Recall and the Scarring Effects of Job Displacement

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Abstract:

Workers who lose their job in mass layoffs, on average, experience a large and persistent decrease in earnings, often referred to as a scarring effect. 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. I contribute to the understanding of the scarring effect of job displacement by exploring how it differs by whether or not workers are recalled to their previous employer. I use administrative employer-employee data from Germany to document these differences. I then develop a job search model that can explain these heterogeneous effects by ex-post recall status, as well as the average scarring effect. I find in the data that earnings losses are not smaller for individuals who are recalled to their previous employer than for workers who move to a new job, and in fact are slightly larger in the short run. I find that these limited differences in earnings losses arise from aggregating differences for workers with a nonemployment duration close to zero (where non-recalled workers experience lower earnings losses) and workers with a longer unemployment duration (where recalled workers experience lower earnings losses). Using the estimated model, I show that this distinction is a major driver of the recalled workers' larger earnings losses in the short run especially, whereas an important factor in explaining similar long-term losses is that these workers are more likely to experience repeated job loss, but lose less human capital in their initial unemployment spell.

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

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1 Introduction

Workers who lose their job are exposed to a large and persistent loss in earnings compared to similar workers who did not lose their job (see e.g. Jacobson et al., 1993). The estimation of this "scarring" effect of job loss generally focuses on workers who lose their job through a mass layoff – I will refer to these workers as "displaced workers" – and do so permanently. 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.[1]

In this paper, I explore the long-run effects of displacement on earnings, estimating and explaining the effects separately for workers who are recalled to their previous employer and those who were not. As recalled workers account for up to 10% of displaced workers, and these workers are generally abstracted from in existing literature, exploring the long-run effects of displacement by recall status contributes to a more complete understanding of the long-run effects of job loss. I make this contribution both in an empirical sense and in the model , where I explicitly account for these recalls.

To estimate the scarring effects of displacement by recall status, I use administrative (employer-employee) data from Germany. These data allow me to reliably identify individuals who are recalled to their former employing establishment. By separating the group of displaced workers into a recalled and non-recalled group, I can then separately estimate the scarring effect of displacement, rather than restricting the sample to omit recalls.[2] My baseline estimation uses the interaction-weighted estimator, as proposed by Sun and Abraham (2021), which allows me to account for the fact that workers displaced in different years may face different effects compared to the control group of never-displaced workers.

Given that human capital losses have previously been argued to play a large role in explaining displaced workers' earnings losses, and some of this human capital is likely to be firm- or job-specific, one might expect recalled workers to experience lower earnings losses than non-

[1]For example, Fujita and Moscarini (2017) found that these workers account for over 40% of U.S. employed workers who move into unemployment upon losing their job (in the United States). For German workers, Mavromaras and Rudolph (1998) find similar albeit slightly lower numbers, whereas Jansson (2002) finds similar numbers in the context of Sweden. In section 3.1, I show that I find recall rates ranging from 30 to 55% in my data (before conditioning on displacement).

[2]In 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.

recalled workers. I estimate that recalled workers indeed experience larger earnings losses in the short run than displaced workers who are not recalled, both compared to a control group of never-displaced workers. However, as observed in figure 1, this difference disappears after a few years. In particular, 1 year after displacement the recalled workers earns approximately 44% less than a worker in the control group, whereas a non-recalled worker earns approximately 36% less than a worker in that same control group, but 10 years after displacement the recalled and non-recalled worker both earn approximately 30% less than a worker in the control group. Estimating the effect on the employment fraction (fraction of the year spent in an employment relation) reveals that this larger short-run earnings loss is primarily driven by employment. Furthermore, I find that a recalled worker is 4 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. Notably, the similar long-run earnings losses of recalled and non-recalled workers mask a substantial amount of heterogeneity within each group. In particular, if one estimates the earnings losses only for workers who transition to a new job within 30 days, non-recalled workers suffer from lower earnings losses than recalled workers (in the short run and in the long run), whereas conditioning on a transition period of more than 30 days yields the opposite result.

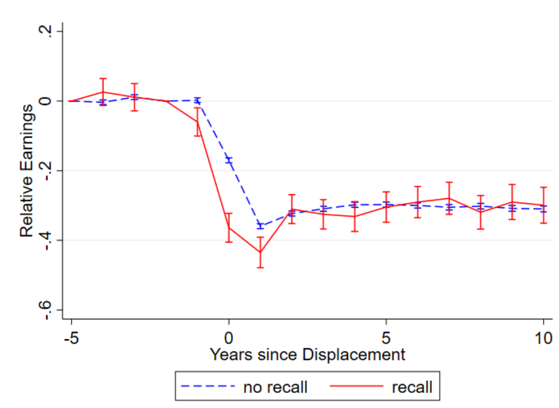

Figure 1: *The estimated effect of displacement on earnings by recall status (observed ex-post), relative to the control group of never-displaced workers, generated using the interaction-weighted estimator from Sun and Abraham (2021). The error bars correspond to 95% pointwise confidence intervals. The details of the estimation procedure are described in sections 2 and 3.3 of the paper.*

Next, I develop a job search model that is able to explain the larger earnings losses experienced by recalled workers, while still also matching the average scarring effect of displacement.

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). This is in addition to elements that have been used in existing models to explain the average scarring effect of displacement[3], such as the aforementioned human capital (which increases or decreases over time depending on employment status) and heterogeneity of firms by productivity and separation rates as in Jarosch (2021). As I allow recalled workers to follow a different path than non-recalled workers while non-employed (as well as afterwards), I can capture several possible explanations for the observed severity of the scarring effect of displacement for recalled workers, such as different transition rates and human capital depreciation rates.

I calibrate the model using the German administrative data, and show that I match the estimation results from the empirical section, despite not explicitly targeting them. I then use model simulations to decompose the difference in earnings loss between recalled and non-recalled displaced workers. I find that the recalled workers' earnings losses in the long run are primarily driven down by the instability of the job to which the worker is recalled, whereas an important factor in the short run is that non-recalled workers often transition immediately into their next job rather than spending some time in unemployment. On the other hand, recalled workers experience a lower human capital depreciation rate, and do not "fall off the job ladder" at the time of their initial displacement, which offsets the negative influence of the aforementioned channels.

When comparing the decomposition of a recalled worker's earnings loss to that of a non-recalled worker's earnings loss, I find that while human capital depreciation may be important to explain the long-run earnings loss for non-recalled workers, its impact for recalled workers (who experience a probability of human capital depreciation close to 0 during their initial nonemployment spell) does not occur until several years after their initial displacement. Indeed, for recalled workers, the human capital loss driving part of their long-run earnings losses is coming from subsequent separations rather than their initial displacement. This, in turn, suggests that while a policy targeting a worker's loss of human capital during nonemployment (such as a retraining program) may be successful in bringing down the earnings losses for non-recalled workers, it will not be very effective in alleviating recalled workers' earnings losses, especially in the short run. Since these recalled workers already face a larger relative earnings loss on average than the non-recalled workers in the short run, it can therefore be concluded that such a policy would not be desirable.

[3] See section 1.1 for a brief discussion of these models.

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, and section 5 focuses on the calibration of the model. Section 6 contains the quantitative analysis of the model, and shows that it recovers the heterogeneity observed in the data, and studies the drivers and implications of these observations. Finally, section 7 concludes.

1.1 Related Literature

In empirically investigating the impact of recalls on the long-term consequences of job loss (and mass layoffs in particular), I contribute to a substantial existing literature. This literature goes back to Jacobson et al. (1993), who used quarterly administrative data from Pennsylvania and found 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, which either built on the result of Jacobson et al. (1993) in other U.S. settings[4], highlighting the important role of working hours in the short run and wages in the long run for explaining these losses (Lachowska et al., 2020), or showed that the results also hold in other countries.[5]

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 documented how the scarring effects of job loss differ depending on where the worker is situated in the earnings distribution before being laid off. In a recent paper, 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. By focusing on ex-post recall status (and education), my paper enriches the literature investigating heterogeneity in the scarring effects of displacement.

Additionally, the empirical section of this paper contributes 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

[4]For example, Kletzer (1998), Couch and Placzek (2010), and Von Wachter et al. (2009).

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

quite extensively, going back to studies such as Feldstein (1976) and Katz (1986). More recently, Nekoei and Weber (2015), as well as Nekoei and Weber (2020) have used detailed administrative data 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. In the context of Germany, Jost (2022) highlights the interplay of recall and fixed-term contracts, finding that recalls are especially common for workers coming off a fixed term contract, in line with evidence found for Spain in Arranz and García-Serrano (2014). Similarly, studies like Hall and Kudlyak (2022) and Forsythe et al. (2020) have highlighted the unusually large role recalls play in labour market dynamics during the Covid-19 pandemic, especially in the early months. However, while the literature on the impact of recall on labour market flows is quite sizeable, the body of existing research on how recalled workers differ from non-recalled workers in terms of their subsequent earnings is very small. Furthermore, the little existing work in this area either uses recalled workers as a control group to compare to "regular" displaced workers (as in Kodrzycki, 2007), or focuses primarily on the role of occupations and unemployment duration (as in Edler et al., 2019). In this paper, I contribute to the research on this topic by focusing on providing a reliable estimate of the earnings consequences of displacement for recalled workers specifically.

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 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.[6] Some recent work has attempted to resolve this issue with some success. The paper closest to mine in terms of the 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 (2022), Jung and Kuhn (2019), Burdett et al. (2020), and Gregory et al. (2021).[7]

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

[7]The result in Huckfeldt (2022) that workers who switch occupations suffer from larger losses than workers who

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. 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), Albertini et al. (2020), and Gertler et al. (2022).[8] However, what all these papers have in common is that they focus exclusively on the impact of recall on labour market flows. As such, they generally refrain from commenting 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.[9] 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, thus allowing for divergence between eventually recalled and non-recalled workers already before the recall actually materializes.

2 Data and Estimation Methods

Throughout this paper I use administrative data from the German Federal Employment Agency's (BA) Institute for Employment Research (IAB). In particular, I use the Sample of Integrated Labour Market Biographies (SIAB), which draws a 2% random sample of the individuals (employed between 1975 and 2017) from the Integrated Employment Biographies (IEB), after which the ob-

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).

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

[9]The exception to this is the model in Gertler et al. (2022), which separately considers workers in temporary unemployment. My model differs from theirs in many dimensions. In particular, whereas their model focuses primarily on the decisions made on the firm side, and therefore incorporates endogenous separations as well as the firm's choice of whether to place a worker on temporary layoff. On the other hand, my model focuses primarily on the worker side, and therefore does not feature the decision by the firm, but does explicitly include the worker's choice between unemployment types and allows for the worker to search while expecting a recall.

servations are matched with the relevant establishment data[10]. Each observation in the original data 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.[11] 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.[12] 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 observation being omitted from estimation procedures. The resulting analysis dataset includes roughly 24.3 million observations, covering approximately 1.6 million individuals. 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, 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.[13] I then define such a worker as displaced if the establishment either closes or experiences a mass layoff.[14] Fol-

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

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

[12]Other reasons for not observing an individual include working (and moving) abroad, and being short-time employed. See Antoni et al. (2019) for a detailed description of missing observations, sampling procedures, and variables included in the dataset.

[13]For example, I exclude "separations" that are caused by maternity leave or sick pay.

[14]I use an extension file that clarifies the reason for an establishment leaving the sample. In particular, I do not

lowing 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. 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. Alternatively, a worker is also considered recalled if the worked started at a different establishment within 31 days, but returned to their pre-displacement establishment either in the same year as the displacement or in the next year (with the recalling establishment being the worker's main employer in the next year).[15]

The empirical estimation results presented in the next section are based on the interaction-weighted estimator from Sun and Abraham (2021). I chose to use this estimator as it is able to take into account that the effects of displacement are likely to be different for workers displaced in different years, while still estimating all effects in a single estimation (and thus avoiding displaced workers appearing in the control group in a different year). In practice, I am estimating the following equation:

$$e_{it} = \alpha_i + \gamma_t + \sum_{C \neq 0} \sum_{\substack{k=-4 \\ k \neq -2}}^{K} \delta_k^C D_{it}^{C,k} + u_{it} \tag{1}$$

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 an error term u_{it}.

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. See appendix D.2 for more details.

[15]I consider this second group to be recalled, as these workers will likely have taken employment at a different establishment only for the purpose of bridging the gap until the recall materializes. Note that due to my definition of separation, I will miss direct recalls with 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). Reducing the required gap from 31 to 5 days does not alter results in any meaningful way. Finally, 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.3.4, excluding workers whose establishment closes from the estimation altogether does not change the results.

The coefficients of interest are a series of coefficients on dummy variables $D_{it}^{C,k}$. These variables equal 1 if individual i from cohort C was displaced in period $t-k$, and 0 otherwise. In my estimation, the definition of the cohort C is equivalent to the year in which the individual is displaced, with $C = 0$ corresponding to the cohort of individuals who I do not observe being displaced at all. The set of dummy variables for this "never-treated" group is omitted, implying that this group acts as the control group. Furthermore, note that rather than omitting one value of k, I follow the discussion in Borusyak et al. (2022) by omitting two values of k. This is because generally the set of relative time indicators $D_{it}^{C,k}$ 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.[16]

Estimation of equation (1) above will yield a set of estimates $\hat{\delta}_k^C$ for all $C \neq 0$ and $k \neq \{-5, -2\}$, which indicate the absolute gain (or loss) in the outcome variable of interest compared to the control group. In order to improve the interpretability of these coefficients, I divide them by the average value of the outcome variable for the control group in the corresponding year t. These relative coefficients are then 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 δ_k^C are estimated in a single estimation procedure, I can then also form corresponding (point-wise) confidence intervals for the resulting weighted averages $\hat{\delta}_k$.

When estimating the equation 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 labour 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, my estimation differs from the existing literature in using the interaction-weighted estimator rather than a "standard" two-way fixed effects estimation. Furthermore, rather than discarding information for female workers, I combine the data of male and female workers.[17]

[16]Note that Borusyak et al. (2022) also propose an alternative estimation themselves. I show in appendix D.3.4 that using their method yields the same results as using the interaction-weighted estimator from Sun and Abraham (2021).

[17]The results presented below are not affected when changing one of these restrictions, e.g. by requiring only 1 year

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 specification 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.

3.1 The Incidence of Displacement and Recall

Before analyzing the detrimental effect displacement can have on a worker's earnings, and how this effect 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.[18]

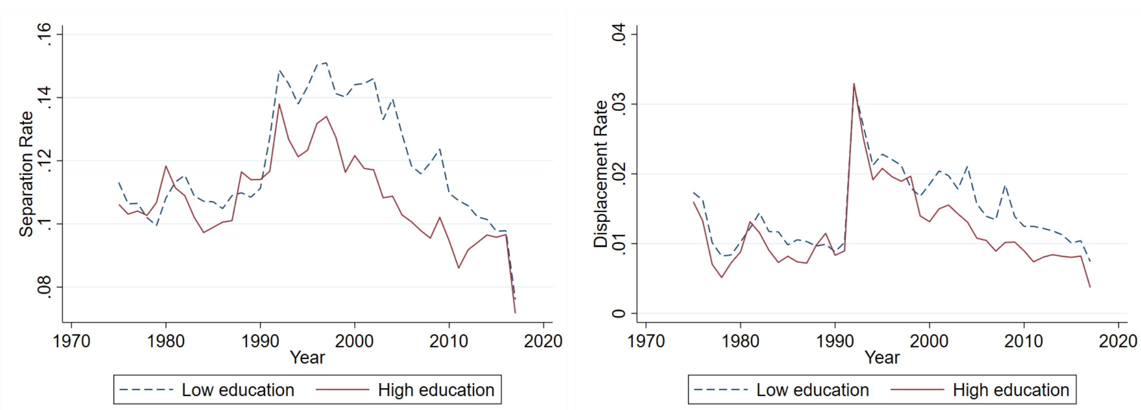

Figure 2: *The incidence of separation (left) and displacement (right) over time, by education level.*

First of all, figure 2 displays 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 this figure, the separation for workers with a relatively low education level averages roughly 12% whereas the displacement rate is roughly 1.5% on average. For highly educated

of pre-displacement establishment tenure, or using only male workers. These results are omitted, but available upon request.

[18] All graphs in this subsection are generated using the complete sample. In other words, I do not apply the restrictions on pre-displacement establishment tenure and establishment size used to generate the restricted sample on which I estimate equation (1). The corresponding graphs for this "restricted sample" can be found in appendix D.3.2.

workers these rates are slightly lower,but with roughly 80% of the workers being categorized in the first group the overall fluctuations of the separation and displacement rates primarily follow those of workers with a low education level. All rates display substantial variation over time, and in particular the aftermath of the German reunification in 1990 is quite clearly visible.[19] 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.

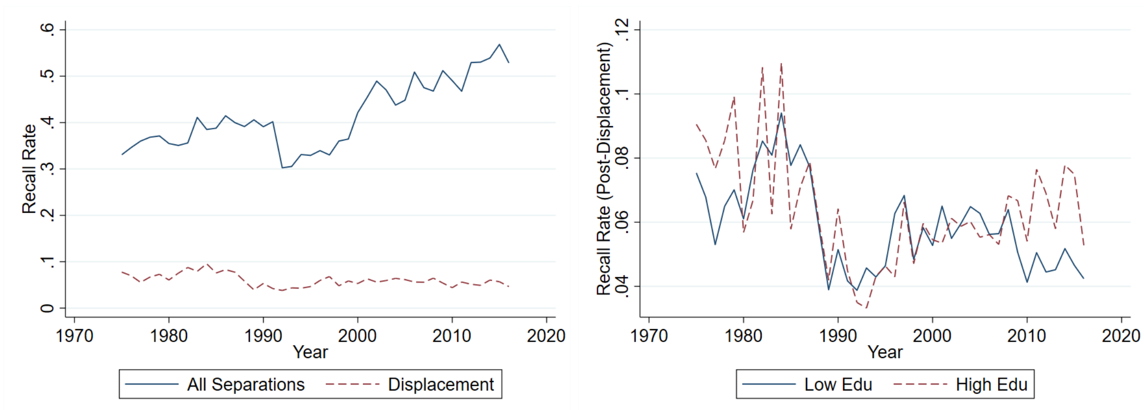

Figure 3: *Left: The incidence of recall within 5 years of job loss over time, unconditionally and conditional on displacement. Right: The incidence of recall within 5 years of job loss, conditional on displacement, over time and by education level.*

Next, figure 3 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 3, the recall rates (conditional on displacement) are fairly similar for the two education levels.

[19]Note that workers from East Germany are generally not included in the data before the reunification, so therefore the jump in separation and displacement rates can also partially be explained as a composition effect. In appendix D.3.1, I show the separation and displacement rates over time for East and West Germany separately.

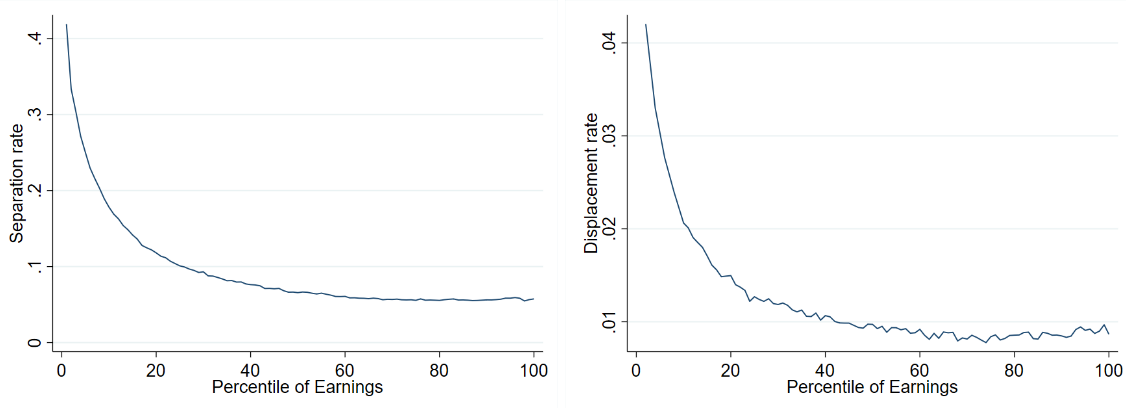

Figure 4: *The incidence of separation (left) and displacement (right) over the recent earnings distribution.*

As shown in figure 4, the separation and displacement rates tend to be higher for individuals located lower on the (recent) earnings distribution.[20] This can be thought of as corresponding with higher quality matches in terms of productivity also being more stable, as posited in the model in Jarosch (2021), and therefore seems to support his idea of a job ladder with slippery bottom rungs (which I will use in my model in section 4 as well). However, it should be noted that the pattern in the data is not quite monotonic throughout the distribution: above the 80th percentile of the distribution, the displacement rates are slightly increasing again.

Figure 5 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 1.5% 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.

[20] Recent earnings are calculated as the average earnings of an individual between years $y-5$ and $y-1$. 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 $y-1$. I then 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).

Figure 5: *The incidence of recall within 5 years of displacement (as a fraction of total displacements), by percentile of the recent earnings distribution.*

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 or 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.

3.2 The Average Scarring Effect of Job Loss

Having investigated the incidence of job loss across the sample, I will now move towards assessing the effects of displacement on earnings.[21] Before moving to the results of estimating equation (1) by ex-post recall status, however, it is worth looking at the average earnings losses first.

Figure 6 shows the estimates of the average scarring effect of displacement on earnings and employment (fraction of the year employed), obtained using the interaction-weighted estimator from Sun and Abraham (2021), as described in section 2.[22] In the left panel, it can be seen that in the short-run, workers who are displaced lose roughly 30-35% of their earnings.[23] This earnings

[21]The results presented here focus on displacement only. As shown in appendix D.3.3, the results continue to hold if I focus on separation instead.

[22]The results are similar when using the alternative method from Borusyak et al. (2022), which I show in appendix D.3.4 for the result in section 3.3. Similar comparisons for other results are available upon request.

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

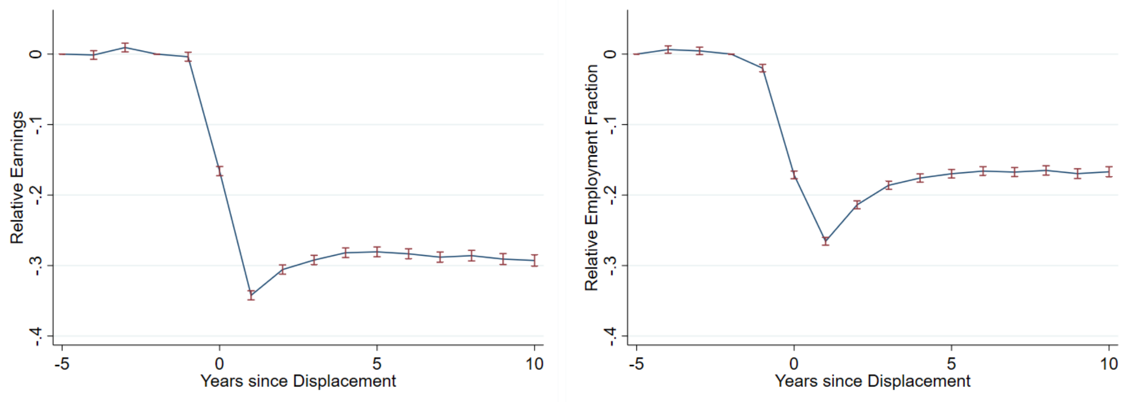

Figure 6: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group of never-displaced workers, using estimated coefficients from equation* (1). *The error bars correspond to 95% pointwise confidence intervals*

loss is shown to be quite persistent, with these displaced workers still earning 30% less 10 years after the job loss took place. Looking at employment fraction, a similar pattern arises, with short-run losses of approximately 25-30% and long-run losses of 15-20%. Comparing these estimates to those obtained in the existing literature (generally using two-way fixed effects estimation), reveals that these results are consistent with the literature for the short-run losses, but not for the long-run losses: while the existing estimates generally suggest that employment fully recovers after roughly 15 years and earnings recover substantially, the interaction-weighted estimator reveals that the recovery stagnates after roughly 5 years, both earnings and employment remain substantially 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, even if there is still a substantial role for wages as well.

3.3 The Scarring Effect of Displacement for Recalled Workers

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, as the average effects likely mask a substantial amount of heterogeneity. 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 one dimension in particular, namely that of 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.3.4, I show that the results presented below are robust to considering some of these other characteristics.

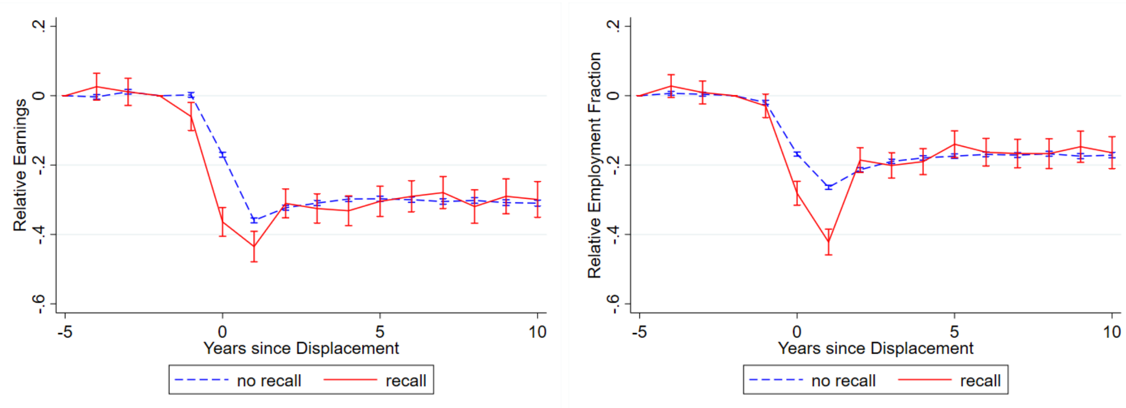

Figure 7: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status, relative to the control group of never-displaced workers, using estimated coefficients from equation* (1)*. The error bars correspond to 95% pointwise confidence intervals.*

In figure 7, I show how the effects of displacement on employment and earnings differs by ex-post recall status.[24] As can be seen in the figure, workers who are recalled suffer from similar earnings losses compared to the non-recalled (but still displaced) worker, and in fact do slightly worse in the short run. Similarly, recalled workers tend to do worse in the short run when it comes to days employed in the year, as shown in the right panel of figure 7. I show in appendix D.3.4 that these results generally continue to hold when the data is further restricted along observable dimensions such as traditionally seasonal industries, gender, and age group.

Figure 8 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 more likely 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 year after displacement (and respectively 15 and 12 percentage points two and three years after displacement). This seems to

[24]As 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.

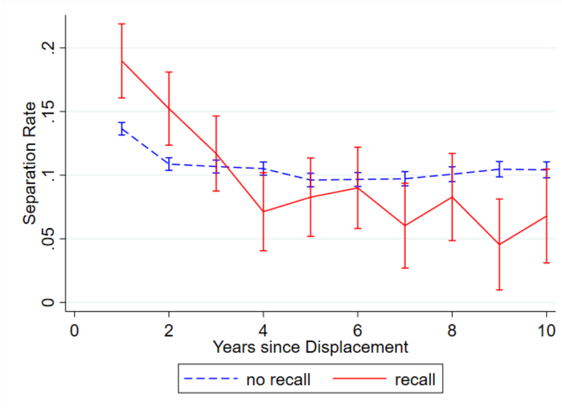

Figure 8: *The effect of displacement on separation rates by ex-post recall status, relative to the control group of never-displaced workers, using estimated coefficients from equation* (1). *The error bars correspond to 95% pointwise confidence intervals. The estimation allows for multiple displacements per individual (classifying the worker according to their first displacement). Only results from period* $k = 1$ *onwards are displayed here. The full graph (starting from* $k = -5$*) is included in appendix D.3.4.*

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.

One might wonder whether recalled workers seem to be doing worse because they spend some time in nonemployment (or alternative employment) by definition, whereas some of the non-recalled workers may transition into a new job immediately. This may occur because workers anticipate their impending layoff and therefore already search for a new job prior to the materialization of the layoff.[25] These workers may already have a new job lined up at the time of the layoff and therefore face lower losses.

In figure 9, I show that conditioning on transitioning within 30 days of the layoff or conditioning on being nonemployed for at least 30 days does indeed yield very different results.[26] Comparing the two panels in figure 9, it can be seen that this is primarily driven by the earnings losses of non-recalled workers changing substantially between the two groups, whereas the earnings losses of the recalled workers do not change much. As a result, the earnings losses for recalled workers are worse than those experienced by non-recalled workers when conditioning on

[25] See Simmons (2021), who investigates this issue in the context of the United Kingdom.

[26] Note that due to the definition of recall, discussed in section 2, recalled workers who transition within 30 days are necessarily workers who were recalled indirectly. In other words, this "transition within 30 days" refers to their transition to a different establishment, rather than their eventual recall (which nevertheless materializes by the end of the year following the initial displacement).

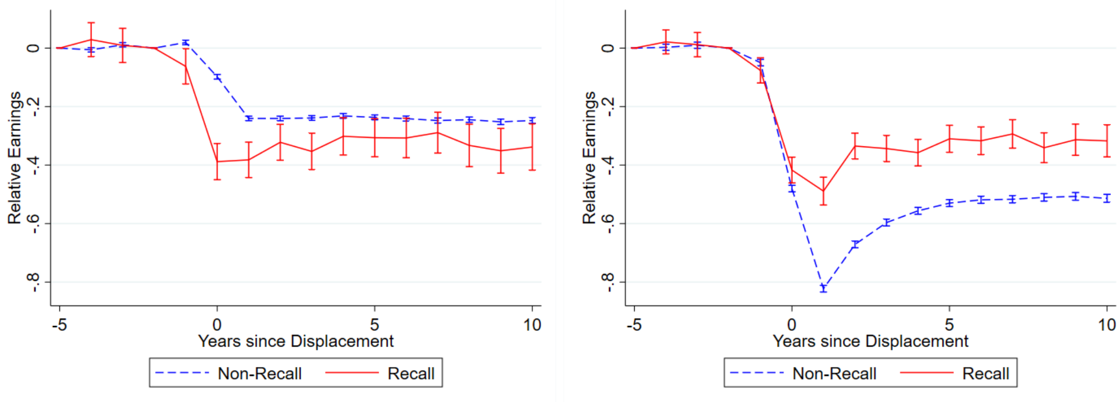

Figure 9: *The effect of displacement on earnings by ex-post recall status, relative to the control group, using estimated coefficients from equation* (1). *The effects are estimated separately for workers who transition directly (within 30 days, left) and workers who spend some time in nonemployment (right) after their displacement. The error bars correspond to 95% pointwise confidence intervals.*

experiencing at most 30 days of nonemployment, whereas the opposite is true when conditioning on experiencing more than 30 days of nonemployment. In figure 7, these two results cancel out, resulting in similar earnings losses on average.

4 Model

In this section, I develop a search model of the labour 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 are heterogeneous along two dimensions.[27] Further, the model explicitly features the possibility of recall, as a separate state, reflecting my observation that workers who are recalled face a potentially different earnings path. By allowing workers who are expecting a recall to be in a different state, I can account for differences between recalled and non-recalled workers, 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 $\theta = [y, \delta]$.

[27] In particular, the model resembles Jarosch (2021) in that firms are heterogeneous with respect to their productivity and separation rate. However, in contrast to that model, workers are heterogeneous in two dimensions as well (rather than one), and the possibility of recall is explicitly featured in the model.

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).[28]

4.1.1 Firms

Each firm can hire at most one worker.[29] 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.[30] 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).[31] The penalty on the separation rate, on the other hand, directly reflects the observation in section 3.3 that recalled workers are more likely to be separated again within a year of being re-employed (see figure 8). Intuitively, this reflects that the worker returns to a job that is more unstable than it was before. Finally, I assume that firms that are unmatched do not produce anything and also don't face any

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

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

[30]With probability $\phi_\varepsilon^{rg} \phi_\varepsilon^r$, this recall takes place in the same model period as the initial displacement.

[31]Instead of explicitly lowering the wage, I chose to lower the productivity of the firm. In practice, this does not affect the wage in any different way.

costs, thus setting the current period 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 labour market, corresponding to the sample restriction in the data where I did not consider workers below the age of 25 and/or workers who are still in school. An unemployed worker meets a firm with probability λ^u_ε, and this firm is drawn from the distribution $G_\varepsilon(\theta)$, where ε changes the marginal distributions of δ and y (see section 5), thus enabling different worker types to meet firms with different characteristics on average, but not restricting the range of δ to certain worker types.[32] If the worker meets a firm, the worker decides whether or not to accept the job. If the worker accepts, she becomes employed and receives wage w. If the worker does not accept, or does not receive an offer, the worker receives $b(s)$, which can be interpreted as the one-period 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 proxy a setting in which the unemployment benefit depends on the last earned wage, while also not ruling out the scenario where unemployed workers reject some job offers.[33] Finally, it should be noted here that I do not explicitly model how the unemployment benefit is financed, though I 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^e_ε, 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,

[32] 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^{ug}_ε. This can be thought of as a simplified way of capturing that workers may anticipate the impending layoff and may therefore search (and find) a new job before the layoff actually materializes, as pointed out in Simmons (2021), and briefly discussed in section 3.3.

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

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 ($\psi_r > 1$) or slower ($\psi_r < 1$) 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 whom she might be employed by in the future, and therefore can keep her job-specific knowledge from depreciating.[34] The worker is recalled to her previous match with probability ϕ^r_ε 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.[35] 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 $\lambda^r\lambda^u_\varepsilon$, 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

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

[35] The 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.

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}:

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

Here, it is explicitly taken into account that in general the match value for the worker, W, depends on the value of the firm characteristics θ, the outside option firm characteristics $\hat{\theta}$, and the worker's human capital, both current (s) and when the worker and firm last bargained ($\hat{s}$).[36] Note that equation (2) can take 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 (2) can be rewritten as equation (3).

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

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

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

$$W_\varepsilon(s,s,\theta,r) = \max\{U_\varepsilon(s), T_\varepsilon(s,\theta)\} + \kappa^r\left(W_\varepsilon^{max}(s,\theta') - \max\{U_\varepsilon(s), T_\varepsilon(s,\theta)\}\right) \tag{6}$$

If the worker is moving between two jobs, from a firm with characteristics θ to a firm with characteristics x, the outside option W^{oo} equals the maximum surplus that could have been obtained at her previous job, $W_\varepsilon^{max}(s,\theta)$, so that equation (2) can be rewritten as equation (4). If the worker is using a job offer from a firm with characteristics x to extract more value from her current employer, the outside option W^{oo} equals the maximum surplus that could have been obtained from this job offer, $W^{max}(s,x)$, and equation (2) can be rewritten as equation (5). 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 3), 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

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

give up the potential recall and move to regular unemployment.[37] 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).

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.[38] Then, in the third stage, workers who started the period as unemployed or employed (and are still in the same state) may receive an offer from a firm, after which they choose to accept or reject it, (re-)bargaining takes place, and workers expecting a recall may choose to move to permanent unemployment. 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:

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

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

As shown in appendix B, equation (7) can be rewritten in terms of W^{max}, U, and parameters

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

[38] Note that by recall choice, I mean only the choice a worker faces when confronted with a separation shock that may not be permanent. As I assume that the worker cannot choose to transition to permanent unemployment from the temporary unemployment state until the recall materialization shock ϕ_ε^r and job search is realized, this second type of recall choice does not take place until the end of the third stage.

only:

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

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:

$$T_\varepsilon(s, \theta) = \ln(b_\varepsilon(s)) + \beta \mathbb{E}_{s'|s,r,\varepsilon} \left\{ \phi_\varepsilon^r W_\varepsilon(s', s', \theta', r) + (1 - \phi_\varepsilon^r) \lambda^r \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^r(s', \theta)} W_\varepsilon(s', s', x, f) dG_\varepsilon(x) \right.$$
$$\left. + (1 - \phi_\varepsilon^r) \left(1 - \lambda^r \lambda_\varepsilon^u \int_{x \in \Theta_\varepsilon^r(s', \theta)} dG_\varepsilon(x) \right) \max\{T_\varepsilon(s', \theta), U_\varepsilon(s')\} \right\} \quad (9)$$

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 (3) and (6):

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

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

$$\begin{aligned}W_\varepsilon(s,\hat{s},\theta,\hat{\theta}) &= \ln(R_\varepsilon(\hat{s},\theta,\hat{\theta})p(s,y)) + \beta\mathbb{E}_{s'|s,e,\varepsilon}\left\{\delta\left[\phi^f_\varepsilon \max\left\{\hat{T}_\varepsilon(s',\theta),\hat{U}_\varepsilon(s')\right\} + (1-\phi^f_\varepsilon)\hat{U}_\varepsilon(s')\right]\right.\\
&+(1-\delta)\left[\lambda^e_\varepsilon\left(\int_{x\in\Theta^1_\varepsilon(s',\theta)} W_\varepsilon(s',s',x,\theta)dG_\varepsilon(x) + \int_{x\in\Theta^2_\varepsilon(s',\hat{s},\theta,\hat{\theta})} W_\varepsilon(s',s',\theta,x)dG_\varepsilon(x)\right)\right.\\
&\left.\left.+\left(1-\lambda^e_\varepsilon\int_{x\in\Theta^1_\varepsilon(s',\theta)\cup\Theta^2_\varepsilon(s',\hat{s},\theta,\hat{\theta})} dG_\varepsilon(x)\right)W_\varepsilon(s',\hat{s},\theta,\hat{\theta})\right]\right\} \qquad (11)\end{aligned}$$

Here, I denote by $\hat{s}$ the value of human capital at the time of the most recent bargaining. Similarly, $\hat{\theta} \in \{[0,1]\times\mathbb{R}_+, u, r, f\}$ represents the firm characteristics corresponding to the job offer that was used for bargaining.[39] The set $\Theta^1_\varepsilon(s,\theta)$ is the set of firm characteristics of the firms from whom the worker (of type ε and with human capital s) would accept an job offer if she is currently employed at a firm with characteristics θ, and $\Theta^2_\varepsilon(s,\hat{s},\theta,\hat{\theta})$ is the set of firm characteristics of the firms whose offers this worker would use to trigger re-bargaining at her current match. Using equations (4) and (5), these sets can be specified as $\Theta^1_\varepsilon(s,\theta) = \{[0,1]\times\mathbb{R}_+ : W^{max}_\varepsilon(s,x) \geq W^{max}_\varepsilon(s,\theta)\}$ and $\Theta^2_\varepsilon(s,\theta) = \{x \in [0,1]\times\mathbb{R}_+ : W^{max}_\varepsilon(s,\theta) > W^{max}_\varepsilon(s,x) \geq W^{max}_\varepsilon(\hat{s},\hat{\theta})\}$.[40] 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 reflect the possibility of these workers being re-employed in the same period, and therefore relate to value functions (10) and (8) above as follows:

$$\hat{T}_\varepsilon(s',\theta) = \phi^{rg}_\varepsilon\phi^r_\varepsilon W_\varepsilon(s',s',\theta',r) + (1-\phi^{rg}_\varepsilon\phi^r_\varepsilon)T_\varepsilon(s',\theta) \qquad (12)$$

$$\hat{U}_\varepsilon(s') = \lambda^{ug}_\varepsilon\int_{x\in\Theta^u_\varepsilon(s')} W_\varepsilon(s',s',x,u)dG_\varepsilon(x) + \left(1-\lambda^{ug}_\varepsilon\int_{x\in\Theta^u_\varepsilon(s')} dG_\varepsilon(x)\right)U_\varepsilon(s') \qquad (13)$$

Using equation (11), 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

[39]If a worker comes out of unemployment, she does not have such a job offer to use for bargaining, and uses the value of unemployment instead. 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 $\hat{\theta} = f$.

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

piece-rate) is already known:

$$W_{\varepsilon}^{max}(s,\theta) = \ln(p(s,y)) + \beta\mathbb{E}_{s'|s,e,\varepsilon}\left\{\delta\left[\phi_{\varepsilon}^{f}\max\left\{\hat{F}_{\varepsilon}(s',\theta),\hat{U}_{\varepsilon}(s')\right\} + (1-\phi_{\varepsilon}^{f})\hat{U}_{\varepsilon}(s')\right]\right.$$
$$\left. +(1-\delta)\left[\lambda_{\varepsilon}^{e}\int_{x\in\Theta_{\varepsilon}^{1}(s',\theta)}\kappa\left(W_{\varepsilon}^{max}(s',x) - W_{\varepsilon}^{max}(s',\theta)\right)dG_{\varepsilon}(x) + W_{\varepsilon}^{max}(s',\theta)\right]\right\} \quad (14)$$

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 (3) to (6), the value functions and the piece-rate function satisfy equations (7) to (14) and equation (B.1), and the distribution of 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, 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 1 shows, these assumptions lead me to a total of 34 parameters that need to be identified. Of these 34 parameters, I will set 5 parameters exogenously, leaving the remaining 29 parameters to be estimated using the indirect inference method from Gourieroux et al. (1993).[41] In the next two subsections, I describe how I set the 5 exogenous parameters, and which moments I use to identify the remaining 29 parameters. The discussion in these two subsections is summarized in tables 2 and 3, and a more detailed description of the estimation of these moments (both in the data and in the model simulation) can be found in appendix A.

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

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

5.1 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 0.8434

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

and 0.1566 respectively.

Parameter(s)	Value(s)	Source
β	0.98726	5% annual interest rate
s_1	0	normalization
$\Delta_s(1)$	0.1	normalization
ϵ_1	0.8434	fraction of workers with education level 1 (SIAB)
ϵ_2	0.1566	fraction of workers with education level 2 (SIAB)

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

Furthermore, as one model period corresponds to one quarter, I set the discount rate $\beta = 0.95^{1/4}$ to reflect an annual interest rate of 5%, and I set $s_1 = 0$ and $\Delta_s(1) = 0.1$ as a normalization, so that the values of human capital coming out of the simulation can be interpreted as relative to the human capital of a worker with education level 1 entering the labour market (s_1), and step-sizes in this human capital can be interpreted as relative to the step-size of a worker with low education ($\Delta_s(1)$). Table 2 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 29 parameters that I calibrate using the indirect inference method from Gourieroux et al. (1993). While the parameters are estimated simultaneously, I divide the parameters into six groups, and I argue that each of these groups are identified by a corresponding group of moments.[42]

The first set of moments consists of 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

[42]Dividing the parameters and moments in groups is an exercise I purely do for exposition purposes. In reality, all parameters directly or indirectly affect all moments, but dividing the parameters and moments into groups clarifies the main considerations leading to the choice of certain moments.

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 labour market entry (identified as a market tenure between 3 and 5 years). As the model generates these wage differences primarily through differences in productivity y and human capital s, these moments help to identify initial human capital levels for education level 2 (s_1 is normalized to 0) as well as the education-specific scale parameter $\mu_{y,\varepsilon}$ of the marginal distribution of y. The median-p25 and p75-p25 ratio of wages (by education level) are then used to complete the identification of the shape parameter η_y and education-specific scale parameter $\mu_{y,\varepsilon}$ of the marginal distribution of y.

The third set of moments provides information regarding job finding probabilities, both on-the-job and from nonemployment. In particular, the fraction of job-to-job transitions that followed a displacement (by education level) helps to identify the meeting probability for newly unemployed workers ($\lambda_{\varepsilon}^{ug}$). After all, such a direct transition of a worker to a new job will be observed as a job-to-job transition. The overall quarterly job-to-job transition rate (by education level) therefore also contributes to identifying this parameter, while also informing the value of the on-the-job meeting rate $\lambda_{\varepsilon}^{e}$. Similarly, the average job finding rates (by education level) closely correspond to the job finding rate of unemployed workers, $\lambda_{\varepsilon}^{u}$.

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 $b(s)$.[43] 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 $\lambda_{\varepsilon}^{e}$ (as on-the-job offers may lead to re-bargaining and therefore a wage change). To identify the human capital transi-

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

tion 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^f_ε and the recall materialization probabilities ϕ^r_ε and $\phi^{rg}\phi^r_\varepsilon$ are likely to be different from the observed recall and recall materialization probabilities. However, given the close relation between the two, I can use the observed probabilities as targets in the calibration. In particular, I use two sets of recall materialization rate, derived from the observed recall materialization rate within two years and within one year, in order to tease out the difference between ϕ^r_ε and $\phi^{rg}\phi^r_\varepsilon$.[44] 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, $\lambda^r\lambda^u_\varepsilon$, and in particular the parameter λ^r.[45]

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 worker of the recalled worker κ^r. Finally, for the identification of the copula parameter ρ, I follow Jarosch (2021) in targeting the regression coefficient γ in the estimation equation (15) below:

$$D^\delta_{i,t} = \alpha_i + \gamma \log(w_{it}) + u_{i,t} \tag{15}$$

In equation (15), the variable $D^\delta_{i,t}$ is a dummy variable that is only filled if the worker i is employed

[44] I choose to simplify the estimation by setting $\phi^{rg}_1 = \phi^{rg}_2 = \phi^{rg}$ as the fairly low number of highly educated recalled workers implies that the recall materialization probability for highly educated workers is fairly noisy.

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

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 29 parameters. Further details of the procedure used to estimate these moments can be found in appendix A.3. Table 3 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 gradient of the separation rate over unemployment duration. Similarly, it can be observed that the model tends to have trouble matching moments for the higher education level. Given that many of the parameters are already education-specific, one might therefore wonder whether it would be worth splitting some of the remaining parameters into education-specific parameters as well (especially the human capital transition probabilities).

When looking at the parameter estimates in table 3, 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.[46] 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 fairly 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.[47] 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 lower, at 0.66, 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 especially ϕ_2^f are substantially higher

[46] One major exception to this is the on-the-job meeting probabilities, which are closer 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}.

[47] For 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 0.93 and 0.66 respectively.

Description of Moment(s)	Data	Model	Parameters
Average rate of job loss, tenure 1-3.5y	0.0304	0.03	$\eta_\delta = 2.69$
Average rate of job loss, tenure 3.5-6y	0.0158	0.025	$\mu_{\delta,1} = 13.9$
Average rate of job loss, tenure 6-9y	0.0116	0.021	$\mu_{\delta,2} = 34.0$
Average rate of job loss, tenure>9y	0.0075	0.016	$c^\delta = 0.15$
Average rate of job loss, by education	0.0242	0.027	
	0.0204	0.011	
Subsequent separation, displacement	0.0806	0.047	
Subsequent separation, recall	0.1659	0.164	
p75-p25 ratio of wages	1.54	1.56	$\eta_y = 12.1$
	1.6174	1.52	$\mu_{y,1} = 2.75$
median-p25 ratio of wages	1.2416	1.24	$\mu_{y,2} = 2.68$
	1.3113	1.23	$s_2 = 0.48$
Educational wage premium (all)	1.5324	1.59	
Educational wage premium (entry)	1.4682	1.51	
Job-to-job transition rate	0.0293	0.022	$\lambda_1^e = 0.042$
	0.0305	0.02	$\lambda_2^e = 0.046$
Displacement among job-to-job transitions	0.4106	0.492	$\lambda_1^{ug} = 0.43$
	0.424	0.417	$\lambda_2^{ug} = 0.77$
Average job finding rate	0.1445	0.217	$\lambda_1^u = 0.21$
	0.1484	0.201	$\lambda_2^u = 0.20$
Replacement rate	0.6	0.635	$b = 0.80$
Yearly wage growth	0.0129	0.013	$\Delta_s(2) = 0.096$
	0.0163	0.012	$\psi_e = 0.031$
Pre- to post-layoff wage, duration<0.5y	-0.056	-0.027	$\psi_u = 0.158$
	-0.0143	-0.045	$\psi_r = 0.064$
Pre- to post-layoff wage, duration 0.5-1y	-0.0933	-0.062	$c^f = 0.166$
	-0.0464	-0.11	
Pre- to post-layoff wage, duration 1-2y	-0.1229	-0.12	
	-0.13	-0.14	
Pre- to post-recall wage, duration 0.25-0.5y	0.0018	0.004	
	0.0415	0.06	
Pre- to post-recall wage, duration 0.5-1y	-0.0148	-0.01	
	-0.0231	-0.05	
Recall rate	0.0661	0.087	$\phi_1^f = 0.091$
	0.0253	0.002	$\phi_2^f = 0.315$
Recall materialization rate (Based on materialization in 2 years)	0.3939	0.353	$\phi_1^r = 0.189$
	0.2458	0.245	$\phi_2^r = 0.079$
Recall materialization rate (Based on materialization in 1 year)	0.3498	0.401	$\phi^{rg} = 1.197$
	0.2013	0.22	$\lambda^r = 0.913$
New job finding rate, workers expecting a recall	0.2927	0.238	
Wage of newly hired worker	0.6795	0.708	$\kappa = 0.93$
Wage of newly recalled worker	0.7086	0.808	$\kappa^r = 0.66$
Coefficient $\hat{\gamma}$ in equation (15)	-0.0215	-0.021	$\rho = -22.5$

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

than the observed recall rates in the data and model simulation. As this set of calibrated parameters implies that almost everyone chooses in favour of a potential recall when offered to do so (with the exception of highly educated workers in a low productivity match), this implies that the role of allowing workers to find new jobs despite expecting to be recalled is quite large. Indeed, this meeting probability is only slightly lower (91%) than 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 non-employed worker is much less likely to lose human capital while expecting to be recalled. In fact, the human capital depreciation rate ($\psi_r \psi_u \approx 0.01$) is fairly close to zero for the worker expecting a recall, and much lower than the depreciation rate faced by a regular unemployed worker. 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)[48] and a substantial penalty on the separation rate c^δ, which implies that after recall the worker's separation rate increases by 15 percentage points.

Moving to the differences between the two education levels, it can be noted that workers with a low education level are more likely to obtain an offer from unemployment ($\lambda_1^u > \lambda_2^u$), but not when employed or newly unemployed ($\lambda_1^e < \lambda_2^e$ and $\lambda_1^{ug} < \lambda_2^{ug}$). The on-the-job meeting probability equals 0 for both education levels, 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 higher level of human capital $s_2 = 0.48 > 0$ (which is almost five low education stepsizes higher than the starting level of a worker with a low education level, which was normalized to 0), while they also experience a slightly smaller change every time they are hit with an appreciation or depreciation shock ($\psi_e, \psi_u, \psi_r \psi_u$), $\Delta_s(2) = 0.096 < 0.1$.

When it comes to the firm distributions the workers draw from upon receiving an offer, these are best illustrated in a diagram. Figure 10 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.

[48]For 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 $e^{0+2.75} \approx 15.6$

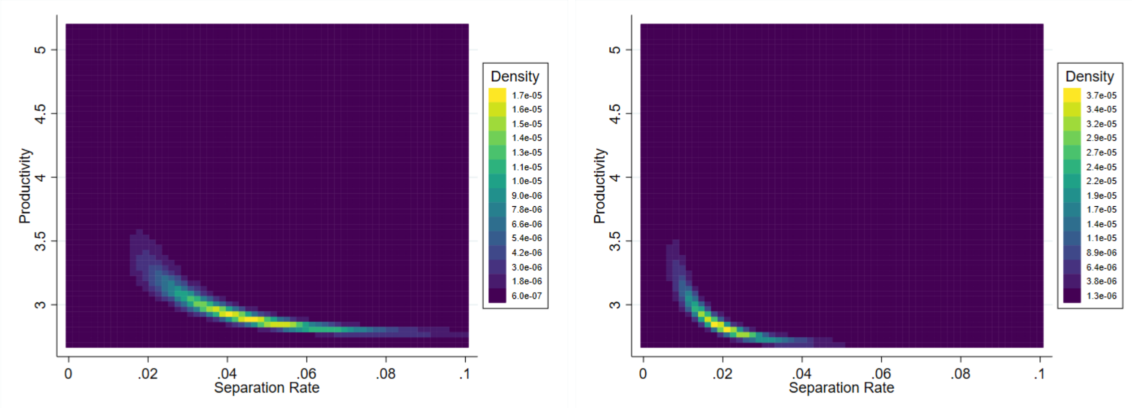

Figure 10: *The joint distribution of firm types faced by workers with a low education level (left) and a high education level (right). A lighter colour in this chart corresponds to a higher density.*

When comparing the two distributions, the first thing that can be noted is that the low education level's minimum productivity is slightly higher than that of the high education level. This is due to $\mu_{y,1} > \mu_{y,2}$, as seen in table 3. 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 briefly comment on possible policy implications of the simulation results.

6.1 Heterogeneity in the scarring effects of displacement

Before moving to the dimension of recall status highlighted in section 3.3, figure 11 displays the average effect of displacement on earnings and employment (defined as the fraction of the year spent in an employment spell). Just like in section 3.2, the effect is estimated by estimating equa-

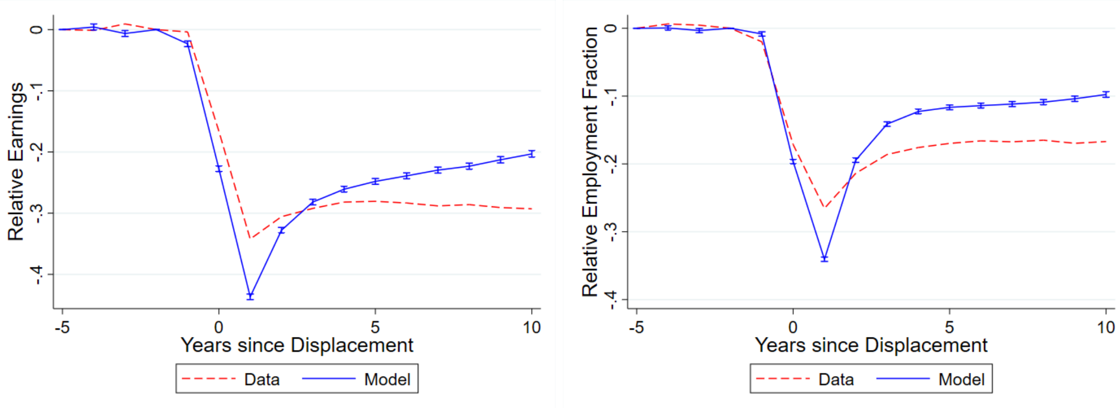

Figure 11: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right), relative to the control group, using model simulation data (solid) and using the data (dashed, corresponding to figure 6).*

tion (1), and thus the results can be compared to figure 6. For this purpose, I have included the results from figure 6 in figure 11 as dashed lines. Making this comparison, it can be seen that while the general shapes of the graph are matched quite well, the model generates slightly too much recovery in earnings and employment compared to the data. This is likely to be caused in part by the model generally overshooting job finding (as seen in table 3), thus leading to more recovery in employment, which in turn leads to more earnings recovery.

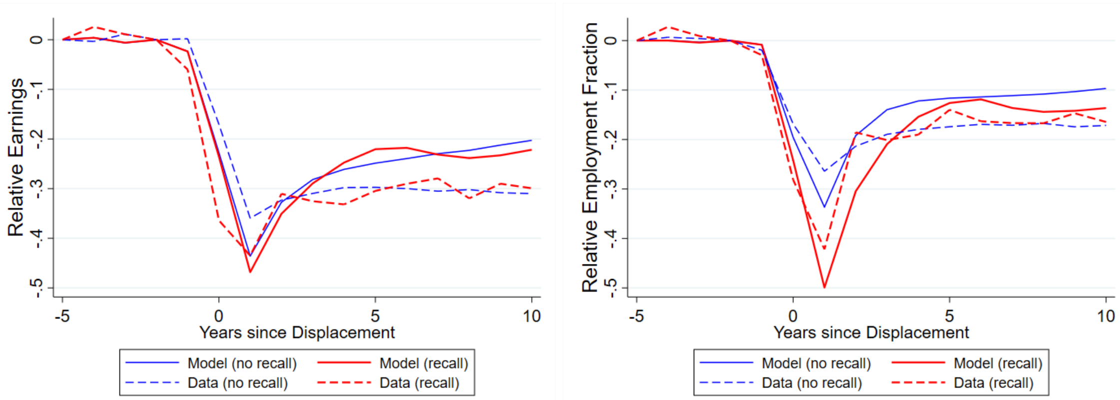

Figure 12: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right) relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data (solid) and using the data (dashed, corresponding to figure 7).*

In figure 12, 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 7. As can be seen from figure 12, the model matches the observation made in section 3.3 that recalled workers do slightly worse than non-recalled workers after displacement (in terms of their earnings and employment) in the short run, even though the effects are fairly similar in the long run. In particular, while the effects on recalled and non-recalled workers generally recover faster than in the data, the 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.

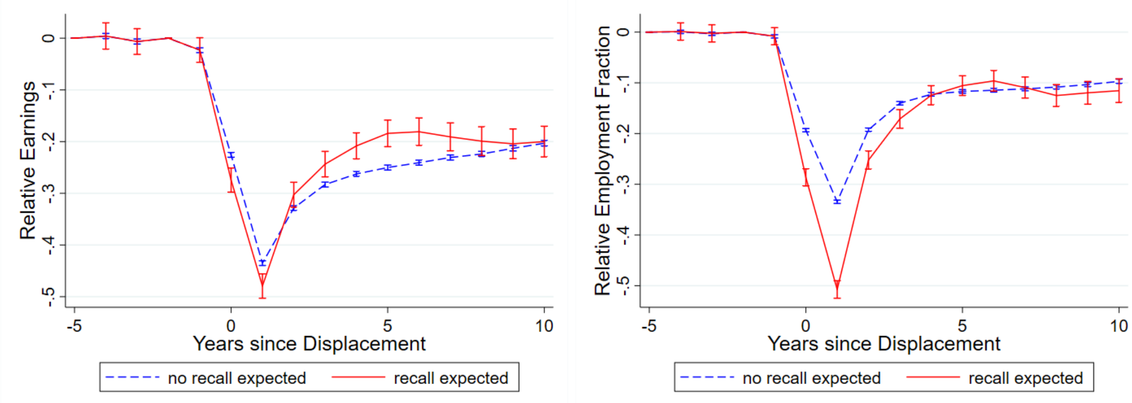

Figure 13: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right) relative to the control group, by post-displacement state, using model simulation data. The red solid line corresponds to workers expecting a recall, and the blue dashed line corresponds to workers moving into unemployment (not necessarily by choice).*

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 13 provides an indication of how one could answer this (second) question. The figure repeats the estimation from figure 12, 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 13 indicates what the expected earnings path is for someone choosing for a potential recall (red) and someone moving to unemployment (blue). As can be seen from comparing figure 13 to the solid lines in figure 12, 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 experience lower earnings losses in the medium to long run, despite being slightly worse off in the short run. The faster recovery in the short run can be attributed to the worker expecting to be recalled having a higher probability of transitioning back to employment than the unemployed worker.[49] 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, almost all workers choose for a potential recall when given the option, with the exception of highly educated workers in a low productivity match.

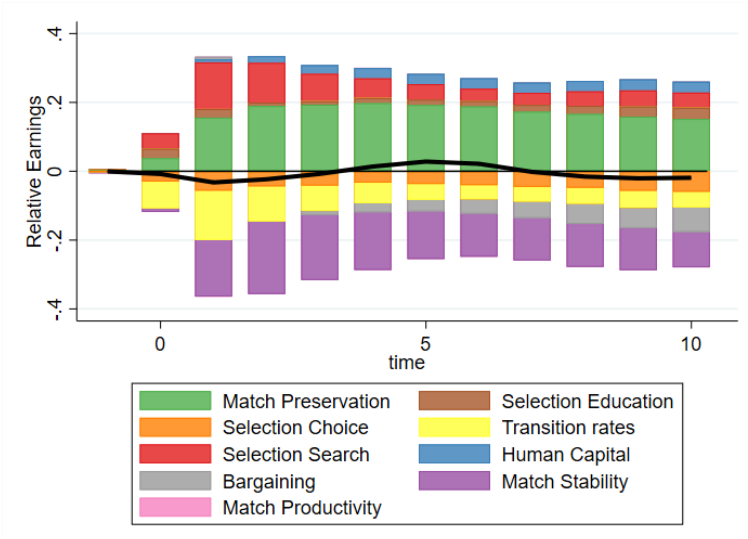

Figure 14: *A decomposition of the difference in the scarring effect of displacement on earnings between (ex-post) recalled and non-recalled workers. The black line represents the total difference, calculated as the difference between the solid red and blue lines in the left panel of figure 12. The decomposition 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 (0,1,5, and 10 years after displacement) can be found in appendix table C.1.*

In figure 14, I fully decompose the differences in estimated post-displacement earnings between recalled and non-recalled workers (as shown in the left panel of figure 12). In particular, I consider all channels (discussed below) through which the ex-post recalled worker is (potentially) 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 14, I find that differences between recalled and non-recalled work-

[49]To be specific, a worker with a low education level expecting to be recalled becomes employed in a model period with probability $\phi_1^r + (1-\phi_1^r)\lambda^r\lambda_1^u = 0.344$, whereas for an unemployed worker this probability equals $\lambda_1^u = 0.21$. Similarly, for a worker with a high education level these probabilities equal 0.247 and 0.2 respectively.

ers are negatively driven by the post-recall match characteristics. In particular, while the impact of the productivity penalty c^f is fairly small in the long run (and barely visible in the figure), the negative difference is largely 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.[50]

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 fairly small impact, reflecting that under this calibration almost all workers choose for the potential recall when offered the choice. The impact of this channel is negative, driven by the group of highly educated workers in low productivity jobs who choose against recall. Similarly, allowing the worker to search while expecting to be recalled (as indicated by $\lambda^r > 0$) has a 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, especially in the short run. Similarly, the finding that the worker expecting to be recalled is much less likely to lose any human capital ("Human Capital") has only a small positive effect, especially in the long run. The effect of different transition rates is strongly negative throughout the simulation, and especially the short run, reflecting primarily the higher immediate transition probabilities λ_ε^{ug} of the worker who chose to move to the regular unemployment state ("Transition rates"). It is also worth noting that the differences between the two education levels also plays a small (positive) role here ("Selection Education"), although this is likely to be a consequence of higher 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, can be observed to be quite large and positive. This reflects that while the displaced workers are negatively selected towards workers who are in a worse match (in terms of productivity and separation rate), the forces of the job ladder are still sufficiently strong such that match they would expect to find when drawing a (random) new employer from the joint distribution $G_\varepsilon(\theta)$ is on average worse than the match they separated

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

from.

Figure 15: *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 12. 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 12) , and backing out the effect on wages as a residual.*

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 12) also allows me to further decompose earnings losses into employment and wage components. In figure 15, I use the results from figure 12 to decompose the earnings loss into employment and wages. Corresponding to my findings in the data (in section 3.3), 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 16, 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 main positive differences for wages are coming from the match preservation and human capital margin. This reflects that the worker does not fall off the job ladder when recalled, and furthermore barely loses any human capital at all, while the general unemployed worker faces a substantial loss of human capital and falls off the ladder. In the long run, this positive difference is increasingly

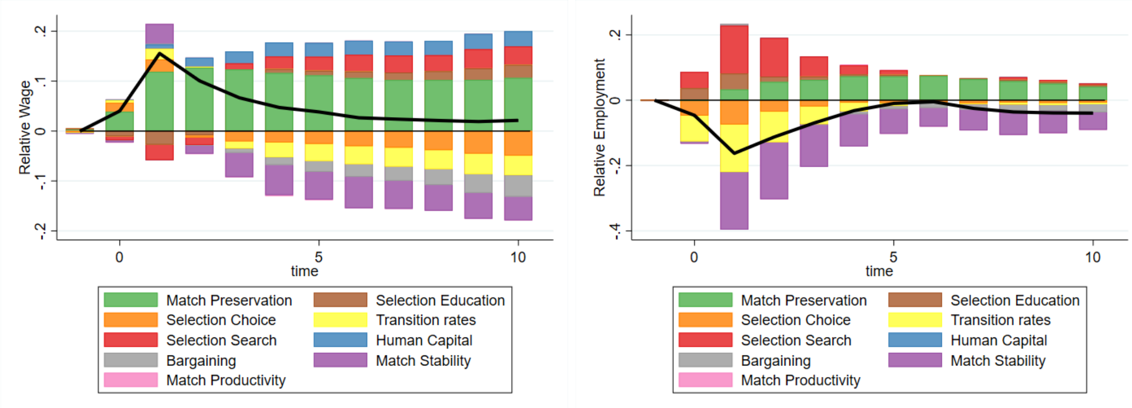

Figure 16: *A decomposition of the difference in the scarring effect of displacement on wages (left) and employment (right) between (ex-post) recalled and non-recalled workers. The black line represents the total difference, as depicted in figure 15. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals. Corresponding numerical values for selected time periods (0,1,5, and 10 years after displacement) can be found in the appendix in tables C.3 and C.2.*

offset by the negative influence of the higher separation rates, higher transition rates, and loss of bargaining power, thus eventually leading to a wage difference close to zero.

In the right panel of figure 16, it can be seen that the human capital channel does not play a role when it comes to employment. For employment, the main drivers are related to the higher separation rate and transition rates 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 the interaction between two channels. 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 a higher separation rate than the in the economy, but nevertheless face a higher expected separation rate when drawing a new match from the join distribution $G_\varepsilon(\theta)$, just like in the data (as seen in figure 8). This is important especially in the long run, as these workers start separating again, 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.[51] The worker stays in this state 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.[52]

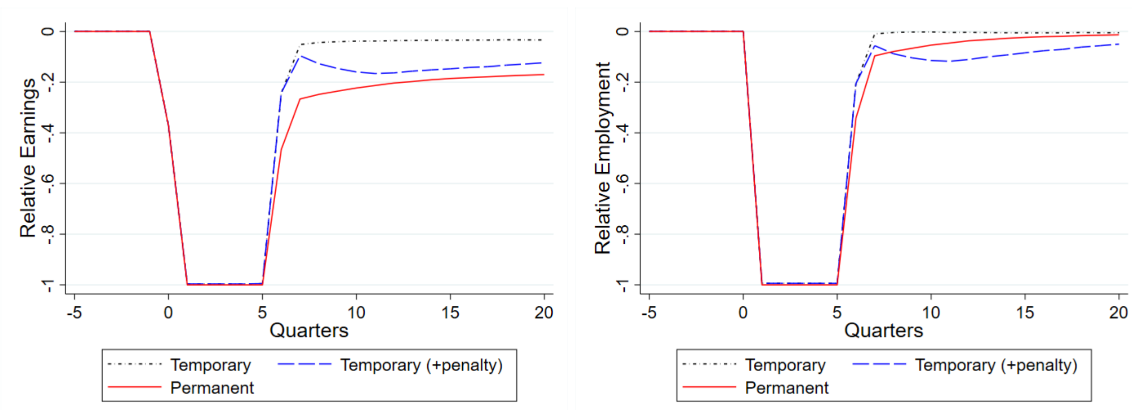

Figure 17: *The effect of a temporary shutdown on the earnings and employment status of affected workers. During the shutdown, workers are assumed to be either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (black, short-dashed).*

In figure 17, 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

[51]Since 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.3 I show that the timing (and duration) of the shutdown does not substantially affect results.

[52]To be specific, I assume that this higher transition probability equals the average of 1 and the "usual" transition probability. In appendix C.3, 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.

(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.[53] 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 I show in appendix C.3, these conclusions on the shutdown's effect on earnings and employment continue to hold when focusing only on workers with a high (or low) education level.

In figure 18, I show the importance of the assumed transition probabilities in the periods 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 17), 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 simulation with immediate 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 (especially in the short run), 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 effects of recall are caused by selection, either through workers choosing for the potential recall option or through workers in the potential recall state finding a (better) new job instead and thus selecting themselves into the ex-post non-recall group.

Secondly, the large difference between the recovery paths under temporary and permanent 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

[53] Given 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).

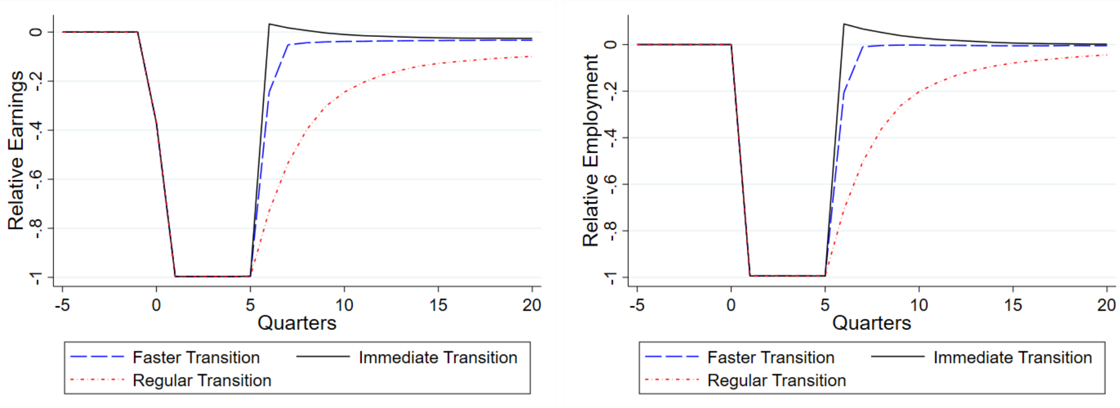

Figure 18: *The effect of a temporary shutdown on the earnings and employment status of affected workers. During the shutdown, workers are assumed to be in the temporary unemployment state without the associated penalties. After the shutdown, workers transition back to employment either immediately (blue, dashed), at a faster rate than usual (black, solid), or at the usual rate (red, short-dashed).*

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 experience similar earnings losses compared to 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.[54] 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.

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

[54]Two 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).

a channel that works in favour of the recalled worker. Indeed, as pointed out in section 5.3, the probability of human capital depreciation for a worker expecting a recall is equal to 1%, so while a regular unemployed worker loses some of their human capital in 16% of the periods they spend in unemployment, this is not the case for the worker expecting a recall. As shown in appendix C.4, this implies that while human capital depreciation (relative to a continuously employed worker) accounts for a similar portion of long-run earnings losses for the non-recalled and recalled worker, it plays a smaller role in explaining the short- and medium-run earnings losses for a recalled worker, thus suggesting that in the case of the recalled worker these losses are driven by the subsequent job losses rather than the initial displacement. 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 until they lose their job again. Indeed, as I show in appendix C.4, an unintended consequence of such a policy would be that it increases the gap between recalled and non-recalled workers in the short run. 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 in the first few years following the displacement.

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 experience slightly larger earnings and employment losses than non-recalled workers in the short run, their average losses are similar in the long run. However, the similarity of these long-run earnings losses mask differences that are uncovered when further distinguishing workers that transition to a new job within 30 days (in which case non-recalled workers experience smaller losses) and workers that take more than 30 days to transition (in which case recalled workers experience smaller losses). Furthermore, I find that recalled workers experience a higher probability of subsequent job loss.

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 find that if the only difference between recalled and non-recalled worker was their next employer, the recalled worker would experience lower earnings losses (as they would not lose their position on the job ladder). In addition, the human capital depreciation channel is almost nonexistent for the recalled worker, thus further alleviating the earnings losses experienced by the recalled worker. On the other hand, recalled workers face a higher separation rate after the recall materializes (and, less importantly, lower productivity), which plays a large negative role in the long run, 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 does not start to materialize until a few years later (when their subsequent separations start occurring). 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, especially in the short run, 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.[55] 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.

When it comes to the model, there are also are a number of ways in which one might imagine expanding the analysis presented in this paper. First of all, the selection channels operating in the model in this paper are partially exogenous, and it would be worth exploring models in which these channels are endogenous instead. The main extension would be to more explicitly incorporate decision making on the firm side of the model, which I largely abstract from in this paper. Going a step further, one might consider exploring an environment with multi-worker firms, where the firm not only decides *whether* the recall any worker, but also decides *which worker* to recall. Similarly, given the research that has pointed out the potential importance of workers involuntarily losing their recall option (e.g. Gertler et al., 2022), including such a "loss-of-recall" channel into the model could be valuable. In order to do so, one would require a reasonable counterpart in the data that could be used to discipline such a channel. To the best of my knowledge, there currently does not exist any research looking into this in the context of the German (or similar) labor market, but conditional on the existence of such data this could be a promising avenue for future research. 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 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.

[55] As 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.

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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 (14) and (8) only depend on functions W^{max} and U and known functions and parameters, use an iterative loop to solve for functions W^{max} and U. In particular:
   (a) Guess an initial matrix for W^{max} (N_y by N_δ by N_s by 2) and U (1 by N_s).[56]
   (b) 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 $\omega_u \in (0, 1]$)
   (c) 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.
   (d) 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 $\omega_s \in (0, 1]$)
   (e) Calculate the distance between the initial W^{max} and the updated W^{max}. If this distance is not close enough to zero, return to step b, setting $U = \hat{U}$ and $W^{max} = \hat{W}^{max}$.
   (f) Calculate the distance between the initial U and the updated U. If this distance is not close enough to zero, return to step b, setting $U = \hat{U}$ and $W^{max} = \hat{W}^{max}$.

6. Using the 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.

[56]The fourth dimension of the matrix W^{max} is used to distinguish whether the match carries a separation rate penalty from a previous recall. In the remainder of the description of this solution method I ignore this for notational convenience. In practice, the two 3-dimensional matrices are closely linked together, using only a single matrix for the value of 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):

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

Further, note that given a known value for W^{max} and U (for every s and θ), the value $T(s,\theta)$ is known:[57]

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

Similarly, for given values W^{max} and U, and T, the values $\hat{U}$ and $\hat{T}$ can be directly calculated using equations (12) and (13). 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:

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

Further, note that:

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

[57] To 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 value function):

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

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

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

The expression above can be simplified further by using the simple structure of the expectations operator. If the match is formed (as denoted by the subscript e), there are only two options for the future level of s, s': With probability ψ_e, $s' = s+1$ (i.e. the previous level plus 1 stepsize, which may not necessarily be the next grid point) and with probability $1-\psi_e$, $s'=s$. The one exception to this is that if the worker is at the maximum value of s, in which case $\psi_e = 0$.[58] Below, I rewrite the value function using this structure. In what follows, I use $\psi = \psi_e$ (for ease of notation):

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

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

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

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

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

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 $r = \ln(R)$):

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

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

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

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

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

To be explicit, this means that the vectors and matrices will look as follows in practice:

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

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

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.[59] With the exception of the yearly wage growth, all moments are estimated using the quarterly data set.

A.3.1 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, λ_ε^u, and λ_ε^{ug}, 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.[60] The job loss rate by tenure

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

[60] Note 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.[61] 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.

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, 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

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

employed workers.[62] 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%). Denoting this average by $\bar{w}_\varepsilon$, the educational wage premium then equals $\bar{w}_2/\bar{w}_1$. When estimating this educational wage premium upon entry, the same procedure is followed, further restricting the sample to workers with a market tenure of 3 to 5 years (i.e. more than exactly 3 years, and less than exactly 6 years).

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

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 1 or 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 rates are calculated by first obtaining the fraction of recalled workers that were recalled within 1 or 2 years. The recall materialization rates are then calculated as the constant quarterly materialization rate such that this fraction would indeed be recalled within 1 or 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):

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

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

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

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

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

A.3.9 Explicit Estimation of the Scarring Effect of Displacement

In 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 of the main text. In other words, I target the outcome of the estimation of the following equation:

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

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

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

Then, to get around having to estimate the fixed effects explicitly, I interpret the equation above as a two-way error component model, and use the two-way within transformation from Hansen (2021). In particular, this means that for both the dependent and independent variables in equation (A.5), I calculate

$\ddot{X}_{it} = X_{it} - \bar{X}_i - \tilde{X}_t + \bar{X}$, where $\bar{X}$ is the average variable over all individuals and time periods, $\tilde{X}_t$ is the average over individuals within a time period t, and $\bar{X}_i$ is the average over all time periods for an individual i. Using this transformation, the equation to be estimated reduces to the following equation:

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

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

B Model Appendix

B.1 Further Value Functions

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

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

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:

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

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

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:[63]

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

$$\begin{aligned}
d_\varepsilon'(s,\hat{s},\theta,u) = {}& (1-\delta)\left(1-\lambda_\varepsilon^e\int_{x\in\Theta_\varepsilon^1(s,\theta)\cup\Theta_\varepsilon^2(s',\hat{s},\theta,u)} dG_\varepsilon(x)\right)\bar{d}_\varepsilon(s,\hat{s},\theta,u)\\
&+g_\varepsilon(\theta)\mathbb{1}_{s=\hat{s}}\mathbb{1}_{\theta\in\Theta_\varepsilon^u(s)}\left(\lambda_\varepsilon^u\bar{u}_\varepsilon(s)+\lambda_\varepsilon^{ug}\iiint\delta(1-\bar{\phi}_\varepsilon^f(s,x))\bar{d}_\varepsilon(s,\tilde{s},x,\hat{x})d\tilde{s}dxd\hat{x}\right)
\end{aligned}\tag{B.5}$$

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

[63] Note 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).

$$d_\varepsilon'(s,\hat{s},\theta,f) = (1-\delta)\left(1 - \lambda_\varepsilon^e \int_{x\in\Theta_\varepsilon^1(s,\theta)\cup\Theta_\varepsilon^2(s',\hat{s},\theta,f)} dG_\varepsilon(x)\right)\bar{d}_\varepsilon(s,\hat{s},\theta,f)$$
$$+ \mathbb{1}_{s=\hat{s}} \int \mathbb{1}_{\theta\in\Theta_\varepsilon^r(s,x)}(1-\phi_\varepsilon^r)\lambda^r \bar{d}_\varepsilon^f(s,x)dx \tag{B.7}$$
$$d_\varepsilon^{f\prime}(s,\theta) = (1-\phi_\varepsilon^r)\left(1-\lambda^r \int_{x\in\Theta_\varepsilon^r(s,\theta)} dG_\varepsilon(x)\right)\mathbb{1}_{F_\varepsilon(s,\theta)>U_\varepsilon(s)}\bar{d}_\varepsilon^f(s,\theta)$$
$$+ \iint \delta\bar{\phi}_\varepsilon^f(s,\theta)(1-\phi_\varepsilon^{rg})\bar{d}_\varepsilon(s,\hat{s},\theta,\hat{x})d\hat{s}d\hat{x} \tag{B.8}$$
$$u_\varepsilon'(s) = \left(1-\lambda_\varepsilon^u \int_{x\in\Theta_\varepsilon^u(s)} dG_\varepsilon(x)\right)\bar{u}_\varepsilon(s)$$
$$+ \int \delta(1-\bar{\phi}_\varepsilon^f(s,\theta))\left(1-\lambda_\varepsilon^{ug}\int_{x\in\Theta_\varepsilon^u(s)} dG_\varepsilon(x)\right)\iint \bar{d}_\varepsilon(s,\hat{s},\theta,\hat{x})d\hat{x}d\hat{s}d\theta \tag{B.9}$$

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, once could display the flows through a diagram, as is done in figure B.1, although it should be noted that this figure focuses primarily on the transition between the three main states, and 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 (11), 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 (9) in terms of W^{max} and U only. In order to do so, I use the bargaining equations (3) and (6), leading to equation (10), mentioned in the main text (in section 4). Given a guess for W^{max}, one can solve the above equation (10) 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 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 (11), by

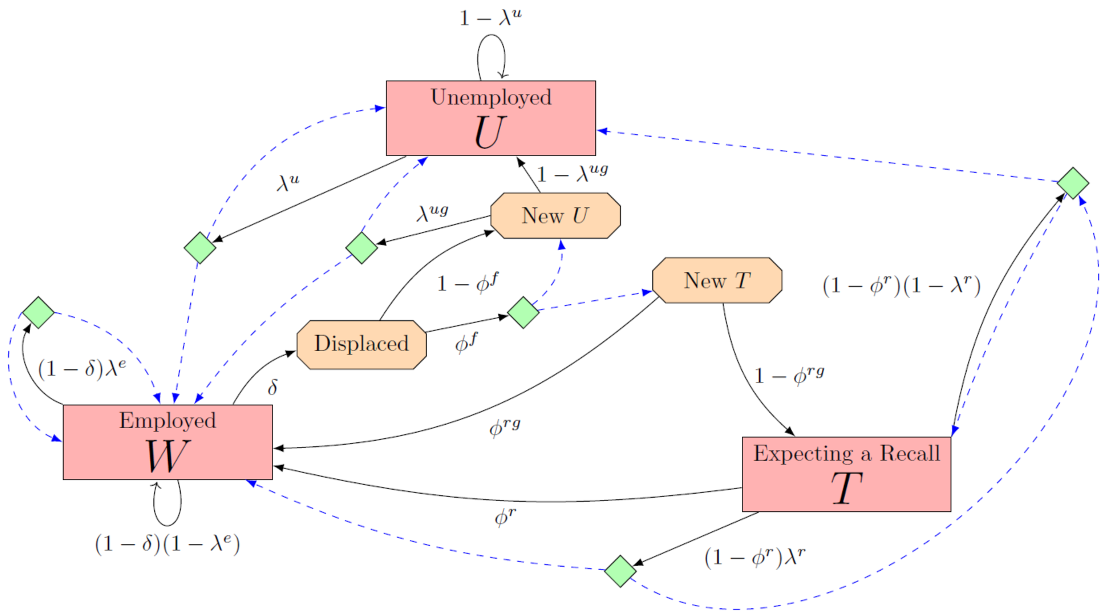


Figure B.1: *A flow chart depicting the flows between the three main states for a worker. Solid arrows depict an exogenous flow, caused by materialization of some probability. Dashed (blue) lines are flows that follow from a decision of the worker, and these decisions are made at decision points (which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

plugging in $R(\hat{s}, \theta, \hat{\theta}) = 1$ and rewriting:

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

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:

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

Finally, to arrive at equation (14), simplify the term inside of the integral by using the bargaining equation $W_\varepsilon(s,s,x,\theta) = W_\varepsilon^{max}(s,\theta) + \kappa\left(W_\varepsilon^{max}(s,x) - W_\varepsilon^{max}(s,\theta)\right)$:

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

In order to solve for both W^{max} and U, I still need to remove the value function W from the value function U, equation (7). To do this, I use the bargaining equation (3):

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

C Additional Simulation Results

C.1 Further Simulation Results

In section 6.1 of the main text, I briefly discussed how the estimated model performs in matching the empirical results from section 3. In this section, I discuss how the model performs in matching differences by education level (included in section D.3.4), and furthermore discuss the implications of the model outside the regression context stressed in the main text.

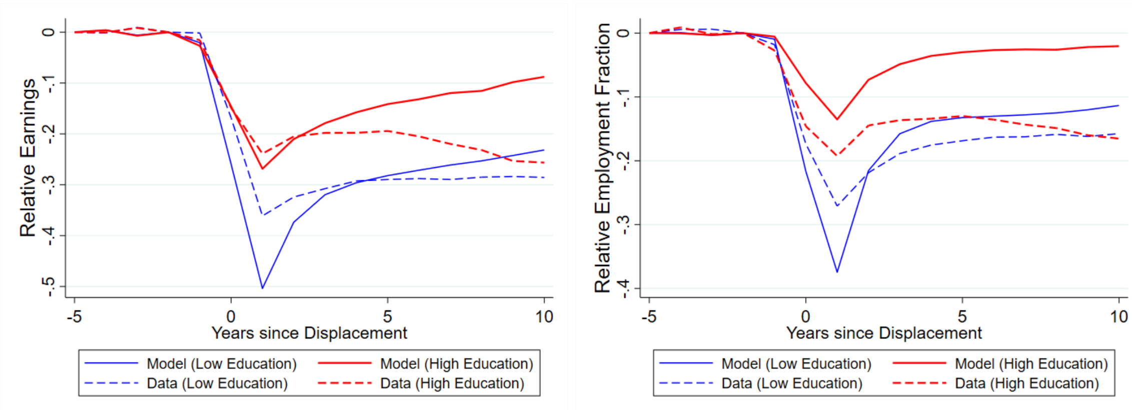


Figure C.1: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right), relative to the control group (by education group), using model simulation data (solid) and using the data (dashed, corresponding to figure D.9).*

Figure C.1 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.9. 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 observations from sections 5 and 6 that the calibration has trouble matching moments for the high education level, while simultaneously overshooting the job finding rates found in the data, and thus overestimating the recovery in earnings and employment found in the data.

While the results above and in section 6.1 of the main text focus on implications of the model that were generated using the same estimation method as in the data (based on equation 1), one can also generate similar implications using a so-called direct counterfactual. After all, the estimation methods used in the data are used in large part because a direct counterfactual is not observable in the data, but such a counterfactual can easily be created in the model simulation. In practice, this amounts to simulating the model twice, where the (initial) displacement is prevented from happening in the second simulation but all other random variable draws are the same between the two simulations. In figures C.2 and C.3, I show the accompanying results and compare them with the regression-based results. As can be seen from the figures, the direct counterfactuals tend to predict a smaller scarring effect and more recovery, for both earnings and employment. However, when it comes to the difference between recalled and non-recalled workers, the two methods reach the same conclusion.

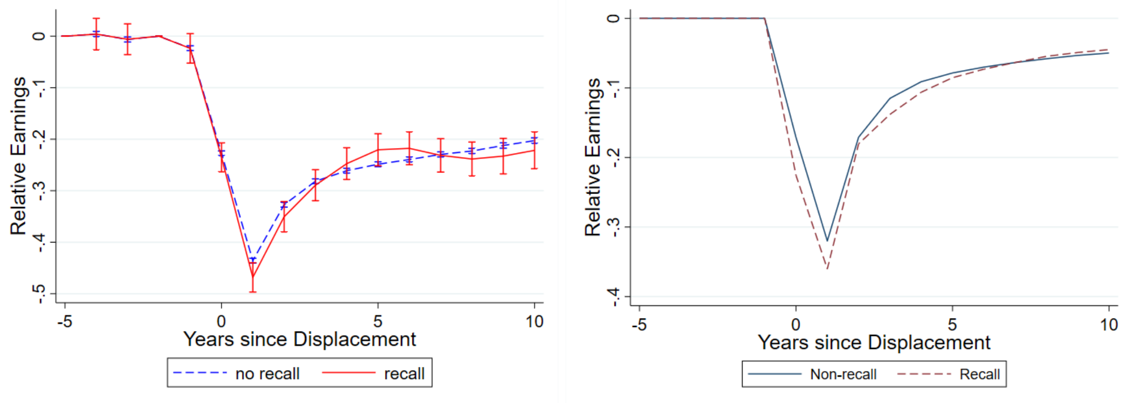


Figure C.2: *The effect of displacement on earnings relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data and using a regression-based approach (left, corresponding to figure 12) or a direct counterfactual (right).*

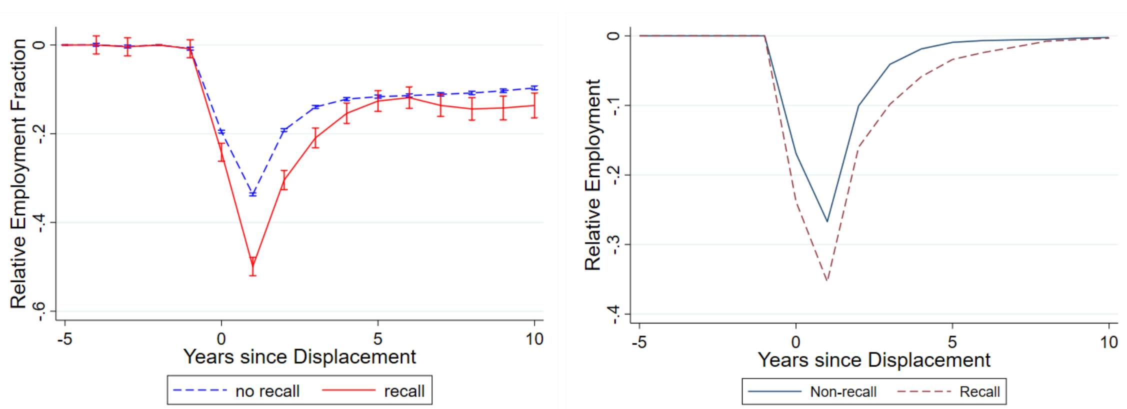


Figure C.3: *The effect of displacement on employment fraction relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data and using a regression-based approach (left, corresponding to figure 12) or a direct counterfactual (right).*

C.2 Further Decomposition Results

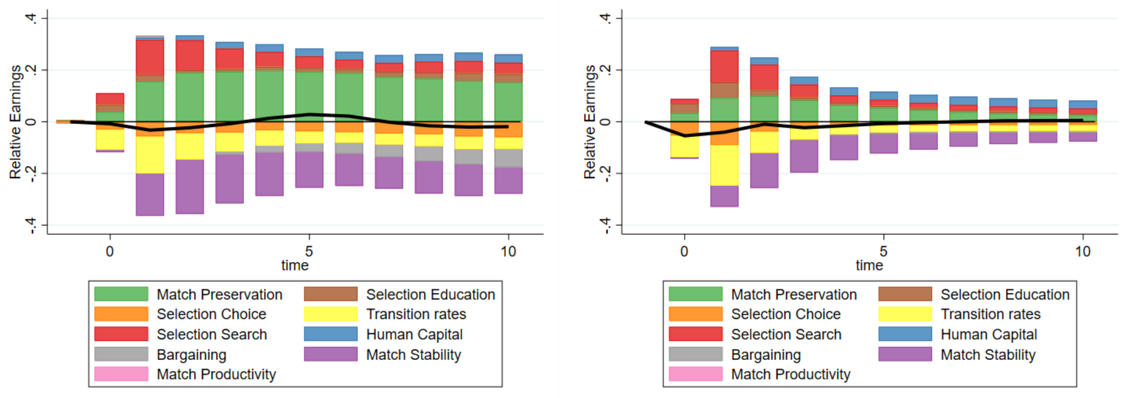


Figure C.4: *A decomposition of the difference in the scarring effect of displacement on earnings between (ex-post) recalled and non-recalled workers, using either a regression-based approach (left) or a direct counterfactual (right). The black line represents the total difference, calculated as the difference between the red and blue lines in figure C.2. 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 (0,1,5, and 10 years after displacement) can be found in table C.1.*

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, using the regression-based model implications. However, as I stressed in the previous section, these results can also be obtained using a direct counterfactual. In figure C.4, I compare the results of this alternative decomposition (in the right panel) with those from the decomposition discussed in the main text (re-printed in the left panel). Similarly, figure C.5 repeats the decomposition of the wage and employment effects from figure 16 using this direct counterfactual. As can be seen in these figures, the two decomposition methods generally yield similar conclusions, even if the size of the effects are different (as stressed in the previous section).

In tables C.1 (earnings), C.2 (employment), and C.3 (wages) I show the numerical values used to construct a selection of the bars in the corresponding figures C.4, 16 and C.5.

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

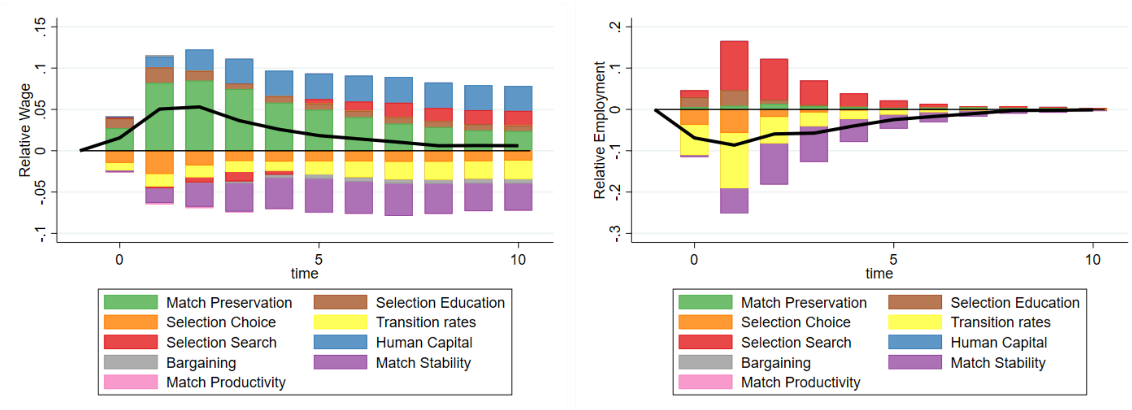


Figure C.5: *A decomposition of the difference in the scarring effect of displacement on wages (left) and employment (right) between (ex-post) recalled and non-recalled workers, using a direct counterfactual simulation. The black line represents the total difference. The decomposition is generated by 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 (0,1,5, and 10 years after displacement) can be found in tables C.3 and C.2.*

	Regression-Based				Direct Counterfactual			
Channel	$k = 0$	$k = 1$	$k = 5$	$k = 10$	$k = 0$	$k = 1$	$k = 5$	$k = 10$
Match Productivity Penalty	-0.000	-0.001	0.000	0.000	-0.000	-0.002	-0.000	-0.000
Match Stability Penalty	-0.009	-0.164	-0.138	-0.102	-0.007	-0.082	-0.076	-0.034
Bargaining	-0.001	0.007	-0.033	-0.072	0.001	0.002	-0.005	-0.007
Human Capital	0.000	0.009	0.03	0.032	0.001	0.013	0.031	0.03
Selection Search	0.045	0.135	0.045	0.044	0.018	0.124	0.023	0.019
Transition Rates	-0.078	-0.144	-0.046	-0.045	-0.083	-0.157	-0.027	-0.023
Selection Choice	-0.03	-0.056	-0.037	-0.06	-0.053	-0.09	-0.014	-0.012
Selection Education	0.027	0.025	0.015	0.033	0.036	0.061	0.008	0.007
Match Preservation	0.038	0.156	0.193	0.152	0.033	0.091	0.053	0.025
Total	-0.008	-0.032	0.028	-0.019	-0.055	-0.04	-0.007	0.005

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 red and blue lines in figure C.2. The decomposition is generated by turning off the indicated channels one by one (in the order in which they are presented in the table), 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 regression-based and direct decompositions depicted in figure C.4.*

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 $\psi_r = 1$.

	Regression-Based				Direct Counterfactual			
Channel	$k=0$	$k=1$	$k=5$	$k=10$	$k=0$	$k=1$	$k=5$	$k=10$
Match Productivity Penalty	0.000	0.000	0.001	-0.000	0	0.000	0.000	0.000
Match Stability Penalty	-0.005	-0.177	-0.076	-0.053	-0.005	-0.061	-0.034	-0.002
Bargaining	-0.002	-0.005	-0.009	-0.025	0	-0.000	0.000	-0.001
Human Capital	0	0	0	0	0	0	0	0
Selection Search	0.05	0.146	0.014	0.005	0.017	0.119	0.018	0.001
Transition Rates	-0.079	-0.145	-0.009	-0.005	-0.073	-0.134	-0.011	-0.001
Selection Choice	-0.047	-0.074	-0.009	-0.007	-0.037	-0.057	-0.001	-0.000
Selection Education	0.037	0.048	0.005	0.005	0.023	0.038	0.000	0.001
Match Preservation	-0.001	0.033	0.073	0.041	0.006	0.009	0.003	0.001
Total	-0.046	-0.163	-0.01	-0.039	-0.069	-0.086	-0.025	-0.001

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 (in the order in which they are presented in the table), 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 decompositions depicted in figure 16 and C.5.*

As mentioned in the main text, a worker expecting to be recalled generally transitions back into employment faster than other unemployed workers, conditional on not transitioning back before even making it to the unemployment state. In order to calculate the impact of these "Transition Rates", I set the transition rates from the two states equal by setting $\phi^r_\varepsilon = \lambda^u_\varepsilon$, and $\phi^{rg}_\varepsilon = \lambda^{ug}_\varepsilon$. In other words, the recall materialization rates are set equal to the job finding rates of the general unemployed worker.[64]

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^f_ε).

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

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^f_ε. 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 $\lambda^r\lambda^u_\varepsilon$. 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 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).

	Regression-Based				Direct Counterfactual			
Channel	$k = 0$	$k = 1$	$k = 5$	$k = 10$	$k = 0$	$k = 1$	$k = 5$	$k = 10$
Match Productivity Penalty	−0.000	−0.001	−0.001	0.000	−0.000	−0.002	−0.000	0.000
Match Stability Penalty	−0.004	0.04	−0.056	−0.047	−0.002	−0.018	−0.041	−0.033
Bargaining	0.002	0.001	−0.022	−0.043	0.001	0.002	−0.005	−0.005
Human Capital	0.001	0.009	0.028	0.03	0.001	0.013	0.031	0.03
Selection Search	−0.008	−0.031	0.028	0.037	0.001	−0.002	0.005	0.018
Transition Rates	0.005	0.021	−0.034	−0.039	−0.009	−0.015	−0.016	−0.023
Selection Choice	0.018	0.025	−0.026	−0.049	−0.015	−0.028	−0.013	−0.012
Selection Education	−0.01	−0.027	0.009	0.026	0.012	0.019	0.008	0.007
Match Preservation	0.038	0.119	0.112	0.106	0.027	0.082	0.05	0.024
Total	0.04	0.156	0.038	0.021	0.016	0.05	0.018	0.006

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 (in the order in which they are presented in the table), 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 16.*

C.3 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.6, the results continue to hold if I assume that transition rates immediately go back to normal. Furthermore, while the results in the main text pooled the two education groups, the results continue

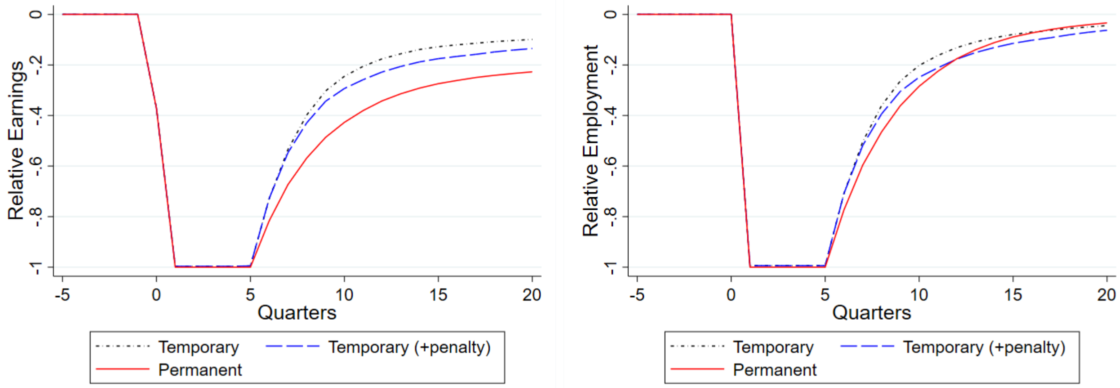


Figure C.6: *The effect of a temporary shutdown on the earnings and employment status of affected workers, without imposing two quarters of subsequent faster transitions. During the shutdown, workers are assumed to be either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (black, short-dashed).*

to hold when focusing on the high education level only, as can be seen in figure C.7.

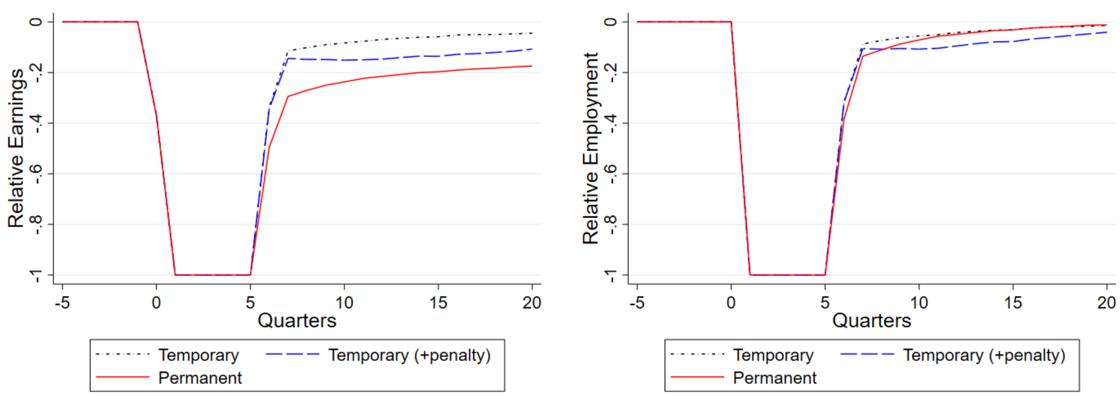


Figure C.7: *The effect of a temporary shutdown on the earnings and employment status of affected workers with a high education level. During the shutdown, workers are assumed to be either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (black, short-dashed).*

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 in the left panel of figure C.8, 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 17 in the main text).

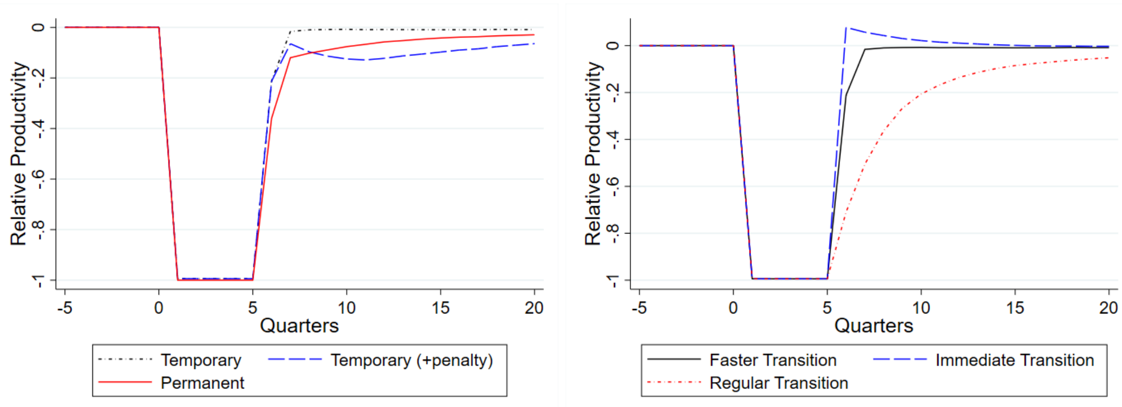


Figure C.8: *The effect of a temporary shutdown on the productivity of affected workers. Left panel: during the shutdown, workers are assumed to be either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (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.9, 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.10 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.10, 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 5.3 of the main text), the difference is small and it does not affect the main results of the simulation exercise.

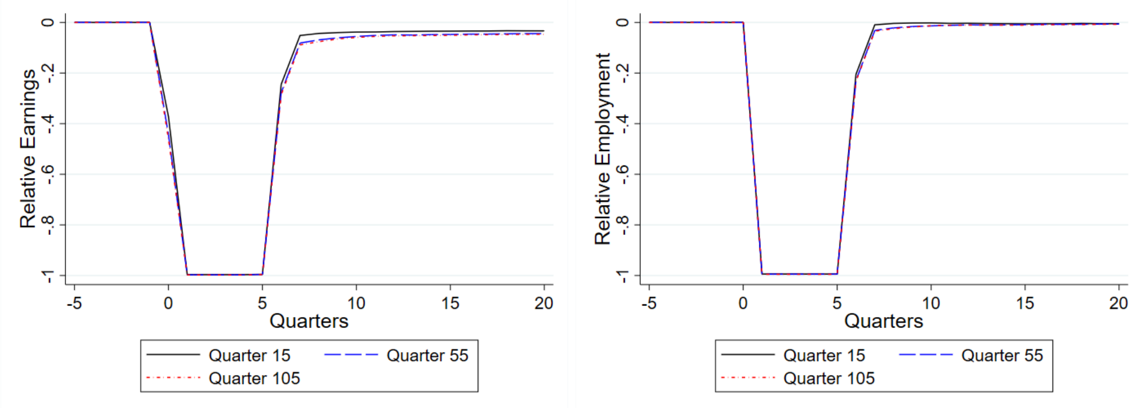


Figure C.9: *The effect of a temporary shutdown on the earnings and employment status of affected workers. During the shutdown, workers are assumed to be either in the temporary unemployment state without the associated penalties, and after the shutdown workers transition back to employment at a faster 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.*

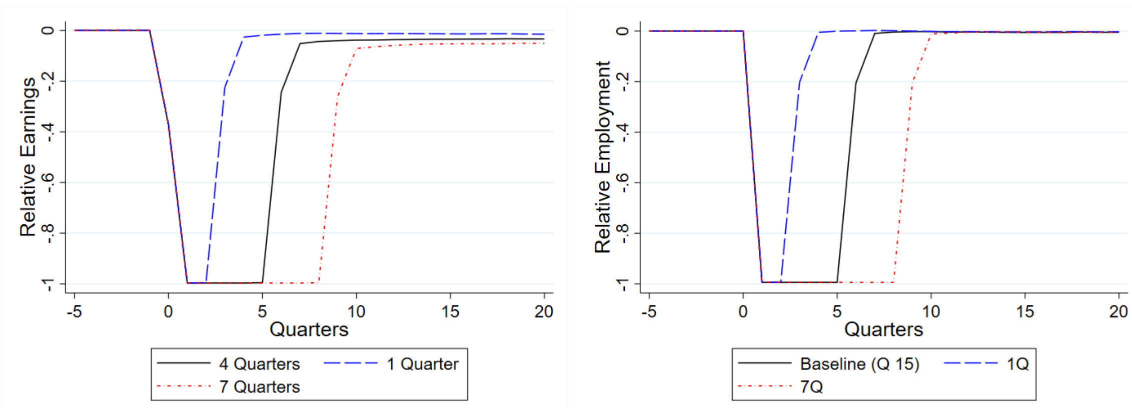


Figure C.10: *The effect of a temporary shutdown on the earnings and employment status of affected workers. During the shutdown, workers are assumed to be either in the temporary unemployment state without the associated penalties, and after the shutdown workers transition back to employment at a faster 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.*

C.4 Policy Implications

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

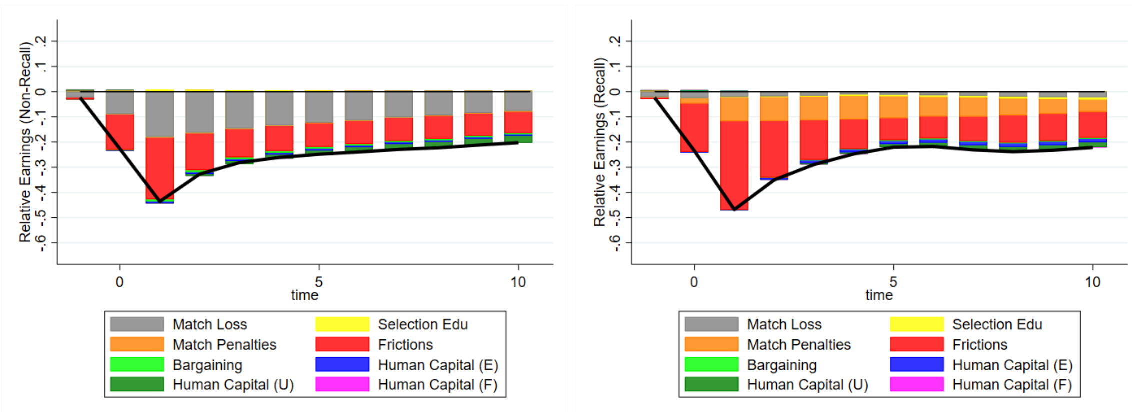


Figure C.11: *A decomposition of the scarring effect of displacement on earnings for (ex-post) non-recalled workers (left) and recalled workers (right).The black line represents the total earnings loss, and corresponds to the solid blue and red lines in the left panel of figure 12. The decomposition 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 (0,1,5, and 10 years after displacement) can be found in the appendix in tables C.4 and C.5.*

First of all, figure C.11 and accompanying tables C.4 and C.5 illustrate my statement in section 6.3 that while human capital depreciation (relative to a continuously employed worker) accounts for a similar portion of long-run earnings losses for the non-recalled and recalled worker, it only plays a minor role in explaining the short-run earnings losses for a recalled worker. This is visible in the figure, where the human capital (relative) depreciation elements are represented by the blue, pink and dark green areas.

As can be observed in the figure, the human capital depreciation for workers expecting a recall (in pink) is generally has a very small impact (for 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 (close to) zero for them. As a result, the bulk (more than 90% in the short run, and more than 50% in the long run) of the earnings losses experienced by the recalled worker are explained by “Match penalties” and “Frictions”, which encompasses the penalties on the productivity and separation rates as well as losses that occur because the worker spends time in nonemployment (anything other than human capital loss). Using a direct counterfactual instead of the regression-based decomposition yields a similar result, although the impact of the “Match penalties” and “Frictions” is smaller in the long run, and a larger role is

	Regression-Based				Direct Counterfactual			
Channel	$k=0$	$k=1$	$k=5$	$k=10$	$k=0$	$k=1$	$k=5$	$k=10$
Match Loss	-0.025	-0.021	-0.012	-0.022	0	0	0	0
Selection Edu	-0.000	-0.002	-0.006	-0.009	0	0	0	0
Match Penalties	-0.021	-0.095	-0.087	-0.049	-0.003	-0.027	-0.032	-0.015
Frictions	-0.192	-0.352	-0.087	-0.103	-0.215	-0.339	-0.027	-0.000
Bargaining	0.003	0.002	-0.003	-0.004	-0.008	0.008	-0.001	-0.001
Human Capital (E)	-0.002	-0.002	-0.012	-0.014	0.001	-0.002	-0.012	-0.01
Human Capital (U)	0.003	0.001	-0.012	-0.019	0.000	0.000	-0.012	-0.017
Human Capital (T)	-0.000	-0.000	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002
Total	-0.235	-0.468	-0.221	-0.222	-0.226	-0.36	-0.085	-0.045

Table C.4: *Summary of the decomposition of 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 12. The decomposition is generated by turning off the indicated channels one by one (presented here in reversed order), 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, with the regression-based numbers reflecting the corresponding decomposition depicted in figure C.11.*

attributed human capital loss (accounting for 64% and 75% of the long-run losses experieced by recalled and non-recalled workers respectively)

Indeed, as can be seen in figure C.12, 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 non-recalled workers is much larger than the group of recalled workers.

Since the decomposition of the average scarring effect of displacement (on earnings) points towards human capital depreciation as one of the 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.13, 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 not help the recalled worker in the short run, and slightly benefit both the recalled and non-recalled worker in the long run. However, while the impact on the recalled worker is fairly small, the non-recalled worker benefits much more, both in absolute terms and relative to their baseline losses.

C.5 Alternative Calibrations

In this section, I consider the robustness of the simulation results in section 6 to an alternative calibration of the model. In particular, while it is reassuring that the model generates earnings losses for

	Regression-Based				Direct Counterfactual			
Channel	$k=0$	$k=1$	$k=5$	$k=10$	$k=0$	$k=1$	$k=5$	$k=10$
Match Loss	-0.089	-0.179	-0.124	-0.077	-0.02	-0.05	-0.023	-0.01
Selection Edu	0.003	0.008	0.004	0.000	-0.000	-0.001	-0.000	-0.000
Match Penalties	-0.001	-0.003	-0.002	-0.003	-0.000	0.000	0.001	0.001
Frictions	-0.141	-0.245	-0.093	-0.085	-0.149	-0.25	-0.013	-0.002
Bargaining	-0.002	-0.008	-0.006	-0.005	-0.002	-0.008	-0.005	-0.002
Human Capital (E)	-0.002	-0.008	-0.008	-0.006	-0.001	-0.005	-0.009	-0.006
Human Capital (U)	0.004	-0.001	-0.019	-0.028	0.000	-0.005	-0.028	-0.031
Human Capital (T)	0.000	0.000	-0.000	-0.000	0	-0.000	0.000	0.000
Total	-0.227	-0.436	-0.249	-0.203	-0.171	-0.32	-0.079	-0.05

Table C.5: *Summary of the decomposition of 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 12. The decomposition is generated by turning off the indicated channels one by one (presented here in reversed order), 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, with the regression-based numbers reflecting the corresponding decomposition depicted in figure C.11.*

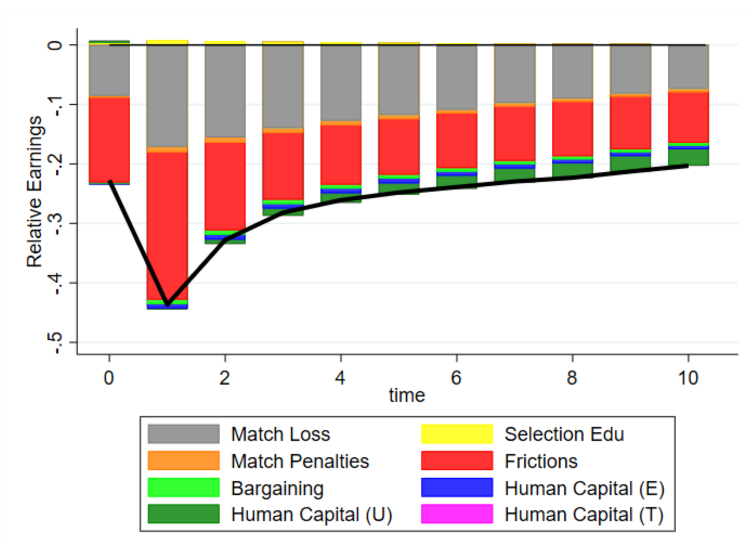


Figure C.12: *A decomposition of the average scarring effect of displacement on earnings.The black line represents the total earnings loss, and corresponds to the solid line in the left panel of figure 11. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals.*

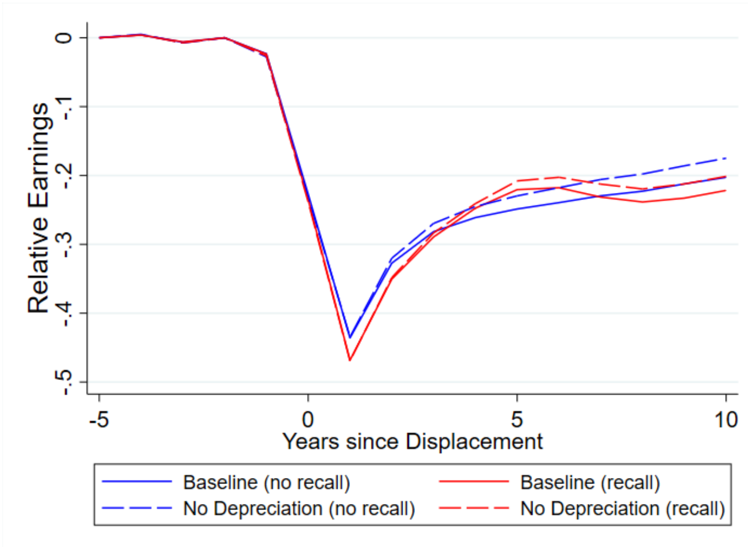


Figure C.13: *The effect of displacement on earnings relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data from the baseline model (solid, corresponding to figure 12) and a counterfactual in which nonemployed workers do not lose human capital during nonemployment ($\psi_u = \psi_r \psi_u = 0$, dashed).*

recalled and non-recalled workers along the lines of those observed in the data, it is worth analyzing whether targeting these empirical results directly might change the results. In particular, while the fit of the model to the empirical results may be similar, one might expect the decomposition of the earnings losses into different channels to change if different (or, in this case, additional) moments are targeted. In table C.6, I present the equivalent of table 3 for the calibration using these additional moments (adding in the results from table 3 for comparison). Note that the additional moments, described in some detail in section A.3.8, are not included in the table explicitly, as they are more naturally described in an event study graph (as done in figure C.14)

Comparing the estimated parameters in the final column of table C.6 to those in the baseline calibration, a few parameters stand out as being quite different. First of all, the marginal distribution of separation rates for the high education level is very concentrated towards low values for δ, as indicated by the high value of $\mu_{\delta,2}$, resulting in a very low unconciditional job loss rate for the highly educated worker. When it comes to match productivity y, the base (minimum) level of productivity is now higher for the highly educated worker $\mu_{y,2} > \mu_{y,1}$. Some of the resulting differences are strengthened by highly educated workers increasing (and decreasing) their human capital in larger steps (as the value of $\Delta_s(2)$ roughly doubled), while they are partially offset by high type workers starting at a much lower human capital level of $s_2 = -0.9$ rather than $s_2 = 0.48$ as in the baseline. The human capital generally changes less often than in the baseline model, as indicated by lower values of ψ_e and ψ_u, with the exception of workers expecting a

		Baseline		Alternative Calibration	
Description of Moment(s)	**Data**	**Model**	**Parameters**	**Model**	**Parameters**
Average rate of job loss, tenure 1-3.5y	0.0304	0.03	$\eta_\delta = 2.69$	0.042	$\eta_\delta = 3.92$
Average rate of job loss, tenure 3.5-6y	0.0158	0.025	$\mu_{\delta,1} = 13.9$	0.036	$\mu_{\delta,1} = 15.9$
Average rate of job loss, tenure 6-9y	0.0116	0.021	$\mu_{\delta,2} = 34.0$	0.030	$\mu_{\delta,2} = 164.3$
Average rate of job loss, tenure>9y	0.0075	0.016	$c^\delta = 0.15$	0.022	$c^\delta = 0.19$
Average rate of job loss, by education	0.0242	0.027		0.041	
	0.0204	0.011		0.003	
Subsequent separation, displacement	0.0806	0.047		0.095	
Subsequent separation, recall	0.1659	0.164		0.188	
p75-p25 ratio of wages	1.54	1.56	$\eta_y = 12.1$	1.36	$\eta_y = 7.39$
	1.6174	1.52	$\mu_{y,1} = 2.75$	2.02	$\mu_{y,1} = 0.92$
median-p25 ratio of wages	1.2416	1.24	$\mu_{y,2} = 2.68$	1.16	$\mu_{y,2} = 1.95$
	1.3113	1.23	$s_2 = 0.48$	1.40	$s_2 = -0.9$
Educational wage premium (all)	1.5324	1.59		2.09	
Educational wage premium (entry)	1.4682	1.51		1.36	
Job-to-job transition rate	0.0293	0.022	$\lambda_1^e = 0.042$	0.041	$\lambda_1^e = 0.054$
	0.0305	0.02	$\lambda_2^e = 0.046$	0.02	$\lambda_2^e = 0.126$
Displacement among job-to-job transitions	0.4106	0.492	$\lambda_1^{ug} = 0.43$	0.639	$\lambda_1^{ug} = 0.77$
	0.424	0.417	$\lambda_2^{ug} = 0.77$	0.104	$\lambda_2^{ug} = 0.7$
Average job finding rate	0.1445	0.217	$\lambda_1^u = 0.21$	0.158	$\lambda_1^u = 0.17$
	0.1484	0.201	$\lambda_2^u = 0.20$	0.124	$\lambda_2^u = 0.1$
Replacement rate	0.6	0.635	$b = 0.80$	1.739	$b = 1.92$
Yearly wage growth	0.0129	0.013	$\Delta_s(2) = 0.096$	0.013	$\Delta_s(2) = 0.2$
	0.0163	0.012	$\psi_e = 0.031$	0.027	$\psi_e = 0.025$
Pre- to post-layoff wage, duration<0.5y	-0.056	-0.027	$\psi_u = 0.158$	-0.039	$\psi_u = 0.097$
	-0.0143	-0.045	$\psi_r = 0.064$	-0.368	$\psi_r = 0.222$
Pre- to post-layoff wage, duration 0.5-1y	-0.0933	-0.062	$c^f = 0.166$	-0.056	$c^f = 0.586$
	-0.0464	-0.11		-0.446	
Pre- to post-layoff wage, duration 1-2y	-0.1229	-0.12		-0.078	
	-0.13	-0.14		-0.589	
Pre- to post-recall wage, duration 0.25-0.5y	0.0018	0.004		-0.043	
	0.0415	0.06		-0.056	
Pre- to post-recall wage, duration 0.5-1y	-0.0148	-0.01		-0.053	
	-0.0231	-0.05		-0.194	
Recall rate	0.0661	0.087	$\phi_1^f = 0.091$	0.238	$\phi_1^f = 0.228$
	0.0253	0.002	$\phi_2^f = 0.315$	0.124	$\phi_2^f = 0.149$
Recall materialization rate	0.3939	0.353	$\phi_1^r = 0.189$	0.201	$\phi_1^r = 0.137$
(Based on materialization in 2 years)	0.2458	0.245	$\phi_2^r = 0.079$	0.393	$\phi_2^r = 0.262$
Recall materialization rate	0.3498	0.401	$\phi^{rg} = 1.197$	0.236	$\phi^{rg} = 1.156$
(Based on materialization in 1 year)	0.2013	0.22	$\lambda^r = 0.913$	0.439	$\lambda^r = 0.557$
New job finding rate, expecting a recall	0.2927	0.238		0.060	
Wage of newly hired worker	0.6795	0.708	$\kappa = 0.93$	0.709	$\kappa = 0.68$
Wage of newly recalled worker	0.7086	0.808	$\kappa^r = 0.66$	0.761	$\kappa^r = 0.54$
Coefficient $\hat{\gamma}$ in equation (15)	-0.0215	-0.021	$\rho = -22.5$	-0.021	$\rho = -18.0$

Table C.6: *A summary of calibration moments, their values in the data and in the calibrated model, and corresponding parameter values, from the baseline calibration and an alternative calibration that directly targets empirical results.*

recall, who face a probability of human capital loss of $\psi_r \psi_u \approx 0.057$ rather than 0.01. In terms of transition rates, it is worth pointing out that the alternative calibration suggests a higher job-to-job offer arrival rate for the high education worker (0.126 instead of 0.046), but this does not seem to translate into a higher simulated job-to-job transition rate.

When comparing the parameters directly related to the recall possibility, it can be seen that the recall offer probability seems more balanced between the two types than it was in the baseline calibration. At the same time, the arrival rate of new job offers while expecting a recall is much lower in the alternative calibration. As a result of these two forces, the realized recall rate in the alternative calibration is much higher than in the data. Finally, it is worth noting that both post-recall penalties (on productivity and separation rate) are higher in the alternative calibration, although the higher penalty on productivity is not enough to substantially increase its impact on the recalled worker, as shown below.

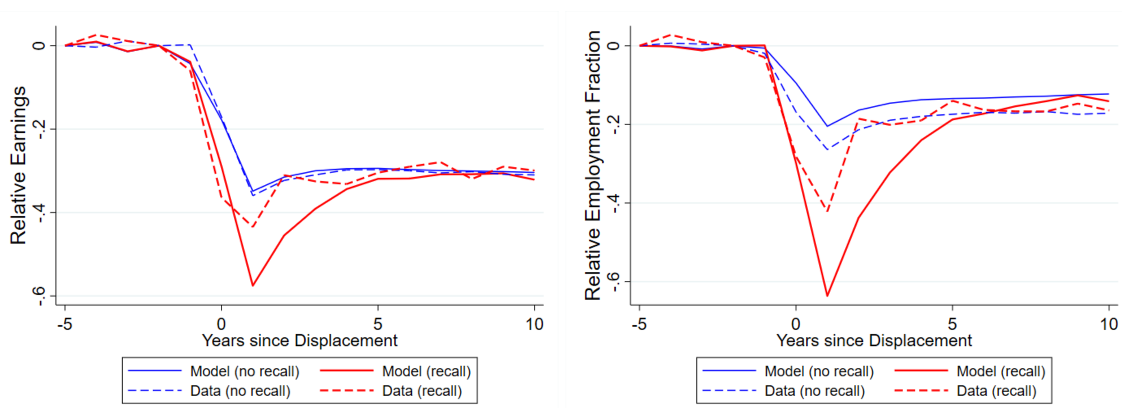


Figure C.14: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right) relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data from the alternative calibration model (solid) and using the data (dashed, corresponding to figure 7).*

In figure C.14, 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 7. As can be seen from figure C.14, the alternative calibration of the model matches that recalled workers do worse than non-recalled workers after displacement (in terms of their earnings and employment) in the short run, but considerably exaggerates that short-run difference. Unlike the calibration in the main text, however, the alternative calibration does well in matching the differences in the long run.

In figure C.15, I fully decompose the differences in estimated post-displacement earnings between recalled and non-recalled workers (as shown in the left panel of figure C.14), just like I did for the

Figure C.15: *A decomposition of the difference in the scarring effect of displacement on earnings between (ex-post) recalled and non-recalled workers, using the alternative calibration of the model. The black line represents the total difference, calculated as the difference between the solid red and blue lines in the left panel of figure C.14. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals.*

main calibration in figure 14. Comparing the decomposition in figure C.15 to the decomposition in figure 14 reveals a very similar picture. Indeed, it still holds that the main negative drivers for the recalled worker are the higher probability of subsequent separation and the differences in transition rates back into employment. The impact of the different transition rates is larger than in the baseline calibration, reflecting high immediate transition rates for regular unemployed workers $\lambda_{\varepsilon}^{ug}$ (which are higher than the baseline especially for the low education worker). This accounts for most of the aforementioned overshooting of earnings losses in the short run. The main positive driver is still the preservation of the match in the case of a recall. In fact, the other two positive drivers are associated with a much lower impact than in the baseline, due to higher human capital depreciation rates and lower new job offer arrival rates among workers expecting a recall (for the human capital and selection search channel, respectively). Finally, it is worth noting that the "Selection Choice" channel has largely disappeared, but it's impact is largely absorbed by the "Selection Education" channel.

In figure C.16, I further decompose the wage and employment differences into the same 9 channels used for the earnings decomposition above. As the black lines in the figure indicate, the wage differences between the recalled and non-recalled workers are generally positive and decreasing over time, whereas the employment differences are generally negative and increasing towards 0 over time. As can be

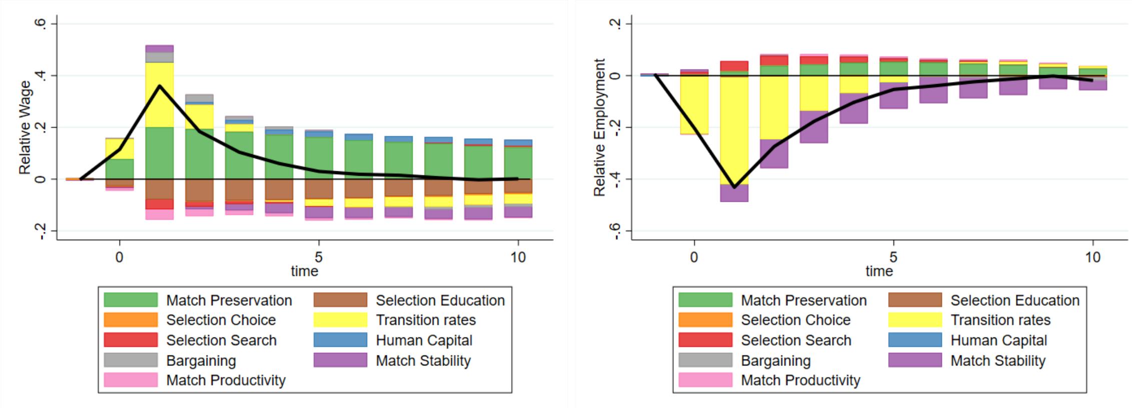


Figure C.16: *A decomposition of the difference in the scarring effect of displacement on wages (left) and employment (right) between (ex-post) recalled and non-recalled workers, using the alternative calibration of the model. The black line represents the total difference. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals.*

seen by comparing the left panel to the left panel of figure 16, the decomposition of the wage differences yield very similar conclusions as in the baseline calibration, with the exception of the aforementioned dampening of the "Human capital" and "Selection Search" channels, mostly offset by a decreased impact of the "Bargaining" and "Selection Choice" channels. Similarly, the decomposition of the employment differences primarily highlights the increased importance of the "Transition Rates" channel, which accounts for the full impact in the short run (with other channels offsetting each other), but gradually decreases in importance and is eventually overtaken by the "Match Stability" channel.

D Data Appendix

D.1 Individual Summary Statistics

	Frequency	Mean	Std.Dev.
Age	24.3m	41.309	9.92
Primeage (aged 35–60)	22.7m	0.6922	0.462
Gender (female)	24.3m	0.4635	0.499
Education (university)	22.9m	0.1561	0.363
Location (east)	19.4m	0.1891	0.392
Self-employed	6.2m	0.0075	0.086
Establishment size	20.3m	1,143.7	4,606.2
Establishment tenure (days)	20.5m	2,222.8	2,260.7
Job tenure (days)	20.5m	2,102.3	2,209.5
Yearly earnings (2015 Euros)[65]	22.5m	27,142.4	20,604.6
Separation	20.1m	0.1209	0.326
Displacement	19.8m	0.0149	0.121
Recall	2.8m	0.4128	0.492

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 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. 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 dataset is based on. Second, both workers residing in East Germany and female workers are slightly undersampled. Finally, separation, displacement, and recall (conditional on separation) rates are in line with those discussed in the main text in section 3.1.

Table D.2 provides an indication of how recalled and non-recalled workers are different in the data, compared to each other and compared to the non-displaced workers. As can be observed from the table, recalled workers are more likely than non-recalled workers to be male, with a lower education level, and coming from a smaller establishment. In line with figure 5, they tend to have lower recent earnings. As a result of this, they are also less likely to have a censored earnings observation.[66] Interestingly, non-recalled workers have higher recent earnings than non-displaced workers, which seems at odds with the observation

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

[66] In the data, the earnings are censored if the actual earnings exceed the threshold above which additional earnings do not lead to additional social security contributions.

from figure 4 that displacement rates decrease over the recent earnings distribution. One possible explanation for this is that many non-displaced workers do not meet the requirements to be included in the recent earnings distribution. Indeed, for non-displaced workers this variable is only slightly more than 50% filled, whereas for non-recalled (recalled) workers the variable is observed for 82% (92%) of the workers.

	Recalled		Non-Recalled		Non-Displaced	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Gender (female)	0.234	0.42	0.351	0.47	0.467	0.50
Education (university)	0.075	0.26	0.142	0.35	0.157	0.36
Establishment size	790	3,365	1,567	3,468	1,129	4,618
Establishment tenure (days)	3,350	1,716	3,750	2,153	2,220	2,269
Recent earnings (percentile)	41.66	29.0	59.96	25.8	50.26	28.89
Earnings censored	0.083	0.28	0.138	0.35	0.073	0.26

Table D.2: *Summary statistics using the yearly sample, by displacement and recall status. The table shows the estimated mean and standard deviation of a number of important variables, measured the year before displacement takes place (if relevant), using the main sample from SIAB (as defined in section 2, without any of the further restrictions imposed for the estimation).*

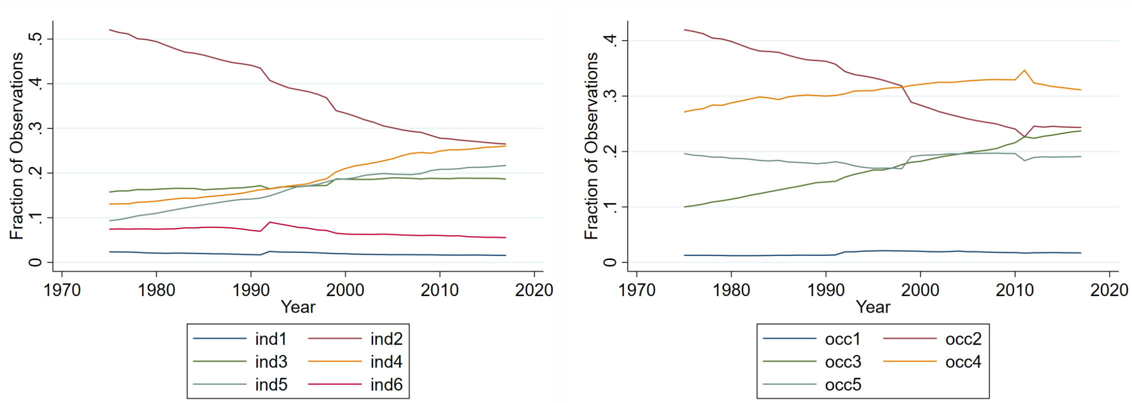


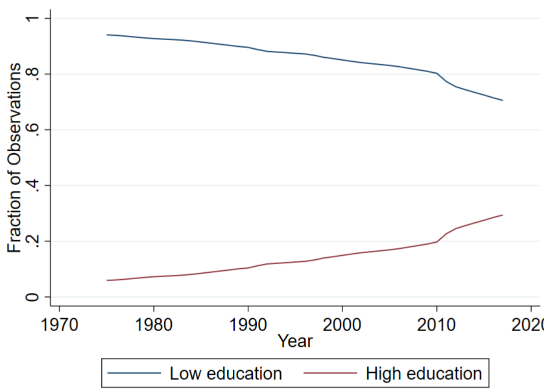
Figure D.1: *The fraction of observations by industry (left) and occupation (right) over time. The labels corresponding to the industry and occupation numbers can be found in footnote 67.*

Figure D.1 shows the fraction of observations accounted for by each major industry and occupation.[67] Looking at how the breakdown of industries and occupations evolves over time, it can be seen that

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

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.

While industry should in principle remain constant for recalled workers, this is not necessarily the case for occupation. After all, the worker could be recalled to the establishment to work in a different position. In practice, this does not seem to occur often: among separated workers who are recalled, the occupational switching rate (at the level of 3-digit occupations) is 11.3%, whereas the corresponding rate for non-recalled workers is 51.6% (with an accompanying major industry switching rate of 33.4%).



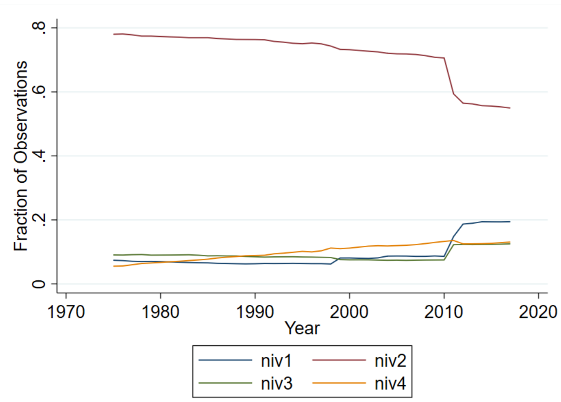


Figure D.2: *The fraction of observations by education (left) and occupational complexity (right) over time. For occupational complexity, a higher category corresponds to a more complex occupation.*

Figure D.2 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. 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.

D.2 Establishments in the Sample

In the previous subsection, I highlighted some of the differences between recalled, non-recalled, and non-displaced workers. However, one could imagine that some of these differences may also be driven by the establishments these workers separated from. In table D.3, I compare recalling, displacing and non-displacing establishments in the data on a limited number of variables. As can be seen in the table, establishments that recall workers generally tend to recall a large fraction (roughly 88% of observed displacements) of their displaced workers. Similarly, conditional on a mass layoff taking place, the size of the layoff tends to be very substantial, with over 70% of the workers observed at that establishment being separated. In line with the observations in the previous subsection, recalling establishments tend to be larger, and furthermore tend to have a higher median wage. Displacing establishments, in turn, tend to be larger and have higher median wages than the average establishment in the data.

	Recalling		Displacing		All	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Establishment size	188.1	1,070	138.7	482	73.7	348
Median wage (percentile)	39.82	27.5	47.2	31.1	52.6	28.3
Displaced (fraction)	0.775	0.31	0.724	0.32	0.013	0.11
Recalled (fraction)	0.881	0.24	0.063	0.24	0.063	0.24

Table D.3: *Summary statistics for establishment using the yearly sample, by displacement and recall status. The table shows the estimated mean and standard deviation of a number of important variables, using the main sample from SIAB (as defined in section 2, without any of the further restrictions imposed for the estimation) and taking out duplicate observations for establishments.*

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 the exiting establishments in the SIAB sample, in terms of industry, age, size, and exit type. I also include a similar description of exiting establishments in the LIAB sample, to stress the similarity between the two datasets in these dimensions, despite the differences highlighted in the previous section.

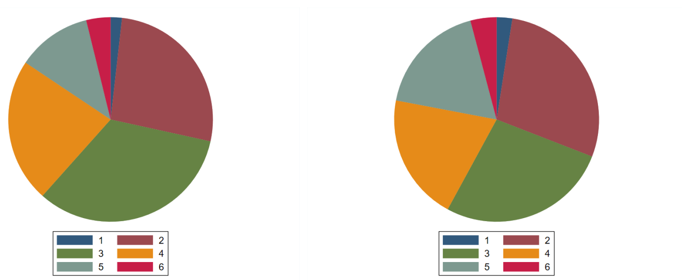


Figure D.3: *Breakdown of exiting establishments (left) and all establishments in the data (right) by major industry*[68].

As shown in figure D.3, 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 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.[69]

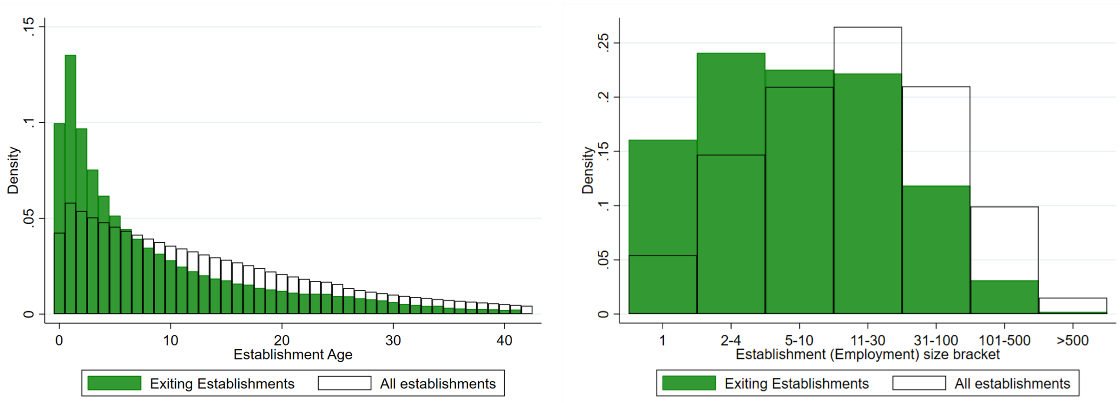


Figure D.4: *The distribution of the exiting establishments (green) and all establishments in the data (black), by establishment age (left) and establishment size group (defined as the number of employees at an establishment, right).*

The left panel of figure D.4 shows how old exiting establishments tend to be when they exit. 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 the right panel of figure D.4 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, however, there are relatively few large establishments in the data.

Since the dataset provides information on what happens to the majority of an establishment's

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

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

former employees after an establishment exits, it is possible to distinguish between several exit types. Using the definitions from Hethey and Schmieder (2010), I define three exit types. Type A exits are interpreted to be a consequence of an establishment ID change, a takeover, or a spinoff. In practice, this means that the exiting establishment had at least 4 employees, and either at least 80% of the (newly entered) establishment at which the majority of workers are re-employed consists of workers from the exiting establishment, or at least 80% of the workers from the exiting establishment find work at the same (previously existing) establishment but do not make up more than 80% of the employment at their new establishment. An exit is classified as type B (establishment death) if either the exiting establishment had 3 employees or less, or no more than 30% of the former employees of the establishment find employment at the same establishment (and if that establishment is an entrant, the former employees of the exiting establishment do not make up more than 80% of the entering establishment's employment). Finally, an exit is classified as type C if it does not satisfy the conditions for type A and B. 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.

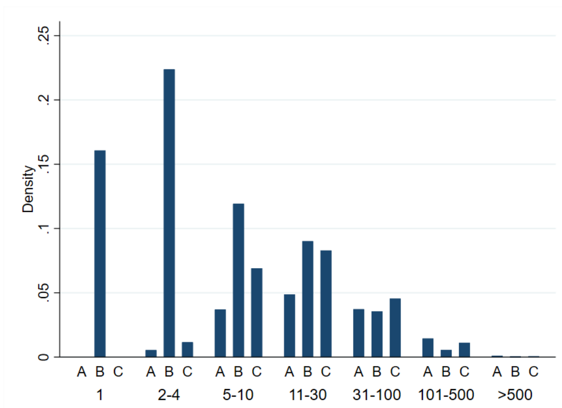


Figure D.5: *The distribution of exiting establishments over exit types A, B, and C (as defined in the text), and size group (defined by the number of employees at an establishment).*

Figure D.5 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 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

Section under (re-)construction

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 in section 4.

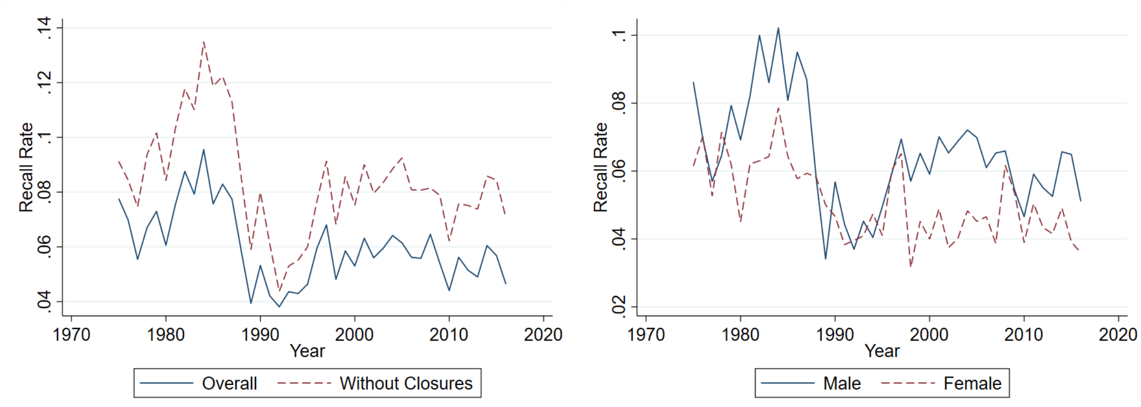


Figure D.6: *Left: The incidence of recall within 5 years of job loss over time, conditional on displacement, with and without including establishment closures in the definition of a displacement. Right: The incidence of recall within 5 years of job loss, conditional on displacement, over time and by gender.*

The left panel of figure D.6 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.6 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 and slightly higher during part of the period covered by the figure.

D.3.2 The Incidence of Displacement, using a Restricted Sample

Section under (re-)construction

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 the sample restrictions from sections 3.2 and 3.3.

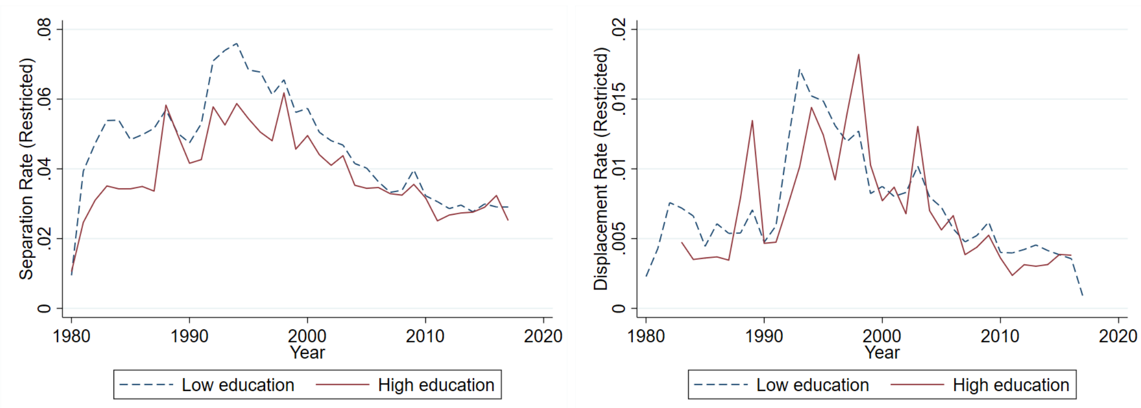


Figure D.7: *The incidence of separation (left) and displacement (right) by education level, over time, with restrictions on worker tenure.*

First of all, figure D.7 displays the restricted separation and displacement rates over time by education level, thus mirroring figure 2 from the main text (which does not impose restrictions on worker tenure). As can be observed by comparing the two figures, imposing restrictions on worker tenure dampens the differences between the low and high educated workers in terms of their separation and displacement rates in the second half of the covered period: while the workers with low educational attainment still have a slightly higher separation and displacement rate on average, the difference is very small.

As shown in figure D.8, the conclusion that the separation and displacement rates in general tend to be higher for individuals located lower on the (recent) earnings distribution continues to hold when worker tenure restrictions are imposed.

D.3.3 Further Observations on the Average Scarring Effect of Displacement

Section under (re-)construction

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

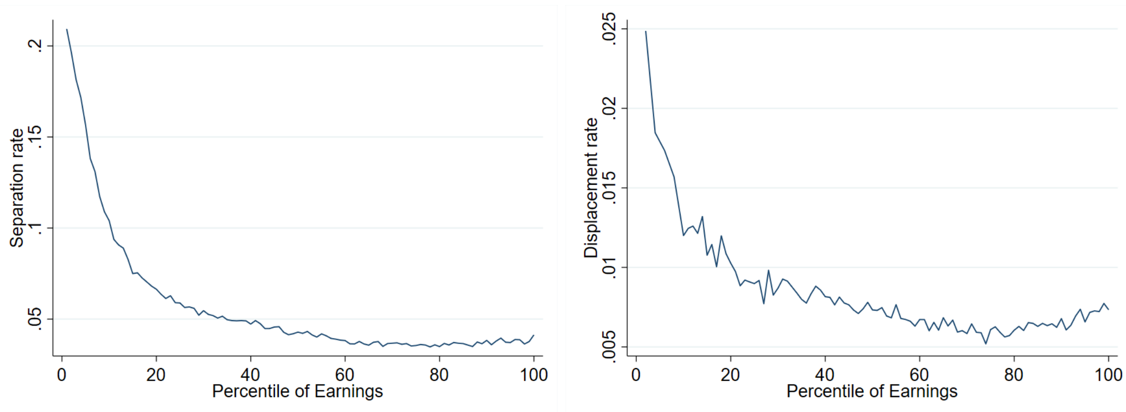


Figure D.8: *The incidence of separation (left) and displacement (right) over the earnings distribution, with restrictions on worker tenure.*

of the main text.

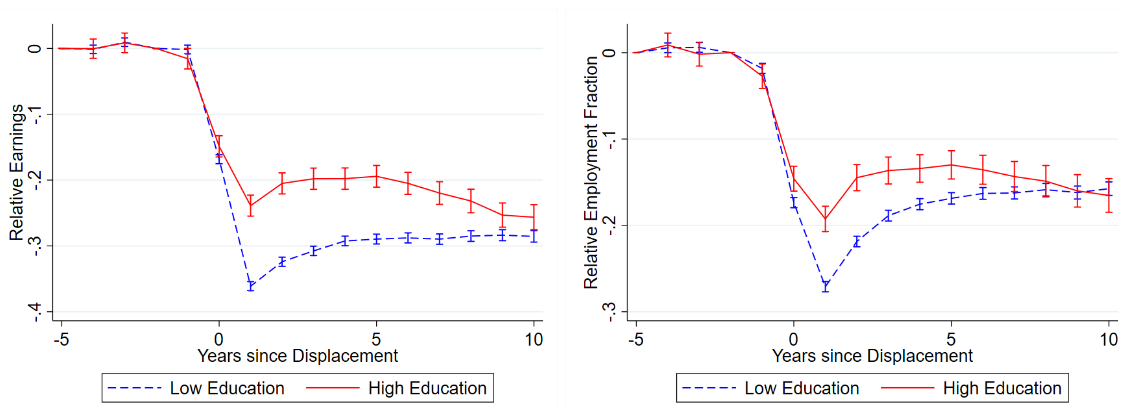


Figure D.9: *The effect of displacement on earnings (left) and employment fraction (right) by education level, relative to the control group of never-displaced workers, using estimated coefficients from equation* (1). *The error bars correspond to 95% pointwise confidence intervals.*

First of all, figure D.9 shows how the average scarring effect of displacement differs by education level (non-University and University), which is of particular interest since I use the education level as the fixed worker type when estimating the model.[70] Comparing the two educational groups, it can be observed that workers with a relatively low education tend to suffer from higher earnings losses in the short run, but the two groups slowly converge, such that the difference earnings losses 10 years after the displacement event is much smaller than the initial difference. This short-run difference is likely partially driven by a

[70]Note that I split the sample by education group for both the treatment and control group. In other words, the effects in figure D.9 are relative to workers in the same education group.

larger initial effect on employment fraction, which suggests that workers with a high education level find a new job faster (on average). In the long run, the two education groups converge, such that the earnings losses of workers with a relatively low education level are only slightly higher than those experienced by highly educated workers 10 years after the displacement takes place.[71]

D.3.4 Further Heterogeneity in the Scarring Effect of Displacement

Section under (re-)construction

In the main text, in section 3.3, I showed how the scarring effect of displacement on both earnings and employment for workers who are recalled to their previous employer compares to that of workers who are not recalled. 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.

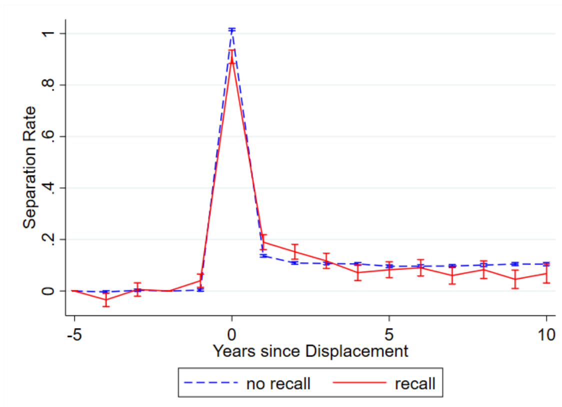


Figure D.10: *The effect of displacement on separation rates by ex-post recall status, relative to the control group, using estimated coefficients from equation* (1). *The error bars correspond to 95% pointwise confidence intervals. Left: estimation allowing for only one displacement per individual; Right: estimation allowing for multiple displacements per individual (classifying the worker according to their first displacement). Compared to figure 8 in the main text, this figure shows the full graph (starting from $k = -5$) rather than only the results from period $k = 1$ onwards.*

As the left panel of figure D.11 shows, the observation that recalled workers do worse in terms of

[71]The 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.

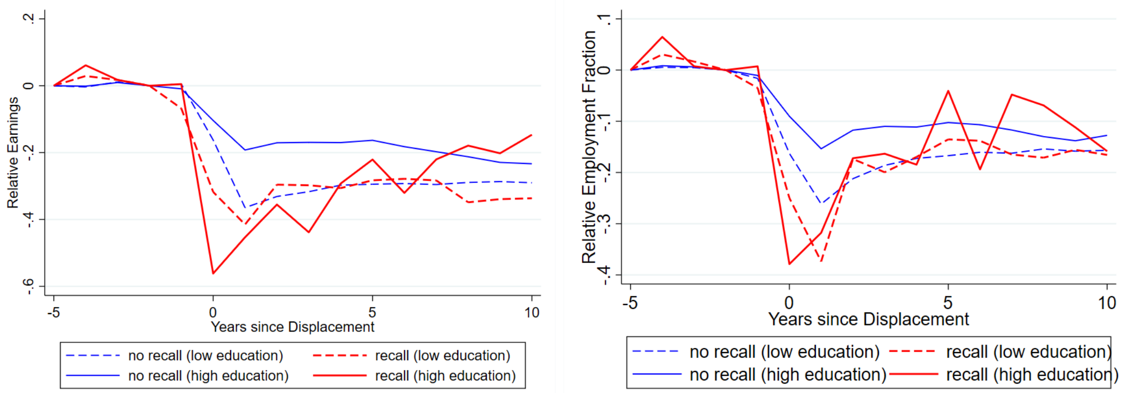


Figure D.11: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status and education level, relative to the control group of never-displaced workers, using estimated coefficients from equation* (1). *The error bars corresponding to 95% pointwise confidence intervals are omitted and available upon request.*

earnings after displacement holds across the education levels considered earlier (in section D.3.3). 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, and takes a longer time to dissipate. This increased volatility arises primarily because the highly educated recall group is fairly small in the SIAB data. 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, especially in the long run, but overall the comparison between recalled and non-recalled workers looks fairly similar for the two education levels.

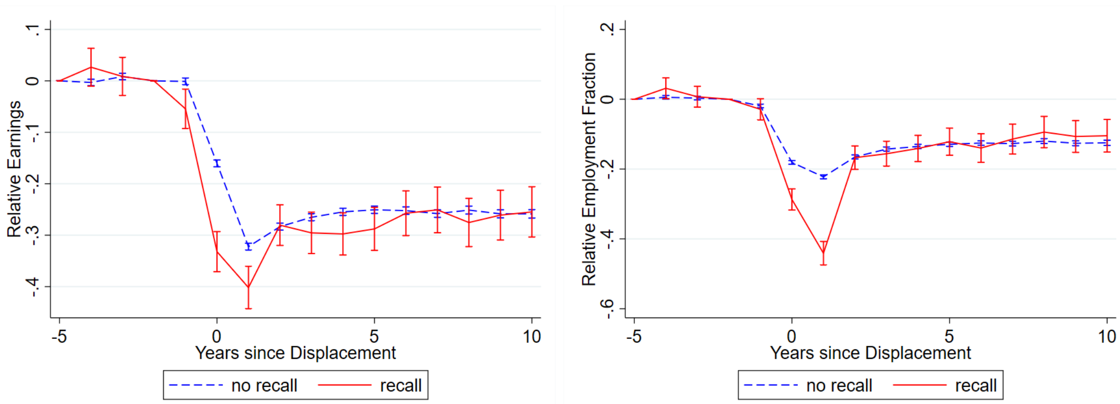


Figure D.12: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status, relative to the control group, using estimated coefficients from equation* (1). *The error bars correspond to 95% pointwise confidence intervals. Compared to figure 7 in the main text, the estimation here only uses earnings (and employment) from full-time jobs.*

In figure D.12, I repeat the analysis from figure 7 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.

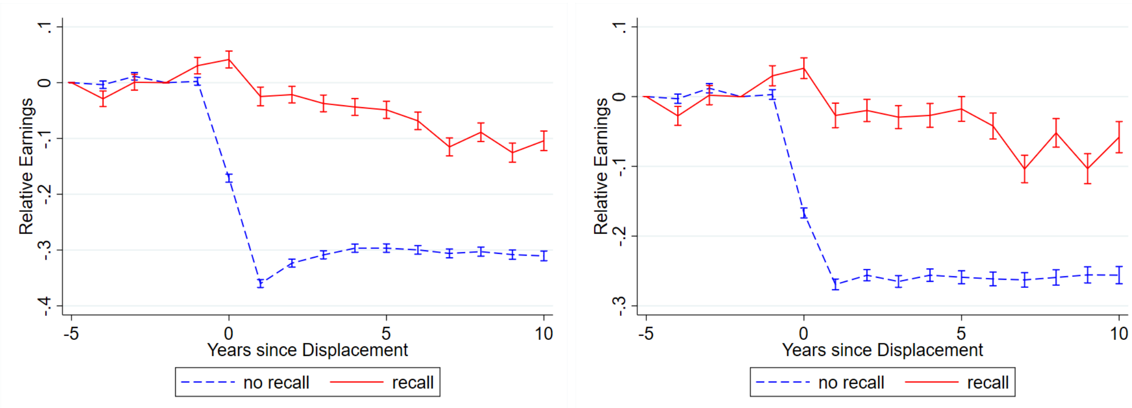


Figure D.13: *The effect of displacement on earnings, by ex-post recall status and relative to the control group, using estimated coefficients from equation* (1). *The error bars correspond to 95% pointwise confidence intervals. The estimation here replaces recalled workers with workers who were not displaced from the establishment that recalled some workers. The right panel furthermore only uses observations at the first employing establishment after displacement.*

Next, I investigate the role of the recalling firm by replacing the group of recalled workers with a group of non-displaced workers from an establishment that displaced and recalled some workers. As can be seen in the left panel of figure D.13, these workers are revealed to be on a downward trend in subsequent years, thus supporting the interpretation of these workers working at an unstable establishment. Indeed, if I restrict observations for both non-recalled and pseudo-recalled workers to those made at the first employing establishment after (pseudo-)displacement, this downward trend largely disappears. Notably, making this restriction also removes much of the recovery pattern among non-recalled workers.

In figure D.14, I show how the effects of displacement by ex-post recall status differ by age group. In particular, it can be observed that workers aged above 40 tend to face larger earnings losses in general, 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. Notably, however, the difference between recalled and non-recalled workers looks similar for both age groups.

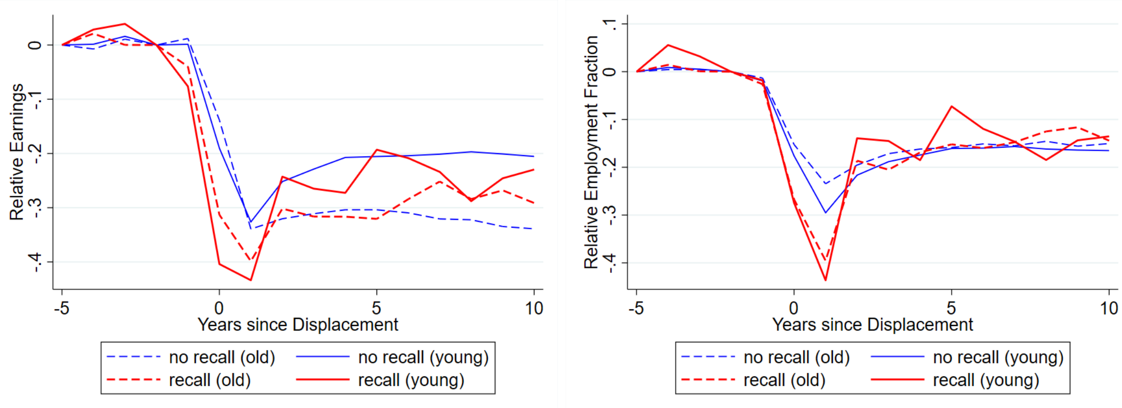


Figure D.14: *The effect of displacement on earnings (left) and employment fraction (right), by ex-post recall status and relative to the control group, using estimated coefficients from equation* (1). *The error bars are omitted for convenience (but available upon request). Compared to figure 7 in the 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.15, 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. In fact, when focusing on male workers the group of recalled and non-recalled workers are almost indistinguishable, similar to the observation in the main text, whereas for female workers the recalled workers experience larger earnings losses both in the short run and in the long run.

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 (but the difference is still clearly present) when focusing on Eastern Germany, the years prior to the Hartz reforms, low complexity occupations, or larger establishments. These results are available upon request.

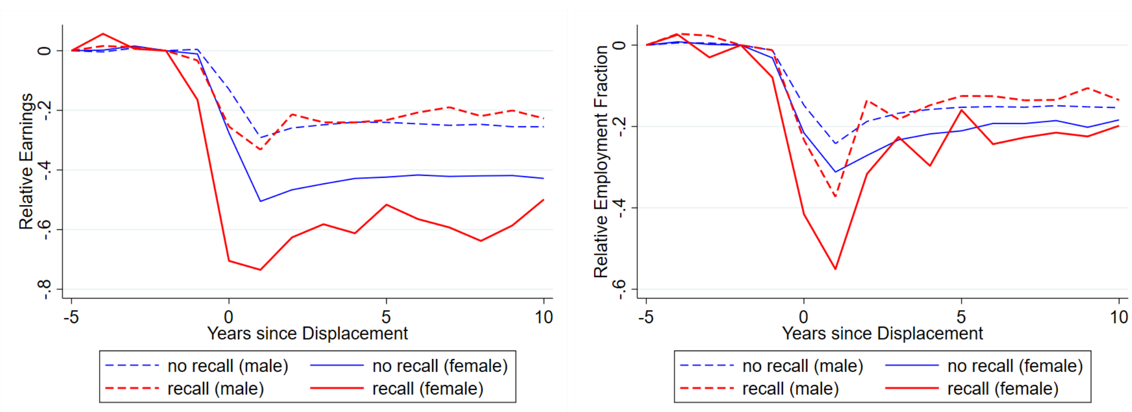


Figure D.15: *The effect of displacement on earnings (left) and employment fraction (right), by ex-post recall status and relative to the control group, using estimated coefficients from equation* (1). *The error bars are omitted for convenience (but available upon request). Compared to figure 7 in the main text, the estimation splits out the effect by gender, separately illustrating the effect for female workers (solid) and male workers (dashed).*