The Heterogeneous Costs of Job Displacements*

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Abstract

A large literature has documented that job displacement entails large and persistent reductions in earnings. I extend this literature by documenting the extent of heterogeneity in the estimated earnings losses associated with job displacements. I explore the ability of several factors to statistically explain the heterogeneity in persistent earnings losses across individuals. I find that age at the time of displacement, the immediate wage change upon reemployment, and educational attainment account for most of the variation in the estimated earnings losses. I leverage the richness of the dataset and partition the displaced worker sample along several dimensions to estimate earnings and employment losses.

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1 Introduction

This paper documents the extent of heterogeneity in the estimated mean earnings losses associated with job displacement using German social security data covering private sector workers from 1975 to 2010. To analyze the heterogeneity in the estimated earnings losses, I first construct two displaced worker samples: I construct the benchmark sample following the criteria of Jarosch (2022), and I construct the mass-layoff displaced worker sample following the criteria of Davis and Von Wachter (2011). I use the less restrictive benchmark sample throughout most of the paper due to the larger number of observations needed to create further subsamples of displaced workers. I repeat the exercises on the mass-layoff sample to show that my results are independent of the sample selection criteria.

Using both displaced worker samples, I first recover the residuals from the standard displaced worker regression framework (Jacobson et al. (1993), Stevens (1997)) for every individual and every year after the displacement event. I present several properties of the residuals such as their average, the distribution of the residuals and some correlates over the years after separation. The variation in the residuals is large over all years. For instance, five years after the job loss event, ten percent of the displaced workers have earnings that are at least 50% lower than the control group's. On the other extreme, ten percent of the displaced workers see their earnings exceed their peers' by around 22%. The gap between the 10th and 90th percentile widens over the years.

As a next step, I explore the ability of several factors to statistically explain the heterogeneity in persistent earnings losses across individuals. In order to do so, I sum up the residuals from the last three years, more precisely, the residuals 13, 14, and 15 years after the displacement event for all individuals. Then, I regress the sum of the residuals on observables to find out which factors at the time of the displacement have significant explanatory power in the long run. I run this regression exercise on both the benchmark and the mass-layoff sample. I regress the sum of the residuals (starting from year 13 after the job loss) on the age at the time of job loss, the immediate wage change upon reemployment, the time it took the displaced worker to find his first full time job after displacement, the size of his new establishment upon reemployment, the size of his previous establishment, the job tenure he had at the time of displacement, a dummy indicating whether the worker switched occupations upon reemployment, and whether the worker holds a college degree or not. Coefficients of variables such as age at the time of the job loss, immediate wage change, the length of the unemployment spell and whether the worker has a college degree are significant and can explain around 9% of the variation. Moreover, I show the regression results only including age at the time of job loss and immediate wage change as the explanatory variables. Both are significant and can explain around 8.4% of the variation.

After estimating how the observables correlate with long run earnings losses, I partition the benchmark displaced worker sample along these factors and estimate earnings losses of each subsample. Partitioning the benchmark sample based on age at the time of job displacement, I find that earnings losses associated with a job displacement both on impact and in the long run are increasing in age. The estimates indicate two striking observations over the life cycle. First, as people age earnings losses are increasing on impact. Second, the pace at which earnings catch up to the earnings of the respective control groups gets flatter as people age. Partitioning the displaced worker sample based on job tenure at the time of displacement shows three patterns: first, losses are increasing with job tenure on impact. Second, the slope of earnings recovery in the long run displays diverging patterns across the groups of displaced workers. Third, persistent losses originating from wage losses are mostly present for those with more job tenure.

I also partition the benchmark sample based on factors that are only observable once the displaced worker finds a new full-time job. The first such factor is the relative wage change upon reemployment. Displaced workers who experience a positive wage change upon reemployment recover over the long run, while those displaced workers who experience a substantial wage reduction upon reemployment suffer large and persistent earnings and employment losses up to 15 years after the displacement event. Estimating earnings and employment losses based on time spent in unemployment between two full-time jobs displays three patterns: first, initial earnings losses are increasing in the time it takes to find a full-time job. Second, the slope of earnings recovery flattens out after four years and the gap between the groups stays constant after the fourth year.

Third, the incompleteness of earnings recovery is increasing in the time spent finding the first full-time job after displacement. Finally, I partition the benchmark displaced worker sample based on the size of the establishment workers find their first full-time job after the separation. I find that there is a substantially large and persistent 10% difference between those displaced workers who find reemployment in a relatively small establishment (with less than 50 people) and those who find reemployment at an establishment with at least 50 employees.

1.1 Related Literature

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) and Davis and Von Wachter (2011). 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), Lachowska 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. I contribute to this literature by leveraging the richness of the dataset to first explore the heterogeneity along several factors, then to partition the sample along these factors and estimate the persistent earnings and employment losses of these subsamples.

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 extent of heterogeneity in the estimated losses, Section 4 introduces the partitioned subsamples and the estimated earnings and employment losses.

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[3], 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[4]. If the individual is reported to be part-time working in the given month, then I assign him a 0.5 as his monthly employment status. 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 job displacement if the worker separates from his employer and receives some unemployment benefit within two

[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. Some variables were deleted, such as number of children, place of residence.

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

[3] There are approximately 310 occupations in the dataset.

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

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, job tenure as months of continuous employment with the same employer. I calculate the immediate wage change associated with a displacement as the % 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. The change in the establishment size is computed as the difference between the size of the establishment of the new full-time employer and the size of the establishment of the previous full-time employer. I follow employment histories month by month, then I aggregate the monthly dataset into an annual panel.

The first five monthly variables that I aggregate into an annual variable are the following. 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]

In the forthcoming sections, I partition the benchmark displaced worker sample along several dimensions. I keep track of several observables at the time of the displacement event and observables that are only observable at the time of the first employment month after the unemployment spell. At the time of displacement, I keep track of age, job tenure, educational attainment, the size of the establishment and the 3-digit occupation code of

[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 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.

the job the displaced worker filled in right before the separation. Once I see the displaced worker being reemployed in a full-time job upon the unemployment spell, I record the length of the unemployment spell in between two full-time jobs, whether the individual changed 3-digit occupations, the new establishment size, and the change in daily wages compared to what the worker received right before the displacement occurred. Thus in the annual panel whenever the dummy indicates that the individual experienced a displacement event in a given year, I record the aforementioned variables as well.

2.2 Displaced Worker Samples

In this section I describe two criteria for creating samples of displaced workers. First, I present how I construct the benchmark displaced worker sample; then I present the mass-layoff displaced worker sample constructed using the Davis and Von Wachter (2011) criterion. I use the less restrictive benchmark sample throughout most of the paper due to the larger number of observations needed to create further subsamples of displaced workers. In this section I argue that using the benchmark displaced worker sample rather than more conventional mass-layoff sample yields very similar results.

2.2.1 Benchmark Displaced Worker Sample

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 **?**. 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 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 **?**. 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.

2.2.2 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,

	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

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[7] 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 2 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[8], 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[9].

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

[8]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.

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

3 Earnings and Employment Losses

In this section I describe the main methodology I use to estimate the earnings and employment losses associated with displacement. Then, I present the results both for the benchmark and the mass-layoff displaced sample. Finally, I investigate the heterogeneity of the regression residuals.

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

3.1 Methodology

Equation 1 presents the benchmark regression framework that I use to estimate earnings and employment losses associated with a displacement.

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

where y_{it} is the outcome variable (log annual earnings, log employment index), $\bar{e}_i$ is the average wage of the worker in the two years before displacement. α_i is the person fixed effect, while γ_t is the year fixed effects. ϵ_{it} represents random factors. D_{it}^k are dummies that indicate displaced workers k years after displacement. For instance, $D_{i,1995}^{-2} = 1$ for individual i in year 1995 if and only if he goes through a displacement event in 1997. All the other dummies in 1995 are set to 0 for individual i. The same individual will have $D_{i,2000}^{3} = 1$ in 2000 and $D_{i,2008}^{11} = 1$ in 2008. As for members of the control group, as previously mentioned, every member of the control group is present for only 19 years.

More precisely, if an individual j qualifies as a member of the control group multiple times, i.e. in 1992, 1993, and 1994, I pick a year randomly, for instance 1993 and then set all the dummies to 0 from 1990 until 2008 for individual j.

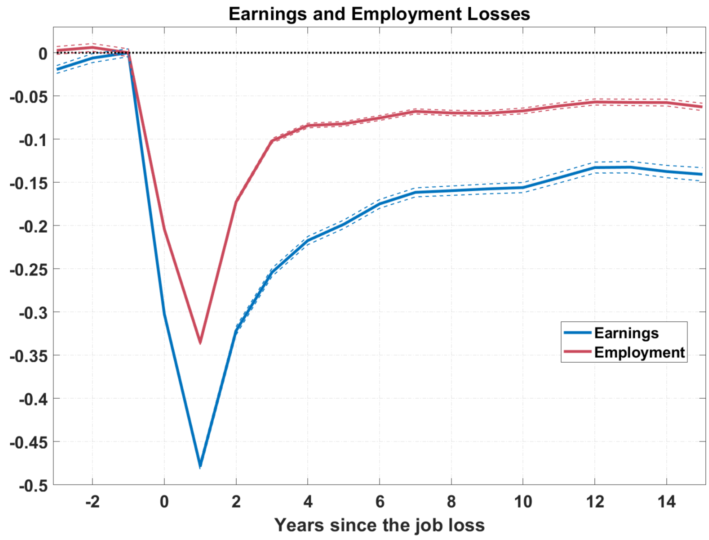

Figure 1: Earnings Losses of Displaced Workers

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.

3.2 Results

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.

Figure 2 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 separation 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 2, 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.

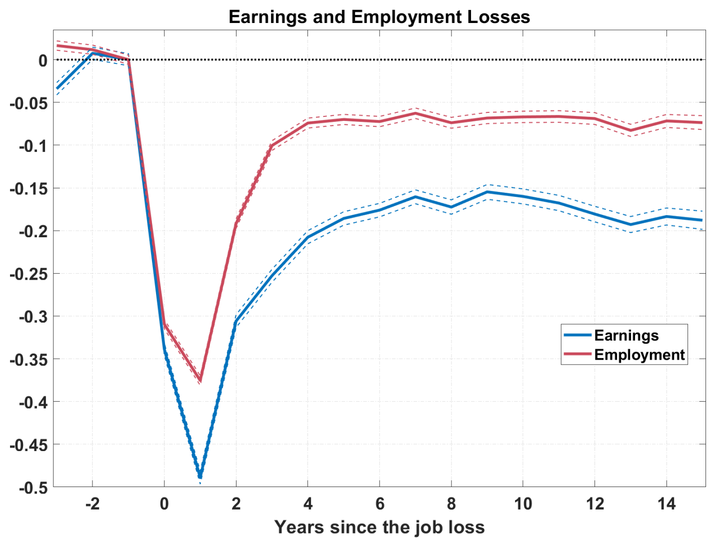

Figure 2: Earnings and Employment Losses of Displaced Workers, Mass-layoff Sample

3.3 Heterogeneity in Effects

The previous subsection reported the average earnings and employment effects associated with displacement. These mean effects have been the main focus of the existing displacement literature. In this subsection, I first document the extent of the heterogeneity in the estimated mean effects, then I assess which factors correlate with individual losses.

To do this, I recover the residual from Equation 1 for every displaced worker and every year after the displacement event. The residual $\epsilon_{it} = y_{it} - \hat{y}_{it}$ is the difference between the realized annual earnings of individual i in year t and the mean estimated annual earnings after the displacement event. If ϵ_{it} is positive, that means that realized earnings are larger than the mean estimated earnings and if ϵ_{it} is negative, then the actual annual earnings after displacement are smaller than the mean estimated earnings.

I calculate these ϵ_{it}s for every displaced worker who is present in the dataset for all 15 years after displacement as I want to be able to compare a series of ϵ_{it} for all years. I then sum up the ϵ_{it}s starting from 5 years after displacement all the way to 15 years after displacement. I have 4 862 displaced workers satisfying the selection criteria. As a first step, I examine some properties of the residuals ϵ_{it}. More precisely I present several properties of the residuals such as their average, the distribution of the residuals and some correlates over the years after separation.

I start my analysis of the heterogeneity of persistent earnings losses by plotting the distribution of $\delta_s + \epsilon_{i,d+s}$ where d is the displacement year for individual i, starting five years after the displacement event. Figure 3 plots the distribution of the $\delta_s + \epsilon_{i,d+s}$s for every year after the job loss. The figure displays the 10th, 25th, 50th, 75th, and the 90th percentile of the residuals of the benchmark regression. As can be seen from Figure 3, the variation in the residuals is large over all years. For instance, five years after the job loss event, ten percent of the displaced workers have earnings that are at least 50% lower than the control group's. On the other extreme, ten percent of the displaced workers see their earnings exceed their peers' by around 22%. The gap between the 10th and 90th percentile widens over the years, fifteen years after the displacement event, the 10th percentile of the $\delta_{15} + \epsilon_{i,15}$s are around 40% lower than the earnings predicted by the benchmark regression, while the 90th percentile is around 42% higher than the predicted earnings.

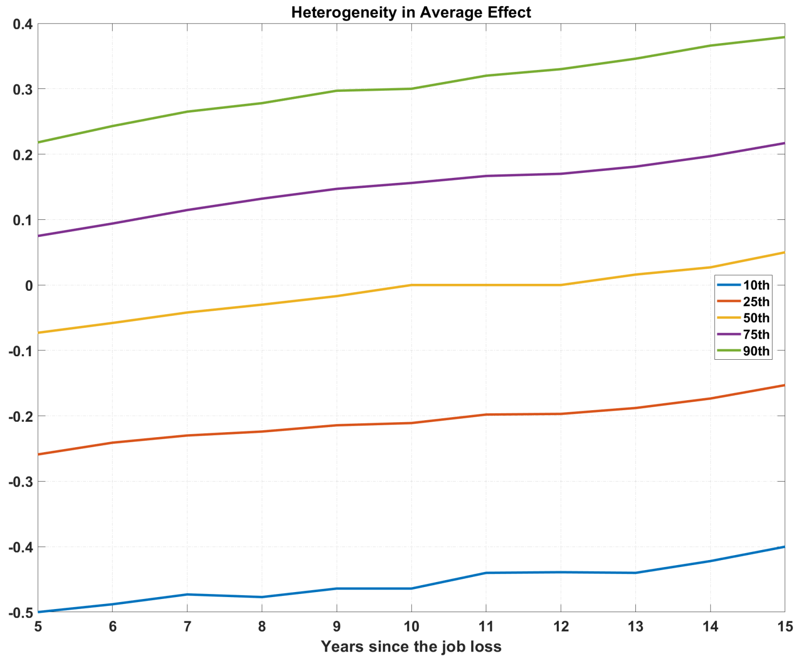

Figure 3: Distribution of $\delta_s + \epsilon_{i,d+s}$ after the displacement event

As the next step of the analysis of individual heterogeneity effects, I define the average sum of residuals (ASR) for individual i in Equation 2:

$$ASR_i = \sum_{s=5}^{15} \frac{\epsilon_{id+s}}{11} \tag{2}$$

where d denotes the displacement year.

I start summing up the errors 5 years after the displacement event in order to focus on the persistent losses. The first years after a job loss might be dominated by temporary factors associated with the initial separation.

Figure 4 shows the correlation between ASR and the errors for each year after displacement starting from year 5.

As the figure shows, the average sum of residuals (ASR) is highly correlated with the residuals each year after displacement. Moreover, the correlation is increasing over the years, thus the ASR can be used to describe persistent earnings losses after displacement. In the next section, I group these displaced workers based on their ASR and try to

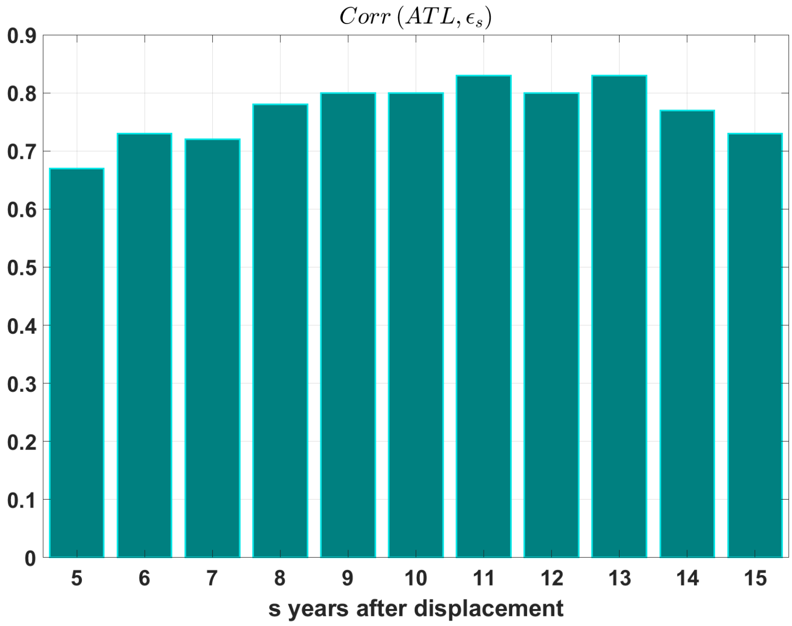

Figure 4: Correlation between ASR and ϵ_s

characterize the groups. I also ask which characteristics could predict high and low ASRs.

4 Explanatory Factors

In this section I explore the ability of several factors to statistically explain the heterogeneity in losses across individuals. To do so, I use a modified version of the ASR and regress it on observables to determine which variables can explain most of the variation in persistent earnings losses. In the previous section I showed that the ASR is highly correlated with the residuals in the long run, this finding leads me to use a modified version of ASR. I only sum up the last three years of the residuals, i.e. $\mathrm{ASR}_i^3 = \sum_{s=13}^{15} \frac{\epsilon_{it+s}}{3}$. Then, I regress this on observables to find out which observables at the time of the displacement have significant explanatory power in the long run.

Table 3 documents the regression results[10]. The first three columns display regression results using the benchmark displaced worker sample, while the last three columns displays the regression results using the mass-layoff sample. In the first and fourth col-

[10] I include the regression results of both the benchmark and the mass-layoff sample when I sum up the last 5 years of residuals in the Appendix. Results are very similar to the case presented in the paper.

umn I regress the sum of the residuals (starting from year 13 after the job loss) on the age at the time of job loss, the immediate wage change upon reemployment, the time it took the displaced worker to find his first full time job after displacement, the size of his new establishment upon reemployment, the size of his previous establishment, the job tenure he had at the time of displacement, a dummy indicating whether the worker switched occupations upon reemployment, and whether the worker holds a college degree or not. Columns (1) and (4) show similar patterns. Coefficients of variables such as age at the time of the job loss, immediate wage change, the length of the unemployment spell and whether the worker has a college degree are significant and can explain around 9% and 10% of the variation in the ASR. Columns (2) and (5) show the regression results only including age at the time of job loss and immediate wage change as the explanatory variables. Both are significant and can explain around 8.4% and 9.5% of the variation in the ASR. Columns (3) and (6) regress the ASR on age at the time of displacement only and find an explanatory power of 4.7% and 6.5%. Therefore age at the time of displacement accounts for around half of the variation in the ASR alone. It is important to note, that all coefficients on age at the time of displacement are significant and negative, meaning that older displaced workers have lower realized annual earnings than the mean estimated annual earnings.

Figures 5 and 6 display the 25th, 50th, and 75th percentile of $\delta_s + \epsilon_{i,d+s}$ partitioned by the age at the time of displacement and whether the individual changes occupations upon finding his first full-time job after separation respectively. Figure 5 shows significant variation in the residuals across age groups in all three percentiles. The difference between the youngest and the oldest job losers are on average around 20%, 15%, and 15% at the 25th, 50th, and the 75th percentile. These differences are 6%, 4% and 4% between those who stay in their 3-digit occupation and those who switch occupations after the displacement event. These differences are in line with what I find in Table 3, namely that age at the time of displacement accounts for around half of the variation in ASR, while the fact that whether the job loser switches occupation or not after the separation does not explain much of the variation of ASR.

	Benchmark Sample			Mass-Layoff Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Age (years)	-0.049***	-.058***	-.059***	-0.068***	-.08***	-.09***
	(.007)	(.004)	(.003)	(.017)	(.011)	(.012)
Wage change (%)	0.63***	1.24***		0.47	1.74***	
	(.182)	(.102)		(.46)	(.288)	
Unemp. spell (months)	-0.024*			-0.06**		
	(.0142)			(.03)		
New estab. size	.00004**			.00004		
	(.00002)			(.00003)		
Establishment size	-.00002			-.000007		
	(.000016)			(.00003)		
Job tenure (months)	.0009			-.003		
	(.0014)			(.003)		
Occ. switch	-.101			-.002		
	(.087)			(.23)		
College	.582***			1.09**		
	(.246)			(.5)		
R^2	0.09	0.084	0.047	0.103	0.095	0.065

Table 3: Regression Results, dependent variable ASR_i^3

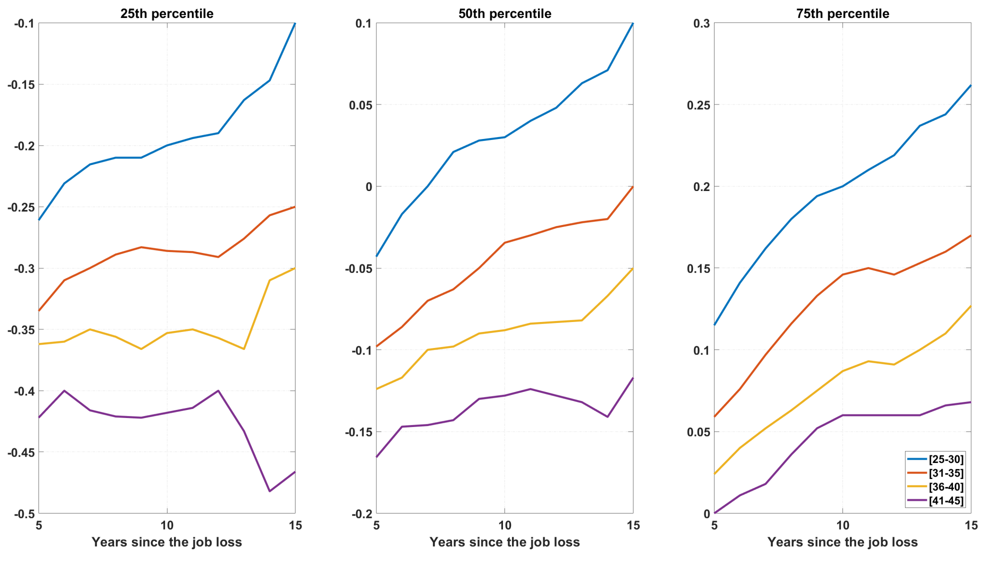

Figure 5: Distribution of $\delta_s + \epsilon_{i,d+s}$ after the displacement event, partitioned by age

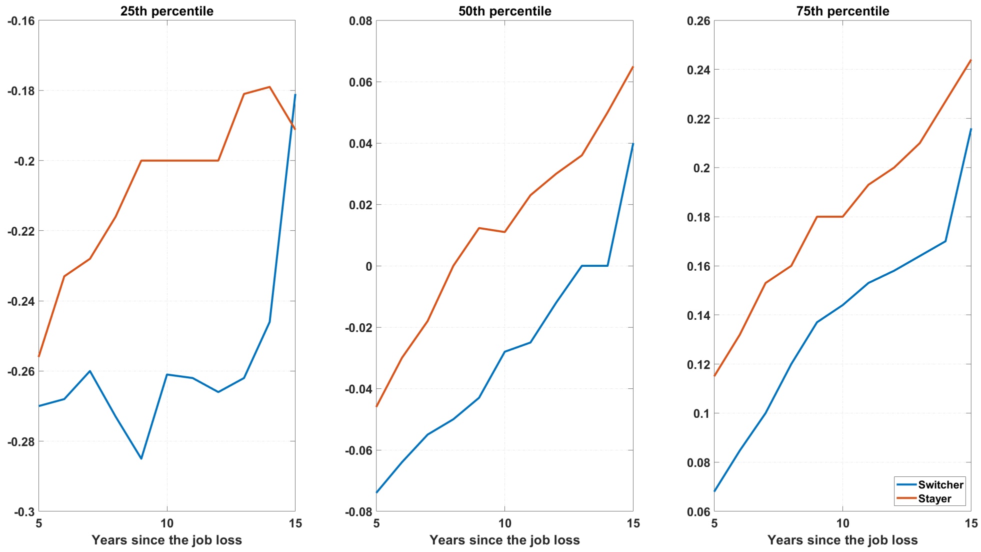

Figure 6: Distribution of $\delta_s + \epsilon_{i,d+s}$ after the displacement event, partitioned by occupation

4.1 Heterogeneous Earnings Losses

Having estimated how well several observables can predict long run earnings losses, in the next section I am going to partition the displaced worker sample along these dimensions, and estimate earnings losses of each subsample. In each subsection, I introduce how I construct the particular partition and then estimate the earnings and employment losses.

4.1.1 Age at the Time of Displacement

In the previous subsection I estimate that age at the time of displacement is the strongest predictor for persistent earnings losses out of the observables I have in the dataset known at the time of displacement. In the following, I will introduce the method how I partition the displaced worker sample into subsamples based on the age at which the displacement occurs and how I construct the control groups for each subsample. To the best of my knowledge, this is the first paper that shows persistent earnings losses conditional on the age at the time of displacement. The economic literature has been looking into certain aspects of the labor market over the life cycle.

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

For each displaced worker subsample, I construct their respective control group from the same age interval. 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 age of 25 and 30 and to not go through a displacement event between the age 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 particular subsection, I change the definition of the control group compared to what I use with the benchmark samples.

	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
Unemp. spell (months)	7.0		7.2		7.4		7.5	
Wage change (%)	-6.4		-8.0		-10.3		-12.0	
Number of obs.	7190	86419	7165	98996	6848	105209	6081	99073

Table 4: Summary Statistics of Displaced Workers, Partition: Age

Table 4 presents summary statistics of the displaced worker subsamples and their respective control groups. For each age-group, the treatment and control group look very similar in terms of average age, while members of the control group have on average higher job tenure. Regarding the [25, 30] age interval, members of the control group have on average 4 months more job tenure, while this difference in the [36, 40] age groups grows to 14 months. The table also documents that as people age, displacement means more time spent in unemployment looking for a new full-time job, and a higher wage reduction upon reemployment on average. While younger displaced workers (between the age of 25 and 30) only suffer a 6% wage reduction on average upon reemployment, older displaced workers (between the age of 41 and 45) experience (on average) a 12% wage drop at their first full-time job after displacement. Higher wage drops could support the idea that a job loss has costs in a number of dimensions. Job-specific human capital is lost, and the longer the relationship that ends, the more specific capital is likely to be lost. This can explain why older people suffer larger wage reductions after an unemployment spell, as they have higher job tenure before the separation.

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

Figure 7 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 and that, after ten years, earnings recover completely. 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 27% relative to 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% relative to 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 dues to longer unemployment spells and larger wage

Figure 7: Earnings Losses of Displaced Workers, Partition: Age

reductions after the unemployment spell. Second, the slope of earnings recovery gets flatter as people age.

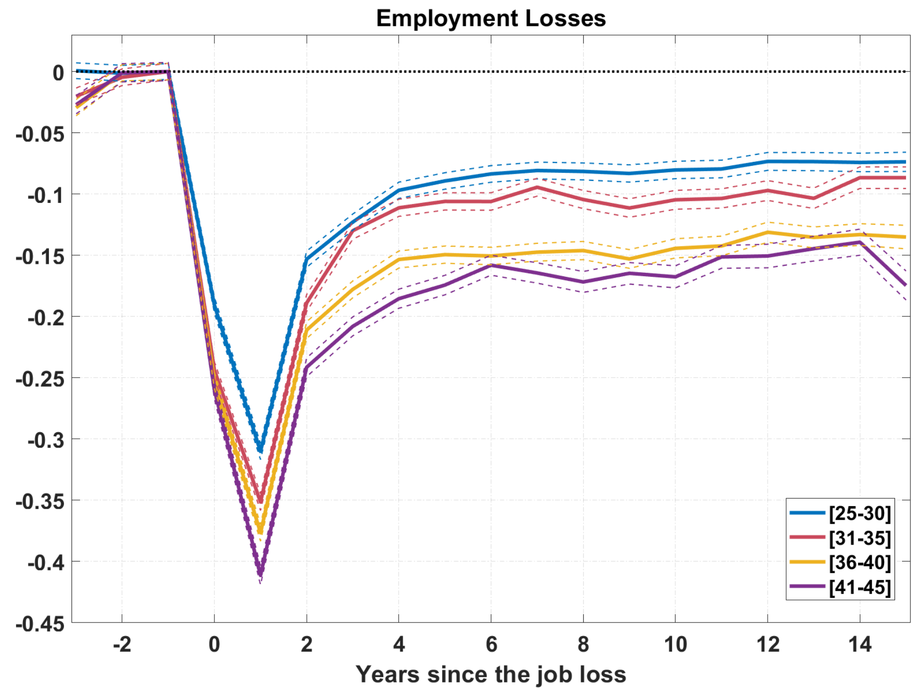

Figure 8: Employment Losses of Displaced Workers, Partition: Age

I run the regression from Equation 1 using the displaced worker subsamples and their control groups as previously with the only difference that the dependent variable is the logged annual employment index. Figure 8 displays the estimated δ_ks for the four age groups in the same graph. 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 of around 6.5% five years after the job loss, while this number is 9% for the $[31, 35]$ age group, 11% for the $[36, 40]$, and 13% 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 afterwards for all age groups.

4.1.2 Job Tenure at the Time of Displacement

In this subsection I partition the displaced worker sample based on the job tenure at the time of displacement.

To construct the displaced workers subsamples based on the job tenure at the time of displacement, I create three subsamples. The first subsample contains displaced workers from the benchmark displaced sample who go through a displacement with job tenure between 3 and 5 years (from 36 to 60 months). The second sample is constructed using displaced workers who lose their jobs with job tenure between 5 and 8 years (from 61 to 96 months), while the third group contains displaced workers with at least 8 years (at least 97 months) of job tenure at the time of displacement.

To compare the earnings of the displaced worker subsamples to matching control groups, I construct a control group that contains individuals with job tenure between 3 and 5 years and I also require them not to go through a displacement event with job tenure between 3 and 5 years. Again, this condition does not require them to stay with the same employer for the job tenure interval, it could be that an individual qualifies as a member of the control group with 37 months of job tenure, stays with his employer for one more year, then switches jobs without an unemployment spell.

Table 5 compares the treatment and control groups in terms of age, job tenure, daily wages. Displaced workers and their respective control groups show similar age and job tenure patterns. Groups with larger job tenure are on average older. Daily wages increase in job tenure both for the displaced and the respective control groups. It is also worth noting that the difference between the treatment and their respective control groups in terms of daily wages is increasing in tenure. Time spent in unemployment is increasing in job tenure. The initial wage change upon reemployment shows a drastic pattern, those who are displaced with job tenure between 3 and 5 years experience a 7.5% wage drop on average while those who are displaced with at least 8 years on the job suffer a 15% wage drop on average upon reemployment.

	3 - 5 years		5 - 8 years		> 8 years	
	Disp.	Cont.	Disp.	Cont.	Disp.	Cont.
Age (years)	34.0	34.5	35.2	35.5	38.2	38.5
Job tenure (months)	46	46	74	75	135	126
Wages (daily, in euros)	91	102	95	113	101	121
Unemp. spell (months)	7.3		7.6		8	
Wage change (%)	-7.5		-10.0		-14.8	
Number of obs.	12158	201659	5870	125882	3309	69325

Table 5: Summary Statistics of Displaced Workers, Partition: Job Tenure

I run the regression from Equation 1 using the displaced worker subsamples and their control groups conditional on their job tenure. More precisely, I run the benchmark regression using only the treatment and control group of the specific job tenure intervals, such as of the [3, 5] years, [5, 8] years, and the more than 8 years on the job tenure. This way every displaced worker subsample of a specific job tenure interval will have their estimated δ_ks from Equation 1.

Figure 9 plots the estimated δ_ks for all three groups of displaced workers. The left panel plots the estimated δ_ks using earnings as the dependent variable while the right panel display the estimated δ_ks using employment as the dependent variable. Earnings recovery of displaced workers with at most 5 years of job tenure at the time of displacement happens at a constant rate, being only around 10% behind their peers in the control group 15 years after displacement. The yellow line plots the estimated δ_ks for displaced workers who had between 5 and 8 years of job tenure at the time of displacement. The slope of the earnings recovery flattens out after around 7 years and slightly decreases to around 17% in the long run. The purple line displays the estimated δ_ks for those displaced workers who have been with their employer for at least 8 years at the time of displacement. Four observations are worth noting: losses are increasing with job tenure on impact. This is due to both more time spent in unemployment and also increasing wage reductions upon reemployment for displaced workers with higher job tenure at the time of displacement. Second, the slope of earnings recovery is the same for all three groups of displaced workers in the first 5 years after displacement. Third, the slope of earnings recovery in the long run displays diverging patterns across the groups of displaced workers. For those who have been with their employer for no longer than 5 years the slope keeps a constant pace, while for those with job tenure between 5 and 8 years earnings recovery flattens out after 7 years. The slope of earnings recovery of displaced workers with at least 8 years of job tenure at the time of displacement flattens out after 5 years and even decreases in the last 6 years. Fourth, persistent losses originating from wage losses are mostly present for those with more job tenure. It is worth noting that displaced workers with at least 8 years of job tenure are on average older, thus the purple line in Figure 9 shows similar patterns as the estimated δ_ks for older displaced workers (purple line) in Figure 7.

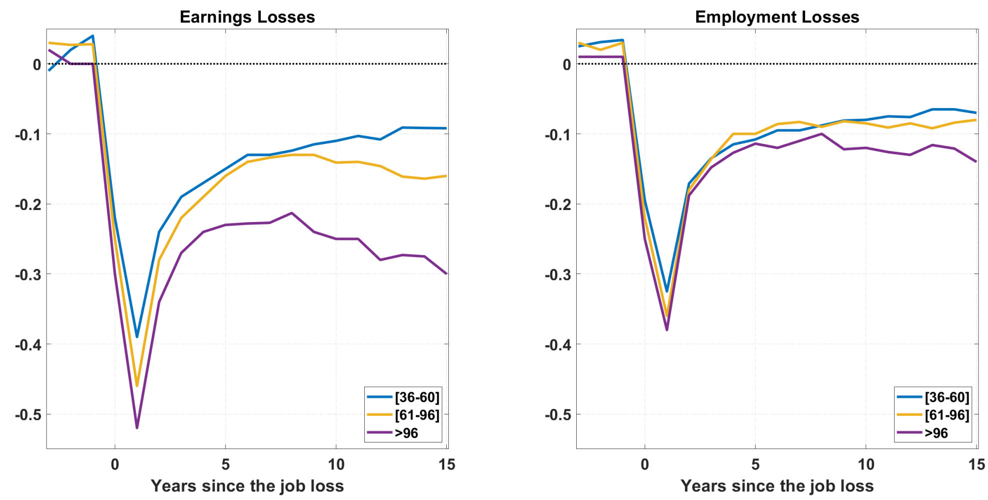

Figure 9: Earnings Losses of Displaced Workers, Partition: Job Tenure

4.1.3 Job Tenure versus Age Effects

Age and job tenure are highly correlated in the data and as Table 4 shows older displaced workers have longer job attachment at the time of displacement. As seen in the previous subsection, displaced workers who had at least 8 years of job tenure at the time of displacement display similar earnings losses as older displaced workers do. 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 find out 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 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 10 and Figure 11.

Figure 10 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

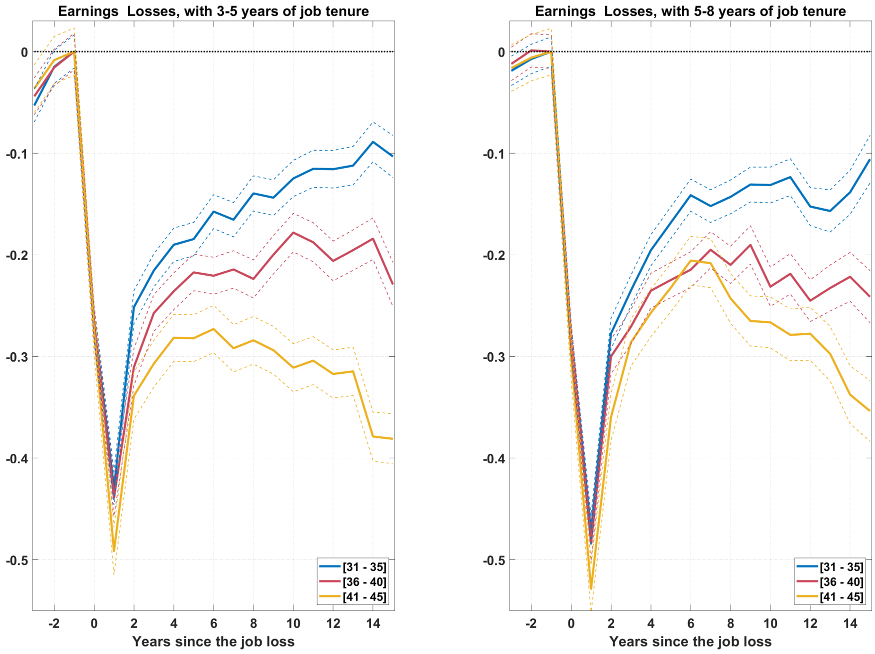

Figure 10: Earnings Losses of Displaced Workers, Conditional on Job Tenure, then three Age Groups

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 earnings recovery across the age groups. As shown before in subsection 4.1.1, the younger displaced worker subsample (between the age of 31 and 35 at the time of displacement) shows an incomplete recovery over the fifteen years, conservatively reducing the gap compared to their respective peers, while the older age groups see their earnings recovery come to a halt and flatten out four years after displacement. In the left panel there is a permanent 7% gap between each pair of consecutive age groups. In the right panel where the minimum job tenure requirement is 5 years this gap is even larger between the age groups. The key message is that the two panels of Figure 10 show that even after controlling for job tenure, age effects are still present and show similar patterns as seen in subsection 4.1.1.

The two panels of Figure 11 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 groups for displaced workers between the age of 36 and 40 while

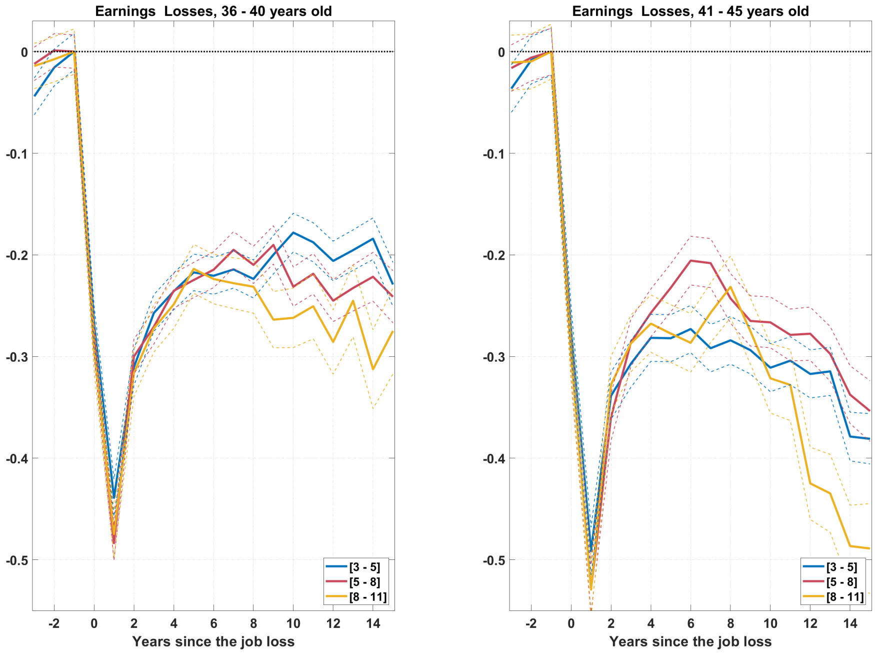

Figure 11: Earnings Losses of Displaced Workers, Conditional on Age, then Job Tenure

the right panel displays the corresponding estimates for workers who get displaced from their job between the age of 41 and 45. The panels document that (i) the shape of recovery after a job loss is similar for each job tenure category before displacement, (ii) conditional on age, long-run earnings losses are fairly comparable for each job tenure category. Persistent earnings losses are around 15% for displaced workers in the left panel, while they are around 20% for displaced workers in the right panel. Thus I can conclude that age effects are dominating my previous findings.

4.1.4 Time Spent in Unemployment

In this subsection I construct three subsamples of the displaced worker sample based on the time they spend in unemployment after the displacement event. To be more precise, I count the months that it takes for displaced workers to find their first full-time job after displacement. It could be that some workers exhaust the unemployment benefits while they are looking for a new job, but I would still count every month in which they are not employed as an unemployed month. The first subsample contains those who find their first full-time job within half a year after displacement. The second subsample contains those who need at least half a year but no more than 12 months to find their first full-time employment. The third subsample contains all displaced workers who need at least 13 months but no more than 36 months to find their first full-time job. As I am partitioning the benchmark displaced worker sample based on how long their initial unemployment spell is, there is no natural way to partition the benchmark control group. Therefor I am using the same control group as in the benchmark displaced worker regression in Section 2.2.1.

Table 6 presents descriptive statistics about the treatment groups. The average age, job tenure, and daily wages at the time of displacement are all very similar across the subsamples of displaced workers. Average time spent in unemployment is 3.5, 9, and 20 months respectively, while daily wages fall drastically as workers spend more time unemployed. Displaced workers who spend a short time unemployed before finding their first full-time job (at most 6 months) experience on average a 4% wage drop at their new job, while those who spend at least a year unemployed suffer a 17% wage reduction compared to their wages right before displacement. This finding is consistent with the idea of Ljungqvist and Sargent (1998) who propose that workers' accumulated human capital depreciates while being unemployed, thus the longer the worker is unemployed, the more human capital he loses.

I construct three sets of dummy variables: D_k^s for displaced workers who are unemployed for up to 6 months, D_k^m for those displaced workers who are unemployed for at least 6 months but no longer than a year, and D_k^l for the those displaced workers who are unemployed for at least a year[11]. I run the regression specification introduced in Equation 3:

$$y_{it} = \Sigma_{k=-3}^{15} D_{it}^{k,s} \delta_k^s + \Sigma_{k=-3}^{15} D_{it}^{k,m} \delta_k^m + \Sigma_{k=-3}^{15} D_{it}^{k,l} \delta_k^l + \lambda \bar{e}_i + \alpha_i + \gamma_t + \epsilon_{it} \tag{3}$$

As previously mentioned, I have now three sets of dummies (D_k^s, D_k^m, D_k^l) denoting a displacement event k years ago for displaced workers with no more than 6 months spent in unemployment (s), for displaced workers spending 7 to 12 months in unemployment

[11] Huckfeldt (2022) uses a similar regression specification partitioning the displaced worker sample based on whether a job loser find a new job in his old occupation or he changes occupations.

(m), and those who more than a year in unemployment (l). For instance, a displaced worker who finds his first full-time job within half a year after the displacement event will have all D_k^m and D_k^l equal 0, while D_k^s will equal 1 if the job loss happened k years ago. Members of the control group will have all D_k^s, D_k^m, D_k^l equal 0.

Figure 12 shows the estimation results for all three subsamples. The blue line shows earnings losses of those who find their first full-time job within half a year of displacement. Earnings drop slightly in year 0 and year 1. The initial small drop in earnings are due to the short time spent in unemployment and the relatively small reduction in wages (4%). The red line shows estimated earnings losses for those who find their first full-time job within a year. The initial drop in year 1 is significant, dominated by the large employment losses, paired also with the significantly larger wage losses (11%) . Recovery is incomplete: it is around 20% 15 years after displacement compared to the benchmark control group. The yellow line plots estimated earnings losses of those displaced workers who spend at least one whole year before finding their first full-time job[12] As members of the third subsample spend at least 13 months in unemployment, I do not estimate δ_1^l. Earnings do not recover over time, and after 15 years, they still lag behind the control group's by around 30% and 15% respectively. Initial earnings losses are increasing in the time it takes to find a full-time job. As Table 6 shows, this is due to increasing wage reductions after reemployment, and mostly because of the increasing employment losses. It is also worth noting that the slope of earnings recovery flattens out after 4 years and the gap between the groups stays constant after year 4. Third, the incompleteness of earnings recovery is increasing in the time spent finding the first full-time job after displacement. The increasing wage reductions across the three subsamples can be explained by the common feature models use to generate persistent earnings losses. More precisely, models building on Ljungqvist and Sargent (1998) assume that accumulated human capital is depreciating while being unemployed, thus the more time one spends in unemployment, the more human capital he loses. The estimated persistent earnings losses of the three subsamples also suggest that workers who spend more time in unemployment lose more (i.e. accumulated human capital) while being unemployed, which is detrimental in the

[12]It could be that some of the displaced workers have a part-time job within a year after displacement, but I focus on the first full-time job after displacement.

long-run as well, as they cannot even catch up to other displaced workers who spend less time finding their first full-time job on average.

	Displaced Worker Subsamples			
	<7 months	7 - 12 months	13 - 36 months	Control
Age (years)	34.4	35.0	35.0	37.0
Job tenure (months)	61	62	62	66
Wages (daily, in euros)	91	94	97	110
Unemp. spell (months)	3.5	9.0	20.0	
Wage change (%)	-4.0	-11.6	-17.0	
Number of obs.	11544	4606	4109	240777

Table 6: Summary Statistics of Displaced Workers, Partition: Time Spent in Unemployment

Figure 12: Earnings Losses of Displaced Workers, Partition: Time in Unemployment

Figure 13 plots the estimated employment losses of the three subsamples in the same figure. Employment losses of the three subsamples follow the same patterns as the estimated earnings losses. Persistent employment losses are increasing in the time spent unemployed after the displacement event. The estimated losses flatten out at around six years after the job loss and the gap between each pair of subsamples of displaced workers. The similar patterns in earnings and employment losses suggest that wage losses must show these patterns of recovery as well.

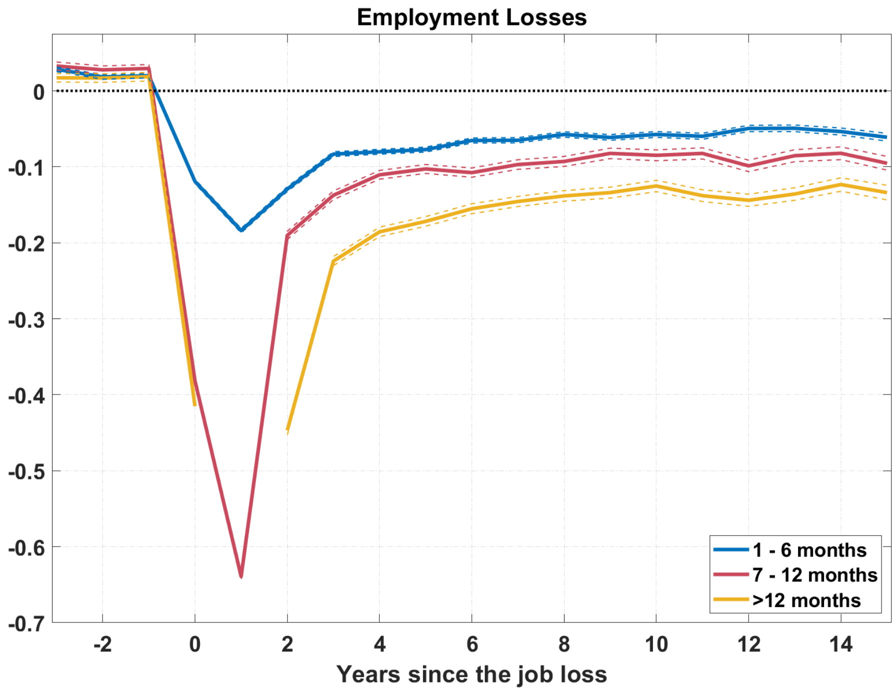

Figure 13: Earnings Losses of Displaced Workers, Partition: Time in Unemployment

4.1.5 Wage change after Reemployment

In this subsection I investigate how one's wages at their first full-time job after displacement compared to their last observed wages can predict persistent earnings losses. If displaced workers have been overpaid relative to their productivity at their previous job and are hired at normal wages, earnings will fall behind the control groups' earnings. Table 3 indicates that the initial wage change upon reemployment can predict persistent earnings losses quite well. Displaced workers with large initial wage reductions tend to suffer larger earnings losses, while those workers who actually experience a wage gain after reemployment see their earnings losses massively overestimated by the benchmark regression.

I construct three sets of dummy variables: D_k^s for displaced workers whose wages decrease by at least 10% at their first full-time job compared to what they received at their previous job, D_k^m for those displaced workers who experience mild wage changes upon reemployment ($[-10\%, +5\%]$), and D_k^l for the those displaced workers whose wages increase with at least 5% at their new job compared to the job they have been displaced from. I run the regression introduced in Equation 3 to estimate the earnings losses of these three subsamples.

Table 7 describes the three subsamples of displaced workers. The average age and job tenure of the three samples look very similar, while those who experience at least a 10% wage reduction at their first full-time job had slightly higher wages as those who experience a mild reduction or even a positive change. Time spent in unemployment is negatively correlated with wage change upon reemployment, more precisely those who find a better paying full-time job spend 3.5 months less being unemployed on average. As the table reports, there is a huge variation in immediate wage change, as the mean is -31% for those who see their wages fall with at least 10%, while the mean is +21% for those who find a better paying job after displacement.

Figure 14 shows the estimated δ_k^s, δ_k^m, δ_k^ls using logged earnings as the dependent variable. The yellow line shows the earnings and employment losses of displaced people whose daily wages at their first full-time job after displacement are at least 5% larger than in the last month at their previous job. One can observe that earnings losses are very small on impact, which can be explained by the fact that wages are actually larger than previously, thus the small 20% dip in year 1 after displacement is due to the dominance of the employment channel. The estimated losses on impact are less than half of what is estimated in the benchmark regression. Recovery is almost complete after 7 years. Long run earnings are estimated to be behind the control group's by only around 3.3%. The red line shows estimated earnings losses for those displaced workers whose daily wages at their first full-time job after displacement are not larger by more than 5% and not smaller by more than 10% than in the last month at their previous employment. The initial losses on impact are larger, due to the employment and wage channels both, although the reduction in wages is bounded from below due to the construction of the partition. Recovery is incomplete in the long run, with earnings lagging behind the control group by around 9% 15 years after displacement. The blue line shows the estimated earnings losses of those workers whose daily wages at their first full-time job after displacement are at least 10% smaller than at their previous job. Earnings losses on impact are around 73% 1 year after displacement, which is due both to the large employment and wage losses. Recovery is rather incomplete, it is still behind the control group's earnings by more than 25% 15 years after displacement.

	Displaced Subsamples			
	< -10%	[-10%, 5%]	>5%	Control
Age (years)	35.0	34.8	34.4	37.0
Job tenure (months)	65	62	59	66
Wages (daily, in euros)	100	97	89	110
Unemp. spell (months)	9.7	7.1	6.0	
Wage change (%)	-23	-2	21	
Number of obs.	8996	5684	5579	240777

Table 7: Summary Statistics of Displaced Workers, Partition: Wage Change

Figure 15 plots the estimated δ_ks using the employment index as the dependent variable. Employment losses are very similar in the long run for all three subsamples indicating that persistent earnings losses of those who suffer larger wage reductions stem mainly from persistent wage losses.

Figure 14: Earnings Losses of Displaced Workers, Partition: Wage Change

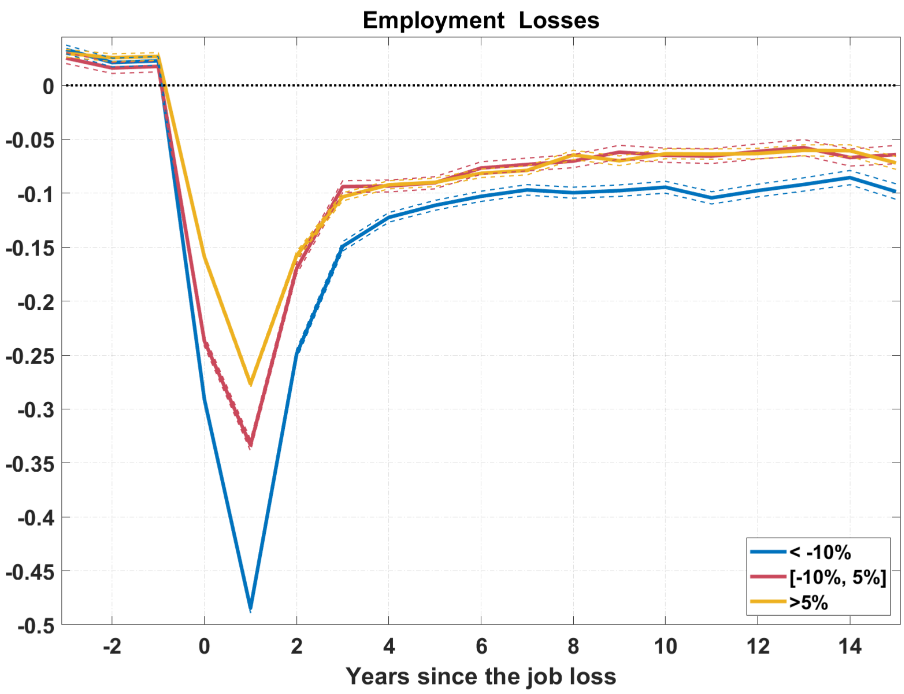

Figure 15: Earnings Losses of Displaced Workers, Partition: Wage Change

4.1.6 Size of New Establishment

In this section, I partition the displaced worker sample into two subsamples, one containing displaced workers who find their first job upon reemployment at a firm that has at most 49 employees, and a second subsample that includes displaced workers whose new employer employs at least 50 employees.

Table 8 presents summary statistics about the subsamples of displaced workers based on the establishment size they find their first full-time job upon reemployment. The two subsamples have the same age, job tenure, and wages at the time of displacement on average. Those displaced workers who end up working for a small establishment spend more time in unemployment (9.7 months) and suffer a much bigger wage loss upon reemployment

	Displaced Subsamples		
	< 50	$\geq$50	Control
Age (years)	34.4	34.7	37.0
Job tenure (months)	62	63	66
Wages (daily, in euros)	98	99	110
Unemp. spell (months)	9.7	7.0	6.0
Wage change (%)	-15.4	-9.5	
Number of obs.	4402	8092	240777

Table 8: Summary Statistics at Baseline, Partition: Size of New Establishment

I construct two sets of dummy variables: D_k^s for displaced workers who find their first full-time job at a small establishment (with less than 50 employees), and D_k^l for those displaced workers who find a job at an establishment with at least 50 employees. I run the regression introduced in Equation 4 to estimate the earnings losses of these two subsamples.

$$y_{it} = \Sigma_{k=-3}^{15} D_{it}^{k,s} \delta_k^s + \Sigma_{k=-3}^{15} D_{it}^{k,l} \delta_k^l + \lambda \bar{e}_i + \alpha_i + \gamma_t + \epsilon_{it} \tag{4}$$

Figure 16 plots the estimated δ_k^s and δ_k^ls using logged earnings as the dependent variable. The blue line plots the estimated earnings of those displaced workers who end up working at a small establishment. As can be seen, the initial drop in earnings is substantial, due both to more time spent in unemployment and larger wage reductions after the unemployment spell. Earnings still lag behind the control group's by around 22% 15 years after the job loss. The red line displays the estimated δ_k^ls for those displaced workers who find a new job at a relatively large establishment (with at least 50 employees). The initial earnings loss is milder due to both shorter unemployment spell and smaller wage reductions upon reemployment. Persistent earnings losses are less than 10% 15 years after the job loss.

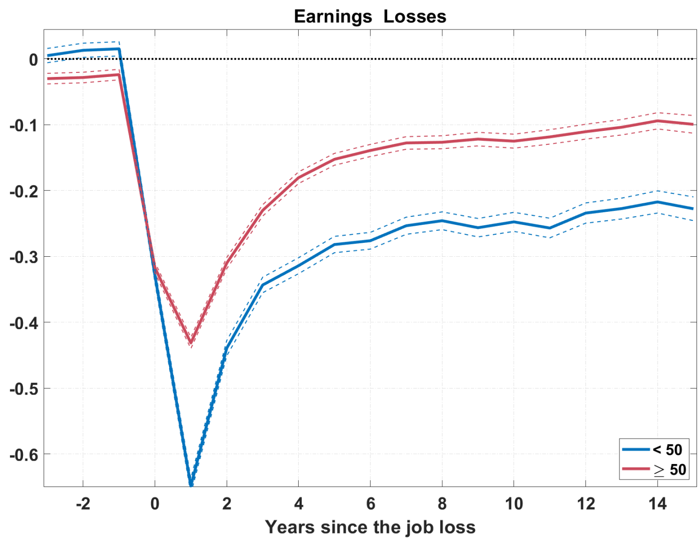

Figure 16: Earnings Losses of Displaced Workers, Partition: Size of New Establishment

Figure 17 plots the estimated δ_k^s and δ_k^ls for employment. The initial drop in earnings losses is almost double for those who find a new job at a small establishment. Those who end up at a small establishment experience larger employment losses on impact.

Two patterns arise: first, estimated employment losses flatten out five years after the displacement event, second, the gap between the two groups stays permanently around 5% in the long run.

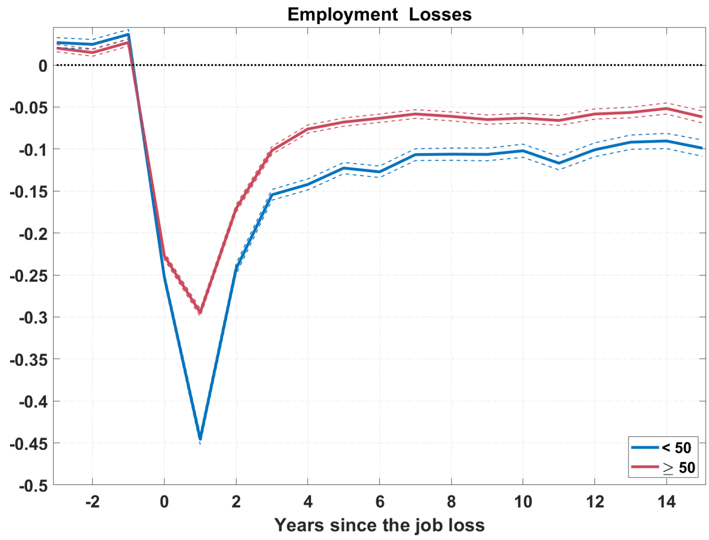

Figure 17: Earnings Losses of Displaced Workers, Partition: Size of New Establishment

5 Conclusion

In this paper I document the extent of heterogeneity in the estimated mean earnings losses associated with job displacement using German social security data covering private sector workers. I show that the variation in the residuals of the benchmark displaced worker regression is large over all years. I explore the ability of several factors to statistically explain the heterogeneity in persistent earnings losses across individuals. I look at several factors that might cause the large heterogeneity in earnings losses: age at the time of job loss, the immediate wage change upon reemployment, the time it takes the displaced worker to find his first full time job after displacement, the size of his new establishment upon reemployment, the size of previous establishment, the job tenure at the time of displacement, whether the worker switched occupations upon reemployment, and educational attainment.

These results serve as a starting point for future research. The estimated earnings and employment losses can guide unemployment policies to better target those who are more likely to experience large and long-lasting losses following a displacement.

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A K-Means Clustering

In order to characterize and group displaced workers based on their average earnings losses, I use the K-means clustering method in this section. Clustering is an unsupervised learning concept, working on unlabeled data. Clustering uses unlabeled data and looks for similarities between groups (clusters) in order to attempt to segment the data into separate clusters. When using clustering methods, we don't actually know the 'true' or correct label/outcome for the data. We only have features. One could just plot out the data and see if one can figure out groupings or discover patterns in the data. Patterns are usually not obvious with multi-dimensional datasets. As there are no labels, we don't know if the grouping we come up with is correct or the best. The main clustering idea is to discover which points are most similar to other points.

Steps of the K-Means clustering:

Step 1 Choose K before clustering

Step 2 Then the method randomly selects K distinct data points. And these points are treated as the cluster points or the center of the clusters.

Step 3 Having defined the cluster points in Step 2, in the next step the method assign all data points to the nearest cluster point. To find the nearest cluster point, the method simply uses a distance metric.

Step 4 In this step, having assigned all data points to one group (cluster), we calculate the center of the cluster points. This gives us the new center of the clusters.

Step 5 Using the newly defined center points of the clusters, we assign each data point to the nearest cluster center.

We repeat Steps 4 and 5 until there are no more reassignments across clusters. Then the final clusters are found.

I follow the listed steps above and choose K = 4. This means that I group displaced workers into four groups. I do the clustering using only the ATLs. This way I group displaced workers into four groups based on how much the benchmark regression in Equation 1 over/underestimates the earnings losses over time.

Until now, papers investigating heterogeneous earnings losses have mostly focused on a particular dimension that can only be observed once the individual finds a new job. More precisely, Huckfeldt (2022) asks how changing one's occupation affects persistent earnings losses. Leenders (2021) compares displaced workers who are recalled to their previous job versus those who find a new employer. Papers that compare earnings losses along a dimension that is already known at the time of displacement are Gregory et al. (2021) that groups job losers based on their labor market histories and shows that only a small fraction of job losers account for the large persistent earnings losses. Leenders (2021) also looks into earnings losses of worker with low and high educational attainment. He finds that job losers with low educational attainment bear substantially larger earnings losses in the long run. To the contrary, Burdett et al. (2020) show very similar earnings losses for displaced workers with low- and high-education.

Papers that partition the displaced worker sample along a dimension only known after reemployment all ask how one feature of the displaced workers' new job compared to their previous job affects their earnings recovery. In the next section, I will list possible dimensions along which one's new job compared to the previous one can affect earnings recovery. These are how new wages compare to the previous, the size of the establishment of the new employer, occupation. One outlier dimension in this section that I will partition the displaced worker sample is time spent in unemployment in between displacement and the first full-time job.

In Table 9 I present some characteristics of the four groups given by the clustering method described before. These characteristics are observable at the time of displacement, such as age, job tenure, and the size of the establishment. The first group contains 156 displaced workers and this group has the largest negative ATL, more precisely the benchmark regression underestimates their earnings losses by 56% each year on average. The second group consists of 1 080 displaced workers. Their earnings are underestimated by 14% on average each year. The third group is the largest with 2 410 displaced workers. Their earnings losses are on average overestimated by the benchmark regression by around 11.6%. The fourth group contains 1 216 displaced workers whose earnings losses are overestimated by 36% on average. The table shows that more than half of the displaced workers' earnings losses are overestimated by the benchmark regression using Equation 1. A very small group of displaced workers (group 1) suffer very significant earnings losses. Figure 18 presents the mean ϵ_t for each group and each year after displacement starting from year 5. The mean errors of groups 2 and 3 are moderate and relatively constant within the $[-20\%, +20\%]$ interval. The mean errors of group 1 are much larger and decreasing over the years, going below -60% ten years after the displacement event. The mean errors of group 4 are increasing over the years, reaching +40% in the last two years.

	1st	2nd	3rd	4th
Age	35	34	32	30
Est. size	698	472	515	870
Job tenure (month)	54	57	52	48
ATL	-56%	-14%	11.6%	35.9%
# Observations	156	1 080	2 410	1 216

Table 9: Summary of group characteristics

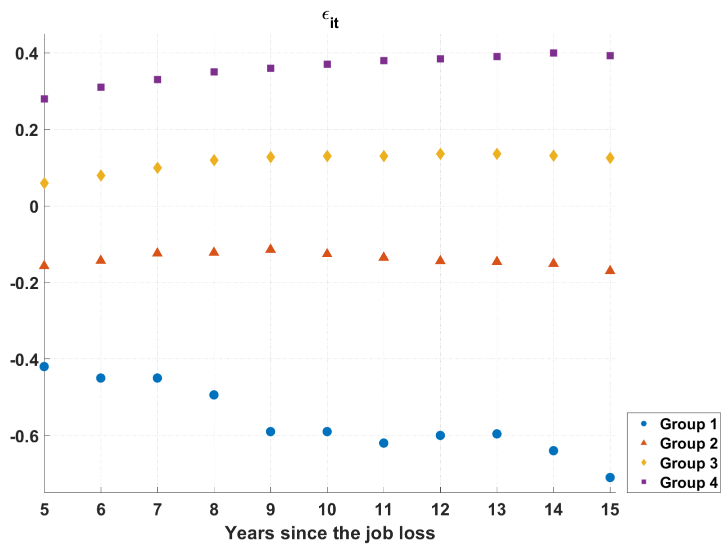

Figure 18: Mean ϵ_s for the clusteres

Table 9 presents some characteristics of displaced workers known at the time of displacement. These characteristics are age, job tenure, and the size of the establishment from which workers are displaced. The table shows that the older the displaced worker, the higher his earnings losses are on average in the long run. While those workers in group 1 are 35 years old at the time of displacement and have their earnings losses underestimated by 56% each year on average, members of group 4 are (on average) only 30 years old at the time of displacement and their earnings losses are grossly overestimated as seen before. The mean establishment size and job tenure do not present such stark differences across the groups. Workers in group 4 have a lower job tenure than workers in other clusters on average. Workers clustered in group 4 are employed at a slightly larger establishment than displaced workers in other groups on average.

Table 10: Dependent variable: ATL

Age	-0.125***		
Establishment size		0	
Job tenure			-0.009***
R^2	0.052	0.001	0.007height

Table 10 shows results from a simple regression using ATL as the dependent variable and age, job tenure, and establishment size as the explanatory variable respectively. Age and job tenure at the time of displacement are significant and negative, while the coefficient of establishment size is 0. To put it differently, the older the worker is at the time of displacement, the more the benchmark regression underestimates his earnings losses in the long run. Similarly, the higher the job tenure the worker has at the establishment at the time of displacement, the more the benchmark regression underestimates his long run earnings losses. Age at the time of displacement has the highest explanatory power with $R^2 = 0.052$.

Table 11 shows characteristics of the same clusters, but these characteristics are only observable once workers find a new full-time job. I summarize the mean of daily wage change at the new job compared to wages at their previous job (Δw), the length of the unemployment spell it takes workers to find their first full-time job after displacement, the change in the size of the employer (Δ size), the size of the new establishment. The table presents stark differences across the clusters. Those in cluster 1 (with an average ATL of -56%) see their wages fall by 25%, spend the longest time in unemployment (9.6

months), find a new full-time job at a much smaller establishment than their previous establishment. These means all improve with ATL. The second group experiences smaller, but still negative wage changes, spend 7.6 months in unemployment, find a new job at a smaller establishment than their previous job. Workers in group 4 who see their long run earnings losses massively overestimated find a job with higher daily wages, at a bigger establishment and only spend 6.4 months in unemployment on average.

	1st	2nd	3rd	4th
Δw	-25.1%	-19.4%	-6.4%	4.6%
U length	9.6	7.6	6.3	6.4
Δ size	-608	-276	-171	326
New est. size	102	198	353	1211
ATL	-56%	-14%	11.6%	35.9%
# Observations	156	1 080	2 410	1 216

Table 11: Summary of group characteristics, observable only after finding a new full-time job

Table 12 shows results from a simple regression using ATL as the dependent variable and listed variables in Table 11 (such as wage change, time spent in unemployment, change in establishment size, and the size of the new establishment) as the explanatory variables respectively. The change in daily wage at the new full-time job compared to the final daily wage right before displacement explains 13.3% of the variation in ATL. The larger the negative daily wage change, the more the benchmark regression underestimates the long run earnings losses on average. Time spent in unemployment before finding the first full-time job and the size of the new establishment both explain around 1% of the variation in ATL.

Table 12: Dependent variable: ATL

Δw	0.053***			
U spell		-0.053***		
Δ size			<0.0001***	
New est size				0.0001***
R^2	0.133	0.01	0.0055	0.01