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

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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. We use a life-cycle model to investigate the extent to which this variation is driven by the design of the social security system. Using German social security data, we first establish that earnings losses, both upon impact and in the long run, generally increase in age. Employment losses, on the other hand, increase in age only until workers approach the window for early retirement. Our structural model features search frictions, human capital, and savings, and contains a detailed representation of the German unemployment insurance, welfare, and pension systems. We use the estimated model to decompose the life-cycle variation in earnings and employment 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, especially later in the working life. Furthermore, while displacement comes at a high welfare cost, workers are able to effectively shield themselves from some of this cost through unemployment insurance and asset accumulation. Finally, while workers with high lifetime income tend to retire early, job loss tends to nudge these workers to postpone their retirement.

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

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

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# 1 Introduction

It is well established that job loss is associated with large earnings losses on average. However, these average effects mask a substantial amount of heterogeneity along many dimensions. In particular, the effects of job loss are likely to differ by age. Intuitively, one might expect older workers to suffer larger losses, since they have climbed the job ladder for longer. Furthermore, older workers spend more time in unemployment on average, and thus suffer from more skill depreciation. As workers approach eligibility for retirement, retirement timing becomes a potential driver of earnings losses, as workers may choose to retire earlier or later in response to a job loss. Finally, other elements of social security, such as unemployment insurance, have age-dependent eligibility rules, which may also affect earnings losses. In this paper, we aim to disentangle the different drivers of earnings and employment losses over the entire working life, and characterize their interactions with different elements of social security.

In order to achieve this goal, we proceed in two steps. First, we use German social security data to empirically establish the extent to which the effects of job loss on earnings and employment vary by worker age at the time of the job loss. We then set up a life-cycle model, which we use to disentangle the different drivers of these earnings and employment losses. In doing so, we contribute to the quantitative literature that aims to account for the effects of job loss (e.g., Jarosch, 2023) by explicitly modeling the different elements of social security, in particular the endogenous nature of retirement timing. We find that this retirement choice is important in accounting for the effect of job loss on earnings and employment for all workers, including those that lose their job at a young age. We thus also contribute to the rich literature on retirement timing (e.g., Merkurieva, 2019), by highlighting the linkages between job loss and retirement across the entire working life.

In order to empirically document life-cycle variation in the the effect of job loss on earnings and employment, we follow the literature by focusing on displacements. Displacements 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. The German social security data we use 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. (2023), but allowing for interactions between the time fixed effect and a set of age indicators, we then construct an average effect of displacement for each of the first 10 years after displacement, separately by the age of the worker at the time of displacement. We do this for the entire working life (ages $25$ to $65$), thus extending the empirical job loss literature (e.g., Jacobson et al. (1993), Davis and Von Wachter, 2011), where workers close to retirement are often omitted in order to prevent the average effect of job loss from being affected by workers retiring.

The empirical results establish that the earnings loss following displacement is generally increasing in age. This is true for both the immediate impact ($1$ year after displacement), where the impact on relative earnings increases from $32\%$ at age $30$ to $45\%$ at age $55$, and the long-run effect ($5$ years after displacement), which increases from $21\%$ at age $30$ to $40\%$ at age $55$. While the employment loss following displacement is increasing in age for most of the working life, we find that the pattern starts to reverse when the worker approaches the age of $60$ and nears the early retirement window (workers can claim retirement benefits from age $63$). This suggests that displaced workers on average tend to retire later than planned.

In order to quantify the extent to which social security drives the observed life-cycle patterns of earnings and employment losses in age, we set up a life-cycle model. The model contains search frictions, a job ladder, and human capital (de-)accumulation, which the existing literature have shown to be successful in accounting for the average earnings loss. In addition, we incorporate a realistic representation of the German unemployment insurance (UI), welfare, and pension systems, after the labor market reforms of the early 2000s. In this system, a worker's retirement benefit depends on their entire earnings history. Furthermore, workers are eligible to receive UI benefits for a limited amount of periods only, and this maximum duration of benefit receipt is increasing in age.

We estimate the model to match moments generated from the German social security data, Luxembourg Wealth Study (LWS, 2023), and the OECD (OECD, 2023). In particular, we do not explicitly target the earnings losses observed in the empirical section of the paper, but instead target a number of moments that are more closely linked to the parameters we are estimating (e.g., we estimate the probability of receiving an on-the-job offer in the model by targeting the average job-to-job transition rate in the data). Nevertheless, we show that the estimated model is able to generate the observed increasing losses in age at displacement, especially when focusing on the medium to long run ($3$ to $5$ years after displacement).

We then use the estimated model to decompose the effects of job loss on earnings and employment, thus quantifying the importance of the social security system as well as the other model elements in driving these effects. Using model simulations, we are able to quantify the effect of job loss on total lifetime income and the number of periods spent in employment, rather than restricting our focus to labor income or employment for a specific year after displacement, as we do in our empirical analysis. For young workers (prior to the age of $45$), we find that the model elements commonly included in existing models – search frictions, a job ladder, and human capital – are largely able to capture the earnings loss, accounting for $93\%$ and $89\%$ of lifetime income losses for workers first displaced at age $30$ and $40$, respectively. For older workers, these elements become less important, accounting for $49\%$ and $61\%$ of lifetime income losses for workers first displaced at age $50$ and $60$, respectively. For these older 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 maximum number of periods a worker can receive unemployment benefits alleviates earnings losses for older displaced workers, whereas the pension system is one of the major drivers of earnings loss for workers displaced after the age of $55$. Finally, we show that in order to explain life-cycle variation in employment loss, it is important to account for the 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.

In line with our results on earnings and employment, we find that the welfare cost of job loss is generally increasing in age at the time of displacement. We show that unemployment insurance plays a valuable role in insuring workers against income and consumption fluctuations, especially at older ages. In particular, we find that removing unemployment insurance leads to a $14\%$ loss in welfare, even though expected lifetime income declines by only $5\%$. Notably, in the absence of unemployment insurance, self-insurance through asset accumulation plays a larger role. If we simultaneously remove both unemployment insurance and asset accumulation, the welfare effect is substantially higher ($24\%$) than the sum of welfare effects of removing each mechanism individually ($14\%$ and $4\%$, respectively).

Given that we found that endogenous retirement timing plays an important role in accounting for the life-cycle variation in employment loss, we further investigate which factors induce workers to retire early or late, and the extent to which workers change their planned retirement age after being displaced. We find that, absent the displacement shock, workers in the model tend to retire earlier if they have high income during their working life. These workers accumulate a large balance of assets during their working life, which allows them to offset the drop in earnings upon retirement. 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, induces some wealthy workers to quit even before they can legally retire, using unemployment insurance to bridge the time to pension collection. Workers with low lifetime earnings do not accumulate enough assets to offset the earnings drop upon retirement, and therefore tend to retire later in the model. Displaced workers decumulate their assets during their unemployment spell. As a consequence, workers with high lifetime income tend to postpone their retirement, as they first need to re-accumulate assets. Since workers with low lifetime income have few assets, they are not heavily affected by this channel. Instead, these low lifetime income workers tend to retire earlier after a displacement, as their reduced post-displacement wage makes the option of retirement more attractive.

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 are more severe if the worker is laid off in a recession (Davis and Von Wachter, 2011, and Schmieder et al., 2023). 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 displacement, and doing so across the entire working life and without grouping ages. The existing

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

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. They generally find 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 but use 5-year age bins. They furthermore distinguish between different types of consequences at different age bins, 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, which is in line with results from our model simulation.

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 while our empirical losses suggest that workers tend to retire later on average, we show in our model simulation that workers adjust their retirement timing in both directions. We contribute to this literature by focusing on earnings loss in addition to employment patterns after a late-career job los.

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, 2023), or lengthy job ladders (Krolikowski, 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

[2]The 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).

use a life-cycle setting. The model in Jung and Kuhn (2019) further differs from the other aforementioned 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 working 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 also contributes 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 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]

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 closes[5] 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 order to only capture job loss that occurred after the Hartz reforms in the early 2000s. Furthermore, we restrict the sample to men, as the social security regulations we model in Section 4 exhibit substantial variation across our sample period for women. Furthermore, this allows us

[3]Some 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.

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

[5]In 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).

[6]Additionally, 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.

to avoid issues arising due to fertility choices and the corresponding social security regulations, which primarily affects women in the German context. The resulting full sample contains close to 6 million observations. 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 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 follow-

[7]This 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.

[8]The 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.

ing equation:

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

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 labor market earnings or the fraction of the year spent in employment. The error term is denoted by $u_{i,t}$, $\alpha_i$ 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 $\delta_k^C$ 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. (2023), 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 $\delta_k^C$.

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 labor market income.[9]

# 3 Empirical Results

## 3.1 Life-Cycle Variation in the Incidence of Job Loss

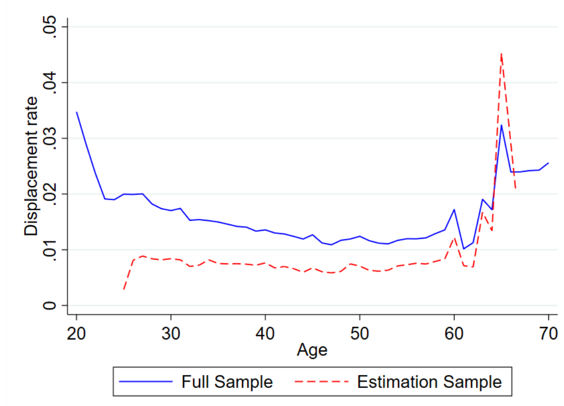


Figure 1: *The incidence of displacement by age, generated from the full sample (solid, blue) and the restricted estimation sample (dashed, red).*

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

[9]Since 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.

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.

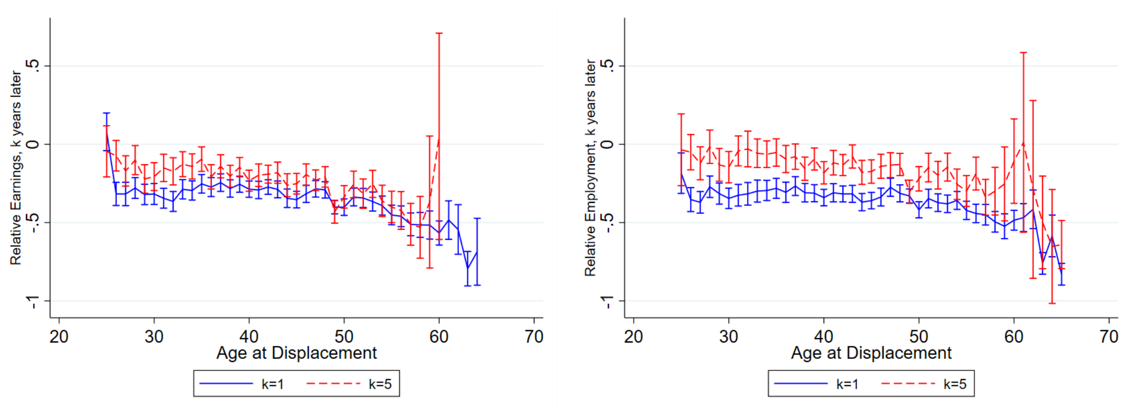


Figure 2: *The estimated effect of displacement on earnings (left) and employment (right), 1 year (solid, blue) or 5 years (dashed, red) after displacement, by age at displacement. Depicted estimates are obtained separately for each displacement age, and depicted along with a 95% pointwise confidence 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 (though not statistically significant) 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 employment 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.

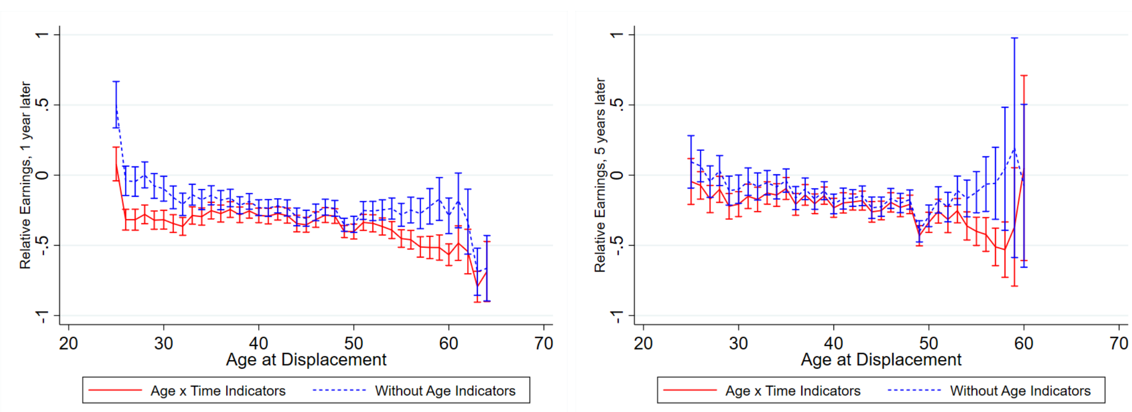


Figure 3: *The estimated effect of displacement on earnings, 1 year (left) or 5 years (right) after displacement, by age at displacement. The figure compares estimates and corresponding 95% pointwise confidence intervals obtained using either time fixed effects (dashed, blue) or an interaction of time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

[10] It 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.

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 labor 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 $\gamma_t$, 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 $\Delta_s$ with probability $\psi_e$ each period in which the worker is employed, and decreases by $\Delta_s$ with probability $\psi_u$ each period in which the worker is unemployed. Unemployed workers receive a job offer with age-dependent probability $\lambda_t^u$ and employed workers with age-invariant probability $\lambda^e$, 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 $\delta_L$ and $\delta_H < \delta_L$. Whenever workers change jobs, their attachment resets to $x_L$. Attachment increases to $x_H$ every period with probability $\xi_x$, 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.[11] 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 $\zeta$ 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 $\beta$. 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.[12] 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,

[11] Note that in the data, there are other forms of separations, such as workers being fired for poor performance. Such separations initiated by the firm are not present in our model.

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

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 $\xi_e$. Furthermore, the value of $e$ does not reset if the worker decides to make a job-to-job transition. If 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 $\omega$ in the model).

The pension system in the model also closely follows the German system after the reforms in the early 2000s.[13] 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[14], 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.

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 $\rho_t$, 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

[13]For 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).

[14]In reality, workers accrue pension points for the entire duration of their UI benefit receipt spell. In ongoing work, we are explicitly incorporating this into the model. Preliminary simulations show that this slight change in the setup does not substantially affect the simulation results.

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 $\Omega_i$, 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 $\rho_{t+1}$. The value function for a continuously unemployed worker in this period can be written as follows:

$$\begin{aligned} U(\Omega_u, t) = \max_{c, a' \geq 0} \Bigg\{ & u(c) + \beta\gamma_t \mathbb{E}_{s'} \Bigg[ \lambda_{t+1}^u \int_{y' \in \Theta^u(\Omega'_u, t+1)} \tilde{W}(\Omega'_w, \Omega'_r, y', x_L, t+1) dF(y') \\ & + \left( 1 - \lambda_{t+1}^u \int_{y' \in \Theta^u(\Omega'_u, t+1)} 1 dF(y') \right) \tilde{U}(\Omega'_u, \Omega'_r, t+1) \Bigg] + \beta(1-\gamma_t) B(a') \Bigg\} \qquad (2) \\ \text{s.t. } & a' + c = \max\{(1+r)a + b(\hat{s}, \hat{y}), \underline{\omega}\} \qquad ; \qquad p' = p \end{aligned}$$

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:

$$\begin{aligned} W(\Omega_w, t) = \max_{c, q'_W \in \{0,1\}, a' \geq 0} \Bigg\{ & u(c) - u_w + \beta\gamma_t \mathbb{E}_{s',x',e'} \Bigg[ \delta_{x'} \tilde{U}^N(\Omega'_u, \Omega'_r, t+1) \\ & + (1-\delta_{x'})(1-q'_W) \left( \lambda^e \int_{y' \in \Theta^e(\Omega'_w, t+1)} \tilde{W}(\Omega'_w, \Omega'_r, y', x_L, t+1) dF(y') \right. \\ & \left. + \left(1 - \lambda^e \int_{y' \in \Theta^e(\Omega'_w, t+1)} 1 dF(y')\right) \tilde{W}(\Omega'_w, \Omega'_r, t+1) \right) \\ & + (1-\delta_{x'}) q'_W \tilde{U}^Q(\Omega'_u, \Omega'_r, t+1) \Bigg] + \beta(1-\gamma_t) B(a') \Bigg\} \\ \text{s.t. } & a' + c = \max\{(1+r)a + w(s,y), \underline{\omega}\} \quad ; \quad p' = p + \min(w(s,y)/\omega, 2) \end{aligned} \tag{3}$$

In equation (3), functions $\Theta^e$, $\tilde{U}^Q$, and $\tilde{U}^N$ are defined in line with the earlier discussion of $\Theta^u$, $\tilde{U}$, 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:

$$R(\Omega_r, t) = \max_{c,a' \geq 0} \{u(c) + \beta\gamma_t R(\Omega_r', p, t+1) + \beta(1-\gamma_t)B(a')\} \tag{4}$$
$$\text{s.t. } a' + c = \max\{(1+r)a + b_R(p/T_w), \underline{\omega}\}$$

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 Estimation

In order to estimate 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 $\lambda_t^u$ depends on age $t$ in a linear fashion. In particular, we assume $\lambda_t^u = \lambda_c^u + \lambda_s^u t$ with constant $\lambda_c^u$ and a slope $\lambda_s^u$ 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 $\mu_y$ and shape parameter $\eta_y$.

Taken together, the above assumptions leave us with a total of $20$ parameters to estimate 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.

| Parameter | Meaning |
|---|---|
| $r$ | interest rate |
| $\beta$ | discount factor |
| $\nu$ | relative risk aversion |
| $\gamma_t$ | survival probability at age $t$ |
| $\phi_1$ | bequest motive, intensity |
| $\phi_2$ | bequest motive, curvature |
| $u_w$ | disutility of work |
| $\omega$ | average earnings subject to social security |
| $\xi_x$ | transition probability to high attachment |
| $\xi_e$ | transition probability to UI eligibility |
| $\psi_e$ | human capital transition, employment |
| $\psi_u$ | human capital transition, unemployment |
| $s_1$ | starting value of human capital |
| $\Delta_s$ | human capital transition size |
| $\eta_y$ | shape parameter, marginal distribution of $y$ |
| $\mu_y$ | scale parameter, marginal distribution of $y$ |
| $\lambda_c^u$ | meeting probability, unemployed workers (constant) |
| $\lambda_f^u \lambda_1^u$ | meeting probability, unemployed workers (retirement age) |
| $\lambda^e$ | meeting probability, employed workers |
| $\delta_L$ | exogenous separation rate, low attachment |
| $\delta_H$ | exogenous separation rate, high attachment |

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

## 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 $\Delta_s$ 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 $\xi_x$ 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.

Aside from the aforementioned $5$ parameters, we also directly import the survival rate $\gamma_t$ from the data. To be specific, we take the age-specific average survival rate (for males only) across all

| Parameter(s) | Value(s) | Source |
|---|---|---|
| $r$ | 0.00985 | 4% annual interest rate |
| $s_1$ | 0 | normalization |
| $\Delta_s$ | 0.1 | normalization |
| $\xi_x$ | 0.083 | expected transition in 12 periods |
| $\xi_e$ | 0.25 | expected transition in 4 periods |

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

cohorts that fall within the period 2005 to 2017 from Destatis (2023). The value of $\gamma_t$ 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 Estimation 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 $\omega$. Since this parameter proxies the average earnings subject to social security in the economy, we target a difference of $0$ between the value of $\omega$ 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 $2\omega$.

Using data from SIAB, we directly inform the value of $\lambda^e$ by targeting the quarterly job-to-job transition rates. The two parameters that inform the values of $\lambda_t^u$ ($\lambda_c^u$ and $\lambda_f^u$) 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 $\delta_L$ and $\delta_H$ 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 $\psi_e$. 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 $\psi_u$. 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 $\mu_y$ and $\eta_y$.

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 ($\nu$, $\phi_1$, and $\phi_2$), 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.

| **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 | $-0.0305$ | $-0.1347$ | $\psi_u = 0.0899$ |
| Pre- to post-layoff wage, duration 0.5-1y | $-0.0777$ | $-0.151$ | |
| Pre- to post-layoff wage, duration 1-2y | $-0.0983$ | $-0.1785$ | |
| Employment-to-population ratio, age 55-59 | $0.844$ | $0.794$ | $u_w = 0.0168$ |
| Employment-to-population ratio, age 60-64 | $0.637$ | $0.661$ | |
| Employment-to-population ratio, age 65-69 | $0.202$ | $0.245$ | |
| p75 of assets, p60-p90 permanent income, age 75-79 vs. 70-74 | $1.1266$ | $0.9985$ | $\tilde{\beta} = 0.9518$, $\nu = 2.84$, $\phi_1 = 140.45$, $\phi_2 = 15.152$ |
| 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 | $1.1357$ | $1.1742$ | |
| p75 of assets, age 45-49 vs. 40-44 | $1.1408$ | $1.1318$ | |
| p75 of assets, age 50-54 vs. 45-49 | $1.1304$ | $1.1365$ | |
| p75 of assets relative to average earnings, age 30-39 | $0.4173$ | $0.3639$ | |
| 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 $\omega$ and average income | $0.0$ | $-0.004$ | $\omega = 12.38$ |

Table 4: *Summary of estimation moments, their values in the data and in the estimated 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 $\omega$.*

## 5.3 Estimation Results and Model Fit

Table 4 summarizes the results of the model estimation. 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.

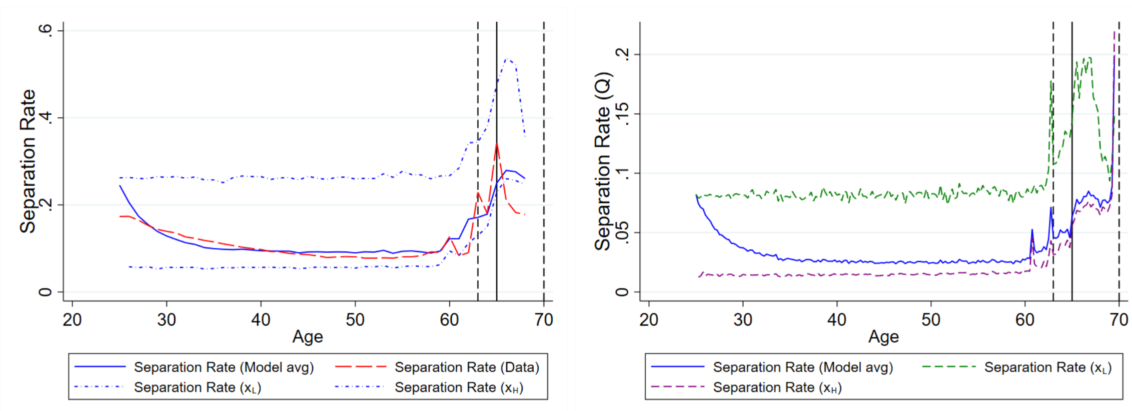


Figure 4: *Left: the yearly separation rate in the data (red, dashed) compared with the average in the model simulation (blue, solid), by age. The dashed blue lines denote the average yearly separation rates in the model simulation conditional on low or high attachment levels. Right: the quarterly separation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

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 occuring 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 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.

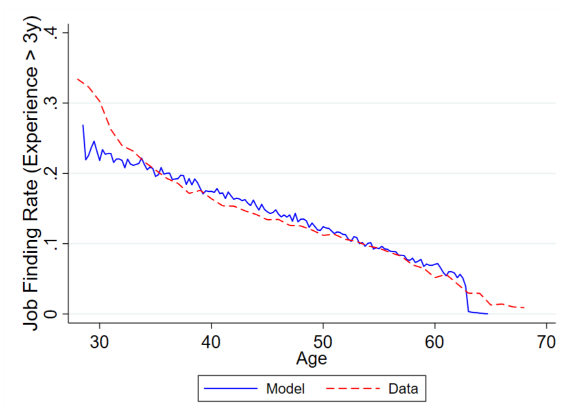


Figure 5: *The average quarterly job finding rate by age in the data (red, dashed) compared to the average in the model simulation (blue, solid), by age and conditional on 3 years of labor market experience.*

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 growth, despite a value for the human capital appreciation rate $\psi_e$ which is roughly in line with rates that have been found in the literature (e.g. Jarosch, 2023).

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 $\eta_y$ 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.

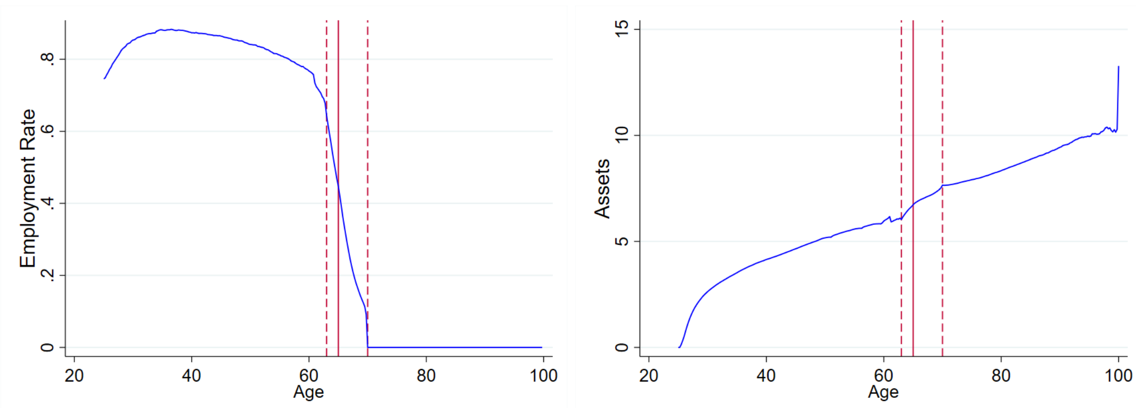


Figure 6: *Average employment-to-population ratio (left) and average asset holdings (right) in the model simulation, by age. The solid red vertical line denotes the regular retirement age, whereas the dashed red vertical lines denote the earliest and latest possible retirement ages in the model.*

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 discount rate $\beta$ and the relative risk aversion $\nu$. 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 (at the given age), 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.

Comparing Figure 7 with its equivalent in the empirical section, it can be observed that the model tends to overshoot the earnings and employment losses in the short run, and implies a stronger recovery over time than estimated in the data.[15] 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, which may partially carry over to later post-displacement periods as well. Nevertheless,

[15]In 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.

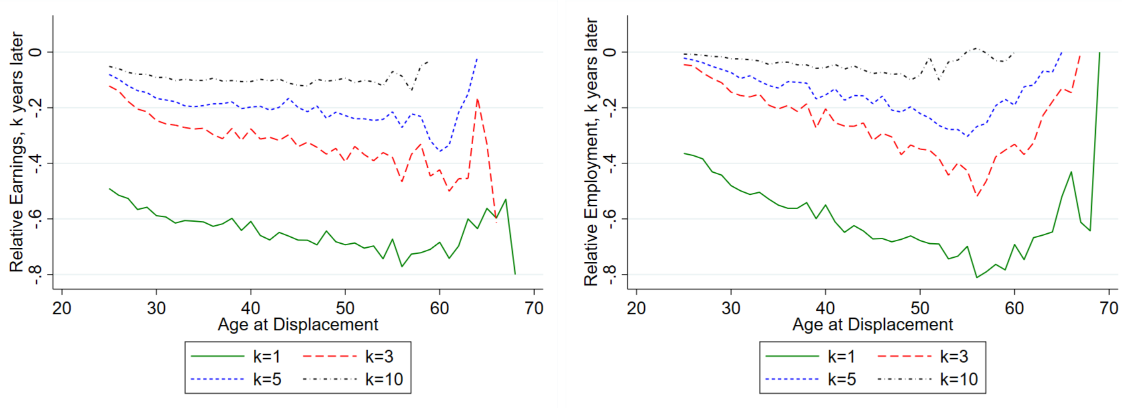


Figure 7: *The estimated effect of displacement on labor earnings (left) and employment fraction (right), by age at displacement and years since displacement, obtained directly from the model simulation.*

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 the 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 in the data, the relative earnings losses start decreasing in age from age $55$ or $60$ onwards. For employment losses, this reversal is even clearer, although it should be noted that the reversal all the way to $0$ at age $70$ (in the right panel of Figure 7) is mechanical, as we do not allow workers in the model to be employed beyond the age of $70$.

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 driving this pattern. However, given that we are not limited by the data and model the full life cycle of the individual, we are able to decompose the effect of displacement on remaining lifetime income rather than earnings in a specific period after displacement.[16] In order to measure remaining lifetime income, 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 present value for the base-

[16]We show in Appendix A.4.1 that the results are similar if we instead focus on the losses observed 3 or 5 years after displacement.

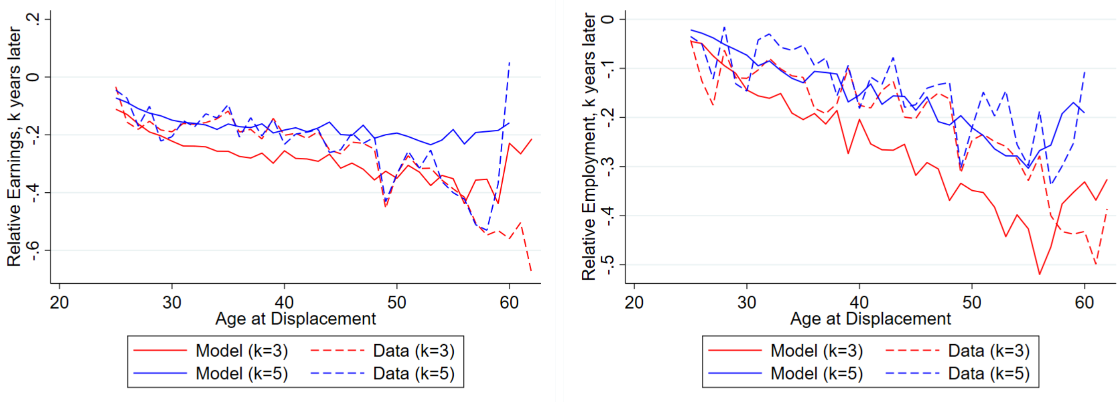


Figure 8: *The estimated effect of displacement on labor earnings (left) and employment fraction (right), 3 years (red) or 5 years (blue) after displacement, by age at displacement, obtained from the data (dashed) and directly from the model simulation (solid).*

line 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 9, the pattern for loss in remaining lifetime income resembles the patterns of lost labor income in a specific period after displacement (such as those depicted in the left panel of Figure 7). Total income losses are primarily driven by losses in labor income, although the losses in labor income are increasingly offset by UI benefits throughout the working life. Pension benefits eventually take over this offsetting role in the retirement window.

We decompose the loss in remaining lifetime income into 6 channels, which are switched off in the simulation one after another, in the order in which they are presented. The results of this decomposition are depicted in the left panel of Figure 9, and the corresponding numerical values can be found in Appendix A.4.1.

The first factor depicted in the decomposition results covers the direct and indirect age dependencies 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. This removes the gradual increase in average UI benefits, which reflects older workers having climbed the job ladder for a longer time prior to being displaced.

The second factor in the decomposition results is the age dependency in survival rates. The contribution of this factor is calculated by removing the mortality risk altogether, 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 job finding rates, is calculated by setting the offer arrival rate $\lambda_t^u$ equal to its average value for workers of all ages.

The contribution of the pension system, the fourth factor in the decomposition exercise, 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, we set the retirement benefit equal to $70\%$ of the average earnings in the economy and assume everyone retires at age $65$.

The fifth factor in the decomposition is labeled "Traditional Elements". This factor includes 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. 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 ($\psi_e$ and $\psi_u$) 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, $\eta_y \mu_y/(\eta_y - 1)$. Finally, the last traditional element is that of search frictions. The search frictions are switched off by setting the job finding rate $\lambda^u$ equal to $1$, such that every worker that loses a job immediately receives a job offer in the next period. After switching off all of these traditional elements, all remaining losses in remaining lifetime income are captured 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 initially facing a higher separation risk in their new job due to lower job attachment.

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 income losses for workers displaced up to to the age of $45$. In particular, using the numerical values presented in Appendix A.4.1, it can be calculated that these "Traditional Elements" account for $92.6\%$ and $88.8\%$ of income losses for workers displaced at the age of $30$ and $40$, respectively. This is primarily driven by 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 older workers is primarily driven by the age dependency in the job finding rate,

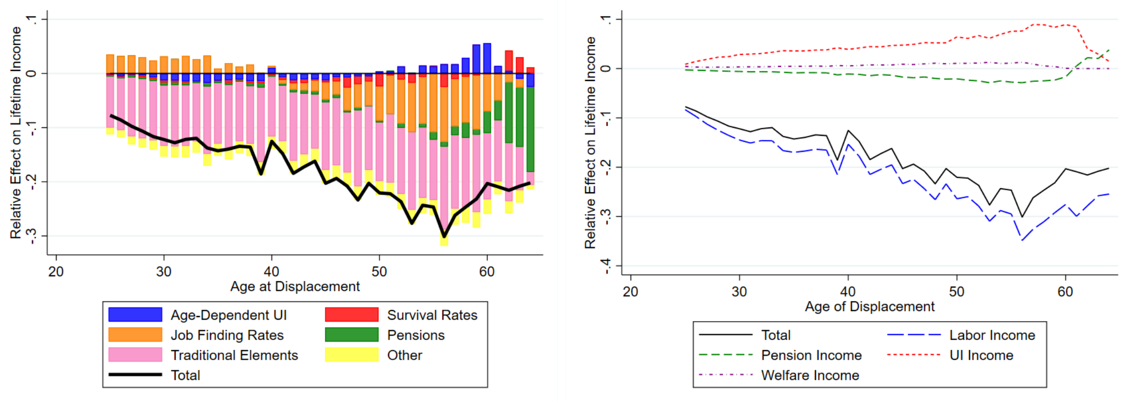


Figure 9: *Relative (remaining) lifetime income losses, by age at displacement and discounted to the time of displacement, decomposed into 6 distinct factors present in the model (left) and into the different earnings sources present in the model (right).*

which becomes increasingly important after the age of $50$. For these older workers, the traditional model elements are no longer sufficient, explaining only $48.9\%$ and $60.6\%$ of income losses for workers displaced at the age of $50$ and $60$, respectively. 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 (early) retirement age, as they become increasingly important in explaining losses in remaining lifetime income. In other words, the inclusion of age dependency in unemployment insurance, mortality risk, and retirement timing are crucial in accounting for the reversal of the pattern of income losses that we observe late in the working life.

While the measures presented in Figure 9 give an indication of the cost of job loss experienced by displaced workers and the extent to which these are alleviated by the different elements of social security (right panel), one might argue that the welfare cost may be higher. After all, Figure 9 indicates the overall income loss over the remaining lifetime and thus does not take into account the welfare cost associated with fluctuations in income and the accompanying fluctuations in consumption. In Figure 10, we show the effect of displacement on an individual worker's welfare. Here, the effect on welfare is measured as the equivalent variation (EV). In other words, we compute the fraction $\Gamma$ such that the remaining lifetime utility of consuming $\Gamma\hat{c}$ equals the remaining lifetime utility of consuming $c$, where $c$ and $\hat{c}$ denote the remaining path of consumption of the displaced worker ($c$) and this same worker in the counterfactual scenario where he was not displaced in the period in question ($\hat{c}$).[17] The solid black line in Figure 10 depicts the welfare loss

[17]Since the utility function is separable between consumption and non-consumption elements (which include the

over age in our baseline simulation. Comparing these welfare losses to the total remaining lifetime income losses we see that, for workers below the age of $60$, the welfare losses are generally much larger than the income losses. For example, a worker displaced at the age of $35$ faces an income loss of approximately $15\%$, but a welfare loss of more than $20\%$. Similarly, a worker displaced at age $50$ faces an income loss of roughly $22\%$ and a welfare loss of roughly $38\%$. Most of these differences are likely driven by income fluctuations.

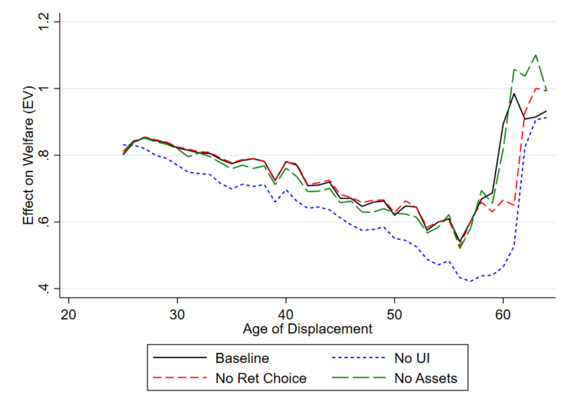


Figure 10: *The welfare cost of displacement, by age at displacement. The welfare cost is calculated as the equivalent variation $-1$, thus representing the factor with which a worker would be willing to change consumption in order to achieve the same present value of remaining lifetime utility.*

To gauge the importance of alternative insurance mechanisms, we additionally show in Figure 10 how large the welfare loss associated with displacement would be in alternative environments in which: (1) there are no UI benefits and associated pension accumulation during UI receipt (blue, short-dashed), (2) workers cannot self-insure through asset accumulation (green, long-dashed), and (3) workers cannot endogenously choose their retirement timing and instead exogenously retire at $65$ (red, dashed). Clearly, the insurance provided by the UI benefits plays a large role in alleviating welfare losses, as indicated by welfare losses in a system without UI being substantially higher throughout the working life. Eliminating asset accumulation in itself does not lead to a large change in the welfare cost of displacement. However, we show in Appendix A.4.1 that eliminating assets in addition to UI substantially exacerbates the associated welfare costs, thus

disutility of work and the value of the bequest), we can take into account differences in the non-consumption utility between the two scenarios when calculating the value of $\Gamma$. In particular, denoting by $U_c^i$ and $U_o^i$ the remaining lifetime utility in scenario $i$ from consumption and other factors respectively, we calculate $\Gamma = \left(\frac{U_c^{\text{displaced}} + U_o^{\text{displaced}} - U_o^{\text{non-displaced}}}{U_c^{\text{non-displaced}}}\right)^{\frac{1}{1-\nu}}$

indicating that the two serve a similar purpose of insuring the worker against consumption fluctuations. The effect of endogenous retirement is only visible for workers close to the retirement age, reflecting that the retirement decision is not as impactful if the displacement does not occur close to the retirement window.

| **Variable** | **Welfare (EV)** | **Welfare (EV, $\beta = 1$)** | **Lifetime Income** |
|---|---|---|---|
| No UI | $0.8627$ | $0.8583$ | $0.9472$ |
| No Retirement Choice | $0.9874$ | $0.9633$ | $0.9931$ |
| No Assets | $0.9629$ | $0.9500$ | $0.9871$ |
| No Assets & UI | $0.7625$ | $0.7691$ | $0.9511$ |
| No Assets & Ret Choice | $0.9513$ | $0.9185$ | $0.9812$ |
| No UI & Ret Choice | $0.8510$ | $0.8248$ | $0.9406$ |
| No UI, Ret Choice, or Assets | $0.7534$ | $0.7432$ | $0.9452$ |

Table 5: *The estimated insurance value of unemployment insurance, asset accumulation, endogenous retirement, and their combination. The insurance measure in the first two columns is calculated as the equivalent variation $-1$ for a worker entering the labor force (at age $25$), and uses either the expected present value of lifetime utility (column 1) or the expected non-discounted sum of lifetime utility (column 2). The third column shows the value in terms of relative expected present value of lifetime income. All numbers are relative to the baseline model simulation.*

The welfare results discussed above indicate that unemployment insurance is important in insuring workers against the welfare cost of displacement. In order to calculate an overall insurance value (rather than a value conditional on displacement taking place) of unemployment insurance, asset accumulation, and endogenous retirement, we calculate an equivalent variation measure based on the lifetime expected utility at the time of labor market entry (age $25$). The results are displayed in Table $5$. As indicated by the first row, the cost in terms of expected utility of removing UI benefits (and accompanying pension point accumulation) is equivalent to imposing a $13.7\%$ penalty on the worker's consumption in each period of life in the scenario with UI benefits. This is in contrast to an expected lifetime income loss of $5.3\%$. Similarly, removing the possibility of self-insurance through assets corresponds to a $3.7\%$ consumption (or welfare) penalty, while expected lifetime income reduces by $1.3\%$. Removing endogenous retirement comes with a welfare cost of $1.3\%$ and a expected lifetime income cost of $0.7\%$. Some of these systems serve similar roles, as exhibited by the fact that the welfare cost of combining the two interventions exceeds the sum of costs of individually implementing these interventions. In particular, while removing asset accumulation and unemployment insurance comes at a welfare cost of $13.7\%$ and $3.7\%$, respectively, when implemented separately, combining the two interventions leads to a welfare cost of

$23.7\%$. Intuitively, this can be explained by the fact that both interventions take away a mechanism through which workers are insured against income fluctuations. In comparison, the impact of endogenous retirement seems much smaller. Some of this difference is due to the fact that the retirement decision takes place late in life and thus is discounted substantially when calculating expected lifetime utility at market entry. To see this, we report the welfare cost without discounting (second column). However, even in the case where we do not apply any discounting, the welfare effect of removing endogenous retirement is $4\%$, compared to the $14\%$ effect of removing UI benefits. It is of course the case that removing UI benefits is a much bigger intervention than removing the choice of retirement timing, as removing UI benefits reduces the income of unemployed workers to the welfare level, whereas the effect of removing endogenous retirement timing is driven by changes between earnings in employment and retirement benefits.

Having investigated the effect of displacement on total income and welfare, and having investigated the role of social security in driving the life-cycle variation in these effects, we now turn to investigating the effect on the extensive margin of employment. In line with our emphasis on lifetime measures, we focus on the total number of years spent in employment. The resulting average effects of displacement on years worked is depicted by the solid line in both panels of Figure 11. In line with the evidence from the data and our observations from the simulation data in the right panel of Figure 7, we find that the cumulative effect of displacement on years worked increases in age at displacement until the age of $55$, after which it starts reversing. In particular, while a worker first displaced at age $25$ loses less than a year of work on average after a displacement, a worker first displaced at age $55$ ends up spending more than $3$ years less in employment than the counterfactual worker who was not displaced that period (and was identical prior).

In the left panel of Figure 11, we decompose the effect of displacement on years worked into the same $6$ factors as used when studying lifetime income in Figure 9. The decomposition shows that the traditional elements, especially search frictions (see Appendix A.4.1), together with the residual category "Other" reflecting higher subsequent separation rates and a minimum $1$ period spent in unemployment, do a good job in explaining lost years in employment for workers losing their job early in their working life. The increasing effect up to age $55$ can be attributed primarily to the decreasing job finding rates. Once the worker passes the age of $55$, however, the role of the pension system becomes increasingly important in explaining the effect, while the age dependencies in the UI system and the survival rates aid in reversing the pattern of increasing effects in age of displacement.


Figure 11: *Lifetime change in years spent in employment, by age at displacement, decomposed into 6 distinct factors present in the model (left) and plotted along different worker states present in the model (right).*

We can further calculate how the lost periods of work are split between unemployment and retirement. The results of this calculation are depicted in the right panel of Figure 11. The plot shows that, for workers displaced prior to the age of 55, most of the lost years of work are replaced by unemployment. For workers displaced after the age of 55, time in retirement becomes increasingly important. In fact, while the effect on years in retirement is slightly negative for workers first displaced prior to the age of 50, thus indicating that these workers tend to retire later on average, the effect turns positive for workers displaced after age 55, which suggests that these workers retire earlier on average. The fact that the average effect on years worked is nevertheless decreasing in magnitude is primarily due to the years spent in unemployment decreasing faster than the increase in years spent in retirement. This can be thought of as driven by the number of remaining years in which a worker can be unemployed or employed, as the model prevents workers from being unemployed beyond the age of 65 and does not allow workers to stay in employment beyond the age of 70. In reality, however, workers can no longer receive UI benefits after 65 but can choose to remain nonemployed without retiring immediately, and workers can stay employed beyond the age of 70.

## 6.2 Interaction between Job Loss and Retirement Timing

Flexibility in retirement timing allows workers to offset some of the costs of job loss by deferring retirement. Indeed, 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 on average retire later in response to a displacement. However, the results in the previous subsection suggest that there is heterogeneity in responses, and some workers may in fact be retiring earlier. In this subsection, we use the model to further investigate 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.

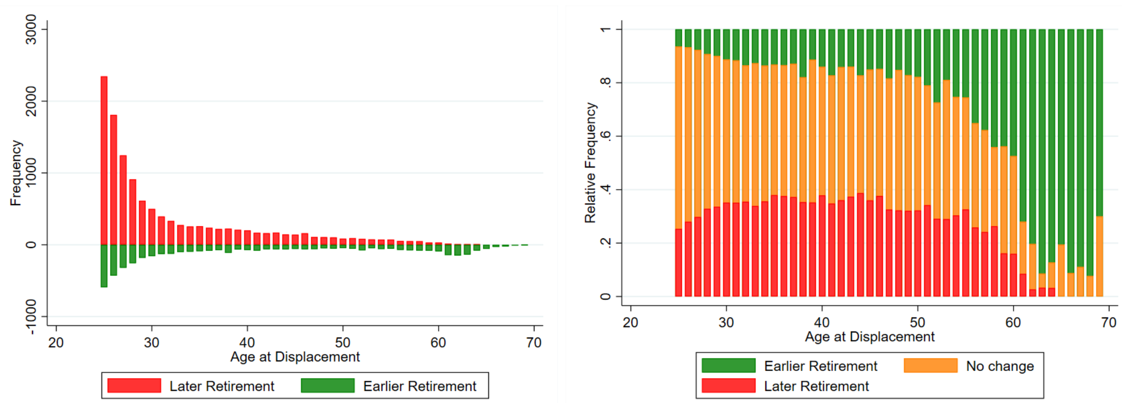


Figure 12: *Frequency of workers retiring later or earlier in response to a displacement in the model simulation, by age at displacement, displayed as the frequency (left) or the frequency relative to the age-specific number of displaced workers.*

In Figure 12, we show how many workers decide to retire either later or earlier in response to a displacement, by age of their first displacement, either in absolute frequency (left panel) or relative to the total population of age-specific displaced workers (right panel). In doing so, we define 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 seen in the left panel of Figure 12. This is a result of our focus on the first displacement, the frequency of which naturally decreases in age as the population of never-displaced workers shrinks over time. Furthermore, as workers become more attached to their jobs, they 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 right 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.

Since the job finding rate in the estimated model is decreasing in age, one might expect that some of the earlier retirements late in the working life may not be voluntary, but rather a consequence of the worker being unable to find a new job. In the left panel of Figure 13, we show that this is indeed the case, and especially so for workers who are displaced at age 60 or above.

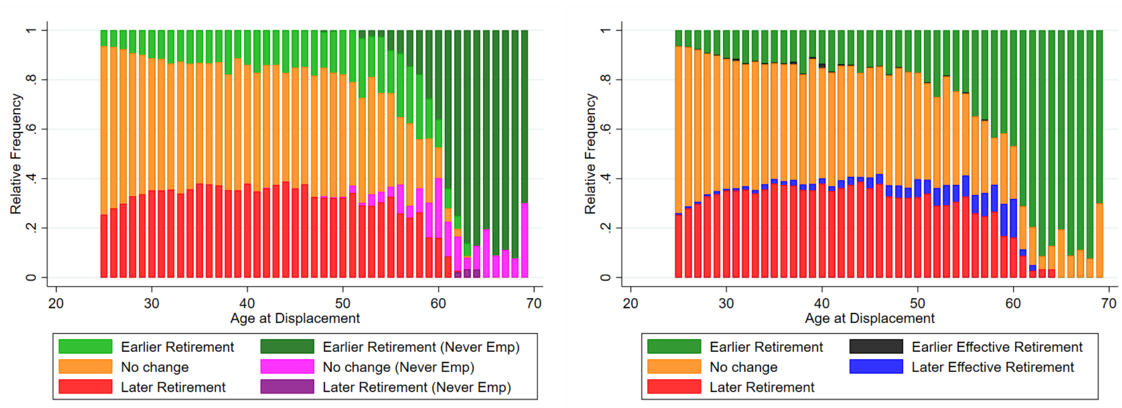


Figure 13: *Relative frequency of workers changing their retirement timing in response to a displacement in the model simulation, by age at displacement. The left panel additionally highlights workers who never return to employment after being displaced, whereas the right panel includes changes in effective retirement (due to changed timing in pre-retirement quits).*

As highlighted previously, workers can quit their job 2 years prior to being eligible for retirement and bridge those two years using UI benefits, and our framework allows for this mechanism. One could think of these workers as effectively retiring two 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 start collecting retirement benefits at 63, they may have decided to quit earlier or later in response to a displacement, thus changing their effective retirement age. In the right panel of Figure 13, 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 not many workers who decide 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, considering effective retirement timing rather than official retirement timing slightly tilts the balance in favor of later retirement. Note that these workers who quit later do not show up as spending more periods in retirement in our decomposition of periods worked in the right panel of Figure 11. This can partially explain why Figure 11 suggests that workers officially retire earlier on average, while the empirical evidence suggests that workers spend more time in employment and thus effectively retire later on average.

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, and how this may change after being displaced. In Figure 14, we plot the average planned retirement age and the change in retirement timing (not taking into account pre-retirement quits) for different combinations of age at displacement and pension points. Here, the planned retirement age is measured as the retirement age in the counterfactual simulation where the worker did not get displaced at this particular age. We observe that pension points tend to increase in age, which reflects the fact that workers accumulate these points throughout their working life. The left panel of Figure 14 shows that in general workers with higher lifetime earnings (as proxied by accumulated pension points) tend to retire early. However, the right panel of Figure 14 illustrates that, for a given age of displacement, these workers with high lifetime earnings tend to respond to a displacement by retiring later than planned.

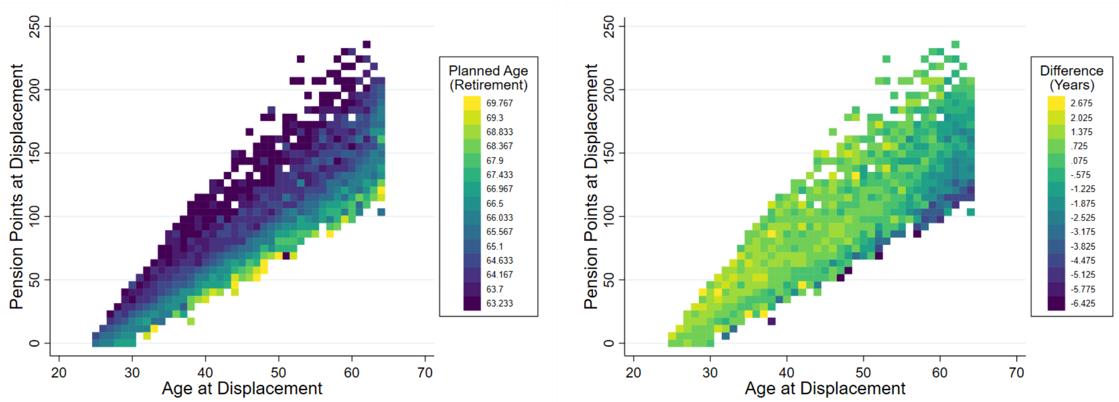


Figure 14: *Average planned retirement age (left) and change in retirement timing upon displacement (right) in the model simulation, conditional on a nonzero change, by age and pension points at displacement. The depicted (change in) retirement timing does not take into account effective retirement timing due to pre-retirement quits.*

In Figure 15, we show that we reach a similar conclusion regarding change in retirement timing if we instead focus on accumulated assets or human capital at the time of displacement, although the pattern is not quite as stark as for accumulated pension points. In particular, workers with high accumulated assets or human capital at the time of displacement tend to postpone their retirement after a displacement. Similarly, we show in Appendix A.4.2 that these are also the workers who were initially planning on retiring early.

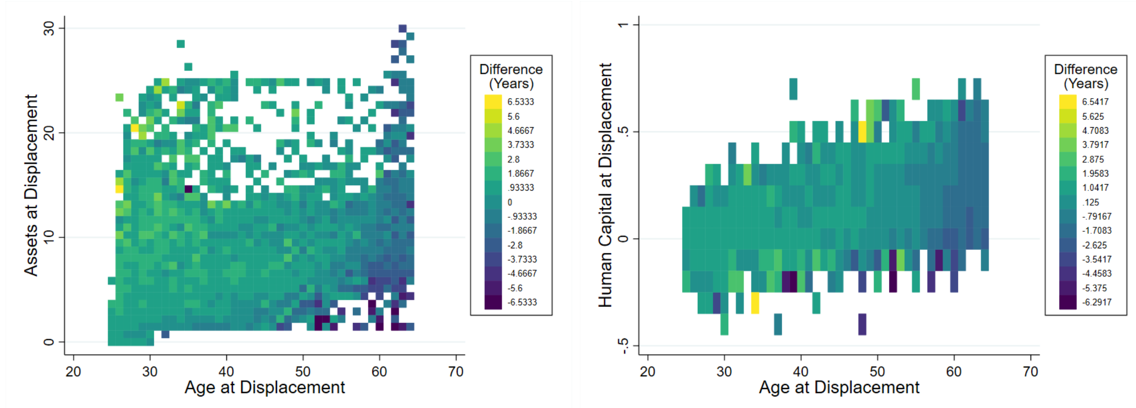


Figure 15: *Average change in retirement timing upon displacement in the model simulation, conditional on a nonzero change, by age and either assets (left) or human capital (right) at displacement. The average change in retirement timing does not take into account changes into effective retirement timing due to pre-retirement quits.*

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.[18] 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 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, but for workers with low lifetime earnings this penalty

[18]Given that workers who quit early tend to be highly attached (as seen in Figure 4), it is likely that these workers tend to have 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 13 that workers who change their quitting time generally do so by postponing.

is not severe enough to deter them from retiring earlier in response to this earnings shock. On the other hand, workers with high levels of assets and pension points tend to retire earlier, as their built up assets and retirement benefit can offset the penalty incurred by retiring early. However, when these workers are displaced, they likely consume some of their assets in order to smooth consumption between periods of employment and unemployment. The resulting decrease in assets implies that they will be less able to offset the penalty of retiring earlier, thus inducing them to postpone retirement in order to re-accumulate assets and reduce the penalty of retiring earlier.

# 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. We then estimate the model using moments generated from German data.

Using the estimated model, we reach three main conclusions. First, while the traditional model elements – search frictions, a job ladder, and human capital – 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 $55$. Second, unemployment insurance (along with self-insurance through asset accumulation) shields the worker against excessive welfare loss due to income and consumption fluctuations, and does so especially effectively if the job loss occurs late in the working life. Nevertheless, we find that welfare losses are increasing in age (until the age of $55$). Third, zooming in on the endogenous 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.

Based on our findings, there are several possible avenues for future research. First, since we demonstrate 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.

Second, we 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, and should in particular consider the effect of such changes on the (age-dependent) job finding rates of other agents in the economy. Similarly, such a model could be used to study cross-country differences in the pension system.

Finally, given that the model highlights the high insurance value of unemployment insurance and the importance of age dependencies in the corresponding regulation, a model similar to ours could be used to investigate the optimal timing of such age dependencies. For example, since we observe the earnings, welfare, and employment losses peaking between $50$ and $55$, it may be worth considering the effects of moving the earliest increase in maximum duration from the age of $50$ to an earlier age, or increasing the size of the existing steps in maximum duration. Furthermore, since the model simulation 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:

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

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

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

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

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:

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

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

$$W(\Omega_w,t)=\max_{c,q'_W\in\{0,1\},a'\geq 0}\Bigg\{u(c)-u_w+\beta\gamma_t\mathbb{E}_{s',x',e'}\Bigg[\delta_{x'}U^N(\Omega'_u,t+1)$$

$$+(1-\delta_{x'})(1-q'_W)\left(\lambda^e\int_{y'\in\Theta^e(\Omega'_w,t+1)}W(\Omega'_w,y',x_L,t+1)dF(y')\right.$$

$$\left.+\left(1-\lambda^e\int_{y'\in\Theta^e(\Omega'_w,t+1)}1dF(y')\right)W(\Omega'_w,t+1)\right)$$

$$+(1-\delta_{x'})q'_WU^Q(\Omega'_u,t+1)\Bigg]+\beta(1-\gamma_t)B(a')\Bigg\} \tag{A.4}$$

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

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 $T_w^+$):

$$W(\Omega_w,t)=\max_{c,a'\geq 0}\Bigg\{u(c)-u_w+\beta\gamma_t\mathbb{E}_{s',x',e'}\Bigg[\left[\delta_{x'}+(1-\delta_{x'})q'_W\right]R(\Omega'_r,\rho_{t+1}p',t+1)$$

$$+(1-\delta_{x'})(1-q'_W)\left(\lambda^e\int_{y'\in\Theta^e(\Omega'_w,t+1)}\tilde{W}(\Omega'_w,\Omega'_r,y',x_L,t+1)dF(y')\right.$$

$$\left.+\left(1-\lambda^e\int_{y'\in\Theta^e(\Omega'_w,t+1)}1dF(y')\right)\tilde{W}(\Omega'_w,\Omega'_r,t+1)\right)\Bigg]+\beta(1-\gamma_t)B(a')\Bigg\} \tag{A.5}$$

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

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

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

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

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

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

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 are 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 $\omega$: $\{0, 0.1\omega, 0.5\omega, \omega, 2\omega, 5\omega, 10\omega, 25\omega, 100\omega\}$.

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 $\Omega_i$). In the cases where the right hand side of the Euler equation involves an expectation over elements of $\Omega_i'$ (such as $s'$ and $y'$), this is incorporated here. Furthermore, acceptance choices are taken into account here, as the acceptance sets $\Theta$ can be obtained by comparing the value functions. Finally, note that the value of $A''$ depends on $\Omega_i'$ 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 on 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.

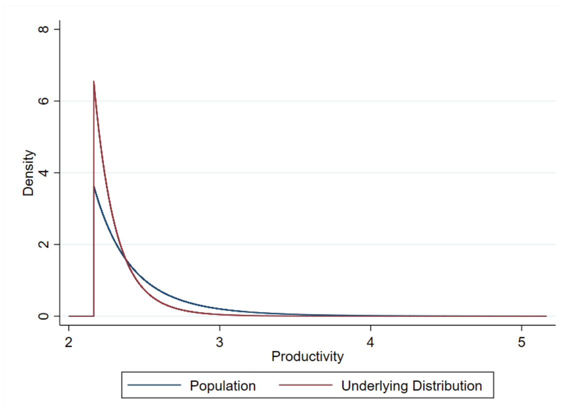


Figure A.1: *The distribution of job productivity $y$ in the estimated model. The plot shows the distribution from which workers make draws (red) as well as the distribution observed in the model simulation (blue, dashed).*

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 the empirical distribution obtained from the model simulation (dashed line). The figure confirms that the distribution of job productivity is quite narrow, as indicated by the high value for $\eta_y$ 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 do seem to push up the job finding rates in the data (as observed in Appendix

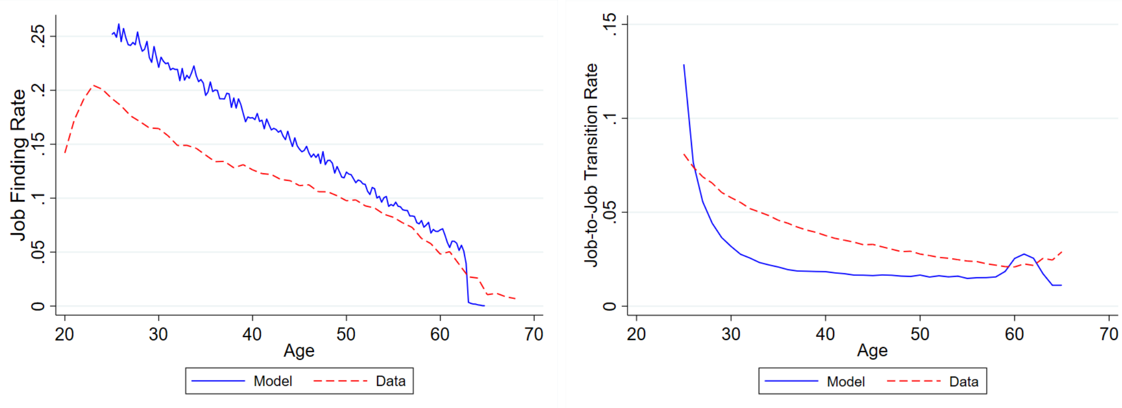


Figure A.2: *The average quarterly job finding rate (left) and job-to-job transition rate (right) by age in the data (red, dashed) compared to the average in the model simulation (blue, solid), by age and not conditional on labor market experience.*

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 $\lambda^e$ 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.

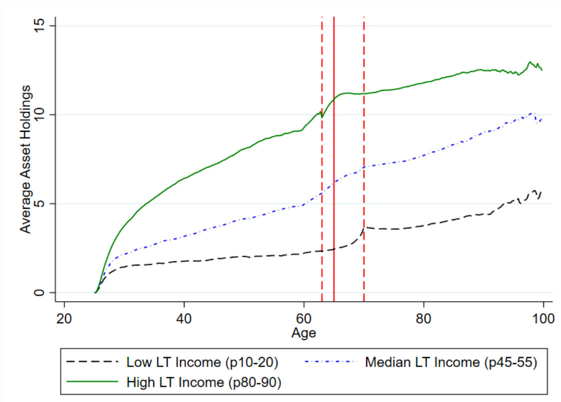


Figure A.3: *Average asset holdings in the model simulation, by age and percentile of lifetime earnings. The solid red vertical line denotes the regular retirement age, whereas the dashed red vertical lines denote the earliest and latest possible retirement ages in the model.*

Finally, Figure A.3 splits the average accumulation of assets (right panel of Figure 6) by percentile of lifetime income. In particular, we highlight a group of workers with low lifetime earnings (between the 10th and 20th percentile), lifetime earnings around the median (between the 45th and 55th percentile), and high lifetime earnings (between the 80th and 90th percentile). Interestingly, the plot shows distinct patterns between workers with low and high lifetime income around the periods of possible endogenous retirement. In particular, a clear kink in asset holdings is visible for workers with high lifetime income, occurring a few years before the early retirement age. This corresponds to these high lifetime income workers quitting to use unemployment insurance as a pathway into retirement. As these workers move into the retirement state at the earliest possible age (63), a small dip in asset holdings is visible. The workers with low lifetime earnings, on the other hand, clearly continue to accumulate assets until very close to the latest retirement age, indicating that these relatively poorer workers tend to retire late.

## 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.

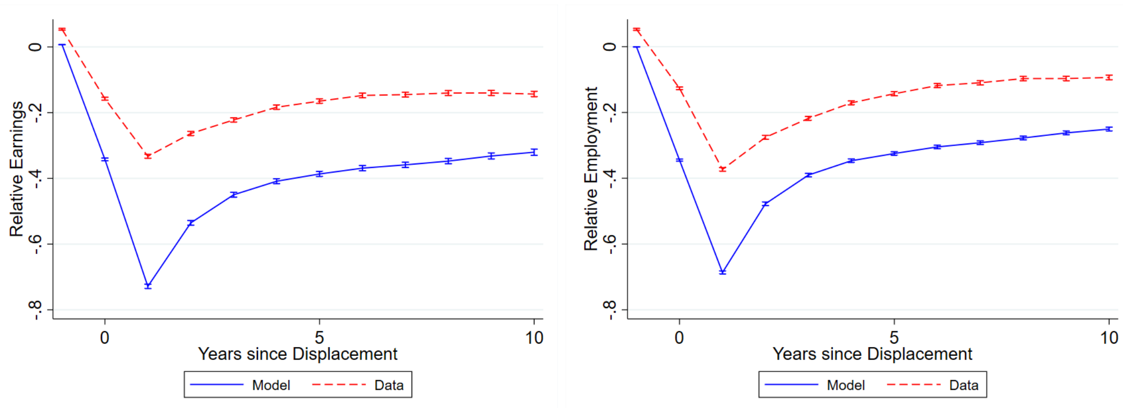


Figure A.4: *The effect of displacement on earnings (left) and employment (fraction of the year spent in an employment spell, right), relative to the control group, using model simulation data (solid) and using the data (dashed, corresponding to Figure B.16).*

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.4, 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.16. As can be seen in Figure A.4, 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 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.

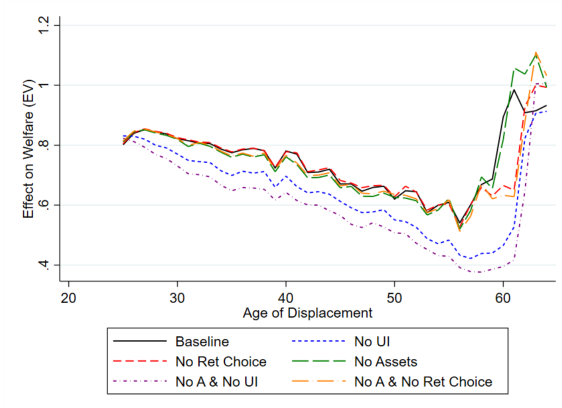


Figure A.5: *The welfare cost of displacement, by age at displacement. The welfare cost is calculated as the equivalent variation* $-1$*, thus representing the factor with which a worker would be willing to change consumption in order to achieve the same present value of remaining lifetime utility.*

In Figure 10, we showed that the insurance value of UI benefits is quite clearly visible when plotting the welfare cost of displacement in the baseline simulation against a scenario in which there are no UI benefits and accompanying accumulation of pension points. We then argued, using lifetime expected utility values, that the insurance effect of UI interacts with the insurance effect of asset accumulation. In Figure A.5, we show that this is visible in the graph plotting the welfare cost of displacement over age as well. In particular, it can be seen that while eliminating asset accumulation by itself does not have a large impact, eliminating asset accumulation in addition to UI benefits has a clearly larger impact than eliminating UI benefits only. For endogenous retirement this is not the case, as seen by the line plotting the welfare cost in a scenario without endogenous retirement and without assets not being substantially different from the line showing the effect of eliminating endogenous retirement only.

In Figure 9, we showed how the loss in remaining lifetime income by age at displacement can be decomposed into 6 broad categories. In Figure A.6, we show the results of the full decomposition of these losses into all 14 factors mentioned in the main text. Furthermore, Table A.1 provides the corresponding numerical values for a few selected displacement ages. The numbers in these tables can be interpreted

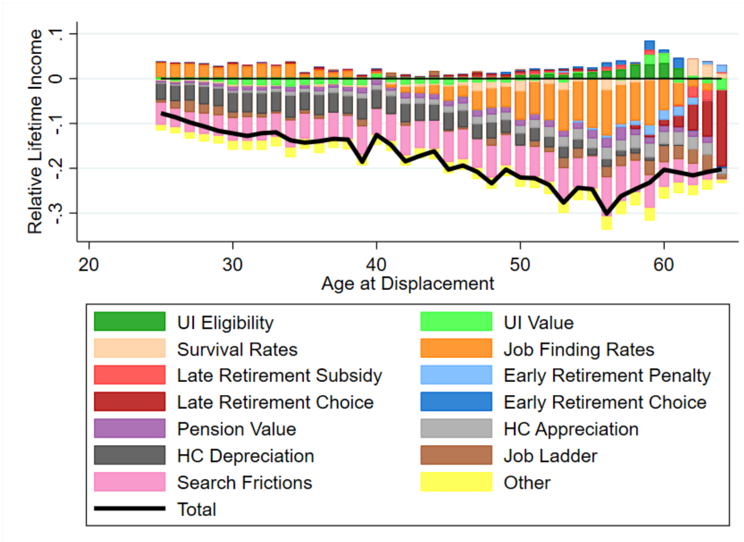


Figure A.6: *Full decomposition of relative (remaining) lifetime income losses into 14 distinct factors present in the model, by age at displacement and discounted to the time of displacement.*

| **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.1: *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.6 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 remaining lifetime income. In order to generate the grouped decomposition from Figure 9, we combine the grouped channels into a single number.*

as the particular factor's contribution to the total loss in remaining lifetime income on top of previously incorporated factors. For example, focusing on workers who were displaced at age 62, the table shows that of the total 21.6% of lower relative (remaining) lifetime income, 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 relative loss in remaining lifetime income for a worker displaced at age 62 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 0.6 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 the relative loss in remaining lifetime income of a worker displaced at the age of 62 by 0.6 percentage points.

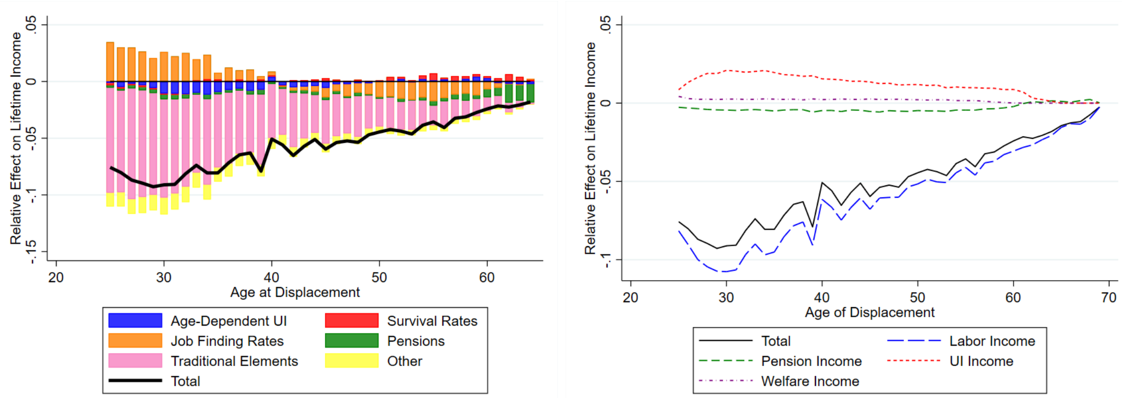


Figure A.7: *Relative (remaining) lifetime income losses, decomposed into 6 distinct factors present in the model (left) and into the different earnings sources present in the model (right), by age at displacement and discounted to the time of labor market entry.*

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.7. 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 understate the importance of age dependencies from the UI and pension systems, as these become important in the periods that are discounted the most.

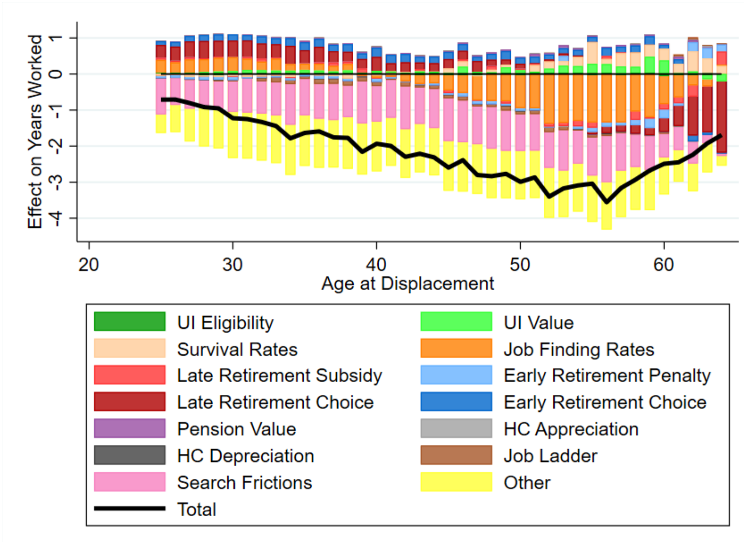


Figure A.8: *Full decomposition of the lifetime loss in years spent in employment into 14 distinct factors present in the model, by age at displacement and discounted to the time of displacement.*

| **Channel** | Age 30 | Age 40 | Age 50 | Age 55 | Age 60 | Age 62 |
|---|---|---|---|---|---|---|
| UI Eligibility | 0.003 | 0.014 | −0.006 | −0.004 | −0.049 | −0.026 |
| UI Value | 0.078 | 0.075 | 0.103 | 0.283 | 0.378 | 0.072 |
| Survival Rates | −0.061 | −0.041 | −0.029 | 0.600 | 0.322 | 0.561 |
| Job Finding Rates | 0.386 | −0.063 | −0.910 | −1.340 | −0.784 | −0.288 |
| Late Retirement Subsidy | −0.017 | −0.022 | 0.045 | −0.146 | −0.150 | −0.314 |
| Early Retirement Penalty | −0.090 | −0.091 | −0.072 | −0.118 | −0.245 | 0.250 |
| Late Retirement Choice | 0.461 | 0.386 | 0.139 | −0.069 | −0.375 | −1.079 |
| Early Retirement Choice | 0.168 | 0.258 | 0.162 | 0.144 | 0.105 | −0.164 |
| Pension Value | 0.003 | 0.014 | 0.023 | 0.032 | 0.039 | 0.056 |
| Human Capital Appreciation | 0.005 | 0.020 | 0.010 | −0.005 | 0.005 | −0.002 |
| Human Capital Depreciation | −0.013 | −0.018 | −0.024 | 0.004 | 0.001 | 0.005 |
| Job Ladder | −0.023 | −0.098 | −0.076 | −0.080 | −0.053 | 0.072 |
| Search Frictions | −0.849 | −0.988 | −1.017 | −1.056 | −0.659 | −0.613 |
| Other | −1.279 | −1.379 | −1.340 | −1.288 | −1.024 | −0.769 |
| Total | −1.226 | −1.934 | −2.991 | −3.041 | −2.489 | −2.238 |

Table A.2: *Summary of the decomposition of the scarring effect of displacement on lifetime years spent in employment, by age at displacement. The total difference corresponds to the solid black line in Figure A.8 and the left panel of Figure 11. 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 lifetime years spent in employment. In order to generate the grouped decomposition from Figure 11, we combine the grouped channels into a single number.*

In Figure A.8, we show the results of the full decomposition of the lifetime loss in periods worked (as depicted in Figure 11) into all 14 factors mentioned in the main text. Furthermore, Table A.2 provides the corresponding numerical values for a few selected displacement ages. The full decomposition depicted in Figures A.6 (remaining lifetime income) and A.8 (lifetime periods worked) 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.6 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. If we focus on employment instead, as done in Figure A.8 and the left panel of Figure 11, 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.

In Figure A.9, we show how the earnings and employment loss by age at displacement, measured 5 years after displacement, can be decomposed into 6 broad categories. In Table A.3, we provide the corresponding numerical values (of all underlying 14 factors) for a few selected displacement ages. Comparing the results of this period-specific decomposition to the results on lifetime income and periods worked discussed in the main text, it can be seen that the fluctuations between different factors are much starker. This is because the ages in which pensions and UI are particularly important were always included in the lifetime calculation, despite being discounted further for workers displaced early in their working life, but are now very clearly visible as we always focus on a particular year. In particular, 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. Generally, the decomposition of these period-specific losses confirms the conclusions reached with the lifetime outcomes. 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.

In Figure A.10, 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 "Other" category is slightly higher compared to Figure A.9, it still holds that the traditional elements explain the bulk of earnings and employment losses prior to the age of 50, and the

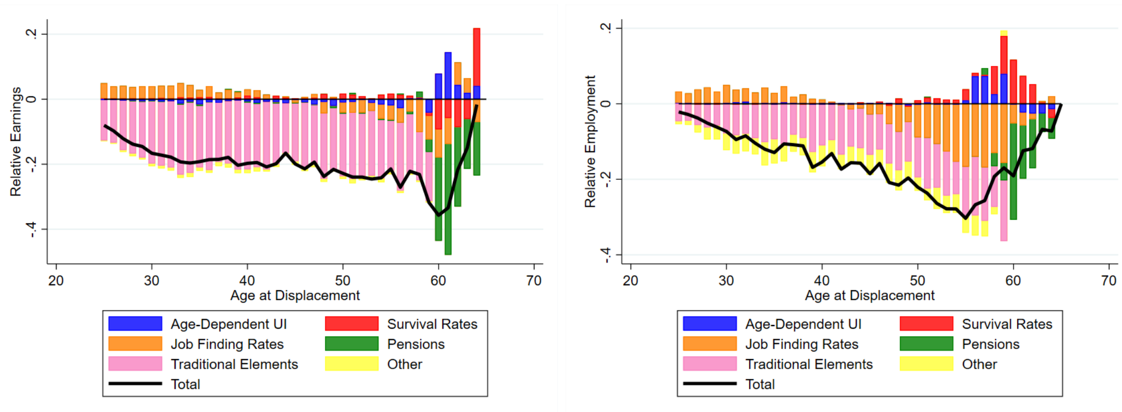


Figure A.9: *Decomposition of relative labor earnings (left) and employment (right) losses (5 years after displacement) into 6 distinct factors present in the model, by age at displacement.*

| | Earnings | | | Employment | | |
|---|---|---|---|---|---|---|
| **Channel** | Age 40 | Age 50 | Age 60 | Age 40 | Age 50 | Age 60 |
| UI Eligibility | 0 | 0.004 | −0.002 | 0 | 0 | −0.011 |
| UI Value | −0.006 | −0.013 | 0.080 | −0.000 | −0.003 | −0.011 |
| Survival Rates | 0.011 | 0.017 | −0.093 | 0.002 | 0.010 | 0.116 |
| Job Finding Rates | 0.019 | −0.032 | −0.087 | 0.009 | −0.086 | −0.050 |
| Late Retirement Subsidy | 0 | 0.003 | −0.085 | 0 | 0 | −0.084 |
| Early Retirement Penalty | 0 | 0 | 0.010 | 0 | 0 | −0.019 |
| Late Retirement Choice | −0.005 | −0.005 | −0.181 | 0 | 0 | −0.152 |
| Early Retirement Choice | 0 | −0.002 | 0 | 0 | 0 | 0 |
| Pension Value | 0.001 | 0 | 0 | 0.000 | 0 | 0 |
| Human Capital Appreciation | 0.006 | 0.009 | 0 | 0 | 0 | 0 |
| Human Capital Depreciation | −0.045 | −0.044 | 0 | 0 | 0 | 0 |
| Job Ladder | −0.007 | −0.021 | 0 | −0.015 | −0.015 | 0 |
| Search Frictions | −0.160 | −0.136 | 0 | −0.094 | −0.092 | 0 |
| Other | −0.012 | −0.008 | 0 | −0.056 | −0.036 | 0 |
| Total | −0.197 | −0.228 | −0.357 | −0.154 | −0.221 | −0.191 |

Table A.3: *Summary of the 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. 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 A.9, we combine the grouped channels into a single number.*


Figure A.10: *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.*

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 "Other" 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, $\delta_L$.

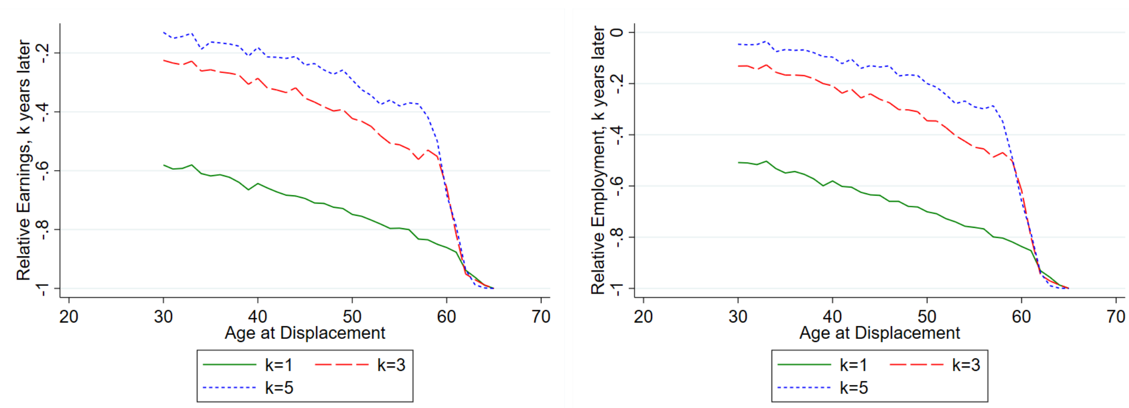


Figure A.11: *The estimated effect of displacement on labor earnings (left) and employment fraction (right), by age at displacement and years since displacement, obtained from the model simulation by using the same estimation method as in the data.*

The age-based earnings and employment losses and their decomposition discussed above 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 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.11, 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 (Figure 7), the estimation-based losses tend to be higher in the short run, especially for employment. 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 the was suggested by the results in the main text. This is clearly visible in Figure A.12, 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.

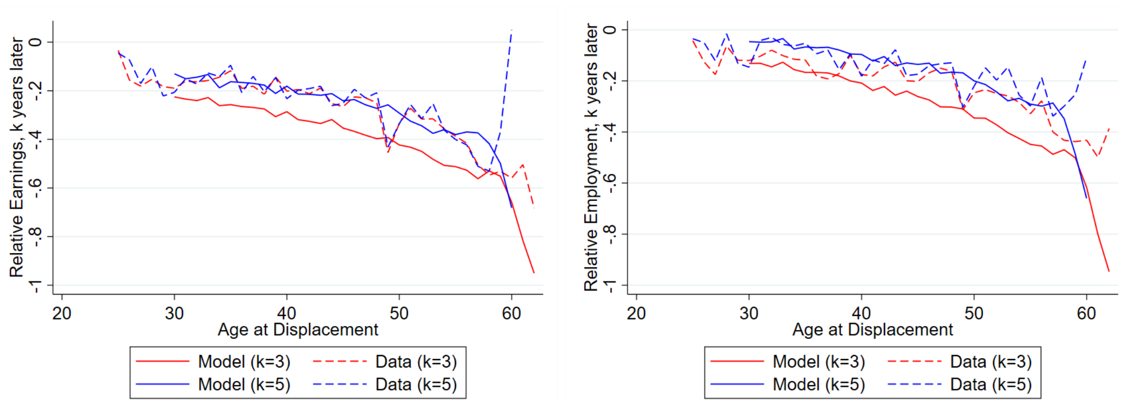


Figure A.12: *The estimated effect of displacement on labor earnings (left) and employment fraction (right), 3 years (red) or 5 years (blue) after displacement, by age at displacement, obtained from the data (dashed) and from the model simulation (solid), using the same estimation method as in the data.*

Naturally, we can decompose the estimation-based earnings and employment losses displayed in Figures A.11 and A.12 in a similar way as we decomposed the losses estimated from the direct counterfactuals in Figure A.9. In Figure A.13, we show the results of this estimation-based decomposition, with a selection of the underlying numerical values reported in Table A.4. Comparing the results in Figure A.13

to those obtained using direct counterfactuals, Figure A.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 a 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".

### 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 that among workers who are displaced, the workers with a low balance of pension points were initially planning to retire later, but decided to retire earlier than planned in response to a displacement. In Figure 14, we showed this by plotting change in retirement age for combinations of age and balance of pension points (both at the time of displacement). However, we can also do a similar analysis by looking at the planned retirement age prior to displacement, and the actual retirement age of the displaced worker. Figure A.14 shows this comparison. The figure shows that workers who are displaced earlier in their working life tend to retire slightly later, as reflected by the light shades moving up slightly for ages below $50$. However, for workers aged between $50$ and $60$, we can see the reversal of the earlier and later retirement as discussed in the text, resulting in a more even spread of retirement age over the distribution of accumulated pension points.

The left panel of Figure A.14 above (which replicates the left panel of Figure 14) showed that generally workers with a lower balance of pension points tend to retire later. However, given that we interpret this as an effect of lifetime earnings, partially working through asset accumulation, we should see a similar pattern when plotting the planned retirement age over assets or human capital. In Figure A.15, we show that this is indeed the case, although the pattern is not quite as clear for human capital.

In the discussion in the main text and above, 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.16 and A.17, we repeat the analysis with these non-changers included in the

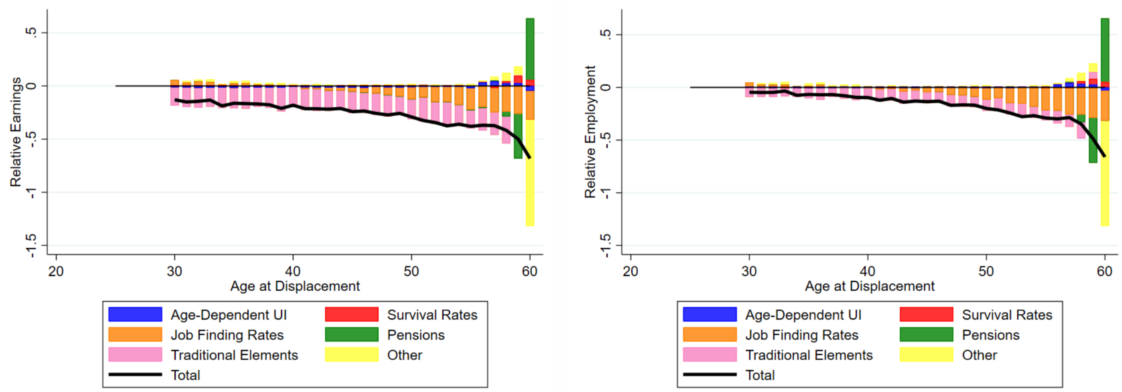


Figure A.13: *Estimation-based decomposition of relative labor earnings (left) and employment (right) losses (5 years after displacement) into 6 distinct factors present in the model, by age at displacement.*

| | Earnings | | | Employment | | |
|---|---|---|---|---|---|---|
| **Channel** | 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.4: *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.13. 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.13, we combine the grouped channels into a single number.*

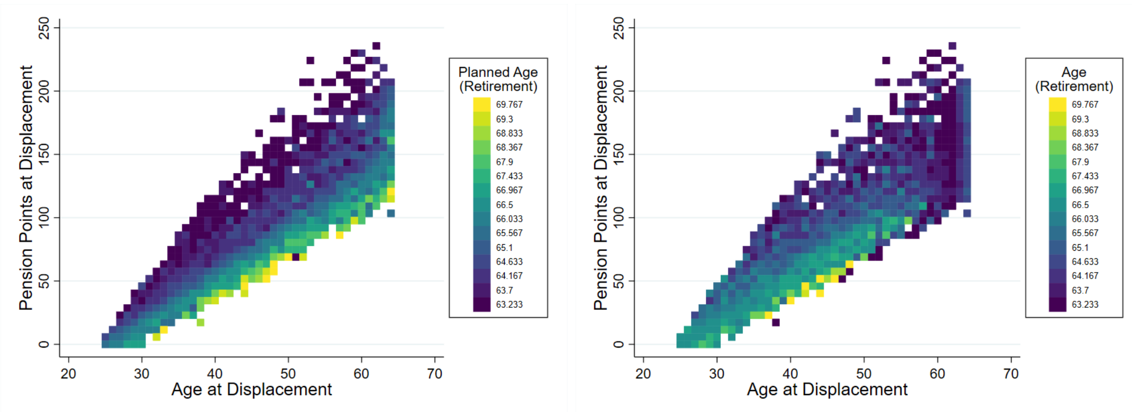


Figure A.14: *Average planned retirement age, prior to displacement (left) and after displacement (right) in the model simulation, conditional on a nonzero change, by age and pension points at displacement. The depicted retirement timing does not take into account effective retirement timing due to pre-retirement quits.*

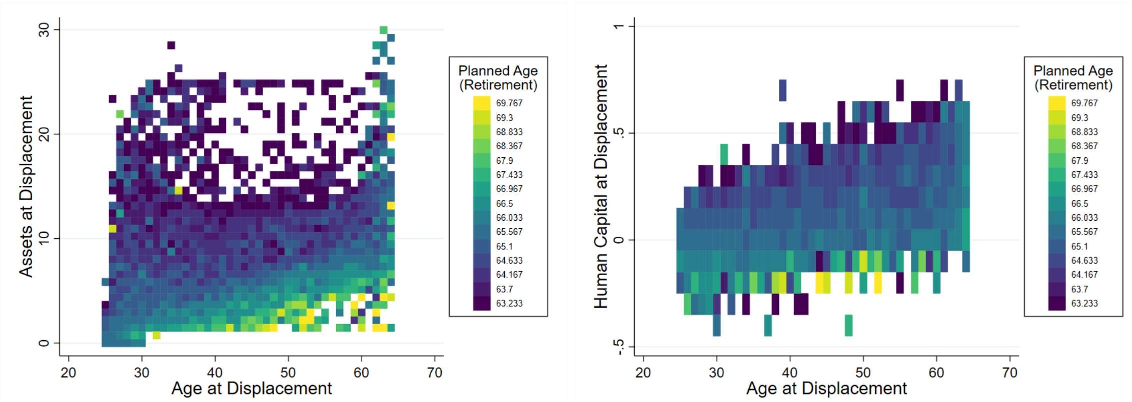


Figure A.15: *Average planned retirement timing (prior to displacement) in the model simulation, conditional on a nonzero change upon displacement, by age and either assets (left) or human capital (right) at displacement.*

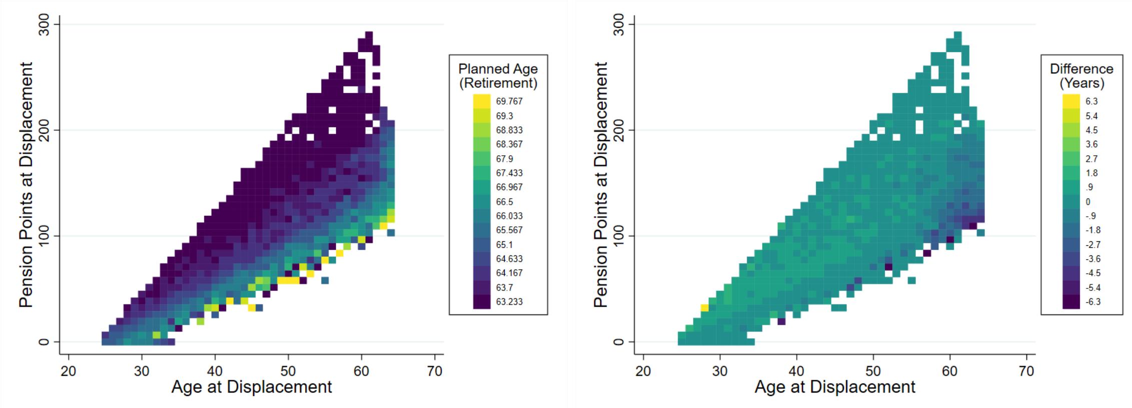


Figure A.16: *Average planned retirement age (left) and change in retirement timing upon displacement (right) in the model simulation, including non-changers, by age and pension points at displacement. The depicted (change in) retirement timing does not take into account effective retirement timing due to pre-retirement quits.*

plots. 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.

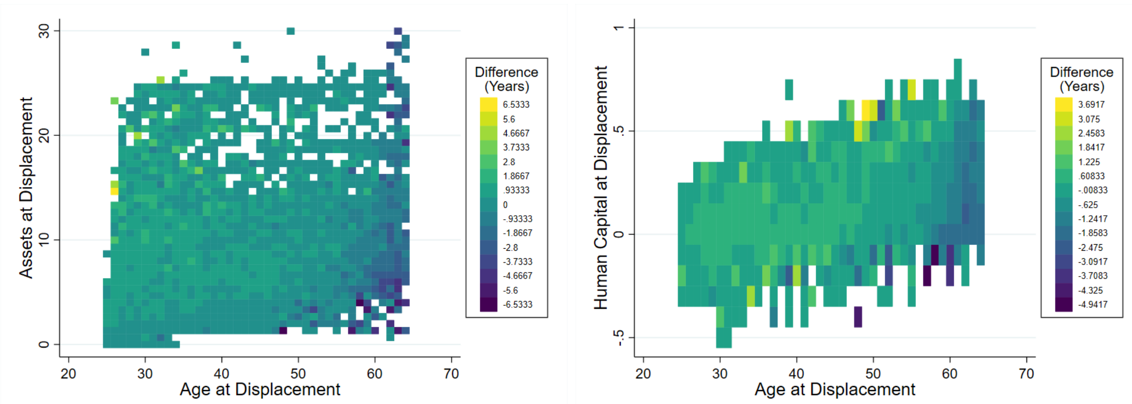


Figure A.17: *Average change in retirement timing upon displacement in the model simulation, including non-changers, by age and either assets (left) or human capital (right) at displacement.*

Finally, we argued in the main text that the state variables considered above (asset holdings, pension points, and human capital) are strongly correlated. While the averages displayed in the figures above 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.18 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.

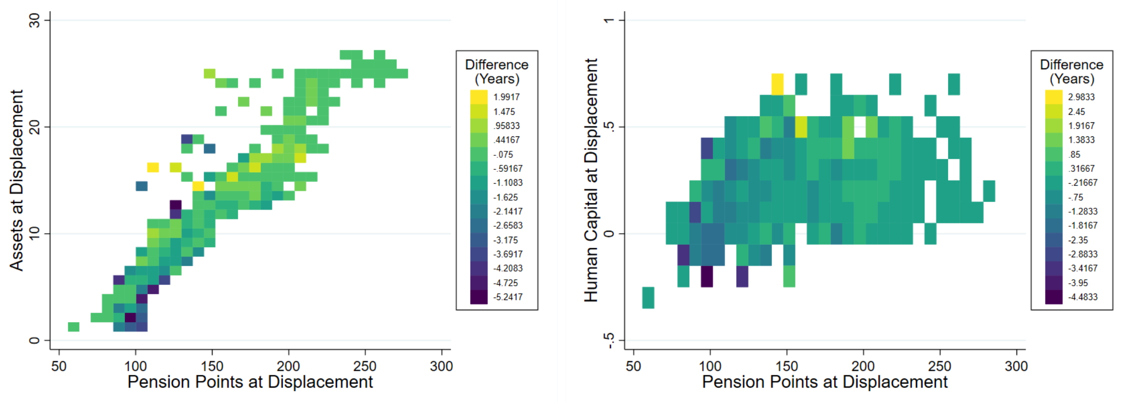


Figure A.18: *Average change in retirement timing upon displacement in the model simulation among workers (first) displaced between the age of 55 and 60, including non-changers, by pension points and either assets (left) or human capital (right) at displacement.*

# B Data Appendix

## B.1 Further Descriptive Analysis

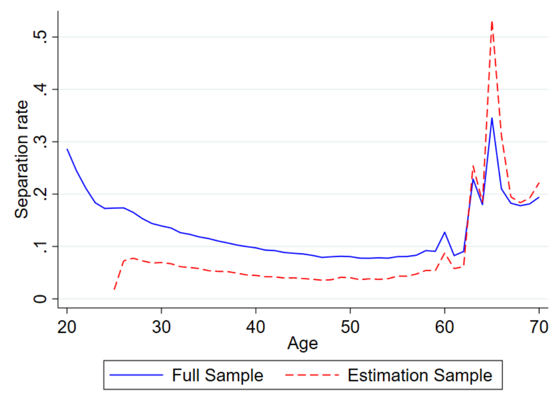


Figure B.1: *The incidence of separation by age, generated from the full sample (solid, blue) and the restricted estimation sample (dashed, red).*

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.1, 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.

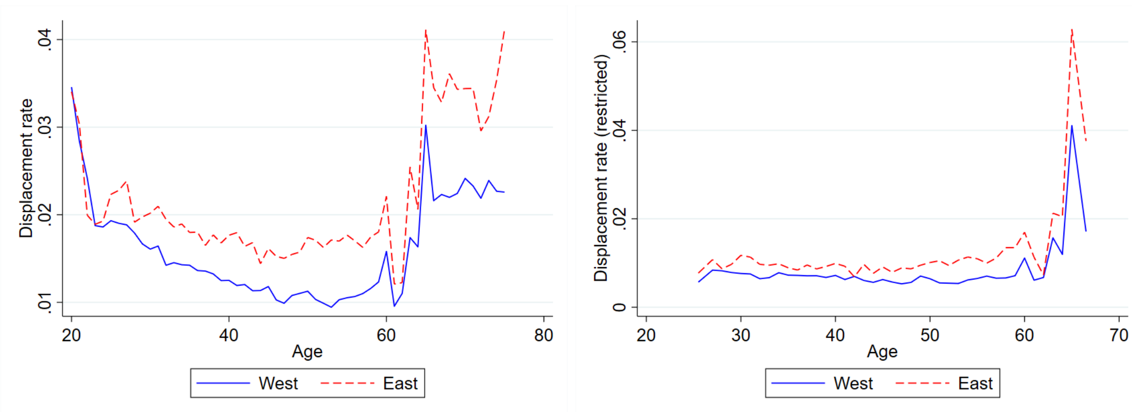


Figure B.2: *The incidence of displacement by age, generated from the full sample (left) and the restricted estimation sample (right), separately for workers located in former West and East Germany.*

In Figure B.2, 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.

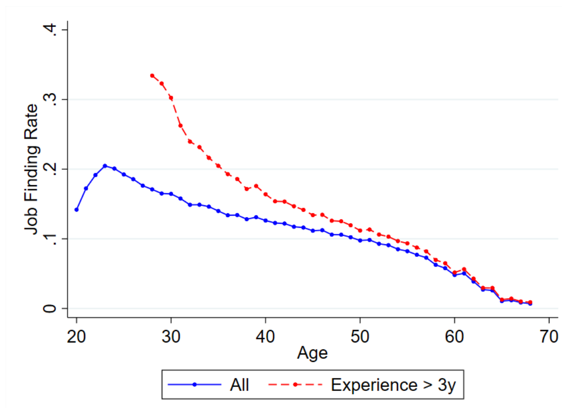


Figure B.3: *The quarterly job finding rate by age, generated from the full sample (solid, blue) and conditional on at least 3 years of market experience (dashed, red).*

In Figure B.3, 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.

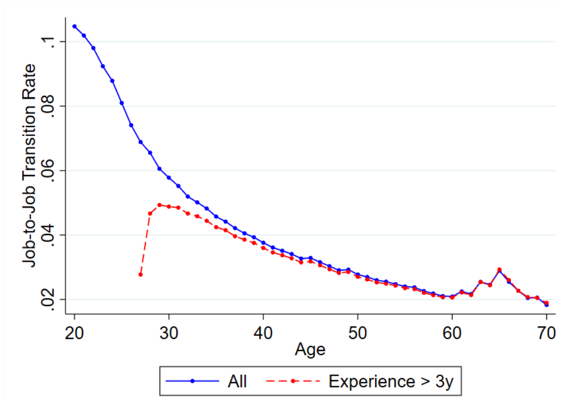


Figure B.4: *The quarterly job-to-job transition rate by age, generated from the full sample (solid, blue) and conditional on at least 3 years of market experience (dashed, red).*

Finally, Figure B.4 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 ($\lambda^e$) 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.5, 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

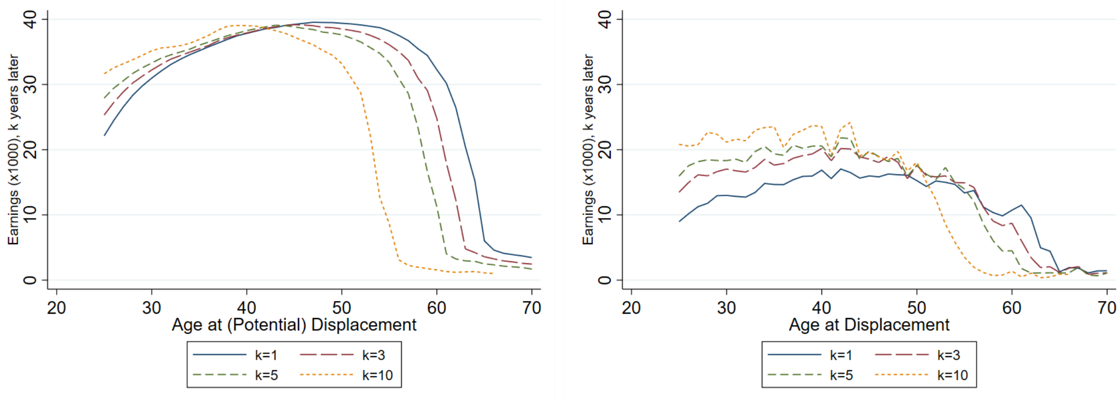


Figure B.5: *Raw average earnings for workers who were displaced (right) or not displaced (left), by age at potential displacement and years since potential displacement.*

shortly after the age of 60, likely reflecting retirement. This is true for both the control group and the treated (displaced) group, so that the relative difference between the two groups, displayed in Figure B.6, becomes quite volatile. Nevertheless, Figure B.6 shows that relative earnings losses experienced by the displaced workers are generally increasing in age until the retirement window, and the pattern partially reverses in the retirement window. This is in line with the conclusions drawn in Section 3.

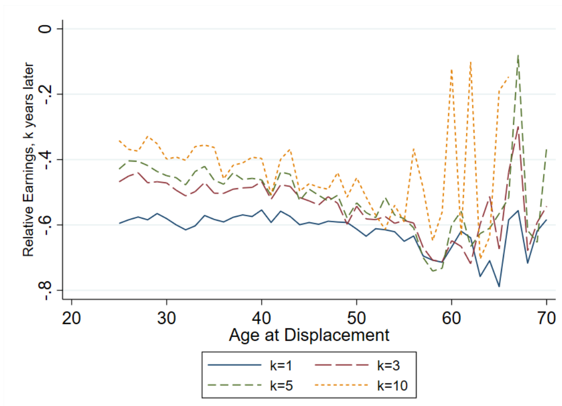


Figure B.6: *Difference in raw average earnings between displaced workers and non-displaced workers, by age at potential displacement and years since potential displacement.*

In Figure B.7, 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

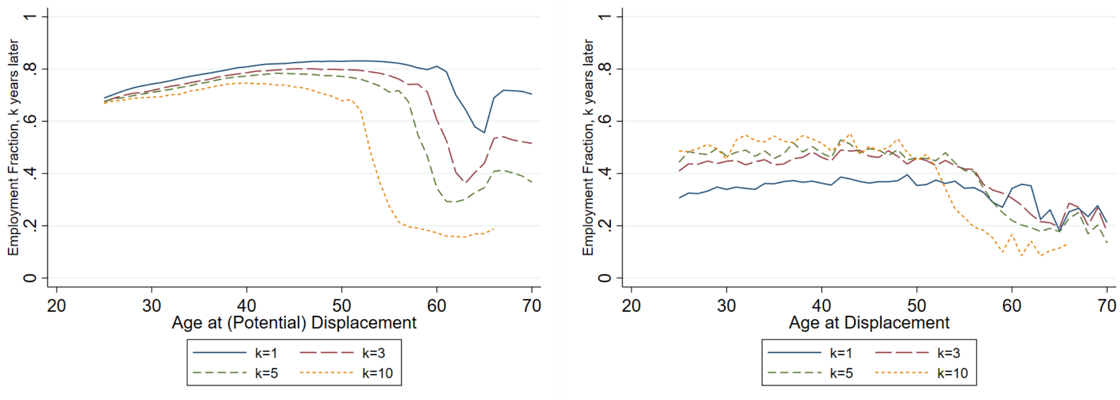


Figure B.7: *Raw employment rates, defined as the fraction of the year spent in an employment spell, among workers who were displaced (right) or not displaced (left), by age at potential displacement and years since potential displacement.*

larger for the control group. This can be seen in Figure B.8, where we plot the average difference 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.7 (and the right panel of Figure 2) being stronger for $k = 3$ and $k = 5$.

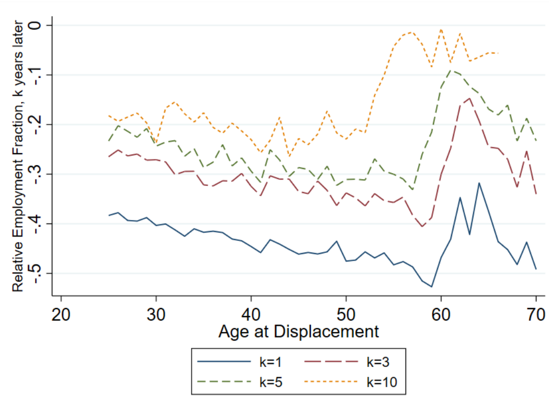


Figure B.8: *Difference in raw employment rates, defined as the fraction of the year spent in an employment spell, between displaced workers and non-displaced workers, by age at potential displacement and years since potential displacement.*

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 subgroups 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.9, we repeat the analysis from Figure B.8 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.9. 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.

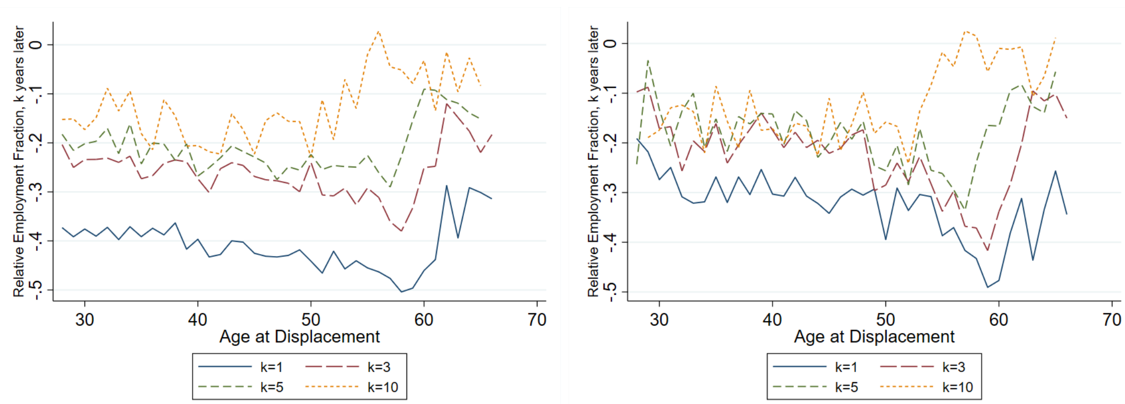


Figure B.9: *Difference in raw employment rates, defined as the fraction of the year spent in an employment spell, between displaced workers and non-displaced workers, by age at potential displacement and years since potential displacement, for workers with recent earnings below (left) or above (right) the median.*

In Figure B.10, 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.

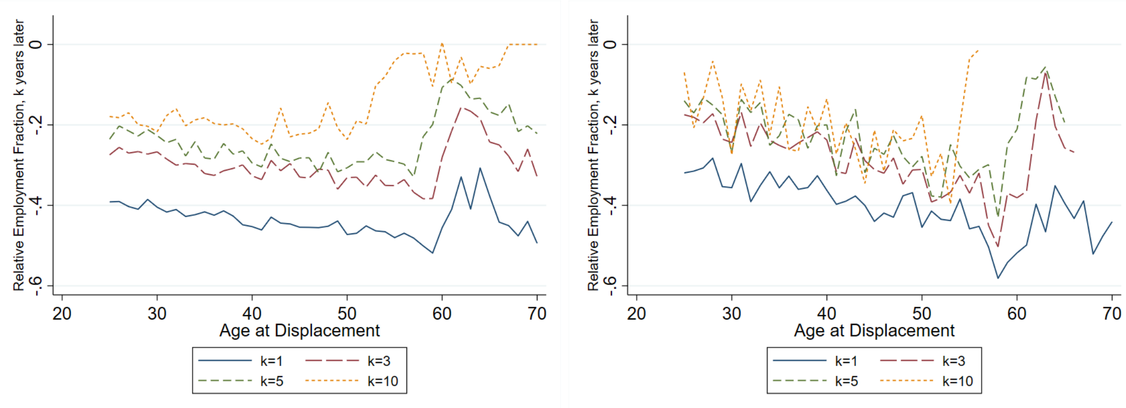


Figure B.10: *Difference in raw employment rates, defined as the fraction of the year spent in an employment spell, between displaced workers and non-displaced workers, by age at potential displacement and years since potential displacement, for workers with a non-university (left) or university (right) 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.

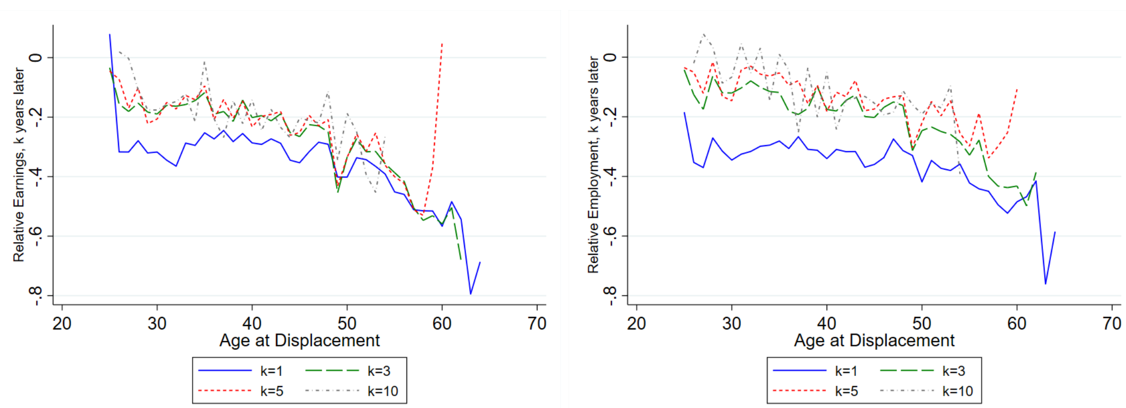


Figure B.11: *The estimated effect of displacement on earnings (left) and employment (right), by time since displacement, and by age at the time of displacement. Depicted estimates are obtained separately for each displacement age. Pointwise confidence intervals are omitted and are available upon request.*

In Figure B.11, 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.11 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.

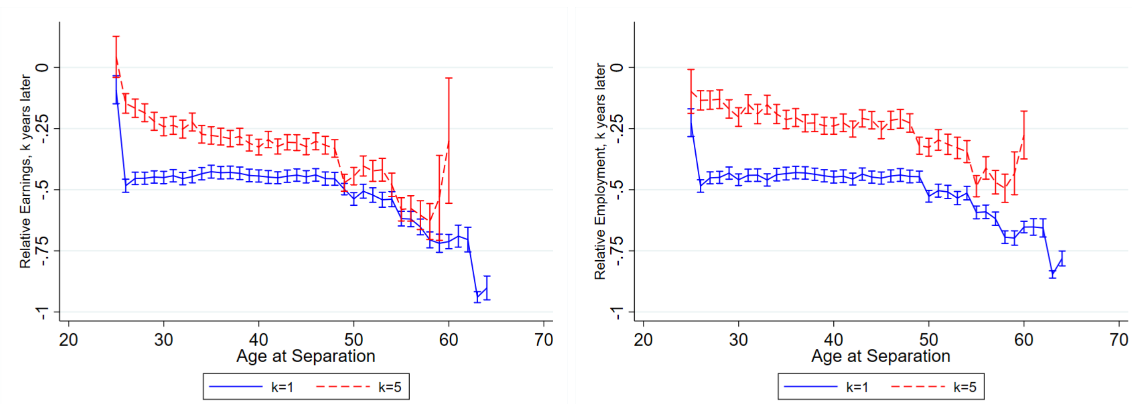


Figure B.12: *The estimated effect of separation on earnings (left) and employment (right), 1 year (solid) or 5 years (dashed) after the job loss, by age at the time of the job loss. Depicted estimates are obtained separately for each separation age.*

In Figure B.12, 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.13, 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.13 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.14 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

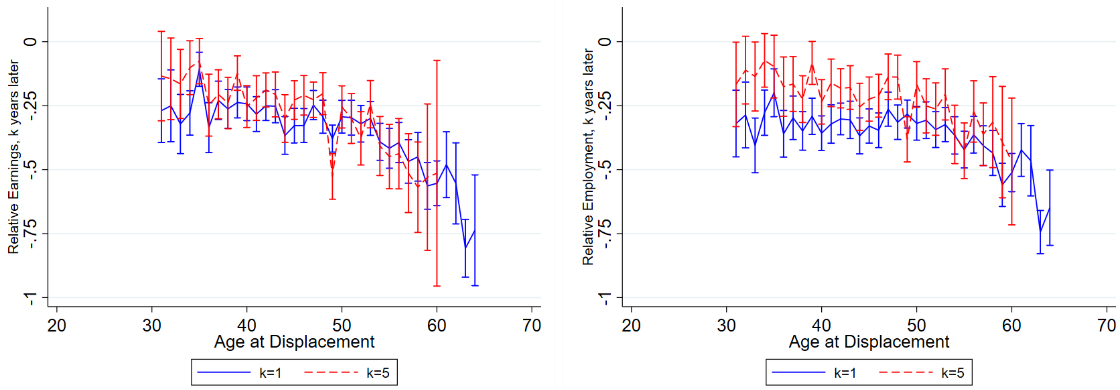


Figure B.13: *The estimated effect of displacement on earnings (left) and employment (right), 1 year (solid) or 5 years (dashed) after displacement, by age at the time of displacement, conditioning on 6 years (rather than 1 year) of pre-displacement establishment tenure. Depicted estimates are obtained separately for each displacement age.*

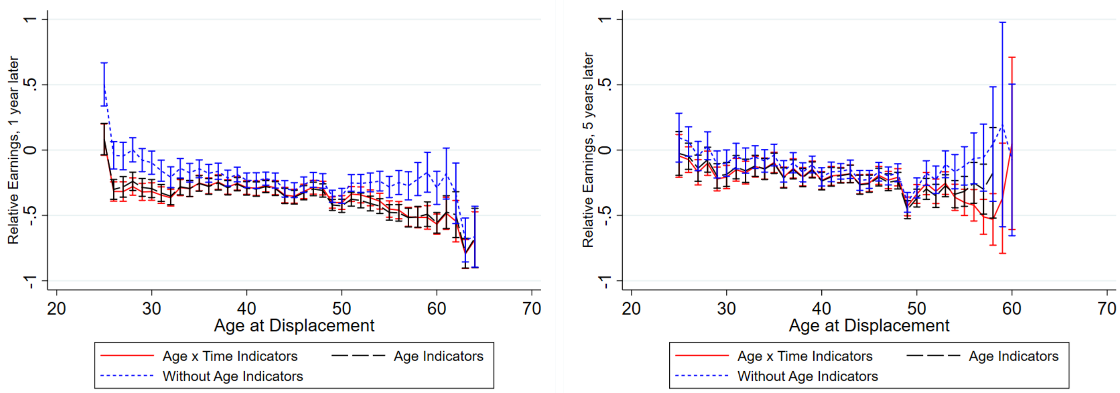


Figure B.14: *The estimated effect of displacement on earnings, 1 year (left) or 5 years (right) after displacement, by age of displacement. The figure compares estimates obtained using either time fixed effects only (short dash, blue), time fixed effects and age indicators (long dash, black), or an 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.14. When focusing on the longer run, as in the right panel of Figure B.14, 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).

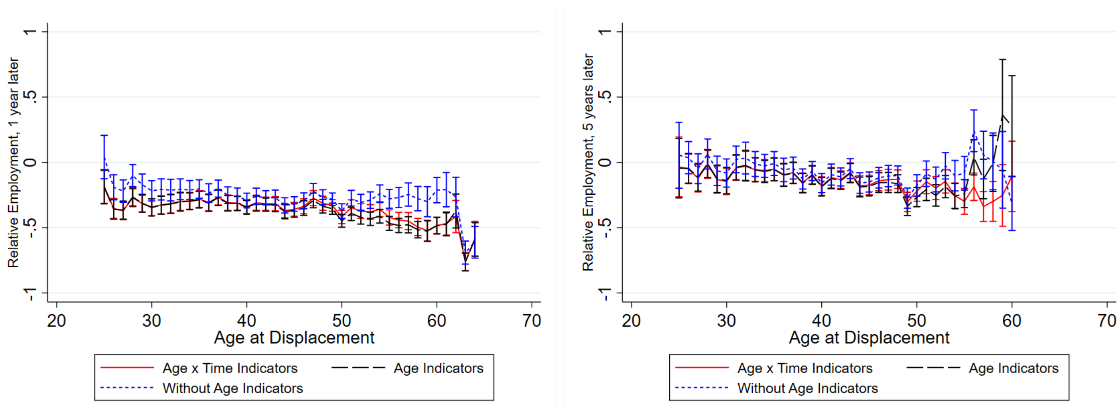


Figure B.15: *The estimated effect of displacement on employment, 1 year (left) or 5 years (right) after displacement, by age of displacement. The figure compares estimates obtained using either time fixed effects only (short dash, blue), time fixed effects and age indicators (long dash, black), or an interaction of time and age indicators (solid, red).*

In Figure B.15, 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.14) and in the main text (Figure 3).

Given the differences between the three estimation methods observed in Figures B.14 and B.15 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.16 shows that this is indeed the case. The estimates in Figure B.16 are obtained using the same methods as described above and in the main text, except for esti-

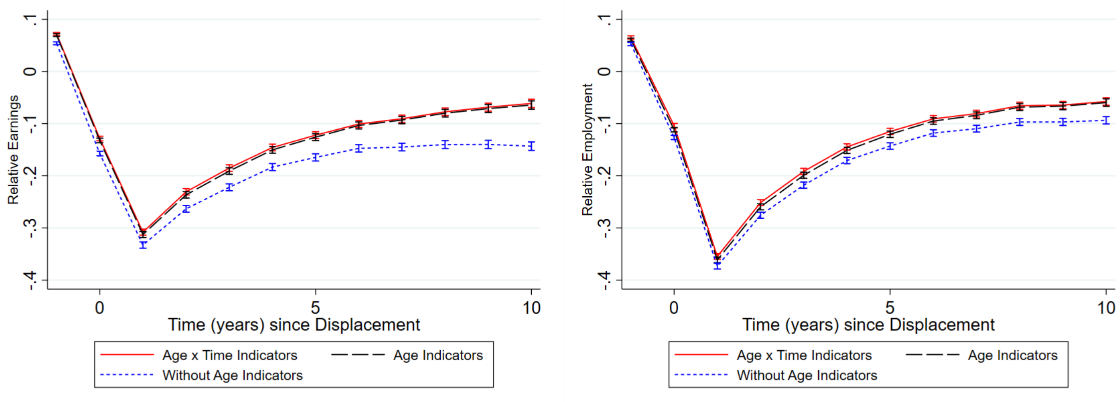


Figure B.16: *The estimated effect of displacement on earnings (left) and employment (right), by year relative to the year of displacement. The figure compares estimates obtained using either time fixed effects only (short dash, blue), time fixed effects and age indicators (long dash, black), or an interaction 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.16, 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.14 and B.15, thus indicating the considerations highlighted when discussing the differences for the age-specific estimates (in Figures 3, B.14, and B.15) are dominated by the issues that arise from using workers of all ages as the control group.

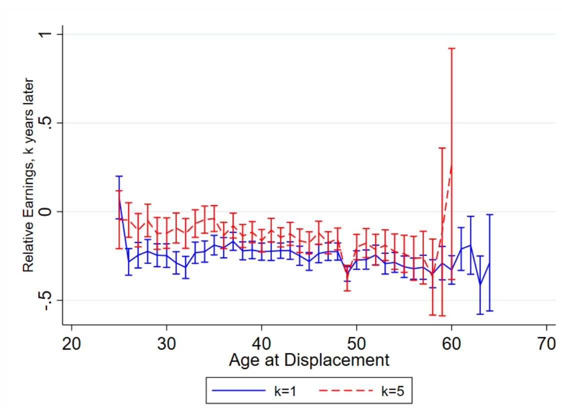


Figure B.17: *The estimated effect of displacement on earnings, 1 year (solid) or 5 years (dashed) after displacement, by age at the time of displacement, conditioning on having positive earnings in any post-displacement period. Depicted estimates are obtained separately for each displacement age.*

In Figure B.17, 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.17 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 or the subsequent reversal in the retirement window.

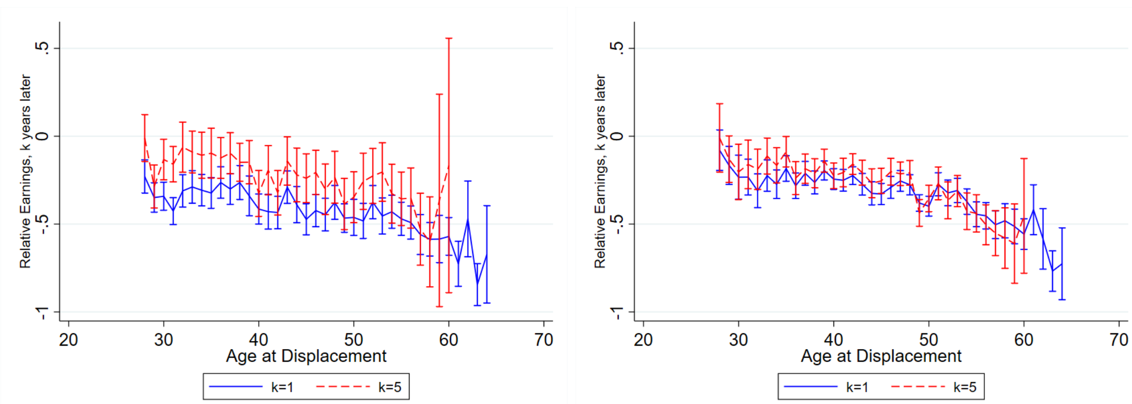


Figure B.18: *The estimated effect of displacement on earnings, 1 year (solid) or 5 years (dashed) after displacement, by age at the time of displacement, conditioning on pre-displacement recent earnings being below the median (left) or above the median (right). Depicted estimates are obtained separately for each displacement age.*

In Figure B.18, 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.18, 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.19 shows.

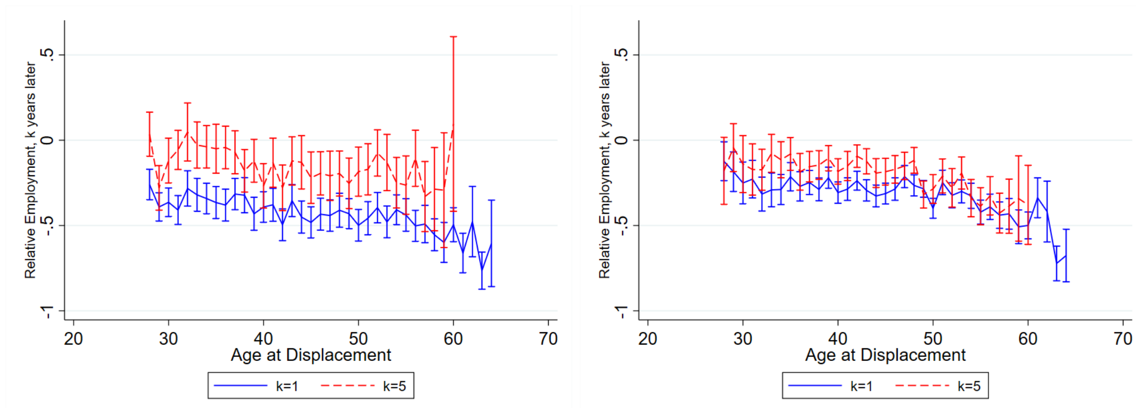


Figure B.19: *The estimated effect of displacement on employment, 1 year (solid) or 5 years (dashed) after displacement, by age at the time of displacement, conditioning on pre-displacement recent earnings being below the median (left) or above the median (right). Depicted estimates are obtained separately for each displacement age.*