Recall and the Scarring Effects of Job Displacement

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Abstract:

This paper studies the scarring effect of job displacement by explicitly considering workers who return to their previous employer. Using German administrative data I show that these "recalled" workers face similar long-run earnings losses and slightly larger short-run losses compared to non-recalled workers. I develop a job search model that accounts for the heterogeneous effects by recall status. The estimated model shows that recalled workers' larger short-run losses are explained by differences in nonemployment duration, whereas long-term losses are similar because recalled workers' increased likelihood of repeated job loss is offset by reduced skills depreciation during the initial nonemployment spell.

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

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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 12% of displaced workers, and these workers are generally abstracted from in existing work, exploring these long-run effects by recall status (both empirically and through a model) contributes to a more complete understanding of the long-run effects of job loss. Furthermore, since recalled workers are not subject to all channels highlighted by the literature as explaining earnings losses (in particular loss of firm-specific human capital), earnings losses experienced by recalled workers are also informative on the sources of non-recalled workers' earnings losses.

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. I then separately estimate the scarring effect of displacement for recalled and non-recalled workers, 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-recalled workers. I estimate that recalled workers instead experience larger earnings losses in the short run than displaced workers who are not recalled, both compared to a control group of never-

[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. For German workers, Mavromaras and Rudolph (1998) find similar, albeit slightly lower, numbers. In Section 2.1, I show that I find recall rates ranging from 33 to 61% 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. (2023) omitted any worker who returns to work for the same employer in the first 10 years after displacement.

displaced workers. However, this difference disappears after a few years. In particular, 1 year after displacement a recalled worker earns approximately 43% less than a worker in the control group, whereas a non-recalled worker earns approximately 36.5% 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 the larger short-run earnings loss is primarily driven by employment. Furthermore, I find that a recalled worker is almost 6 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. 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 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.

Next, I develop a model that is able to explain the differences in earnings losses experienced by recalled and non-recalled workers, while still also matching the average scarring effect of displacement. In particular, I explicitly distinguish between workers who are expecting to be recalled and workers who are not (interpreting them as two different states). In addition, I use elements that have been used in existing models to explain the average scarring effect of displacement, such as the aforementioned human capital and heterogeneity of firms by productivity and separation rates (as in Jarosch, 2023). By allowing recalled workers to follow a different path than non-recalled workers (starting before the recall materializes), I 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 estimate the model using the German administrative data, and show that the model accounts for the 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 exacerbated 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 on their earnings loss (relative to that of non-recalled workers).

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 does not occur until several years after their initial displacement. This is because recalled workers experience a probability of human capital depreciation close to 0 during their initial nonemployment spell. Indeed, for recalled workers, the part of their long-run earnings losses driven by human capital loss is coming from subsequent separations rather than from 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 as 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.

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), and generally finds that workers who are displaced suffer a large and persistent earnings loss, and highlights the important role of working hours in the short run and wages in the long run for explaining these average losses (Lachowska et al., 2020).[3] Recently, the focus of this literature has shifted towards investigating heterogeneity in this scarring effect of displacement (see e.g. Guvenen et al., 2017, Athey et al., 2023, and Gulyas and Pytka, 2021). By focusing on ex-post recall status, my paper enriches this literature.

Additionally, the empirical section of this paper contributes to the growing literature analyzing the incidence and consequences of recalls. The topic of recall has been studied quite extensively, going back to studies such as Feldstein (1976) and Katz (1986), with recent work in Nekoei and Weber (2015) and Nekoei and Weber (2020) distinguishing between the expectation of recall and the actual materialization of recall.[4] The topic of recall has gained additional atten-

[3] Although the research mentioned in the main text focuses on US workers,Burda and Mertens (2001), Nedelkoska et al. (2015), and Schmieder et al. (2023) have found similar results in the context of Germany, whereas Bertheau et al. (2023) illustrate how effects differ between countries (although they do not include Germany).

[4] 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.

tion during the Covid-19 pandemic, with studies like Hall and Kudlyak (2022) and Forsythe et al. (2022) highlighting the unusually large role recalls played in labour market dynamics during early months of the pandemic. However, the body of existing research on how recalled workers differ from non-recalled workers in terms of their subsequent earnings is limited. In this paper, I contribute to this literature by focusing on providing a reliable estimate of the earnings consequences of displacement for recalled workers.

This paper also contributes to the literature providing theoretical analysis of the long-term consequences of displacement, and does so 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. Some recent work has attempted to resolve this issue with some success. The paper closest to mine in terms of the model is Jarosch (2023), who proposes a model in which firms differ not only in terms of productivity, but also in their separation rate, thereby allowing for workers to experience several subsequent displacements after the initial one (as observed earlier by Stevens, 1997). This, combined with depreciation of human capital, enables the model to reproduce the average earnings loss after displacement. 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).[5]

Finally, I contribute to the theoretical analysis of recalls by explicitly distinguishing between nonemployed workers expecting a recall and not expecting a recall. The existing body of literature that builds the possibility of recall into a model 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. (2023), and Gertler et al. (2022).[6] However, the existing work generally focuses exclusively on the impact of recall on labour market flows, and refrains from commenting on how workers' earnings are affected. Furthermore, the

[5] Huckfeldt (2022) shows that workers who switch occupations suffer larger losses than workers who stay in their former occupation. This may seem to contradict my result that recalled workers face similar earnings losses as 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 to the same occupation (although most of them do, as I show in Table 1). Indeed, as I do not explicitly consider occupational switching after displacement, this can 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).

[6] 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).

way recall is often modeled is by considering the current job to be "paused" while the worker is unemployed.[7] In my model, this is not quite the case, as I make a sharp distinction between workers with a potential recall and other unemployed workers, thus allowing for divergence between eventually recalled and non-recalled workers before the recall actually materializes.

The rest of this paper is organized as follows: Section 1 describes the data and methodology used to generate the empirical results, which are presented in Section 2. Section 3 then presents the search model, while Section 4 discusses the calibration of the model. Section 5 presents the quantitative results from the model. Finally, Section 6 concludes.

1 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 private sector workers (employed between 1975 and 2017), whose observations are matched with the relevant establishment data[8]. Each observation in the original data represents one spell of employment or non-employment, and is marked by a start and end date. From this spell-level data I 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.[9] Further restricting observations to individuals aged between 25 and 60 leads to a large dataset which nevertheless has some gaps in some workers' time series. These gaps mainly occur because individuals are not observed if they are employed for the government, self-employed, or not receiving any social security benefits during nonemployment.[10] The resulting (yearly) analysis dataset

[7] 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, 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.

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

[9] To be specific, the yearly dataset is used to obtain the empirical results from Section 2, whereas I use the quarterly dataset to obtain the moment values used to estimate the model in Section 4. 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 earnings in that period.

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

includes roughly 24.3 million observations. Further summary statistics on both workers and establishments, both across the entire sample and by ex-post recall status, are presented in Section 2.1, as well as in Appendix C.1 and C.2.

For the purpose of estimating the specification described below, I define a worker as separated in some period t if the 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 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.[11] I then define such a worker as displaced if the establishment either closes or experiences a mass layoff.[12] Following the literature, an establishment is defined to experience a mass layoff if the employment at the establishment in the next period is at most 80% of the establishment's maximum employment over the previous five years, and the establishment has a net outflow of at least 20% of its workforce in the displacement year. 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 worker 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).[13]

The empirical estimation results presented in the next section are based on the interaction-weighted estimator from Sun and Abraham (2021). This estimator allows the average effect of displacement to be different for workers displaced in different years, while all effects are still estimated in a single estimation (so that displaced workers do not appear in the control group in

[11]For example, I exclude "separations" that are caused by maternity leave or sick pay, and drop trainees, casual workers, and partially retired workers.

[12]I use an extension file that clarifies the reason for an establishment leaving the sample. In particular, I do not consider an establishment to be closed if a large portion of the workers at the establishment finds employment at a common establishment after the closure. See appendix C.2 for more details.

[13]I consider this second group to be (indirectly) 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 Appendices C.3.1 and C.3.3, however, excluding these workers does not substantially alter the recall rate or empirical estimation results.

a different year). In practice, I estimate the average effect of displacement using equation (1), whereas equation (1') is used to estimate the effect of displacement by recall status:

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

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

In equation (1), i refers to the individual and t to the year. The dependent variable, e_{it}, refers to the outcome variable of interest. In most cases, this is the individual's yearly earnings or the fraction of the year spent in an employment relationship. Other outcome variables include the (yearly) job loss rate and the (yearly) average daily wage. Explanatory variables include an individual fixed effect α_i and a time fixed effect γ_t, as well as an error term u_{it}. The variables of interest are a series of indicator variables $D_{it}^{C,k}$, which equal 1 if individual i from cohort C was displaced in period $t-k$. A cohort C is defined as the calendar year of displacement, 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. I follow the discussion in Borusyak et al. (2024) 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 $k = -2$. The second omitted period is the earliest period, $k = -5$, thereby maximizing the distance between the two omitted periods and making the results less sensitive to fluctuations in these periods.

When I analyze the effects of displacement by recall status, I estimate equation (1'). This equation is an adjusted version of equation (1), in which I allow the effect of displacement to be different for workers with a different ex-post recall status, as denoted by superscript r on the indicator variable $D_{it}^{C,r,k}$ and its corresponding coefficient $\delta_k^{C,r}$.

Estimation of equation (1) yields 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 interpret 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 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 also form (point-wise) confidence intervals for the resulting values $\hat{\delta}_k$.[14]

When estimating equation (1) or (1'), I 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 attachment to the job), and working at establishments with at least 50 employees (to avoid classifying a job loss as a mass layoff when only a limited amount of workers lose their job).[15] However, my estimation differs from the existing literature in using the interaction-weighted estimator rather than a "standard" two-way fixed effects estimation.

2 Empirical Results

2.1 The Incidence of Displacement and Recall

Before analyzing the effect of displacement on earnings, it is worth investigating how common a separation or displacement event (as well as subsequent recall) is. This subsection presents separation, displacement, and recall rates for the entire sample.[16]

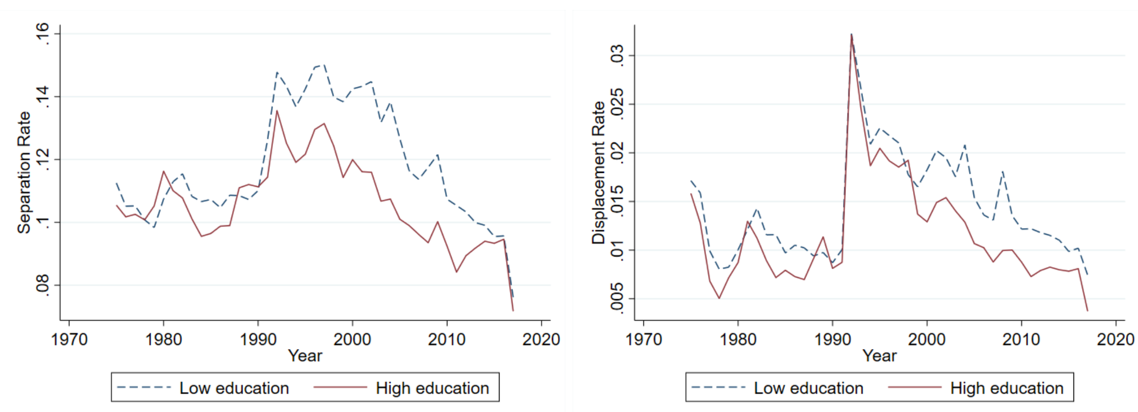


Figure 1: *The incidence of separation (left) and displacement (right) over time, by education level.*

First of all, Figure 1 displays the separation and displacement rates over time by education group, which I use as the worker type in the model estimation in Section 4. Education is

[14] After estimating equation (1'), the same procedure is followed for recalled and non-recalled workers separately, thus resulting in two sets of values, $\hat{\delta}_k^r$ for $r = \{0, 1\}$.

[15] In Appendix C.3.3, I show how the results presented below are affected by requiring only 1 year of pre-displacement establishment tenure.

[16] All graphs in this subsection are generated using a sample in which 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" are available upon request.

defined as Non-University (low) or University (high), with roughly 85% of the workers categorized in the first group. For low-educated workers, the separation rate averages roughly 12% whereas the displacement rate is roughly 1.5% on average. For highly educated workers these rates are slightly lower. All rates display substantial variation over time, and in particular the aftermath of the German reunification in 1990 is clearly visible.[17] While separation and displacement rates peak around recessions, these peaks are relatively mild in magnitude. For example, separation and displacement rates increased during the Great Recession but remained below pre-2005 levels.

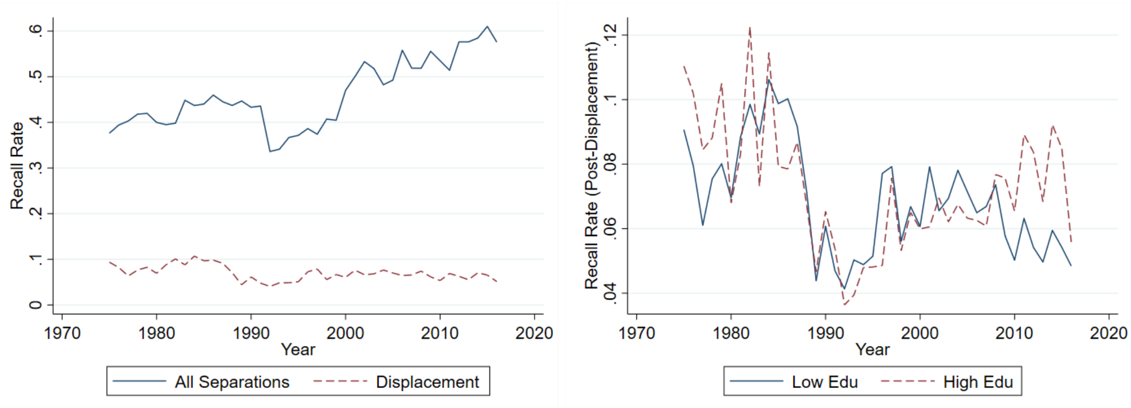


Figure 2: *Left: The incidence of recall within 5 years of job loss over time, unconditionally and conditional on displacement. Right: The incidence of recall within 5 years of job loss, conditional on displacement, over time and by education level.*

Next, Figure 2 shows the incidence of recall (within 5 years), unconditionally or conditional on displacement. The unconditional incidence of recall is fairly high, taking values between 33% and 61%, which is in line with existing work such as Fujita and Moscarini (2017) and Mavromaras and Rudolph (1998). Notably, while there is a clear upward trend visible in the unconditional incidence of recall since the 1990s, this is not the case for the recall rate conditional on displacement (which is the focus throughout this paper). The recall rate conditional on displacement is much lower, and fluctuates between 4% and 8% in recent decades. This indicates that generally roughly 6 to 7 percent of the workers who are displaced (including workers whose employing establishment shut down) return to their previous employer. The right panel of Figure 2 shows that the recall rates (conditional on displacement) are fairly similar for the two education levels. In Appendix C.3.1, I discuss how displacement and recall rates vary over the earnings distribution, and

[17] 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. Graphs separately plotting the separation and displacement rates for workers in East and West Germany are available upon request.

show how observed rates are affected by removing establishment closures or indirect recalls.

	Recalled		Non-Recalled		Full Sample	
	Mean	(Std.Dev.)	Mean	(Std.Dev.)	Mean	(Std.Dev.)
Gender (female)	0.286	(0.45)	0.436	(0.50)	0.464	(0.50)
Age	39.74	(9.36)	38.87	(7.86)	41.29	(9.91)
Education (university)	0.063	(0.24)	0.125	(0.33)	0.156	(0.36)
Establishment size	268.8	(1,563)	633.9	(2,136)	1,144	(4,606)
Establishment tenure (days)	1,092	(1,388)	1,344	(1,742)	2,223	(2,261)
Yearly earnings (2015 Euros)	17,571	(14,509)	22,302	(19,202)	27,142	(20,605)
Occupational Change (3-digit)	0.135	(0.34)	0.505	(0.50)	-	-

Table 1: *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 1, without any of the further restrictions imposed for the regression-based analysis).*

Table 1 provides an indication of how different recalled and non-recalled workers are, compared to each other and compared to the full sample.[18] The table shows that recalled workers are more likely than non-recalled workers to be male, have a lower education level, come from a smaller establishment, and tend to have lower yearly earnings from employment. Furthermore, non-recalled workers are more likely to switch occupations (at the 3-digit level) upon being displaced than recalled workers, indicating that recalled workers often (but not always) return to a similar job when being recalled. This continues to hold if I focus on 1-digit occupations, where the occupational mobility rate is 5.7% for recalled and 20.9% for non-recalled workers.

	Time to re-employment				
Time to re-separation	< 1mo	1-3mo	3-6mo	6-12mo	> 12mo
< 1 month	0.015	0.012	0.017	0.023	0.010
1-3 months	0.025	0.028	0.038	0.063	0.019
3-6 months	0.038	0.027	0.053	0.070	0.016
6-12 months	0.059	0.062	0.213	0.045	0.024
> 12 months	0.009	0.006	0.041	0.050	0.034

Table 2: *Distribution of (ex-post) recalled workers over different combinations of time to re-employment and time to re-separation (in months). The table lists the fraction of workers falling into the relevant combination of categories, relative to the total number of displaced and subsequently recalled workers for whom both re-employment and re-separation is observed.*

[18]Note that the "Full Sample" also includes full-year nonemployed workers (with the exception of the summary statistics on establishment-related variables, which are missing for these workers), and thus also includes workers who will not be in either of the treatment and control group in the regression-based analysis.

One potential concern when discussing the incidence (and consequences) of recall is that these recalls may be driven by seasonal workers. While this issue is likely to be less important when considering displacements rather than all separations (as displacements are defined using establishment-level data measured on a yearly basis), it is worth investigating how many recalls in my sample of displaced workers may be driven by seasonality. In Table 2, I document how displaced and subsequently recalled workers are spread among different categories of time to re-employment and time to re-separation (measured from the point of re-employment).[19] A comparable tabulation for non-recalled workers can be found in Appendix C.3.1. If the recall reflects seasonality, I would expect the time to re-employment and the time to re-separation to add up to approximately a year, with time to re-employment being at least 3 months and at most 12 months. Based on Table 2, this applies for up to 38% of recalled workers. I show in Appendix C.3.3 that the estimation results discussed below are not driven by these potentially seasonal workers.

2.2 The Average Scarring Effect of Job Loss

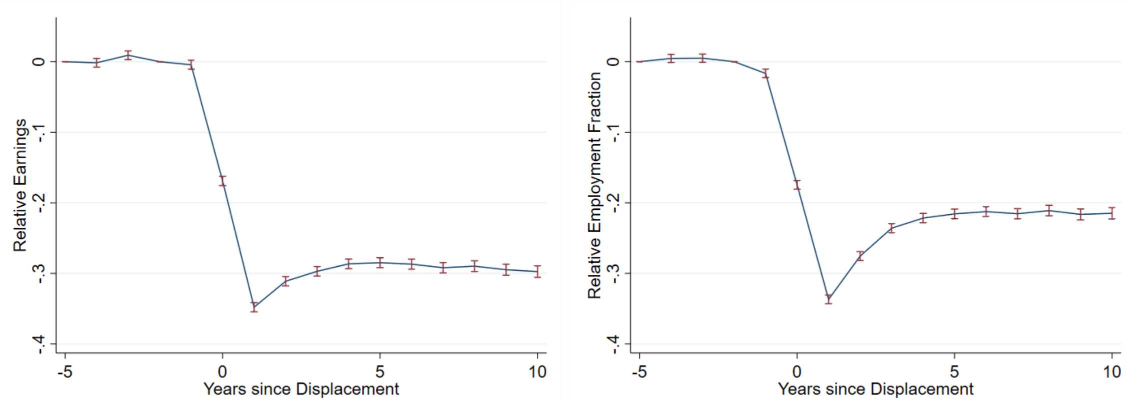


Figure 3: *The effect of displacement on earnings (left) and employment fraction (right), relative to the control group of never-displaced workers, using estimated coefficients from equation* (1). *The error bars correspond to 95% pointwise confidence intervals*

Figure 3 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 1. Workers who are displaced lose roughly 30-35% of their earnings in the short run.[20] This earnings loss is shown to be quite persistent, with

[19] Workers who are listed as being re-employed within one month are by definition workers who were indirectly recalled. Using time to recall instead of time to re-employment yields similar conclusions, as seen in Appendix C.3.1.

[20] To be 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.

these displaced workers still earning 30% less 10 years after the job loss took place. For employment fraction a similar pattern arises, with short-run losses of approximately 30-35% and long-run losses of more than 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 (e.g. Schmieder et al., 2023) for short-run losses, but not for long-run losses: While 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, with both earnings and employment remaining substantially below that of the control group. This is quite a striking difference, and suggests a larger role for employment in explaining the long-run effects of displacement than traditionally proposed in the literature, even if a substantial role for wages remains as well, as confirmed in Appendix C.3.2.[21]

2.3 The Scarring Effect of Displacement for Recalled Workers

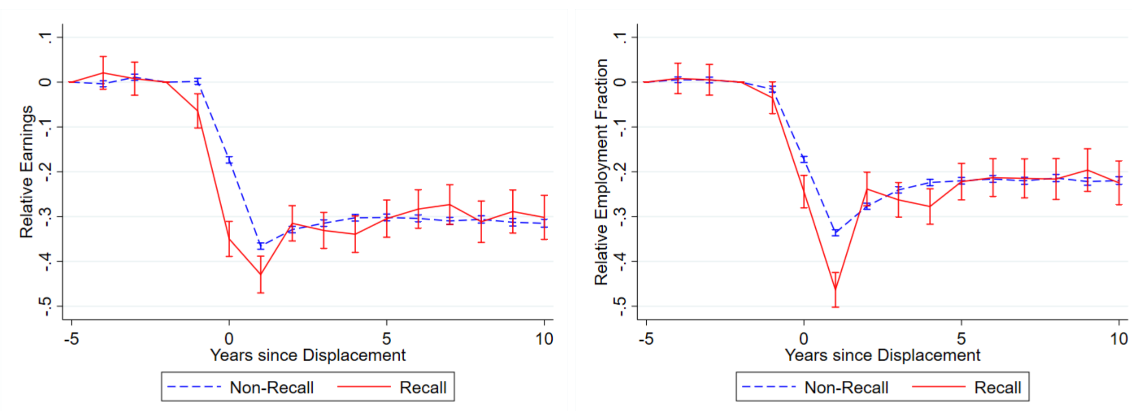


Figure 4: *The effect of displacement on earnings (left) and employment fraction (right) by ex-post recall status, relative to the control group of never-displaced workers, using estimated coefficients from equation* (1'). *The error bars correspond to 95% pointwise confidence intervals.*

In Figure 4, I show how the effects of displacement on employment and earnings differs by ex-post recall status.[22] The results show that workers who are recalled suffer from similar earnings losses compared to non-recalled (displaced) workers, and in fact do slightly worse in the short run.

[21] When comparing results to those in the existing literature, it should be noted that the estimates presented in this paper differ slightly in their interpretation, due to the use of a slightly different estimation method. In particular, while the one-shot estimation used in this paper implies that the control group consists of never-displaced workers, estimates using a standard TWFE estimation method can be interpreted as relative to workers who were not displaced *in a particular year of interest*. As some of those workers may be displaced in a later year, this can potentially explain the stronger recovery seen in estimates obtained using a standard TWFE estimation.

[22] 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,

Similarly, recalled workers tend to do worse in the short run when it comes to days employed in the year. In fact, the difference between recalled and non-recalled workers is larger for employment than it is for earnings, thus suggesting that this difference is partially offset by recalled workers doing better in terms of wages in the short run (which I confirm in Appendix C.3.3).

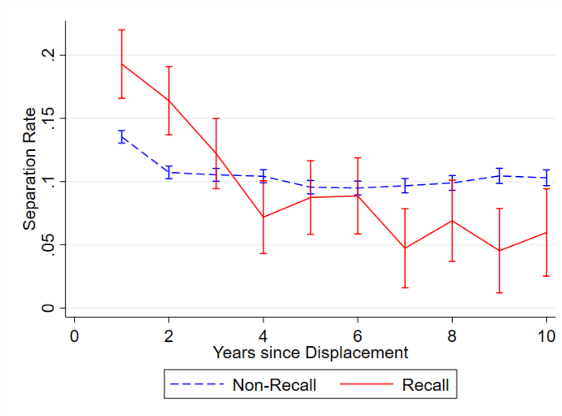


Figure 5: *The effect of displacement on separation rates by ex-post recall status, relative to the control group of never-displaced workers, using estimated coefficients from equation* (1'). *The error bars correspond to 95% pointwise confidence intervals. The estimation allows for multiple displacements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

In Figure 5, I show the estimated effect of ex-post recall status on subsequent job loss rates. Recalled workers are more likely to be separated again shortly after being recalled. While non-recalled workers are roughly 13.5 percentage points more likely to be separated than the control group one year after their initial displacement (and 10 to 11 percentage points more likely two and three years after displacement), recalled workers are more than 19 percentage points more likely than the control group to be separated again in the first year after displacement (and 16 and 12 percentage points two and three years after displacement). This seems to indicate that recalled workers return to an unstable job.

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, e.g. because they anticipated their impending layoff and already searched for a new job prior to the materialization of the layoff.[23]

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.

[23]See Simmons (2024), who investigates this issue in the context of the United States, United Kingdom, and other European countries.

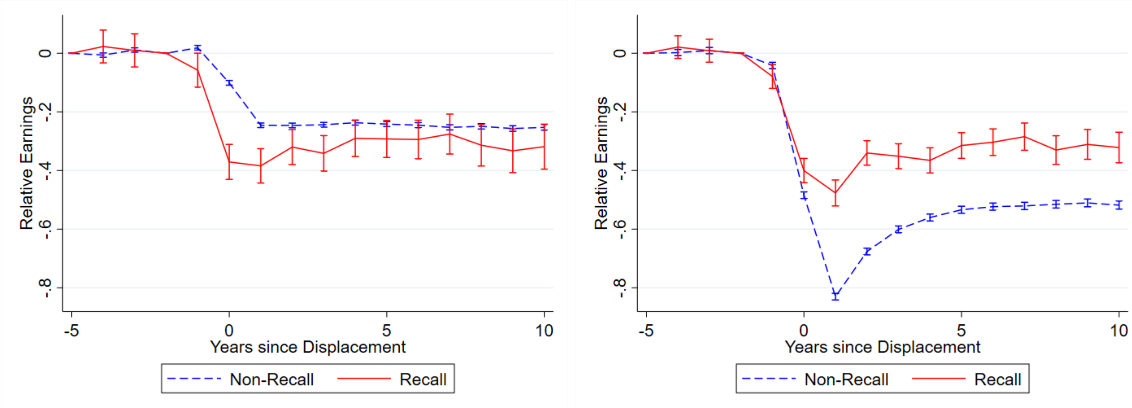


Figure 6: *The effect of displacement on earnings by ex-post recall status, relative to the control group, using estimated coefficients from equation* (1'). *Effects are estimated separately for workers who transition directly (within 30 days, left) and workers who spend some time in nonemployment (right) after their displacement. The error bars correspond to 95% pointwise confidence intervals.*

Figure 6 shows 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.[24] This is primarily driven by the earnings losses of non-recalled workers differing substantially between the two groups, whereas the earnings losses of the recalled workers do not differ much. As a result, the earnings losses for recalled workers are worse than those experienced by non-recalled workers when conditioning on experiencing at most 30 days of nonemployment, whereas the opposite is true when conditioning on experiencing more than 30 days of nonemployment. In aggregate, these two results cancel out, resulting in similar earnings losses on average.

3 Model

In this section, I develop a search model of the labour market, with the aim of explaining the heterogeneity I observed in Section 2. In order to do so, the discrete-time model discussed below 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 may be recalled to be in a different state, I can account for differences between recalled and non-recalled workers, both after their non-employment spell and during their non-employment spell.

[24]Note that due to the definition of recall, 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 following year).

3.1 Environment

The economy is populated by workers and firms, both of which differ in two dimensions.[25] In line with Jarosch (2023), firms differ in productivity y and separation risk δ, as summarized by vector $\theta = [y, \delta]$. Workers differ in human capital s and type ε, and can be either employed, unemployed, or non-employed with a potential future recall. Worker type ε is fixed over time, and interpreted as the worker's education when calibrating the model. Human capital s evolves over time, increasing by $\Delta_s(\varepsilon)$ with probability ψ_e when employed, and decreasing by $\Delta_s(\varepsilon)$ when non-employed, with probability ψ_u if unemployed or $\psi_r \psi_u$ if non-employed with a potential recall.[26]

3.1.1 Firms

Each firm can hire at most one worker. 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. 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 unemployed and unmatched status. However, with probability ϕ_ε^f the job destruction may only be temporary and the worker can choose a potential recall.[27] Nevertheless, the productivity of the match is reduced by c^f upon recall, 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.[28] The intuition behind the recall productivity penalty is that the firm is likely to incur costs for firing and re-hiring the worker and may have undergone 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).[29] The penalty on the separation rate directly reflects the observation in Section 2.3 that recalled workers are more likely to be separated again within a year of being re-employed, which I interpret as evidence of the worker returning to an unstable firm.[30]

[25]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 refer to the production entity as a firm.

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

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

[28]Note that the productivity and separation rate penalties are only applied once, so these penalties do not compound if the worker is separated and recalled a second time.

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

[30]This interpretation of the penalties is further supported in Appendix C.3.3, where I show that non-displaced workers from these firms tend to experience a downward trajectory in their earnings in the years after the (pseudo-

3.1.2 Workers

Workers are assumed to be infinitely-lived, and unable to transfer resources between periods. I assume a log utility function, with a discount rate β. Each worker enters the market as unemployed and with human capital s_{ε}. Their education type ε is determined prior to entering the labour market. An unemployed worker meets a firm with probability $\lambda_{\varepsilon}^{u}$, and this firm is drawn from the distribution $G_{\varepsilon}(\theta)$, where ε changes the marginal distributions of δ and y, thus enabling different worker types to meet firms with different characteristics on average, but not restricting the range of δ to certain worker types.[31] 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). I set this value equal to a fraction of the lowest possible production a worker could produce in a match: $b(s) = bp(s, y^{min})$. This proxies a setting in which the unemployment benefit depends on the last earned wage, while not ruling out the scenario where unemployed workers reject some job offers.[32]

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 $\lambda_{\varepsilon}^{e}$, and if she does the offer is again drawn from distribution $G_{\varepsilon}(\theta)$. Upon receiving such an offer, the employed worker can decide to switch to the new firm or to reject the offer. If the worker decides to reject the offer, it can be used to re-bargain with the current employer.

If the worker is non-employed with a potential recall, she receives $b(s)$ (just like the regular unemployed worker). While she is non-employed with a potential recall, the worker's human capital decreases by $\Delta_s(\varepsilon)$ with probability $\psi_r\psi_u$, reflecting that a worker with a potential recall may either experience faster ($\psi_r > 1$) or slower ($\psi_r < 1$) depreciation of human capital than a regularly unemployed worker. In particular, one could argue that the depreciation is faster because the worker has less incentives 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

)displacement as well.

[31] 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 $\lambda_{\varepsilon}^{ug}$. This can be thought of as a simplified way of capturing that workers may anticipate the impending layoff and may therefore search (and find) a new job before the layoff actually materializes, as pointed out in Simmons (2024), and briefly discussed in Section 2.3.

[32] 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 $\lambda_{\varepsilon}^{u}$ and $\lambda_{\varepsilon}^{e}$, such that the unemployed worker accepts any job offer, as in the model in Bagger et al. (2014).

might be employed by in the future, and therefore can keep her job-specific knowledge from depreciating. The worker is recalled to her previous match with probability ϕ_{ε}^{r} every period. When the recall materializes, the firm characteristics change as described in subsection 3.1.1.[33] If the recall does not materialize in a period, the worker meets a new employer with probability $\lambda^r \lambda_{\varepsilon}^{u}$, where λ^r is expected to be below 1 (but not restricted as such). If the worker meets a new employer, this employer is again drawn from distribution $G_{\varepsilon}(\theta)$, and the worker can decide whether to accept the offer (leading to a wage w). Finally, if the worker does not get recalled and also does not meet a new firm (or rejects the offer from the new firm), she can decide move to the regular state of unemployment, thus giving up the potential recall.

3.1.3 Wage Setting

In determining the wages, I follow a similar procedure to Bagger et al. (2014). At the time of bargaining the worker and firm agree on a piece-rate $R = e^r$, and the worker receives a wage of $w = Rp(s, y) = e^{r+s+y}$ until either the match is destroyed (because of separation or because the worker switches firms) or until the worker receives an offer that triggers re-bargaining.

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

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

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 ($\hat{s}$).[34] Equation (2)

[33]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.

[34]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 (6) I set $\hat{s} = s$.

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 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 non-employment with a potential recall, $T(s,\theta)$, thus reflecting that upon rejecting the offer, the worker can choose to give up the potential recall and move to regular unemployment.[35] Furthermore, since the maximum value obtained from the match changed due to the penalties on production and separation rate, the firm characteristic used 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).[36]

3.2 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

[35]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.

[36]Note that if the worker finds a new job while still having a potential recall, the corresponding value $W(s,s,x,f)$ follows equation (3), replacing the value of the outside option by $\max\{U_\varepsilon(s), T_\varepsilon(s,\theta)\}$.

second stage, recall materialization, separation, and recall choice take place.[37] In the third stage, workers may receive an offer from a firm (unless they moved to or from the potential recall state in the previous stage), after which they choose to accept or reject it, (re-)bargaining takes place, and non-employed workers with a potential recall may choose to move to permanent unemployment. Finally, production and wages (and unemployment benefits) are realized at the end of the period.

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). The value of unemployment U for a worker of type ε with human capital s can be written out as follows:

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

Here, the set $\Theta^u_\varepsilon(s)$ is the set of firm characteristics of the firms from whom the worker of type ε would accept an job offer if her current human capital level is s. Using equation (3), this set can be specified as $\Theta^u_\varepsilon(s) = \{x \in [0, 1] \times \mathbb{R}_+ : W^{max}_\varepsilon(s, x) \geq U_\varepsilon(s)\}$. As shown in Appendix A.3, equation (3) can be used to rewrite (7) in terms of W^{max}, U, and parameters only:

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

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

$$\begin{aligned} T_\varepsilon(s, \theta) = \ln(b_\varepsilon(s)) + \beta \mathbb{E}_{s'|s,r,\varepsilon} \Bigg\{ \phi^r_\varepsilon W_\varepsilon(s', s', \theta', r) + (1 - \phi^r_\varepsilon)\lambda^r \lambda^u_\varepsilon \int_{x \in \Theta^r_\varepsilon(s', \theta)} W_\varepsilon(s', s', x, f) dG_\varepsilon(x) \\ + (1 - \phi^r_\varepsilon) \left(1 - \lambda^r \lambda^u_\varepsilon \int_{x \in \Theta^r_\varepsilon(s', \theta)} dG_\varepsilon(x)\right) \max\{T_\varepsilon(s', \theta), U_\varepsilon(s')\} \Bigg\} \end{aligned} \tag{9}$$

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 still having the potential of a recall may use either the value of unemployment or the

[37] 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^r_ε and job search is realized, this second type of recall choice does not take place until the end of the third stage.

value of non-employment with a potential recall as their outside option, thereby also allowing for the set of accepted offers $\Theta^r_\varepsilon(s',\theta)$ to be slightly different from the corresponding set for an unemployed worker ($\Theta^u_\varepsilon(s')$). Note that since the worker loses her outside option upon separating (even if the separation is temporary), the value function 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 $p(s,y') = p(s,y) - c^f$. Just like value function $U_\varepsilon(s)$, this value function $T_\varepsilon(s,\theta)$ can be rewritten using the bargaining equations (3) and (6):

$$T_\varepsilon(s,\theta) = \ln(b_\varepsilon(s)) + \beta\mathbb{E}_{s'|s,r,\varepsilon}\Bigg\{\phi^r_\varepsilon\kappa^r W^{max}_\varepsilon(s',\theta') + \phi^r_\varepsilon(1-\kappa^r)\max\{T_\varepsilon(s',\theta),U_\varepsilon(s')\} \tag{10}$$
$$+(1-\phi^r_\varepsilon)\left(\lambda^r\lambda^u_\varepsilon\int_{x\in\Theta^r_\varepsilon(s',\theta)}\kappa\left(W^{max}_\varepsilon(s',x) - \max\{T_\varepsilon(s',\theta),U_\varepsilon(s')\}\right)dG_\varepsilon(x) + \max\{T_\varepsilon(s',\theta),U_\varepsilon(s')\}\right)\Bigg\}$$

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

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

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.[38] The set $\Theta^1_\varepsilon(s,\theta)$ is the set of characteristics of 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 characteristics of firms whose offers would be used by this worker to trigger re-bargaining at her current match. Using equations (4) and (5), these sets can be specified as $\Theta^1_\varepsilon(s,\theta) = \{[0,1]\times\mathbb{R}_+ : W^{max}_\varepsilon(s,x) \geq W^{max}_\varepsilon(s,\theta)\}$ and $\Theta^2_\varepsilon(s,\theta) = \{x \in [0,1]\times\mathbb{R}_+ : W^{max}_\varepsilon(s,\theta) > W^{max}_\varepsilon(s,x) \geq W^{max}_\varepsilon(\hat{s},\hat{\theta})\}$.[39] Note that $\hat{T}$ and $\hat{U}$

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

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

correspond to the value of a newly separated worker who chose to either potentially be recalled or move into unemployment, with some abuse of notation (since these are not separate states). These values reflect the possibility of these workers being re-employed in the same period, and therefore relate to value functions (10) and (8) as follows:

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

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

Using equation (11), the value for W^{max} can be deduced for every combination of ε, s and θ, by setting $R_\varepsilon(\hat{s},\theta,\hat{\theta}) = 1$ and using bargaining equations (4) and (5). The resulting expression, which is derived in Appendix A.3, no longer depends on the bargaining benchmark, as the outcome of the bargaining (which is the piece-rate) is already known:

$$\begin{aligned} W_\varepsilon^{max}(s,\theta) = \ln(p(s,y)) + \beta\mathbb{E}_{s'|s,e,\varepsilon}\Bigg\{\delta\left[\phi_\varepsilon^f \max\left\{\hat{T}_\varepsilon(s',\theta),\hat{U}_\varepsilon(s')\right\} + (1-\phi_\varepsilon^f)\hat{U}_\varepsilon(s')\right] \\ +(1-\delta)\left[\lambda_\varepsilon^e\int_{x\in\Theta_\varepsilon^1(s',\theta)}\kappa\left(W_\varepsilon^{max}(s',x) - W_\varepsilon^{max}(s',\theta)\right)dG_\varepsilon(x) + W_\varepsilon^{max}(s',\theta)\right]\Bigg\} \end{aligned} \tag{14}$$

One could also set up a value function of a producing firm, $J_\varepsilon(s,\hat{s},\theta,\hat{\theta})$. However, since the above equations suffice to solve and simulate the model for a given set of parameters, these value functions and the flow equations are deferred to Appendix A.1 and A.2 respectively.

3.3 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 (A.1), and the distribution of workers across different states evolves according to equations (A.4) to (A.9).

4 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 make parametric assumptions

previously bargained piece-rate.

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, 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 (2023) 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 interpret the worker type ε as the education level. These assumptions yield a total of 34 parameters that need to be identified. Of these 34 parameters, I set 5 exogenously, leaving the remaining 29 parameters to be estimated using indirect inference (Gourieroux et al., 1993). In the next two subsections, I describe how I set the 5 exogenous parameters, and which moments I use to identify the remaining 29 parameters.

4.1 Exogenously Set Parameters

As I interpret ε to correspond to the worker's education level, I set the share of workers with education levels 1 and 2 to equal equal that in the data, at 0.8435 and 0.1565 respectively. 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%. I set $s_1 = 0$ and $\Delta_s(1) = 0.1$ as a normalization, so that the simulated values of human capital 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 ($\Delta_s(1)$).

4.2 Calibration Moments

Next, I identify 43 moments that together identify the values of the 29 parameters that I estimate using the indirect inference method from Gourieroux et al. (1993). While the parameters are estimated simultaneously, I divide the parameters into six groups, and argue that each of these groups are largely identified by a corresponding group of moments.

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 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 focuses on the average wage level by education level and its variance. Given the direct link between production and wages in the model, I use these moments to identify the marginal distribution of firm productivity y, as well as the starting level of human capital for highly educated workers, s_2. In particular, I use the average educational wage premium for the high education level, 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 non-employment. In particular, the fraction of job-to-job transitions that coincided with a displacement (by education level) helps to identify the meeting probability for newly unemployed workers (λ_ε^{ug}). After all, such direct transitions to a new job will be observed job-to-job transitions. The overall quarterly job-to-job transition rate (by education level) therefore also contributes to identifying this parameter, while also informing the value of the on-the-job meeting rate λ_ε^e. Similarly, the average job finding rates (by education level) closely correspond to the job finding rate of unemployed workers, λ_ε^u.

The next set of moments focuses on wage growth within and between job spells. 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 $b(s)$. I follow Gregory (2023) in taking this moment from OECD (2020). 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. To identify the human capital transition rate during unemployment (ψ_u), I use the average difference between pre- and post-layoff wages, conditional on education level and non-employment duration (up to 0.5, 0.5 to 1, or 1 to 2 years). Similarly, to identify the human capital transition rate for workers who are non-employed with a potential recall (ψ_r) and 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).

As the model allows for a choice between unemployment and potential recall upon separation, the potential recall offer probability ϕ_ε^f and the recall materialization probabilities ϕ_ε^r and $\phi^{rg}\phi_\varepsilon^r$ are likely different from the observed recall and recall materialization probabilities. However, given the close relation between the two, I can use the observed probabilities as calibration targets. 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_ε^r and $\phi^{rg}\phi_\varepsilon^r$.[40] Similarly, I use information on the fraction of workers expecting a recall who find a new job instead to inform the probability of meeting a new employer, $\lambda^r\lambda_\varepsilon^u$, and in particular the parameter λ^r.[41]

The final group consists of all remaining parameters (κ, κ^r, and ρ), which are identified using information on workers' starting wages and the observed correlation between wages and separation rates. In particular, I use the average wage of a new worker (hired out of unemployment) relative to the average wage to identify the bargaining power κ, and the average wage of a newly recalled worker (relative to the average wage) to identify the bargaining power of the recalled worker κ^r.[42] Finally, for the identification of the copula parameter ρ, I follow a strategy similar to that in Jarosch (2023) by targeting the regression coefficient γ in the estimation equation (15) below:

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

In equation (15), the variable $D_{i,t}^{\delta}$ is a dummy variable that is only filled if the worker i is employed in period t and still observed in period $t+1$. It equals 1 if the worker is separated from their job between t and $t+1$. The explanatory variables include an individual fixed effect α_i and the natural logarithm of the worker's wage in period t, $w_{i,t}$.

Description of Moment(s)	Data	Model	Parameters
Average rate of job loss, tenure 1-3.5y	0.031	0.028	$\eta_\delta = 2.26$
Average rate of job loss, tenure 3.5-6y	0.016	0.023	$\mu_{\delta,1} = 11.1$
Average rate of job loss, tenure 6-9y	0.012	0.019	$\mu_{\delta,2} = 76.8$
Average rate of job loss, tenure>9y	0.008	0.012	$c^\delta = 0.152$
Average rate of job loss, by education	0.024	0.025	
	0.02	0.005	
Subsequent separation, displacement	0.081	0.047	
Subsequent separation, recall	0.168	0.163	
p75-p25 ratio of wages	1.541	1.465	$\eta_y = 6.7$
	1.626	1.569	$\mu_{y,1} = 0.99$
Median-p25 ratio of wages	1.242	1.203	$\mu_{y,2} = 1.36$
	1.313	1.233	$s_2 = -0.028$
Educational wage premium (all)	1.533	1.595	
Educational wage premium (entry)	1.466	1.468	
Job-to-job transition rate	0.028	0.023	$\lambda_1^e = 0.053$
	0.03	0.008	$\lambda_2^e = 0.014$
Displacement among job-to-job transitions	0.422	0.434	$\lambda_1^{ug} = 0.422$
	0.436	0.413	$\lambda_2^{ug} = 0.667$
Average job finding rate	0.141	0.152	$\lambda_1^u = 0.145$
	0.146	0.139	$\lambda_2^u = 0.14$
Replacement rate	0.6	0.604	$b = 0.715$
Yearly wage growth	0.013	0.011	$\Delta_s(2) = 0.13$
	0.016	0.014	$\psi_e = 0.026$
Pre- to post-layoff wage, duration<0.5y	-0.046	-0.068	$\psi_u = 0.113$
	-0.01	-0.031	$\psi_r = 0.042$
Pre- to post-layoff wage, duration 0.5-1y	-0.103	-0.117	$c^f = 0.368$
	-0.064	-0.051	
Pre- to post-layoff wage, duration 1-2y	-0.125	-0.132	
	-0.122	-0.1	
Pre- to post-recall wage, duration 0.25-0.5y	-0.02	-0.059	
	0.03	0.005	
Pre- to post-recall wage, duration 0.5-1y	-0.01	-0.066	
	0.002	-0.03	
Recall rate	0.067	0.062	$\phi_1^f = 0.071$
	0.027	0.01	$\phi_2^f = 0.278$
Recall materialization rate	0.393	0.334	$\phi_1^r = 0.174$
(Based on materialization in 2 years)	0.253	0.259	$\phi_2^r = 0.123$
Recall materialization rate	0.35	0.37	$\phi^{rg} = 1.017$
(Based on materialization in 1 year)	0.204	0.212	$\lambda^r = 0.894$
New job finding rate, workers expecting a recall	0.293	0.269	
Wage of newly hired worker	0.684	0.717	$\kappa = 0.96$
Wage of newly recalled worker	0.725	0.763	$\kappa^r = 0.73$
Coefficient $\hat{\gamma}$ in equation (15)	-0.021	-0.021	$\rho = -20.5$

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

4.3 Calibration Results and Model Fit

Table 3 summarizes the estimated moment values and their model counterparts. The model fits the moments quite well. Nevertheless, the model has trouble matching a few moments. For example, it can be observed that the model tends to have trouble matching transition rates for the higher education level.

The parameter estimates in Table 3 are largely comparable to Jarosch (2023) and Gregory (2023).[43] In general, however, it can be said that a few values stand out. In particular, the estimated value for the worker's bargaining power, $\kappa = 0.96$, is quite high. This is not uncommon in models like the one proposed in this paper, and may be a consequence of the calibration procedure attempting to match measures of wage dispersion (the p75-p25 and median-p25 wage ratios) by alleviating the impact of changing outside options.[44] 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 0.73.

It is also worth noting that the recall rates ϕ_1^f and especially ϕ_2^f are higher than the observed recall rates in the data and model simulation. For highly educated workers, this is because only workers with a high productivity job will choose for a potential recall. However, for workers with a low education, this set of calibrated parameters implies that almost everyone chooses in favour of a potential recall when offered to do so. This implies that the role of allowing workers to find new jobs despite holding a potential recall is quite large. Indeed, this meeting probability is only slightly lower (89.4%) than the corresponding meeting probabilities for unemployed workers (as illustrated by the value of λ^r). For this reason, the recall materialization rates ϕ_1^r and ϕ_2^r also do not quite line up with the rates found in the data and model simulation.

[40] I choose to simplify the estimation by setting $\phi_1^{rg} = \phi_2^{rg} = \phi^{rg}$ as the fairly low number of highly educated recalled workers implies that the recall materialization probability for highly educated workers is quite noisy.

[41] This moment cannot be estimated from my data, and the data equivalent of this moment is based on results in Nekoei and Weber (2015). For the model equivalent, I assume that workers expecting a recall are the non-employed workers with a potential recall.

[42] Note that the identification of κ^r relies on the assumption that recalled workers lose their outside option, which makes them comparable to new hires in general. The identification of production penalty c^f, on the other hand, relies on the individual-specific comparison between pre- and post-displacement earnings for recalled workers, and the identification of ψ_r relies on the dependence of this individual-specific comparison on non-employment duration.

[43] 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}.

[44] For comparison, Jarosch (2023) and Gregory (2023) find bargaining weights of 0.928 and 0.66 respectively.

In general, a non-employed worker is much less likely to lose human capital if she has a potential recall. In fact, the human capital depreciation rate ($\psi_r\psi_u \approx 0.005$) is fairly close to zero for the worker with a potential 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)[45] and a substantial penalty on the separation rate c^δ, which implies that after recall the worker's separation rate increases by more than 15 percentage points.

Moving to the differences between the two education levels, it can be noted that workers with a high education level are more likely to obtain an offer upon entering unemployment ($\lambda_1^{ug} < \lambda_2^{ug}$), but not when unemployed for a longer time or when employed ($\lambda_1^u < \lambda_2^u$ and $\lambda_1^e > \lambda_2^e$). Furthermore, compared to the worker with a low education level, a highly educated worker has a slightly lower starting level of human capital $s_2 = -0.028 < 0 = s_1$, but they also experience a larger change ($\Delta_s(2) = 0.13 > 0.1 = \Delta_s(1)$) every time they are hit with an appreciation or depreciation shock ($\psi_e, \psi_u, \psi_r\psi_u$).

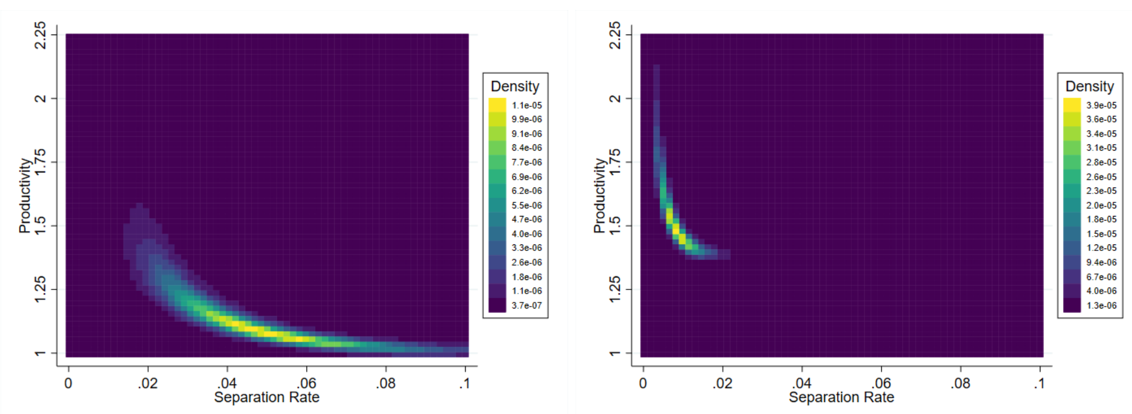


Figure 7: *The joint distribution of firm types faced by workers with a low education level (left) and a high education level (right). A lighter colour in this chart corresponds to a higher density.*

The firm distributions the workers draw from upon receiving an offer are best illustrated in a diagram. Figure 7 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 heavily right-skewed. When comparing the two distributions,

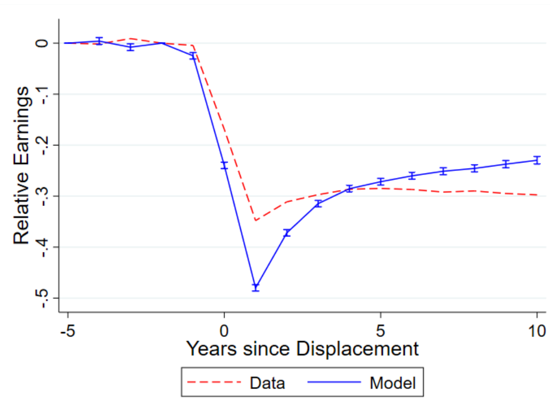
[45] To provide context to the magnitude of the production penalty, note that the value of the lowest possible value of production for a worker of education level 1 with the starting level of human capital, $p(s_1, y^{min})$ equals $e^{0+0.99} \approx 2.69$

the first thing that can be noted is that the high education level's minimum productivity is higher than that of the low 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.

5 Simulation Results

In this section, I present the results of the model simulation, using calibrated parameter values from the previous section. I start by comparing the predictions of the model regarding the scarring effects of displacement to the data. As these patterns were not explicitly targeted in the calibration, this can be thought of as a test of the model's performance. I then 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, I briefly comment on possible policy implications of the results.

5.1 Heterogeneity in the scarring effects of displacement



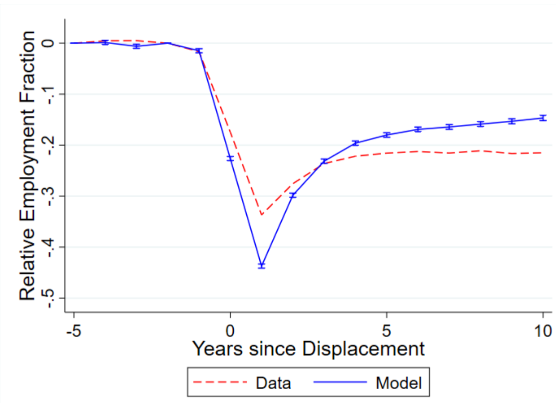


Figure 8: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right), relative to the control group, using model simulation data (solid) and using the data (dashed, corresponding to Figure 3).*

Figure 8 compares the average effect of displacement on earnings and employment in the model and the data (both estimated using equation 1). While the shapes of the graphs are quite similar, the model generates too much recovery in earnings and employment (and slightly overshoots the initial impact) compared to the data. This is likely caused in part by the model implying a lower subsequent separation rate than the data, thus leading to more recovery in employment, which in turn leads to more recovery in earnings.

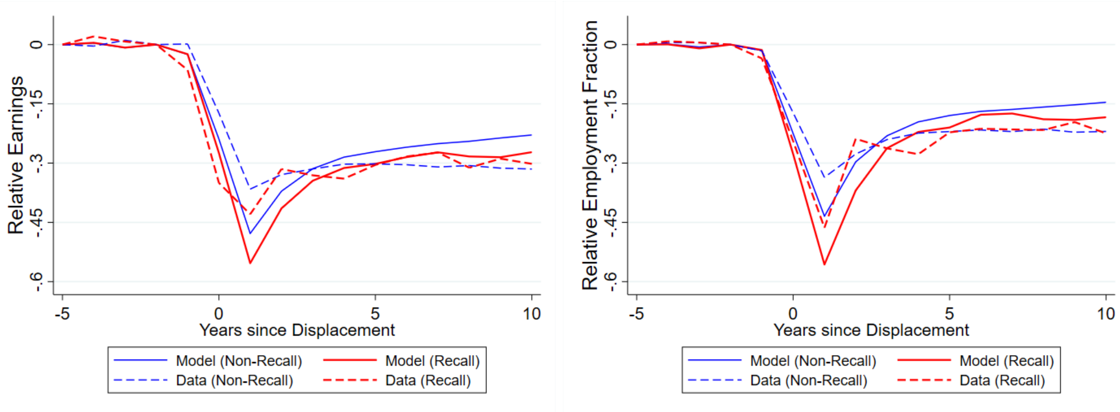


Figure 9: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right) relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data (solid) and using the data (dashed, corresponding to Figure 4).*

Figure 9 compares the model-predicted 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 with the data. The model matches the observation 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.[46] In particular, while recalled and non-recalled workers generally recover faster in the model than in the data, the gap between the scarring effects for recalled and non-recalled workers is very similar to the data. This is true of both earnings and employment.

In Figure 10, I fully decompose the differences in estimated post-displacement earnings between recalled and non-recalled workers. 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 (cumulatively) in order to generate counterfactual earnings differences between recalled and non-recalled workers.[47] I find that differences between recalled and non-recalled workers are negatively driven by the post-recall match characteristics. In

[46]While the model-generated earnings and employment losses are estimated to be slightly larger for (ex-post) recalled workers, as shown in Figure 9, the difference between recalled and non-recalled workers is not statistically significant. The corresponding graphs with pointwise intervals are depicted in Appendix B.1. In Appendix B.5, I show that the decomposition results discussed below are very similar if I were to directly target the regression results from Figure 4 when calibrating the model.

[47]For a detailed explanation of this decomposition exercise, see Appendix B.2. This Appendix also includes results of an alternative decomposition in which I use a direct counterfactual simulation (introduced in Appendix B.1) to esti-

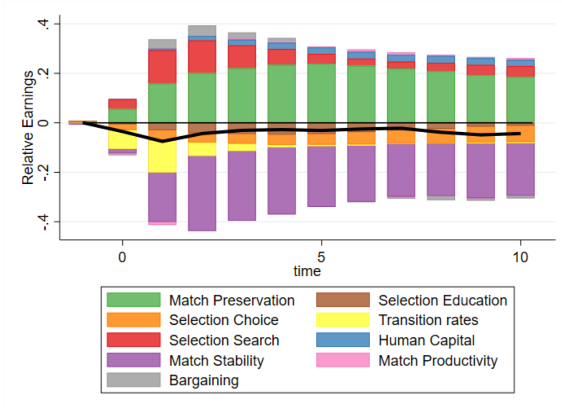


Figure 10: *A decomposition of the difference in the scarring effect of displacement on earnings between (ex-post) recalled and non-recalled workers. The black line represents the total difference, calculated as the difference between the solid red and blue lines in the left panel of Figure 9. The decomposition 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 B.1.*

particular, 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}, and in the figure by "Match Stability"), whereas the impact of the productivity penalty c^{f} is fairly small in the long run (and the corresponding element "Match Productivity" is barely visible in the figure). 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 recovery multiple times, both in terms of human capital and in terms of repeated loss of outside option.

A few other channels are shown in Figure 10 to have a negative impact. A major channel negatively affecting the difference in short-run relative earnings losses is that of the "Transition rates". The effect of this channel is strongly negative, reflecting primarily the higher immediate transition probabilities $\lambda_{\varepsilon}^{ug}$ of the worker who chose to move to the regular unemployment state. While the bargaining power is much lower for a recalled worker, as observed in Section 4.3, the negative impact of this difference ("Bargaining") turns out to be quite minor compared to other channels. In fact, the impact of the bargaining power turns out positive in the short run, likely reflecting that the absence of the bargaining channel entices workers in worse jobs to choose the potential recall option. The differences between the two education levels also plays a small negative role ("Selection Education"). A final channel worth mentioning here is the "Selection Choice"

mate earnings differences instead of estimating Equation (1') on model-simulated data, as I do for the decompositions depicted here.

channel, which reflects the impact of allowing the worker to choose between the regular unemployment state and the state of non-employment with a potential recall. This channel has a negative impact because workers who choose against a potential recall (and therefore self-select into the non-recall group), which are highly educated workers with a low level of human capital or a low current job productivity, tend to be the workers experiencing the smallest earnings loss. Removing this choice forces some of these workers into the recall group, thus reducing the average earnings loss experienced by recalled workers while increasing the average earnings loss of non-recalled workers.

The aforementioned negative drivers are largely offset by a set of positive drivers. The largest of these is the residual element named "Match Preservation", which reflects the difference between the two states if all parameters would be the same. 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 the match they would find when drawing a (random) new employer from the joint distribution $G_{\varepsilon}(\theta)$ is on average worse than the match they separated from. Allowing the worker to search while holding a potential recall (as indicated by $\lambda^r > 0$) has a positive impact, denoted "Selection Search" in the figure. Similarly, the finding that the worker holding a potential recall is much less likely to lose any human capital ("Human Capital") has a small positive effect, especially in the long run.

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, also allows me to further decompose earnings losses into employment and wage components. In Figure 11, I use the results of the model-estimated effect of displacement (on earnings, employment, and wages) to decompose the earnings loss into employment and wages. Corresponding to my findings in the data, I find that the short-term difference is entirely driven by the employment margin. The wage margin goes in the opposite direction, suggesting that conditional on employment the recalled workers earn more. Note that the simple combination of employment and wages does not always fully explain the estimated earnings loss, as indicated by the "Other" category in Figure 11. This residual can be thought of as reflecting a correlation term, as discussed in Schmieder et al. (2023).

In the right panel of Figure 11, I further decompose the employment differences into the same 9 channels used for the earnings decomposition above. A similar decomposition for wages can be found in Appendix B.2. The human capital channel does not play a role when it comes to

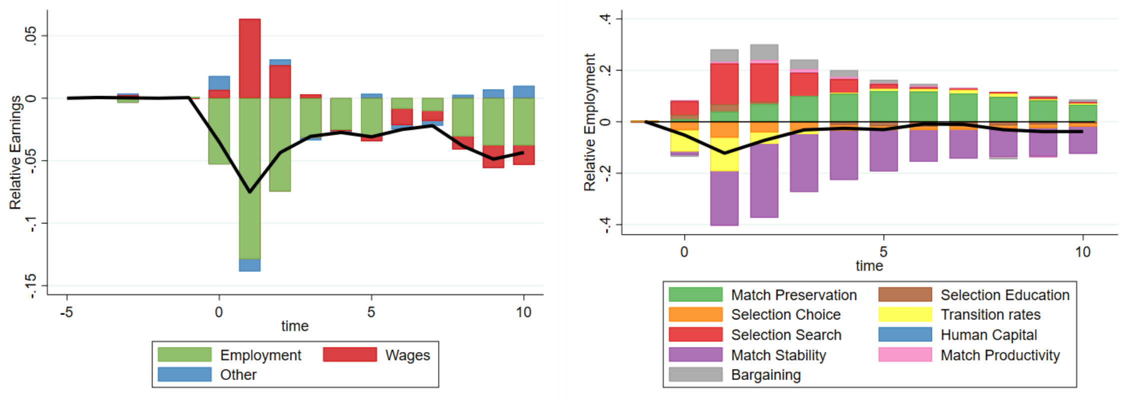


Figure 11: *A decomposition of the difference in the scarring effect of displacement on earnings between (ex-post) recalled and non-recalled workers, into earnings and employment (left), and a decomposition of the difference in the scarring effect of displacement on employment between (ex-post) recalled and non-recalled workers (right). The black line represents the total difference, calculated as the difference between the solid red and blue lines in Figure 9. The decomposition on the left is generated by using the estimation for employment and wages, and backing out the remaining effect as a residual. The decomposition on the right 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 B.2.*

employment. For employment, the main negative drivers are related to the higher separation rate and lower immediate transition rates faced by the recalled worker. Absent these factors, the (ex-post) recalled worker would likely be doing better in terms of employment (in the long run). This is primarily driven by the fact that displaced workers in general come from matches of a higher separation rate than the average in the economy, but nevertheless face an even higher expected separation rate when drawing a new match from the joint distribution $G_\varepsilon(\theta)$. This is important especially in the long run, as these workers start separating again, and this is reflected by the positive "Match Preservation" channel in the decomposition.

5.2 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 non-employment at the start of the shutdown.[48] The affected worker stays in this state of non-employment 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.[49]

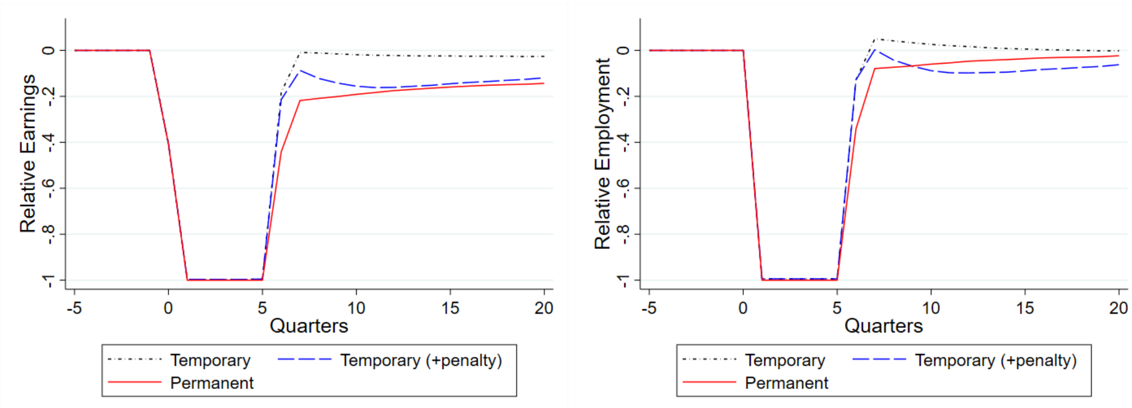


Figure 12: *The effect of a temporary shutdown on the earnings and employment status of affected workers. During the shutdown, workers are assumed to be either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (black, short-dashed).*

In Figure 12, I show how the effect of the shutdown on earnings and employment of the affected worker depends on the type of non-employment experienced by the affected worker. In the left panel, it can be seen that the worker who moves into the temporary unemployment state (non-employment with a potential 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, although the penalties eliminate most of this advantage after the initial recovery.[50] As shown in the right panel, a worker forced into temporary unemployment may be worse off in the long run

[48]By randomly selecting the affected workers, I shut down the selection channels in the model. As such, the experiment can be thought of as simulating a situation where an entire sector shuts down (such as in the Covid-19 pandemic). Since 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, but it can be shown that the timing does not affect results.

[49]I assume that this higher transition probability equals the average of 1 and the "usual" transition probability. In Appendix B.3, I show that the conclusions from this simulation exercise are not affected by this assumption.

[50]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).

in terms of employment if the recall comes with the usual penalties. As I show in Appendix B.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.

Overall, this simulation exercise serves to emphasize two points. First of all, contrary to what the figures in Section 2.3 may suggest, especially in the short run, being recalled by their former employer may not necessarily be as bad for the worker's outcomes as a permanent displacement. 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 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.

5.3 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 3. 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, such as the firm choosing who to (potentially) recall and congestion externalities in the labour market (which I abstract from by setting exogenous offer arrival rates). Nevertheless, some lessons can still be drawn from the results in the previous subsections.

The decomposition of the differences between recalled and non-recalled workers' earnings loss after displacement highlighted the depreciation of human capital as a channel that works in favour of the recalled worker. This is driven by workers holding a potential recall facing a human capital depreciation probability of only 0.5%, whereas this probability is 11.3% for a regularly unemployed worker. In Appendix B.4, I show that this implies that human capital depreciation (relative to a continuously employed worker) plays a fairly minor role in explaining the earnings losses for a recalled worker. 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 relatively large role for human capital depreciation, in line with what the existing literature has found. A natural response to the decomposition of the average scarring effect of displacement might be to suggest a policy that would help the non-employed 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, I show that an unintended consequence of such a policy would be to increases the gap between recalled and non-recalled workers. In other words, given that the recalled worker tends to do worse in the short run, 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.

6 Conclusion

In this paper, I study the scarring effect of displacement on earnings and employment, focusing in particular on how these effects differ based on 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 than non-recalled displaced workers.

As the existing theoretical models cannot account for these observations, I develop a model of the labour market in which I explicitly allow for recall by dividing newly non-employed workers into two separate states, according to whether or not the workers may be recalled in the future. 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 account for 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 by ex-post recall status. 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.

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 widespread usage of short-time employment policies throughout Europe during the Covid-19 pandemic.

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For Online Publication: Online Appendix

A Model Appendix

A.1 Further Value Functions

As mentioned in Section 3, the model can be solved using value functions from the worker side only. However, the value function J for a firm of type θ, employing a worker of type ε with human capital s, can still be set up, and looks as follows:

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

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 potentially recalling, which can be decomposed into the separation period-specific part and a general value for a firm potentially recalling their former worker:

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

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

A.2 Worker Flows

The description of the model in the main text (Section 3) can be used to construct a number of worker flow equations. In what follows, denote by $d_\varepsilon(s,\hat{s},\theta,\hat{\theta})$ the density of employed workers of type ε with current human capital s, negotiation benchmark human capital $\hat{s}$, matched to a firm with characteristics $\theta \in [0,1] \times \mathbb{R}_+$, 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 holding a potential recall. Further, let $d_\varepsilon^f(s,\theta)$ be the density of workers with current human capital s holding a potential recall 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:

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

The flow equations are then as follows:[51]

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

$$
\begin{aligned}
d'_\varepsilon(s, \hat{s}, \theta, u) = {}& (1-\delta)\left(1 - \lambda^e_\varepsilon \int_{x \in \Theta^1_\varepsilon(s,\theta) \cup \Theta^2_\varepsilon(s', \hat{s}, \theta, u)} dG_\varepsilon(x)\right) \bar{d}_\varepsilon(s, \hat{s}, \theta, u) \\
& + g_\varepsilon(\theta) \mathbb{1}_{s=\hat{s}} \mathbb{1}_{\theta \in \Theta^u_\varepsilon(s)} \left(\lambda^u_\varepsilon \bar{u}_\varepsilon(s) + \lambda^{ug}_\varepsilon \iiint \delta_x (1 - \bar{\phi}^f_\varepsilon(s, x)) \bar{d}_\varepsilon(s, \tilde{s}, x, \hat{x}) d\tilde{s} dx d\hat{x}\right) \qquad \text{(A.5)}
\end{aligned}
$$

$$
\begin{aligned}
d'_\varepsilon(s, \hat{s}, \theta, r) = {}& (1-\delta)\left(1 - \lambda^e_\varepsilon \int_{x \in \Theta^1_\varepsilon(s,\theta) \cup \Theta^2_\varepsilon(s', \hat{s}, \theta, r)} dG_\varepsilon(x)\right) \bar{d}_\varepsilon(s, \hat{s}, \theta, r) \\
& + \mathbb{1}_{s=\hat{s}} \int \mathbb{1}_{\theta' \in \Theta^f_\varepsilon(\theta)} \left(\phi^r_\varepsilon \bar{d}^f_\varepsilon(s, \theta') + \bar{\phi}^f_\varepsilon(s, \theta') \phi^{rg}_\varepsilon \iint \bar{d}_\varepsilon(s, \hat{s}, \theta', \hat{x}) d\hat{s} d\hat{x}\right) d\theta' \qquad \text{(A.6)}
\end{aligned}
$$

$$
\begin{aligned}
d'_\varepsilon(s, \hat{s}, \theta, f) = {}& (1-\delta)\left(1 - \lambda^e_\varepsilon \int_{x \in \Theta^1_\varepsilon(s,\theta) \cup \Theta^2_\varepsilon(s', \hat{s}, \theta, f)} dG_\varepsilon(x)\right) \bar{d}_\varepsilon(s, \hat{s}, \theta, f) \\
& + \mathbb{1}_{s=\hat{s}} \int \mathbb{1}_{\theta \in \Theta^r_\varepsilon(s,x)} (1 - \phi^r_\varepsilon) \lambda^r \bar{d}^f_\varepsilon(s, x) dx \qquad \text{(A.7)}
\end{aligned}
$$

$$
\begin{aligned}
d^{f\prime}_\varepsilon(s, \theta) = {}& (1 - \phi^r_\varepsilon)\left(1 - \lambda^r \int_{x \in \Theta^r_\varepsilon(s,\theta)} dG_\varepsilon(x)\right) \mathbb{1}_{F_\varepsilon(s,\theta) > U_\varepsilon(s)} \bar{d}^f_\varepsilon(s, \theta) \\
& + \iint \delta \bar{\phi}^f_\varepsilon(s, \theta)(1 - \phi^{rg}_\varepsilon) \bar{d}_\varepsilon(s, \hat{s}, \theta, \hat{x}) d\hat{s} d\hat{x} \qquad \text{(A.8)}
\end{aligned}
$$

[51] Note that when I integrate over y in equation (A.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 (A.5), (A.6), (A.8), and (A.9). Furthermore, note that I distinguish between different values of δ such that $\delta \in \theta$, $\hat{\delta} \in \hat{\theta}$, and $\delta_x \in x$.

$$u'_\varepsilon(s) = \left(1 - \lambda^u_\varepsilon \int_{x \in \Theta^u_\varepsilon(s)} dG_\varepsilon(x)\right) \bar{u}_\varepsilon(s)$$
$$+ \int \delta(1 - \bar{\phi}^f_\varepsilon(s,\theta)) \left(1 - \lambda^{ug}_\varepsilon \int_{x \in \Theta^u_\varepsilon(s)} dG_\varepsilon(x)\right) \iint \bar{d}_\varepsilon(s,\hat{s},\theta,\hat{x}) d\hat{x} d\hat{s} d\theta \tag{A.9}$$

where

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

A.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. $w(s,\hat{s},\theta,\hat{\theta}) = p(s,y)$). I derive this function by rewriting 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 non-employment with a potential 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). 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 non-employed worker (either holding a potential recall or not), $\hat{T}(s,\theta)$ and $\hat{U}(s)$. Using these calculations (and leaving in $\hat{T}$ and $\hat{U}$), I can then start to rewrite equation (11), by plugging in $R(\hat{s},\theta,\hat{\theta}) = 1$ and rewriting:

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

To simplify the equation above, I 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. Finally, to arrive at equation (14), I simplify the term inside of the integral by using the bargaining equation

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

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

Similarly, I can use the bargaining equation (3) to remove the value function W from the value function U, equation (7):

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

B Additional Simulation Results

B.1 Further Simulation Results

In Section 5.1 of the main text, I briefly discussed how the estimated model performs in matching the empirical results from Section 2. In this section, I discuss how the model performs outside the regression context stressed in the main text.

While the results in Section 5.1 of the main text focus on implications of the model that were generated using the same estimation method as in the data, 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

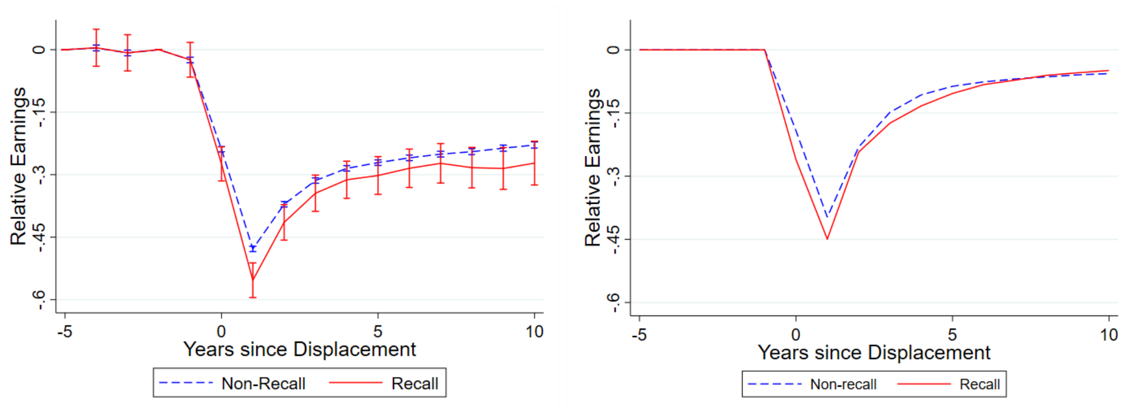

Figure B.1: *The effect of displacement on earnings relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data and using a regression-based approach (left, corresponding to Figure 9) or a direct counterfactual (right).*

second simulation but all other random variable draws are the same between the two simulations. In Figures B.1 and B.2, 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 slightly smaller scarring effect and especially predict 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.

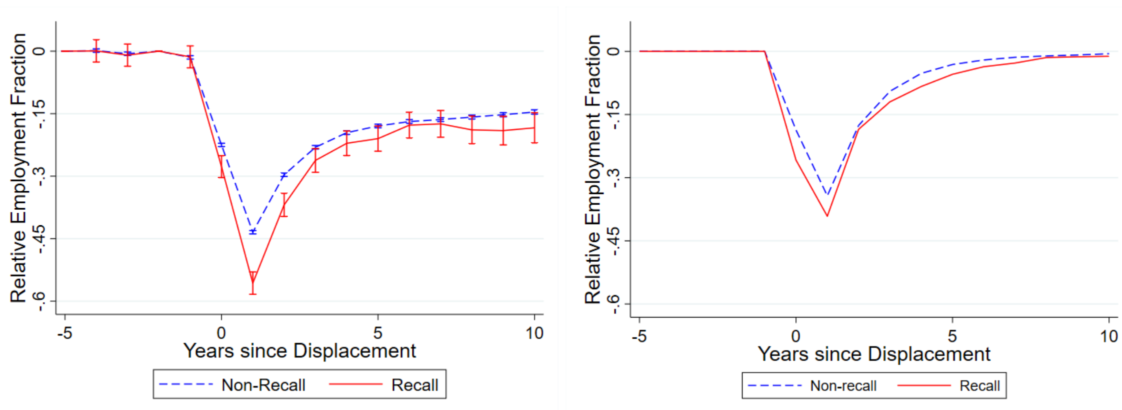

Figure B.2: *The effect of displacement on employment fraction relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data and using a regression-based approach (left, corresponding to Figure 9) or a direct counterfactual (right).*

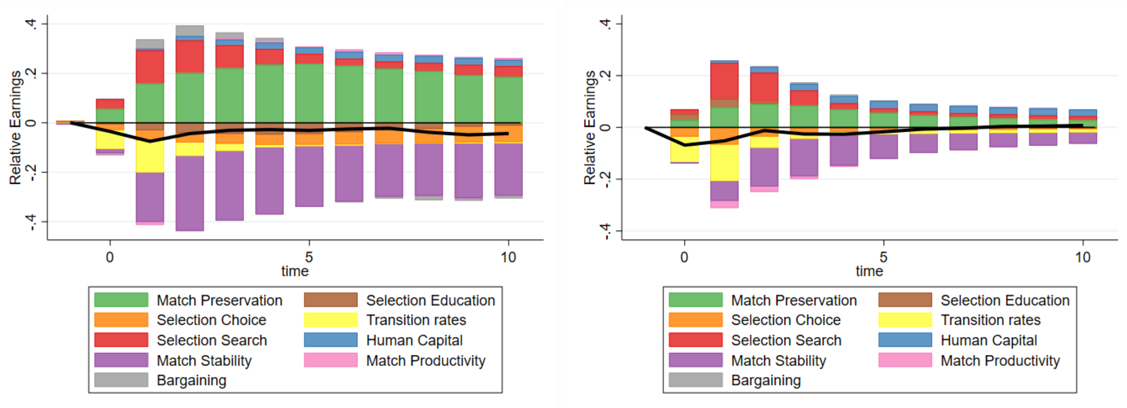

Figure B.3: *A decomposition of the difference in the scarring effect of displacement on earnings between (ex-post) recalled and non-recalled workers, using either a regression-based approach (left) or a direct counterfactual (right). The black line represents the total difference, calculated as the difference between the red and blue lines in Figure B.1. 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 B.1.*

B.2 Further Decomposition Results

In the main text, in Section 5.1, I used the calibrated model to decompose the difference in the scarring effects of displacement (on earnings and employment) 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 Figures B.3 and B.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 B.5 repeats both decomposition exercises with a focus on wages instead. The two decomposition methods generally yield similar conclusions. The main positive differences for wages are coming from the match preservation, human capital, and search (during non-employment with a potential recall) margin. This reflects that the worker does not fall off the job ladder when recalled (only accepting a competing offer if it dominates the potential recall), and furthermore barely loses any human capital, 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 offset by the negative influence of higher separation rates, selection into the potential recall state, higher transition rates, and loss of bargaining power, thus eventually leading to a wage difference close to zero.

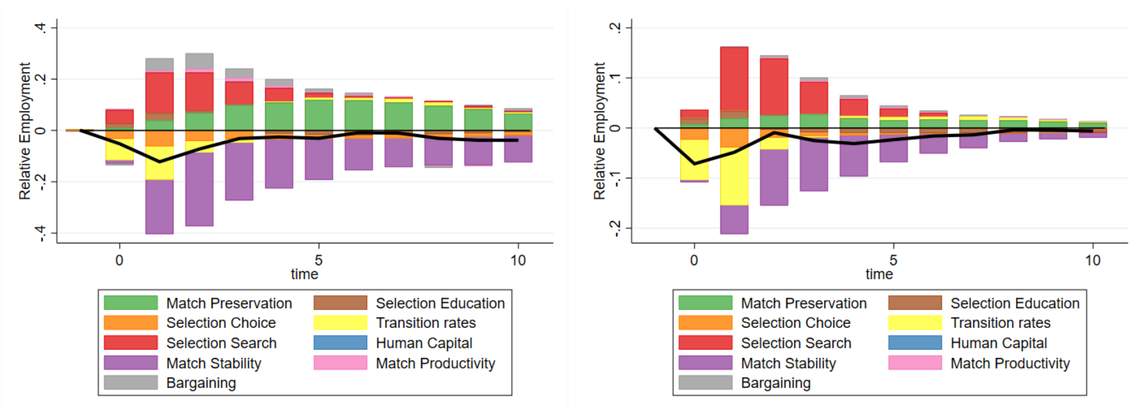

Figure B.4: *A decomposition of the difference in the scarring effect of displacement on employment between (ex-post) recalled and non-recalled workers, using either a regression-based approach (left) or a direct counterfactual (right). The black line represents the total difference. The decomposition 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 B.2.*

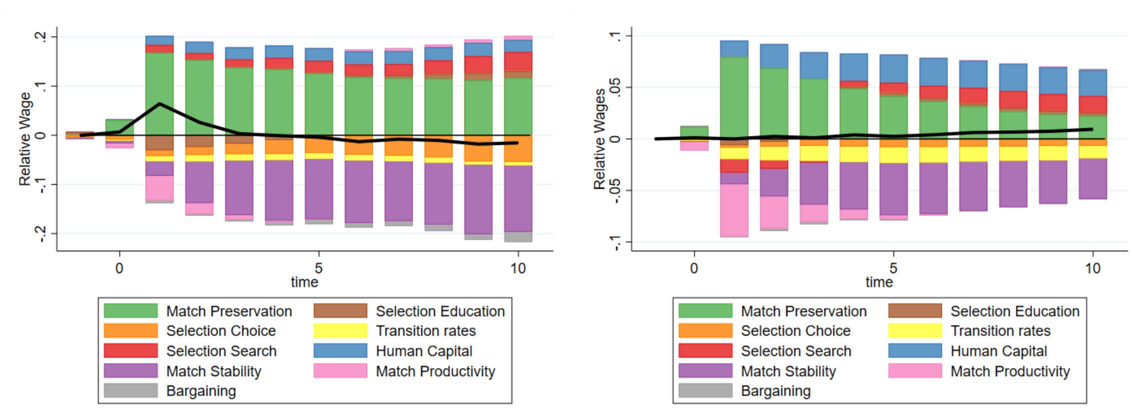

Figure B.5: *A decomposition of the difference in the scarring effect of displacement on wages between (ex-post) recalled and non-recalled workers, using either a regression-based approach (left) or a direct counterfactual (right). The black line represents the total difference. The decomposition is 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 B.3.*

In Tables B.1 (earnings), B.2 (employment), and B.3 (wages) I show the numerical values used to construct a selection of the bars in the corresponding Figures B.3, B.4 and B.5. In these tables, I separate the differential effects of displacement on earnings, employment, and wages (denoted "Total") between (ex-post) recalled and non-recalled workers into the 9 channels that could potentially drive these differences in the model. Below, I discuss how these channels are incorporated into the model presented in Section 3.

	Regression-Based				Direct Counterfactual			
Channel	$k=0$	$k=1$	$k=5$	$k=10$	$k=0$	$k=1$	$k=5$	$k=10$
Bargaining	-0.004	0.038	0.001	-0.011	-0.000	0.001	0.004	0.001
Match Productivity Penalty	-0.004	-0.012	0.004	0.008	0.001	-0.028	-0.001	0.001
Match Stability Penalty	-0.018	-0.200	-0.246	-0.212	-0.006	-0.077	-0.094	-0.044
Human Capital	0.001	0.006	0.026	0.025	0.001	0.009	0.027	0.025
Selection Search	0.040	0.134	0.040	0.044	0.018	0.138	0.017	0.016
Transition Rates	-0.076	-0.129	-0.006	-0.005	-0.098	-0.141	-0.013	-0.012
Selection Choice	-0.024	-0.041	-0.044	-0.066	-0.036	-0.066	-0.010	-0.007
Selection Education	-0.006	-0.030	-0.045	-0.011	0.022	0.033	-0.003	-0.001
Match Preservation	0.056	0.159	0.239	0.185	0.028	0.078	0.056	0.027
Total	-0.035	-0.075	-0.031	-0.043	-0.069	-0.052	-0.017	0.008

Table B.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 B.1. The decomposition is generated by turning off the indicated channels one by one (in the presented 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, as depicted in Figure B.3.*

The first listed channel, 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. The next two channels listed in the tables correspond directly to the two penalty parameters c^f ("Match Productivity Penalty") and c^δ ("Match Stability Penalty"). The contribution of these channels is calculated by setting these parameters to zero. The "Human Capital" channel corresponds to the difference between human capital depreciation rates ψ_u and $\psi_r \psi_u$, and its contribution is calculated by setting $\psi_r = 1$.

In the model, a non-employed worker holding a potential recall generally transitions back into employment faster than other unemployed workers, conditional on not transitioning back before entering 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 $\phi^{rg}_\varepsilon =$

	Regression-Based				Direct Counterfactual			
Channel	$k = 0$	$k = 1$	$k = 5$	$k = 10$	$k = 0$	$k = 1$	$k = 5$	$k = 10$
Bargaining	-0.007	0.048	0.013	0.010	0	0.002	0.005	0.001
Match Productivity Penalty	0.005	0.008	0.003	0.000	0	0.000	0.002	0.001
Match Stability Penalty	-0.014	-0.212	-0.161	-0.105	-0.005	-0.058	-0.056	-0.010
Human Capital	-0.000	0.000	0.000	-0.000	0	0	0	0
Selection Search	0.052	0.158	0.019	0.006	0.017	0.128	0.017	-0.001
Transition Rates	-0.083	-0.130	0.009	0.004	-0.080	-0.115	0.006	0.002
Selection Choice	-0.033	-0.062	-0.016	-0.013	-0.023	-0.039	-0.003	-0.001
Selection Education	0.018	0.030	-0.017	-0.007	0.012	0.015	-0.010	-0.008
Match Preservation	0.010	0.039	0.119	0.066	0.007	0.019	0.016	0.010
Total	-0.052	-0.122	-0.030	-0.038	-0.071	-0.048	-0.023	-0.006

Table B.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 presented order), 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, as depicted in Figure B.4.*

$\lambda_{\varepsilon}^{ug}$.[52]

Finally, the model contains four explicit selection channels, which can be referred to as selection into displacement, selection into potential recall, selection out of potential recall, 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 potential recall, “Selection Choice”, refers to the worker being able to choose whether or not move into the state of non-employment with a potential recall upon being offered as such (which happens at rate ϕ_{ε}^{f}). The contribution of this channel is calculated by removing this choice, thus forcing a worker into the potential recall state with probability ϕ_{ε}^{f}. The selection out of potential recall, “Selection Search”, is incorporated into the model by allowing the non-employed worker with potential recall to search for a new job, which arrives at a rate $\lambda^r \lambda_{\varepsilon}^{u}$. 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 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

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

is that the workers holding a potential recall move back to their previous job, whereas the other non-employed workers draw a new job from the distribution $G_1(\theta)$.

	Regression-Based				Direct Counterfactual			
Channel	$k = 0$	$k = 1$	$k = 5$	$k = 10$	$k = 0$	$k = 1$	$k = 5$	$k = 10$
Bargaining	0.001	−0.006	−0.009	−0.020	0.000	−0.001	−0.001	0.001
Match Productivity Penalty	−0.010	−0.050	−0.001	0.008	−0.008	−0.051	−0.004	0.001
Match Stability Penalty	−0.006	−0.030	−0.123	−0.135	−0.000	−0.011	−0.051	−0.040
Human Capital	0.001	0.019	0.025	0.024	0.001	0.016	0.027	0.025
Selection Search	0.001	0.016	0.026	0.039	−0.000	−0.013	0.010	0.016
Transition Rates	−0.002	−0.011	−0.012	−0.007	−0.002	−0.011	−0.015	−0.012
Selection Choice	−0.007	−0.012	−0.032	−0.054	−0.000	−0.002	−0.008	−0.007
Selection Education	−0.002	−0.030	−0.004	0.014	−0.000	−0.006	0.003	0.003
Match Preservation	0.031	0.168	0.126	0.116	0.012	0.079	0.041	0.022
Total	0.007	0.064	−0.004	−0.015	0.001	0.000	0.002	0.009

Table B.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 presented order), 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, as depicted in Figure B.5.*

B.3 A Shutdown Simulation

In Section 5.2, 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. In Figure B.6, 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). 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 12), 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, the recovery initially overshoots the counterfactual outcome (in which the worker did not experience the shutdown). This is 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.

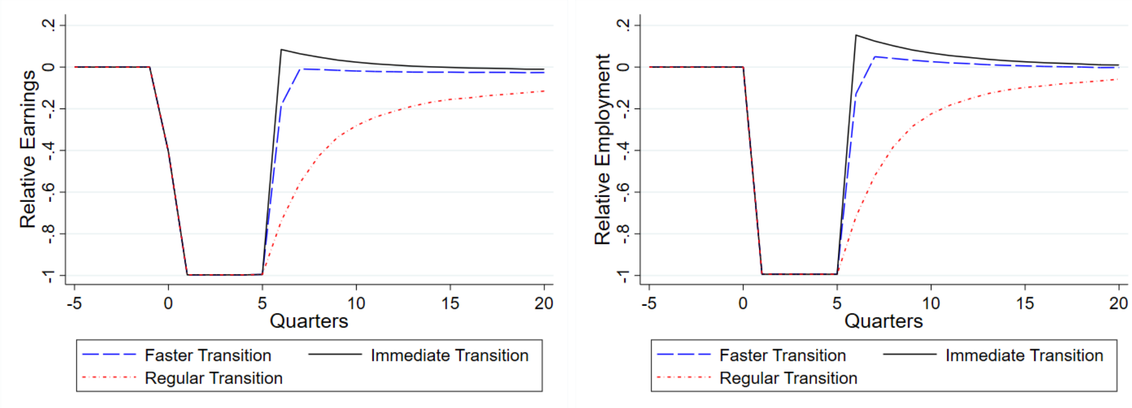

Figure B.6: *The effect of a temporary shutdown on the earnings and employment status of affected workers. During the shutdown, workers are assumed to be in the temporary unemployment state without the associated penalties. After the shutdown, workers transition back to employment either immediately (blue, dashed), at a faster rate than usual (black, solid), or at the usual rate (red, short-dashed).*

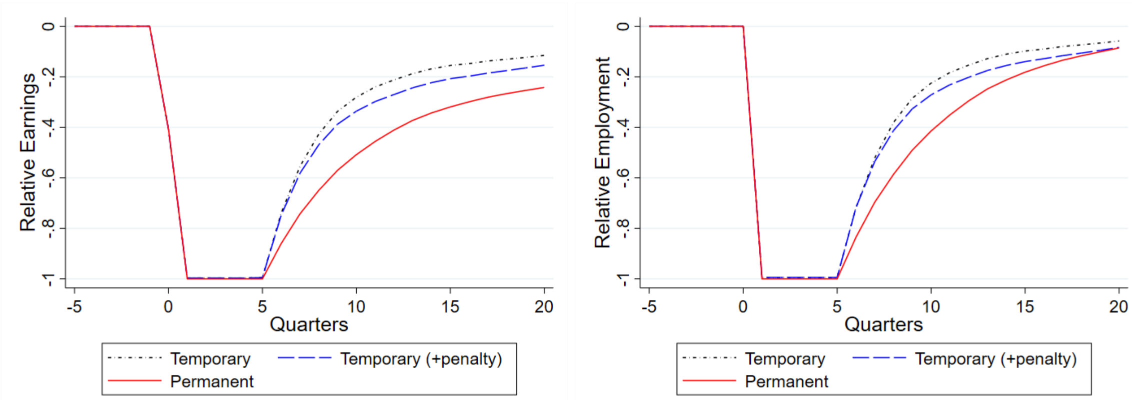

Figure B.7: *The effect of a temporary shutdown on the earnings and employment status of affected workers, without imposing two quarters of subsequent faster transitions. During the shutdown, workers are either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (black, short-dashed).*

In Figure B.7, I explicitly show that the results from Section 5.2 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 to hold when focusing on the high education level only, as can be seen in Figure B.8.

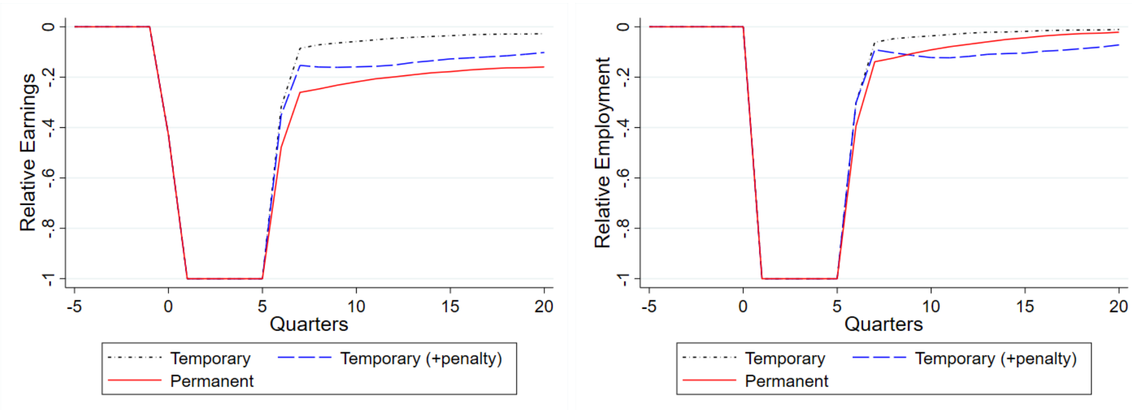

Figure B.8: *The effect of a temporary shutdown on the earnings and employment status of affected workers with a high education level. During the shutdown, workers are either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) 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 Figure B.9, the result similarly does not necessarily hold when focusing on productivity. 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 12 in the main text).

B.4 Policy Implications

In Section 5.3, 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).

First of all, Figure B.10 and accompanying Tables B.4 and B.5 illustrate my statement in Section 5.3 that human capital depreciation (relative to a continuously employed worker) accounts for a larger portion of long-run earnings losses for the non-recalled worker than for a recalled worker, especially in the short run. This is visible in the figure, where the human capital (relative) depreciation elements are represented by the blue, pink and dark green areas.

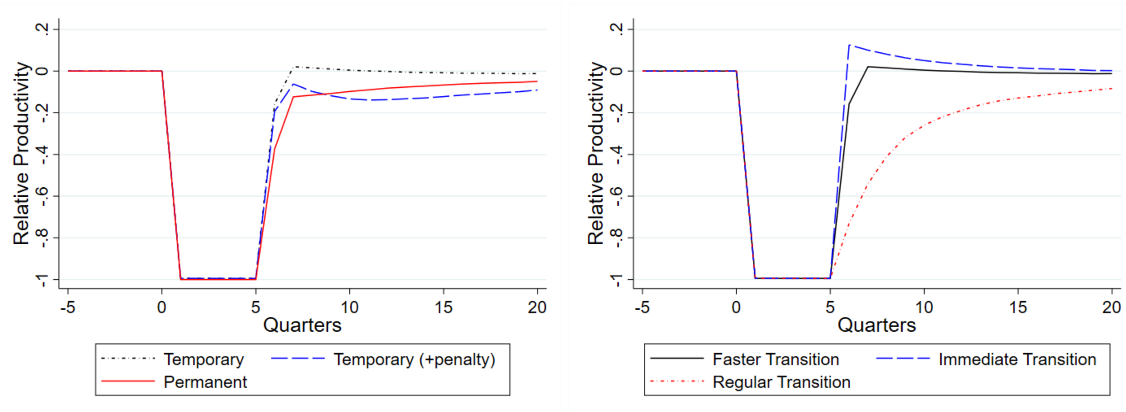

Figure B.9: *The effect of a temporary shutdown on the productivity of affected workers. Left panel: during the shutdown, workers are either in the permanent unemployment state (red, solid) or in the temporary unemployment state with the associated penalties (blue, dashed) or without penalties (black, short-dashed), and after the shutdown workers transition back to employment at a faster rate than usual. Right panel: during the shutdown workers are 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).*

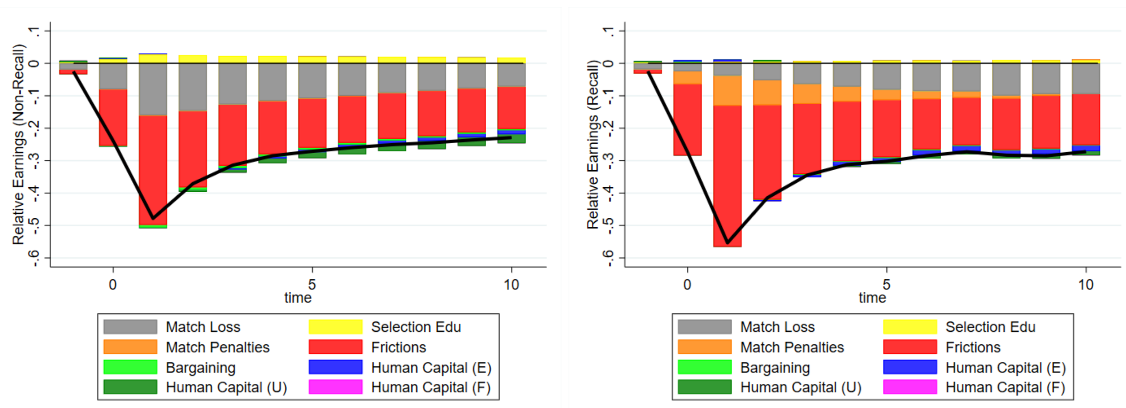

Figure B.10: *A decomposition of the scarring effect of displacement on earnings for (ex-post) non-recalled workers (left) and recalled workers (right).The black line represents the total earnings loss, and corresponds to the solid blue and red lines in the left panel of Figure 9. The decomposition is 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 B.4 and B.5.*

	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	-0.038	-0.081	-0.094	0.000	-0.002	-0.012	-0.008
Selection Edu	0.003	0.004	0.008	0.009	-0.000	0.000	0.000	-0.000
Match Penalties	-0.039	-0.092	-0.032	0.003	-0.029	-0.070	-0.023	-0.007
Frictions	-0.220	-0.435	-0.176	-0.157	-0.228	-0.383	-0.043	-0.006
Bargaining	0.002	0.001	-0.003	-0.002	-0.002	0.006	-0.002	-0.001
Human Capital (E)	0.005	0.007	-0.012	-0.017	-0.001	0.001	-0.011	-0.009
Human Capital (U)	0.004	0.001	-0.006	-0.013	-0.000	-0.001	-0.010	-0.015
Human Capital (T)	-0.000	-0.000	-0.000	-0.000	0	-0.000	-0.001	-0.001
Total	-0.274	-0.553	-0.302	-0.272	-0.261	-0.449	-0.103	-0.049

Table B.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 9. 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 B.10.*

As can be observed in the figure, the human capital depreciation for non-employed workers holding a potential recall (in pink) has a very small impact (for recalled workers), due to this depreciation rate being so close to zero. Similarly, because the recalled worker does not lose their match, the match loss element is (close to) zero for them in the short run. As a result, the bulk (roughly 95%) of the short-run earnings losses experienced by the recalled worker are explained by "Match penalties" and "Frictions": the penalties on the productivity and separation rates as well as losses that occur because the worker spends time in non-employment (anything other than human capital loss). In the long run, (subsequent) match losses become important as well, accounting for roughly 35% of the earnings losses 10 years after the displacement takes place. Using a direct counterfactual instead of the regression-based decomposition yields a similar result, although the impact of the "Frictions" channel is smaller in the long run, and a larger role is attributed human capital loss. Specifically, human capital loss accounts for 51% and 79% of the long-run losses (experienced by recalled and non-recalled workers respectively) in the direct counterfactual, whereas it accounted for 11% and 17.5% of the long-run earnings losses in the regression-based approach.

As the left panel of Figure B.11 shows, the decomposition of the average scarring effect of displacement looks 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

	Regression-Based				Direct Counterfactual			
Channel	$k=0$	$k=1$	$k=5$	$k=10$	$k=0$	$k=1$	$k=5$	$k=10$
Match Loss	-0.080	-0.160	-0.108	-0.071	-0.016	-0.045	-0.021	-0.009
Selection Edu	0.012	0.027	0.021	0.018	0.002	0.006	0.004	0.002
Match Penalties	-0.001	-0.002	-0.001	-0.001	0.000	0.000	0.000	0.000
Frictions	-0.173	-0.336	-0.151	-0.130	-0.174	-0.345	-0.023	-0.005
Bargaining	-0.002	-0.008	-0.006	-0.004	-0.002	-0.007	-0.005	-0.001
Human Capital (E)	0.002	0.003	-0.008	-0.012	-0.001	-0.003	-0.011	-0.009
Human Capital (U)	0.003	-0.002	-0.018	-0.028	-0.000	-0.005	-0.031	-0.035
Human Capital (T)	0.000	-0.000	-0.000	-0.000	0	0	-0.000	-0.000
Total	-0.239	-0.478	-0.271	-0.229	-0.192	-0.398	-0.086	-0.056

Table B.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 9. 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 B.10.*

decomposition of the average scarring effect of displacement (on earnings) points towards human capital depreciation as one of the drivers of the large long-run losses, it is natural to expect that a policy aimed at helping displaced workers may be targeted at bringing down the depreciation probability of human capital for non-employed workers. The right panel of Figure B.11 considers the extreme case of zero human capital depreciation (i.e. $\psi_u = 0$, and therefore also $\psi_r\psi_u = 0$). The figure shows that 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 more.

B.5 Alternative Calibrations

In this section, I analyze the robustness of the simulation results in Section 5 to an alternative calibration of the model. In this alternative calibration, I estimate the model by directly targeting the scarring effects of displacement by (ex-post) recall status that were estimated in Section 2.3 of the main text, in addition to the moments targeted in the baseline estimation. In other words, I target the outcome of the estimation of the following equation:

$$e_{it} = \alpha_i + \gamma_t + \sum_{C\neq 0} \sum_{\substack{k=-4 \\ k\neq -2}}^{10} \delta_k^C D_{it}^{C,k} + u_{it} \tag{B.12}$$

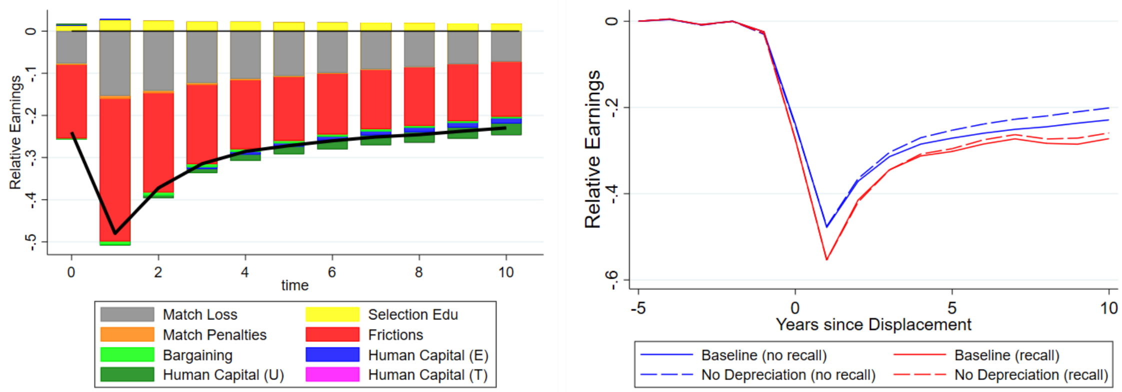

Figure B.11: *Left: A decomposition of the average scarring effect of displacement on earnings. The black line represents the total earnings loss. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals. Right: The effect of displacement on earnings relative to the control group, by ex-post recall status, using model simulation data from the baseline model (solid) and a counterfactual in which non-employed workers do not lose human capital during non-employment ($\psi_u = \psi_r \psi_u = 0$, dashed).*

In the data, this equation can be estimated using standard fixed effects estimation. Given the number of individuals in the simulation (and therefore the number of individual fixed effects), however, this is too computationally intensive to execute in each iteration of the calibration. Fortunately, the structure of the model and its simulation allow me to make several simplifications. First, the different cohorts in the data pick up effects of differences in economic conditions at the time of displacement, but there are no such differences in the model. Therefore, I do not allow for different estimates by cohort in the model equivalent. 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 (B.12), 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:

$$\ddot{e}_{it} = \sum_{\substack{k=-4 \\ k \neq -2}}^{10} \delta_k \ddot{D}_{it}^k + \ddot{u}_{it} \tag{B.13}$$

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. Therefore, the targeting of the scarring effect is not as precise as it would be if I were to estimate (B.12) directly, but the transformation does make this (imperfect) targeting feasible, and therefore allows me to use this for an alternative calibration. Using this alternative calibration, I then analyze whether targeting these empirical results directly might change results.

In Table B.6, I present the equivalent of Table 3 for the calibration using these additional moments (adding in the baseline results from Table 3 for comparison). The additional moments are not included in the table explicitly, as they are more naturally described in an event study graph (as done in Figure B.12)

Comparing the estimated parameters in the final column of Table B.6 to those in the baseline calibration, a few parameter values stand out. First of all, the marginal distribution of separation rates for the high education level is still very concentrated towards low values for δ, as indicated by the high value of $\mu_{\delta,2}$, resulting in a very low unconditional job loss rate for the highly educated worker. When it comes to match productivity y, the difference between the minimum levels of productivity ($\mu_{y,2} - \mu_{y,1}$) is now higher. In addition, highly educated workers changing their human capital in larger steps (as the value of $\Delta_s(2)$ increased). Some of the resulting differences are partially offset by high type workers starting at a much lower human capital level of $s_2 = -0.394$, rather than $s_2 = -0.028$ as in the baseline. The human capital equally often as in the baseline model during regular unemployment, as indicated by the unchanged value of ψ_u, but this is not the case for non-employed workers holding a potential recall, who face a depreciation probability of $\psi_r \psi_u \approx 0.035$ rather than 0.005. 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 (0.103 instead of 0.014), translating 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 for workers with a low education is much higher than it was in the baseline calibration. At the same time, the arrival rate of new job offers while holding a potential 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 the post-recall penalty on the separation rate is lower in the alternative calibration. This would make the potential recall option more attractive for a worker when given the offer, which can explain

		Baseline		Alternative Calibration	
Description of Moment(s)	**Data**	**Model**	**Parameters**	**Model**	**Parameters**
Average rate of job loss, tenure 1-3.5y	0.031	0.028	$\eta_\delta = 2.26$	0.047	$\eta_\delta = 4.02$
Average rate of job loss, tenure 3.5-6y	0.016	0.023	$\mu_{\delta,1} = 11.1$	0.042	$\mu_{\delta,1} = 14.0$
Average rate of job loss, tenure 6-9y	0.012	0.019	$\mu_{\delta,2} = 76.8$	0.036	$\mu_{\delta,2} = 136.3$
Average rate of job loss, tenure>9y	0.008	0.013	$c^\delta = 0.152$	0.026	$c^\delta = 0.066$
Average rate of job loss, by education	0.024	0.025		0.047	
	0.02	0.005		0.004	
Subsequent separation, displacement	0.081	0.047		0.07	
Subsequent separation, recall	0.168	0.163		0.109	
p75-p25 ratio of wages	1.541	1.465	$\eta_y = 6.7$	1.277	$\eta_y = 9.54$
	1.626	1.569	$\mu_{y,1} = 0.99$	2.192	$\mu_{y,1} = 0.87$
Median-p25 ratio of wages	1.242	1.203	$\mu_{y,2} = 1.36$	1.13	$\mu_{y,2} = 1.85$
	1.313	1.233	$s_2 = -0.028$	1.597	$s_2 = -0.394$
Educational wage premium (all)	1.533	1.595		2.133	
Educational wage premium (entry)	1.466	1.468		1.476	
Job-to-job transition rate	0.028	0.023	$\lambda_1^e = 0.053$	0.038	$\lambda_1^e = 0.027$
	0.03	0.008	$\lambda_2^e = 0.014$	0.02	$\lambda_2^e = 0.103$
Displacement among job-to-job transitions	0.422	0.434	$\lambda_1^{ug} = 0.422$	0.763	$\lambda_1^{ug} = 0.742$
	0.436	0.413	$\lambda_2^{ug} = 0.667$	0.121	$\lambda_2^{ug} = 0.685$
Average job finding rate	0.141	0.152	$\lambda_1^u = 0.145$	0.143	$\lambda_1^u = 0.127$
	0.146	0.139	$\lambda_2^u = 0.14$	0.064	$\lambda_2^u = 0.043$
Replacement rate	0.6	0.604	$b = 0.715$	1.528	$b = 1.593$
Yearly wage growth	0.013	0.011	$\Delta_s(2) = 0.13$	0.006	$\Delta_s(2) = 0.22$
	0.016	0.014	$\psi_e = 0.026$	0.022	$\psi_e = 0.01$
Pre- to post-layoff wage, duration<0.5y	-0.046	-0.068	$\psi_u = 0.113$	-0.028	$\psi_u = 0.113$
	-0.01	-0.031	$\psi_r = 0.042$	-0.256	$\psi_r = 0.306$
Pre- to post-layoff wage, duration 0.5-1y	-0.103	-0.117	$c^f = 0.368$	-0.046	$c^f = 0.423$
	-0.064	-0.051		-0.29	
Pre- to post-layoff wage, duration 1-2y	-0.125	-0.132		-0.067	
	-0.122	-0.1		-0.448	
Pre- to post-recall wage, duration 0.25-0.5y	-0.02	-0.059		-0.026	
	0.03	0.005		0.052	
Pre- to post-recall wage, duration 0.5-1y	-0.01	-0.066		-0.034	
	0.002	-0.03		-0.115	
Recall rate	0.067	0.062	$\phi_1^f = 0.071$	0.216	$\phi_1^f = 0.209$
	0.027	0.01	$\phi_2^f = 0.278$	0.195	$\phi_2^f = 0.172$
Recall materialization rate	0.393	0.334	$\phi_1^r = 0.174$	0.216	$\phi_1^r = 0.148$
(Based on materialization in 2 years)	0.253	0.259	$\phi_2^r = 0.123$	0.284	$\phi_2^r = 0.225$
Recall materialization rate	0.35	0.37	$\phi^{rg} = 1.017$	0.251	$\phi^{rg} = 1.118$
(Based on materialization in 1 year)	0.204	0.212	$\lambda^r = 0.894$	0.342	$\lambda^r = 0.53$
New job finding rate, expecting a recall	0.293	0.269		0.071	
Wage of newly hired worker	0.684	0.717	$\kappa = 0.96$	0.739	$\kappa = 0.785$
Wage of newly recalled worker	0.725	0.763	$\kappa^r = 0.73$	0.799	$\kappa^r = 0.577$
Coefficient $\hat{\gamma}$ in equation (15)	-0.021	-0.021	$\rho = -20.5$	-0.018	$\rho = -19.51$

Table B.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.*

why the recall rate for workers with a high education is much higher than in the baseline, despite the fact that the recall offer probability decreased.

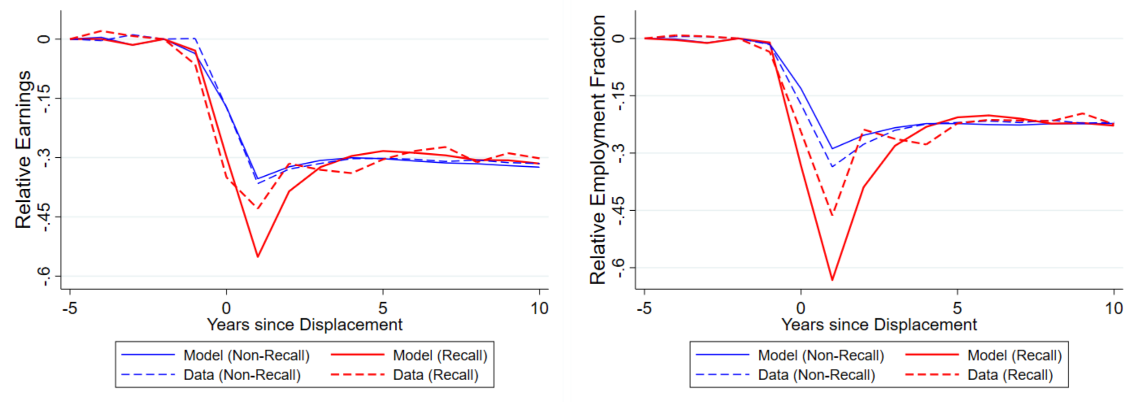

Figure B.12: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right) relative to the control group, by ex-post recall status (materialization of recall within 5 years), using model simulation data from the alternative calibration model (solid) and using the data (dashed, corresponding to Figure 4).*

In Figure B.12, I show the estimated effect of displacement on earnings and employment fraction by ex-post recall status, compared to the results in Figure 4. As can be seen from Figure B.12, the alternative calibration of the model matches recalled workers doing 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 also does well in matching the differences in the long run.

In Figure B.13, I fully decompose the differences in estimated post-displacement earnings between recalled and non-recalled workers (as shown in the left panel of Figure B.12), just like I did for the main calibration in Figure 10. Comparing the decomposition in Figure B.13 to the decomposition in Figure 10 reveals a very similar picture. In particular, 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 with low education, λ_1^{ug}. 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 impact of the "Selection Search" channel is much lower than in the baseline, due to lower new job offer arrival rates among workers holding a potential recall.

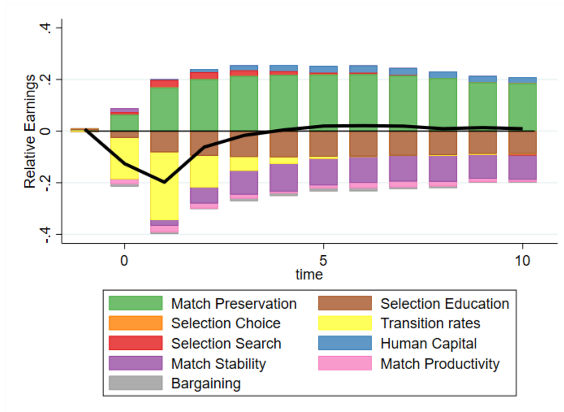

Figure B.13: *A decomposition of the difference in the scarring effect of displacement on earnings between (ex-post) recalled and non-recalled workers, using the alternative calibration of the model. The black line represents the total difference, calculated as the difference between the solid red and blue lines in the left panel of Figure B.12. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals.*

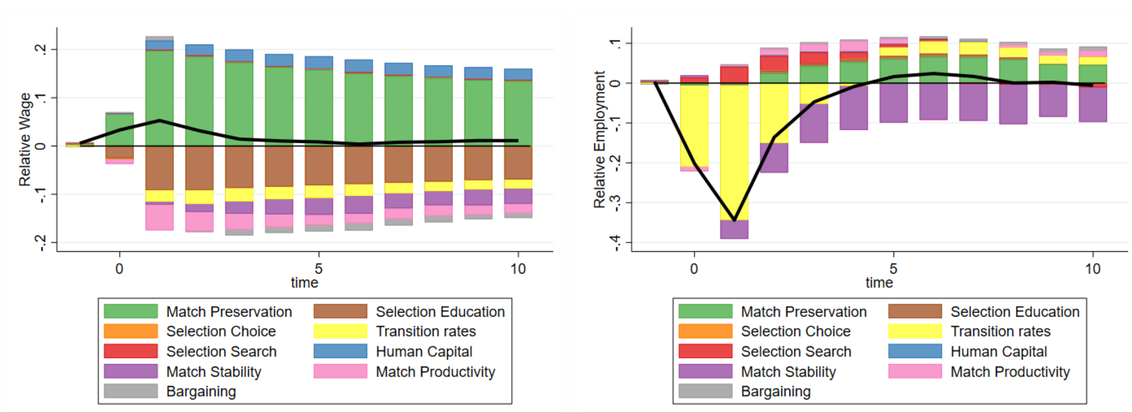

Figure B.14: *A decomposition of the difference in the scarring effect of displacement on wages (left) and employment (right) between (ex-post) recalled and non-recalled workers, using the alternative calibration of the model. The black line represents the total difference. The decomposition is generated by turning off the indicated channels one by one (starting with those depicted on the outside), thus generating counterfactuals.*

In Figure B.14, 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 negative in the short run and converge towards 0 within a few years. As can be seen by comparing the left panel to the left panel of Figure B.5, the decomposition of the wage differences yield very similar conclusions, with the exception of the aforementioned dampening "Selection Search" channel, mostly offset by a decreased impact of the "Selection Choice" channel. At the same time, it can be observed that the "Selection Education" channel is much more important than in the baseline, reflecting the much higher recall rate among highly educated workers compared to the baseline estimation. 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, but gradually decreases in importance and is eventually overtaken by the "Match Stability" channel.

C Data Appendix

C.1 Individual Summary Statistics

	Frequency	Mean	(Std.Dev.)
Age	24.3m	41.291	(9.91)
Primeage (aged 35–60)	22.7m	0.6922	(0.462)
Gender (female)	24.3m	0.4635	(0.499)
Education (university)	23.0m	0.1561	(0.363)
Location (east)	19.5m	0.1891	(0.392)
Self-employed	6.2m	0.0075	(0.086)
Establishment size	20.3m	1,143.7	(4,606)
Establishment tenure (days)	20.5m	2,222.8	(2,261)
Job tenure (days)	20.5m	2,102.3	(2,209)
Yearly earnings (2015 Euros)[53]	22.5m	27,142.4	(20,605)
Separation	20.1m	0.1195	(0.324)
Displacement	19.8m	0.0147	(0.120)
Recall (conditional on end of spell)	3.0m	0.4577	(0.498)

Table C.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 1, without any of the further restrictions imposed for the estimation).*

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

Table C.1 presents summary statistics for a number of worker-related variables mentioned throughout the main text. A few observations can be made from these summary statistics, including some that were already mentioned in the main text. First, the data substantially undersamples 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 analysis is based on. Second, both workers residing in East Germany and female workers are slightly undersampled. Finally, separation, displacement, and recall (conditional on an employment spell ending) rates are in line with those discussed in the main text in Section 2.1.

C.2 Establishments in the Sample

In Section 2.1, 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 C.2, I compare recalling, displacing and non-displacing establishments in the data on a number of variables. As can be seen in the table, establishments that recall workers generally tend to recall a large fraction (roughly 89% 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 72% of the workers observed at that establishment being separated. In line with the observations in Section 2.1, recalling establishments tend to be larger, and tend to have a lower median wage. Displacing establishments, in turn, tend to be larger and have lower median wages than the average establishment in the data.

	Recalling		Displacing		All	
	Mean	(Std.Dev.)	Mean	(Std.Dev.)	Mean	(Std.Dev.)
Establishment size	179.6	(1,036)	140.2	(486)	73.7	(348)
Median wage (percentile)	40.1	(27.5)	47.1	(31.0)	52.6	(28.3)
Displaced (fraction)	0.775	(0.31)	0.720	(0.33)	0.013	(0.11)
Recalled (fraction)	0.886	(0.24)	0.074	(0.25)	0.074	(0.25)

Table C.2: *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 1, without any of the further restrictions imposed for the estimation) and taking out duplicate observations for establishments.*

The high fraction of workers being displaced (conditional on displacement taking place) can partially be explained by the fact that establishment closures are included in my definition of a displacement. However, it should be noted that in order for an establishment exit to be denoted as a closure, a few more restrictions need to be satisfied. Since the dataset provides information on what happens to the majority of an establishment's former employees after an establishment exits, it is possible to distinguish between several exit types. Using 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 (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 new establishment's employment). Finally, an exit is classified as type C if it does not satisfy the conditions for type A and B. When defining displacement, I use only exits of type B.

C.3 Further Empirical Results

C.3.1 Further observations on the incidence of recall

In this subsection, I further analyze the incidence of recall conditional on displacement, beyond the analysis in Section 2.1. In particular, I show how displacement and subsequent recall rates differ over the earnings distribution, and focus on the impact of including establishment closures and indirect recalls into the definitions of displacement and subsequent recalls.

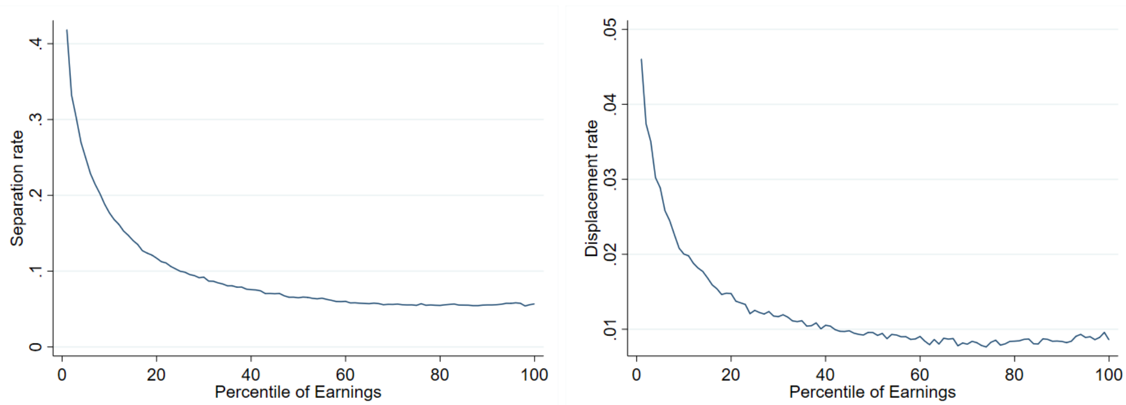

Figure C.1: *The incidence of separation (left) and displacement (right) over the recent earnings distribution.*

In Figure C.1, I show that the separation and displacement rates tend to be higher for individuals located lower on the (recent) earnings distribution.[54] This can be thought of as supporting the idea of a job ladder with slippery bottom rungs, where higher productivity matches are also more stable, as implied by the estimated model in Jarosch (2023). However, it should be noted that the pattern in the data is not quite monotonic throughout the distribution: above the 70th percentile of the distribution, the displacement rates are slightly increasing again.

Figure C.2: *The incidence of recall within 5 years of displacement (as a fraction of total displacements), by percentile of the recent earnings distribution.*

Figure C.2 shows the incidence of recall (within 5 years) after displacement, over the recent earnings distribution. 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 may follow a very different path after job loss if they expect to be recalled (as investigated in the analysis below), it is important to consider these workers separately.

Figure C.3 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 cannot be recalled, these closures mechanically drive down the recall rate. Indeed, as can be observed in the figure, excluding these establish-

[54] The construction of the recent earnings distribution largely follows Guvenen et al. (2017). 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 on 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 (below 35 and 35 to 60), gender, and location (East and West).

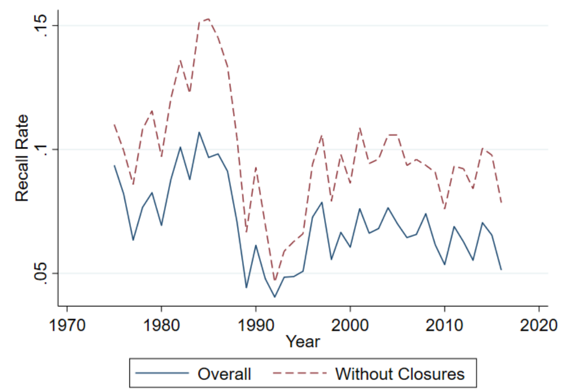

Figure C.3: *The incidence of recall within 5 years of job loss over time, conditional on displacement, with and without including establishment closures in the definition of a displacement.*

ment closures leads to an increase in the recall rate of approximately 2.5 percentage points (from an average of 6.6% to an average of 9%).

Figure C.4: *The incidence of recall within 5 years of job loss over time (left) and the recent earnings distribution (right), conditional on displacement, with and without including indirect recalls.*

Figure C.4 shows how the recall rates are affected by including so-called "indirect" recalls, that is, counting workers who return to their former establishment (within 5 years) after working somewhere else in between. Including these recalls naturally increases the recall rate. However, as the figure shows, the additional recalls are generally spread out over time and over pre-displacement earnings, so that excluding these indirect recalls from the estimation does not seem to strongly bias the sample towards a certain year or towards workers with higher or lower pre-displacement earnings.

In Table 2 in the main text, I showed how recalled workers are distributed along different

	Time to recall				
Time to re-separation	$<$ 1mo	1-4mo	4-8mo	8-12mo	$>$ 12mo
$<$ 1 month	0	0.021	0.022	0.018	0.017
1-3 months	0	0.045	0.040	0.055	0.034
3-6 months	0	0.040	0.088	0.039	0.038
6-12 months	0	0.122	0.139	0.070	0.073
12-24 months	0	0.008	0.020	0.017	0.029
$>$ 24 months	0	0.008	0.020	0.015	0.022

Table C.3: *Distribution of (ex-post) recalled workers over different combinations of time to recall and time to re-separation (in months). The table lists the fraction of workers falling into the relevant combination of categories, relative to the total number of displaced and recalled workers for whom both recall and re-separation is observed.*

combinations of time to re-separation and time to re-employment. Table C.3 repeats the analysis from Table 2, but uses the time to recall instead of the time to re-employment, noting that the two may be different for indirect recalls. Indeed, due to the definition of a recall discussed in Section 1, the time to recall is always at least 1 month. Using the table, it can be calculated that the majority (78.7%) of recalls materialize within a year of the displacement. Following the main text in flagging workers as potentially seasonal if their time to recall is between 4 and 12 months and their time to recall and time to re-separation add up to approximately a year, Table C.3 flags up to 26.6% of the recalled workers as potentially seasonal. Doing the same exercise only for directly recalled workers flags up to 26.5% of these directly recalled workers as potentially seasonal. In Table C.4, I show what this distribution looks like for non-recalled workers (using time to re-employment). Based on this table, and the same reasoning as in the main text, one could argue that approximately 11% of the non-recalled workers may be seasonal workers.

	Time to re-employment				
Time to re-separation	$<$ 1mo	1-3mo	3-6mo	6-12mo	$>$ 12mo
$<$ 1 month	0.025	0.009	0.008	0.011	0.025
1-3 months	0.052	0.014	0.013	0.019	0.040
3-6 months	0.072	0.016	0.015	0.026	0.042
6-12 months	0.146	0.032	0.036	0.033	0.057
$>$ 12 months	0.155	0.017	0.023	0.036	0.079

Table C.4: *Distribution of (ex-post) non-recalled workers over different combinations of time to re-employment and time to re-separation (in months). The table lists the fraction of workers falling into the relevant combination of categories, relative to the total number of displaced and non-recalled workers for whom both re-employment and re-separation is observed.*

C.3.2 Further Observations on the Average Scarring Effect of Displacement

In this subsection, I provide further results to illustrate the robustness of the results in Section 2.2.

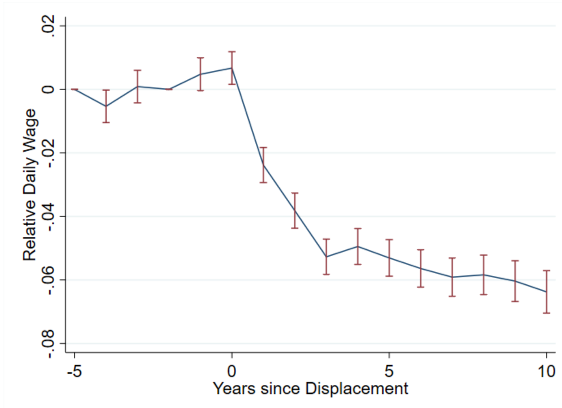

Figure C.5: *The effect of displacement on daily wages, relative to the control group, using estimated coefficients from equation 1, and using a sample that excludes the top and bottom 5% of the daily wages. The error bars correspond to 95% pointwise confidence intervals.*

As I mention in section 2.2, the estimated scarring effects of displacement on earnings and employment fraction seem to suggest that the daily wage of the displaced worker plays a large role (though smaller than that of employment). In figure C.5, I confirm this hypothesis by showing the results of estimating equation (1) using the (daily) wage as the dependent variable. In order to do so, I slightly trim the sample to omit the top and bottom 5% of the observed wages. I do this because the data contain some very high wages which are otherwise likely to influence the results.[55] It is indeed the case that the displaced workers tend to experience a wage loss of roughly 6% in the long run. This wage loss does not materialize immediately following the displacement but rather takes a few years to materialize, thus suggesting that this wage loss may be primarily driven by the displaced workers that are unemployed for an extended period of time before finding a new job.

While obtaining the results displayed in Figure 3 in the main text, I did not include any observation where the earnings for the individual are missing when creating my estimation sample. I chose not to include these observations as these missing values may not in fact be zero, given that

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

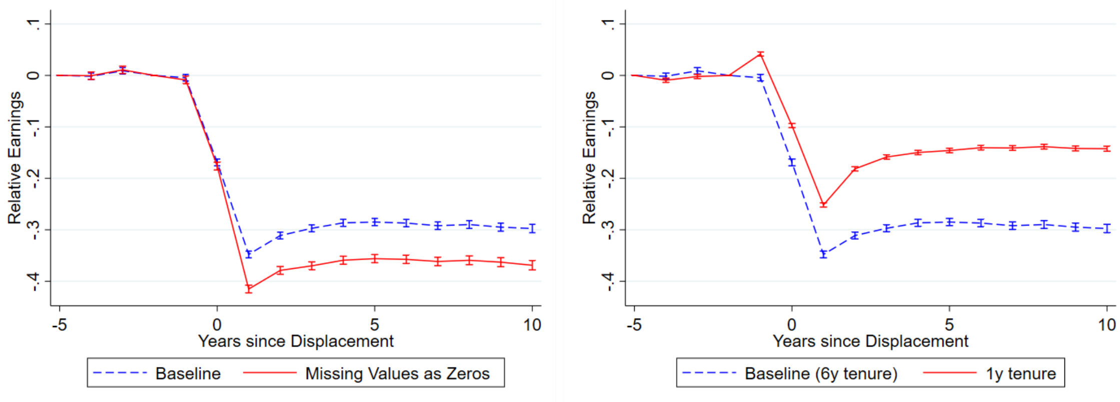

Figure C.6: *The effect of displacement on earnings, relative to the control group, using estimated coefficients from equation 1. The solid line mirrors the estimate from the left panel of Figure 3, whereas the dashed line estimates the effect including missing values (interpreted as zero earnings) in the left panel and relaxing sample restrictions on pre-displacement tenure.*

there are many possible reasons for the earnings to be missing (including self-employment and employment in the public sector, as indicated in Section 1). Include these missing values as zeros in the estimation slightly inflates the estimated effect, as seen in the left panel Figure C.6.

Other sample restrictions imposed to obtain the estimation sample used in the main text include strong restrictions on the worker's pre-displacement tenure and establishment size, requiring 6 years of pre-displacement tenure and an establishment size of at least 50 workers. In the right panel of Figure C.6, I show how sensitive the average earnings losses from Figure 3 are to relaxing (but not removing) the restrictions on tenure. Relaxing restrictions on pre-displacement tenure substantially dampens the estimated earnings loss. This seems consistent with the notion of some of the lost human capital upon displacement being firm-specific. Alternatively, it could correspond to lower tenured workers being younger on average, and younger workers generally experiencing smaller earnings losses after displacement (as shown in Leenders and Wallenius (2024)).[56]

Figure C.7 shows how the average scarring effect of displacement differs by education level (non-University and University), which is of interest as I use the education level as the fixed worker type when estimating the model.[57] I find that workers with a relatively low education tend to suffer from higher earnings losses in the short run, but the two groups slowly converge,

[56]The estimates of the earnings loss do not change in a substantial way when relaxing the requirement on pre-displacement establishment size. These results are therefore omitted from the text, and available upon request.

[57]Note that I split the sample by education group for both the treatment and control group. In other words, the effects in Figure C.7 are relative to workers in the same education group.

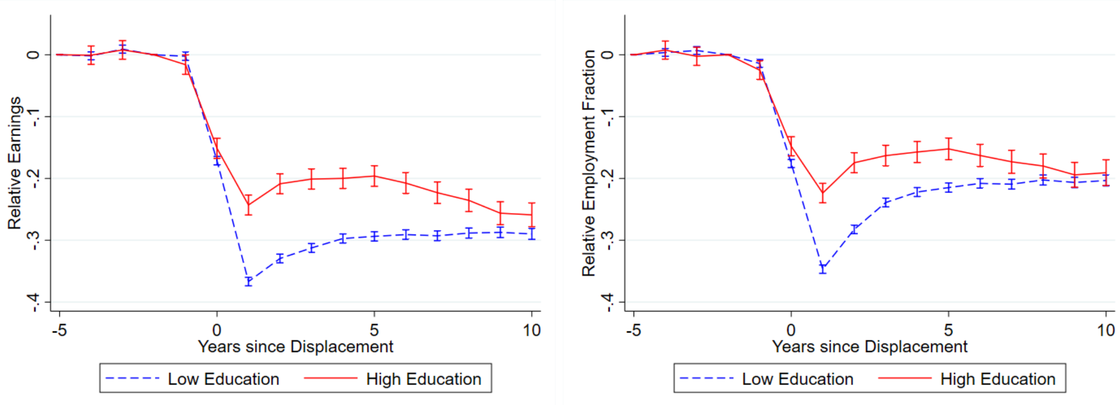

Figure C.7: *The effect of displacement on earnings (left) and employment fraction (right) by education level, relative to the control group of never-displaced workers, using estimated coefficients from equation* (1)*. The error bars correspond to 95% pointwise confidence intervals.*

such that the difference in earnings losses 10 years after the displacement event is much smaller than the initial difference. The short-run difference is partially driven by a larger initial effect on employment fraction, suggesting that highly educated workers find a new job faster.[58]

C.3.3 Further Heterogeneity in the Scarring Effect of Displacement

In Section 2.3, I showed how the scarring effect of displacement 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 these results.

Complementary to my discussion of the effect of displacement on earnings and employment by ex-post recall status in the main text, Figure C.8 shows how the effect of displacement on daily wages is different for recalled and non-recalled workers. As noted in the main text, it can be seen that recalled workers do better in terms of wages in the short run, both compared to non-recalled workers and compared to the control group of never-displaced workers. However, this effect is very short-lived, and disappears by year 2 after displacement.

In Figure 6, I showed that earnings losses are worse for recalled workers than for non-recalled workers when conditioning on experiencing at most 30 days of nonemployment (and vice versa if conditioning on being nonemployed for more than 30 days). The same picture arises when

[58]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. (2023) 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.

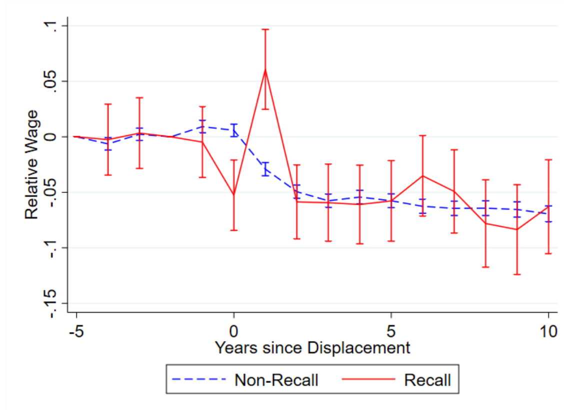

Figure C.8: *The effect of displacement on daily wages by ex-post recall status, relative to the control group, using estimated coefficients from equation 1', and using a sample that excludes the top and bottom 5% of the daily wages. The error bars correspond to 95% pointwise confidence intervals.*

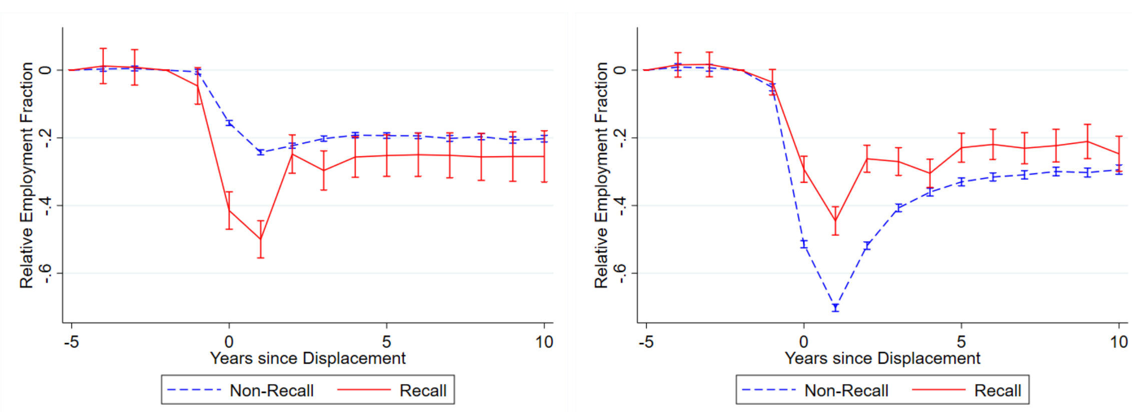

Figure C.9: *The effect of displacement on employment fraction by ex-post recall status, relative to the control group, using estimated coefficients from equation* (1'). *The effects are estimated separately for workers who transition within 30 days (left) and workers who spend time in nonemployment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

looking at employment fraction, as seen in Figure C.9. This seems to support the narrative of pre-layoff search, thus suggesting that immediate transitions should be taken into account when modeling the earnings losses experienced by displaced workers, as I do in Section 3.

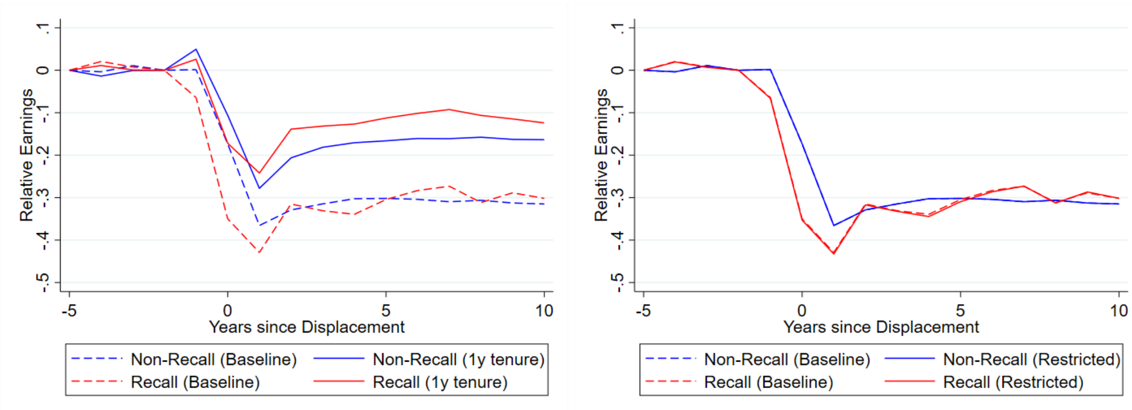

Figure C.10: *The effect of displacement on earnings by ex-post recall status, relative to the control group, using estimated coefficients from equation 1'. The dashed lines mirror the estimate from the left panel of Figure 4, whereas the solid lines estimate the effect either after relaxing sample restrictions on pre-displacement establishment tenure (left) or after excluding workers from the traditionally seasonal industries of agriculture and hospitality (right).*

In line with the discussion in Subsection C.3.2, the left panel of Figure C.10 shows how the estimated post-displacement earnings loss by ex-post recall status changes when relaxing the sample restrictions on pre-displacement establishment tenure. Similar to what was observed for the average earnings losses in Figure C.6, relaxing the restrictions on establishment tenure reduces the earnings losses. This change is stronger for recalled workers than for non-recalled workers, so that this sample indicates that recalled workers do better than non-recalled workers after displacement.[59]

The right panel of Figure C.10 shows that the comparison between recalled and non-recalled workers in Figure 4 of the main text is not likely to be driven by workers from seasonal industries. After all, omitting workers in industries that traditionally show strong seasonal patterns (agriculture and hospitality) does not substantially alter the results. Similarly, Figure C.11 shows that results are not largely affected by taking out potentially seasonal workers from the estimation sample, defining workers as potentially seasonal if their time to recall (or re-employment) and time

[59]Note that these changes in the results indicate that loss of firm-specific human capital may not play a large role in explaining earnings losses after displacement. After all, a large role for firm-specific human capital would imply that tenure is more important for non-recalled workers than for recalled workers (as recalled workers do not lose their firm-specific human capital), whereas Figure C.10 suggests that the opposite is true in the data.

to re-separation adds up to a number between 11 and 13 months.[60] If anything, removing these potentially seasonal layoffs and recalls strengthens my result that recalled workers do worse in the short run.

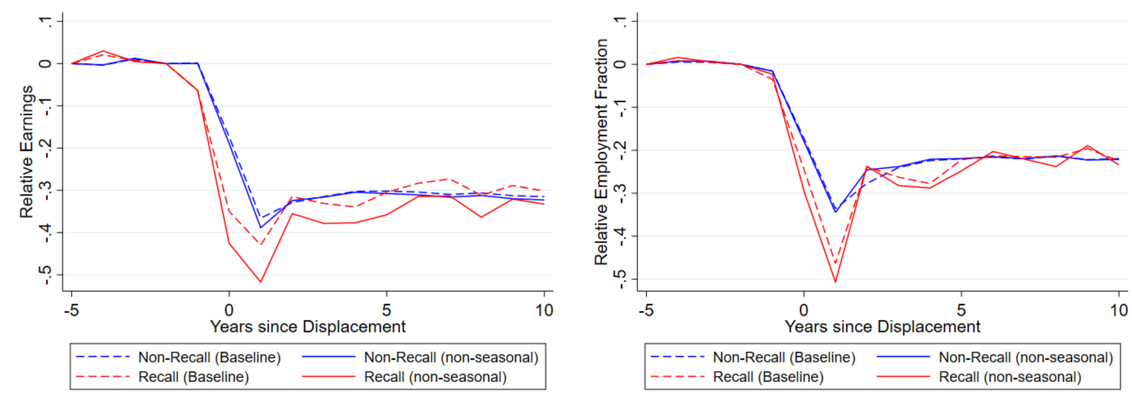

Figure C.11: *The effect of displacement on earnings (left) and employment (right) by ex-post recall status, relative to the control group, using estimated coefficients from equation 1'. The dashed lines mirror the estimate from the left panel of Figure 4, whereas the solid lines estimate the effect after excluding potentially seasonal workers, as measured by time to recall (or re-employment) and time to re-separation adding up to approximately a year.*

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 C.12, 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 these "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.

Figure C.13 shows how the results change when I use only earnings at the recalling establishment (for the recall group) or first post-displacement employer (for the non-recall group). As can be seen in the figure, the difference in the short-term earnings loss slightly grows, but it remains true that the two groups perform similarly in the long run. This remains true when additionally conditioning on still working at this employer 5 years after the initial displacement, even though this greatly reduces magnitude of the earnings loss for both groups, as the right panel

[60]Following this definition, 33.7% of the recalls and 12.8% of the non-recall displacements in the restricted sample are marked as potentially seasonal and taken out of the estimation here.

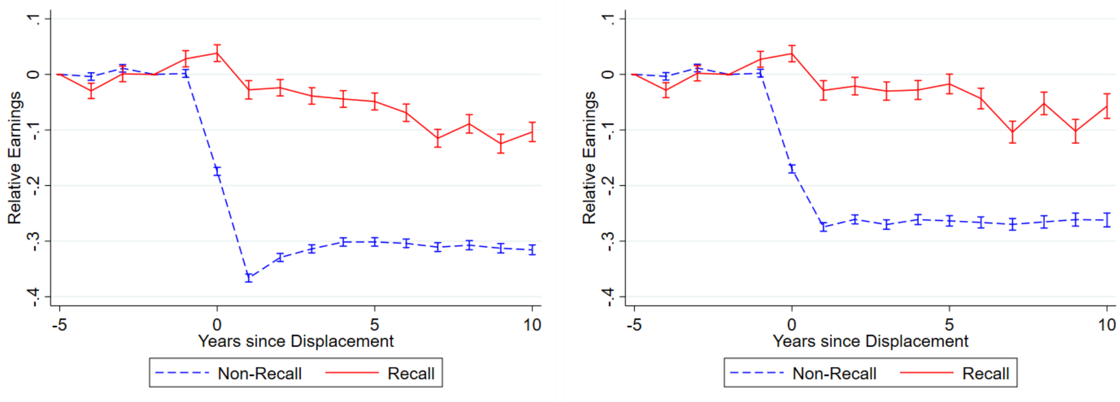

Figure C.12: *The effect of displacement on earnings, by ex-post recall status and relative to the control group, using estimated coefficients from equation* (1'). *The error bars correspond to 95% pointwise confidence intervals. The estimation here replaces recalled workers with workers who were not displaced from the establishment that recalled some workers. The right panel additionally only uses observations at the first employing establishment after displacement.*

shows.

Another potential concern with the comparison between recalled and non-recalled workers is that the group of non-recalled workers also includes workers that were displaced from an establishment that closed, thus leaving no room for a recall choice. As can be seen in the left panel of Figure C.14, however, omitting workers displaced from a closing establishment does not substantially affect the conclusion made in the main text (based on Figure 4). Similarly, removing indirect recalls from the sample does not substantially alter the results, as the right panel shows.

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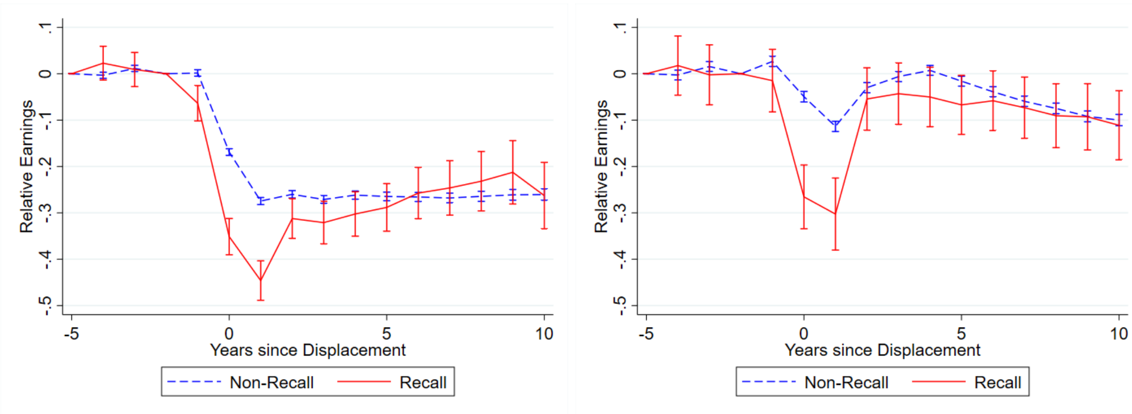

Figure C.13: *The effect of displacement on earnings, by ex-post recall status and relative to the control group, using estimated coefficients from equation* (1'). *The error bars correspond to 95% pointwise confidence intervals. Compared to the left panel of Figure 4, this estimation only uses earnings from the establishment to which the worker is recalled (left), or restricts the sample to workers who still work for their first post-displacement employer 5 years after displacement (right).*

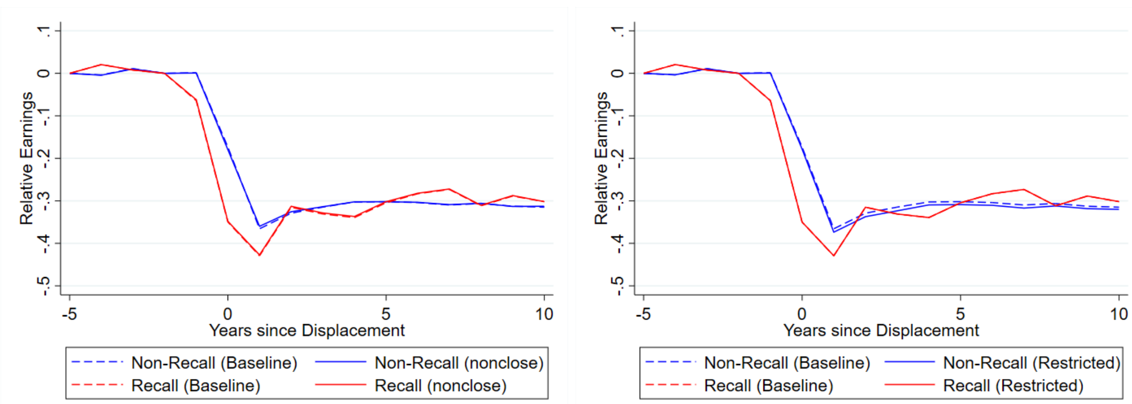

Figure C.14: *The effect of displacement on earnings, by ex-post recall status and relative to the control group, using estimated coefficients from equation* (1'). *The error bars correspond to 95% pointwise confidence intervals. Compared to Figure 4 in the main text (dashed lines here), the estimation excludes workers who were displaced from a closing establishment (left) or who were recalled after working for someone else (right).*

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