

Social Security and Life-Cycle Variation in the Cost of Job Loss*

Frank Leenders[†] Johanna Wallenius[‡]

**** Preliminary Draft ****

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Abstract:

In this paper, we study how the effect of displacement on subsequent earnings and employment differs by the worker's age at the time of the displacement. Furthermore, we investigate the extent to which this life-cycle variation is driven by the design of the social security system. Using German social security data, we find that the earnings losses, both upon impact and in the long run, generally increase in age. Employment loss, on the other hand, increases in age only until workers approach the window for early retirement, after which it starts decreasing. We develop a life-cycle model with search frictions, human capital, and savings, which contains a detailed representation of the German unemployment insurance, welfare, and pension systems. The model is estimated to match moments generated from German data, and used to decompose the life-cycle variation in earnings losses. We find that the age-dependencies embedded in the social security system, along with mortality risk and age-dependent job finding rates, are important in accounting for the age gradients in post-displacement earnings and employment losses. Furthermore, while workers with high lifetime income tend to retire early, job loss tends to nudge these workers to postpone their retirement. The opposite is true for workers with low lifetime income.

JEL Classifications: E21, E24, H55, J24, J26, J64

Keywords: Job Loss, Job Displacement, Job Search, Social Security, Retirement

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[†]frank.leenders@hhs.se, Department of Economics, Stockholm School of Economics.

[‡]johanna.wallenius@hhs.se, Department of Economics, Stockholm School of Economics.

1 Introduction

A large literature has established that job loss is associated with large earnings losses on average. Nevertheless, the extent to which these losses differ over the life cycle, and especially the role social security plays in shaping this life-cycle variation, is not as well documented, as the literature generally tends to restrict attention to prime-age workers. However, for workers who are (close to) eligible for early retirement at the time of their job loss, a number of additional drivers of earnings loss may come into play. In particular, since workers tend to have a lower wage after displacement (Lachowska et al., 2020), it may be more attractive for these workers to retire early and start collecting the retirement benefits they have accumulated over their working life. Conversely, since workers tend to have higher earnings late in the life cycle, losing their job may have a large impact on their potential retirement income, and thus incentivize them to remain in the work force for longer than they had initially planned.

In this paper, we investigate how the effect of job loss on earnings and employment varies depending on the worker’s age at the time of job loss, and the extent to which the design of the social security system can account for this variation over the life cycle. Following the literature, we focus on displacements, which are roughly defined as job loss events that occur as part of a mass layoff event, and are therefore less likely to be directly driven by the worker’s own productivity.

In order to empirically investigate the extent to which the effect of displacement on earnings and employment varies by the worker’s age at the time of the job loss, we use German social security data. These data contain information on both the employer and the employee, allowing us to reliably identify workers who lost their job as part of a mass layoff. Using the imputation-based estimator from Borusyak et al. (2022), we then construct an average effect of displacement for each of the first 10 years after the displacement, separately by the age of the worker at the time of displacement.

The empirical results indicate that the earnings loss following displacement is generally increasing in age. This is true for both the immediate impact and the long-run effect (10 years after displacement). While including a set of age indicators in the estimation does not substantially affect results for workers displaced at the age of 45 or earlier, this is not the case for older workers. For workers who are displaced after the age of 45, omitting the set of age indicators attenuates the estimated earnings loss, misleadingly suggesting that earnings losses start decreasing in age of

displacement after the age of 45. While the employment loss following displacement is increasing in age for most of the working life, we find that the pattern reverses once the worker nears the early retirement window. This indicates that some workers react to a displacement by changing their retirement timing, and do so in such a way that displaced workers on average tend to leave the labor force later.

In order to quantify the extent to which social security drives the observed life-cycle pattern of earnings and employment losses in age, we set up a life-cycle model. This model contains a combination of search frictions and human capital accumulation (and depreciation) that existing literature has shown to be successful in accounting for the average earnings loss. In addition, we incorporate a realistic representation of the German unemployment insurance, welfare, and pension systems, after the labor market reforms of the early 2000s.

We calibrate the model to match moments generated from the German social security data, Luxembourg Wealth Study (LWS, 2023), and OECD (OECD, 2023). In particular, we do not explicitly target the earnings losses observed in the empirical section of the paper, but instead elect to target a number of moments that are more closely linked to the parameters we are estimating. Nevertheless, we show that the estimated model is able to replicate the observed increasing losses in age of displacement, especially when focusing on the medium to long run (3 to 5 years after displacement).

We then use the estimated model to decompose these losses, thus quantifying the importance of the social security system as well as the other model elements in driving the earnings losses. In doing so, we find that the model elements that are traditionally included in models that aim to explain post-displacement earnings losses are decently able to capture the observed earnings loss for workers who are displaced early in their working life (prior to the age of 45). These model elements include human capital appreciation and depreciation, search frictions, and the existence of a job ladder (in productivity). For workers who are displaced after the age of 45, these traditional elements are no longer sufficient in explaining earnings and employment losses. For these workers, the age-dependent nature of social security, mortality risk, and age-varying job finding rates become increasingly important. In particular, the age-dependency in the unemployment insurance system tends to alleviate earnings losses for older displaced workers, but the pension system is one of the major drivers of earnings loss for workers displaced after the age of 55. This is primarily driven by fact that the pension system allows workers to choose the age at which they move into retirement, thus allowing workers to retire earlier or later in response to a displacement.

Since workers in the model are able to choose (and later adjust) the age at which they move into the absorbing retirement state, we can investigate which factors are correlated with workers choosing to retire early. Furthermore, we can use counterfactual simulations to show whether workers change their planned retirement age after being displaced. In general, workers in the model tend to retire earlier if they have high income during their working life. In fact, the age-dependency of the unemployment insurance system, and in particular the number of periods in which a worker can receive unemployment benefits, induce some highly experienced workers to quit even before they can legally retire, using unemployment insurance to bridge the time to pension collection. A displacement event tends to push workers in the opposite direction. After displacement, low earnings workers generally decide to retire earlier, compared to their planned retirement age prior to displacement, whereas high earning workers decide to retire or quit into unemployment later.

The rest of the paper is organized as follows: In the next subsection, we review the related literature and outline our contribution. Section 2 describes the data used to generate the empirical results, which are presented in Section 3. Section 4 presents the model. Section 5 outlines the estimation method and model fit, while Section 6 discusses the results of the model simulation and counterfactual experiments. Section 7 concludes.

1.1 Related Literature

This paper relates to a large literature investigating the consequences of displacement on labor market outcomes. This literature goes back to the seminal work of Jacobson et al. (1993), who found large and persistent earnings losses among US workers. Burda and Mertens, 2001 found comparable results for Germany. These losses have been shown to be driven by hours in the short run and wages in the long run (Lachowska et al., 2020), and more severe if the worker is laid off in a recession (Davis and Von Wachter, 2011, and Schmieder et al., 2020). In recent years, the literature has turned to explicitly investigating heterogeneity in these earnings losses.¹ Some of the existing literature has also sought to examine the impact of social security systems, in particular unemployment insurance (UI), on earnings losses (e.g. East and Simon, 2020, and Engbom et al., 2015).

We contribute to this literature by focusing on how losses differ by age at the time of

¹This includes work that explicitly investigates a certain dimension, such as gender (Illing et al., 2021) or recent earnings (Guvenen et al., 2017 and Leenders, 2023), and work using machine learning techniques to examine a large number of dimensions together, such as Gulyas and Pytka (2020) and Athey et al. (2022).

displacement, and doing so across the entire working life (and without grouping ages). The existing work that has investigated the age dimension, such as Couch et al. (2009), Heisig and Radl (2017), Ichino et al. (2017), and Albrecht (2022), has generally focused on a limited set of age groups that did not cover the entire working life, generally finding higher losses for older workers, which is in line with our results. The work closest to ours in this dimension is Salvanes et al. (2021), who (empirically) consider the entire life-cycle, and furthermore distinguish between different types of consequences at different ages, finding a particularly large role for early retirement late in the working life, and a large role for human capital early in the working life.

Since early retirement is one of the potential channels through which earnings losses could be different for older workers, this paper also relates to a literature examining retirement choice and its interaction with unemployment. In the context of the United States, Chan and Stevens (2001) and Chan and Stevens (2004) find that job loss leads workers to re-evaluate their retirement timing, often leading men to retire early. Indeed, as pointed out in Marmora and Ritter (2015), workers may decide to stay unemployed first and then retire once UI eligibility runs out, thus effectively retiring upon becoming unemployed. This channel of late-career job loss leading to earlier retirement has also been found in European countries, such as Germany (Tatsiramos, 2010), and appears in our model as well. We contribute to this literature by focusing on earnings loss in addition to employment patterns after a job loss, and by providing a structural explanation of the patterns observed in our data as well as the literature.

By proposing a model that can account for post-displacement earnings losses over the life cycle, this paper also contributes to the literature providing a structural explanation of the observed earnings losses. This literature followed work by Pries (2004) and Davis and Von Wachter (2011), who showed that existing simple job search models were unable to explain persistent earnings losses after a job loss. Following this observation, a number of papers have been successful in proposing models to explain average earnings losses, generally stressing the importance of search frictions and human capital depreciation (Burdett et al., 2020).² In addition, existing models have stressed the importance of occupational switches (Huckfeldt, 2022), repeated separations (Jarosch, 2021), or lengthy job ladders (Krolkowski, 2017). The two models that are closest to the one proposed in this paper are set out in Jung and Kuhn (2019) and Albrecht (2022), both of which use a life-cycle setting. The model in Jung and Kuhn (2019) further differs from the other afore-

²The exception to this is Gregory et al. (2021), who argue that earnings losses can be explained without the human capital element if one is willing to assume different types of workers (who face different productivity distributions and transition rates).

mentioned models by stressing a lack of mean reversion from the non-displaced workers rather than a lack of recovery among displaced workers as an explanation for the persistence of losses. The model proposed in Albrecht (2022) takes a different route from the aforementioned models by adding displacement to a model of human capital formation (rather than adding human capital to a search model), and it is shown that this model is able to explain increasing earnings losses in age for younger workers. While both models incorporate a life-cycle element, they also both explicitly omit the retirement choice (and subsequent pension income), and instead opt for a fixed length of the work life. Our paper therefore contributes to this literature by explicitly adding the retirement dimension into the model.

Finally, given the importance of the retirement channel in the model, this paper can also be thought of as contributing to a large literature providing a theoretical or quantitative analysis of (early) retirement decisions. This literature has found a large role for health insurance and especially Medicare on retirement behavior (French and Jones, 2011), although the effect of health shocks themselves are rather low on either retirement timing (French, 2005) or post-retirement asset accumulation (Horioka and Ventura, 2022). The setup of the social security system has been found to be important in explaining cross-country differences in retirement behavior (Erosa et al., 2012; Laun and Wallenius, 2016) as well as aggregate unemployment rates (Kitao et al., 2017). In Michelacci and Ruffo (2015), a model quite similar to ours is proposed, although their focus is not on the consequences of job loss, and they impose an exogenous retirement decision. Merkurieva (2019) investigates the effect of job loss on retirement decisions, but imposes an exogenous displacement penalty to capture the cost of job loss. Finally, Nam (2022) and Haan and Prowse (2022) model the U.S. and German social security systems (prior to the reforms of the early 2000s) in some detail, but focus primarily on analyzing the welfare effects of these systems rather than their impact on post-displacement earnings losses. As such, we view our contribution to this literature as incorporating an endogenous earnings loss into a model with an endogenous choice of retirement timing.

2 Data and Empirical Methodology

In order to generate the empirical results presented in the next section, we use the Sample of Integrated Labour Market Biographies, referred to as the SIAB (Antoni et al., 2019b), administered by the Research Data Center (FDZ) of the German Federal Employment Agency (BA) at the Institute

for Employment Research (IAB). This dataset consists of a 2% random sample of the German population in the Integrated Employment Biographies (IEB), which in turn includes all individuals who held a private sector job subject to social security or entered the social security system (for example by receiving benefits or participating in a training measure) at any point between 1975 and 2017.³ In the SIAB, each observation covers at most one employment or non-employment spell and at most one year. Spells that last longer than a year are broken up into smaller spells of a year. For the purpose of generating our empirical results, we collapse this dataset into a yearly panel, thus combining all information from a given (calendar) year into a single observation, while retaining the establishment information from the main employer only.⁴ We restrict the sample to men, in order to avoid issues arising due to fertility choices and the corresponding social security regulations. Imposing similar conditions, we also create a quarterly panel, which we use to estimate the values of some moments targeted in the model estimation.

In the data, we define a worker as separated in a given year if his employment spell with the employer ended in that year, and he no longer works for the same employer in the next year (or returned after being away for more than 31 days). In addition, we exclude terminated employment spells that were marked as casual employment, traineeships, and employment during (partial or full) retirement. Conditional on being separated, we then impose two more requirements for this worker to be considered as displaced. First, we require the reason for the end of the spell, which employers must report to social security, to point towards potential displacement, thus ruling out separations that occur because of quits, expired temporary contracts, or health-related leaves. Second, we require the separation to coincide with a mass layoff at the establishment. Following the literature, a mass layoff is said to occur either if the establishment closes⁵ or if the establishment experiences an outflow of at least 20% of its workforce.⁶

After imposing the above conditions and definitions, we impose two more restrictions in order to arrive at our full sample. In particular, we only include observations from 2005 or later, in

³Some types of jobs or training are not recorded until later, the last type being added from 2005. See Antoni et al. (2019a) for more information about the dataset.

⁴Generally, the main employer is defined as the employer from which the individual has the highest earnings from fulltime work in a certain year.

⁵In the case of establishment closure, we additionally rule out apparent closures where more than 80% of the establishment's former workforce found employment at a common establishment, following the definitions of different types of establishment exits by Hethey and Schmieder (2010).

⁶Additionally, we require the establishment's workforce in the next year to be at most 80% of its maximum size from the prior 5 years (which in turn must be at least 20 workers). For establishments where both the inflow and outflow meet the criterion of representing 20% of the workforce, we additionally require the net outflow to be at least 20% of the workforce.

order to only capture job loss that occurred after the Hartz reforms in the early 2000s. The resulting full sample contains close to 6 million observations. In generating the estimation-based results in the next section, we further restrict the sample to individuals with at least 1 year of establishment tenure at an establishment with at least 50 employees.⁷ This further reduces the sample size to approximately 2 million observations. However, it should be noted that these restrictions are only imposed at the time of the job loss event, and do not necessarily need to hold in the years before or after the event, thus increasing the true sample size used for the estimation. This restricted sample can thus best be thought of as the sample of individuals who would be classified as separated or displaced if they lose their job in the observed year. In Table 1, we summarize a number of key variables for the full sample as well as the restricted sample.

	Full Sample			Estimation Sample		
	Frequency	Mean	Std.Dev.	Frequency	Mean	Std.Dev.
Age	5.96m	40.87	13.80	2.02m	44.26	9.92
Location (East)	5.55m	0.203	0.40	2.01m	0.163	0.37
Establishment size	4.93m	1,016	4,363	2.02m	1,893	6,003
Establishment tenure (days)	4.99m	2,330	2,820	2.02m	3,654	2,927
Yearly earnings (2015 Euros)	5.58m	27,041	23,543	2.02m	45,042	19,834
Employment (fraction of year)	5.58m	0.689	0.398	2.02m	0.902	0.248
Full-time (indicator)	4.99m	0.174	0.379	1.88m	0.067	0.251
Separation	4.57m	0.123	0.33	2.02m	0.0074	0.086
Displacement	4.51m	0.0137	0.116	2.02m	0.0074	0.086
Estimation Sample ⁸	5.96m	0.339	0.47	2.02m	1	0

Table 1: *Summary statistics using the yearly full and restricted (estimation) samples. The table shows the estimated mean and standard deviation of a number of key variables.*

The estimation results presented in the next section are based on the estimation of an event-study framework. This framework can generally be thought of as represented by the following equation:

$$e_{it} = \alpha_i + \gamma_{h(i,t),t} + \sum_{C \neq 0} \sum_{k=-1}^K \delta_k^C D_{it}^{C,k} + u_{it} \quad (1)$$

⁷This is roughly in line with the restrictions commonly imposed in the displacement literature, although the literature tends to impose stronger restrictions on pre-displacement tenure. In Appendix B.3, we discuss how our results change when imposing this stricter condition instead.

⁸The variable "Estimation Sample" is an indicator for being included in the restricted sample used for generating estimation-based results. As such, it restricts the sample to individuals employed at an establishment with at least 50 workers and with an establishment tenure of at least 1 year.

In the equation above, subscript i refers to the individual, t to the year of observation, and $h(i, t)$ to the age of individual i in year t . The variable $e_{i,t}$ is the dependent variable, which is either yearly earnings or the fraction of the year spent in employment. The error term is denoted by $u_{i,t}$, α_i is an individual fixed effect, and $\gamma_{h(i,t),t}$ is a fixed effect for combinations of observation year and age. This interaction with age is not commonly used in the literature, but shown in Section 3 to be important in the context of this paper. The summation term is the object of interest, as it summarizes the effect of the treatment (displacement) depending on the cohort C to which the displaced worker belongs, which corresponds to the year of displacement (with $C = 0$ being the group of never-treated workers), and the time that has passed since displacement k , which ranges from -1 (the year prior to displacement) to K (which in most cases will be set to 10). In other words, variable $D_{it}^{C,k}$ indicates that individual i was displaced k periods prior to period t , with the time of treatment $t - k$ corresponding to C . Combining the estimated coefficients δ_k^C across cohorts yields a set of coefficients $\tilde{\delta}_k$, which can be plotted over k to generate an event-study graph.

In order to estimate equation (1), we use the imputation-based estimator from Borusyak et al. (2022), henceforth referred to as the imputation estimator. This method proceeds by first estimating the two fixed effect terms using only observations of the never-treated and not-yet-treated (which are observations from treated individuals more than 1 period ahead of the treatment). Using these estimated fixed effects, a counterfactual is imputed for each treated observation, after which the estimated individual treatment effect equals the difference between this imputed counterfactual and the actual observed value of $e_{i,t}$. Averaging this individual treatment effect across all individuals in each combination of C and k then yields an estimate of the coefficient δ_k^C .

Since we are primarily interested in how the effect of displacement depends on age at the time of displacement, we estimate equation (1) separately for each age. In other words, in each of these estimations, the treatment is defined as displacement at a particular age (rather than displacement in general). As such, the control group of “never-treated” consists of workers who were not displaced at the age of interest, but may have been displaced at a different age. Prior to performing the estimation for a particular age H , we trim the restricted sample to contain only observations for individuals aged between $H - 5$ and $H + 10$. Furthermore, since workers no longer appear in the dataset after retiring, we assume that any missing observation corresponds to a year in which the individual did not have any labour market income.⁹

⁹Since a worker needs to be employed at age H in order to be included in the control group, this assumption only affects years other than the potential treatment year. Furthermore, note that in cases where we observe the person to have died, we discard any observations made (or assumed to be made) after death.

3 Empirical Results

3.1 Life-Cycle Variation in the Incidence of Job Loss

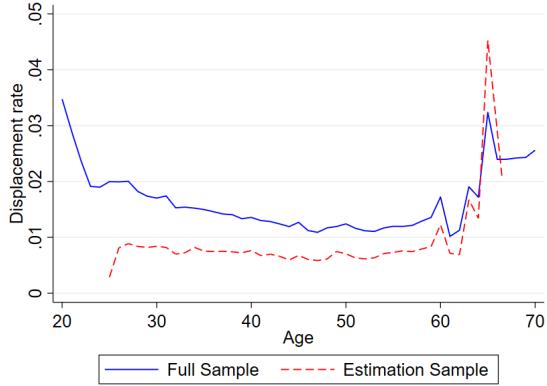


Figure 1: *The incidence of displacement by age, generated from the full sample (solid, blue) and the restricted estimation sample (dashed, red).*

Prior to examining variation in the effect of job loss on subsequent earnings and employment over the life cycle, it is worth considering how common these job loss events are at different points in the life cycle. In Figure 1, we show how displacement rates vary by age. Using the full sample, a U-shaped pattern appears, indicating higher displacement rates near the start and end of the working life. In Appendix B.1, we show that a similar conclusion can be reached when focusing on separations rather than displacements, or when separately plotting displacement rates for workers located in areas that used to be in East or West Germany before the German reunification. The fact that displacement rates are decreasing in age during the first half of the working life is in line with displacement rates declining in experience. Indeed, when we impose the sample restrictions used for the estimation in the next subsection (based on tenure and establishment size), this decreasing pattern largely disappears, suggesting that it is driven primarily by workers with low establishment tenure. However, the fact that displacement rates are increasing in age during the second half of the working life remains true when imposing sample restrictions, suggesting that this increase is not driven by the job hopping pattern described in the existing literature.

3.2 Life-Cycle Variation in the Cost of Job Loss

We now move our focus towards examining the cost of job loss, and its variation over the life cycle. In Figure 2, we show the results of estimating equation 1 using the imputation estimator discussed in Section 2. For expositional purposes, we depict only the estimated earnings

losses 1 year and 5 years after the displacement takes place. In Appendix B.3, we show that our conclusions hold for other values of k between 1 and 10, whereas Appendix B.2 highlights that similar results can be obtained without using any estimation procedures.

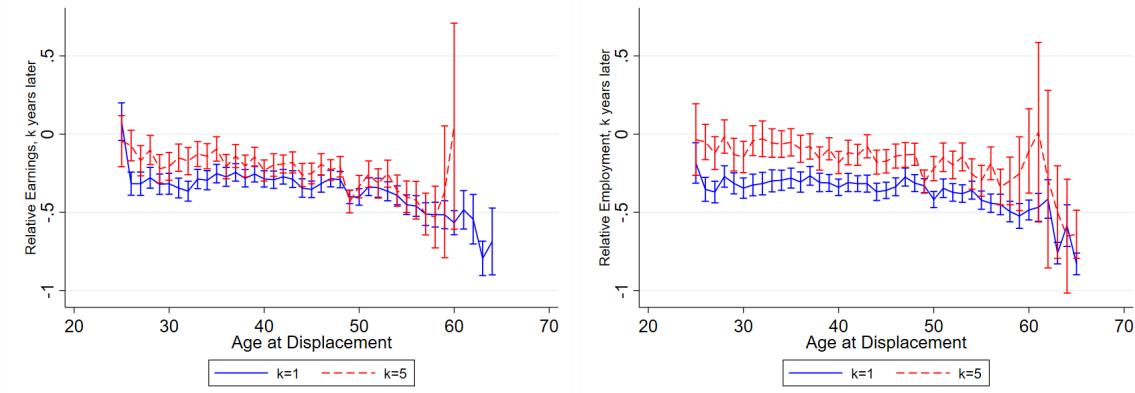


Figure 2: *The estimated effect of displacement on earnings (left) and employment (right), 1 year (solid, blue) or 5 years (dashed, red) after displacement, by age at displacement. Depicted estimates are obtained separately for each displacement age, and depicted along with a 95% pointwise confidence interval.*

The left panel of Figure 2 shows how the estimated earnings losses after displacement differ by age of displacement, in the short run (measured 1 year after displacement) and in the longer run (measured 5 years after displacement). The figure shows that the longer-run impact is lower in magnitude, indicating some recovery, but often not significantly so, thus indicating that the earnings loss is quite persistent. Furthermore, earnings losses increase in the worker's age at the time of displacement. This is generally true both for the immediate impact and the longer-run impact. However, a partial reversal can be observed for the longer-run impact close to the age of retirement, with earnings losses 5 years after displacement for those displaced at the age of 59 and 60 being less severe than for those displaced at the age of 57 or 58.¹⁰

If the upcoming retirement age plays a role in explaining the apparent alleviation of estimated longer-run earnings losses for workers, we would expect to see a similar pattern when estimating employment losses. The right panel of Figure 2 shows how the estimated employ-

¹⁰It should be noted that the reversal for $k = 5$ is quite large compared to the reversal observed for other values of k , as shown in Appendix B.3. Furthermore, it can be observed in the left panel of Figure 2 that while the point estimates are lower (in absolute value), the accompanying standard errors are also much larger. Since this issue is further exacerbated for workers displaced after 60, for whom $k = 5$ corresponds to ages beyond the regular retirement age of 65, we omit the corresponding estimates from the left panel of Figure 2.

ment losses after displacement differ by age of displacement. Compared to the earnings losses, the employment losses are shown to recover more over time, as indicated by the larger difference between the estimates for $k = 1$ and $k = 5$ across all depicted ages. Like earnings losses, employment losses are also generally increasing in age at the time of displacement, though the gradient is not as large for employment losses. Nevertheless, a reversal of the pattern is again visible for the longer-run impact close to the age of retirement, with employment losses decreasing in age for workers aged between 58 and 61 (for whom $k = 5$ falls around the regular retirement age of 65). This suggests that displaced workers on average tend to slightly postpone their retirement compared to the control group.

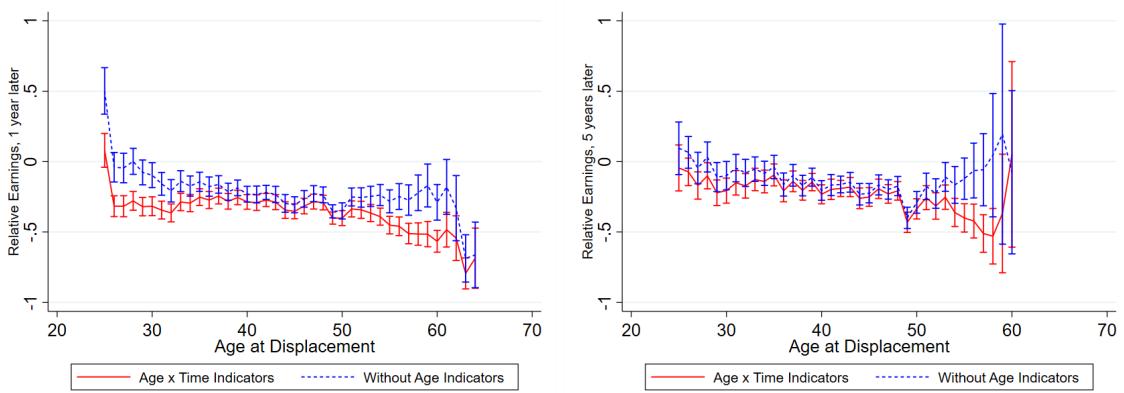


Figure 3: *The estimated effect of displacement on earnings, 1 year (left) or 5 years (right) after displacement, by age at displacement. The figure compares estimates and corresponding 95% pointwise confidence intervals obtained using either time fixed effects (dashed, blue) or an interaction of time and age indicators (solid, red).*

As noted in Section 2, we slightly depart from the existing literature by interacting the time fixed effects with age fixed effects in the estimation. In Figure 3, we show how including this interaction changes the pattern of estimated earnings losses over the life cycle. While estimates in the first half of the working life are not affected, the effect on estimates for ages closer to retirement are substantial. Omitting the age indicator would lead one to conclude that longer-run earnings losses are not increasing in age anymore for workers displaced after the age of 50, whereas our baseline estimate with the age indicators (which corresponds to the result from the left panel Figure 2) suggest a continued increase in longer-run earnings losses until age 58. This indicates that the age of displacement becomes important as retirement draws closer. Intuitively, by not including the age indicators in the estimation we would implicitly assume that we can use anyone

in the sample as a valid comparison to generate the counterfactual, regardless of their age. The fact that including the age indicator exacerbates the estimated earnings loss reflects that it increases the counterfactual outcome, which in turn reflects that workers in the control group are more likely to still be employed if we condition on them being the same age as the treated individual than if we were to simply average the earnings of control workers regardless of their age. This occurs in the second half of the life cycle as it becomes increasingly likely that workers near the end of the study period are retired. To clarify this point with an example, consider the estimation of earnings losses 1 year after displacement at the age of 60. Given that the workers in the control group were employed at the age of 60, and were not displaced, it is likely that the majority of the control group is still employed at age 61. However, note that the estimation sample includes observations of workers aged between 55 and 70, and the average age will generally be increasing over time as workers need to be observed at age 60 in order for them to be included in the estimation sample. Then, considering a worker who was displaced close to the end of the sample period, such as in 2015, the observations used to estimate the time fixed effect will include workers of a relatively high average age, many of whom will likely be retired and have zero labour market earnings, thus dragging down the estimated time fixed effect, and in turn dragging down the estimated counterfactual. As shown in Appendix B.3, a similar effect occurs when focusing on employment rather than on earnings. Furthermore, we also show in Appendix B.3 that including the age indicators but not interacting them with the time fixed effect will help, but not completely account for the aforementioned effect.

4 Model

We now present a life-cycle model of the labor market, developed with the aim of explaining the life-cycle variation in the cost of job loss documented in the previous section.

4.1 Environment

4.1.1 Firms

Since the model is set up from the viewpoint of a worker, firms are passive in this model. The firms that operate in the model are heterogeneous in their productivity y , which follows a cumulative distribution function $F(y)$. In the background, one can think of these firms being able to hire at most one worker, whose (general) human capital level is denoted by s , and paying this worker a wage equal to production, $w(s, y) = f(s, y) = e^{s+y}$. Alternatively, one could think of the

production function taking some other form, but wages being set by the aforementioned equation, for example due to collective bargaining agreements.

4.1.2 Workers

Agents in the model live for at most T periods. Each period, they face age-dependent mortality risk, represented by survival probability γ_t , where $t \in [1, T]$ is the age of the individual. Agents are in the labor force (either employed or unemployed) for at least the first T_W^- periods of their life. From period T_W^- onwards, workers can choose to leave the labor force and retire, and they need to do so by period T_W^+ at the latest. Retirement is an absorbing state, so once workers choose to retire they cannot return to the labor force. Note that this implies that we refer to retirement as the start of retirement benefit collection, which in most cases will coincide with the worker stopping work in a period from T_W^- onwards.

Workers are heterogeneous in their accumulated general human capital s . This human capital starts at a value s_1 in period 1, and subsequently increases by Δ_s with probability ψ_e each period in which the worker is employed, and decreases by Δ_s with probability ψ_u each period in which the worker is unemployed. Unemployed workers receive a job offer with age-dependent probability λ_t^u and employed workers with age-invariant probability λ^e , and decide whether or not to accept this job and the accompanying wage. While employed, workers face exogenous separation risk, determined by their job attachment x . This job attachment can take two values, low x_L and high x_H , with accompanying exogenous separation rates δ_L and $\delta_H < \delta_L$. Whenever workers change jobs, their attachment resets to x_L . Attachment increases to x_H every period with probability ξ_x , which is constant across all jobs and individuals. In addition, workers can decide to quit their job. If they do so, they will not receive unemployment benefits for one period (see next subsection). In terms of the definitions used in the empirical section of the paper, one can think of the exogenous separation as displacement, whereas the more general definition of separation also includes quits. Note that workers can only be unemployed up to the regular retirement age $T_W \in [T_W^-, T_W^+]$. After this, any worker who quits or is displaced moves into the absorbing retirement state.

Individuals receive earnings, consisting of a wage and benefits (as discussed in the next subsection), and choose consumption c and savings a in order to maximize lifetime expected utility. Savings cannot be negative ($a \geq 0$) and earn a rate of return r . The period utility function is CRRA, $u = \frac{(c+\zeta)^{1-\nu}}{1-\nu}$, where ζ is a small number added to avoid computational issues surrounding infinite

marginal utility or (negative) infinite utility around the lower bound for consumption. In addition, employed workers face an additive disutility of work u_w . Agents discount utility at a rate β . Any assets remaining at the end of life, either accidentally or intentionally, are left as a bequest. The utility from bequests in the final period of life is given by $B(a) = \phi_1(\phi_2 + a)^{1-\nu}/(1-\nu)$, following De Nardi et al. (2010).

4.1.3 Social Security

The model contains three types of social security: unemployment insurance, welfare benefits, and pension benefits. In this subsection, we describe how we incorporate these three systems into the model.

The unemployment insurance system follows the German system after the reforms in the early 2000s.¹¹ The German system can be divided into two parts: the traditional unemployment insurance, represented by a benefit b , and the unemployment assistance, which resembles a welfare payment and is modeled as such.

When a worker separates into unemployment, he is eligible to receive the traditional unemployment insurance (UI) benefit for a limited number of periods. In reality, the duration of eligibility (if any) depends on the worker's recent working history. In particular, in order to receive any eligibility, the worker must have been employed in at least 4 of the last 8 quarters. Then, conditional on meeting this threshold, the worker is eligible for the UI benefit for a number of months equal to half the number of months worked in the past 3 years (for workers aged 50-54, 55-57, or 58-65, this period is extended to 3.5, 4, and 5 years respectively). This employment history could in principle be incorporated in the model through some vector \mathbb{H}_t . In a quarterly model, in order to accurately represent the worker's history over the last 5 years (as required in order to calculate eligibility for workers aged 58 to 65), this vector would need to contain 20 elements, each representing the worker's employment state in one of the past 20 periods. This would imply 2^{20} possible values, making solving the model computationally infeasible. In order to avoid this issue, we simplify by assuming that the worker's eligibility for UI benefits activates stochastically, as represented by state variable e_t . To be precise, when a worker finds a job from unemployment, e equals zero. Each period of employment, e changes to 1 with probability ξ_e . Furthermore, the value of e does not reset if the worker decides to make a job-to-job transition. If

¹¹For a detailed description of the unemployment insurance system and its reforms, see Wörz (2011b), Schludi (2017), and Schneider and Rinne (2019).

the worker becomes unemployed with $e = 0$, he is not eligible to receive UI benefits. However, if he becomes unemployed with $e = 1$, he is eligible to receive UI benefits for the age-dependent maximum number of periods. Once a worker runs out of eligibility, he moves into the noneligibility state in which he does not receive any UI benefits, but is still eligible for welfare and faces the same transition rates as any other unemployed worker.

If a worker receives the UI benefit, its value depends on the job from which he separated into unemployment. To be specific, the regulation stipulates that the benefit equals 67% of previous (net) earnings if the worker has children, and 60% if not. Since the model does not include a fertility choice, the model uses the 60% replacement rate. Thus, the worker receives a benefit of $b(\hat{s}, \hat{y}) = 0.6w(\hat{s}, \hat{y})$, where \hat{s} denotes the level of human capital at the time of separation (which may differ from the current human capital level due to depreciation), and \hat{y} denotes the productivity of the job from which the worker separated. Finally, a worker is penalized for quitting by reducing their benefit in the first period of unemployment to 0, even though that first period counts towards their unemployment duration for the purpose of determining eligibility of future UI receipt.

The welfare benefit ensures that workers have a certain minimum amount of disposable income, taking into account any wealth they have built up. In other words, it ensures that the sum of asset, labor, UI, and pension income meets a certain lower threshold, denoted by $\underline{\omega}$. If this threshold is not met, the worker receives assistance to top up his disposable income. Denoting the income from labor, UI benefits, and pensions by \mathcal{Y} , the budget constraint takes the form $a' + c = \max\{(1+r)a + \mathcal{Y}, \underline{\omega}\}$. The threshold equals $\underline{\omega} = 0.1\omega$, reflecting that the threshold is set at 10% of the average earnings in the economy (proxied by parameter ω in the model).

The pension system in the model also closely follows the German system after the reforms in the early 2000s.¹² In this system, pension benefits are determined by a worker's lifetime earnings, through accumulated pension points p . Workers are awarded pension points every period, and their point accumulation in a period is determined by comparing their earnings to the average earnings in the economy. In particular, a worker earning a wage of x times the average earnings in the economy will earn x points in the period, up to a maximum of 2. A worker can also accrue pension points during unemployment, but only for the first 6 months of eligibility, and only based on 80% of his pre-unemployment earnings. If they entered unemployment by quitting, they do not accrue any pension points during the first period (3 months) of unemployment.

¹²For a detailed description of the pension system and its recent reforms, see Börsch-Supan and Wilke (2004), Wörz (2011a), and Börsch-Supan et al. (2020).

Since the replacement rate for a worker with a full lifetime of average earnings is approximately 70% in the German system (Börsch-Supan et al., 2020), benefits are set to match this. In other words, a worker who retired at the regular retirement age of T_w with p points accumulated throughout his working life will earn a pension income of $b_R(p/T_w)$ times the average income, where b_R is set to 0.7. Note that there is no explicit minimum or maximum benefit, but the fact that workers can only earn up to 2 points per period effectively imposes a ceiling to the pension payment. A lower bound is implemented by extending the welfare benefit discussed above into the periods of retirement.

Whether a worker retires early (between T_W^- and T_W) or late (between T_W and T_W^+) affects his pension in two ways: First, the worker accumulates less (more) points directly due to working for a lower (higher) number of periods. Second, the number of points is adjusted at the time of retirement entry to penalize (reward) workers retiring early (late). In particular, a worker retiring early incurs a penalty of 0.3% for each month of early retirement, whereas a worker retiring late is rewarded with an increase of 0.5% for every month of deferred retirement. In the model, this adjustment factor is denoted by ρ_t , where the subscript t denotes that the adjustment is age-dependent.

4.2 Timing and Value Functions

In our model, each period can be divided into eight stages. In the first stage, the worker learns the updated values of his human capital s , attachment x and potential eligibility e . In the second stage, the exogenous separations materialize, after which workers who are still employed decide whether or not to quit in the third stage. In the fourth stage, workers meet with firms and decide whether to accept the corresponding offers. In the fifth stage, workers who are eligible to retire make their retirement choice. In the sixth stage, production takes place and workers are paid their wage and UI, welfare, and pension benefits (if applicable). After this, in the seventh stage, workers make their consumption and savings decisions. Finally, mortality risk is realized in the eighth and final stage.

Given the above description of the model setup and timing, we can summarize the model by setting up the value functions. Since the model contains a large number of state variables, we summarize a worker's state when entering the production stage of a period by Ω_i , where i indicates the worker's employment status. For non-retired individuals, we summarize the state when entering the production stage as $\Omega_w = (s, a, y, x, p, e)$ if they are employed, and

$\Omega_u = (s, a, \hat{s}, \hat{y}, p, E)$ if they are unemployed, where E denotes the number of remaining periods of eligibility. With some abuse of notation, we summarize the worker's state entering next period's production stage by $\Omega'_w = (s', a', y, x', p', e')$ if the worker is employed and did not change jobs, $\Omega'_u = (s', a', \hat{s}, \hat{y}, p', E')$ if the worker is unemployed, and $(\Omega'_w, y', x_L) = (s', a', y', x_L, p', e')$ if the worker moved to a new job with productivity y' . Similarly, we summarize the worker's state when entering the production stage while retired as $\Omega_r = (a, p)$, where p indicates his accumulated number of pension points after adjustment for early or late retirement. Next period's state is summarized by $\Omega'_r = (a', p)$, reflecting that while the worker's asset level may change, their accumulated pension points no longer change after they entered retirement.

Consider a worker entering the production stage of a period $t \in [T_W^-, T_w)$, not having retired before. In addition to the notation introduced above, we denote by $(\Omega'_r, \rho_{t+1}p') = (a', \rho_{t+1}p')$ their future state if they decided to retire and incurred an adjustment of their pension points according to ρ_{t+1} . The value function for a continuously unemployed worker in this period can be written as follows:

$$U(\Omega_u, t) = \max_{c, a' \geq 0} \left\{ u(c) + \beta \gamma_t \mathbb{E}_{s'} \left[\lambda_{t+1}^u \int_{y' \in \Theta^u(\Omega'_u, t+1)} \tilde{W}(\Omega'_w, \Omega'_r, y', x_L, t+1) dF(y') \right. \right. \\ \left. \left. + \left(1 - \lambda_{t+1}^u \int_{y' \in \Theta^u(\Omega'_u, t+1)} 1 dF(y') \right) \tilde{U}(\Omega'_u, \Omega'_r, t+1) \right] + \beta(1 - \gamma_t) B(a') \right\} \quad (2)$$

s.t. $a' + c = \max\{(1+r)a + b(\hat{s}, \hat{y}), \underline{\omega}\} \quad ; \quad p' = p$

In equation (2), the set $\Theta^u(\Omega'_u, t+1)$ is the set of jobs that would be accepted by the worker (in the next period), $\Theta^u(\Omega'_u, t+1) = \{y' : W(s', A', y', x_L, p', e', t+1) \geq U(\Omega'_u, t+1)\}$ with $e' = 0$. Furthermore, note that $b(\hat{s}, \hat{y}) = 0$ if the worker is not eligible to receive UI benefits. Finally, we represent the retirement choice by taking the maxima of two value functions, one of which is the value of (early) retirement, whenever this choice can be made. In particular, denoting the value of employment and retirement by W and R respectively:

$$\tilde{W}(\Omega'_w, \Omega'_r, y', x_L, t+1) = \max \{W(\Omega'_w, y', x_L, t+1), R(\Omega'_r, \rho_{t+1}p', t+1)\}$$

$$\tilde{U}(\Omega'_u, \Omega'_r, t+1) = \max \{U(\Omega'_u, t+1), R(\Omega'_r, \rho_{t+1}p', t+1)\}$$

As can be observed from equation (2), the value function U assumes $p' = p$, thus not incorporating any changes in the worker's accumulated pension points. As such, it only applies to continuously unemployed workers. As we show in Appendix A.1, the value functions for newly unemployed

workers can be obtained by adding accumulation of pension points and setting the benefit $b(\hat{s}, \hat{y})$ to 0 if the worker quit their previous job. The corresponding value functions are denoted by U^N for displaced workers and by U^Q for a worker who quit his previous job.

The value function for an employed worker in period $t \in [T_W^-, T_w)$ is as follows, defining q'_W as the worker's quit decision:

$$W(\Omega_w, t) = \max_{c, q'_W \in \{0, 1\}, a' \geq 0} \left\{ u(c) - u_w + \beta \gamma_t \mathbb{E}_{s', x', e'} \left[\delta_{x'} \tilde{U}^N(\Omega'_u, \Omega'_r, t+1) \right. \right. \\ \left. \left. + (1 - \delta_{x'}) (1 - q'_W) \left(\lambda^e \int_{y' \in \Theta^e(\Omega'_w, t+1)} \tilde{W}(\Omega'_w, \Omega'_r, y', x_L, t+1) dF(y') \right. \right. \right. \\ \left. \left. \left. + \left(1 - \lambda^e \int_{y' \in \Theta^e(\Omega'_w, t+1)} 1 dF(y') \right) \tilde{W}(\Omega'_w, \Omega'_r, t+1) \right) \right. \right. \\ \left. \left. + (1 - \delta_{x'}) q'_W \tilde{U}^Q(\Omega'_u, \Omega'_r, t+1) \right] + \beta(1 - \gamma_t) B(a') \right\} \quad (3)$$

s.t. $a' + c = \max\{(1+r)a + w(s, y), \underline{\omega}\}$; $p' = p + \min(w(s, y)/\omega, 2)$

In equation (3), functions Θ^e , \tilde{U}^Q , and \tilde{U}^N are defined in line with the earlier discussion of Θ^u , \tilde{U} , and \tilde{W} . As we show in Appendix A.1, the value functions for employment and continued unemployment for periods prior to early retirement ($t < T_W^-$), or for the regular and late retirement ages ($t \in [T_W, T_w^+]$), can be obtained from equations (2) and (3) by shutting down the decision margins that are not relevant for the periods under consideration.

Finally, since the retirement stage is an absorbing state, the corresponding value function R is fairly simple:

$$R(\Omega_r, t) = \max_{c, a' \geq 0} \{u(c) + \beta \gamma_t R(\Omega'_r, p, t+1) + \beta(1 - \gamma_t) B(a')\} \quad (4)$$

s.t. $a' + c = \max\{(1+r)a + b_R(p/T_w), \underline{\omega}\}$

Taken together, we can define the equilibrium to consist of sequences of value functions $\{R(\Omega_r, t)\}_{t=T_W^-}^T$, $\{U(\Omega_u, t), U^N(\Omega_u, t), U^Q(\Omega_u, t)\}_{t=1}^{T_W}$, and $\{W(\Omega_w, t)\}_{t=1}^{T_w^+}$, and sequences of policy functions $\{c_r^*(\Omega_r, t), a_r^*(\Omega_r, t+1)\}_{t=T_W^-}^T$, $\{c_u^*(\Omega_u, t), a_u^*(\Omega_u, t+1), c_{un}^*(\Omega_u, t), a_{un}^*(\Omega_u, t+1), c_{uq}^*(\Omega_u, t), a_{uq}^*(\Omega_u, t+1)\}_{t=1}^{T_w^+}$, and $\{c_w^*(\Omega_w, t), a_w^*(\Omega_w, t+1)\}_{t=1}^{T_w^+}$ that satisfy equations (2) to (4) (and (A.1) to (A.5)), given distribution $F(y)$ and initial asset level $a_1 = 0$. In appendix A.2, we provide some details on how we find this equilibrium for a given set of parameters.

5 Calibration

In order to calibrate the model, we need to make a number of additional assumptions. First, we assume that a model period corresponds to a quarter. Furthermore, we assume that workers enter the model at age 25 and die by age 100 at the latest, so $T = 300$. Since the threshold age for early retirement is 63 and the regular retirement age is 65, we set $T_W^- = 152$ and $T_W = 160$. While there is no legal upper limit to the retirement age, we set the maximum retirement age to 70, $T_W^+ = 180$. While we do not assume any structure on the age-dependency of the survival rates (since those are set outside of the estimation exercise), we reduce the parameter space by assuming that the job finding rate λ_t^u depends on age t in a linear fashion. In particular, we assume $\lambda_t^u = \lambda_c^u + \lambda_s^u t$ with constant λ_c^u and a slope λ_s^u such that the job finding rate equals $\lambda_{T_W}^u = \lambda_f^u \lambda_1^u$ at the regular retirement age T_W . Finally, we assume that the distribution of job productivity $F(y)$ follows a Pareto distribution, with scale parameter μ_y and shape parameter η_y .

Parameter	Meaning
r	interest rate
β	discount factor
ν	relative risk aversion
γ_t	survival probability at age t
ϕ_1	bequest motive, intensity
ϕ_2	bequest motive, curvature
u_w	disutility of work
ω	average earnings subject to social security
ξ_x	transition probability to high attachment
ξ_e	transition probability to UI eligibility
ψ_e	human capital transition, employment
ψ_u	human capital transition, unemployment
s_1	starting value of human capital
Δ_s	human capital transition size
η_y	shape parameter, marginal distribution of y
μ_y	scale parameter, marginal distribution of y
λ_c^u	meeting probability, unemployed workers (constant)
$\lambda_f^u \lambda_1^u$	meeting probability, unemployed workers (retirement age)
λ^e	meeting probability, employed workers
δ_L	exogenous separation rate, low attachment
δ_H	exogenous separation rate, high attachment

Table 2: *Summary of all model parameters and their interpretation.*

Taken together, the above assumptions leave us with a total of 20 parameters to calibrate in addition to the age-dependent survival probabilities. These parameters, and their interpretation, are summarized in Table 2. We set the values for 5 parameters exogenously. The remaining 15

parameters are estimated using simulated method of moments.

5.1 Exogenously Set Parameters

Table 3 lists the values of the 5 exogenously set parameters which are age-invariant. In line with the literature, we set the annual interest rate equal to 4%. Since a model period corresponds to a quarter, this implies that r takes a value of approximately 0.985%. The human capital grid is normalized such that the starting value s_1 is 0 and the stepsize Δ_s is 0.1. This implies that the simulated human capital values will have a straightforward interpretation, as a positive value will imply that the value of s is higher than the starting value, and dividing the simulated value of s by 0.1 indicates how many steps away from the starting value s is. In line with Kitao et al. (2017), we set the expected transition time from low to high job attachment (which informs the exogenous separation rate) to 12 quarters. This implies that the quarterly transition probability ξ_x equals approximately 8.3%. Similarly, we assume that it takes 4 quarters for a worker to become eligible for UI in case of separation, thus implying $\xi_e = 0.25$. By doing so, we proxy the legal requirement of having worked 4 of the last 8 quarters in order to be eligible to receive UI benefits.

Parameter(s)	Value(s)	Source
r	0.00985	4% annual interest rate
s_1	0	normalization
Δ_s	0.1	normalization
ξ_x	0.083	expected transition in 12 periods
ξ_e	0.25	expected transition in 4 periods

Table 3: *Summary of all exogenously set age-invariant parameters.*

Aside from the aforementioned 5 parameters, we also directly import the survival rate γ_t from the data. To be specific, we take the age-specific average survival rate (for males only) across all cohorts that fall within the period 2005 to 2017 from Destatis (2023). The value of γ_t is set to match this age-specific average, assuming the survival rate is constant within a year. Since the model is quarterly, this implies that the survival probability changes every 4 model periods.

5.2 Calibration Moments

We estimate the remaining 15 parameters using simulated method of moments, targeting a set of 27 moments. The targeted values of these moments are estimated using the quarterly panel created from the SIAB data, as discussed in Section 2, German cross-sectional data (from 2007,

2012, and 2017) from the Luxembourg Wealth Study (LWS, 2023), and aggregate statistics provided by the OECD (OECD, 2023). The latter two data sources are used exclusively for moments related to the accumulation of assets (LWS) and the employment-to-population ratio (OECD). The only moment that is not directly based on the data is the moment used to target ω . Since this parameter proxies the average earnings subject to social security in the economy, we target a difference of 0 between the value of ω and the realized average earnings in the model simulation. Note that targeting only the earnings that are subject to social security implies that we censor any earnings above the threshold of 2ω .

Using data from SIAB, we directly inform the value of λ^e by targeting the quarterly job-to-job transition rates. The two parameters that inform the values of λ_t^u (λ_c^u and λ_f^u) are set by targeting the quarterly job finding rates for workers aged between 25 and 40 and for workers aged from 40 to 55. Similarly, estimates for separation rates δ_L and δ_H are obtained by targeting the quarterly rates of job loss for workers tenured between 1 and 6 quarters and for workers with more than 6 quarters of (establishment) tenure. Since in the model the only earnings growth for workers staying with their job is driven by human capital accumulation, we use the quarterly earnings growth for these so-called stayers to estimate ψ_e . In the model, wage losses after a layoff can be caused by human capital depreciation as well as differences in job productivity. The distribution of job productivities does not depend on the duration of an unemployment spell, whereas the expected loss in human capital increases in this duration. We can therefore use the relation between unemployment duration and the difference between pre- and post-layoff wages to estimate the value of ψ_u . Specifically, we target this wage difference for workers who spent less than 0.5 year, between 0.5 and 1 year, and between 1 and 2 years in unemployment. Finally, we use the direct relation between productivity and wages to argue that the distribution of wages in the economy is informative about the distribution of job productivity $F(y)$. Therefore, we use moments describing the wage dispersion, namely the p75-p25 and median-p25 wage ratios, to inform the values of μ_y and η_y .

Naturally, we cannot directly observe the disutility of work in the data. However, the disutility of work u_w plays a substantial role in informing the worker's decision of when to move into retirement. Therefore, we set the value for u_w by targeting the employment-to-population ratio, specifically the 2017 German male employment-to-population ratio for age brackets 55-59, 60-64, and 65-69, observed from the OECD.

In order to obtain estimates for the remaining three parameters (ν , ϕ_1 , and ϕ_2), we obtain

a number of moments describing accumulation of assets over the life-cycle from the Luxembourg Wealth Study (LWS). For these moments, we generally target the 75th percentile of asset holdings, as the median holdings are sufficiently close to zero to make the moment values sensitive to the selection of the sample in the LWS. We target the ratio of the 75th percentile of asset holdings and the average earnings subject to social security in the economy, focusing in particular on age groups 30-39, 40-49, 50-59, 60-69, 70-74, and 75-79. For young workers, who are still more than 10 years removed from the regular retirement age, we additionally target the ratios of 75th percentiles of asset holdings between different age groups, specifically age groups 40-44, 45-49, and 50-54 relative to age groups 35-39, 40-44, and 45-49 respectively. Finally, we use a set of moments describing asset accumulation (or decumulation) after retirement by permanent income, as these moments can be particularly informative about the strength of the bequest motive. We proxy the worker's permanent income by pension income, as the pension income is calculated using the worker's lifetime income, and compare the 75th percentile of asset holdings for workers in the p10-p40 and p60-p90 bracket of permanent income, for age groups 70-74 and 75-79. This set of moments is completed by the ratio of 75th percentile of asset holdings among workers in the p60-p90 bracket of permanent income between these two age groups.

5.3 Calibration Results and Model Fit

Table 4 summarizes the results of the model calibration. Generally, the model does a decent job of matching the moment values obtained from the data, despite the fact that the structure of the model makes it difficult to match certain moments. In particular, the model is able to match the separation rates observed in the data quite well, even if a quarterly separation rate of approximately 8.7% among workers with low attachment is quite high. In the left panel of Figure 4, we show that the model also matches the empirical patterns in separation rates over the working life quite well, even though these patterns were not explicitly targeted. The distinct separation rates for workers with different attachment levels enables the model to generate the initial decrease in the separation rate.

The model can also match the three visible peaks in the separation rate, the latter two of which occur around the early and regular retirement age with the first one occurring a few years before the early retirement age. The peaks in the model simulation are especially clearly visible in the right panel of Figure 4, where we plot the quarterly separation rates instead of the yearly separation rates. Using these higher frequency rates, a clear spike in separations occurs at the earliest age at

Description of Moment(s)	Data	Model	Parameters
Average rate of job loss, tenure 1-6q	0.0576	0.0634	$\delta_L = 0.087$
Average rate of job loss, tenure>6q	0.0159	0.0174	$\delta_H = 0.014$
p75-p25 ratio of wages	1.8438	1.4079	$\mu_y = 2.17$
Median-p25 ratio of wages	1.3238	1.1681	$\eta_y = 14.19$
Job-to-job transition rate	0.0345	0.0185	$\lambda^e = 0.3635$
Average job finding rate, age 25-40	0.2034	0.2016	$\lambda_c^u = 0.258$
Average job finding rate, age 40-55	0.1223	0.1279	$\lambda_f^u = 0.162$
Quarterly earnings growth	0.0039	0.0016	$\psi_e = 0.0153$
Pre- to post-layoff wage, duration<0.5y	-0.0305	-0.1347	
Pre- to post-layoff wage, duration 0.5-1y	-0.0777	-0.151	
Pre- to post-layoff wage, duration 1-2y	-0.0983	-0.1785	$\psi_u = 0.0899$
Employment-to-population ratio, age 55-59	0.844	0.794	
Employment-to-population ratio, age 60-64	0.637	0.661	$u_w = 0.0168$
Employment-to-population ratio, age 65-69	0.202	0.245	
p75 of assets, p60-p90 permanent income, age 75-79 vs. 70-74	1.1266	0.9985	
p75 of assets, age 70-74, p60-p90 vs. p10-p40 permanent income	3.269	5.1972	
p75 of assets, age 75-79, p60-p90 vs. p10-p40 permanent income	2.2547	3.7752	
p75 of assets, age 40-44 vs. 35-39	1.1357	1.1742	$\tilde{\beta} = 0.9518$
p75 of assets, age 45-49 vs. 40-44	1.1408	1.1318	$\nu = 2.84$
p75 of assets, age 50-54 vs. 45-49	1.1304	1.1365	$\phi_1 = 140.45$
p75 of assets relative to average earnings, age 30-39	0.4173	0.3639	$\phi_2 = 15.152$
p75 of assets relative to average earnings, age 40-49	0.414	0.5125	
p75 of assets relative to average earnings, age 50-59	0.6678	0.6549	
p75 of assets relative to average earnings, age 60-69	0.7813	0.8668	
p75 of assets relative to average earnings, age 70-74	1.1619	0.9522	
p75 of assets relative to average earnings, age 75-79	0.9675	0.9576	
Difference between ω and average income	0.0	-0.004	$\omega = 12.38$

Table 4: *Summary of calibration moments, their values in the data and in the calibrated model, and corresponding parameter values. Data values in the first section of the table are estimated using SIAB, data values in the second section of the table are taken from the OECD, data values in the third section of the table are estimated using LWS, and the fourth section follows from the definition of ω .*

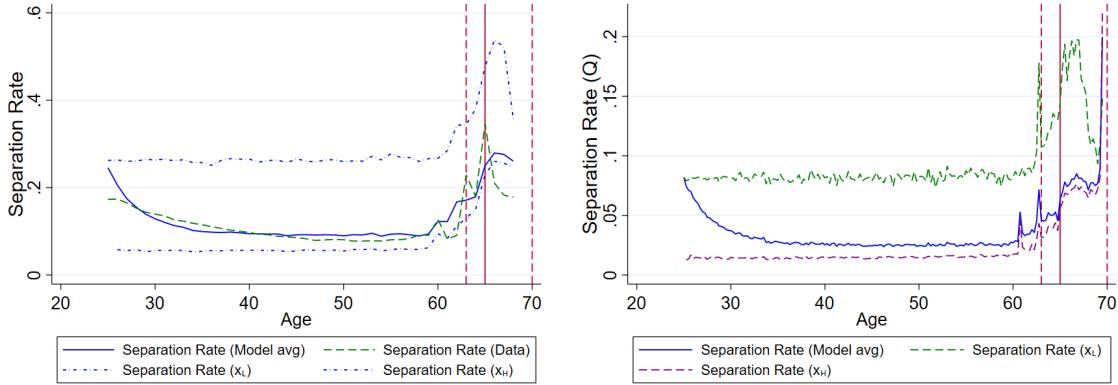


Figure 4: *Left:* the yearly separation rate in the data (green, dashed) compared with the average in the model simulation (blue, solid), by age. The dashed blue lines denote the average yearly separation rates in the model simulation conditional on low or high attachment levels. *Right:* the quarterly separation rate in the model simulation, overall (solid, blue) and separately for workers with low attachment (dashed, green) and high attachment (dashed, purple). In both graphs, the solid red vertical line denotes the regular retirement age, whereas the dashed red vertical lines denote the earliest and latest possible retirement ages in the model.

which workers can move into the retirement state (as indicated by the vertical dashed line). This spike seems to be driven by workers of both attachment levels. The peak at the regular retirement age can be seen as more of a permanent jump up in the separation rates in the model, rather than a spike. This is likely a consequence of the change from a penalty of 0.3% per month of early retirement to a subsidy of 0.5% per month of late retirement. Finally, a clear spike is visible at the age of 61, exactly 8 periods prior to the earliest retirement age. This spike, driven primarily by highly attached workers, reflects a pathway into early retirement through which workers can effectively retire at 61 despite not officially moving into the retirement state until the age of 63, bridging the gap using UI benefits (which last for 8 periods at that age). Naturally, matching these peaks in the age profile for separations crucially depends on modelling the age-dependent duration of eligibility for UI benefits in some detail.

As we show in Figure 5, the model does well in matching the job finding rates we observe in the data, even if the model tends to overshoot the life-cycle pattern in unconditional job finding rates (as we show in Appendix A.3). On the other hand, the model has trouble matching the observed job-to-job transition rate, despite a high quarterly offer arrival rate of 36.35%. This is likely a consequence of our simple wage structure, which leaves no room for (re-)bargaining between the worker and firm. As a result, the model also underestimates the quarterly earnings

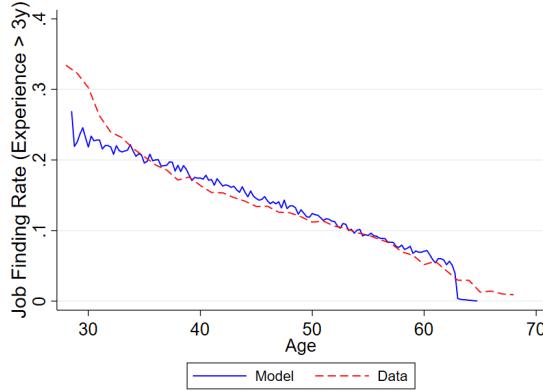


Figure 5: The average quarterly job finding rate by age in the data (red, dashed) compared to the average in the model simulation (blue, solid), by age and conditional on 3 years of labor market experience.

growth, despite a value for the human capital appreciation rate ψ_e which is roughly in line with rates that have been found in the literature (e.g. Jarosch, 2021).

As is common in these types of models, the model tends to produce less wage dispersion than in the data. Indeed, the high value of parameter η_y indicates that the underlying distribution of job productivity y is fairly narrow, as depicted in Appendix A.3. This may also play a role in explaining the fairly low value of the estimated disutility of work u_w . Nevertheless, the model performs quite well in matching the employment-to-population ratio for workers around the retirement age. As we show in the left panel of Figure 6, the model implies that throughout the working life, roughly 80 to 85% of the workers are employed.

Shifting attention to moments related to asset accumulation, it can be seen in Table 4 that the model has some trouble matching the exact values of the first set of moments, which capture the saving and dissaving patterns of retired workers depending on their lifetime income. In part, this can be explained by the fact that these moments are estimated with a fairly high standard error and are therefore not assigned a high weight in the estimation procedure. Indeed, the model performs reasonably well in matching the general pattern of asset accumulation over the life cycle, as indicated by the remaining moments in Table 4. The right panel of Figure 6 shows that a similar pattern can be observed when focusing on the average asset holdings rather than the 75th percentile.

Early in the life cycle, the pattern of asset accumulation is primarily driven by the dis-

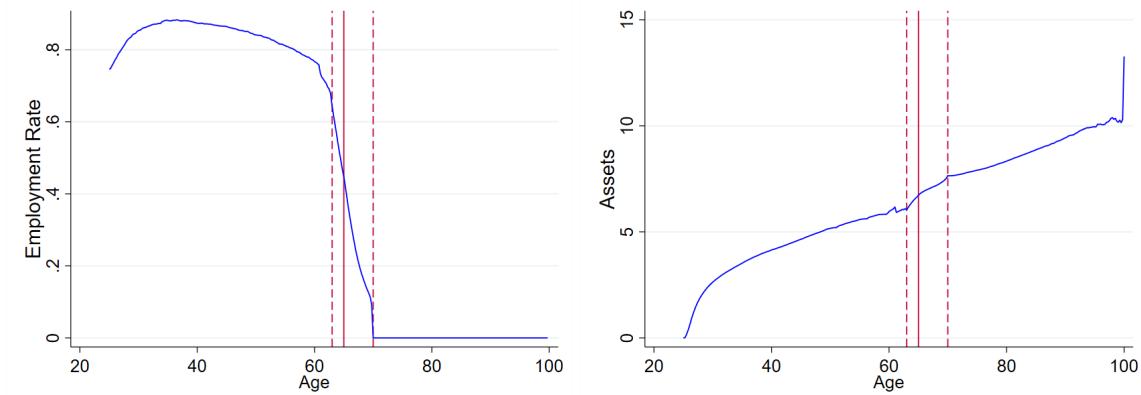


Figure 6: Average employment-to-population ratio (left) and average asset holdings (right) in the model simulation, by age. The solid red vertical line denotes the regular retirement age, whereas the dashed red vertical lines denote the earliest and latest possible retirement ages in the model.

count rate β and the relative risk aversion ν . The yearly value of $\tilde{\beta}$ equals 0.9518 (corresponding to quarterly $\beta \approx 0.9877$), which is lower than the (yearly) value of $1/(1 + \tilde{r}) \approx 0.9615$, thus indicating that workers are relatively impatient in the model. The value of $\nu = 2.84$ is generally quite comparable to values found in the literature. For comparison, using a sample of German men, Haan and Prowse (2022) find a value of 2.586. Later in the life cycle, the bequest function becomes increasingly important. To provide some interpretation of the estimated values of $\phi_1 = 140.45$ and $\phi_2 = 15.152$, it can be shown that workers entering the final period of life will decide to leave a nonzero bequest if their income is above 2.668. This value is fairly low, given that the average quarterly earnings in the economy equal $\omega = 12.38$, thus indicating that bequests are a luxury (since the threshold is strictly positive), but not very strongly so. Conditional on leaving a bequest, it can be shown that the marginal propensity to consume out of final period income is fairly low at approximately 0.15.

6 Simulation Results

In this section, we present the implications of the estimated model. In particular, Subsection 6.1 shows how the model performs in matching the life-cycle variation in the cost of job loss we documented in Section 3, and which channels in the model are particularly important in generating this result. In Subsection 6.2, we focus on the interaction between job loss and retirement timing.

6.1 Life-Cycle Variation in the Cost of Job Loss

Figure 7 shows the pattern of relative earnings and employment losses after a job loss by age at the time of displacement. While the interpretation of the figure is similar to Figure 2 in Section 3, it should be noted that the construction of Figure 7 did not utilize the same estimation technique. Rather, the effects in Figure 7 are estimated by directly comparing the model simulation to a counterfactual model simulation in which the worker did not get displaced, while the two followed identical paths up to the time of displacement. In Appendix A.4.1, we show that we reach similar conclusions if we instead use the same estimation method as in the data.

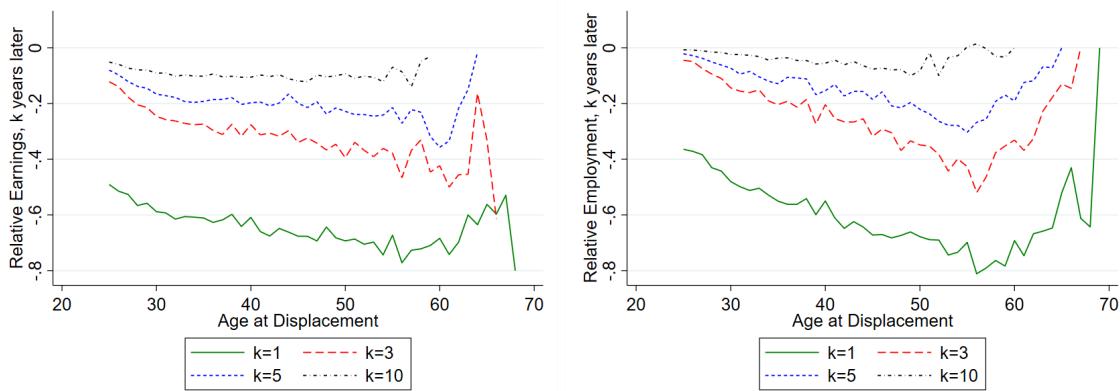


Figure 7: *The estimated effect of displacement on labor earnings (left) and employment fraction (right), by age at displacement and years since displacement, obtained directly from the model simulation.*

Comparing Figure 7 with its equivalent in the empirical section of this paper, it can be observed that the model tends to overshoot the earnings and employment losses in the short run, and implies a stronger recovery pattern over time than estimated in the data.¹³ Some of the overshooting of short-run losses can be attributed to the model not allowing workers to find a job in the period of displacement, and this may partially carry over to later post-displacement periods as well. Nevertheless, the model is clearly able to match the life-cycle variation we observed in the data, as emphasized in Figure 8, where we compare estimates of earnings and employment losses 3 and 5 years after displacement from the data and the model estimation. In general, earnings and employment losses are increasing in age at displacement, but only until the point in the working life where the retirement decision starts to become immediately relevant. Just like we observed

¹³In Appendix A.4.1, we show this more explicitly by comparing the average earnings and employment losses between the data and the model simulation in an event-study plot.

in the data, the relative earnings losses start decreasing in age from age 55 to 60 onwards. For employment losses, this reversal is even clearer, although it should be noted that the reversal all the way to 0 at the age of 70 is mechanical in the model simulation, as we do not allow workers to be employed beyond the age of 70.

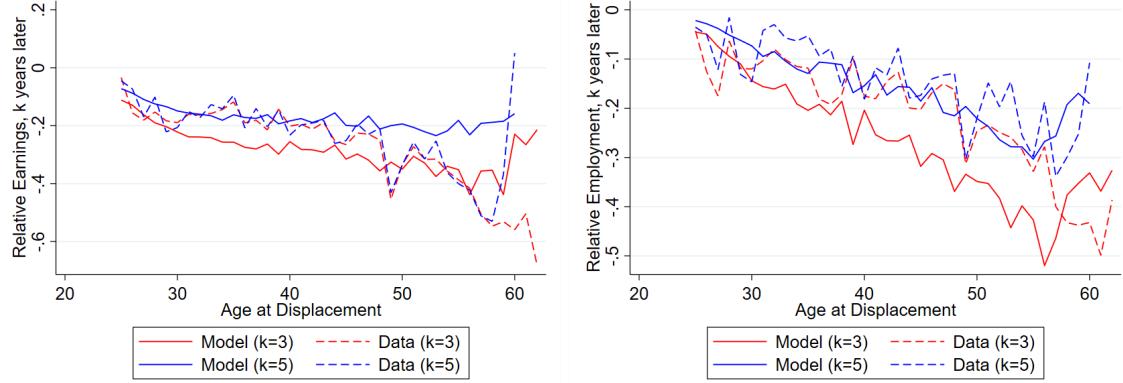


Figure 8: *The estimated effect of displacement on labor earnings (left) and employment fraction (right), 3 years (red) or 5 years (blue) after displacement, by age at displacement, obtained from the data (dashed) and directly from the model simulation (solid).*

Given that the model is able to match both the increasing earnings and employment loss in age for prime-aged workers and the reversal in this pattern close to the retirement age, we now investigate which elements of the model are important in achieving this. We do so by decomposing the earnings and employment losses into 6 channels, which are switched off in the simulation one after another, in the order in which they are presented in the results. The results of this decomposition are depicted in Figure 9. The numerical values corresponding to the results can be found in Appendix A.4.1.

The first factor depicted in the decomposition results covers the direct and indirect age dependency in the UI system. The direct age dependency is removed from the simulation by removing the age dependency in the maximum duration of benefit receipt, setting this maximum duration to 4 periods for all workers, regardless of their age. The indirect age dependency is then removed by setting the value of the UI benefit equal to 60% of average earnings in the economy, rather than 60% of the specific worker's previous earnings, thus removing the gradual increase in average UI benefits as workers climbed the job ladder for a longer time prior to being displaced.

The second factor depicted in the decomposition results covers the age dependency in the survival rates. The contribution of this factor is calculated by removing the mortality risk alto-

gether, and instead assuming that all workers live until the age of 80 with certainty. Similarly, the contribution of the third factor, the age dependency in the job finding rate, is calculated by setting the offer arrival rate λ_t^u equal to its average value for workers of all ages.

The contribution of the pension system, depicted as the fourth factor in the decomposition results, can be thought of as consisting of five separate elements, namely the penalty and subsidy associated with retiring early and late, the possibility of choosing this early and late retirement, and the dependency of retirement benefits on lifetime earnings. In order to estimate the contribution of the pension system, we switch off all five of these elements in order, in particular setting the retirement benefit equal to 70% of the average earnings in the economy and assuming everyone retires at age 65.

The fifth factor in the decomposition is labeled as “Traditional Elements”. This factor includes the four elements of the model that are not directly age dependent, but are traditionally included in models that attempt to explain the scarring effect of displacement, as described in the introduction of this paper. The first and second of these elements are the appreciation of human capital during employment and the depreciation of human capital during unemployment, which are switched off by setting their corresponding probabilities (ψ_e and ψ_u) equal to zero. The third element is the existence of a job ladder, which is removed by assuming that all jobs have the same productivity y , equal to the mean of the estimated underlying distribution, which equals $\eta_y \mu_y / (\eta_y - 1)$. Finally, the last traditional element is that of search frictions. The search frictions are switched off in the model by setting the job finding rate λ^u equal to 1, such that every worker that loses a job will immediately receive a job offer in the next period. After switching off all of these traditional elements, all remaining earnings and employment loss is labeled under the sixth and last factor, “Other”. This final category includes losses that are driven by the worker not immediately finding a new job in the period of displacement, and facing a higher separation risk in their next job due to their lower attachment to the new job.

Analyzing the results of the decomposition exercise depicted in Figure 9 reveals that the so-called “Traditional Elements” do a good job in explaining the majority of earnings losses for workers displaced prior to the age of 50. This is primarily driven by the search frictions and human capital depreciation (see Appendix A.4.1, where we show the decomposition of each factor into the aforementioned sub-factors). The pattern of increasing losses in age for prime-aged workers is primarily driven by the age dependency in the job finding rate. The elements of social security and the mortality risk are shown to be the main factors driving the reversal of the pattern close to the

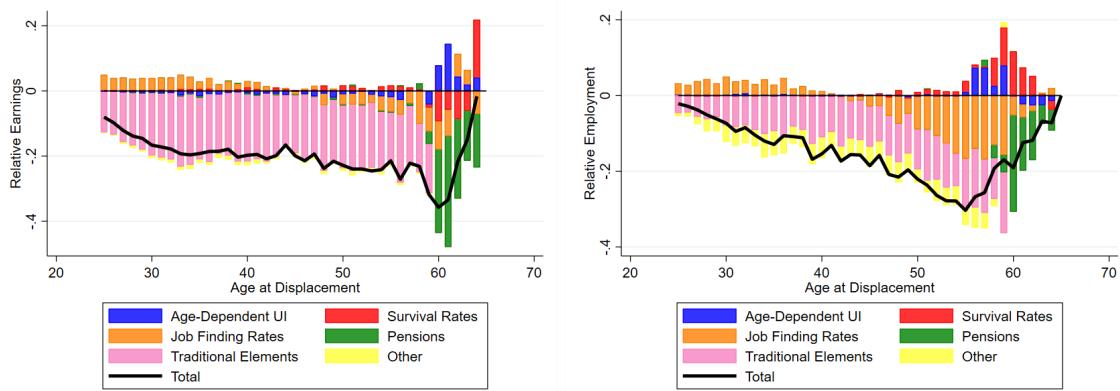


Figure 9: *Decomposition of relative labor earnings (left) and employment (right) losses (5 years after displacement) into 6 distinct factors present in the model, by age at displacement.*

(early) retirement age. In other words, the inclusion of age dependency in unemployment insurance, mortality risk, and retirement timing is crucial in accounting for the reversal of the pattern of earnings and employment losses that we observe late in the working life.

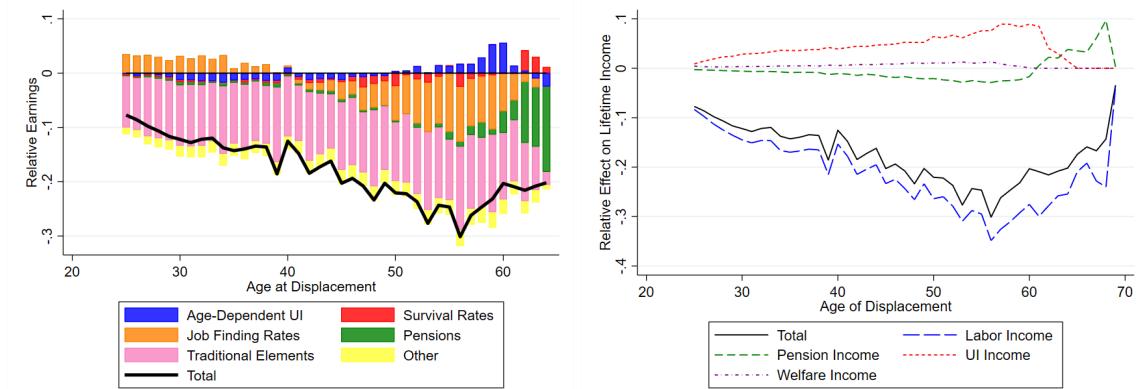


Figure 10: *Relative (remaining) lifetime income losses into 6 distinct factors present in the model, by age at displacement and discounted to the time of displacement, decomposed into 6 distinct factors present in the model (left) and into the different earnings sources present in the model (right)*

The decomposition exercise discussed above focused on the decomposition of the earnings and employment losses observed 5 years after the displacement, and we show in Appendix A.4.1 that the results are similar if we instead focus on the losses observed 3 years after displacement. However, given that we observe workers for the entire remainder of their life in the model simulation, we can also decompose the effect of displacement on lifetime income. In order to do

so, we calculate total income in all periods after displacement in which the worker is still alive. Discounting the resulting income to the period of displacement then yields a measure of the present value of the remaining lifetime income at the time of displacement. Calculating this for the baseline scenario as well as the counterfactual scenario in which the worker was not displaced in this period then yields a measure of the effect of displacement on remaining lifetime income. As we show in the right panel of Figure 10, the pattern of this effect over the working life looks fairly similar to the patterns of labor income in a specific period after displacement (such as those discussed above for 5 years after displacement). The pattern is generally primarily driven by losses in labor income, although it can be seen that the losses in labor income are increasingly offset by UI benefits throughout the working life, while the pension benefits eventually take over this offsetting role in the retirement window.

We can decompose the losses in remaining lifetime income into the same six factors as those discussed above, using the same method as before. The result of this decomposition is depicted in the left panel of Figure 10. The results show a similar picture as the decomposition of labor income 5 years after displacement (the left panel of Figure 9), although the patterns are generally less volatile due to the decomposition taking into account the entire remaining lifetime rather than a single year. Nevertheless, a similar conclusion can be drawn from this alternative decomposition exercise. As before, the traditional elements in the model can explain the bulk of the losses in the first half of the working life, with the age dependency in the job finding rate explaining the increasing loss in age of displacement over this period. The pension and unemployment insurance systems are the primary drivers of the reversal in the pattern in the years leading up to the (early) retirement age, thus serving to re-emphasize the importance of accounting for the age variation in social security regulations in accounting for the effects of job loss late in the working life.

6.2 Interaction between Job Loss and Retirement Timing

When discussing the reversal in the life-cycle pattern of employment losses in Section 3, we noted that the reversal seemed to indicate that workers are retiring later in response to a displacement. Having seen in the previous subsection that the model generates a similar reversal in the pattern, this subsection further investigates the determinants of workers' retirement choice. In particular, we investigate what determines whether (and in which direction) workers change their retirement timing after a job loss.

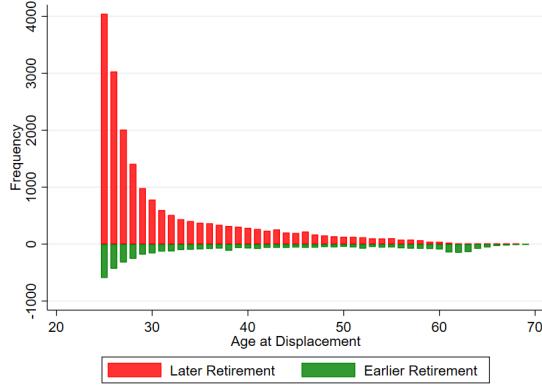


Figure 11: *Frequency of workers retiring later or earlier in response to a displacement in the model simulation, by age at displacement.*

In Figure 11, we show how many workers decide to retire either later or earlier in response to a displacement, by age of their first displacement, defining retirement as moving into the absorbing retirement state (and starting to collect benefits). As can be seen from the figure, it is not necessarily the case that all displaced workers change their timing in the same direction: while many workers decide to retire later, especially after being displaced early in their working life, some workers decide to retire earlier.

Naturally, the total frequency of retirement changes decreases in age as a result of our focus on the first displacement, which naturally decrease in age as the population of never-displaced workers shrinks over time. Furthermore, as workers become more attached to their job, they will face a lower displacement rate ($\delta_H < \delta_L$) in the model. Therefore, we also plot the frequency of early and late retirement relative to the total number of displaced workers, in the left panel of Figure 12. The results of this exercise show that throughout the working life workers are heterogeneous in how they adjust their retirement timing after a displacement, although we can generally observe an increase over age in the share of workers who decide to retire earlier. In particular, if we focus on workers aged 55 to 60, the age range during which we see the pattern in employment losses starting to reverse, there is a roughly equal fraction of workers deciding to retire earlier and later.

In Figure 4, we argued that the model contains a pathway into early retirement via unemployment, where workers quit their job 2 years prior to being eligible for early retirement, and bridge those two years using UI benefits. One could think of these workers as effectively retiring

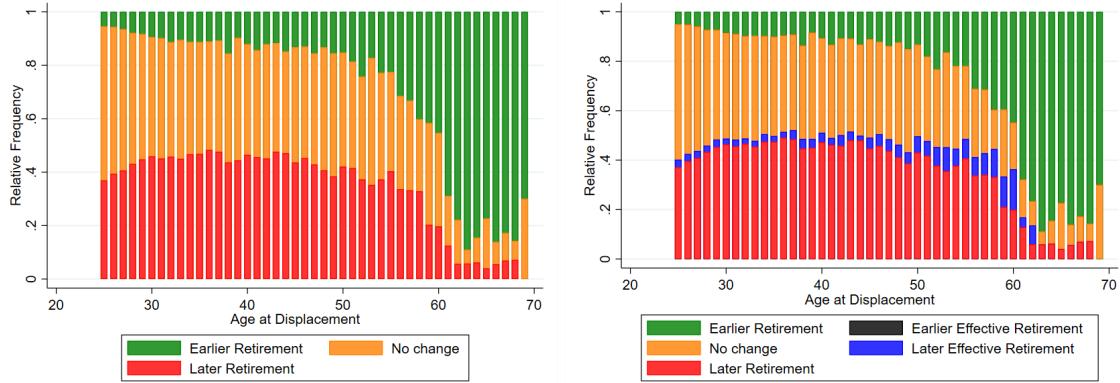


Figure 12: *Relative frequency of workers changing their retirement timing in response to a displacement in the model simulation, by age at displacement. The right panel additionally includes changes in effective retirement (due to changed timing in pre-retirement quits).*

2 years prior to the time at which they move into the absorbing retirement state. As such, while some of these workers may not have changed their actual retirement timing, and still retire at 63, they may have decided to quit earlier or later in response to a displacement, thus effectively retiring earlier or later. In the right panel of Figure 12, we show how this impacts the split of displaced workers between those retiring earlier, retiring later, or not changing their retirement timing. As the figure shows, there is no worker who decides to quit earlier following a displacement, but a substantial group of workers decide to quit later. Importantly, all of these workers were planning on quitting early and still quit prior to their official retirement, and therefore were classified as "No change" in the left panel. Therefore, it can be concluded that considering effective retirement timing rather than official retirement timing slightly tilts the balance in favor of later retirement.

Given that we observe heterogeneity in the effect of displacement on workers' retirement timing, we can use the model to try and understand who retires later and who retires earlier after being displaced. In Figures 13 and 14, we provide an indication by showing the average change in retirement timing (not taking into account pre-retirement quits) for different combinations of age at displacement and either pension points, asset holdings, or human capital (all measured at the time of displacement). Generally, we can observe in these figures that pension points, asset holdings, and human capital tend to increase in age. However, we can also observe that for a given age of displacement, workers with low values in any of these three state variables tend to exhibit a more negative reaction in terms of their retirement timing.

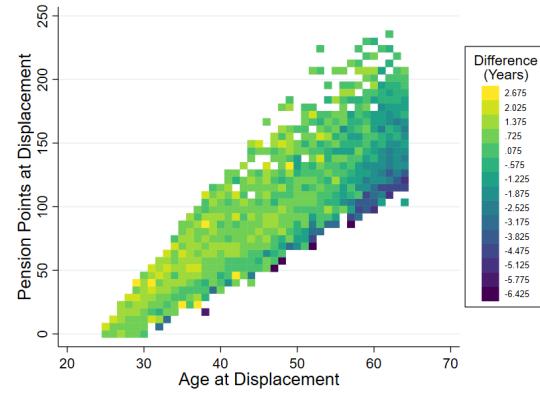


Figure 13: Average change in retirement timing upon displacement in the model simulation, conditional on a nonzero change, by age and pension points at displacement. The average change in retirement timing does not take into account changes into effective retirement timing due to pre-retirement quits.

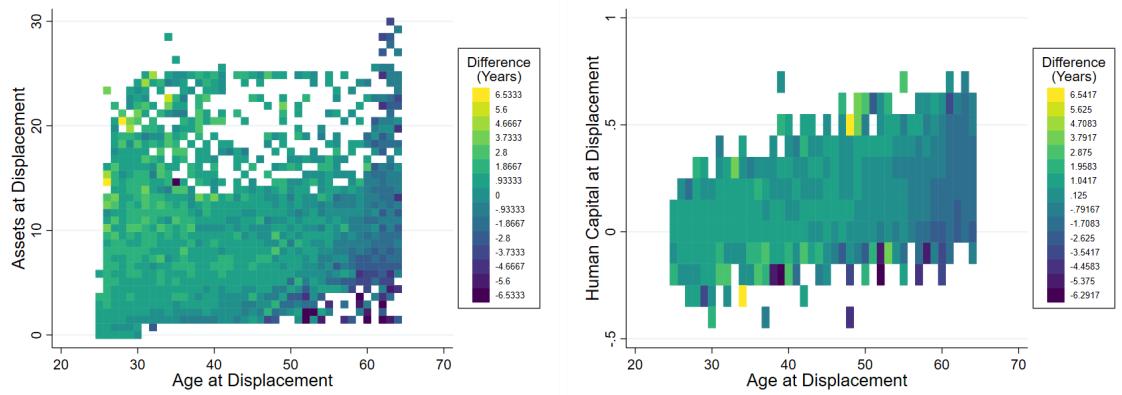


Figure 14: Average change in retirement timing upon displacement in the model simulation, conditional on a nonzero change, by age and either assets (left) or human capital (right) at displacement. The average change in retirement timing does not take into account changes into effective retirement timing due to pre-retirement quits.

In Table 5, we further investigate this, specifically by comparing workers who get displaced between the age of 55 and 60 and decide to retire earlier or later (or not change) to each other and to a sample of all workers who were employed at the age of 55. As can be seen in the table, the workers' pension points, asset holdings, and human capital are highly correlated, as we further emphasize in Appendix A.4.2 by plotting these measures against each other. Comparing the columns specific to displaced workers who decided to retire earlier or later after being displaced reveals a similar picture as the figures above: workers who retire earlier tend to have lower earnings as well as pension points, assets, and human capital prior to displacement. However, these workers also initially planned to retire later than the other groups prior to being displaced.¹⁴

Variable	Earlier	Later	No Change	All (age 55)
Earnings	14.0	15.6	18.6	13.7
Job Productivity	2.44	2.50	2.63	2.48
Pension Points	130.3	137.9	157.2	116.3
Assets	9.16	10.7	14.0	7.51
Human Capital	0.182	0.20	0.20	0.07
Planned Retirement Age	65.54	64.57	63.60	64.98

Table 5: *Summary statistics for the pre-displacement states of workers (first) displaced between the age of 55 and 60 in the simulation, by the effect on their retirement timing, compared to a sample of all (employed) 55-year-olds in the model simulation. The classification according to change in retirement timing does not take into account changes into effective retirement timing due to pre-retirement quits.*

Taken together, the analysis above reveals that, in the model simulation, workers with higher lifetime labor income, and therefore also higher asset holdings, pension points, and human capital (due to the correlation between these measures) on average tend to retire earlier. However, if workers face job loss, the adjustment they make in their retirement timing generally goes in the opposite direction: workers with lower lifetime earnings tend to retire earlier, relative to their own pre-displacement retirement plans.¹⁵ This reflects a change in the trade-off that workers face when deciding upon retirement. In general, workers trade off earnings in their job (or future jobs) against the benefits they would receive in case of retirement. If workers lose their job, they face a negative

¹⁴The planned retirement age is defined as the retirement age of a counterfactual worker who did not get displaced, but was identical to the displaced worker prior to the displacement.

¹⁵Given that workers who quit early tend to be highly attached (as seen in Figure 4), it is likely that these workers tend to have a high lifetime income. As such, the pattern highlighted in this section would lead one to predict that such workers retire later after a displacement. This is consistent with the observation in Figure 12 that workers who change their quitting time only do so by postponing.

shock to their earnings from employment. As a result, workers may decide to retire earlier, as the alternative of staying in the labor force is less attractive. This is partially offset by the fact that workers receive a penalty for retiring earlier. Since this penalty is larger (in absolute terms) for workers who had larger lifetime earnings, the incentive to retire earlier is weaker for them, thus resulting in the observed gradient in the change of retirement timing over different proxies of accumulated lifetime income.

7 Conclusion

This paper studies how the earnings and employment loss following a job displacement depends on the worker's age at the time of displacement. Using social security data from Germany, we find that the post-displacement earnings loss is generally increasing in age at displacement. However, the post-displacement employment loss is only increasing until the worker is close to reaching the age at which they are eligible for early retirement, after which the employment loss is decreasing in age.

In order to investigate the role of social security systems, as well as other sources of age dependency in the labor market (such as the age-dependency of mortality risk and job finding rates), we set up a life-cycle model. In this model we include elements that have previously been found to be important to explain earnings loss after displacement, in particular human capital appreciation and depreciation, search frictions, and the existence of a job ladder (in productivity). Furthermore, we incorporate a realistic representation of the German systems of unemployment insurance, welfare, and pensions, after the labor market reforms of the early 2000s.

After estimating the model using moments generated from German data, we show that, while the aforementioned traditional model elements allow the model to match the pattern of earnings and employment losses in age of displacement for workers displaced prior to the age of 45, the social security system and other sources of age dependency become increasingly important for workers displaced later in their working life. In particular, the endogenous nature of the retirement choice plays a large role in explaining earnings and employment losses for workers displaced after the age of 55. Zooming in on this choice of retirement timing, we find that workers with high lifetime income tend to retire early, in some cases even quitting into unemployment prior to the earliest retirement age and using UI benefits to bridge the gap. However, these workers also tend to postpone their retirement after being displaced. For workers with lower lifetime income, the

opposite pattern holds: while these workers tend to retire late, a displacement nudges them into an earlier retirement compared to their pre-displacement plans.

Since this paper demonstrates the importance of age-dependencies in the labor market in modeling earnings losses across the working life, future research could explore the role of further age dependencies that are not modelled in our paper. For example, one could imagine age-dependency in the offer arrival rate for job-to-job transitions to be important. If one is also interested in matching the short-run earnings loss, one important extension of the model would be to allow for workers to transition into a new job in the same period as their displacement.

Our results highlight the importance of the pension system and the endogenous nature of retirement timing. In future research, a model similar to ours can be used to study retirement reform, and in particular its impact on retirement timing. Such reform could include changes in the earliest retirement age (while keeping the statutory age constant), as well as changes in the penalty and subsidy associated with retiring earlier or later than the statutory retirement age. Finally, given that the model highlights unemployment insurance as a potential pathway into early retirement, an extended version of our model could be used to shed further light on this phenomenon and how to mitigate it.

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A Model Appendix

A.1 Further Value Functions

In section 4, we summarized the model using the value functions of an employed and continuously unemployed worker at times where the worker could choose to retire early, $t \in [T_W^-, T_W)$. As mentioned in the main text, the value functions for newly unemployed workers and for other model periods can be obtained from these functions by making the appropriate changes. In this section, we present these other value functions.

First, consider a newly unemployed worker in a period where they can choose to retire early, $t \in [T_W^-, T_W)$. We can distinguish between a worker who entered unemployment by quitting their new job (with corresponding value function U^Q) and a worker who entered unemployment due to exogenous separation (with corresponding value function U^N). The corresponding value functions are as follows:

$$U^Q(\Omega_u, t) = \max_{c, a' \geq 0} \left\{ u(c) + \beta \gamma_t \mathbb{E}_{s'} \left[\lambda_{t+1}^u \int_{y' \in \Theta^{uq}(\Omega'_u, t+1)} \tilde{W}(\Omega'_w, \Omega'_r, y', x_L, p, t+1) dF(y') \right. \right. \\ \left. \left. + \left(1 - \lambda_{t+1}^u \int_{y' \in \Theta^{uq}(\Omega'_u, t+1)} 1 dF(y') \right) \tilde{U}(\Omega'_u, \Omega'_r, t+1) \right] + \beta(1 - \gamma_t) B(a') \right\} \quad (\text{A.1})$$

s.t. $A' + c = \max\{(1+r)a, \underline{\omega}\}$; $p' = p + \min(0.8w(\hat{s}, \hat{y})/\omega, 2)$

$$U^N(\Omega_u, t) = \max_{c, a' \geq 0} \left\{ u(c) + \beta \gamma_t \mathbb{E}_{s'} \left[\lambda_{t+1}^u \int_{y' \in \Theta^{un}(\Omega'_u, t+1)} \tilde{W}(\Omega'_w, \Omega'_r, y', x_L, t+1) dF(y') \right. \right. \\ \left. \left. + \left(1 - \lambda_{t+1}^u \int_{y' \in \Theta^{un}(\Omega'_u, t+1)} 1 dF(y') \right) \tilde{U}(\Omega'_u, \Omega'_r, \hat{p}', t+1) \right] + \beta(1 - \gamma_t) B(a') \right\} \quad (\text{A.2})$$

s.t. $a' + c = \max\{(1+r)a + b(\hat{s}, \hat{y}), \underline{\omega}\}$;
 $p' = p + \min(0.8w(\hat{s}, \hat{y})/\omega, 2)$; $\hat{p}' = p' + \min(0.8w(\hat{s}, \hat{y})/\omega, 2)$

Next, consider a worker who is entering a period $t < T_W^-$, and therefore does not make a retirement decision. The value functions for a continuously unemployed and employed worker this period are as follows:

$$U(\Omega_u, t) = \max_{c, a' \geq 0} \left\{ u(c) + \beta \gamma_t \mathbb{E}_{s'} \left[\lambda_{t+1}^u \int_{y' \in \Theta^u(\Omega'_u, t+1)} W(\Omega'_w, y', x_L, t+1) dF(y') \right. \right. \\ \left. \left. + \left(1 - \lambda_{t+1}^u \int_{y' \in \Theta^u(\Omega'_u, t+1)} 1 dF(y') \right) U(\Omega'_u, t+1) \right] + \beta(1 - \gamma_t) B(a') \right\} \quad (\text{A.3})$$

s.t. $a' + c = \max\{(1+r)a + b(\hat{s}, \hat{y}), \underline{\omega}\}$; $p' = p$

$$\begin{aligned}
W(\Omega_w, t) = & \max_{c, q'_W \in \{0, 1\}, a' \geq 0} \left\{ u(c) - u_w + \beta \gamma_t \mathbb{E}_{s', x', e'} \left[\delta_{x'} U^N(\Omega'_w, t+1) \right. \right. \\
& + (1 - \delta_{x'}) (1 - q'_W) \left(\lambda^e \int_{y' \in \Theta^e(\Omega'_w, t+1)} W(\Omega'_w, y', x_L, t+1) dF(y') \right. \\
& + \left(1 - \lambda^e \int_{y' \in \Theta^e(\Omega'_w, t+1)} 1 dF(y') \right) W(\Omega'_w, t+1) \\
& \left. \left. + (1 - \delta_{x'}) q'_W U^Q(\Omega'_w, t+1) \right] + \beta (1 - \gamma_t) B(a') \right\} \\
& \text{s.t. } a' + c = \max \{(1+r)a + w(s, y), \underline{\omega}\} \quad ; \quad p' = p + \min(w(s, y)/\omega, 2)
\end{aligned} \tag{A.4}$$

Finally, consider a worker entering a period $t \in [T_W, T_w^+]$ not having retired before. The value function for such a worker looks very familiar to equation (3) in the main text, but incorporates the fact that a worker automatically moves into retirement if they exogenously separate or quit (and exogenously separate with probability 1 in period T_w^+):

$$\begin{aligned}
W(\Omega_w, t) = & \max_{c, a' \geq 0} \left\{ u(c) - u_w + \beta \gamma_t \mathbb{E}_{s', x', e'} \left[[\delta_{x'} + (1 - \delta_{x'}) q'_W] R(\Omega'_r, \rho_{t+1} p', t+1) \right. \right. \\
& + (1 - \delta_{x'}) (1 - q'_W) \left(\lambda^e \int_{y' \in \Theta^e(\Omega'_w, t+1)} \tilde{W}(\Omega'_w, \Omega'_r, y', x_L, t+1) dF(y') \right. \\
& \left. \left. + \left(1 - \lambda^e \int_{y' \in \Theta^e(\Omega'_w, t+1)} 1 dF(y') \right) \tilde{W}(\Omega'_w, \Omega'_r, t+1) \right] + \beta (1 - \gamma_t) B(a') \right\} \\
& \text{s.t. } a' + c = \max \{(1+r)a + w(s, y), \underline{\omega}\} \quad ; \quad p' = p + \min(w(s, y)/\omega, 2)
\end{aligned} \tag{A.5}$$

Note that if the worker is in the final period T_w^+ , they no longer have a choice of retirement. This can be incorporated by setting $\tilde{W}(\Omega'_w, \Omega'_r, y', x_L, t+1) = R(\Omega'_r, \rho_{t+1} p', t+1)$ for workers in this period. Similarly, an unemployed worker in the regular retirement age T_W cannot choose to continue being unemployed. For these workers, the value function can be obtained from equations (2), (A.1), or (A.2) by setting $\tilde{U}(\Omega'_u, \Omega'_r, t+1) = R(\Omega'_r, p', t+1)$

A.2 Solution Method

Due to the large number of state variables, the model presented in Section 4 must be solved numerically. We opt to solve the model backwards, using grids for all continuous state variables (s, y, p , and a).

In obtaining the policy functions for consumption and saving, we stay close to the methods one would have used when solving the model analytically. That is, rather than evaluating the value functions at each possible value of a' on the grid, we evaluate the Euler equation at each point of the grid, and use

interpolation to infer the approximate solution of the Euler equation. In doing so, we can allow for solutions in between the grid points, thus alleviating some of the issues that may arise from using a relatively sparse asset grid. Below are the Euler equations for a continuously unemployed (equation A.6) and employed (equation A.7) worker at an age where the worker is eligible for early retirement. These Euler equations are the most elaborate versions, and can be rewritten to apply to other parts of the life cycle (or newly unemployed workers) by taking out choices that are no longer applicable. The Euler equations take as given the worker's optimal decision at other stages of the (next) period, in particular the quit and retirement decision, and tomorrow's savings decision. The retirement decision is denoted by $q_i'^R$, where $i \in \{W, U, UN, UQ\}$ is the worker's employment status in the next period. Next period's savings decision is denoted by A'' , but it should be noted that this decision will naturally depend on the values of the state variables in the next period

$$\begin{aligned}
& [\max\{(1+r)a + \mathbb{1}\{E > 0\}b(\hat{s}, \hat{y}), \underline{\omega}\} - a' + \zeta]^{-\nu} \\
&= \beta \gamma_t \mathbb{E}_{s'} \left[\int_{y' \in \Theta^u(\Omega'_u, t+1)} \lambda_{t+1}^u (1+r) \left(q_W'^R(y') [\max\{(1+r)a' + b_R(\rho_{t+1}p/T_w), \underline{\omega}\} - A'' + \zeta]^{-\nu} \right. \right. \\
&\quad \left. \left. + (1 - q_W'^R(y')) [\max\{(1+r)a' + w(s', y'), \underline{\omega}\} - A'' + \zeta]^{-\nu} \right) dF(y') + \right. \\
&\quad \left(1 - \lambda_{t+1}^u \int_{y' \in \Theta^u(\Omega'_u, t+1)} 1 dF(y') \right) (1+r) \left(q_U'^R [\max\{(1+r)a' + b_R(\rho_{t+1}p/T_w), \underline{\omega}\} - A'' + \zeta]^{-\nu} \right. \\
&\quad \left. \left. + (1 - q_U'^R) [\max\{(1+r)a' + \mathbb{1}\{E' > 0\}b(\hat{s}, \hat{y}), \underline{\omega}\} - A'' + \zeta]^{-\nu} \right) \right] + \beta(1 - \gamma_t)\phi_1 (\phi_2 + a')^{-\nu}
\end{aligned} \tag{A.6}$$

$$\begin{aligned}
& [\max\{(1+r)a + w(s, y), \underline{\omega}\} - a' + \zeta]^{-\nu} = \\
& \beta \gamma_t \mathbb{E}_{s', x', e'} \left[\delta_{x'} (1+r) \left(q_{UN}'^R [\max\{(1+r)a' + b_R(\rho_{t+1}p'/T_w), \underline{\omega}\} - A'' + \zeta]^{-\nu} \right. \right. \\
& \left. \left. + (1 - q_{UN}'^R) [\max\{(1+r)a' + e'b(s', y), \underline{\omega}\} - A'' + \zeta]^{-\nu} \right) \right. \\
& \left. + (1 - \delta_{x'}) (1 - q_W') \left(\int_{y' \in \Theta^e(\Omega_w', t+1)} \lambda^e (1+r) \left(q_W'^R(y') [\max\{(1+r)a' + b_R(\rho_{t+1}p'/T_w), \underline{\omega}\} - A'' + \zeta]^{-\nu} \right. \right. \right. \\
& \left. \left. \left. + (1 - q_W'^R(y')) [\max\{(1+r)a' + w(s', y'), \underline{\omega}\} - A'' + \zeta]^{-\nu} \right) dF(y') + \right. \right. \\
& \left. \left. \left(1 - \lambda^e \int_{y' \in \Theta^e(\Omega_w', t+1)} 1 dF(y') \right) (1+r) \left(q_W'^R(y) [\max\{(1+r)a' + b_R(\rho_{t+1}p'/T_w), \underline{\omega}\} - A'' + \zeta]^{-\nu} \right. \right. \right. \\
& \left. \left. \left. + (1 - q_W'^R(y)) [\max\{(1+r)a' + w(s', y), \underline{\omega}\} - A'' + \zeta]^{-\nu} \right) \right) \right. \\
& \left. + (1 - \delta_{x'}) q_W' (1+r) \left(q_{UQ}'^R [\max\{(1+r)a' + b_R(\rho_{t+1}p'/T_w), \underline{\omega}\} - A'' + \zeta]^{-\nu} \right. \right. \\
& \left. \left. + (1 - q_{UQ}'^R) [\max\{(1+r)a', \underline{\omega}\} - A'' + \zeta]^{-\nu} \right) \right] \\
& + \beta (1 - \gamma_t) \phi_1 (\phi_2 + a')^{-\nu}
\end{aligned} \tag{A.7}$$

Similarly, the Euler equation for a retired worker is as follows:

$$\begin{aligned}
& [\max\{(1+r)a + b_R(p/T_w), \underline{\omega}\} - a' + \zeta]^{-\nu} = \beta \gamma_t (1+r) [\max\{(1+r)a' + b_R(p/T_w), \underline{\omega}\} - A'' + \zeta]^{-\nu} \\
& + \beta (1 - \gamma_t) \phi_1 (\phi_2 + a')^{-\nu}
\end{aligned} \tag{A.8}$$

For a given set of parameters, we are now ready to solve the model backwards. In particular, this involves the following steps:

1. Set up the grid for s to solve over. In particular, we set the middle value for s equal to s_1 , and let the maximum grid point be such that 99.9% of workers would expect to stay below it even if they were employed at all times. Remaining gridpoints between the max and the middle are set by dividing the max location by 3 and using integer arithmetic, so that the majority of the gridpoints is near the middle (where workers start). Gridpoints below the middle are set in a similar way (using workers who are unemployed at all times), although we divide the difference between the min and max location by 4 rather than 3 when filling the grid. This procedure yields a grid with a size of $N_s = 9$.
2. Set up the grid for y , using a Pareto distribution, and such that each grid point is at the half way point of a bin, where each bin has equal cumulative probability. Further, we add three extra gridpoints at the end, situated at the 95th, 99th and 99.9th percentiles of the distribution. This yields a grid with a

size of $N_y = 10$.

3. Set up the grid for p . In particular, take an asset grid with $N_p = 9$ gridpoints, the first $N_p - 2$ of which are equally spaced between the minimum of $p = 0$ and the maximum based on earning twice (or more) the average earnings for all T_w^+ periods, i.e. $p_{max} = 2\rho_{T_w^+} T_w^+$. The final two gridpoints are placed between the lowest and second-lowest grid points, at quarter-distance and half-distance.
4. Set up the grid for a . In particular, take an asset grid with $N_a = 9$ gridpoints, the values of which depend on ω : $\{0, 0.1\omega, 0.5\omega, \omega, 2\omega, 5\omega, 10\omega, 25\omega, 100\omega\}$.
5. For the last period, $t = T$, we can solve the problem explicitly for each value of a on the main grid, by finding a' that maximizes $R(a, p, T)$ (i.e. directly find a' that satisfies the FOC). This optimal a' becomes $a_r^*(a.p, T)$, and can then be plugged back into $R(a, p, T)$ to find the value to be used in the next step. Because the problem can be solved explicitly, there is no need for a grid search:

$$a_r^*(a.p, T) = \left[\max\{(1+r)a + b_R(p/T_w), \underline{\omega}\} + \zeta - \phi_2(\beta\phi_1)^{-1/\nu} \right] / \left[1 + (\beta\phi_1)^{-1/\nu} \right]$$

$$R(a, p, T) = (\max\{(1+r)a + b_R(p/T_w), \underline{\omega}\} - a_r^*(a.p, T) + \zeta)^{1-\nu} / (1-\nu) + \beta B(a_r^*(a.p, T))$$

6. Iterate backwards: Since retirement is an absorbing state, the easiest way to do this is to solve all retirement value and policy functions first, and then start iterating backwards again for all the other states. Explicitly, in each period t ,
 - (a) The values for the policy and value function(s) at $t + 1$ are now known. This means that we can compute the value of the quit and retirement decisions in the next period, as well as the right hand side of Euler equations (A.6) to (A.8) (whichever is relevant for period t), for each value of a' on the asset grid (and other variables in Ω_i). In the cases where the right hand side of the Euler equation involves an expectation over elements of Ω'_i (such as s' and y'), this is incorporated here. Furthermore, acceptance choices are taken into account here, as the acceptance sets Θ can be obtained by comparing the value functions. Finally, note that the value of A'' depends on Ω'_i and $t + 1$.
 - (b) Under the condition that the right hand side is decreasing in a' , we can now use the Euler equation to back out the optimal value for a' . In doing so, interpolate between the different grid points if necessary. This recovers the policy functions $a_r^*(\Omega_r, t)$, $a_u^*(\Omega_u, t)$, $a_{un}^*(\Omega_u, t)$, $a_{uq}^*(\Omega_u, t)$, and $a_w^*(\Omega_w, t)$. Note that this will also require checking the non-negativity constraints on both assets and consumption. In cases where the right hand side is always larger than the left hand side this would suggest extrapolation beyond the largest grid point, but this

tends to cause nonmonotonicities in the resulting policy and value functions. To avoid this, set a maximum asset level at the highest grid point.

- (c) Finally, plug these policy functions back into the value functions (4) to (A.5) to obtain $R(\Omega_r, t)$, $U(\Omega_u, t)$, $U^N(\Omega_u, t)$, $U^Q(\Omega_u, t)$, and $W(\Omega_w, t)$.

A.3 Further Model Description

In this subsection, we provide further details to describe the structure of the estimated model, in order to provide further insights into the interpretation of the model estimation beyond that provided in Section 5 of the main text.

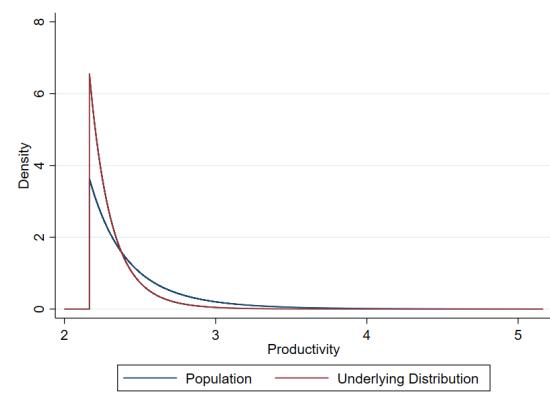


Figure A.1: *The distribution of job productivity y in the estimated model. The plot shows the distribution from which workers make draws (red) as well as the distribution observed in the model simulation (blue, dashed).*

In Figure A.1, we plot the distribution of productivity from which workers draw their job offers when such an offer arrives. Furthermore, we add (as a dashed line) the empirical distribution obtained from the model simulation. The figure confirms that the distribution of job productivity is quite narrow, as indicated by the high value for η_y in the estimation. However, the empirical distribution is slightly wider, as workers climb the job ladder over time by moving to higher productivity jobs, and thus are more likely to stay in a job further to the right in the original distribution.

In Figure A.2 we show how the life-cycle behavior of the job finding rate and job-to-job transition rates compare to the data. As can be seen in the left panel, the job finding rate in the model is slightly higher than in the data for younger workers, which is driven by the fact that we target the job finding rate for workers with higher labor market experience, and while the market experience does not substantially affect job finding rates in the model, they seem to have pushed up the job finding rates in the data (as observed in

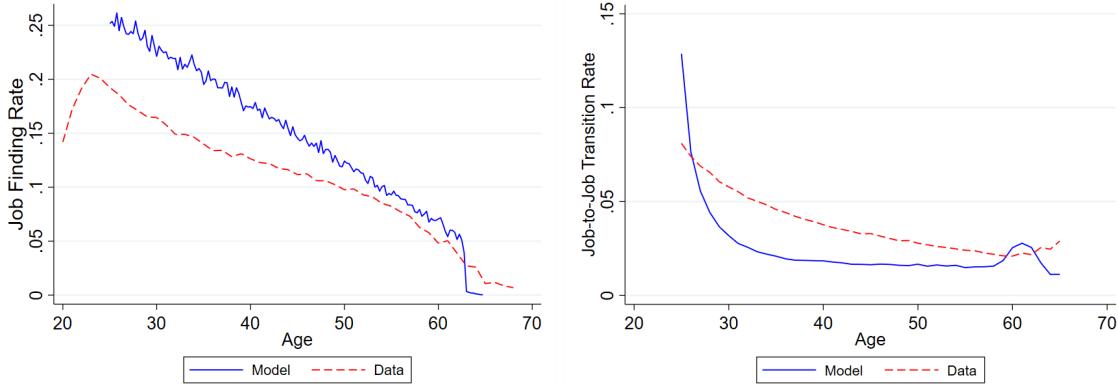


Figure A.2: *The average quarterly job finding rate (left) and job-to-job transition rate (right) by age in the data (red, dashed) compared to the average in the model simulation (blue, solid), by age and not conditional on labor market experience.*

Appendix B.1 as well). When it comes to the job-to-job transition rate, it is clear that the model does not quite match the slope over the life cycle. However, this is not necessarily surprising since the underlying parameter λ^e is not age-dependent in the model. The fact that the job-to-job transition rate in the model is nevertheless downward sloping in age is encouraging.

A.4 Further Simulation Results

A.4.1 Life-Cycle Variation in the Cost of Job Loss

In this Appendix subsection, we provide some additional simulation results from the model, with a focus on model implications regarding the life-cycle variation in the cost of job loss. In particular, we provide some more detailed decompositions, and show how the results change when we shift focus to slightly different estimation methods and focus periods.

In the main text, in Section 6.1, we noted that the model tends to overshoot the age-specific losses in the short run as well as the subsequent recovery pattern, despite providing a satisfactory fit for earnings and employment losses when measured 3 to 5 years after displacement. In Figure A.3, we show how the model simulation compares to the data in terms of the average cost of job loss. In line with the discussion in Appendix B.3, these results are obtained by estimating Equation (1) only once for the entire sample, while not including any age indicators. As such, the dashed line representing the data equivalent corresponds to the dashed blue lines in Figure B.30. As can be seen in Figure A.3, the model overshoots initial average earnings and employment losses, and the gap in average losses between the data and the model does not substantially close over time. This might indicate that if we were to adjust the model to bring it further in line with short run losses in earnings and employment, the model may also perform much better in matching

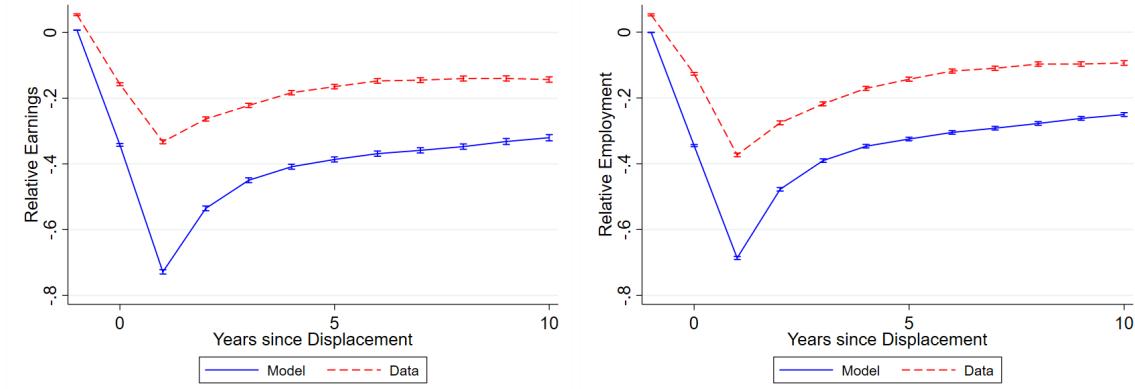


Figure A.3: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right), relative to the control group, using model simulation data (solid) and using the data (dashed, corresponding to Figure B.30).*

average losses in the long run. As briefly discussed in the concluding section of the main text, Section 7, one such adjustment could be to allow workers to find a new job within the same period as the displacement.

In Figure 9, we showed how the earnings and employment loss by age at displacement, measured 5 years after displacement, can be decomposed into 6 broad categories. In Figures A.4 (earnings) and A.5 (employment), we show the full decomposition into the underlying 14 factors mentioned in the main text. Furthermore, Tables A.1 and A.2 provide the corresponding numerical values for a few selected displacement ages. The numbers in these tables can be interpreted as the particular factor's contribution to the total earnings or employment loss on top of previously incorporated factors. For example, focusing on workers who were displaced at age 60, Table A.1 shows that of the total 35.7% of lower relative earnings 5 years after displacement, 0.2 percentage points can be attributed to age-dependent UI eligibility rules. In other words, if the duration of UI eligibility was not age-dependent, and instead set to 4 periods regardless of the age of displacement, the earnings losses for a worker displaced at age 60 and measured 5 years post-displacement would be 0.2 percentage points lower. Similarly, the same column shows that dependency of the value of the UI benefit on previous earnings alleviates losses by 8 percentage points, compared to the earnings losses where only the first factor was eliminated. In other words, compared to a simulation where the UI benefit duration is not age dependent, but everything else is as in the baseline simulation, eliminating the dependence of the UI benefit value on previous earnings would increase earnings losses of a worker displaced at the age of 60 (as measured 5 years after displacement) by 8 percentage points.

The full decomposition depicted in Figures A.4 (earnings) and A.5 (employment) confirm some of the statements in the main text on the particular factors that drive the impact of the broad categories of factors depicted there. For example, Figure A.4 shows that the impact of the “Traditional Elements” observed in the left panel of Figure 9 is driven primarily by search frictions and human capital depreciation.

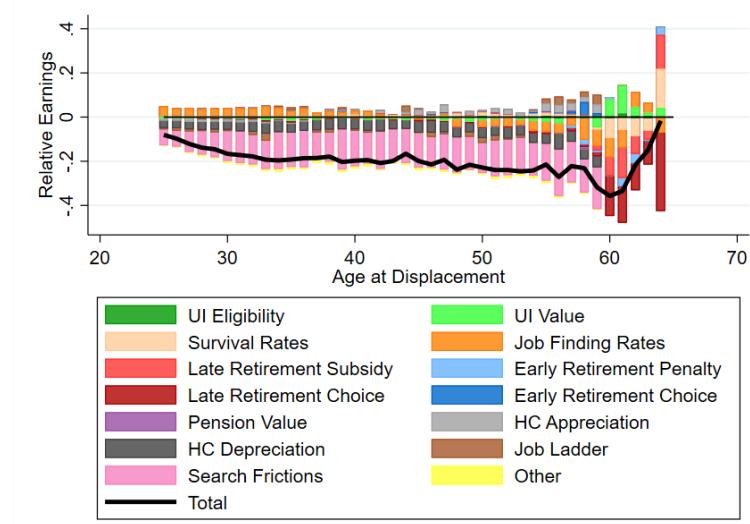


Figure A.4: *Full decomposition of relative labor earnings losses (5 years after displacement) into 14 distinct factors present in the model, by age at displacement.*

Channel	Age 30	Age 40	Age 50	Age 55	Age 60	Age 62
UI Eligibility	0	0	0.004	0.002	-0.002	-0.000
UI Value	-0.005	-0.006	-0.013	-0.021	0.080	0.044
Survival Rates	0.003	0.011	0.017	0.017	-0.093	-0.086
Job Finding Rates	0.037	0.019	-0.032	-0.044	-0.087	0.069
Late Retirement Subsidy	0	0	0.003	-0.004	-0.085	-0.081
Early Retirement Penalty	0	0	0	0.002	0.010	-0.042
Late Retirement Choice	-0.002	-0.005	-0.005	-0.008	-0.181	-0.121
Early Retirement Choice	0.001	0	-0.002	0.003	0	0
Pension Value	0.000	0.001	0	0.004	0	0
Human Capital Appreciation	-0.013	0.006	0.009	0.036	0	0
Human Capital Depreciation	-0.038	-0.045	-0.044	-0.044	0	0
Job Ladder	-0.006	-0.007	-0.021	0.021	0	0
Search Frictions	-0.135	-0.160	-0.136	-0.168	0	0
Other	-0.008	-0.012	-0.008	-0.010	0	0
Total	-0.166	-0.197	-0.228	-0.214	-0.357	-0.217

Table A.1: *Summary of the decomposition of the scarring effect of displacement on earnings, by age at displacement, 5 years after the event takes place. The total difference corresponds to the solid black line in Figure A.4 and the left panel of Figure 9. The decomposition is generated by turning off the indicated channels one by one (in the order presented here), thus generating counterfactuals. The numbers reflect the contribution of each channel to the scarring effect of displacement on earnings, 5 years after displacement. In order to generate the grouped decomposition from Figure 9, we combine the grouped channels into a single number.*

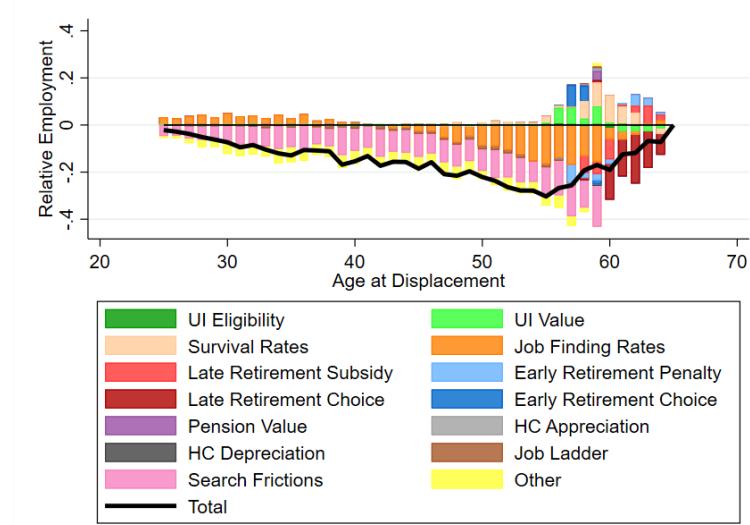


Figure A.5: *Full decomposition of relative employment losses (5 years after displacement) into 14 distinct factors present in the model, by age at displacement.*

Channel	Age 30	Age 40	Age 50	Age 55	Age 60	Age 62
UI Eligibility	0	0	0	0.002	-0.011	-0.002
UI Value	0.002	-0.000	-0.003	0.007	-0.011	-0.002
Survival Rates	0.001	0.002	0.010	0.029	0.116	0.052
Job Finding Rates	0.048	0.009	-0.086	-0.167	-0.050	-0.015
Late Retirement Subsidy	0	0	0	0	-0.084	0.029
Early Retirement Penalty	0	0	0	-0.001	-0.019	0.048
Late Retirement Choice	0	0	0	0	-0.152	-0.207
Early Retirement Choice	0	0	0	0.001	0	0
Pension Value	0	0.000	0	0	0	0
Human Capital Appreciation	0	0	0	0	0	0
Human Capital Depreciation	0	0	0	0	0	0
Job Ladder	-0.003	-0.015	-0.015	-0.012	0	0
Search Frictions	-0.075	-0.094	-0.092	-0.120	0	0
Other	-0.045	-0.056	-0.036	-0.043	0	0
Total	-0.073	-0.154	-0.221	-0.3034	-0.191	-0.119

Table A.2: *Summary of the decomposition of the scarring effect of displacement on employment, by age at displacement, 5 years after the event takes place. The total difference corresponds to the solid black line in Figure A.5 and the right panel of Figure 9. The decomposition is generated by turning off the indicated channels one by one (in the order presented here), thus generating counterfactuals. The numbers reflect the contribution of each channel to the scarring effect of displacement on employment, 5 years after displacement. In order to generate the grouped decomposition from Figure 9, we combine the grouped channels into a single number.*

If we focus on employment instead, as done in Figure A.5 and the right panel of Figure 9, the impact of the human capital depreciation disappears, and the overall impact of the “Traditional Elements” is almost exclusively driven by search frictions. Similarly, we can see that the impact of age dependencies in UI and the pension system, which are shown to be important in generating the reversal of the patterns of earnings and employment losses over age after the age of 55, are driven primarily by the dependency of UI benefits on prior earnings and the possibility of late retirement. Notably, the impact of any factor switched off after “Late Retirement Choice” is zero by definition for workers displaced at the age of 60 or later. This is because removing the possibility of late retirement forces these workers to be in the retirement state 5 years after displacement, regardless of whether they were displaced or not, so that their difference in employment and labor earnings is by definition zero.

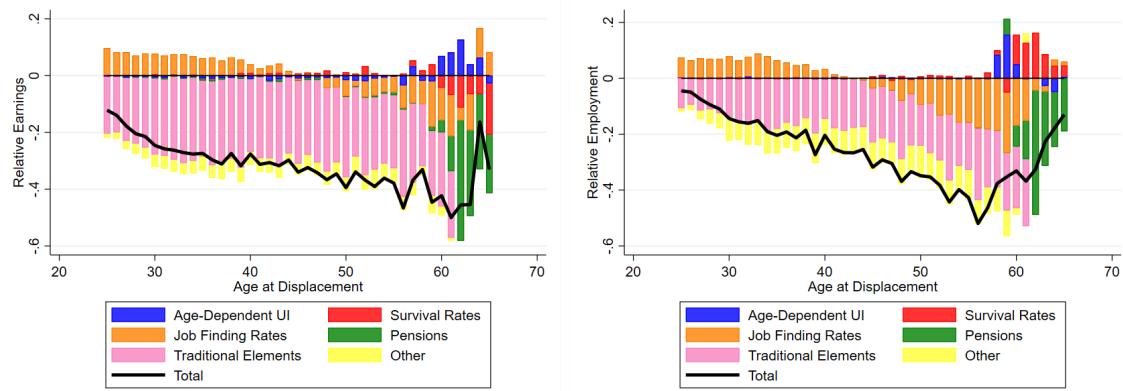


Figure A.6: *Decomposition of relative labor earnings (left) and employment (right) losses (3 years after displacement) into 6 distinct factors present in the model, by age at displacement.*

In Figure A.6, we show that the conclusions from the decomposition of earnings and employment losses do not change when we measure the losses 3 years (rather than 5 years) after displacement. Indeed, while the impact of the “Others” category is slightly higher compared to Figure 9, it still holds that the traditional elements explain the bulk of earnings and employment losses prior to the age of 50, and the age dependency in UI and pensions is important in explaining the reversal of the age pattern in the losses after the age of 55. The increased impact of the “Others” category can be attributed primarily to the fact that workers are more likely to be separated in the first few periods in their new job, as they will be facing the separation rate of a low attachment worker, δ_L .

The age-based earnings and employment losses and their decomposition discussed above and in Section 6.1 of the main text are based on a direct counterfactual generated from the model simulation by removing the displacement in question from the simulation and comparing the subsequent path of the

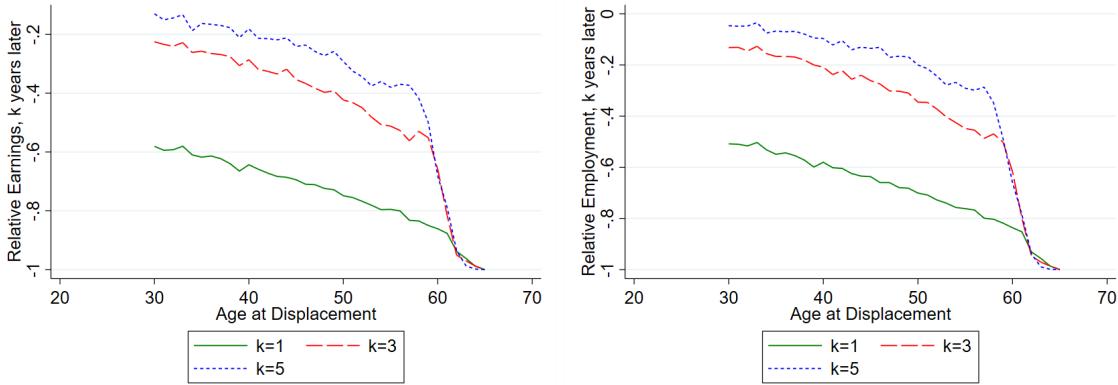


Figure A.7: *The estimated effect of displacement on labor earnings (left) and employment fraction (right), by age at displacement and years since displacement, obtained from the model simulation by using the same estimation method as in the data.*

worker to the displaced worker who was identical up to that point of the simulation. However, in the empirical sections of the paper this counterfactual was indirectly generated, using time fixed effects of the individual estimated prior to displacement, and age and time fixed effects estimated from a sample that included the non-displaced workers. In Figure A.7, we show the estimated earnings and employment losses that would be estimated by using the empirical methods on the simulation data. As can be seen by comparing these estimation-based losses to those obtained from the direct counterfactual (as displayed in Figure 7, the estimation-based losses tend to be higher in the short run. In general, the estimation-based results reaffirm that the model is able to generate increasing earnings and employment losses in age of displacement. However, the estimation-based results suggest that the model has some trouble matching the reversal in employment losses, contrary to what was suggested by the results in the main text. This is clearly visible in Figure A.8, which compares the estimation-based results from the model to the results from the data, specifically for the losses measured 3 and 5 years after displacement. A potential explanation for this discrepancy between the estimation-based results and the simulation results based on direct counterfactuals lies in our observation in Section 6.2 that workers who retire later after a displacement were initially planning on retiring earlier, whereas workers who retire earlier after a displacement were initially planning on retiring later. On average, one can think of this as a mean-reversing pattern, which may be hard for the imputation-based estimation method to pick up on, as its imputation is based on a time-age component which is constant across all individuals and an individual component which does not vary over time and age.

Naturally, we can decompose the estimation-based earnings and employment losses displayed in Figures A.7 and A.8 in a similar way as we decomposed the losses estimated from the direct counterfactuals

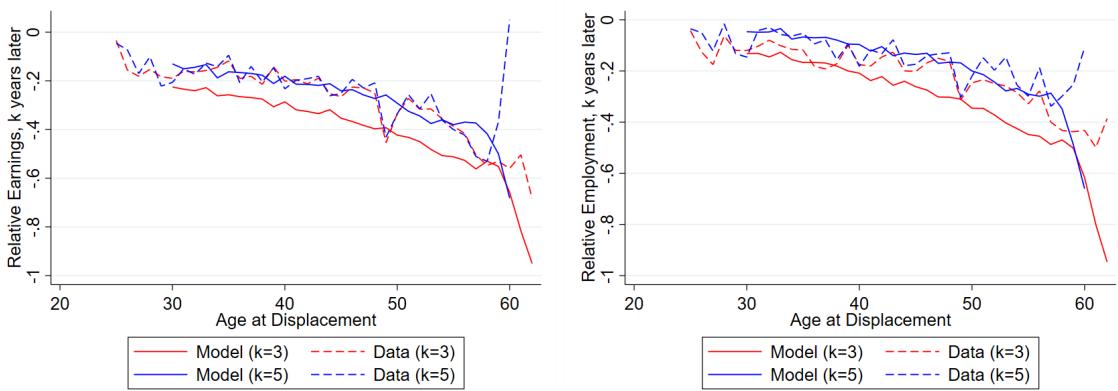


Figure A.8: *The estimated effect of displacement on labor earnings (left) and employment fraction (right), 3 years (red) or 5 years (blue) after displacement, by age at displacement, obtained from the data (dashed) and from the model simulation (solid), using the same estimation method as in the data.*

in Figure 9. In Figure A.9, we show the results of this estimation-based decomposition, with a selection of the underlying numerical values reported in Table A.3. Comparing the results in Figure A.9 to those obtained using direct counterfactuals, Figure 9, confirms that the traditional elements enable the model to explain the majority of earnings and employment losses prior to the age of 45. After the age of 45, the age variation in job finding rates becomes increasingly important, whereas the age dependencies from the pension system and (to a lesser extent) the UI system become important after the age of 55. This is roughly in line with the results from the decomposition using direct counterfactuals, although it should be mentioned that the full decomposition reveals some further fluctuations among other factors, which are likely to be induced by the estimation procedure, such as the large positive influence of the job ladder for workers displaced at the age of 59. Furthermore, the fact that the counterfactual is based on estimated fixed effects leads to the effect never truly reducing to zero for older workers after the late retirement option is taken away, contrary to the direct counterfactuals. As a result, the relative loss tends to fall to -1 instead, and since this cannot be explained by taking out factors in the model, this contribution is labeled as “Other”.

In Figure 10, we showed that the decomposition results look quite similar if we focus on the loss in remaining lifetime income (from all sources) rather than lost labor income (or employment) at a particular time after displacement. In Figure A.10, we show the results of the full decomposition of these losses in (remaining) lifetime income. Notably, the fluctuations we observe over the life cycle between different factors when focusing on a particular time are much less severe when focusing on remaining lifetime income. This is because the ages in which pensions and UI are particularly important are always included in the calculation, even if they are discounted more for workers displaced early in their working life. Generally, the (full) decomposition of remaining lifetime income confirms the conclusions reached

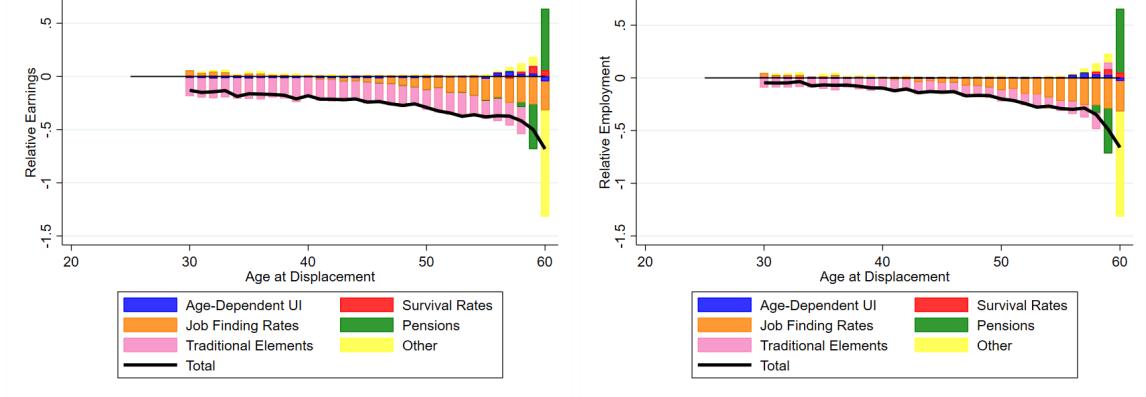


Figure A.9: *Estimation-based decomposition of relative labor earnings (left) and employment (right) losses (5 years after displacement) into 6 distinct factors present in the model, by age at displacement.*

Channel	Earnings			Employment		
	Age 40	Age 50	Age 59	Age 40	Age 50	Age 59
UI Eligibility	0.001	-0.002	0.031	0.000	0.000	0.030
UI Value	-0.009	-0.010	-0.004	0.003	-0.001	-0.003
Survival Rates	0.004	0.003	0.067	0.000	0.004	0.053
Job Finding Rates	0.001	-0.113	-0.263	-0.004	-0.114	-0.290
Late Retirement Subsidy	0.000	0.000	-0.078	0.000	-0.000	-0.081
Early Retirement Penalty	0.000	0.000	0.012	0.000	0.000	0.013
Late Retirement Choice	0.000	0.000	-0.051	-0.000	-0.000	-0.055
Early Retirement Choice	-0.000	0.001	-0.136	0.000	-0.000	-0.158
Pension Value	0.000	-0.003	-0.167	-0.000	0.001	-0.145
Human Capital Appreciation	-0.015	-0.014	0.087	0	0.000	0.083
Human Capital Depreciation	-0.054	-0.056	-0.157	0.000	-0.000	-0.095
Job Ladder	-0.035	-0.040	0.185	-0.022	-0.031	0.186
Search Frictions	-0.085	-0.076	-0.108	-0.085	-0.076	-0.108
Other	0.012	0.018	0.083	0.012	0.018	0.083
Total	-0.181	-0.292	-0.499	-0.096	-0.200	-0.518

Table A.3: *Summary of the estimation-based decomposition of the scarring effect of displacement on earnings and employment, by age at displacement, 5 years after the event takes place. The total difference corresponds to the solid black line in Figure A.9. The decomposition is generated by turning off the indicated channels one by one (in the order presented here), thus generating counterfactuals, and running the estimation procedure on the resulting simulated data. The numbers reflect the contribution of each channel to the scarring effect of displacement, 5 years after displacement. In order to generate the grouped decomposition from Figure A.9, we combine the grouped channels into a single number.*

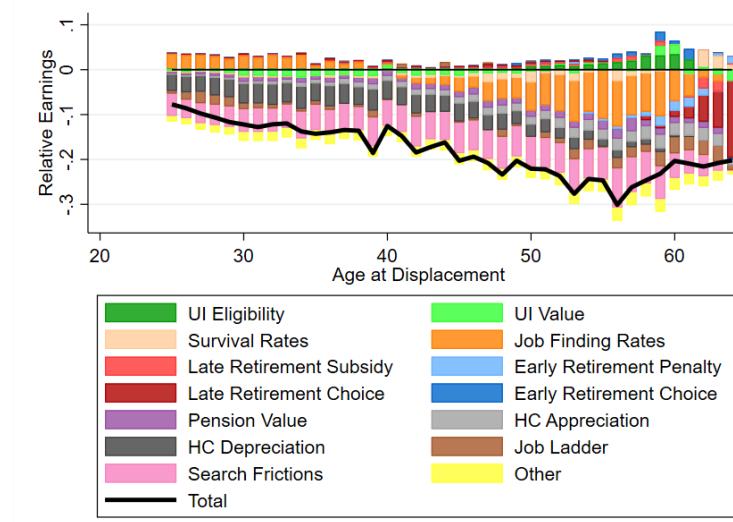


Figure A.10: *Full decomposition of relative (remaining) lifetime income losses into 14 distinct factors present in the model, by age at displacement and discounted to the time of displacement.*

Channel	Age 30	Age 40	Age 50	Age 55	Age 60	Age 62
UI Eligibility	0.000	0.001	0.008	0.014	0.035	-0.002
UI Value	-0.013	0.010	-0.004	-0.001	0.021	0.006
Survival Rates	-0.004	-0.003	-0.023	0.001	-0.002	0.038
Job Finding Rates	0.032	0.004	-0.063	-0.108	-0.068	-0.016
Late Retirement Subsidy	0.001	0.002	0.004	0.001	-0.000	-0.024
Early Retirement Penalty	-0.001	-0.001	-0.001	-0.006	-0.021	-0.016
Late Retirement Choice	0.003	0.004	0.004	0.004	-0.013	-0.058
Early Retirement Choice	0.000	0.001	0.002	0.005	0.009	-0.001
Pension Value	-0.009	-0.010	-0.013	-0.018	-0.014	-0.013
Human Capital Appreciation	-0.005	-0.011	-0.017	-0.022	-0.027	-0.028
Human Capital Depreciation	-0.044	-0.042	-0.027	-0.016	-0.005	0.000
Job Ladder	-0.013	-0.001	0.002	-0.002	-0.036	-0.032
Search Frictions	-0.051	-0.057	-0.066	-0.071	-0.055	-0.047
Other	-0.020	-0.023	-0.026	-0.027	-0.027	-0.022
Total	-0.122	-0.125	-0.221	-0.247	-0.203	-0.216

Table A.4: *Summary of the decomposition of the scarring effect of displacement on (remaining) lifetime income, by age at displacement. The total difference corresponds to the solid black line in Figure A.10 and the left panel of Figure 10. The decomposition is generated by turning off the indicated channels one by one (in the order presented here), thus generating counterfactuals. The numbers reflect the contribution of each channel to the scarring effect of displacement on earnings, 5 years after displacement. In order to generate the grouped decomposition from Figure 10, we combine the grouped channels into a single number.*

with the year-specific losses. In particular, losses among workers displaced early in their working life are primarily driven by search frictions and human capital depreciation. Later in the working life, the importance of the possibility of late retirement becomes particularly important, although this is partially offset by age dependencies in the UI system, driven by both the dependence of benefit values on previous earnings and the age-dependent maximum duration of benefit receipt.

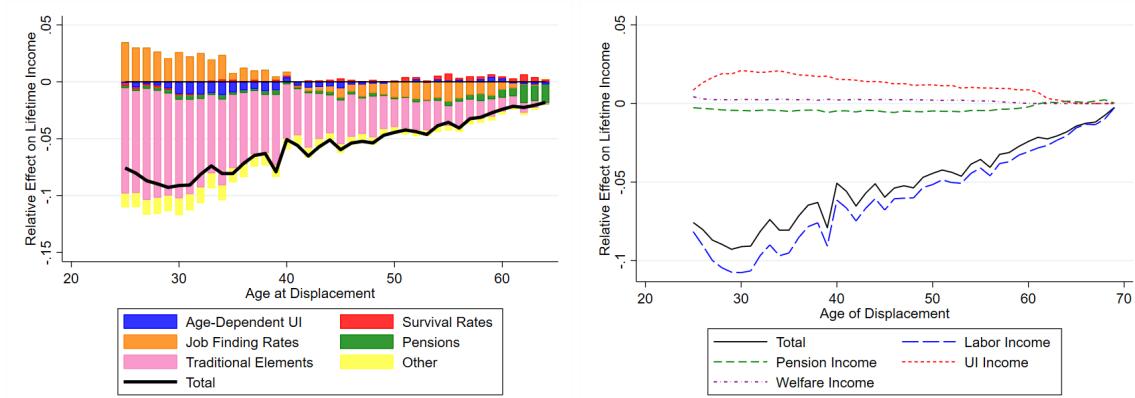


Figure A.11: *Relative (remaining) lifetime income losses into 6 distinct factors present in the model, by age at displacement and discounted to the time of labor market entry, decomposed into 6 distinct factors present in the model (left) and into the different earnings sources present in the model (right).*

While the losses in remaining lifetime income discussed above discount back the observed losses to the age of displacement, one may also be interested in the difference in a worker's full lifetime income. The corresponding results, where differences in lifetime income are discounted to the period prior to labor market entry, are depicted in Figure A.11. The figure shows that while the relative remaining lifetime income losses are increasing in age throughout most of the life-cycle, this is no longer the case if we discount all losses to the point of labor market entry. In other words, the alleviating effect of further discounting losses is stronger than the forces of the model that increase earnings losses in age. As such, a decomposition that discounts all losses to the point of labor market entry is likely to underestimate the importance of age dependencies from the UI and pension system, as these become important in the periods that are discounted the most.

A.4.2 Interaction between Job Loss and Retirement Timing

In our discussion on the determinants of earlier or later retirement in response to displacement (in Section 6.2), we showed how workers with low pension points, assets, and human capital tend to retire earlier, using a set of plots that omitted workers who did not change their retirement timing. In Figures A.12 and A.13, we

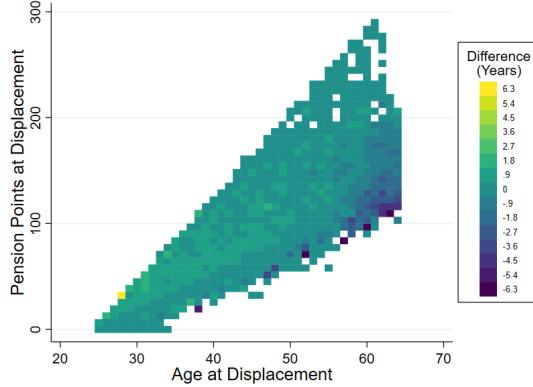


Figure A.12: *Average change in retirement timing upon displacement in the model simulation, including non-changers, by age and pension points at displacement.*

repeat the analysis with these non-changers included in the plot. As can be seen from the figures, including these workers does not change the conclusion, even if the gradient is not as stark due to the zeros being included in the average change in retirement.

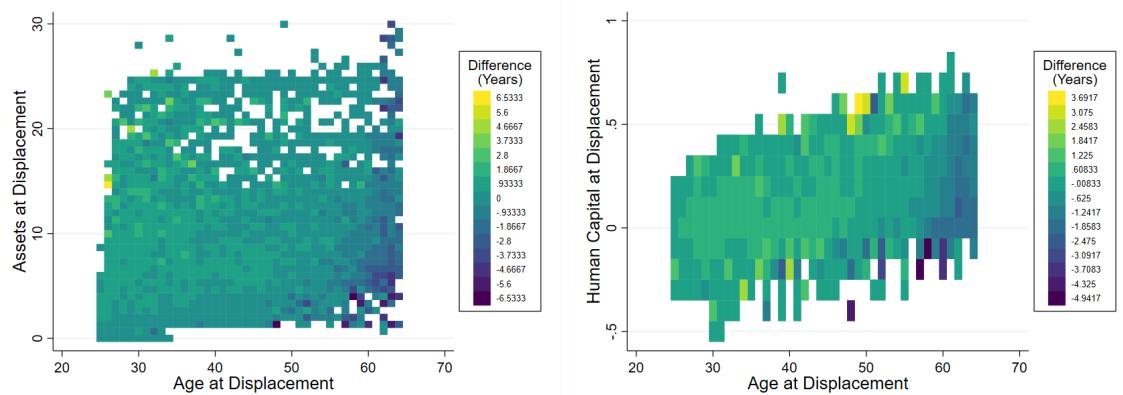


Figure A.13: *Average change in retirement timing upon displacement in the model simulation, including non-changers, by age and either assets (left) or human capital (right) at displacement.*

Finally, we used Table 5 in the main text to argue that the state variables considered above (asset holdings, pension points, and human capital) are strongly correlated. While the averages displayed in the table can give us an indication of such correlation, we can get a clearer picture by plotting these variables against each other, as done in Figure A.14 for workers displaced between the age of 55 and 60. The Figure shows a clear positive correlation, especially between asset holdings and pension points (in the left panel). Furthermore, the color gradients in the Figure show that the decision to retire earlier or later is not necessarily driven by one of these variables in isolation, but rather by a combination of the variables.

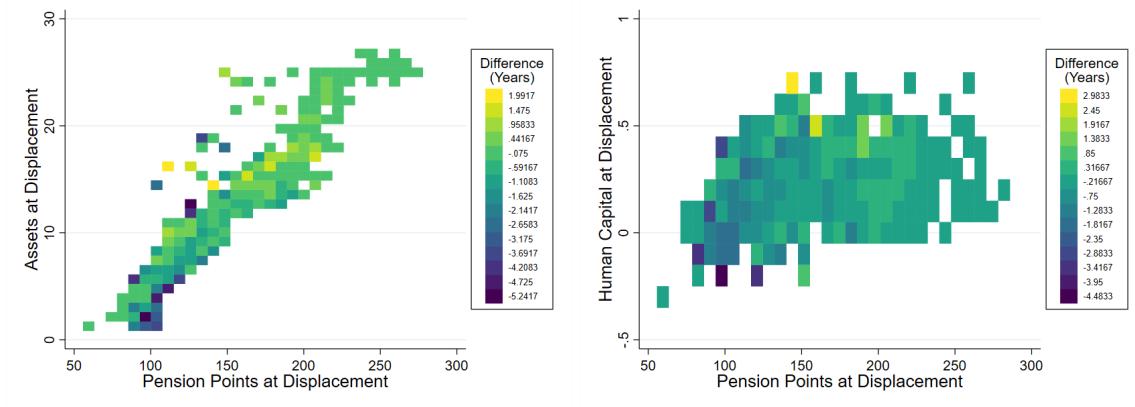


Figure A.14: *Average change in retirement timing upon displacement in the model simulation among workers (first) displaced between the age of 55 and 60, including non-changers, by pension points and either assets (left) or human capital (right) at displacement.*

B Data Appendix

B.1 Further Descriptive Analysis

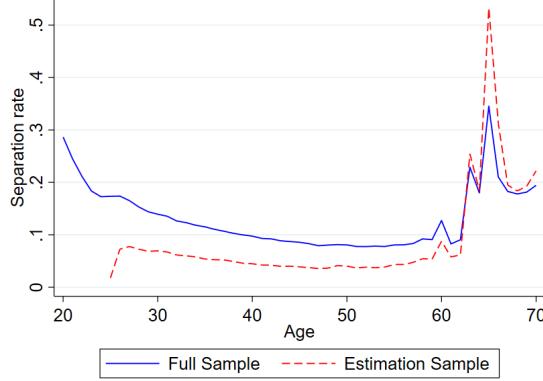


Figure B.15: *The incidence of separation by age, generated from the full sample (solid, blue) and the restricted estimation sample (dashed, red).*

In Section 3.1 of the main text, we illustrated that the displacement rate follows a U-shaped pattern in age, with the initial decrease driven by low-tenure workers. In Figure B.15, we show that this is not an artifact of us focusing on displacements: when plotting separation rates over age, a very similar U-shaped pattern arises, although the magnitude of the separation rates is almost 10 times as high as the

magnitude of the displacement rates.

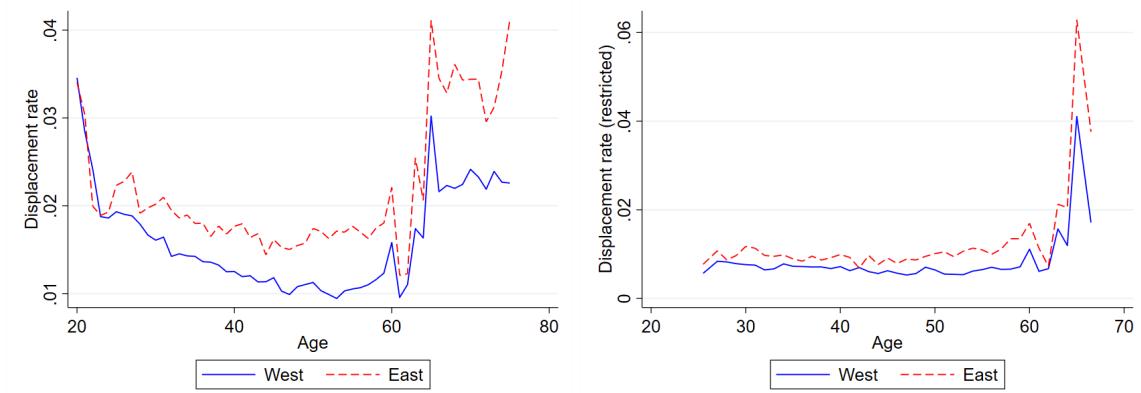


Figure B.16: *The incidence of displacement by age, generated from the full sample (left) and the restricted estimation sample (right), separately for workers located in former West and East Germany.*

In Figure B.16, we show that the U-shaped pattern of the displacement rate over age is not driven by workers living in areas of former East or West Germany: although displacement rates are generally higher in the east, the same U-shaped pattern arises for both subsamples. Similarly, the initial decrease disappear for both subsamples when conditioning on a job tenure of at least 1 year.

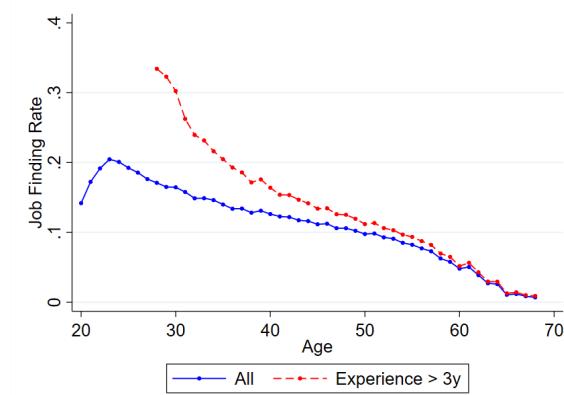


Figure B.17: *The quarterly job finding rate by age, generated from the full sample (solid, blue) and conditional on at least 3 years of market experience (dashed, red).*

In Figure B.17, we plot quarterly job finding rates over age. In line with how these job finding rates were defined for the purpose of the model estimation in Section 5, the job finding rate depicts the

fraction of full-quarter unemployed workers who were employed for at least a day in the next quarter. The figure shows the corresponding values for both the full sample and the sample that only contains observations for workers with at least 3 years of market experience (defined as cumulative tenure across all jobs), the latter being the sample used for estimating the moments described in Section 5. For both samples, it can be seen that job finding rates are decreasing in age (from age 25 onwards). Additionally, the decrease is fairly linear, which we exploit in the setup of the model in Section 4.

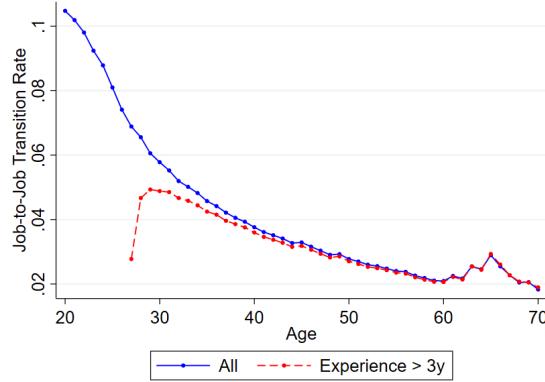


Figure B.18: *The quarterly job-to-job transition rate by age, generated from the full sample (solid, blue) and conditional on at least 3 years of market experience (dashed, red).*

Finally, Figure B.18 plots the yearly job-to-job transition rate over age. This job-to-job transition rate generally exhibits a decreasing pattern over age, just like the job finding rate. However, the variation across the life-cycle is not as large for the job finding rates, with unconditional job-to-job transition rates varying between roughly 0.02 and 0.1. Because of this, and because the presence of a job ladder will naturally generate a decreasing job-to-job transition rate over the life-cycle (albeit weaker than displayed here), we decided not to let the offer arrival rate for job-to-job transitions (λ^e) in the model depend on age.

B.2 Additional Results from the Raw Data

In this section, we show the results of directly calculating post-displacement differences in employment or earnings between the treatment and control group, without using any estimation methods. As we show below, the conclusions obtained from these calculations are in line with those obtained from the estimation in Section 3, and are in fact stronger in several cases.

In Figure B.19, we plot the average earnings of displaced and non-displaced workers by age of (potential) displacement. The figure shows that workers generally start rapidly reducing their earnings shortly after the age of 60, likely reflecting retirement. This is true for both the control group and the treated

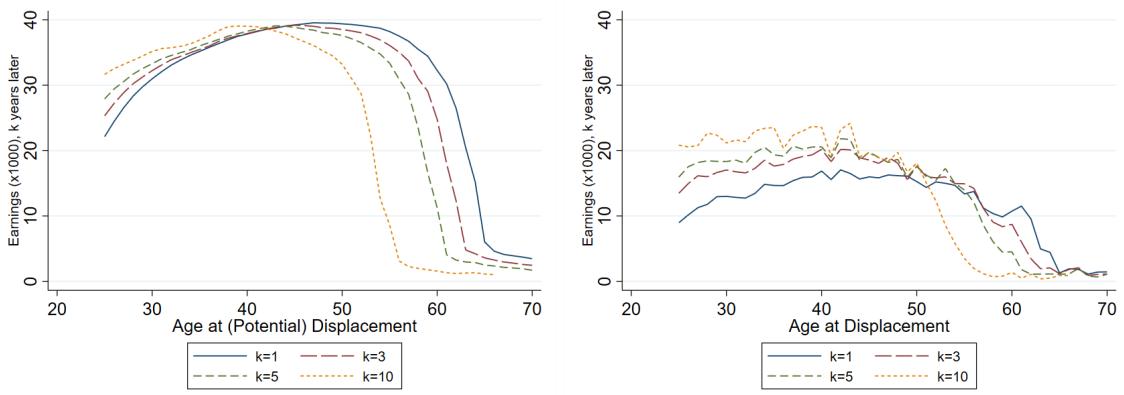


Figure B.19: *Raw average earnings for workers who were displaced (right) or not displaced (left), by age at potential displacement and years since potential displacement.*

(displaced) group, so that the relative difference between the two groups, displayed in Figure B.20, becomes quite volatile. Nevertheless, Figure B.20 shows that relative earnings losses experienced by the displaced workers are generally increasing in age until the retirement window start, and the pattern partially reverses in the retirement window. This is in line with the conclusions drawn in Section 3.

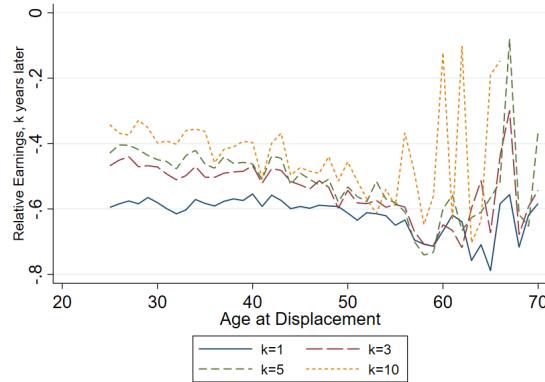


Figure B.20: *Difference in raw average earnings between displaced workers and non-displaced workers, by age at potential displacement and years since potential displacement.*

In Figure B.21, we compare the average employment fraction of the displaced workers and the control group of non-displaced workers. The figure shows that workers generally start rapidly reducing their employment shortly after the age of 60, again likely reflecting (early) retirement. This is true for both the control group and the treated (displaced) group, but the proportional reduction at this early retirement age is larger for the control group. This can be seen in Figure B.22, where we plot the average difference

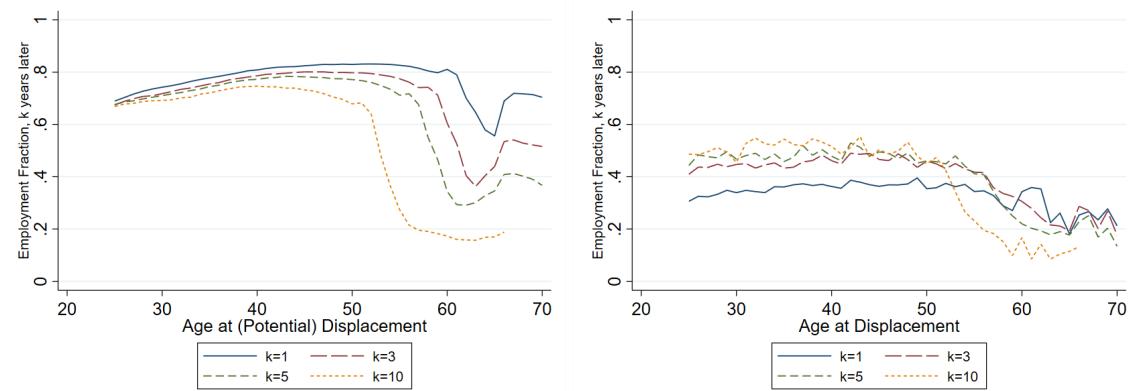


Figure B.21: *Raw employment rates, defined as the fraction of the year spent in an employment spell, among workers who were displaced (right) or not displaced (left), by age at potential displacement and years since potential displacement.*

between the treatment and control groups. The lower proportion of workers choosing to retire early shows up as an uptick in the average difference around this age of early retirement, which is corrected over time. This suggests that displaced workers on average tend to slightly postpone their retirement compared to the control group. This is the case especially for workers who are displaced a few years before their planned retirement, as indicated by the uptick in Figure B.21 (and the right panel of Figure 2) being stronger for $k = 3$ and $k = 5$.

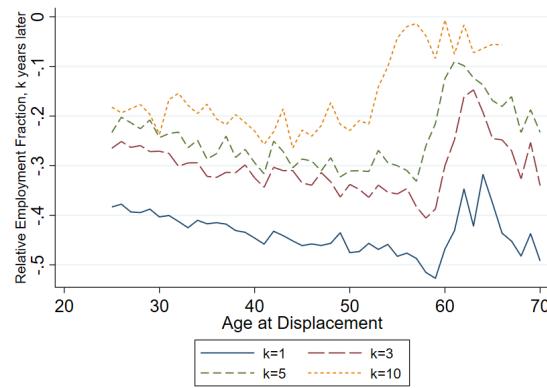


Figure B.22: *Difference in raw employment rates, defined as the fraction of the year spent in an employment spell, between displaced workers and non-displaced workers, by age at potential displacement and years since potential displacement.*

The conclusions drawn above and in Section 3 are based on average patterns across all displaced (and non-displaced) workers. However, one might expect that these patterns are driven primarily by sub-

groups of this population. In particular, if workers decide to postpone retirement for financial reasons, one might expect this to be especially salient among workers who have not built up much wealth during their working life. Unfortunately, we do not observe wealth in the SIAB data, so we have to rely on other (indirect) measures instead. In Figure B.23, we repeat the analysis from Figure B.22 separately for workers whose recent earnings are above or below the median of the distribution. Here, recent earnings are defined as the average earnings over the previous five years, taking into account only years with nonzero earnings, and discarding any observations from workers who are not aged between 25 and 70 or who are self-employed. The distribution over these recent earnings is then formed separately for each (calendar) year of observation, furthermore generating separate distributions for young (aged below 50) and older (aged 50 and higher) workers as well as for workers located in (former) East and West Germany. Calculating relative employment losses separately for workers whose recent earnings situate them above or below the median of their relevant distribution generates the results depicted in Figure B.23. Comparing the two figures, it can be concluded that the reversal in the pattern of employment losses around the retirement window is happening for both lower and higher earning workers. If anything, the reversal is slightly stronger for the workers who have recent earnings above the median.

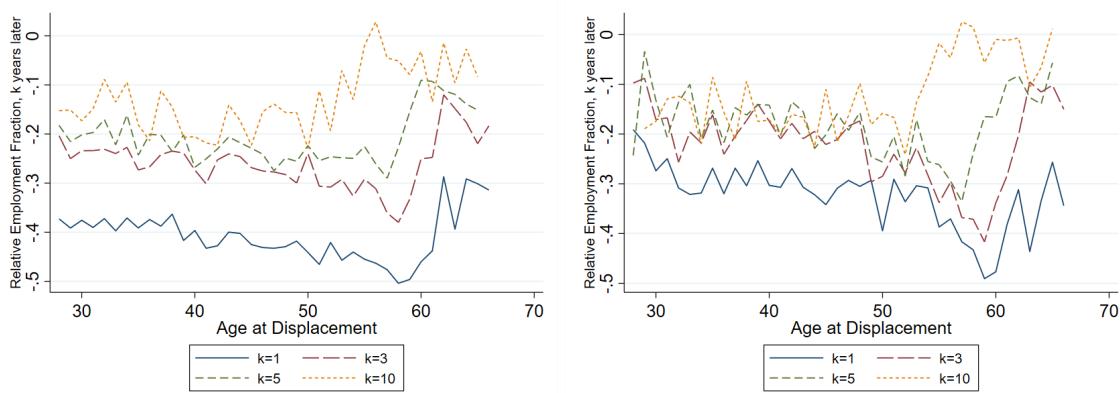


Figure B.23: *Difference in raw employment rates, defined as the fraction of the year spent in an employment spell, between displaced workers and non-displaced workers, by age at potential displacement and years since potential displacement, for workers with recent earnings below (left) or above (right) the median.*

In Figure B.24, we separately plot the employment losses for workers whose education level is below the university level and workers with a university education. Again, the pattern of increasing losses across the working life with a reversal near the retirement window persists for both groups of workers, with the pattern (and reversal) being stronger for the higher educated workers.

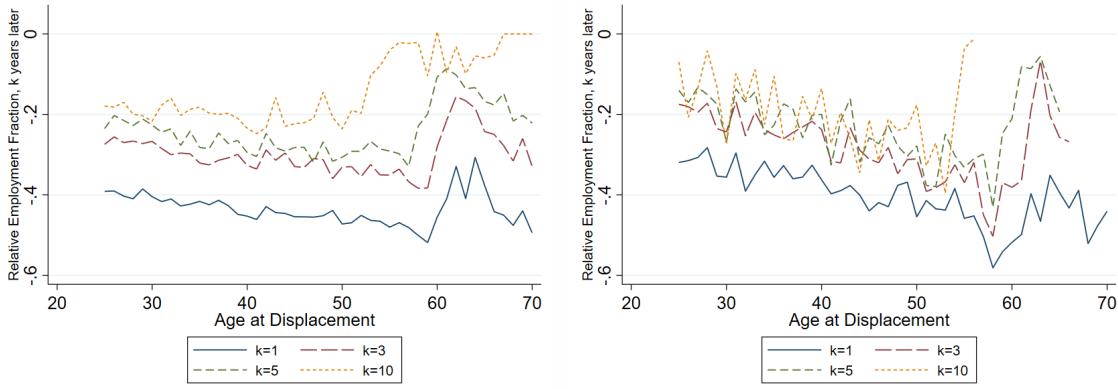


Figure B.24: *Difference in raw employment rates, defined as the fraction of the year spent in an employment spell, between displaced workers and non-displaced workers, by age at potential displacement and years since potential displacement, for workers with a non-university (left) or university (right) education.*

B.3 Additional Empirical Estimation Results

In this section, we show a set of additional results, to illustrate the robustness of our empirical results from section 3.2 to a number of alternative sample restrictions.

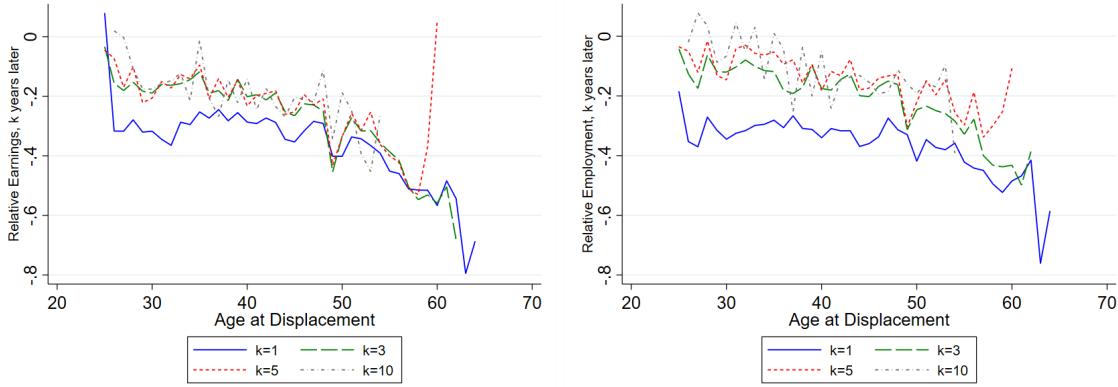


Figure B.25: *The estimated effect of displacement on earnings (left) and employment (right), by time since displacement, and by age at the time of displacement. Depicted estimates are obtained separately for each displacement age. Pointwise confidence intervals are omitted and are available upon request.*

In Figure B.25, we show the estimation results presented in Figure 2 for more values of k . While adding more values of k leads the figure to be considerably more cluttered, the figure still serves to stress that earnings losses are generally larger for workers who are displaced later in their working life, and this

holds for earnings losses in the short run as well as in the long run. For years that fall in the (early) retirement window, a partial reversal is visible especially for employment, whereas the reversal in earnings is clearly visible for $k = 5$ only. Furthermore, Figure B.25 also shows that the recovery in earnings after a displacement is generally very limited, as indicated by the lines for different values of k being very close together in the figure.

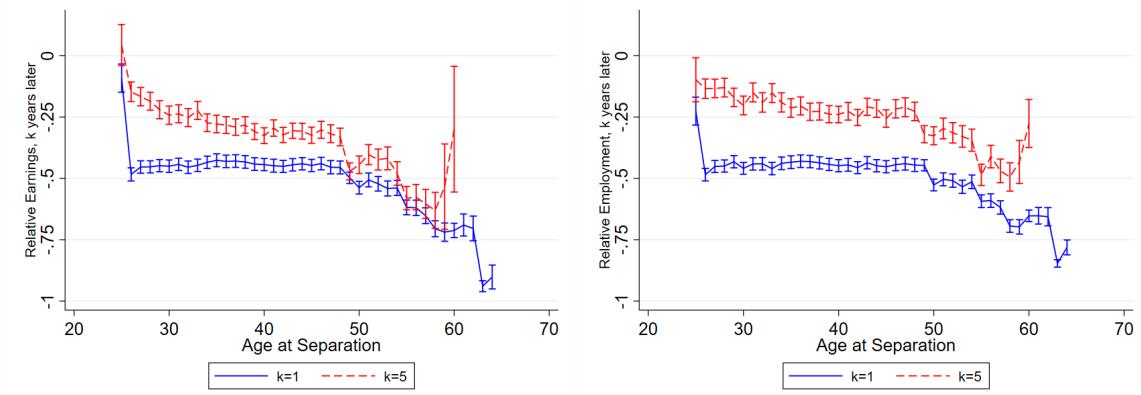


Figure B.26: *The estimated effect of separation on earnings (left) and employment (right), 1 year (solid) or 5 years (dashed) after the job loss, by age at the time of the job loss. Depicted estimates are obtained separately for each separation age.*

In Figure B.26, we show how the results obtained from Figure 2 change if we consider separations instead of displacements. Focusing on separation instead of displacement increases the magnitude of the estimated earnings and employment losses (and recovery), but does not alter our conclusion that losses are increasing in age at the time of job loss, with a reversal in the (early) retirement window especially for $k = 5$.

In Figure B.27, we show how the estimation results from Figure 2 change if we apply more stringent sample restrictions, requiring 6 years instead of 1 year of pre-displacement establishment tenure. The estimates depicted in Figure B.27 confirm the conclusion from the main text that earnings and employment losses are generally increasing in age at the time of displacement. However, the pattern reversal around the retirement age that was visible in Figure 2 as well as in the figures based on raw calculations in Appendix B.2 is not visible here, indicating that the reversal is not driven by high-tenured workers.

In Figure 3, we illustrated the importance of including the age indicator into the estimation of earnings losses. Figure B.28 repeats the same exercise, with the addition of a third alternative, in which both time and age indicators are included, but not interacted. In other words, this alternative can be thought of as

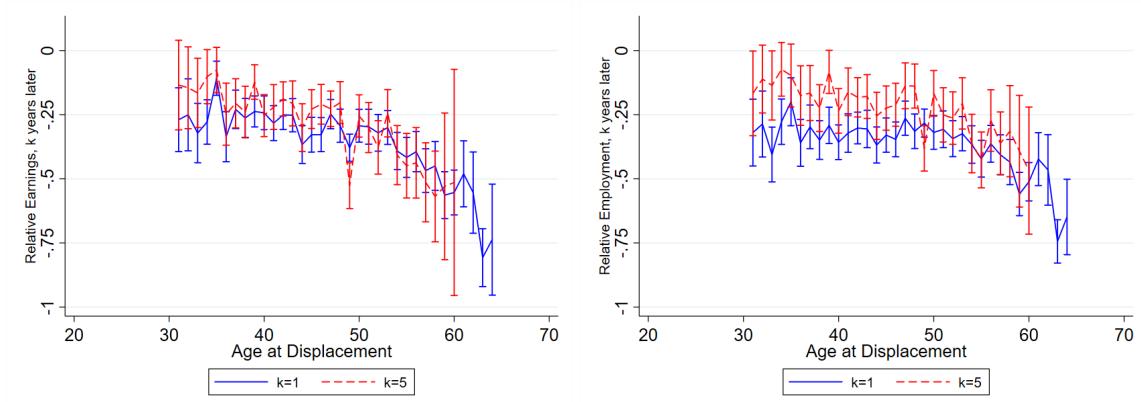


Figure B.27: *The estimated effect of displacement on earnings (left) and employment (right), 1 year (solid) or 5 years (dashed) after displacement, by age at the time of displacement, conditioning on 6 years (rather than 1 year) of pre-displacement establishment tenure. Depicted estimates are obtained separately for each displacement age.*

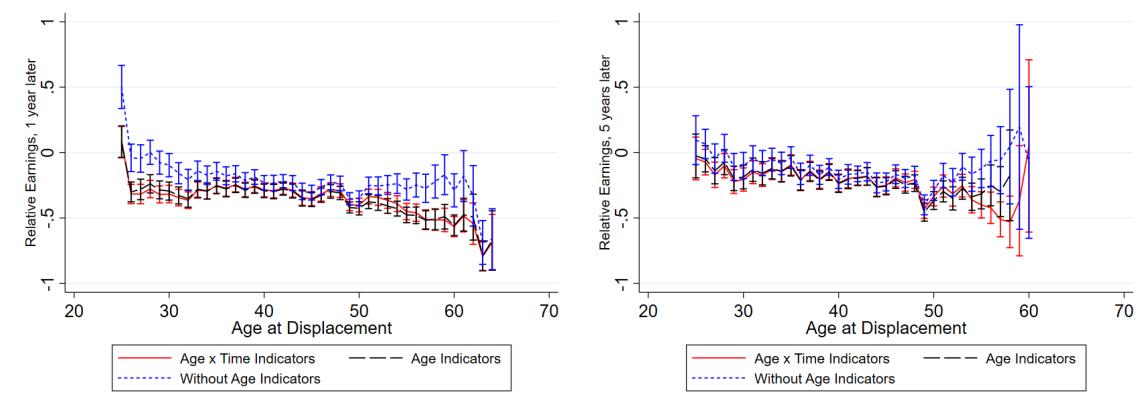


Figure B.28: *The estimated effect of displacement on earnings, 1 year (left) or 5 years (right) after displacement, by age of displacement. The figure compares estimates obtained using either time fixed effects only (short dash, blue), time fixed effects and age indicators (long dash, black), or an interaction of time and age indicators (solid, red).*

representing a version of equation (1) with $\gamma_{h(i,t),t} = \Phi_{h(i,t)} + \Psi_t$. As alluded to in the main text, including the age indicator without interacting it with the time fixed effect has largely the same effect as including the interaction. This is especially true for results focusing on the short run, as can be observed by the two estimates being almost identical in the left panel of Figure B.28. When focusing on the longer run, as in the right panel of Figure B.28, there is a difference between the two versions for ages close to retirement, with the non-interacted version placing the reversal of the slope slightly earlier. This difference indicates that some of the longer-run impact of age may be specific to the year in which the person was observed. One factor introducing such year-age specific effects may be the (anticipation of) gradual changes in policy, such as the gradual increase of the retirement age from 65 to 67 by 2029 (starting in 2012).

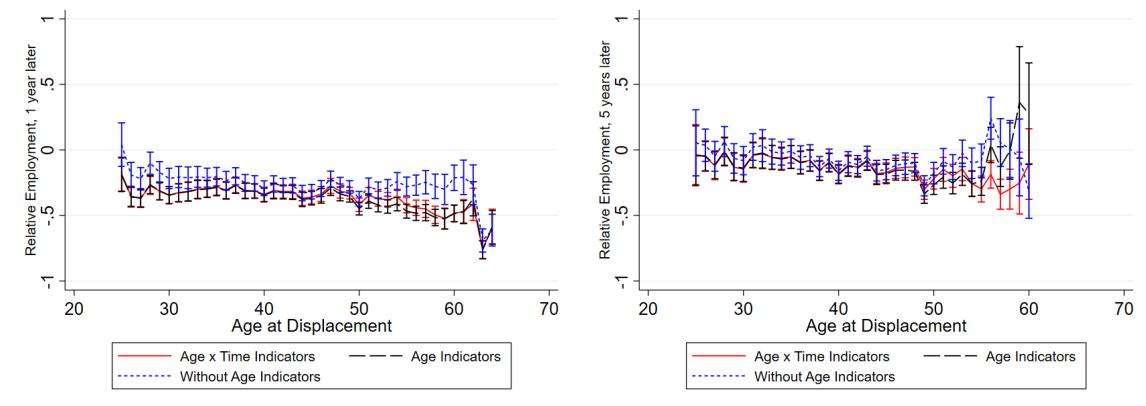


Figure B.29: *The estimated effect of displacement on employment, 1 year (left) or 5 years (right) after displacement, by age of displacement. The figure compares estimates obtained using either time fixed effects only (short dash, blue), time fixed effects and age indicators (long dash, black), or an interaction of time and age indicators (solid, red).*

In Figure B.29, we show that including the age indicator in the estimation of the effect of displacement on employment has a similar effect. Omitting the age indicator from the estimation leads to results that suggest a decreasing employment loss in age during the second half of the working life, especially for $k = 5$, whereas this reversal does not appear until the retirement window when including the age indicator, especially if this indicator is interacted with the time fixed effect. This difference is likely driven by the same considerations as those discussed above (Figure B.28) and in the main text (Figure 3).

Given the differences between the three estimation methods observed in Figures B.28 and B.29 one might naturally expect the estimation results to be slightly different for the average (across ages) effect of displacement on earnings and employment as well. Figure B.30 shows that this is indeed the case. The estimates in Figure B.30 are obtained using the same methods as described above and in the main text, except for esti-

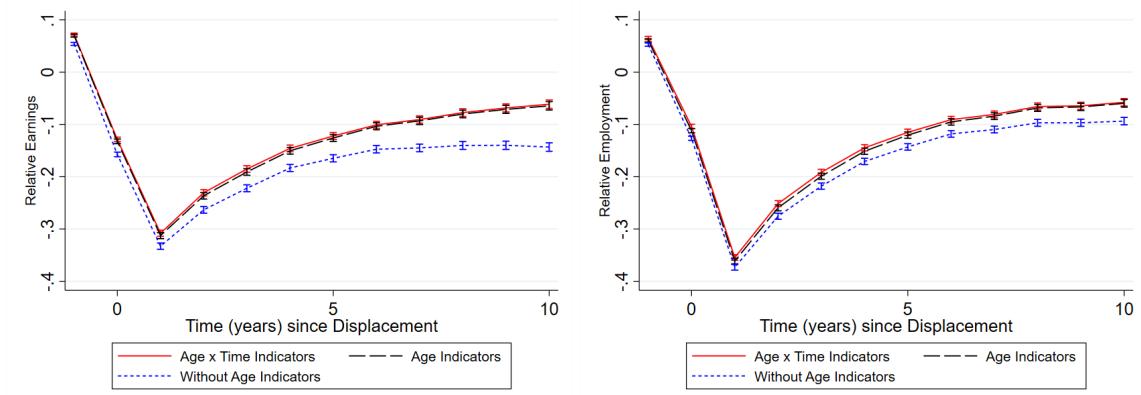


Figure B.30: *The estimated effect of displacement on earnings (left) and employment (right), by year relative to the year of displacement. The figure compares estimates obtained using either time fixed effects only (short dash, blue), time fixed effects and age indicators (long dash, black), or an interaction of time and age indicators (solid, red).*

mating equation (1) or its equivalent only once instead of separately for each age of displacement. As such, it does not allow for the effect of displacement to be different for different ages, as highlighted throughout this paper. As shown in Figure B.30, this results in an estimated scarring effect of displacement that is slightly more severe and persistent than the estimations in which age are taken into account. Notably, the effect goes in the opposite direction compared to Figures B.28 and B.29, thus indicating the considerations highlighted when discussing the differences for the age-specific estimates (in Figures 3, B.28, and B.29) are dominated by the issues that arise from using workers of all ages as the control group.

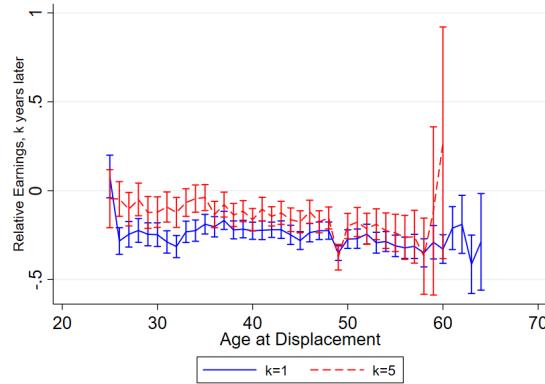


Figure B.31: *The estimated effect of displacement on earnings, 1 year (solid) or 5 years (dashed) after displacement, by age at the time of displacement, conditioning on having positive earnings in any post-displacement period. Depicted estimates are obtained separately for each displacement age.*

In Figure B.31, we plot the results of estimating earnings losses conditional on having positive earnings in a future period (without restricting the future period in which these earnings are recorded). Comparing Figure B.31 to the unrestricted equivalent, the left panel of Figure 2, we can conclude that while this restriction leads to a slight decrease in the magnitude of the earnings losses, it does not change the observed increase in earnings losses in age and subsequent reversal in the retirement window.

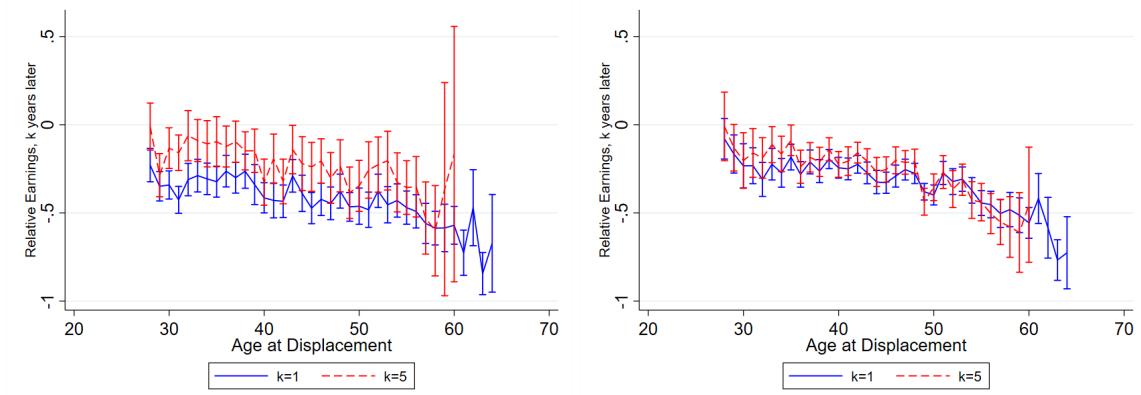


Figure B.32: *The estimated effect of displacement on earnings, 1 year (solid) or 5 years (dashed) after displacement, by age at the time of displacement, conditioning on pre-displacement recent earnings being below the median (left) or above the median (right). Depicted estimates are obtained separately for each displacement age.*

In Figure B.32, we show how the estimated pattern of earnings losses over the working life is affected by separately estimating these losses for workers with pre-displacement recent earnings below and above the median, where recent earnings and its distribution is defined as described in Appendix B.2. Comparing the two panels of Figure B.32, it can be seen that earnings losses are generally increasing in age for both groups. The partial reversal of this pattern in the retirement window is especially visible for the workers with low pre-displacement earnings, although it is also present for workers with high pre-displacement earnings. Finally, it is worth noting that the earnings losses among workers with low pre-displacement earnings show more recovery, partially driven by higher losses in the short run ($k = 1$). A similar picture arises when focusing on employment instead, as Figure B.33 shows.

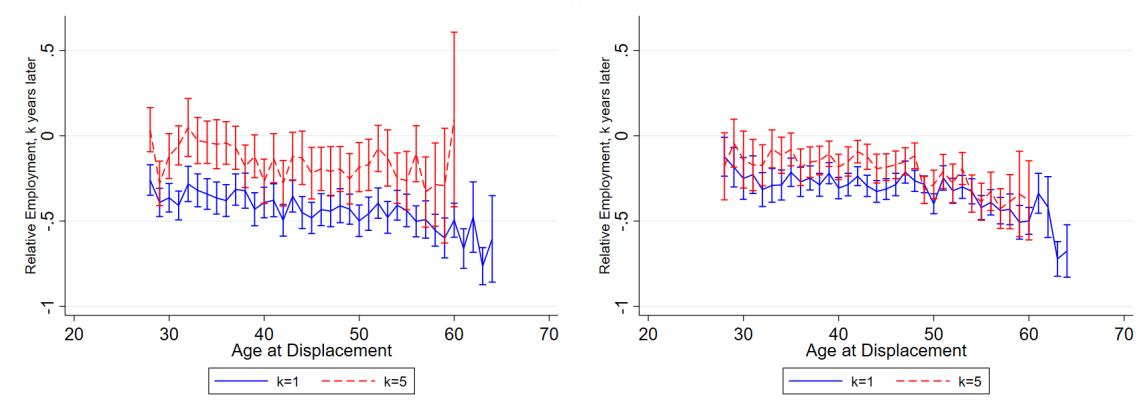


Figure B.33: *The estimated effect of displacement on employment, 1 year (solid) or 5 years (dashed) after displacement, by age at the time of displacement, conditioning on pre-displacement recent earnings being below the median (left) or above the median (right). Depicted estimates are obtained separately for each displacement age.*