Earnings Losses and Human Capital Accumulation over the Life Cycle*

Dorisz Albrecht

Abstract

A large literature has documented that job displacement entails large and persistent reductions in earnings. I extend this literature by documenting several new empirical findings about how these earnings losses vary over the life cycle. In particular, I show that earnings losses are increasing in the age at the time of the job displacement and that the earnings recovery flattens out earlier for older displaced workers. To account for these empirical patterns, I propose a Ben-Porath model with two novel features. First, I expose the workers to job displacement shocks that lead to unemployment spells. Second, I allow workers to accumulate two types of human capital over their life cycle: general and specific. Specific human capital is lost when a worker experiences a displacement. I calibrate the model to match salient features of life cycle earnings and employment dynamics and show that the model can generate the large differences in earnings losses over the life cycle, as well as the shape of employment losses following a job displacement.

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1 Introduction

A job displacement entails substantial and persistent reductions in earnings and employment. They magnify the cost of business cycles (Krebs (2007), Davis and Von Wachter (2011)) and increase the probability of recurring job losses (Pries (2004), Jarosch (2022)). Understanding the sources of the persistent consequences of job displacement has taken priority for unemployment policies. This paper examines job displacements from a new perspective and asks how a job displacement affects workers' earnings and employment over the life cycle. Understanding the costs of a job displacement from the early years in the labor market up to the end is important for macroeconomic issues such as the increase in youth unemployment or policies like training programs for the unemployed.

This paper first documents five patterns associated with job displacement over the life cycle using German social security data covering private sector workers from 1975 to 2010. First, I document that losing one's job takes an increasing toll on displaced workers as they age. I observe that time spent in unemployment and initial wage reduction upon job displacement are both increasing in the age at the time of displacement. The observed wage reduction of the oldest age group is twice as large as of those workers who lose their job below the age of 30. Second, these initial moments translate into more persistent employment losses for older displaced workers. Third, earnings losses are persistent over the life cycle and earnings recovery flattens out earlier for older displaced workers. Fourth, these persistent earnings losses and the differences across younger and older displaced workers are present even after conditioning on job tenure. Fifth, the persistence of earnings losses is higher for workers displaced from occupations that present higher earnings growth potential over the life cycle.

To understand these findings in the data, I build on the standard Ben-Porath (1967) model with two novel features: first, I introduce the possibility of losing one's job, thus becoming unemployed in the model; second, I introduce two types (general and specific) of human capital. Human capital dynamics lie at the center of the model. Both general and specific human capital are accumulated over the life cycle. The main difference between the two types is that specific human capital is lost upon a job displacement. In the model each employed worker makes a decision each period about how to allocate their time between production and learning. Time devoted to learning is in turn allocated between general versus specific skills. A worker's decision about how much time to allocate to production versus acquiring the two types of human capital is effectively a trade-off between consumption today versus consumption in the future. The cost of human capital accumulation is the forgone wages while the return is the increase in their stock of human capital which translates into increased future wages. A key feature of the model is that the return on investment in human capital decreases over time as the length of the remaining time horizon decreases.

I calibrate the model targeting moments from the data about unemployment dynamics and the evolution of earnings over the life cycle. More specifically, I match the trajectory of earnings growth over the life cycle between the ages of 23 and 60. I also match the contribution of experience and job tenure to wage growth following the methodology of Topel (1991). The estimated model also captures the decline in job separation rate as a function of job tenure. The model is successful in generating large and persistent differences in earnings losses over the life cycle. This is due to workers of different ages responding to a job loss substantially differently in terms of rebuilding the lost stock of human capital. The model captures more than two thirds of the difference in terms of the persistent earnings losses between the youngest and the oldest displaced workers. The model can also generate the shape and the size of the estimated employment losses associated with a job displacement. Moreover, it captures the increasing persistent employment losses over the life cycle. This is due to the separation probability that is linked to the stock of accumulated specific human capital. As older displaced workers spend less and less time rebuilding their lost human capital, they are also more likely to experience repeated job losses. Jarosch (2022) shows that displaced workers are more likely to go through repeated unemployment spells upon a job displacement.

I highlight the underlying mechanism of the model with two counterfactuals. I show that the response to a job displacement is substantially different over the life cycle in terms of time spent rebuilding lost human capital. The mechanism is generated through the application of Ben-Porath (1967) to a novel setting. In this setting a job displacement is considered a break in one's career that forces an individual to restart their career with different starting conditions. Thus the central economic mechanism of the model is how age affects investment decisions in specific human capital. In the first counterfactual, I estimate the direct effect of unemployment on people's earnings and find that going through an unemployment spell without losing one's human capital is more detrimental to younger displaced workers. This is due to the higher learning productivity in the earlier years of the life cycle. In the second counterfactual, I shut down displaced workers' optimal human capital investment channel. I find that without the optimal human capital investment response to a job displacement, displaced workers' earnings losses would be smaller initially, but their persistent earnings losses would be much bigger. This is because the reduced investment in learning translates into lower wages in the long run and puts a halt on catching up to non-displaced workers.

1.1 Related Literature

The paper is the first to study the effects of a job displacement on earnings and employment over the entire life cycle. The paper estimates the mean earnings and employment losses associated with a job displacement and finds similar results to what the literature has documented recently (Jacobson et al. (1993), Stevens (1997), Davis and Von Wachter (2011), Jarosch (2022), Krolikowski (2017), Couch and Placzek (2010), Flaaen et al. (2019), Schmieder et al. (2022), Lachowska et al. (2020), Jung and Kuhn (2019)). My regression specification is following closely Jacobson et al. (1993) and Davis and Von Wachter (2011) while I borrow the sample construction criteria from Jarosch (2022). Moreover, the paper contributes to the growing sub-literature that investigates the sources and the heterogeneity in the cost of job displacement (Burdett et al. (2020), Gregory et al. (2021), Pytka and Gulyas (2021), Leenders (2021), Schmieder et al. (2022), Huckfeldt (2022), Albrecht (2022)). These papers have recently found substantial differences in long-term earnings losses based on educational attainment, labor market histories, or occupation switches. My paper adds age at the time of displacement as a good predictor for long-term earnings losses. I show in the data section that younger displaced workers recover almost completely within fifteen years after a job displacement while older displaced workers tend to lag behind their peers' earnings by 30%. I emphasize these age affects by documenting five novel findings in the data that describes the costs of a job displacement over the entire life cycle.

Both the empirical and the theoretical part of the paper relates to the growing literature that aims to understand the persistent earnings losses upon a job displacement. The majority of the literature uses a job ladder model to explain the observed earnings and employment dynamics. While Krolikowski (2017) builds a substantially long job ladder that takes time to climb back up after a separation, Jarosch (2022) uses a job ladder with slippery bottom rungs. Pries (2004) also emphasizes recurring job losses when explaining aggregate unemployment dynamics. Hubmer (2018) builds a job ladder model over the life cycle but focuses on life cycle earnings dynamics. Jung and Kuhn (2019) focus on the nondisplaced workers' earnings path rather than the earnings recovery of the displaced. Burdett et al. (2020) and Ljungqvist and Sargent (1998) emphasize the loss of human capital with models where employment losses are temporary. The model presented in this paper builds a life cycle model that focuses on human capital accumulation. It can account for both persistent earnings and employment losses over the life cycle. The model extends Ben-Porath (1967) by an unemployment state and two types of human capital. A job displacement in the model will force workers to restart their careers from different starting conditions and a shorter time horizon.

The paper also contributes to the strand of literature that documents labor market features over the life cycle. There has been a lot of progress in documenting and understanding labor market mobility over the life cycle, such as the job shopping process in the early years in the labor market yielding a declining job-to-job mobility over the life cycle (Neumark (2002), Topel and Ward (1992), Jung and Kuhn (2019)), the declining separation rate over the life cycle that results in lifetime jobs (Hall (1980), Farber et al. (1993)). Regarding the earnings growth profile over the life cycle, the model matches the faster growth in the early years in the labor market and a slower growth in later years following the estimation method in Huggett et al. (2011). The model also accounts for returns on experience and job-tenure using the estimation strategy in Topel (1991). The model generates larger earnings losses for older displaced workers on impact that resonates findings in the US (Farber et al. (1993)) and can also account for the large differences across age groups in long term earnings losses associated with a job displacement. Humlum (2019) estimates that welfare losses associated with being replaced by robots is mostly concentrated on older production workers as younger workers can more easily switch to better jobs in tech.

The paper is organized as follows. Section 2 presents the data, the sample selection criteria, and the displaced worker regression framework. Section 3 documents the empirical findings, Section 4 describes the model, and Section 5 estimates model parameters. Section 6 and 7 present results and analyze the underlying mechanism of the model.

2 Data

In this section I describe the main data source of this paper and the partitioning methods used to construct distinct samples of displaced workers.

2.1 Data Description

I use a monthly panel dataset of a 2% random sample of German households provided by the Research Data Center of the German Federal Employment Agency at the Institute for Employment Research (IAB). I use the sample from 1975 until 2010 due to changes in how some variables are recorded after 2010[1]. I restrict my baseline sample to males between the age of 22 and 60. The dataset - among other variables - contains information about the individuals' age, daily wages[2], employment status, type of the employment, unemployment benefit receipt, occupation at the three-digit level, and establishment ID.

I define an individual as employed and set his monthly employment status as 1, if he is liable to social security and has a full-time job in that month[3]. If the individual is reported to be part-time working in a given month, then I assign him a 0.5 as his monthly

[1]Due to data protection, some variables are provided in modified version: the nationality variable is reduced to a German dummy variable, hence I can only observe whether the individual is of German nationality or not. The employment status variable is aggregated from 31 to 14 categories. The daily wage is rounded to the nearest integer Euro value.

[2]Wages are in real terms, deflated by CPI of Germany, 2015 being the base year

[3]The dataset has a specific variable that indicates whether the job is a full-time job or not.

employment status[4]. If the individual is neither full-time, nor part-time employed, his employment status is set to 0 in that month.

Monthly earnings equal the daily wages reported when the individual is employed in that month, while it is set to 0 when the individual is not employed in a given month. I identify the end of an employment spell as a separation if the individual is full-time employed at an establishment in a given month but not employed in the next month. I cannot observe the reason for a separation, so in order to avoid counting workers who quit their job as displaced workers, I denote a separation as a displacement if the worker separates from his employer and receives some unemployment benefit within two months of the separation[5].

The richness of the dataset allows me to track workers' employment histories at a monthly frequency over many years. I build their employment and job tenure histories, job losses, job-to-job transitions, and the changes in their daily wages. I define employment tenure as months of continuous employment, and job tenure as months of continuous employment with the same employer. I calculate the immediate wage change associated with a displacement as the percentage change in the observed daily wage in the first month of a new full-time job compared to the daily wage observed in the last month of employment at the individual's previous full-time job. I compute time spent in unemployment as the number of months it takes for an individual to find his first full-time job after separating from his previous full-time job.

I aggregate five monthly variables into an annual variable the following way. Starting with the monthly dataset, I create the annual employment index by summing up their monthly employment status. I compute annual earnings as the sum of their monthly earnings during the whole year divided by 12, while I compute the annual wages as the sum of the monthly earnings divided by the annual employment index. Furthermore, I create a dummy indicating whether the individual experiences a displacement in a given year. Finally, I keep track of the job tenure at the time of displacement[6].

[4]These monthly characteristics are reported on the first day of the month.

[5]This condition is taken from Jarosch (2022)

[6]Note that if an individual experiences more than one displacement in a given year, I only record

2.2 Benchmark Displaced Worker Sample

In the following section I describe the benchmark displaced worker sample that I am going to partition further when I present the earnings losses of displaced workers using German administrative data.

I first introduce the benchmark displaced worker sample that I use in order to assess the earnings losses over the years after displacement. For a worker to qualify as a displaced worker in the benchmark sample, he must meet the following criteria: (i) he separates from his full-time employer and receives unemployment benefit within 2 months of the separation, (ii) he has at least three years of job-tenure (full-time) at the time of separation, (iii) is between the age of 25 and 45 at the time of displacement, (iv) has observable earnings for at least 3 years prior to displacement, (v) finds a full-time job within three years of the job loss, (vi) his daily wage in the last month of employment at his previous job and the daily wage in the first month at his new full-time job are both observable, and finally that (vii) the first full-time job after the separation is not with his previous employer, in other words he is not recalled by his old firm. Most of these conditions coincide with the sample selection criteria in Davis and Von Wachter (2011). Condition (v) excludes those individuals who move away, retire or for some reason are not in the labor force for a long time. Including those individuals would most likely increase the earnings losses after displacement, so their exclusion gives more conservative estimates.

I compare displaced workers in the sample to a very similar group of workers; the control group contains workers who have at least 3 years of job-tenure, are between 25 and 45 years of age, have observable earnings for at least 3 years on the job, and stay with their employer for at least one more year. If an individual qualifies as a displaced worker more than once throughout his presence in the panel, I only follow the first displacement, such as in Stevens (1997). If an individual qualifies as a member of the control group more than once over the years, I randomly select one year in which he qualifies as a member

the job tenure at the first separation event. This is because in the next section I condition on displaced workers who lose their jobs with at least 36 months of job tenure at the time of the job loss. If an individual goes through a separation more than once in a given calendar year, only the first separation can be from a position with at least 3 years of job tenure.

of the control group and construct a set of dummies around that year. As is standard in the displacement literature, I follow the members of the treatment and the control group before and after the year the members are chosen. To be more precise, I follow the individuals up to three years before and up to fifteen years after the displacement year. To give an example, if an individual qualifies as a member of the control group in multiple years i.e. in 1990, 1991, 1992, and 1993, I randomly choose one year, for instance 1992 and only use the observations from years $\in [1989, 2007]$. This way every individual-year observation is present exactly once in the sample. If an individual qualifies as a displaced worker more than once throughout his presence in the panel, I only follow the first displacement, such as in Stevens (1997). I identify 20,246 displaced workers who satisfy all the conditions listed above.

Table 1 presents summary statistics about the age, earnings, and job-tenure of the displaced workers and the control group. Displaced workers are slightly younger than their peers in the control group, earn less by around 15€ a day, and have on average slightly less tenure at the time of displacement (50 vs. 58 months). Displaced workers spend on average 7.3 months in unemployment before finding their first full-time job, and see their daily wages reduced by an average of 9% on their first full-time job.

	Displaced	Control
Age (years)	36	37
Job tenure (months)	81	82
Wages (daily, in euros)	92	107
Number of obs.	20 246	204 321

Table 1: Summary Statistics of Benchmark Displaced Sample and Control Group

2.3 Methodology

In this section I first describe the regression framework that I use to estimate the earnings losses in the sample. Then I present the estimation results using the benchmark displaced worker sample.

Throughout the paper I use the following regression specification to estimate earnings and employment losses associated with a displacement. I refer to Equation 1 as the benchmark displaced worker regression.

$$y_{it} = \sum_{k=-3}^{15} D_{it}^{k}\delta_k + \lambda\bar{e}_i + \beta X_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{1}$$

where y_{it} is the outcome variable (log annual earnings, log annual employment index), D_{it}^{k} are dummies that indicate displaced workers k years after displacement. $\bar{e}_i$ is the average wage of the worker in the two years before displacement. X_{it} controls for age and age squared of worker i in year t. α_i is the person fixed effect, while γ_t is the year fixed effects. ϵ_{it} represents random factors.

The framework is very similar to the one used in Davis and Von Wachter (2011). There are three main differences between Equation 1 and the regression framework in Equation (1) in Davis and Von Wachter (2011). First, I do not run the regression year by year, rather I stack the individual-year observations on each other. Second, I only follow workers three years prior and fifteen years post displacement, while they follow them five years prior and twenty years post displacement. Third, I use logged outcome variables rather than variables in levels, thus my estimates reflect percentage deviations from the control group. Fourth, Davis and Von Wachter (2011) look at displacements through the age of 50, while I restrict my sample to be between 25 and 45 at the time of displacement.

Figure 1 displays the estimated earnings losses relative to the control group's earnings. The reduction in earnings is significant and long-lasting for displaced workers. Compared to the control group's earnings level, 5 years after displacement earnings are around 20% lower, 10 years after they are around 15%, and 15 years after losing one's job, earnings recovery is still incomplete, lagging behind the control group by around 13%. I find similar earnings losses as what Jarosch (2022) documents using German administrative data as well. The estimated employment losses are displayed in Figure 1 with a red line. Employment losses are substantial throughout the years being at around 5% below the control group fifteen years after displacement. The difference between the earnings and employment losses suggests significant wage losses after a job loss[7].

[7]Online Appendix A presents the estimates for the mass-layoff sample.

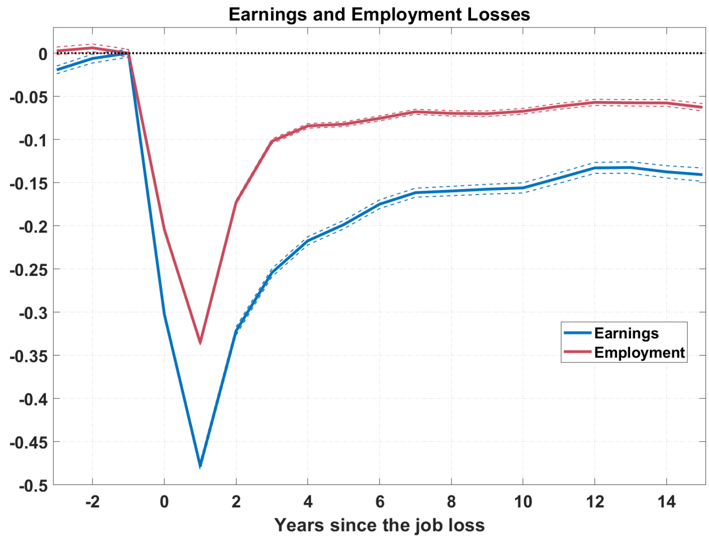

Figure 1: Earnings and Employment Losses of Displaced Workers

3 Displacement over the Life Cycle

Until now, the displaced worker literature has mainly focused on the average effects with few exceptions like Huckfeldt (2022) or Gregory et al. (2021). In this section I go beyond estimating the average effects of a job displacement and ask how earnings and employment losses look at different stages of the life cycle.

I partition the benchmark displaced worker sample into four age groups, then I document five patterns about a job displacement over the life cycle:

1. Upon displacement immediate wage losses and time spent in unemployment are increasing in age at the time of displacement.

2. Earnings losses associated with a job displacement both on impact and in the long run are increasing in age at the time of displacement.

3. Employment losses associated with a job displacement are increasing in age at the time of displacement, while long term employment losses follow a similar pattern over the life cycle.

4. I disentangle job tenure and age effects in the displaced worker framework and show that age effects are still present even after conditioning on job tenure at the time of displacement.

5. Long term earnings losses associated with a job displacement are higher in occupations with higher earnings growth potential over the life cycle. Moreover, I show that this pattern is present even within age groups.

Before presenting the empirical evidence on how a job loss affects workers heterogeneously over the life cycle, I first introduce the subsamples of displaced workers that I use in my empirical analysis.

To construct the subsamples, I partition the displaced worker sample based on age at the time of displacement. Specifically, I construct four subsamples from the benchmark sample, the first subsample contains displaced workers who are between the ages of 25 and 30 at the time of the displacement, the second subsample contains workers who are between the age of 31 and 35 at the time of displacement, the third subsample is those individuals who are between the ages of 36 and 40 at the time of displacement, while the last subsample contains those individuals who are between the ages of 41 and 45 at the time of displacement.

For each displaced worker subsample, I construct a control group from the same age group. For instance, to qualify as a member of the control group for the displaced worker subsample between the age of 25 to 30, I require individuals in the control group to be between the ages of 25 and 30 and to not experience a displacement event between the ages of 25 and 30. The last condition does not require members of the control group to be employed by the same employer in the specified age interval for all 5 years, just that they do not separate from their jobs and receive unemployment benefits within two months. If an individual qualifies as a control group member more than once in the age interval $[25, 30]$, then I randomly select one year and keep that as the base year. This way, every person is present in the sample once for 19 years. Therefore, for this partitioning, I change the definition of the control group compared to what I use with the benchmark sample.

Table 2 presents summary statistics for the displaced worker subsamples and their respective control groups. The first row contains the average age of each group in years, the second row presents the average full-time job tenure of the groups in months, the third

	25-30		31-35		36-40		41-45	
	Disp.	Cont.	Disp.	Cont.	Disp.	Cont.	Disp.	Cont.
Age (years)	28	28	33	33	38	38	43	43
Job tenure (months)	56	63	81	84	97	99	106	110
Wages (daily, in euros)	86	99	95	109	97	114	97	116
Number of obs.	7190	86419	7165	98996	6848	105209	6081	99073

Table 2: Summary Statistics of Displaced Workers and their Control Groups, Partition: Age

row documents the average daily wages in euros in the year they qualify as a member of their respective group. The last row of the table presents the number of individuals that qualify as a member of their respective group. Table 2 shows that members of the displaced worker subsamples and their respective control groups are of the same age while members of the control groups have higher job tenure and daily wages on average than displaced workers of similar age.

3.1 Immediate Consequences of Displacement

In this subsection I document what happens in the short run after a job displacement as a function of age at displacement. Table 3 presents two short run consequences of a displacement event over the life cycle. The first row of the table displays the average number of months a displaced worker spends between the displacement and their first full-time job. Time spent in between two full-time jobs is increasing in age at the time of job loss. The difference across the age groups is small, as members of the youngest displaced group spend 7 months in between two full-time jobs on average, the oldest group spends 7.5 months without a full-time job on average after the displacement event.

The second row of Table 3 presents the average percentage change of the daily wages of the displaced worker groups. It shows the difference between the last observed daily wage in their last full-time job and the first observed daily wage at their first full-time job after the job loss. The immediate average wage reduction upon job loss is also increasing in age. However, the increase across age groups is much more substantial as the youngest group suffers a 6% wage drop on average, while this number is 12% for the oldest displaced group.

	25 - 30	31 - 35	36 - 40	41 - 45
Unemployment spell (months)	7.0	7.2	7.4	7.5
Wage change (%)	-6.4	-8.0	-10.3	-12.0
Number of observations	7 190	6947	6848	6081

Table 3: Summary Statistics of Displaced Workers, Partition: Age

3.2 Earnings Losses over the Life Cycle

I run the regression from Equation 1 using the displaced worker subsamples and their control groups. Every displaced worker subsample of a specific age group will have their estimated δ_ks from Equation 1.

Figure 2: Earnings Losses of Displaced Workers, Partition: Age

Figure 2 presents the estimated δ_ks for each age-group. The figure shows that on average, individuals displaced between the age of 25 and 30 almost catch up to their peers over time, lagging behind their control group's earnings by only 4% after fifteen years. The red line shows the estimated earnings losses after displacement for those who go through a displacement event between the age of 31 and 35. The figure documents that this age group does not recover completely, earnings are around 17% behind the control group's earnings even after 15 years. The yellow line shows the estimated δ_ks for the age group of [36,40]. Their persistent earnings losses are about 26% lower than their control group's earnings. The purple line shows the average earnings losses of displaced workers who have lost their jobs between the age of 41 and 45. The long run earnings losses average at about 34% behind their respective control group's. The figure shows two striking observations over the life cycle. First, as people age earnings losses are increasing on impact. As the summary statistics show, this is due both to longer unemployment spells and larger wage reductions after the unemployment spell. Second, the pace at which earnings catch up to the earnings of the respective control groups gets flatter as people age. It is also worth noting that the gap between two consecutive age groups consolidate around six years after the separation occurs with the exception of the youngest group.

3.3 Employment Losses over the Life Cycle

In this subsection I run the regression from Equation 1 using the displaced worker subsamples and their control groups using the logged annual employment index as the dependent variable.

Figure 3 displays the estimated δ_ks for the four age groups in the same graph. As the figure shows, employment losses are persistent for all four age groups. Employment losses over the life cycle show two similarities with earnings losses: (i) initial employment losses are increasing in age, (ii) losses in the long run are larger for older displaced workers. Younger displaced workers between the age of 25 and 30 have employment losses around 7% five years after the job loss, while this number is 9% for the $[31, 35]$ age group, 13% for the $[36, 40]$, and 16.5% for the $[41, 45]$ age group. One stark difference in the estimated employment losses compared to the earnings losses is that employment losses flatten out five years after the displacement year and stay relatively flat throughout the years

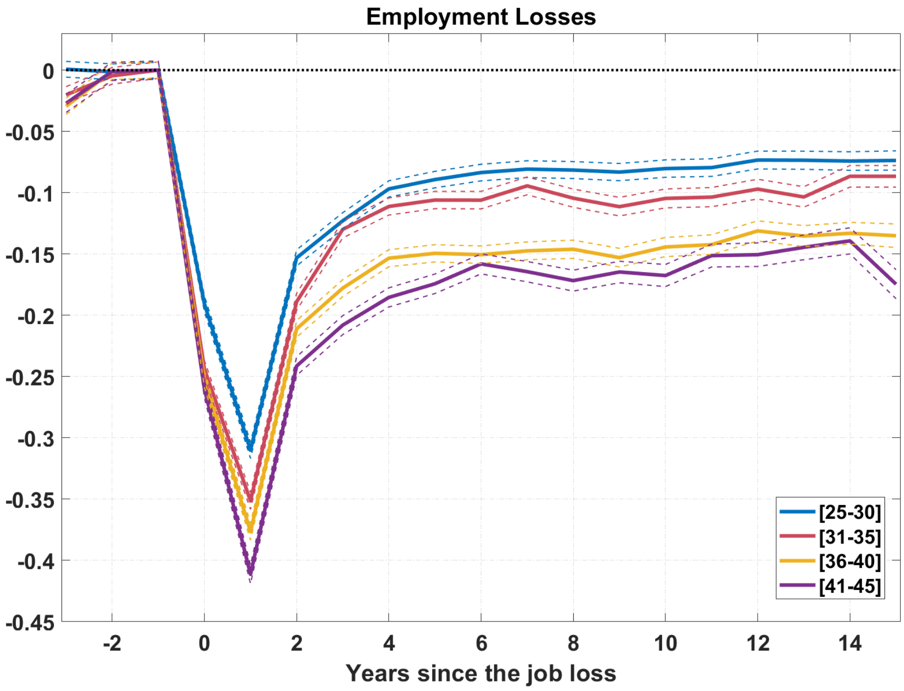

Figure 3: Employment Losses of Displaced Workers, Partition: Age

afterwards for all age groups.

3.4 Job Tenure versus Age Effects

Age and job tenure are highly correlated in the data and as Table 2 shows older displaced workers have longer job attachment at the time of displacement. A natural question arises: are these mostly age effects or job tenure effects showing up as age effects in the estimation process?

In order to assess whether higher and more persistent earnings losses for older displaced workers are mainly driven by longer job tenure at the time of displacement, I partition the displaced worker subsamples further in the following way. For each age group of displaced workers I create three subsamples based on their job tenure at the time of job loss. For instance, I partition the subsample of displaced workers between the age of 36 and 40 into three groups: (i) displaced workers who have job tenure between 3 and 5 years (from 36 to 60 months), (ii) displaced workers who have job tenure between 5 and 8 years (from 61 to 96 months), and (iii) displaced workers who have job tenure between 8 and 11 years (from 97 to 132 months). I do this partitioning with all age groups except for the youngest group as its members are not old enough to have such high job tenure at the time of displacement. Once I have the newly defined subsamples of displaced workers, I run the benchmark regression from Equation 1 using the subsamples with their particular control groups. For example the subsample of displaced workers who lose their job between the age of 36 and 40 and with job tenure between 5 and 8 years is used with the control group of workers who do not experience a job loss between the age of 36 and 40 and have job tenure between 5 and 8 years. I estimate the δ_ks from Equation 1 for each subsample and plot them in Figure 4 and Figure 5.

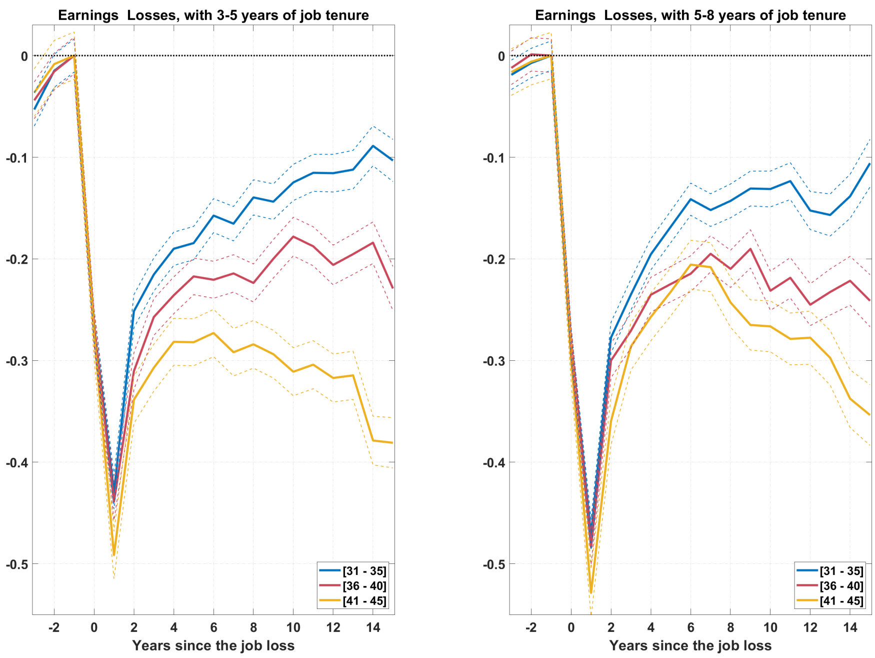

Figure 4: Earnings Losses of Displaced Workers, Conditional on Job Tenure, then three Age Groups

Figure 4 displays the estimated earnings losses conditional on job tenure at the time of displacement. The left panel plots the δ_ks for three age groups of displaced workers who have job tenure between 3 and 5 years when they lose their jobs, while the right panel shows these losses for the same age groups who had between 5 and 8 years of job tenure at the time of the job loss. Both panels show that the oldest displaced worker subsamples lose more on impact even when I condition on job tenure. In both panels the earnings recovery of all three age groups seem to follow a similar path in the first three years after the job loss. After the first three years the estimated δ_ks show an increasingly incomplete and divergent earnings recovery across the age groups. Earnings losses on impact are higher for all age groups in the right panel suggesting that higher job tenure does entail higher losses on impact.

The implications of both panels in Figure 4 are that members of the 31 - 35 age group keep reducing the earnings gap relative to their control group over the years, consolidating the gap at around 10% fifteen years after the separation occurs. The middle age group of displaced workers between the age of 36 and 40 display a very conservative recovery after four years, being around 23% behind their peers in both panels in the long run. The oldest age group shows promising earnings recovery in the early years after the separation, however this recovery comes to a halt and even declines resulting in an earnings losses of around 36% in the long run. In both panels the earnings losses estimates are very similar for all age groups, indicating that even after conditioning on job tenure, age effects are dominant.

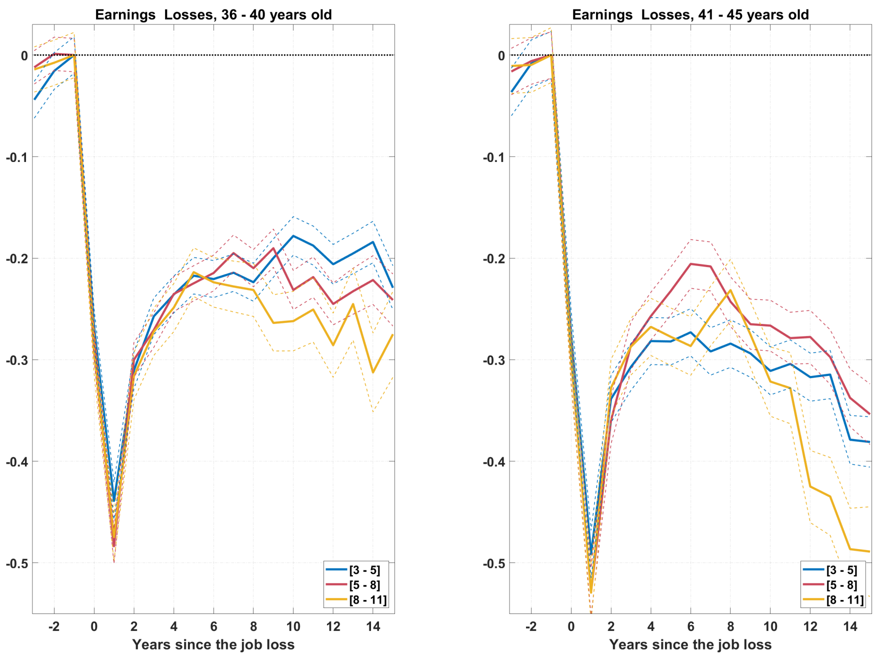

Figure 5: Earnings Losses of Displaced Workers, Conditional on Age, then Job Tenure

Next I carry out a very similar exercise, but now I first condition on age at the time of job loss, then run the benchmark regression specification on three job tenure categories. This exercise examines to which extent job tenure effects are present after conditioning on age at the time of the job displacement.

The two panels of Figure 5 compare the earnings losses of older displaced workers with different job tenures at the time of displacement. The left panel plots the estimated δ_ks of three job tenure categories for displaced workers between the age of 36 and 40 while the right panel displays the corresponding estimates for workers who get displaced from their job between the age of 41 and 45. The estimated earnings losses of the three job tenure categories are very similar over the years, with the highest job tenure category experiencing slightly bigger losses over the years. The implications of the two panels of Figure 5 are that older displaced workers have higher persistent earnings losses over the years no matter which job tenure category they are in. More importantly, the two panels suggest that after conditioning on age, job tenure effects do not show big variations in the long run. Thus I can conclude that age effects are dominating my previous findings.

3.5 Specific Human Capital

In this subsection I present the fifth pattern about earnings losses over the life cycle. More precisely, I examine how much earnings losses vary when a worker is displaced from an occupation with low or high lifetime earnings growth potential. I first describe how I define low and high lifetime earnings growth potential occupations, then I run the benchmark displaced worker regression specification on the newly constructed subsamples.

The data have 342 three-digit occupations and I rank these occupations as follows. I run a simple linear regression to estimate the age effects on mean earnings for each three-digit occupation. I follow the methodology from Huggett et al. (2011) and use their "cohort effect" measure of age effects on earnings. Specifically, I run the following regression for each three-digit occupation in the data:

$$\ln(\text{earnings}_{j,t,o}) = \alpha_{c,o} + \beta_{j,o} + \epsilon_{j,t,o} \tag{2}$$

where earnings are assumed to be generated by cohort (c) and age (j) effects for each occupation (o) and year (t). I then compute the ratio of the age effects $\frac{\beta_{46,o}}{\beta_{23,o}}$ for every occupation and rank occupations accordingly. The ratio shows how much earnings grow over the life cycle in each occupation. Having ranked occupations based on earnings growth over the life cycle, I estimate earnings losses of displaced workers who lost their job in an occupation that ranked in the lowest 50 occupations in terms of life cycle earnings growth and of those displaced workers who lost their job in an occupation that ranked in the top 50 occupations. Figure 6 plots the estimated δ_ks using control groups whose members are chosen from the bottom and top 50 occupations only.

Figure 6: Earnings Losses of Displaced Workers

The figure shows that workers displaced from occupations that display low earnings growth over the life cycle experience a smaller immediate decline in their earnings and also suffer smaller persistent earnings losses after the job displacement. Immediate and persistent earnings losses are larger by around 10% for those who lose their job from a top 50 occupation.

The gap between job losers from the bottom and top 50 occupations is significant and present even when I partition the samples further and estimate earnings losses for different age groups. Figure 7 displays the estimated earnings losses for the youngest group (between 25 and 30 at the time of the job displacement) and the oldest group (between 41 and 45). The left panel shows that the loss on impact is quite similar, there is only around a 6% difference between the top and bottom occupations. However, the difference on impact is very different for the older group. The gap between the two groups in the right panel of Figure 7 is more than 11% in the first year after displacement. This stark difference might suggest that at a younger age there is not much difference in lost accumulated specific human capital from the top and bottom occupations, while later on in the life cycle differences in lost specific human capital might account for larger declines on impact.

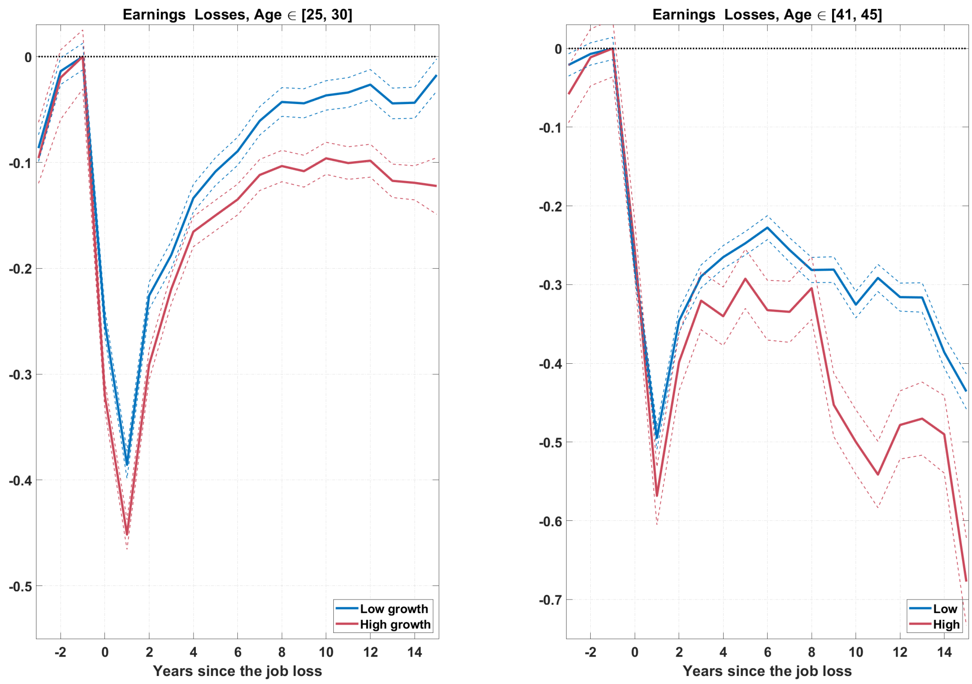

Figure 7: Earnings Losses of Displaced Workers

Both panels of the figure display similar patterns as to what I estimate for the two age groups in the previous subsection. More precisely, the youngest age group show a fast and complete earnings recovery over the years while the oldest age group show an incomplete earnings recovery with earnings starting to decline six years after the displacement event. Persistent earnings losses differ by around 10% in the left panel while this gap increases to 20% in the right panel. Thus experiencing a job displacement from an occupation with high earnings growth potential is increasingly damaging over the life cycle. Differences in accumulated specific knowledge over the life cycle could potentially explain these differences between top and bottom occupations.

4 Model

In this section I assess the extent to which a Ben Porath model extended to include labor market frictions and a distinction between general and specific human capital can account for the patterns documented in the previous section.

Setting

The model is set in discrete time with finitely-lived workers who live and work for 45 years. A model period is a month. Workers have linear preferences over consumption, and they discount the future by factor β. Workers in the model are either employed or unemployed. Employed workers can allocate their time between producing output and accumulation of human capital. The cost of human capital accumulation is the forgone wages while the return is the increase in their stock of human capital which translates into increased future wages. General human capital can be accumulated over the life cycle and is subject to depreciation during unemployment. Specific human capital is accumulated while on a job and is destroyed upon separation. A key feature of the model is that the return on investment in human capital decreases over time as the length of the time horizon decreases.

Wages and Earnings

A worker's wages are dependent on the amount of his accumulated general and specific human capital. Wages are given by the following Cobb-Douglas wage-function:

$$w_t = (h_t^g)^\gamma \cdot (h_t^s)^{1-\gamma} \tag{3}$$

where the elasticity of general human capital is γ, with $0 < \gamma < 1$. A worker's earnings are given by their wages multiplied by the fraction of time he spends working.

$$e_t = (h_t^g)^\gamma \cdot (h_t^s)^{1-\gamma} \cdot (1 - i_t^g - i_t^s) \tag{4}$$

where $(1 - i_t^g - i_t^s)$ is the fraction of time the worker spends with output production while $(i_t^g + i_t^s)$ is the time the worker spends investing in building his human capital stock at age t. Employed workers make separate decision about how much time they want to spend on accumulating each type of human capital. i_t^g denotes the amount of time a worker spends acquiring general human capital at age t, while i_t^s is the amount of time a worker spend building specific human capital at age t.

Human Capital Dynamics

Human capital dynamics lie at the center of the model. Both general and specific human capital are accumulated over the life cycle. The worker starts each period with two stocks of human capital, general and specific. Each period that the worker starts employed, the worker can decide how he allocates his time between output production and learning that can add to his stocks of human capital. It could happen that the worker's optimal decision is not to spend any time on acquiring human capital and just spend all his time working.

General Human Capital Every worker starts his life with the initial general human capital stock h_0^g. A worker with general human capital h_t^g at age t with time i_t^g allocated to investment in general human capital sees his general human capital stock evolve as follows:

$$h_{t+1}^g = (1-\delta)h_t^g + A_t(h_t^g i_t^g)^\alpha \tag{5}$$

where δ fraction of the existing human capital stock becomes obsolete every period, the α parameter governs the degree of diminishing marginal returns in the general human capital production. A_t controls the productivity of learning on-the-job . This productivity is age-dependent and provides an additional reason why workers at different stages of their career differ in the amount of human capital investment they undertake. The path of the learning ability of general human capital is as follows:

$$A_t = a_1 + a_2 \cdot \left(\frac{t-1}{T-1}\right)^{\xi_A}$$

a_1, a_2, and ξ_A are estimated jointly with other model parameters. This functional form allows learning to become more difficult over time. General human capital is built over the life cycle and is not destroyed when a separation occurs. However, it does depreciate at rate ϕ in unemployment:

$$h^g_{t+1} = h^g_t \cdot (1-\phi)$$

Specific Human Capital The novel part of the model is the second type of human capital that is accumulated on-the-job and is destroyed when a separation occurs. Workers can decide how much time they allocate to specific human capital investment independently from their general human capital investment decision. Each worker starts a new job with specific human capital h^s_{min} and builds their stock of specific human capital while being on the job. Once a separation occurs, the worker loses all of his accumulated specific human capital and starts a new job with h^s_{min} after an unemployment spell. The law of motion for specific human capital for a worker that does not separate is:

$$h^s_{t+1} = (1-\delta)h^s_t + B(h^s_t)(h^s_t i^s_t)^\alpha \tag{6}$$

The specific human capital production function is very similar to how general human capital evolves. The depreciation rate δ and the parameter α governing the diminishing marginal returns in the specific human capital production are common parameters for the two types. The only difference is coming from the $B(h^s_t)$ term in the accumulation function. Rather than being age-dependent, the productivity of learning is now dependent on the stock of accumulated specific human capital. The productivity of learning in the job-specific human capital production function takes the following functional form:

$$B(x) = b_1 + b2 \cdot \left(\frac{x-1}{T-1}\right)^{\xi_B}$$

The $B(\cdot)$ function is then interpolated onto the specific human capital grid. This functional form assumes that specific human capital is easier to accumulate at the beginning of an employment spell. As $B(\cdot)$ only depends on specific human capital but not age, every displaced worker will start at the same level of learning productivity $B(h^s_{min})$ at his new job. Because tenure and specific human capital are positively correlated, this specification will imply a positive correlation between tenure and learning ability, but the causal relationship is between specific human capital and learning. I do this for tractability.

Job separation, job finding probability

The job finding probability is constant, denoted by λ and is set to match the average unemployment length in the data. As shown earlier in Table 3, the length of the unemployment spell upon a job displacement does not vary much with age, thus I set λ as a constant, not dependent on age.

In the data I observe the rate at which workers with different job tenure go through a separation event. As specific human capital is accumulated while on the job, it is highly correlated with job tenure in the model thus closely matching what I find in the data. To keep the state space small, I follow the same logic as before and make the job separation function dependent on specific human capital. This will generate a high correlation between separations and job tenure.

$$\sigma(x) = \frac{1}{\kappa} - \psi \left(\frac{x-1}{T-1} \right)^{\xi_\sigma} \tag{7}$$

The $\sigma(\cdot)$ function is then interpolated onto the specific human capital grid. An extra separation probability θ is added if the specific human capital stock is lower than a threshold $h^s_\star$. This term is needed in order to match job separation probabilities conditional on job tenure in the data[8].

Value functions

The model has three state variables: the general and specific human capital, and age. An employed worker consumes the produced output and makes investment decisions of how much time is allocated to general and specific human capital acquisition. The cost of learning is in the form of lower wages and thus a lower level of consumption today while the benefit of learning is in the form of higher future wages and thus a higher level of future consumption. The worker faces unemployment risk with probability $\sigma(h^s_t)$ and

[8] The parameter θ helps with the substantial decline in the separation rate shown in Figure 9 after 12 months of job tenure. Without this extra term in the function and functions depending on specific human capital ($B(\cdot)$, $\sigma(\cdot)$) would have extreme values for low values of specific human capital stock.

discounts the future at rate β. The value function of an employed worker keeps track of both stocks of human capital:

$$
\begin{aligned}
W_t(h_t^g, h_t^s) = & \max_{i_t^g \in [0,1], i_t^s \in [0,1]} c_t + \\
& \beta \left((1 - \sigma(h_t^s)) W_{t+1}(h_{t+1}^g, h_{t+1}^s) + \sigma(h_t^s) U_{t+1}(h_{t+1}^g, h_{\min}^s) \right)
\end{aligned}
$$

$$
\begin{aligned}
\text{s.t.} \quad h_{t+1}^g &= (1-\delta) h_t^g + A_t (h_t^g i_t^g)^\alpha \\
h_{t+1}^s &= (1-\delta) h_t^s + B(h_t^s)(h_t^s i_t^s)^\alpha \\
c_t &= (h_t^g)^\gamma \cdot (h_t^s)^{1-\gamma} (1 - i_t^g - i_t^s)
\end{aligned}
$$

Unemployed individuals do not make investment decisions; they simply collect unemployment benefits b and find a job with probability λ each period. The fraction ψ of accumulated general human capital depreciates each month the individual spends in unemployment. Once the worker finds a new job, he can start rebuilding his lost human capital.

$$
\begin{aligned}
U_t(h_t^g) &= b + \beta \left[\lambda W_{t+1}(h_{t+1}^g, h_{\min}^s) + (1-\lambda) U_{t+1}(h_{t+1}^g, h_{\min}^s) \right] \\
\text{s.t.} \quad h_{t+1}^g &= h_t^g \cdot (1 - \phi)
\end{aligned}
$$

General Discussion

After the detailed description of the model, let me summarize the underlying forces. I extend the standard Ben Porath model with the risk of losing one's job which destroys the stock of accumulated specific human capital. Each period that a worker starts employed, he must make a decision how he allocates his time between production and learning. A worker's decision about how much time to allocate to production versus acquiring the two types of human capital is effectively a trade-off between consumption today versus consumption in the future.

Younger workers are expected to spend more of their time investing in human capital and enjoying the returns in the future. The benefit of accumulating human capital at the beginning of the worker's career is the expected higher future consumption for longer time period. The risk of accumulating human capital is that specific human capital is lost upon job displacement. Thus after a separation occurs, the worker can no longer enjoy the previously expected high future consumption stream.

Older people might not find it optimal to forego earnings today and wait for the returns in the future. As life progresses, older workers find themselves with a shorter time horizon left from their career. As people age, one unit of the consumption good in later years becomes more important as it is discounted by less, meaning that the present value return of learning decline very rapidly in the later stages of one's career.

5 Calibration

In this section I describe how I calibrate the model from the previous section. I first introduce the set of parameters that is set externally then I describe the parameters that are estimated jointly while targeting a set of moments. The moments I pick to match are informative about the unemployment dynamics and the evolution of earnings over the life cycle.

Table 4 collects the parameters calibrated outside the model. I set 6 parameters of the model using life cycle and job displacement estimates from the literature, and also moments from the data. The discount factor β is set to be 0.996 which translates into a 4.7% annual interest rate. I set the job finding rate $\lambda = 1/7$ to match the average unemployment length of 7 months in the data. Unemployment benefits are set at 0.4 while the parameter α which determines the diminishing marginal return in human capital production is set at 0.7 taken directly form Huggett et al. (2011). The parameter θ is set to be 0.025 in order to match the sudden drop in separation rate in Figure 9 after twelve months of job tenure.

Parameter	Description	Value
β	Discount factor	0.996
λ	Job finding probability	1/7
b	Unemployment benefit	0.4
α	Curvature of human capital investment	0.7
κ	Job separation constant	120
θ	Extra separation probability	2.5%

Table 4: Selected parameter values

Table 5 lists the parameters that I estimate using the Simulated Method of Moments and their estimated value as well[9]. I estimate the eight parameters of the accumulation functions for both types of human capital $((a_1, a_2, b_1, b_2, \xi_A, \xi_b, \delta, \phi))$. I estimate three parameters $(\xi_\sigma, \psi, h^s_\star)$ of the separation function $\sigma(\cdot)$. Finally, I estimate the elasticity of general human capital in the wage function and the minimum values of both types of human capital. I estimate the 14 listed parameters by minimizing the distance between moments from the data and their model-generated counterparts.

Parameter	Description	Estimated value
a_1	Lower bound of productivity of learning (general human capital)	0.01
a_2	Upper bound of productivity of learning (general human capital)	0.0092
b_1	Lower bound of productivity of learning (specific human capital)	0.012
b_2	Upper bound of productivity of learning (specific human capital)	0.0084
ξ_A	Curvature parameter on A	7.48
ξ_B	Curvature parameter on B	0.511
ξ_σ	Curvature parameter on σ function	0.327
ψ	Job separation parameter	0.0061
$h^s_\star$	Threshold for job separation probability	0.586
δ	Depreciation rate of human capital during employment	0.0002
ϕ	Depreciation rate of human capital during unemployment	0.006
γ	General human capital elasticity	0.567
h^g_{start}	Starting value of general human capital	0.688
h^s_{start}	Starting value of general human capital	0.524

Table 5: Parameters to be calibrated

I am targeting 13 moments listed in Table 6. First, I focus on matching mean earnings growth over the life cycle. I estimate the age effects in earnings over the life cycle following the methodology in Huggett et al. (2011):

[9]Online Appendix B presents the calibrated A_t, $B(h^s)$, and $\sigma(h^s)$ functions.

$$\ln(\text{earnings}_{j,t}) = \alpha_c + \beta_j + \epsilon_{j,t} \tag{8}$$

The β_j coefficients estimate the age effects on log earnings net of cohort effects. I target several points in the earnings profile relative to the the earnings at age 23. Let $\omega_j = \exp(\beta_j)/\exp(\beta_{23})$ denote the earnings growth at age j relative to age the of 23. The targets are $\{\omega_{25}, \omega_{30}, \omega_{35}, \omega_{40}, \omega_{45}\, \omega_{50}, \omega_{55}\}$. Matching these moments of the data is crucial in life cycle models as it guarantees a realistic earnings path.

Figure 8 displays the mean earnings profile over the life cycle estimated in the data and in the model using Equation 8. As can be seen, the model can match the earnings growth over the life cycle pretty well. Earnings double by the age of 48, and start declining after the age of 50 in the model.

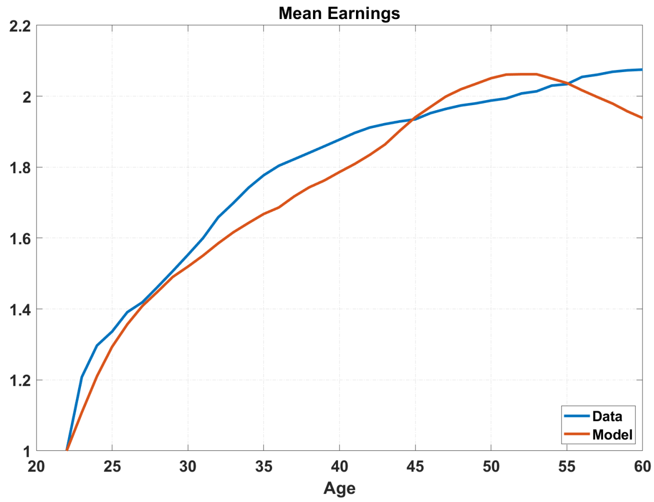

Figure 8: Mean earnings over the Life Cycle

Next, I follow the two-stage estimation strategy of Topel (1991) to tease out the return on general versus job-specific human capital. In the model experience is linked to the stock of accumulated general human capital as workers acquire it throughout their working life. Job tenure will be highly correlated with the accumulated stock of specific human capital in the model. Therefore, matching the contribution of experience and job tenure to wage growth in the model naturally informs parameters of the evolution functions of the two types of human capital. In the first stage, I estimate the within-job wage growth in the data as follows:

$$y_{it} - y_{i,t-1} = \beta_1 + \beta_2 + \epsilon_{it} - \epsilon_{i,t-1} \tag{9}$$

where $y_{it} - y_{i,t-1}$ is the first difference of log wages of individuals who stay with their employer in two consecutive years. The estimated $\widehat{\beta_1 + \beta_2}$ is a consistent estimate of the average within-job wage growth if $\epsilon_{it} - \epsilon_{i,t-1}$ has mean zero.

In the second stage of the estimation process of experience and tenure effects on earnings, the following regression specification is used to estimate the return to job tenure:

$$y - T \cdot (\widehat{\beta_1 + \beta_2}) = X_0 \cdot \beta_1 + e \tag{10}$$

where T is current job tenure, $\hat{B} = \widehat{\beta_1 + \beta_2}$, and X_0 is initial experience on the current job. This equation yields a consistent estimate of β_1, and thus of the return to job tenure. The return on experience is then computed as $\hat{B} - \beta_1$.

The Topel regression coefficients from the data suggest that an additional year of employment experience adds 1.8% to earnings while an additional year of job seniority adds on average 1.5% to earnings. The calibrated model overestimates the employment experience coefficient while underestimating the contribution of job seniority on earnings. One extra year of experience adds 2.1% to earnings while one extra year of tenure adds 1.4% to earnings.

To help calibrate the parameters of the separation function $\sigma(\cdot)$, I target three job separation probabilities as a function of job tenure. More precisely, I target the job loss rate at 6, 12, and 18 months of job tenure.

Figure 9 compares the job loss rate as a function of job tenure in the data and the model. Overall, the model generates a decent fit of the job loss rate throughout the first five years of a job. The model misses the sharp decline in the separation rate after the first six months of the firm-worker match and displays a more cautious decrease of the separation rate.

Finally, I target the average earnings losses of displaced workers one year after the

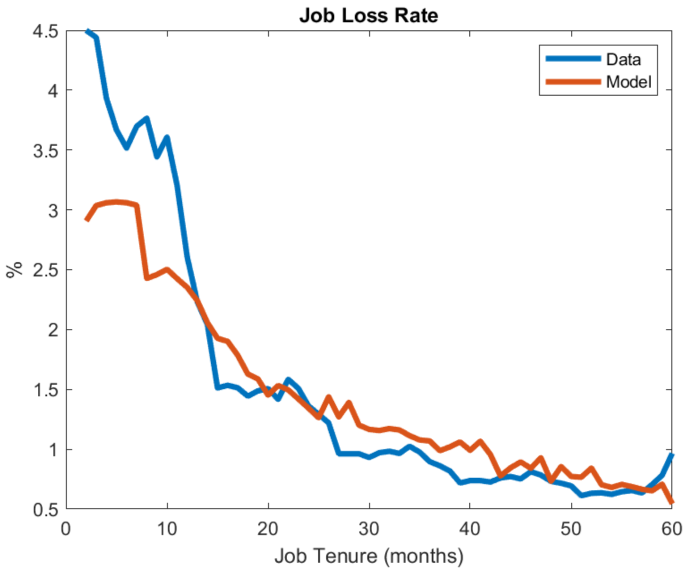

Figure 9: Job Loss Rate against Job Tenure

job loss which heavily influences the parameter γ which is the share of general human capital in the wage function. The general human capital share is estimated to be 0.572. That is, the share of general versus specific human capital in the wage function is 57%-43%. This estimate means that general human capital contributes more to wages and earnings.

Table 6 contains the estimated parameters of the model and also displays the targeted moments of the data and their model-generated counterparts.

Moment	Data	Model
Average rate of job loss, tenure 6m	3.5%	3.06%
Average rate of job loss, tenure 12m	2.60%	2.35%
Average rate of job loss, tenure 18m	1.44%	1.62%
ω_{25}	1.33	1.29
ω_{30}	1.55	1.52
ω_{35}	1.77	1.67
ω_{40}	1.87	1.79
ω_{45}	1.93	1.94
ω_{50}	1.98	2.05
ω_{55}	2.03	2.03
Topel regression β_1	0.018	0.021
Topel regression β_2	0.015	0.014
Earnings Losses in year 1	47.7%	53.8%

Table 6: Estimated parameters

6 Results

In this section I examine the extent to which my framework can capture the life cycle patterns for earnings losses after a displacement event. As shown in the empirical section, earnings and employment losses following displacement vary over the life cycle, both in terms of the immediate loss and also the path of recovery over the years after the separation.

6.1 Earnings Losses

First, I report how my model performs in terms of earnings losses. I follow the same criteria as in the data to construct the displaced worker subsamples. Figure 10 displays the estimated earnings losses of the four age groups in the model (right panel) compared to the estimates from the data (left panel). Three patterns emerge in my model. First, earnings losses are increasing in the age at the time of job displacement. Second, earnings losses are more persistent in the long run for older age groups. Third, differences in terms of earnings losses are increasing across the age groups in the early years after the separation, then they consolidate around eight years after the job displacement.

In terms of persistent earnings losses, my model can match long run losses for the three older age groups quite well. My model overstates the earnings losses of the youngest age group, which is not surprising. The nature of the Ben Porath model does not make it possible to get complete recovery for any of the age groups. This is because once a worker loses his job and his accumulated specific human capital as a consequence, he faces a very similar problem as when he started his career at the age 20 in the model. The only three differences are the higher stock of general human capital, the lower learning productivity of the A_t function, and a shorter time horizon left from their career. As displaced workers face a shorter time period, they will not be able to catch up to their peers who do not experience a job displacement.

As mentioned before, the losses are increasing across the age groups on impact and in the long run. The model successfully generates heterogeneous recoveries for the age groups. Moreover, the model can also generate the increasing earnings difference between

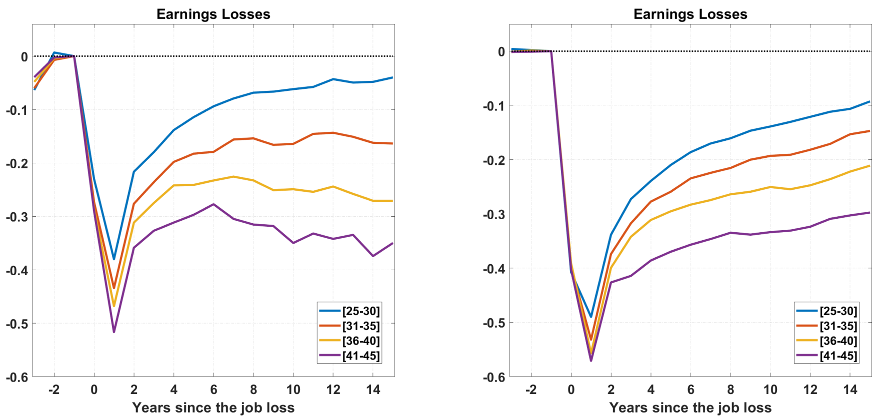

Figure 10: Earnings Losses, Data (left panel) and Model (right panel)

the two youngest age groups over the years after the separation occurs. This is due to the fact that the youngest age group keeps decreasing the gap relative to their control group, while older age groups display more conservative earnings recoveries in the long run.

Overall, the model can generate a 24.5% difference in terms of earnings losses across the age groups fifteen years after the job displacement event. In the data this difference is 34.4% which means that the model can account for slightly more than two thirds of the persistent differences.

6.2 Employment Losses

Next, I examine how well the model does in terms of employment losses over the life cycle. In the data I find persistent long run employment losses that are increasing with the age at the time of the job displacement. However, the shape of employment losses are very similar over the life cycle, which is different to the earnings losses.

Figure 11 displays the estimated employment losses, the left panel shows the estimated losses in the data while the right panel shows the estimated losses from the model. Employment losses are the same on impact for all age groups as the job finding rate is constant in the model, matching the average time spent within two full-time jobs of 7 months. The model can generate the flattening out of the losses around four years after

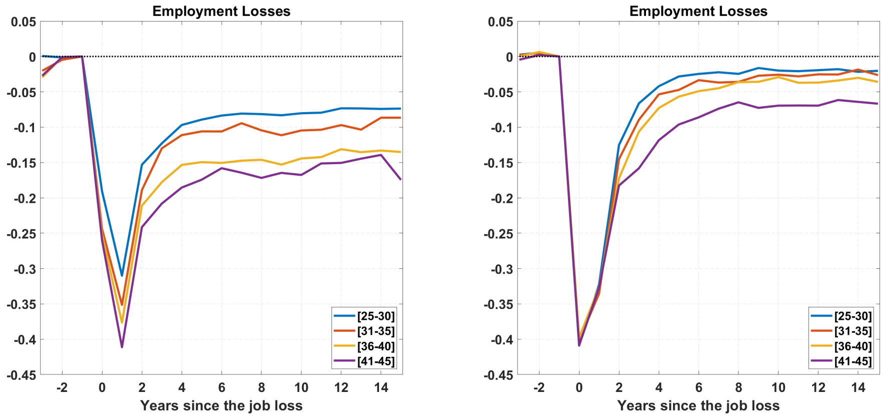

Figure 11: Employment Losses, Data (left panel) and Model (right panel)

the job loss. The model can also match the fact that older displaced workers suffer larger employment losses over the years. However, the model fails to match the size of the persistent employment losses for all age groups. The model underestimates the persistent employment losses fifteen years after the displacement event. The persistent employment losses for the three younger age groups are between 2% and 4% relative to their control group. Members of the oldest age group experience an 8% employment loss in the long run. The model can generate slightly more than 50% of the persistent employment losses of the oldest age group, while only 30% of the other three age groups.

7 Underlying Mechanism

In this section I provide insight into which model features generate the long term earnings losses and the substantial differences across the age groups. In my model, due to the nature of the Ben Porath model, workers spend more time accumulating human capital in the early years of their career, yielding high earnings growth early on in the worker's life then slowing down substantially later in the career. I introduce two additional forces in my model: the possibility of job displacement, and two types of human capital, one of which is lost upon separation. In this section I show how these forces shape the earnings losses over the life cycle.

7.1 Human Capital Stock in the Model

In this subsection, I investigate how earnings losses look for the four age groups if only the employment status is lost upon displacement. In my model, upon displacement the worker loses his accumulated specific human capital, then goes through months of unemployment where he sees his general human capital depreciate. Upon reemployment, the worker optimizes his time spent on rebuilding some of his lost human capital.

In addition to general human capital depreciating, the cost of time spent not working is time spent not learning and not accumulating human capital. As I estimate the learning productivity of general human capital to be decreasing in age, a standard Ben Porath model would imply that time spent in unemployment will be more damaging for younger age groups.

Throughout the exercise, I look at earnings losses of each age group had they not lost their accumulated specific human capital upon separation. More specifically, I only allow the effect of an unemployment spell on earnings to take place without the burden of the depletion of specific human capital. This means that in this exercise specific human capital behaves like general human capital and the accumulated stock is kept after an unemployment spell. Upon reemployment, the worker starts his new job with the same amount of specific human capital that he had when he was displaced from his previous job. This way, I disentangle the permanent earnings losses coming from time spent in unemployment.

Figure 12 plots the model generated earnings losses in the left panel while the right panel plots the implied earnings losses of each age group in case of no lost specific human capital upon a job displacement. Comparing the two panels of Figure 12, two patterns arise: losses and differences across the age groups are compressed, and the order of the severity of earnings losses is flipped.

To be more specific about the first pattern, earnings losses on impact are approximately halved. This is mainly because wages do not decline as there is no lost human

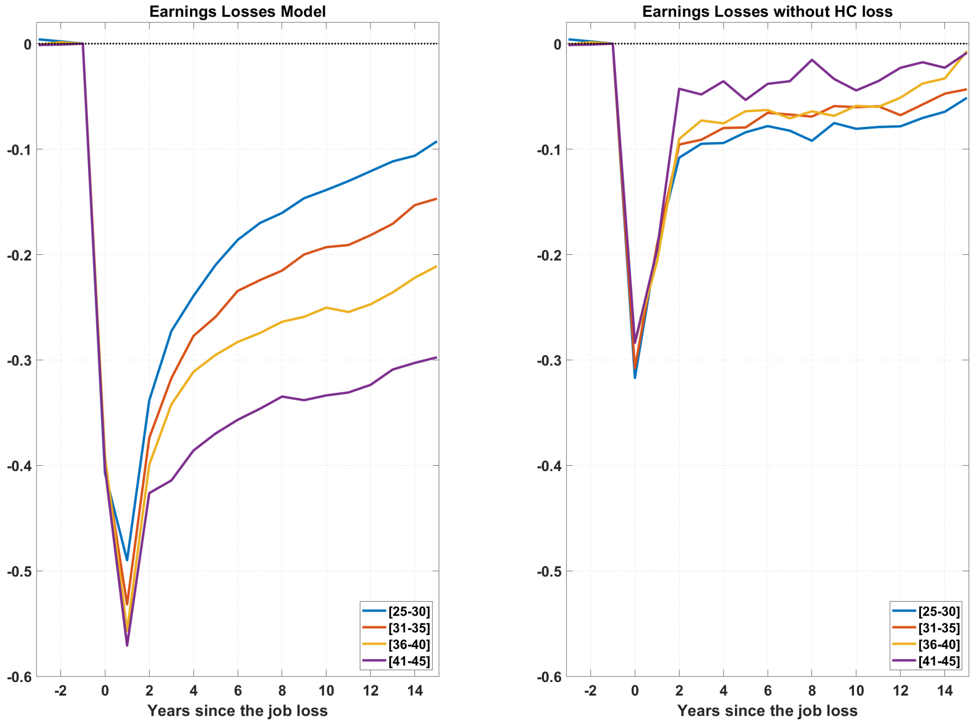

Figure 12: Job Loss without Human Capital Loss

capital. In addition to the stock of accumulated specific human capital staying intact, the separation probability does not jump back to the highest level[10].

To be more specific about the second pattern, and as previously anticipated, the youngest age group suffers the biggest earnings losses on impact, and overall throughout the fifteen years after the separation occurs. The two oldest age groups catch up to their peers in terms of earnings over the fifteen years. Members of the youngest age group experience larger earnings losses than any other age group. Their earnings are still approximately 5% lower than the control group's in the long run. This is mainly due to the fact that the time younger displaced workers spend not working is much more productive than for the oldest group. Moreover, during the time that younger displaced workers spend not working their peers in the control group continue to learn. On the other hand, when older workers go through an unemployment spell, the time they spend in unemployment without accumulating human capital is less productive and by that age,

[10] The $\sigma(\cdot)$ separation function has the maximum value when the specific human capital is at the minimum level, which happens to be at the first month of a new job.

most of the human capital stocks are already accumulated. This means that older age groups only lose a small fraction of their general human capital stock, but they do not pay the extra cost of falling behind their peers due to missing out on highly productive learning while not working.

With this exercise I conclude that time spent in unemployment is more damaging for younger workers. The impact of an unemployment spell on persistent earnings losses is small, at most 5% for the youngest age group. Moreover, an unemployment spell cannot generate the observed large differences across the age groups in any way.

7.2 Response to a Job Displacement in the Model

In this subsection, I focus on what role the loss of specific human capital plays on earnings losses. Upon a job displacement, the accumulated specific human capital stock is depleted in my model. That yields a large decline in wages and also an increase in job separation probability. Upon reemployment, workers must decide whether they increase their time spent on rebuilding their lost human capital or focus on production without recovering most of their lost human capital. Due to the nature of the Ben Porath model, younger workers are expected to rebuild a big chunk of their lost human capital, while older displaced workers are expected to spend most of their time with production rather than learning.

The differences across age groups and how responsive they are to a job displacement can be explained by Figure 13. I run the benchmark regression from Equation 1 using $\log(i_t^s + i_t^g)$ as the dependent variable. Thus I look at how much more or less the displaced age groups spend on investing in human capital relative to their respective control groups.

All four age groups experience a decline in time spent on human capital investment in the displacement year simply because of the unemployment spell. The two younger age groups then increase their time spent on accumulating human capital by 34% and 17% compared to their peers. On the other hand, the two oldest groups actually reduce their time spent on acquiring human capital compared to their peers by 47% and 25%. Thus instead of rebuilding their lost stock of specific human capital, the two oldest displaced groups focus on production and increasing their earnings by spending more time working.

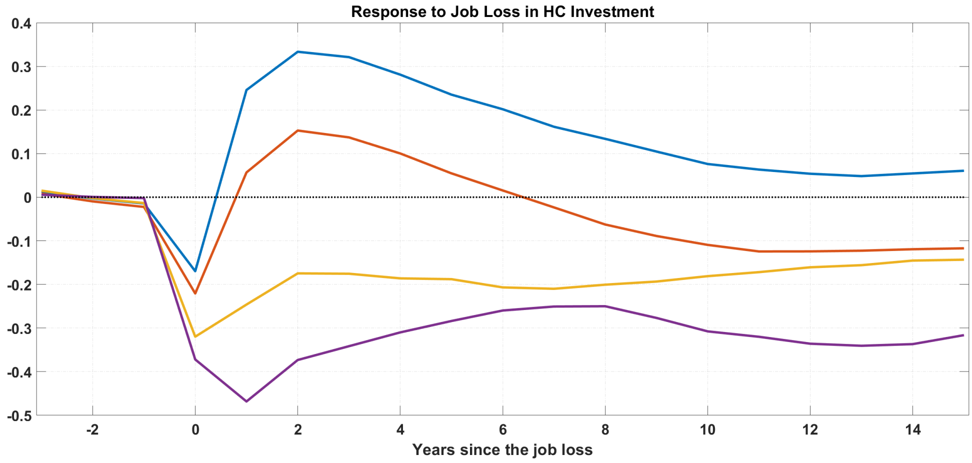

Figure 13: Response to a Job Loss in Human Capital Investment

Figure 13 sheds some light on the differences in earnings losses in the long run as well. Only the youngest age group keeps their human capital investments above their peers' all fifteen years after the job loss. This translates into a steep and continuous earnings growth that yields a decreasing gap between the displaced and the control group. The displaced group with members experiencing a job loss between the ages of 31 and 35 first increase their time spent on human capital accumulation then gradually reduce it over the years, keeping it slightly below their control group seven years after the displacement. This investment path yields a steep earnings recovery at first, then a slower recovery after eight years. The two oldest age groups even reduce their human capital investments.

My second exercise aims to show how the four age groups respond to a job loss in terms of rebuilding their lost human capital. In this exercise, the four age groups go through the unemployment spell and lose their accumulated specific human capital. I shut down the displaced workers' optimal human capital investment channel as follows: instead of letting displaced workers choose how much time they spend accumulating and rebuilding specific human capital, I force them to do exactly what their respective control group chooses. In the model, the trade-off is earning more today by spending more time producing rather then learning, or earning less today and investing time in acquiring human capital that will substantially increase earnings in the future.

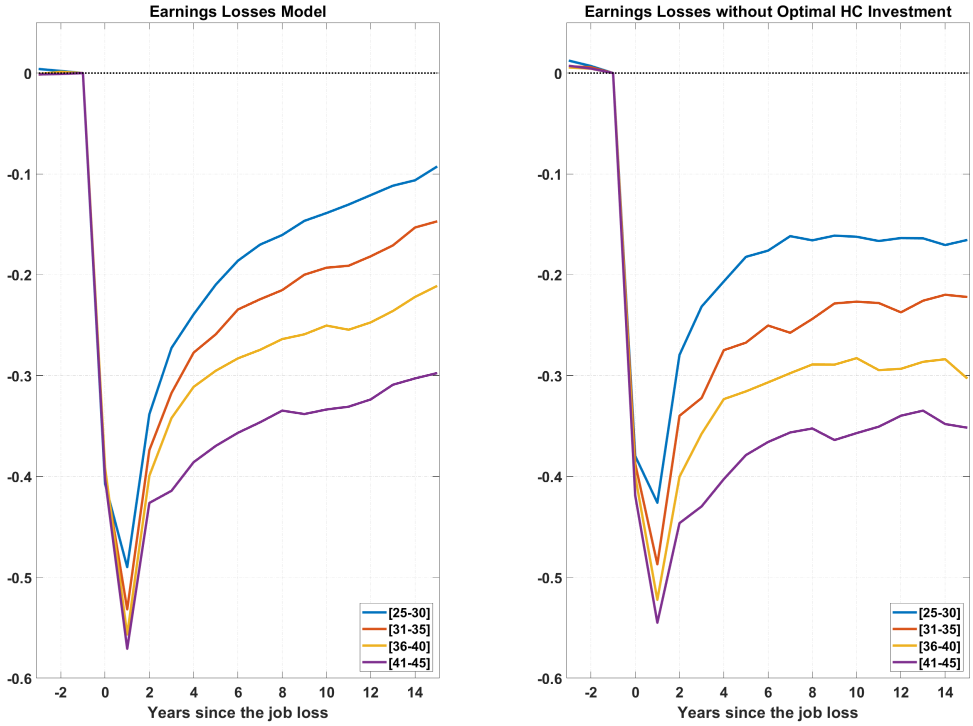

Figure 14: Job Loss without Optimal Human Capital Investment

Figure 14 plots the results of this exercise. The left panel shows the model generated earnings losses using the estimated parameters and letting workers follow the optimal human capital investment paths. The right panel plots earnings losses of the four age groups had they followed the same human capital investment strategy as their respective control group. Three patterns arise in the right panel: differences on impact increase, estimated earnings losses flatten out six years after the separation occurs, and persistent earnings losses are shifted down for all age groups.

These patterns can be explained by Figure 13. Once reemployed, the two youngest age group would increase their time learning which would dampen their earnings on impact. This exercise however forces these groups to spend less time learning, and thus more time producing which increases their wages in the first years after reemployment. As time progresses, the reduced investment in learning translates into lower wages in the long run and puts a halt on catching up to their control groups. On the other hand, the losses of the two oldest age groups are larger on impact. This is due to the fact that optimally, they would spend less time learning than their peers in the control group. By forcing them to spend more time learning, their earnings are reduced on impact. In the long run, their persistent earnings losses increase due to the fact that even though they rebuild more of their specific human capital stock than they would optimally do, their earnings are lower due to the reduced time spent on production and thus earning money.

This exercise shows that optimal human capital investment generates substantial differences in earnings losses on impact, moreover it also governs the shape of the long term earnings losses.

8 Conclusion

This paper has documented that persistent mean earnings and employment losses upon a job displacement substantially differ over the life cycle. Workers who are displaced between the ages of 41 and 45 experience seven times larger earnings losses than those workers who are displaced between the ages of 25 and 30. I propose a life cycle model with two types of human capital that are accumulated while on-the-job. Upon displacement the accumulated stock of specific human capital is lost. Older workers thus lose more human capital on average as they have had more time to accumulate human capital throughout their career while younger displaced workers suffer smaller losses on impact. Moreover, separation probabilities are tied to the stock of accumulated human capital which means that displaced workers are more likely to experience recurring job losses once reemployed.

The estimated model can match the large differences in persistent earnings losses and the shape of the estimated employment losses of the age groups. The model offers an explanation to the observed differences suggesting that workers respond to a job displacement differently in terms of reinvestment in specific human capital over the life cycle. I estimate that younger workers respond to a job loss by spending 34% more time rebuilding their lost human capital while older displaced workers reduce their time spent accumulating human capital by around 47%.

These results serve as a starting point for future research. The model suggests that the direct effect of an unemployment spell scars the youngest displaced workers the most, thus studying the long-term effects of the increase in youth unemployment on earnings is an urgent issue. The model can be used to study the effects of policies such as training programs on earnings dynamics at different ages. The empirical findings suggest that these policies are of first order as the aging of the labor force could result in larger mean earnings losses in the future.

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A Mass-Layoff Sample

I describe the mass-layoff displaced worker sample in this section. For a worker to qualify as a displaced worker, he needs to meet all conditions outlined in the benchmark sample, with only two exceptions. I no longer require displaced workers to receive unemployment benefits within two months of the separation and I only impose a one-year job tenure requirement at the time of displacement, but instead, I require them to separate from a firm that goes through a mass-layoff. I follow Davis and Von Wachter (2011) to identify a mass-layoff[11] event in year y as follows: (i) the firm has at least 50 employees in year y-1, (ii) the number of employees decreases by 20% to 99% from year y-1 to year y+1, (iii) the labor force of the firm in year y-1 is no more than 130% of the employment in year y-2, (iv) labor force of the firm in year y+1 is less than 90% of the employment in year y-2. These conditions ensure that firms going through temporary fluctuations in employment are not included, though, some layoffs are excluded with these strict conditions.

Table 7 shows summary statistics of the mass-layoff displaced worker sample and its control group. As can be seen, the mass-layoff worker sample look similar in terms of age, job tenure, and daily wages to its control group. Compared to the benchmark sample in Table 1, displaced workers who go through a mass-layoff spend more time in unemployment[12], experience a higher wage reduction (11.4%) on average compared to the benchmark displaced worker sample (9%). The number of displaced workers going through a mass-layoff event is 3 959, while the benchmark displaced worker sample has 20,246 distinct observations[13].

Figure 15 displays the estimated earnings and employment losses of the mass-layoff displaced worker sample relative to the control group. The reduction in earnings is significant and long-lasting for displaced workers. Compared to the control group's earnings level, 5 years after displacement earnings are around 20% lower, then it flattens out at around 18.5% in the long run. The estimated employment losses mirror the shape of the earnings losses over the years. There is a large reduction on impact due to the separa-

[11] Small changes are made when identifying a mass-layoff, see Davis and Von Wachter (2011) for further comparison

[12] Displaced workers going through a mass-layoff event are not required to receive unemployment benefit, thus it would be more accurate to say that they spend more time non-employed.

[13] The small size of the mass-layoff sample do not let me partition it like I do the benchmark sample.

	Mass-Layoff	Control
Age (years)	34.2	36.6
Job tenure (months)	63	64
Wages (daily, in euros)	90	112
Unemp. spell (months)	8.4	
Wage change (%)	-11.8	
Number of obs.	3 959	223 872

Table 7: Summary Statistics of the Mass-Layoff Sample and its Control Group

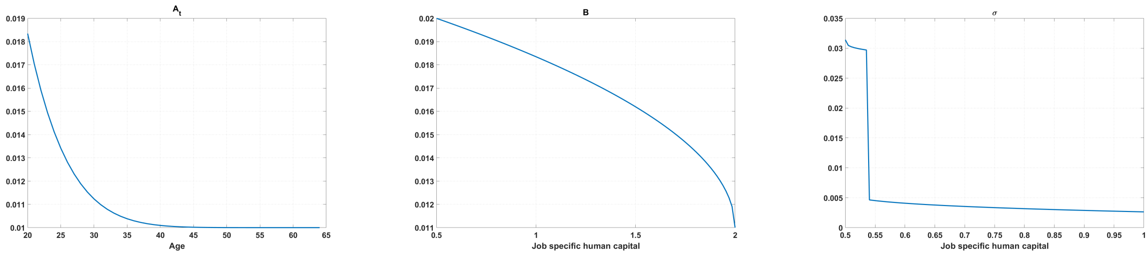
tion followed by time spent in unemployment. In the long run, employment losses are substantial at around 7.5% fifteen years after the displacement event.

Comparing Figures 1 and 15, the estimated losses both in terms of earnings and employment are slightly higher for the mass-layoff sample, but the patterns over the years are very similar.

Figure 15: Earnings and Employment Losses of Displaced Workers, Mass-layoff Sample

B Functions: A, B, and σ

Figure 16 plots the estimated A_t, B, and σ functions. Panel (a) displays the learning productivity of general human capital over the life cycle. The learning productivity of general human capital is rapidly declining over the early years of the life cycle. Panel (b) plots the estimated learning productivity function of specific human capital over the human capital grid. Contrary to the panel (a), the learning productivity of specific human capital declines slower over the human capital grid. Panel (c) shows the estimated job separation function over the specific human capital grid. At the beginning of a job match, the separation probability is the highest, then after reaching the threshold level of accumulated specific human capital ($h^s_\star$), the separation probability drops by θ and slowly declines afterwards.



(a) A_t function (b) $B(h^s)$ function (c) $\sigma(h^s)$ function

Figure 16: Estimated learning productivity functions (panels (a) and (b)) and job separation probability function (panel (c))