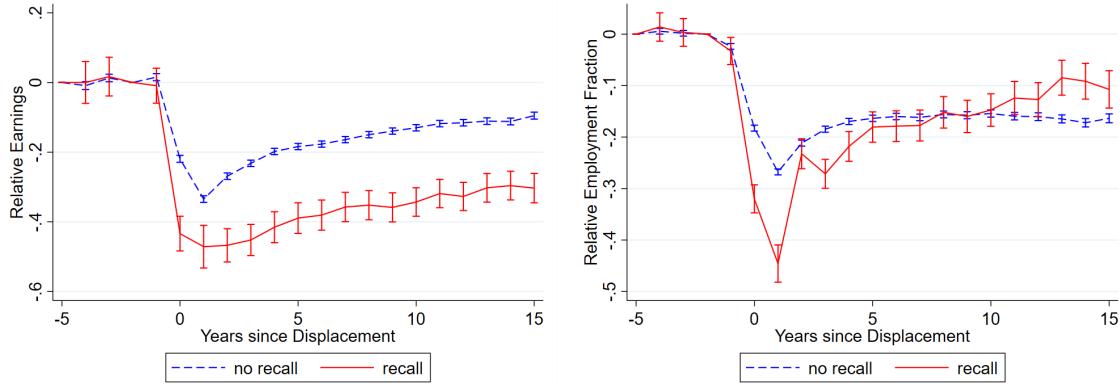


Figure D.39: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status, relative to the control group, using estimated coefficients from equation (2). The error bars correspond to 95% pointwise confidence intervals. Compared to figure 13 in the main text, the estimation here allows for multiple displacements per individual (classifying the worker according to their first displacement).*

Moving on to the estimation using the interaction-weighted estimator from specification (2), figure D.39 repeats the analysis of figure 13 allowing for workers that experience multiple displacement spells.¹⁰¹ As can be seen by comparing figure D.39 and figure 13, 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.40, I show how the results obtained using the interaction-weighted estimator compare to those obtained using the three-step estimation method from Borusyak et al. (2021), which was introduced in appendix D.3.4. In figure D.40, it can be observed that using this three-step method produces slightly smaller estimates of the scarring effect of displacement by ex-post recall status. However, this is the case for both the recalled and non-recalled groups, so that the difference between the two groups is similar to the difference found in the main text. As shown in figure D.41, this also holds when focusing on wages and job

¹⁰¹Recall 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.

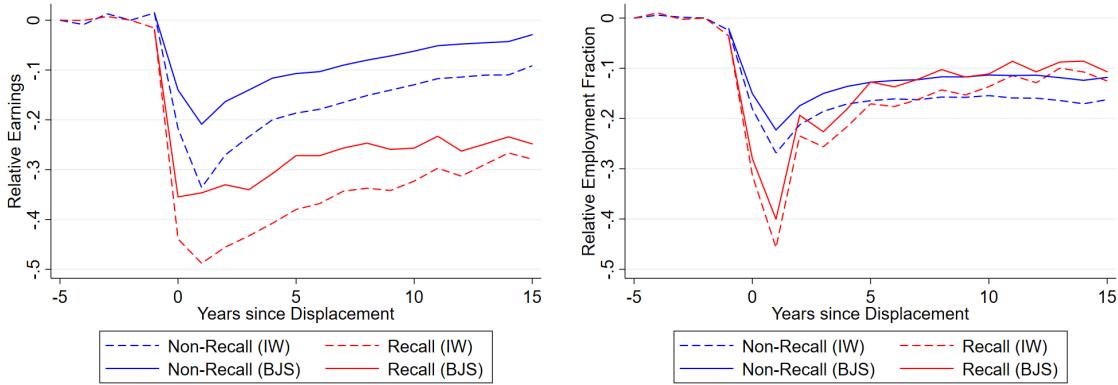


Figure D.40: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status, relative to the control group, using either estimated coefficients from equation 2 (dashed) or estimated coefficients from the three-step method in Borusyak et al. (2021) (solid).*

loss probabilities instead. The full results obtained using the interaction-weighted estimator can be found in figure D.42.

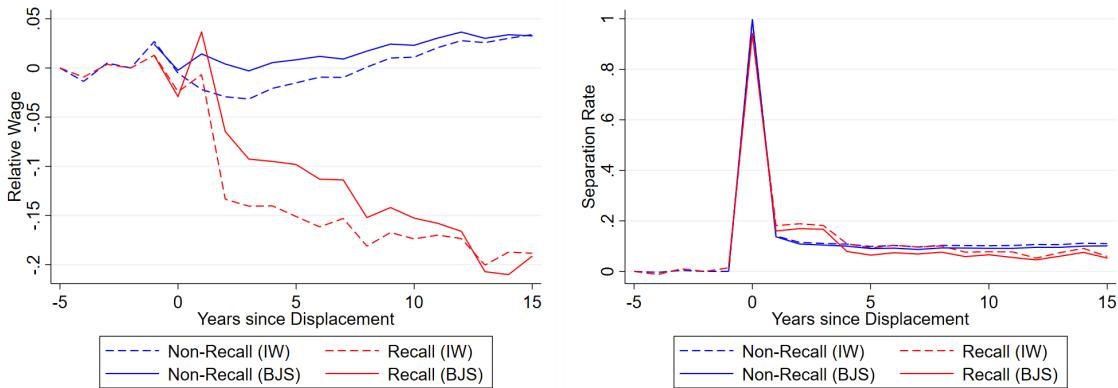


Figure D.41: *The effect of displacement on wages (left) and job loss probabilities (right) by ex-post recall status, relative to the control group, using either estimated coefficients from equation 2 (dashed) or estimated coefficients from the three-step method in Borusyak et al. (2021) (solid).*

In figure D.43, I repeat the analysis from figure 13 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 on the difference between recalled and non-recalled workers remain intact, with the note that some of the differences in the earnings loss between non-recalled and recalled workers more than 5 years after displacement are no longer statistically significant.

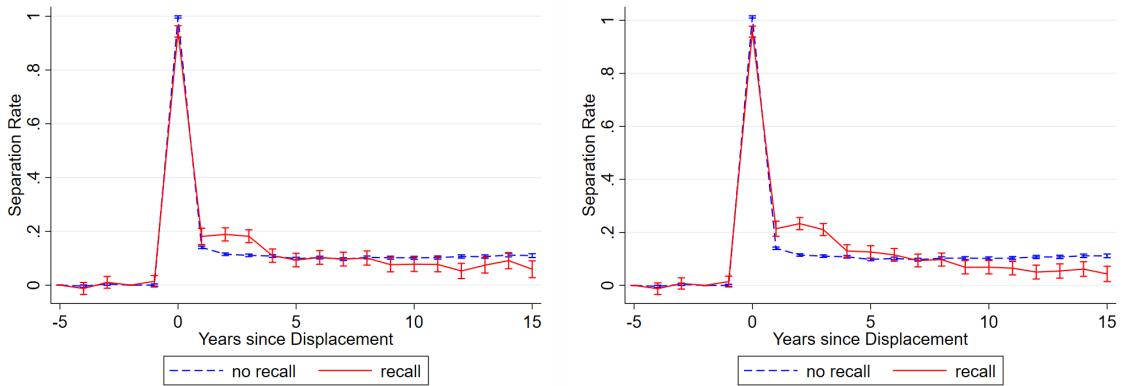


Figure D.42: *The effect of displacement on separation rates by ex-post recall status, relative to the control group, using estimated coefficients from equation (2). The error bars correspond to 95% pointwise confidence intervals.* Left: estimation allowing for only one displacement per individual; Right: estimation allowing for multiple displacements per individual (classifying the worker according to their first displacement). Compared to figure 14 in the main text, this figure shows the full graph (starting from $k = -5$) rather than only the results from period $k = 1$ onwards.

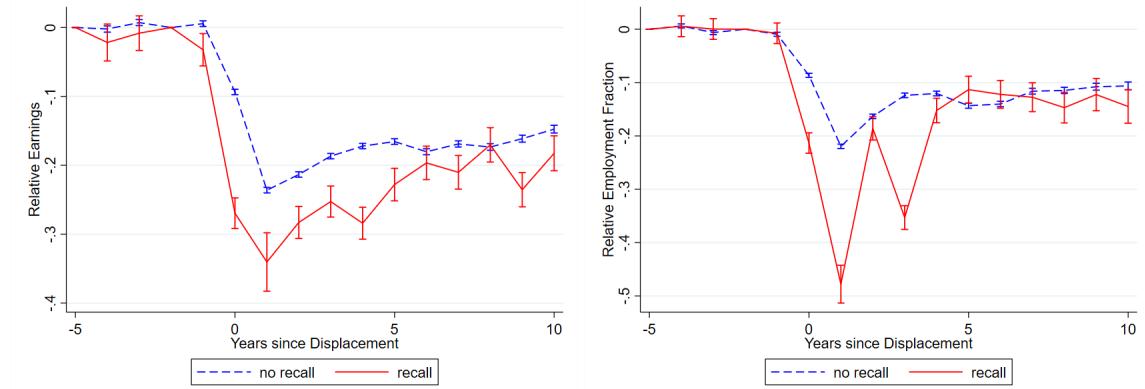


Figure D.43: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status, relative to the control group, using estimated coefficients from equation (2) and using data from LIAB. The error bars correspond to 95% pointwise confidence intervals.* Compared to figure 13 in the main text, the estimation here only uses earnings (and employment) from full-time jobs.

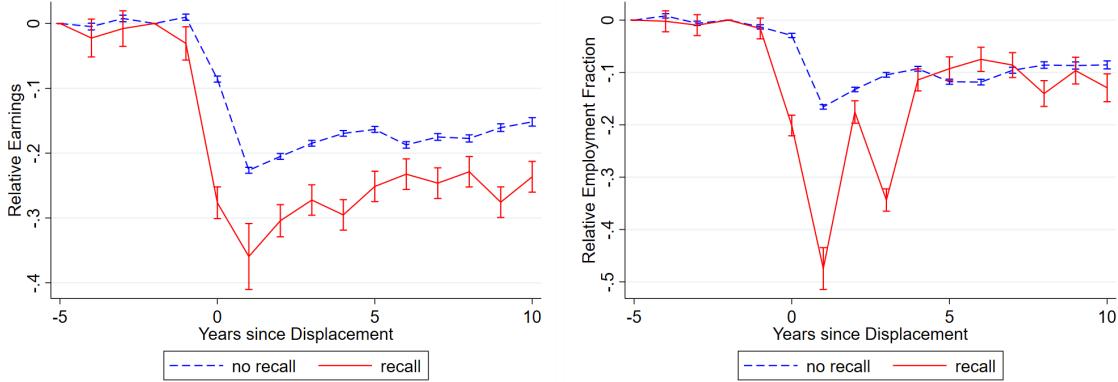


Figure D.44: *The effect of displacement on earnings, by ex-post recall status and relative to the control group, using estimated coefficients from equation (2) and using data from LIAB. The error bars correspond to 95% pointwise confidence intervals. The estimation here only includes workers who were not displaced (control group) or workers who were displaced from an establishment that did not close.*

Another potential concern with the comparison between recalled and non-recalled workers is that the group of non-recalled workers also includes workers that were displaced from an establishment that closed, thus leaving no room for a recall choice. As can be seen in figure D.44, however, omitting the workers that were displaced from a closing establishment does not substantially affect the conclusion made in the main text (based on figure 13): in fact, the estimated earnings and employment loss for non-recalled workers is slightly lower, thus widening the gap between recalled and non-recalled workers.

Figure D.45 shows that the larger earnings loss experienced by recalled workers cannot be explained solely by lower earnings at the recalling establishment. In the figure, I show how the estimation changes when I use only earnings at the recalling establishment (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.

In figure D.46, I show that the gap in the earnings loss experienced by recalled and non-recalled workers is slightly smaller if the worker is displaced in a recession. This is primarily due to the relative earnings loss experienced by the recalled worker being higher in booms, possibly reflecting more opportunities to move into a new job within a short amount of time (and therefore a higher penalty for not doing

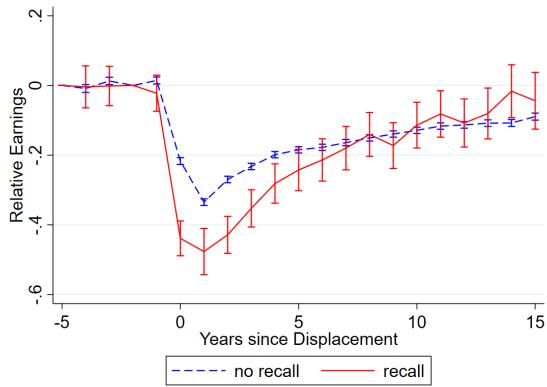


Figure D.45: *The effect of displacement on earnings, by ex-post recall status and relative to the control group, using estimated coefficients from equation (2). The error bars correspond to 95% pointwise confidence intervals. Compared to the left panel of figure 13 in the main text, the estimation here only uses earnings from the establishment to which the recalled worker is recalled.*

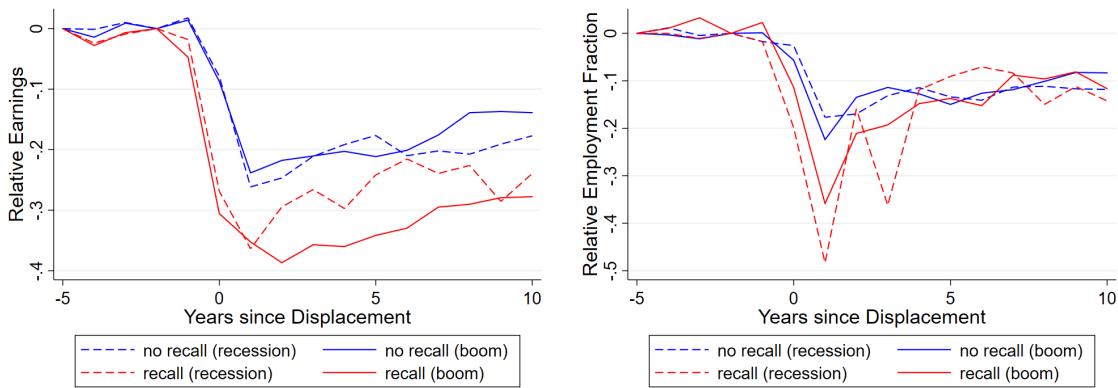


Figure D.46: *The effect of displacement on earnings (left) and employment fraction (right), by ex-post recall status and relative to the control group, using estimated coefficients from equation (2) and using data from LIAB. The error bars are omitted for convenience (but available upon request). Compared to figure 13 in the main text, the estimation splits out the effect by economic conditions at the time of displacement, roughly categorized as recession (dashed) and boom (solid).*

so). Nevertheless, it should be noted that the general result that recalled workers experience larger earnings losses continues to hold in recessions.

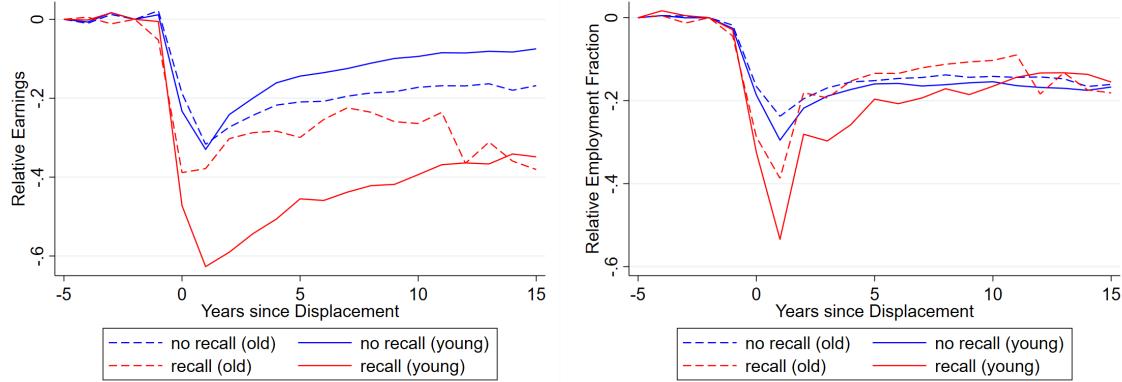


Figure D.47: *The effect of displacement on earnings (left) and employment fraction (right), by ex-post recall status and relative to the control group, using estimated coefficients from equation (2). The error bars are omitted for convenience (but available upon request). Compared to figure 13 in the main text, the estimation splits out the effect by age of the worker at the time of displacement, separately estimating the effect for workers aged below 40 (solid) and workers aged 40 and up (dashed).*

In figure D.47, I show how the effects of displacement by ex-post recall status differ by age group. In particular, it can be observed that for workers aged above 40, the difference between recalled and non-recalled workers is much smaller than for younger workers, even if the effect on employment fraction is fairly comparable between the two age groups. Part of the explanation for this observation may lie in older workers likely having worked for their previous employer for a longer time, and therefore having built up more firm-specific knowledge, which may drive up their earnings relative to the (counterfactual) earnings they would have had if they were to move to a new firm instead.

Figure D.48 shows that the comparison between recalled and non-recalled workers in figure 13 of the main text is not likely to be driven by seasonal workers. After all, omitting workers in industries that traditionally show strong seasonal patterns (agriculture and hospitality) does not substantially alter the results compared to figure 13 in the main text (and in fact yields a stronger result).¹⁰²

¹⁰²In principle, one could estimate the result separately by industry. Doing this exercise reveals that none of the industries (for which there are enough observations) the recalled worker is strictly better off than the non-recalled worker when it comes to their relative earnings after displacement. However, for the manufacturing and construction industries it should be noted that the recalled workers are also not clearly strictly worse off. The corresponding results are available upon request.

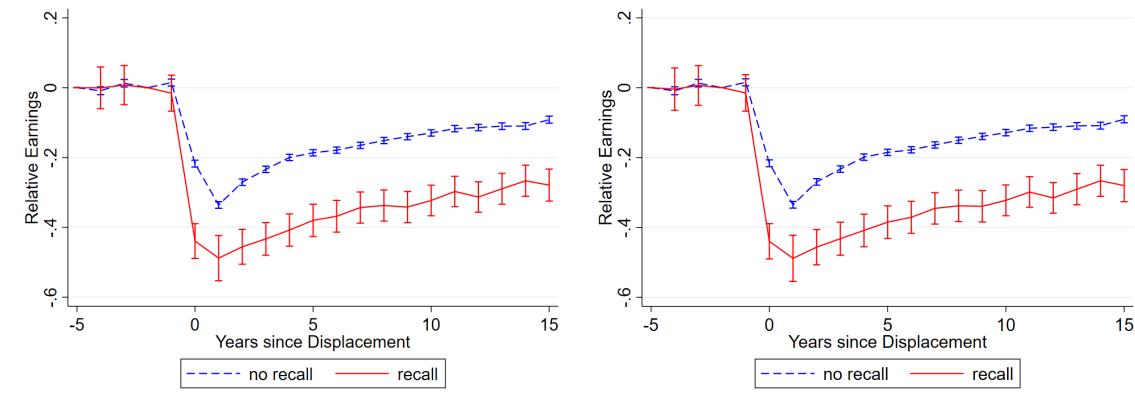


Figure D.48: *The effect of displacement on earnings, by ex-post recall status and relative to the control group, using estimated coefficients from equation (2). The error bars correspond to 95% pointwise confidence intervals. The left panel replicates the left panel of figure 13 in the main text, whereas the estimation in the right panel excludes workers from traditionally seasonal industries (agriculture and hospitality).*

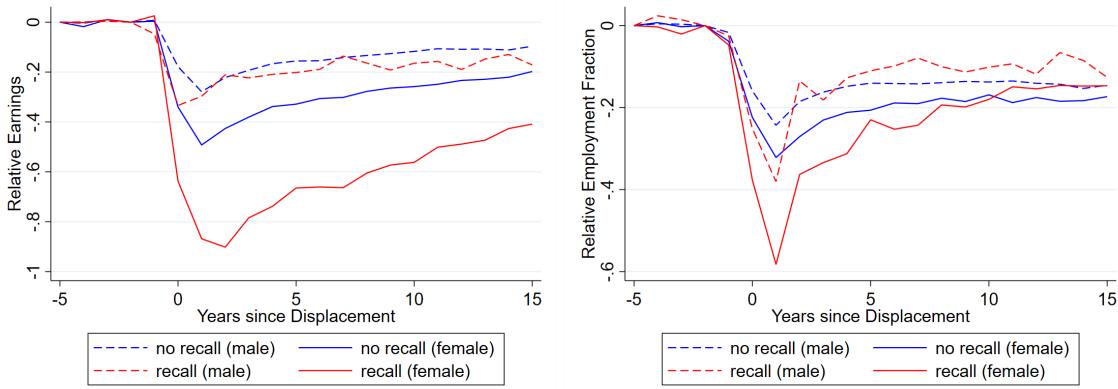


Figure D.49: *The effect of displacement on earnings (left) and employment fraction (right), by ex-post recall status and relative to the control group, using estimated coefficients from equation (2). The error bars are omitted for convenience (but available upon request). Compared to figure 13 in the main text, the estimation splits out the effect by gender, separately illustrating the effect for female workers (solid) and male workers (dashed).*

In figure D.49, I show that the difference between recalled and non-recalled workers identified in the main text tends to be higher for female workers than for male workers. This is partially a composition effect: male workers are more likely to work in industries in which the difference between recalled and non-recalled workers is small (manufacturing and construction) and the observations from male workers are also more likely to come from the earlier years in the data. Indeed, as figure D.50 shows, focusing on male workers aged below 40 for whom displacement is observed after 1991 partially restores the clear difference between recalled and non-recalled workers.

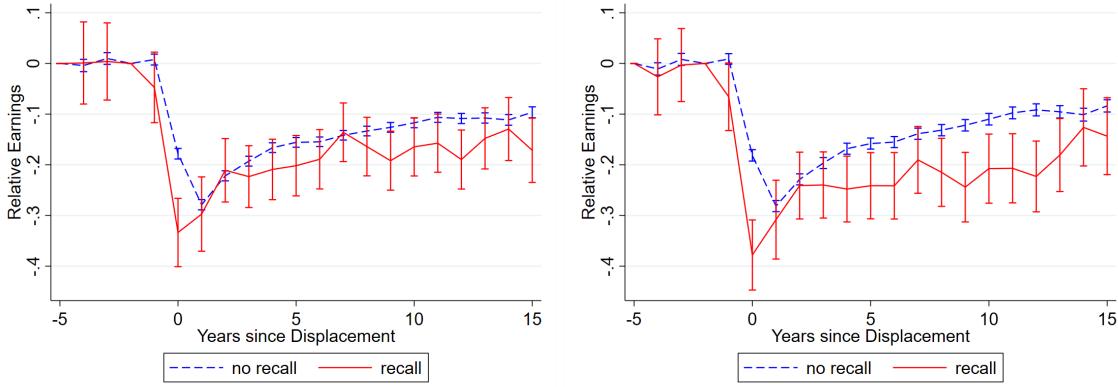


Figure D.50: *The effect of displacement on earnings, by ex-post recall status and relative to the control group, using estimated coefficients from equation (2), and using male workers only. The error bars correspond to 95% pointwise confidence intervals. The left panel repeats the corresponding estimates figure D.49 above, whereas the right panel uses only observations made after 1991.*

As I mention 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. Therefore, the results above are merely a small selection of the dimensions along which I can split out the effect of displacement by ex-post recall status. Among others, I can also show that the difference between the recalled and non-recalled worker tends to be smaller when focusing on Eastern Germany, the years prior to the Hartz reforms, low complexity occupations, or larger establishments. These results are available upon request.

D.3.7 Heterogeneity in the Scarring Effect of Displacement, using LIAB

In this section, I will use the LIAB to re-affirm the main conclusions from section 3.3 of the main text.

The first factor that I investigated, in subsection 3.3.1, was the individual's educational background. In figure D.51, I plot the results of the estimation when splitting the sample by education (non-

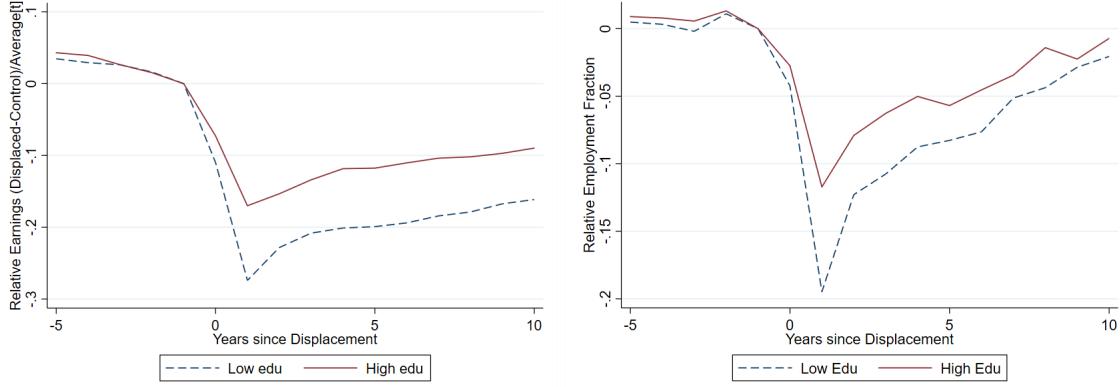


Figure D.51: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group (by education group), using LIAB and using estimated coefficients from equation (1).*

University and University), using LIAB and the “standard TWFE” specification (1). As seen in the main text, workers with a relatively low education tend to suffer from higher earnings losses, both in the short- and long term, as well as a larger initial (and long-run) effect on employment status.

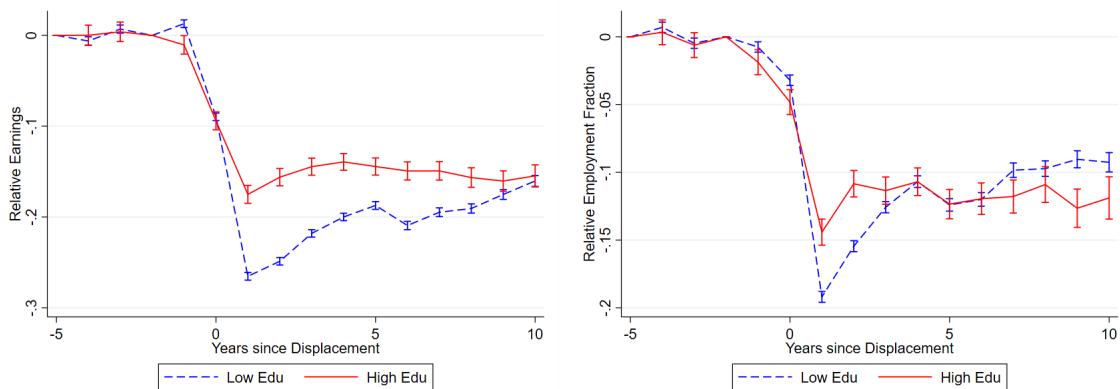


Figure D.52: *The effect of displacement on earnings (left) and employment fraction (right) by education level, relative to the control group, using estimated coefficients from equation (2), and using LIAB. The error bars correspond to 95% pointwise confidence intervals.*

In figure D.52, 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, and the two groups converge towards the end of the sample (noting that this is after 10 years here, rather than after 20 years as in the corresponding figure 11). In terms of employment, the results are very similar to those in figure 11 in the main text: workers with a lower edu-

cation level do worse than workers with a high education level in the short run. However, workers with a low education level exhibit some recovery over time, while the highly educated workers do not show much recovery, leading to the lower educated worker to do better than the highly educated worker (in terms of employment) 10 years after displacement.

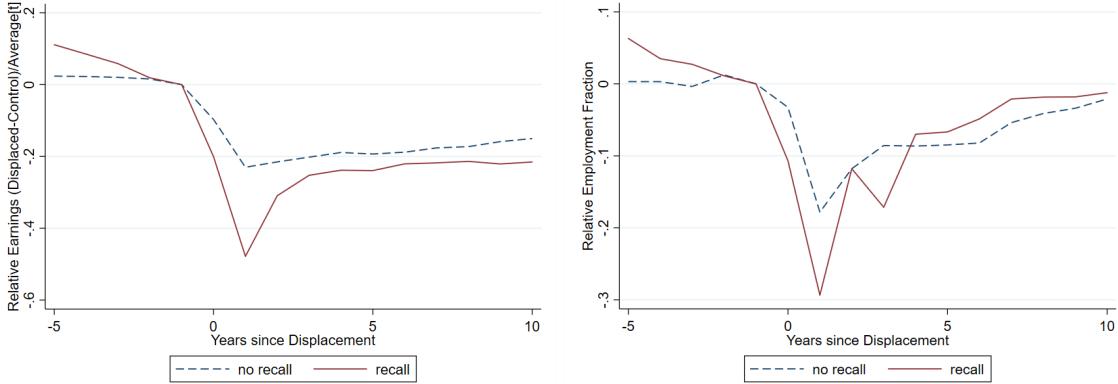


Figure D.53: *The effect of displacement on earnings (left) and employment fraction (right) relative to the control group, by ex-post recall status (materialization of recall within 5 years), using estimated coefficients from equation (1) and using data from LIAB.*

In figure D.53, I show how the effects of displacement on employment and earnings differs by ex-post recall status using LIAB (the counterpart of figure 12 in the main text). Just like in the main text, I find that workers who are recalled suffer from larger earnings losses, and do worse in the short run only when it comes to days employed in the year. As shown in figure D.54, this result once again continues to hold when using the interaction-weighted estimator from specification (2), although the difference between recalled and non-recalled is slightly smaller here than in the corresponding figure 13 in the main text. The estimation for employment fraction shows a clear “double-dip” for recalled workers. This double dip is partially due to the structure of the data, which samples on establishments. In this case, as seen in figure D.55, taking out the first (1998) cohort from the estimation results in the double dip disappearing, thus suggesting that it may have been caused by a large number of people being laid off from and recalled to a single (large) establishment in that year.

Figure D.56 confirms (using LIAB) that recalled workers are much more likely to be separated again shortly after being recalled. Compared to the corresponding figure 14 in the main text, the difference is only clear in the first year (rather than the first three years) after displacement, where non-recalled workers are roughly 18 percentage points more likely to be separated than the control group, and recalled workers are more than 30 percentage points more likely to be separated again (compared to the control group). Once

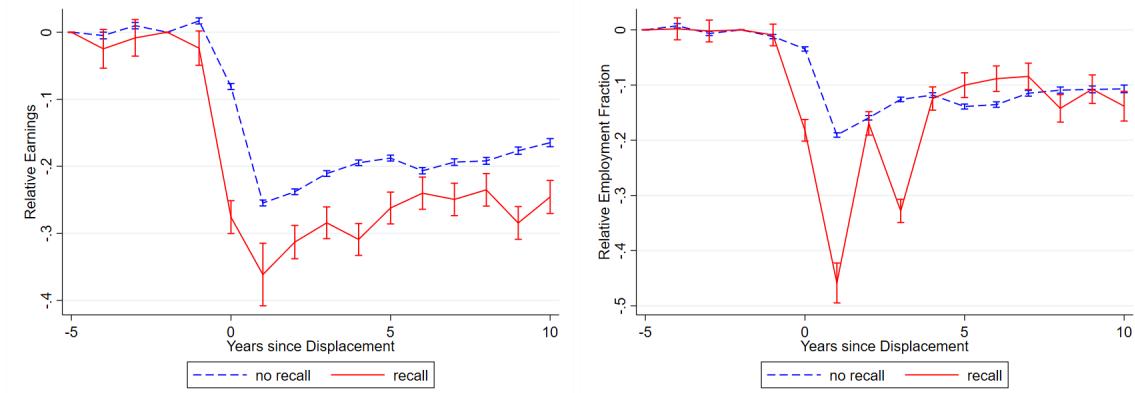


Figure D.54: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status, relative to the control group, using estimated coefficients from equation (2) and using data from LIAB. The error bars correspond to 95% pointwise confidence intervals.*

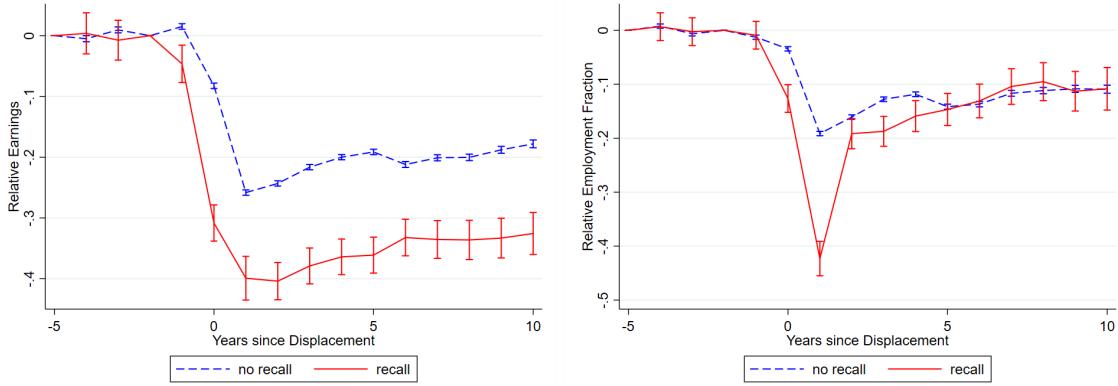


Figure D.55: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status, relative to the control group, using estimated coefficients from equation (2) corresponding to post-1998 cohorts, and using data from LIAB. The error bars correspond to 95% pointwise confidence intervals.*

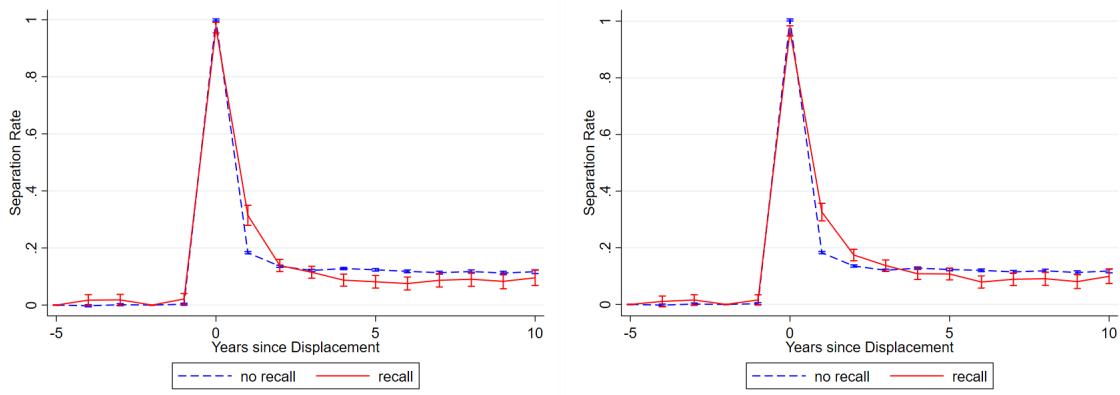


Figure D.56: *The effect of displacement on separation rates by ex-post recall status, relative to the control group, using estimated coefficients from equation 2 and using data from LIAB. The error bars correspond to 95% pointwise confidence intervals. Left: estimation allowing for only one displacement per individual; Right: estimation allowing for multiple displacements per individual (classifying the worker according to their first displacement).*

again, 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 D.56.

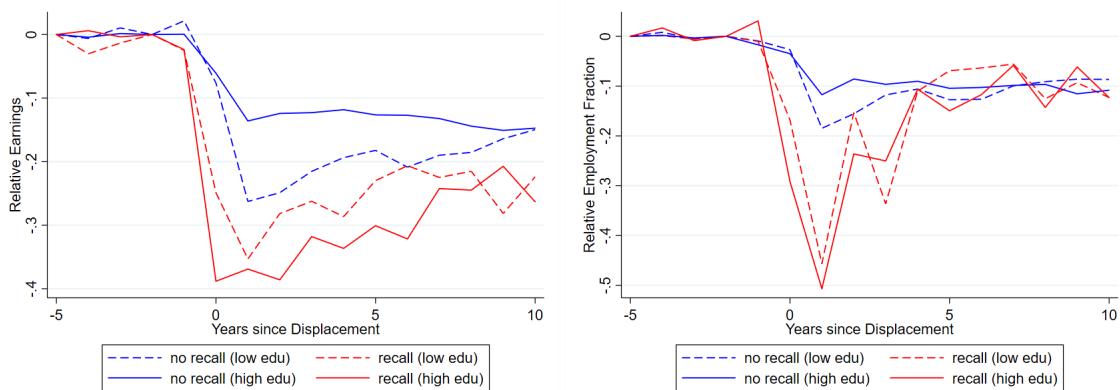


Figure D.57: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status and education level, relative to the control group, using estimated coefficients from equation (2) and using data from LIAB. The error bars corresponding to 95% pointwise confidence intervals are omitted and available upon request.*

In figure D.57, I show that the observations on the scarring effects experienced by recalled workers (as opposed to non-recalled displaced workers) hold across the two education levels. However, it is worth noting that the difference in earnings loss between recalled and non-recalled workers in the LIAB 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 D.51, 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.