The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany*

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Abstract

We document the sources behind costs of job loss over the business cycle using administrative data from Germany. Losses in annual earnings in Germany after displacement are large, persistent, and highly cyclical, nearly doubling in size during economic downturns. We show that part of these losses and their cyclicality is driven by unemployment. However, the longer-term earnings losses we find and their cyclicality are mainly driven by declines in wages. An important factor behind the long-lasting declines in wages and their cyclicality are changes in employer characteristics, as workers switch to smaller and lower-paying firms after job displacement, in particular in recessions. The findings point to important and persistent effects of luck in the labor market that employment-based programs such as unemployment insurance can only partly offset.

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1 Introduction

A sizable body of research has documented the high costs of job loss and ensuing unemployment on the side of workers. In particular, several papers suggest that workers displaced during mass layoffs experience large losses in annual earnings lasting over 15 to 20 years (e.g., Jacobson et al., 1993, Couch and Placzek, 2010,von Wachter et al., 2011).[1] The existing literature has also shown that earnings losses after job displacement have an important cyclical component (e.g., Farber (2016)). Using U.S. data, Davis and von Wachter (2011) show that although life-time earnings losses after job displacements occurring in booms are substantial, the earnings loss due to job displacements occurring in recessions is about twice as high. With displacement rates[2] reaching ten to fifteen percent of employment in large recessions, this implies that a substantial fraction of workers suffers large permanent reductions in their life-time earnings.

The finding of large and persistent effects of job displacement and their cyclicality has potentially important implications for understanding the functioning of the labor market and how it responds and contributes to recessions. However, several important open questions remain about the sources of earnings losses and their cyclicality. For example, does the cyclicality of earnings losses arise mainly from an increase in the incidence and duration of unemployment and nonemployment in recessions? If so, then cyclical earnings losses can be understood as a byproduct of unemployment, and the focus on unemployment insurance as main policy response to assist affected workers is appropriate. However, a presence of a strong cyclical component in losses of *wages* is more difficult to explain, and poses greater challenges for current policy approaches heavily focused on unemployment. Measuring and understanding changes in wage losses at job displacement is difficult, since changes in the composition of displaced workers, changes in available job types, and wage declines within

[1] In addition to earnings and employment, the economics literature has studied a large number of other potential effects of job loss on outcomes, such as health (Schaller and Stevens, 2015), mortality (Sullivan and Von Wachter, 2009), retirement (Chan and Huff Stevens, 2001) and the children of displaced workers (Lindo, 2011; Rege et al., 2011).

[2] For example, as measured in the CPS Displaced Worker Survey (Farber (2011)) or in administrative data (Song and von Wachter (2014)).

worker and job categories may all be at play. Yet, an understanding of these dynamics would provide important insights in both labor market dynamics in recessions and appropriate policy responses.

The existing literature suggests that all of these channels may be at play. Clearly, job losers displaced in recessions tend to have longer nonemployment spells, and have lower hours even conditional on finding a job (e.g., Farber (2016); Lachowska et al. (2017)), leading to larger earnings losses in recessions. In addition, longer nonemployment spells have been shown to causally reduce reemployment wages (Schmieder et al. (2013)). The existing literature has also examined several channels by which wages of job losers are directly affected by job loss. Since at least Topel (1990), the literature has broadly distinguished between losses in job-specific skills and losses in employer-specific wage components, often thought of as rents. Several papers have studied how tenure in the prior job, and industry and occupation changes at job loss can lead to substantially larger losses (e.g., Jacobson et al. (1993)Neal (1995)Poletaev and Robinson (2008)). At the same time, an increasing liteature suggests that employer characteristics are important for explaining the wage structure (e.g., Abowd et al. (1999)Card et al. (2013), Song et al. (2016)), and the cost of job loss as well. It is well known that job losers leaving larger employers experience larger earnings losses (e.g., Jacobson et al. (1993),Schoeni and Dardia (2003)). More recently, using rarely available administrative data on earnings and hours from the state of Washington, Lachowska et al. (2017) show that workers displaced during the Great Recession experienced persistent wage losses that were substantially larger if workers lost a job at a high-paying establishment as measured by estimated fixed effects. These losses could be accentuated in recessions, when average employer quality tends to decline (e.g.,Okun (1973)Haltiwanger et al., forthcoming).

In this paper we fill several gaps in the empirical understanding of the costs of job loss and their cyclicality using social security data from Germany. The data covers three decades of job displacements with a detail on daily employment transitions, wages and employment, and firm and worker characteristics not currently available elsewhere. Using this data, we provide an analysis of the long-term earnings losses of displaced workers in Germany, carefully ensuring comparability of our results to recent estimates using similar data from the U.S. Second, going beyond existing estimates from the U.S., we decompose the cyclical earnings losses we find into wage and employment losses in terms of days worked over the short and long-run after job loss. The resulting decomposition highlights the potential effect of changes in worker composition as job losers exit and enter the labor market and over the business cycle. Third, we analyze a key source of cyclical movements in wage losses, changes in displaced workers' firm characteristics over the business cycle.

In a final step, we account for the effect of changes in employer characteristics at job loss in explaining the cyclical wage losses we find, and contrast its effect to that of other channels isolated in the literature. Thereby, given increasing evidence of differential displacement rates and earnings losses over the business cycle, a key step is to control for changes in the composition of the types of workers and the types of displacing firms over the business cycle. To effectively do so, we depart from the canonical estimation approach in the literature on job displacement, and directly model the individual wage loss vis-a-vis a matched control observation. This allows to effectively account for composition changes along several dimensions and analyze various channels behind the cyclicality of the cost of job loss in a unified regression model.

As comparable studies in the U.S., we find that workers in stable jobs separating from their main employer in the course of a mass-layoff during recessions suffer reductions in annual earnings of about 15% lasting at least 15 years. This suggests that job displacement has highly detrimental effects on earnings even in a labor market with a tighter safety net and lower earnings inequality. Also consistent with U.S. based findings, we find that there is a very high degree of cyclicality in earnings losses in Germany, with losses in recessions more than doubling the losses in booms, mirroring closely comparable findings in the United States.

In contrast to most U.S. studies based on administrative data, we are able to differentiate between earnings and wage losses, a crucial question for understanding the cost of job loss. We find that although temporary reductions in time worked explain part of the reductions in earnings, the majority of the long-term effect is driven by a lasting decline in daily wages. We find this cyclicality is partly explained by longer unemployment durations of job losers during recessions. This suggests that some of the loss and recovery in earnings in U.S. studies, and part of their cyclicality, are likely driven by reductions in time worked. Yet, fluctuations in employment can explain earnings losses and their cyclicality only in the short term. We find that the pattern of longer-term earnings losses after job displacement are entirely explained by cyclical wage losses.

Our third main findings pertains to the role of firm characteristics in explaining the large cost of job loss. We find that displaced workers experience substantial reductions in firm size and firm wages, and that these reductions are larger in recessions. These results are robust for controlling for changes in the composition of workers over the business cycle. Our accounting regressions suggest that over half of average wage losses and a large part of their cyclicality appear to be driven by changes in firm characteristics alone. We find this effect is primarily driven by changes in characteristics of the post-displacement employer. Henc,e changes in the job composition in the labor market available to job losers over the business cycle appears to play a role in explaining persistent and cyclical declines in wages upon job displacement.[3]

These results are consistent with a growing literature showing that different firms appear to pay different wages to similar workers (e.g., Abowd et al., 1999, Card et al., 2013,Song et al. (2016)), and that employer characteristics appear to worsen in recessions (e.g., Haltiwanger et al., forthcoming). These findings imply that losses in firm-specific wage components play a large role in understanding the cost of job displacement. While we do find that in recessions workers from high-wage employers are more likely to lose their jobs, changes in characteristics of new employers are the overwhelming driver of our findings. The fact that displaced workers searching for new jobs in a worse job environment suffer persistent earnings suggests an important and persistent role for luck in the labor market.

[3]We also show that payments from the generous German unemployment insurance system only replace about 25 percent of displaced workers' lost earnings. This effect is likely to be even smaller in the American labor market, where unemployment insurance is shorter lived and covers a smaller fraction of the unemployed. However since UI benefits are contingent on not working while not insuring against wage losses, income from UI benefits is also highly cyclical, thus playing a larger role in making up for earnings losses during recessions. In fact, when we look at income losses (earnings plus UI income) over the business cycle, we find that income losses are less cyclical than earnings losses, suggesting an important role for UI benefits to smooth income during particularly difficult economic times.

Our results do not preclude a role for losses in specific skills that may pertain to industry and occupation. However, while we do find that industry and occupation switchers suffer greater losses, we also show that the incidence of industry switching declines in recession, and that even for those finding jobs in the same industry losses in firm wage premiums plays a key role in understanding wage losses.

The rest of the paper is organized as follows. Section 2 gives an overview of our definitions of job displacement and describes the data. In Section 3, we benchmark our findings to comparable estimates from the U.S. by providing basic event-study estimates of the effect of job displacement on earnings, wages, and time worked. In Section 4, we then analyze the effect of job loss on earnings, employment, and wages over the business cycle. We also discuss the role of unemployment insurance receipt as a means to smooth long-term displacement-related earnings losses. In Section 5, we analyze how employer characteristics of displaced workers change over the business cycle. Finally, in Section 6 we assess to what extent these changes can explain the large and cyclical wage losses we find. The last section concludes.

2 Data and Methods

2.1 German Administrative Data

We use data from the social security system in Germany, which is generated from employer-submitted employment records and provided by the Institute for Employment Research (IAB). This data consists of complete day-to-day information on earnings and time worked in each employment spell occurring in employment covered by social security. The data also contains basic demographic characteristics including education, as well as information on occupation and industry. This data has been complemented with information on receipt of unemployment (from the *Leistungsempfängerdatei*). In addition, the worker-level data has been merged with information on employers (obtained from the *Betriebshistorikdatei*).

2.2 Measuring Job Displacement at Mass-Layoffs

To study the long-term effects of job displacement, we exploit the fact that the data covers longitudinal information on workers and firms since 1975. The goal of our empirical approach is to remain as comparable as possible to state-of-the-art studies based on administrative earnings records from the U.S. literature, while exploiting advantages specific to the German data we use. In particular, availability of daily information on earnings, employment, and unemployment insurance receipt will allow us to better date job separations and analyze daily wages, time worked, and other sources of income as additional outcomes. The data also allows us to compute various measures of firm characteristics, as further explained below.

As for comparable data sources in the U.S. and other countries, there is no direct information regarding the reason of a job separation. We follow the existing U.S. literature and define a job displacement as the event that a worker with three years of tenure leaves his main employer in the course of a mass-layoff event. The analysis of workers leaving stable jobs has several advantages. It focuses on workers who in all likelihood expected to remain in their job in the absence of a mass-layoff, and thus were likely to be surprised by being displaced. Moreover, given the steep reduction in job mobility with even a few years of job tenure in Germany, very few of these workers were likely to have moved voluntarily. This reduces the potential measurement error in the definition of job displacement.

We work with two definitions of a mass-layoff event. First, we define a mass-layoff to occur either when the firm's employment permanently declines by thirty or more percent over a short period of time. Second, we also consider the case when firms permanently close. To make these definitions meaningful, we consider only workers whose employers had at least 50 employees in the year prior to the employment drop and did not have large employment fluctuations in the years before. This definition allows us to replicate findings in the U.S. literature. Smaller firms are subject to larger percentage employment fluctuations, such that these measures of mass-layoff are less meaningful.

A key step in measuring mass-layoff events is to distinguish between actual permanent reductions in firms' employment and events such as mergers, takeovers, outsourcing, or changes in firm identification numbers. Since such events occur frequently in administrative data, we have constructed a complete cross-flow matrix of worker flows between establishments. Using this flow matrix, we only consider a reduction an employment a mass-layoff event, if no more than 20 percent of the laid-off workers are going to a single employer (i.e., if there is no large flow of workers to a different establishment). This is a common methodology used, say, by the U.S. Census to adjust longitudinal firm-level employment information. Not adjusting our mass-layoff data in this way would imply potentially serious measurement-error, likely biasing our results towards finding no effect of displacement on earnings.[4]

By focusing on job separations of high-tenured workers during mass-layoffs at medium-sized to large employers we obtain a very clean measure of job displacement that is comparable with the existing literature. A common criticism is that this may focus on workers that are more likely to have larger earnings losses at displacement. von Wachter et al. (2011) and Hildreth et al. (2009) have shown that this is not the case for the restriction on higher-tenured workers. However, it is well known that larger firms pay more, and loss in a wage premium associated with firm size may be one explanation of the larger earnings losses we find (e.g., von Wachter and Bender (2006)).

2.3 Constructing sample of displaced workers and control group

Baseline restrictions We construct our analysis sample using a two step method. First we choose for each year t all workers that satisfy the following baseline restrictions on June 30th for that year: the individual works fulltime at an establishment with at least 50 employees, is between age 24 and 50, and has at least 3 years of tenure.[5] Furthermore we exclude individuals employed in the following sectors: mining, public administration, defense, activities of private households and extra-territorial organizations.[6] Finally we focus our main analysis in this paper on men for two reasons: First, to facilitate comparisons with the earlier literature that

[4]For an exploration of these cutoffs in the context of Germany see Hethey-Maier and Schmieder (2013)

[5]These restrictions follow largely the existing literature, with a few additional restrictions. Most notably, we drop workers younger than age 24, since they may not have fully entered the labor force. We also drop workers older than age 50, who had access to partial retirement programs in Germany during that period.

[6]Specifically we exclude sectors C, L, P, and Q of ISIC Rev. 3.1.

has typically focused on men with high labor force attachment and, second, since the higher labor force attachment of men leads to less selection issues into employment and allows for simpler interpretation of the results. We have, however, replicated the entire analysis for women only as well as for a pooled sample of men and women. The results are quite similar and will be discussed below.

Within this sample, we define an individual as displaced (between year t and $t+1$) if a) the individual leaves the establishment between t and $t+1$ and is not employed at the year t establishment in any of the years $t+1$, $t+2$, ..., $t+10$ and b) the establishment has a mass-layoff (or plant closing) between year t and $t+1$.

Propensity Score Matching Displaced and non-outsourced workers may differ in many ways that will make them difficult to compare. In order to obtain a comparison group for the displaced workers in our design, we use propensity score matching. We first take all workers who satisfy our baseline restrictions in a given year and are therefore at risk of being displaced in a mass layoff or plant closing.

We then use a step matching estimator where we match within 1 digit industries based on a number of matching variables. Specifically for each 1 digit industry, we estimate the propensity of being displaced using establishment size in year t, the worker's log wage in year $t-1$ and $t-2$, as well as education, tenure and age in year t as predictors. For each displaced worker we assign a single comparison worker, using the non-displaced worker with the closest propensity score (without replacement).

This yields a group of displaced workers and very comparable non-displaced workers working at similar firms (same industry and size). Note that there is no restriction that workers in the comparison group have to stay at the same establishment between year t and $t+1$, nor that they cannot be displaced in future years. Observable characteristics between displaced and non-displaced workers prior to displacement are very similar and the two groups exhibit almost identical pre-displacement trends in wages, earnings and employment.[7]

[7] We also estimated the main results using alternative matching algorithms, such as not matching on industry, matching within counties, or matching on fewer variables and found almost identical results.

2.4 Outcome Variables

From this data, the main outcomes we consider in this study are total annual earnings, total annual income (consisting of earnings plus payments form unemployment insurance), the daily wage on June 30th of year, whether or not an individual is working on June 30th, as well as days worked or in unemployment per year. All earnings, income, and wage measures have been deflated using the Consumer Price Index and represent Euros in 2000 prices. Our main outcome variable, total annual earnings, is comparable to similar measures available in administrative U.S. data. Detailed information on unemployment insurance and days worked is typically not available in comparable U.S. data sources.

We also used the data to estimate the canonic error-components model popularized by Abowd et al. (1999) [henceforth AKM]. We follow the implementation for Germany by Card et al. (2013) [henceforth CHK]. However, since we need to compare firm effects over time, and the AKM model estimates the effects relative to an omitted baseline firm, as in Goldschmidt and Schmieder (2017) we estimate the model jointly for the entire time period. The regression model we estimate is

$$\ln(w_{it}) = \psi_{J(i,t)} + \alpha_i + \theta_t + x'_{it}\beta + \epsilon_{it}, \tag{1}$$

where $\psi_{J(i,t)}$ represents a vector of establishment fixed effects, α_i a vector of individual fixed effects and θ_t and $X_{it}\beta$ are year effects and time varying observables. The residual, ϵ_{it}, captures purely transitory earnings fluctuations. In addition, the residual will also contain any worker-firm specific (match) components in earnings, which we will denote by $m_{iJ(i,t)}$.

The AKM model has proven to be an empirically successful extension of the standard human capital earnings function and has developed into the workhorse model for incorporating firm components into traditional earnings regressions. Despite well-known limitations, we believe that there is sufficient support for the model to treat the estimated firm fixed effects as useful measures of employer characteristics. To benchmark our findings, we also use more common measures, such as firm size and average firm turnover rates.

A caveat is that the data only covers employment in social security liable jobs and receipt of unemployment insurance and assistance. There are a number of reasons why individuals may drop out of the data over time: they could drop out of the labor force, work in self-employment, work in a government job, move abroad, go into early retirement or die. Over time a sizable fraction of individuals do disappear from the coverage of our data. Treating all year-person observations where individuals are fully missing from the data as years with zero earnings would likely overestimate the earnings losses of displaced workers, since certainly some of them have earnings either abroad or in self employment. There is no perfect solution to this, but as a compromise we only use information on individuals that work in covered employment or receive unemployment benefits for at least one day in a given year, since otherwise we have little information on individuals' activities. This is likely to understate our wage losses, since some workers may exit the labor force for more than a year in response to earnings losses. Here, we depart from von Wachter et al. (2011), whose study of U.S. earnings losses includes zero earnings even if an individual drops out of the labor force for multiple years.

3 The Long-Term Effect of Job Loss on Earnings and Wages

3.1 Average labor market outcomes of displaced workers

Figure 1 shows average labor market outcomes in the two groups of workers (displaced and non-displaced). We are here pooling workers who were displaced in any year between 1980 and 2007 as well as their respective non-displaced comparison workers. Due to the propensity score matching method, this yields readily interpretable results even without controlling for any variables (such as worker characteristics, calendar year, or displacement year effects). It is particularly noteworthy that in all 4 sub-figures, the pre-displacement trends up to year -2 are virtually identical suggesting that our matching procedure has outlined a very comparable control group (we are matching based on characteristics in year -2, in order to allow for displaced worker to have diverging pre-displacement trends in year -1, e.g. due to the fact that they are in declining establishments).

Figure 1 (a) shows total yearly earnings in the two groups. The figure reveals stark earnings losses in the year of displacement, earnings are almost 10,000 Euro lower in year 0 for the displaced workers or slightly less than 30 percent. While subsequent years show some recovery, this is slow and even after 10 years, displaced workers still have about 5,000 Euro lower earnings then non-displaced workers. Note that the control group earnings are increasing up to year -1, but show a change in slopes from then onwards. This is explained by the fact that workers in both groups are by definition employed in the years prior to displacement but there is not restriction after year 0. Thus people dropping out of social security liable jobs (e.g. due to unemployment, paternity leave, moving out of Germany, moving into self-employment, ...) reduce average earnings after year 0. To avoid attributing this earnings reduction to job loss, below we will compare earnings trends of displaced workers directly to non-displaced workers in order to get causal estimates of the displacement effects.

Figure 1 (b) and (c) show how these losses are explained by employment losses and wage losses, respectively. Employment drops very sharply initially - only about 50 percent of displaced worker are employed on June 30th of the displacement year, but also recovers faster than earnings. Nevertheless, only after 10 years have most of the differences in employment probabilities have disappeared. Wages on the other hand drop by about 8-9 percent initially with the gap actually widening slightly over time to 10 percent. Thus almost all of the long-term losses in earnings are explained by lower wages among the displaced workers, rather than by employment losses.

Figure 1 (d) shows income from UI benefits in the 2 groups. UI income increases sharply at the time of displacement and appears to replace about 25 percent of the earnings losses in the first year among the full sample of displaced workers. However, it then declines quickly and the difference between the two groups disappears after around 5 years, showing - not surprisingly given the short-term nature of UI benefits - that UI benefits do little to compensate long-term earnings losses for displaced workers.

3.2 Regression analysis of labor market outcomes of displaced workers

In order to obtain results of the effects of displacement that can control for other characteristics, we estimated regression models of the form:

$$y_{it} = \sum_{j=-4}^{14} \delta_j I(t = t^* + j) I(disp) + \alpha_t + \theta_i + x_{it}\beta + \varepsilon_{it} \tag{2}$$

where $I(disp)$ is an indicator for whether the person is a displaced worker, t^* is the displacement year and t is the current year. The main coefficients of interest are δ_j, which measure the change in earnings of displaced workers with respect to the baseline year (t^*-5), *relative* to the evolution of earnings of non-displaced workers.[8] The α_t are year fixed effects that capture the evolution of earnings for the control group. The regression also includes worker fixed effects, θ_i, and time-varying control variables (x_{it}), chiefly worker age. Since our matching procedure implies that worker characteristics in the treatment and control groups are very similar at baseline, the inclusion of both the worker FE and the x_{it} make little relatively difference to the estimates.

Figure 2 shows estimates of this regression for different left hand side variables. The patterns were foreshadowed in our descriptive findings in Figure 1 for the same four variables. The figures imply that there is a strong initial effect of job loss on earnings, an ensuing recovery lasting 5-10 years, and a substantial long-term effect still visible 15 years after job loss.[9] From an analysis of employment and wages, it is clear that the large short-term effect and the initial recovery is chiefly driven by a persistent but ultimately temporary decline in employment. In a separate analysis we have found that job displacement has a a similar effect on days worked, suggesting that the employment effect occurs through within-year changes in employment.[10] The effect on wages shows a large immediate effect and exhibits little in

[8] I.e., the specification omits δ_{t^*-5} and one of the year dummies to avoid collinearity. Essentially these are absorbed in the constant (γ_0). This means the δ_j can be interpreted as the difference between the two groups after taking out the initial difference in year $t^* - 5$.

[9] As found in other studies, there is a small pre-displacement dip in earnings, which can partly arise because the timing of the firm-level shock and the worker separation may deviate. Hence, workers leaving in the year after the firm-level shock may have experienced a decline in earnings on the job. It may also be that there already is a reduction in days or hours worked at the firm in the year before a separation.

[10] Note that in the current analysis, we do not distinguish between full- and part-time workers, but plan to

terms of recovery. It it important to note that since this figure is conditional on having found employment, it *understates* the wage decline if high-wage workers are more likely to self-select into employment. Finally, the causal effect of job displacement on UI income shown in the final panel confirms that, consistent with the nature of the program and our findings on employment spells, UI plays an important role in buffering the earnings loss. However, given an important part of the loss is in hourly wages, UI falls far short in replacing the average amount of lost income.

These findings are striking, since they resemble very closely in shape and magnitude comparable estimates for the U.S. (e.g, Jacobson et al., 1993, Couch and Placzek, 2010, von Wachter et al., 2011). On the one hand, this may not be surprising, since we deliberately structured our analysis to replicate these studies in the way we defined displacements, our sample, and our estimation approach. On the other hand, much has been speculated about how the U.S., with more dynamic job creation, higher levels of job mobility, and less generous unemployment insurance may imply a faster recovery rate than a continental European labor market such as Germany. Our estimates suggest that high UI and social benefits alone do not seem to lead to a substantially different path of recovery than in the U.S. (e.g., Ljungqvist and Sargent 1998, 2008), despite the fact that UI benefits have been shown to raise unemployment and lower wages (Schmieder et al. (2016)). Clearly, the composition of displaced workers and the type of shocks they effectively suffer may be different in the two labor markets, and so the close correspondence should be interpreted with caution. But the congruence we observe in Figure 2 is nevertheless telling about how labor market shocks can have very detrimental and long lasting effects on workers in very different institutional settings.

3.3 Decomposing Earnings Losses into Wage and Employment Losses

The previous results clearly showed that displaced workers experience large employment losses - especially over the short run -, as well as sizable and long lasting wage losses. In this subsection we investigate what share of earnings losses after displacement are explained by

do so in the future to assess changes in the intensive margin of employment. The data does not contain a measure of hours worked.

those two channels using a simple decomposition. Note that earnings y in a year are the product of the number of days worked by an individual N_d and the average daily wage in that year w: $y = N_d w$. Taking expectations over the population of displaced workers we get that:

$$E[y] = E[N_d w] = E[N_d]\, E[w] + Cov(N_d, w)$$

Denote y_t^D earnings if a person is displaced in year t after displacement. Denote y_t^S the counterfactual earnings if a person is not displaced ('stayer'). The earnings losses of a displaced worker are given as: $\Delta = y_t^S - y_t^D$. We omit the t subscript in the following.

Expected earnings losses:

$$\begin{aligned}
E[\Delta] &= E[N_d^S w^S] - E[N_d^D w^D] \\
&= E[N_d^S]\, E[w^S] + Cov(N_d^S, w^S) - E[N_d^D]\, E[w^D] - Cov(N_d^D, w^D) \\
&= E[N_d^S]\, E[w^S] - E[N_d^D]\, E[w^D] + Cov(N_d^S, w^S) - Cov(N_d^D, w^D) \\
&= \left(E[N_d^S] - E[N_d^D]\right) E[w^S] + E[N_d^D] \left(E[w^S] - E[w^D]\right) + Cov(N_d^S, w^S) - Cov(N_d^D, w^D) \\
&= \Delta E[N_d] E[w^S] + E[N_d^D]\, \Delta E[w] + \Delta Cov(N_d, w)
\end{aligned}$$

Thus the Earnings Loss of a Displaced Worker relative to the Control worker can be written as:

$$E[\Delta] = \Delta E[N_d] E[w^S] + E[N_d^D]\, \Delta E[w] + \Delta Cov(N_d, w)$$

Expressed as a percentage of stayer earnings:

$$\frac{E[\Delta]}{E[y^s]} = \frac{\Delta E[N_d] E[w^S]}{E[y^s]} + \frac{E[N_d^D]\, \Delta E[w]}{E[y^s]} + \frac{\Delta Cov(N_d, w)}{E[y^s]} \qquad (3)$$

Thus earnings losses of displaced workers can be decomposed into three components: 1) the change in days worked between the displaced workers and the control group, 2) the change in wages between the two groups, and 3) the change in the covariance between the two.

This last last term can be interpreted as the selection of who is employed. If the covariance term becomes larger in the group of displaced workers than in the control group, this would indicated that the individuals with larger employment losses have lower wages while workers who still work the most have the highest wages.

Figure 3 shows the results of the decomposition in equation (2) over a 14 year period post-displacement. Note that the decomposition is only defined for workers for whom we observe a wage in a given year and thus who work for at least one day. We thus drop worker-year observations where workers are not working at all from this analysis and the earnings losses are therefore slightly less than before. Nevertheless, the figure still shows very large earnings losses in the first year (t=0) after displacement of more than 35%. The earnings losses then shrink to around 10 percent after 5 years, after which recovery is very slow. The other 3 lines show the components of our decomposition. In year 0 and 1 after job loss the employment losses clearly dominate and explain most of the earnings losses. While the wage losses initially account for a smaller drop in earnings, they are much more persistent and after year 3 become more important than the earnings losses. Finally the covariance term is quite striking: it is positive and quite large in the years following job loss. For example, the positive selection into who is working the most among displaced workers leads to a 10 percent increase in earnings relative from what would be expected simply from the drop in average wages and average days worked. This term declines over time however and in the long run this type of selection plays little role for the earnings losses, which eventually are fully explained by the long-run wage losses.

4 The Effect of Job Loss on Wages and Employment Over the Business Cycle

Figure 4 shows earnings losses of displaced workers separately by year of displacement obtained by replication the regression in equation (2) separately by displacement year. Vertical bars indicate recession years in Germany (defined as a year of negative GDP growth). The figure reveals a strong cyclical pattern in the earnings loss from job displacement. While losses were only about 5000 Euro in the displacement year in 1979-1980, they were more than 10,000

Euros for workers displaced in the 1982 recession. After 1982 losses became smaller until they increased again during the 1993 recession. In the mid 1990s Germany entered a period of prolonged high unemployment rates and sluggish growth (eurosclerosis) and during this time period earnings losses of displaced workers stayed very high, only to come down briefly before the 2003 recession. After the 32003 recession (and the Hartz labor market reforms) earnings losses fell again as the economy and the labor market recovered.

Turning to employment and wage losses, Figure 5 shows a highly cyclical pattern for number of days worked of displaced workers, with the largest losses for workers who lose their jobs during recessions or in the following year. The cyclicality is similar or even more pronounced than for yearly earnings. This indicates that an important part of the cyclicality of earnings losses at displacement are driven by employment losses. However, Figure 6 shows that wage losses are still cyclical, though somewhat less cyclical than earnings losses, especially during the early 1980s.

Figure 7 and Table 2 explore the cyclicality of the effects of job loss further. Figure 7 plots the short-term effects of job loss on annual earnings and log daily wages for each displacement year directly against the prevailing national unemployment rate. The coefficients from a univariate regression corresponding to the displayed fitted lines in the two panels of Figure 7 are shown in Table 2 (rows 2 and 3 of column 1, respectively). To better compare the cyclicality of earnings and log wages, row 2 of column 1 also displays the same regression of the percentage loss in earnings.[11] Column 5 of Table 2 Panel A displays the predicted change in the effect of job loss from raising the rate of unemployment by 5 points from 4 to 9 percent (the corresponding levels are shown columns 3 and 4). Panel B of Table 2 uses the year over year change in the unemployment rate as an alternative measure of the state of the labor market and finds very similar results.

The results in Figure 7 and Table 2 confirm that both earnings and wages losses are strongly countercyclical. For each point increase in the unemployment rate, the earnings loss rises by

[11]Note that the two estimates are not strictly comparable, since the percent loss for earnings is obtained by dividing the estimated loss in levels by pre-displacement average earnings, whereas the effect on wages is based on a log specification.

about 2% (row 2), whereas wages are reduced by 1.5% (row 3). It is clear from the Figure 7 that the relationships are very precisely estimated. The strong cyclicality of employment losses shown in Figure 5 and row 4 of Table 2 imply that he cyclicality of earnings losses arises both from employment reductions and wage reductions.

To explore more formally how much of the cyclicality of earnings losses is explained by the losses in days worked and losses in wages, we calculate the decomposition from equation (2) above for each cohort of job losers for earnings within 3 years after job loss. Figure A-3 shows the four components in a time series, with apparent but varying degrees of cyclicality. To explore he cyclicality directly, Figure 8 a) shows the earnings losses, while Figure 8 b)-d) show the 3 components of the decomposition. Note that as explained in Section 3.4, the decomposition is only defined for observations with positive earnings, which is responsible for the small difference between Figure 7 a) and Figure 8 a). The scale of the y-axis in Panels a) to d) is identical and the units are comparable. Thus the decomposition shows that employment losses and wage losses play a similar role for explaining the overall cyclicality of earnings losses. Interestingly, the covariance term is positively correlated with the unemployment rate, indicating that selection is stronger during deep recessions. We return to the source of cyclicality of wage losses in Section 5.

Using the unique features of our data, we can explore to what extent the relatively generous German UI system is able to dampen the cyclicality of earnings losses. Since UI benefits only insure against earnings losses stemming from unemployment, we would expect that UI benefits may have some impact on the cyclicality of total income. Indeed, Table 2, row 7, panels A and B, show that the of UI benefits received in the first years after job loss rises significantly in recessions - for example from 660 Euro when the unemployment rate is falling to more than 1100 Euro when the unemployment rate is increasing by 1 percentage points. In row 6 in Table 2, we directly analyze the cyclicality loss in total income at job displacement (defined as total annual earnings plus receipt of UI). Despite the large swings in benefit receipt, the cyclicality of the losses in annual earnings (row 2, column 1) change little once UI income is added (row 4, column 1). This partly reflects the fact that in Germany, in contrast to the

U.S., neither the duration nor the level of UI benefits is extended in recession. It also implies that other factors affecting the overall role of UI, such as the benefit take-up rate, do not vary substantially with the cycle.

Nevertheless, a comparison of the total predicted earnings loss with and without UI – shown in rows 1 and 6 of columns 3 and 4 – imply that the total earnings loss is reduced by 15-20% due to the presence of UI. Hence, UI still provides an important buffer against the effect of job loss. Given that UI benefits only offer a replacement rate of around 63 - 68 percent over this time period and given that wage losses are not insured, it is not surprising that UI benefits can only reduce earnings losses up to a certain amount.

5 The Effect of Job Loss on Employer Characteristics Over the Business Cycle

A key question in the literature on job displacement is what explains the long-lasting and cyclical wage losses we find in Figures 2, 6 and 7. It is generally difficult to distinguish between the core hypotheses in the existing literature. Yet, the high-quality information on workers' employers before and after job displacement available in our data allows us to make inference about one such core hypothesis, namely that displaced workers lose quasi-rents provided by the firm. We cannot measure such rents directly, but we have access to several measures that have been associated with such rents in the labor literature. First, it has long been speculated that larger firms pay higher wages and provide more pleasant work environments generally. Second, it is usually thought that systematic wage differences across firms reflect rent sharing between workers and firms.

Hence, we proceed in two steps. In a first step, we analyze whether the incidence of job displacement differs by job type, and whether a job displacement changes the "quality" of a worker's employer. For the latter exercise, we simply estimate the same regression in equation (2) with two measures of firm characteristics as outcome variables – log employment size of the establishment and the establishment fixed effects – i.e., average differences in wage levels between firms not explained by worker characteristics. In a second step, we assess directly whether such changes in firm characteristics can help to explain the effect of job displacement on wages and its cyclicality. That is, we reestimate equation (2) with log wages as dependent variable, but include characteristics of the employer as control variables.

5.1 The Effect of Job Loss on Firm Characteristics in the Cross Section

Figure 13 explores how losses in firm effects and wages differ by earnings level of the displacing firm. Panel (a) shows the average loss in establishment fixed effects for different quartiles of the (worker weighted) pre-displacement distribution of establishment fixed effects. Panel (b) shows the same for the average loss in log daily wages by establishment fixed effect quartiles. The pattern is clear - workers coming from firms with high fixed effects have much larger short- and long-term losses in both establishment fixed effects and daily wages. There is a clear pattern of mean reversion in firm effects occurring at job loss. Yet, even for workers displaced from the lowest fixed effect class there are persistent losses in firm quality and daily wages.

Figure 14 further explores the differences in earnings losses by initial establishment effects job loss. Panel (a) of Figure 14 shows that the mean reversion at job loss is far from complete. Panels (b) and (c) show the 3-year losses in establishment effects and the 3 year losses in wages by initial establishment fixed effects as scatterplots. The coefficient of the regression line in Panel (b) is -0.5; a full elimination of the differences would have implied a constant term of zero and a slope coefficient in Panel (b) of minus 1. The coefficient of the regression line in Panel (c) is 0.4; if the loss in firm fixed effect would be the only driver in wage losses, the coefficients would have been the same. Figure (d) directly shows the scatter plot of losses in wages and losses in firm effects. The slope of the regression line is 0.8, consistent with our findings in Table 3. Panels (c) and (d) confirm that the loss in firm effects is a major driver of wage losses, but that losses occur for other reasons as well.

Figure 13 also shows that job losers recovery patterns also differs by establishment effect of the displacing firm. While neither group fully obtains the old level in establishment fixed effects, workers displaced from high fixed effect firms experience at least some recovery in establishment effects after job loss (those from low fixed effect firms experience little recovery).

Moreover, for these workers, the entire loss and recovery in daily wages appears to be driven by losses in firm effects. In contrast, workers displaced from lower fixed effect firms experience wage losses that are larger than the loss in establishment fixed effects, and a recovery in wages beyond that of firm effects.

5.2 The Effect of Job Loss on Firm Characteristics Over the Business Cycle

Clearly, firm characteristics only have the potential to explain the cyclicality of wage losses if the incidence of job displacement by firm type varies over the business cycle. It is well known that firms of different size and different average wages experience different net employment growth over the business cycle in the U.S. (e.g., Haltiwanger et al., forthcoming). For Germany, we obtain a similar finding when we split firms by high and low firm fixed effects. Figure 10 shows the fraction of establishments with at least 50 employees that experience a plant closing or mass layoff in each year, depending on whether they are a high or low establishment fixed effect employer. Figure 10 a) shows that the mass layoff rate is higher and much more cyclical for establishments with fixed effects above the median, while panel b) shows that the same is true for plant closings. This suggests that one reason for wage losses to be larger during recessions is that during economic downturns, more workers are displaced from high paying establishments and these workers tend to experience larger wage losses.

We also find that changes in establishments characteristics are more pronounced during recessions. Figure 11 shows changes in the (a) log employment size and (b) average wage of the employing establishment relative to non-displaced workers over time. There is clearly a very large decline in both establishment size and the average wage of the employer relative to non-displaced workers: establishment size goes down by about a full 100 log points, while average establishment daily wages are reduced by about 5 to 10 Euros. Figure 12 and Table 2, Panel B show that both of these effects correlate systematically with the unemployment rate at job loss, particularly the reduction in mean establishment wages.

6 Loss in Firm Quality as Source of Earnings Losses for Job Losers

6.1 Approach to Decomposing the Source of Wage Losses

The findings in Section 5 suggest that the large wage losses at job loss and their cyclicality documented in Sections 3.3 and 4 could be partly explained by losses in firm characteristics. To assess this question directly, we begin by presenting some results based on the sample pooling all displacement years that was used in Section 3 to obtain our benchmark estimates. Panel (a) of Figure 15 shows a series of estimates for the effect of job loss on log daily wages, in which we control for changes in several job characteristics at displacement; these include industry and occupation dummies, log establishment size and mean establishment wages, and establishment fixed effects. It is clear that changes in industry and occupation has a small effect . In contrast, including firm characteristics leads to a reduction of the wage loss of about 50%. This suggests that losses in firm-specific wage components are strongly correlated with wage losses at job loss. However, the association does not necessarily imply a causal relationship if workers with larger or smaller wage losses tend to have different losses in establishment fixed effects.

We next study the role of losses in establishment FE in explaining the cyclicality of wage losses over the business cycle we found. To do so, we need to address directly the question of composition changes in the pool of job losers over the business cycle. Such changes in the characteristics of job losers could be partly responsible for the degree of cyclicality in wage losses described in Section 4 if workers particularly prone to experiencing large wage losses are more likely to be laid off in recessions. Hence, it is important to obtain a measure of the degree of cyclicality of earnings losses that controls for such variation. In so far as such high-loss workers are more likely to move from high to low fixed effect firms, controlling for such composition changes also helps to address whether losses in establishment FE are indeed the cause of the large job losses we find.

To hold composition changes fixed, we modify our main regression approach somewhat. In a first step, we use the fact that we have paired each job loser in our sample with a statistical twin via our matching procedure, and calculate an individual-level estimate of the wage loss at job loss:

$$\Delta_{dd} w_{it} = \Delta_d w_{it} - \Delta_{nd} w_{it}$$

where $\Delta_d w_{it}$ is the short-term individual wage change before (-5 to -1 years) and after (1 to 3 years) job displacement (and $\Delta_{nd} w_{it}$ is the wage change for the best match from the control group). One can think of $\Delta_{dd} w_{it}$ as the treatment effect from job loss for each worker. To investigate the cyclicality of the cost of job loss we then run the following regression model:

$$\Delta_{dd} w_{it} = \beta\, UR + \gamma\, \hat{\psi}_{J(i,t)} + \delta\, \hat{\alpha}_i + t\pi_1 + t^2\pi_2 + \varepsilon_{it}$$

where UR is either the level of unemployment rate or the annual change in the unemployment rate. Given the high stock of long-term unemployed in Germany, the change often provides a better measure of cyclical variation. To control for a long-term trend in wage losses observed in the data, all models include a quadratic time trend. The key parameter of interest is β, the cyclicality of the wage loss at job displacement. We begin by estimating the model without control variables. To then control for changes in worker and firm composition we control for $\hat{\alpha}_i$ (the estimated individual FE) and $\hat{\psi}_{J(i,t)}$ (the estimated establishment FE *before* displacement). Finally, in order to assess the role played by the loss in establishment FE we augment this model by replacing the level for the establishment FE with its change at job loss. To control for the fact that there may be a trend towards certain types of firms among non-displaced workers, too, we use as main control $\Delta_{dd}\hat{\psi}_{J(i,t)}$, the loss in establishment FE among job losers relative to the change in the control group:

$$\Delta_{dd} w_{it} = \beta\, UR + \gamma\, \Delta_{dd}\hat{\psi}_{J(i,t)} + \delta\, \hat{\alpha}_i + t\pi_1 + t^2\pi_2 + \varepsilon_{it}.$$

Comparing the coefficient estimate with and without controlling for losses in establishment FE will indicate to what extent losses in firm quality over the business cycle are a key driver of the cost of job loss.

There are two important caveats to bear in mind. First, clearly firm characteristics may be endogenous, and hence care has to be taken in interpreting these estimates as causal effect of changes on employer characteristics on earnings losses. Yet, the correlation is informative, and if workers are positively selected into firms with higher wages, the estimates serve as a lower bound of the remaining cost of job displacement. In addition, we replicate the main result using purely annual variation in average changes in earnings and firm characteristics, which are not affected of selective entry into firm characteristics. Second, systematic wage differences across firms may in principle not only capture rents, but other components of the wage structure, such as compensating differentials. While no conclusive evidence is available, several findings in the literature point to firm effects as signifying desirable employers.[12]

6.2 Firm-Level Determinants of the Cost of Job Loss Over the Business Cycle

Table 3 contains our main results from these regressions. The first column confirms that wage losses at job loss have a systematic cyclical component based on both of our measures of the unemployment rate (the level in Panel A and the year to year change in Panel B). To get a sense of the magnitudes, during our sample period the unemployment rate in Germany varied from between 3-4% in the early 1980s to over 10% in the large recession in the mid-2000s. According to the estimate in column (1) , a five point rise in the unemployment rate from 5% to 10% is predicted to lead to a rise in the wage loss of 5 log points, or about half of the mean log wage loss. Similarly in a year when the UR increases by 2 percentage point (not untypical in a recession), the log wage loss increases by around 6 points. Column (3) shows that the coefficients decrease by about one third once we control for changes in worker and firm composition, suggesting that some of the cyclicality is explained by changes in the composition of displaced workers and the displacing firms. This result is virtually the same whether we use the worker FE or education as a measure of worker characteristics. In column (6) we instead include the change in firm fixed effects as a control variable. The estimates of

[12] To estimate firm effects, we follow the procedure in Card, Heining, and Kline (2013), with one important exception. To avoid dealing with the fact that firm effects are normalized to an omitted firm, we do not estimate firm effects separately for different periods. Instead, we estimate one set of firm effects for each firms, using all available workers in the entire sample for that firm. Hence, firm effects are by definition stable over time, and the only way a worker can experience a change in firm effects over time is by moving employers.

the cyclicality of job loss decline by around one half relative to the raw result, confirming the visual impression that losses in firm wage premiums are a key driver of the variation in the cost of job loss over the business cycle. Finally in column (7) we control for the change in the firm fixed effect, but force the coefficient on the firm fixed effect to be equal to 1, in which case the change in the firm fixed effect can explain even more of the cyclicality. Qualitatively the amount of cyclicality that is explained by the change in firm fixed effects is very similar whether we use the level or change in the unemployment rate. It is important to note that this finding does not simply derive from the fact that workers from high FE firms are more likely to lose their jobs in recession. If that were the case, controlling for changes in the composition of which firms workers came from alone would explain the cyclicality of losses, which is not the case. These findings are also visible in Panel (b) of Figure 15, which shows the corresponding scatter plot – the strong correlation with the unemployment rate present in Panel b) of Figure 7 is substantially reduced.

Overall, the important role of firm characteristics we find for explaining about 60% of the level of wage losses, and about half of the cyclical variability points to an important role of losses in rents from a job displacement. These findings underscore an important role of luck in the labor market, and the business cycle appears to play an important role in shaping worker career outcome by changing the firm-composition of employment opportunities. These findings are robust to variations in samples or in the way we measure the business cycle. In particular, the results tend to be similar if not stronger when we measure the wage loss ten years after a job loss in Table 5. Similarly, in Table 6 shows that the findings are confirmed, or even stronger, for women (a more in depth anlysis of the effect of job loss for women is contained in the Appendix). The results are aslo similar when we measure the cycle by the change in the unemployment rate or the level in the unemployment rate.

One concern with the individual-level estimates presented in Table 3 is that the establishment FE of the new employer is a choice variable for the displaced worker. This could bias our estimates of the importance of changes in establishment FE upward or downward, depending on the nature of the underlying selection problem. For example, if in recessions workers with smaller wage losses are more likely to find reemployment at better firms, then our estimates would *understate* the role of establishment FE for explaining the degree of cyclicality. Given supply of high-wage jobs has been shown to be very cyclical, it is likely that competition in the labor market raises the amount of such positive selection.

To address this question, we pursued an alternative, group-level estimation strategy, where we regress the mean annual wage loss on the mean annual loss in establishment FE. Effectively, we use the coefficients from our main results discussed in Section 4 as outcome and control variables instead of the individual losses we use in Table 3. It turns out that this approach is identical to using year dummies as instruments for the change in firm fixed effects. Since the regression model also includes the unemployment rate as our main variable of interest, it captures the effect of other factors varying over the business cycle affecting the cost of job loss, and hence the coefficient on the mean loss in establishment FE can be interpreted as the causal effect of changes in establishment FE over the business cycle on wage losses. The results (not shown in the paper) suggest that it is likely that the individual-level model tend to *understate* the degree of importance of losses in firm fixed effects at job loss. Hence, it appears unlikely that our individual-level results are entirely driven by positive selection of workers into firms by their latent wage growth (the worker effects control for selection by permanent earnings potential). However, the presence of omitted variables fluctuating over the business cycle could bias these results upwards, and hence we rely on our individual-level models.

6.3 Other Explanations of the Cost of Job Loss Over the Business Cycle

We also examined a range of other potential mechanisms behind the cost of job loss and their correlation with losses in establishment fixed effects. From an empirical point of view, previous analyses can be grouped into four categories: a) variation in cost of job loss by demographic characteristics, such as gender, education, or labor market experience; b) variation in employer characteristics (e.g., firm size, firm fixed effect); c) variation in pre-displacement career outcomes, such as job, occupation, or industry tenure, prior occupation or prior industry; d) variation in post-displacement career outcomes, such as non-employment duration, switching primary industry or occupation, or recurring job loss.

In our regression analysis, we have included several variables from each of these categories, and have found them to matter in expected ways. For example, we find that job losers with longer labor market experience, higher job tenure, or lower education tend to experience larger earnings losses. However, we find that demographic factors and pre-displacement career background does not help to explain variation in the cost of job loss over the business cycle. Instead, here we focus on post-displacement career outcomes, chiefly duration in nonemployment and incidence of industry and occupation switching, both of which were found to correlate strongly with the cost of job loss over the business cycle. In particular, earnings losses for industry and occupation switchers have been interpreted to mean that displaced workers lose industry and occupation specific skills.

Table 4 shows coefficients from comparable regressions of losses in log wages in which we have included additional variables. The table makes several points. Clearly the effect of the duration of nonemployment after job loss (and prior to reemployment) plays an important role in explaining the cost of job loss and its cyclicality. Controlling for pre-displacement establishment effects does not affect the coefficient, implying that workers coming from high-wage firms do not search for jobs longer. In contrast, including the change in establishment effects explains about half of the effect (two thirds if we set the coefficient to one). This suggests that an important part of the loss in wages due to nonemployment duration is due to entry into lower paying firms, consistent with findings in Schmieder et al. (2016).

Turning to changes industry and occupation affiliation, these have a substantial effect on cost of job loss. However, conditional on nonemployment duration, they have little effect on the degree of cyclicality. Interestingly, controlling for changes in establishment fixed effects substantially reduces the negative effect of industry and occupation switching. This suggests that an important reason those moves lead to large losses is that they lead to reemployment at lower-wage firms. This is also consistent with the assumptions of the AKM model that suggest that conditional on worker and firm effects, such interaction components explain only a moderate amount of the variation of wages.

It is worth pointing out that these results do not necessarily preclude a role of factors such as losses in specific skills or other forms of human capital for explaining the remainder of wage losses. To get a broad sense of the potential importance of this channel for explaining the cyclicality of our results, we analyze the incidence of changes in industry and occupation mobility after job displacement over the business cycle. The resulting Figure A-8 shows that the rate of industry switching indeed increases somewhat in recessionsTo assess this in a more direct fashion, we replicated our main Table 3 only for workers who stayed within the same industry. The results, shown in Table 7, indicate that controlling for industry switching the cyclicality of wage losses is reduced, although still cyclical. Controlling for changes in establishment FE still cuts the cyclicality between 30 and 50% relative to the baseline in Column (1), suggesting that losses in establishment fixed effects and changes in industry affiliation partly operate independently to explain cyclical job losses over the business cycle

7 Conclusion

In this paper we have used administrative data from Germany covering over three decades to analyze the sources behind large, persistent, and cyclical costs of job loss. This data allow us to make three important contributions to the existing literature. First, our data allow us to distinguish between losses in employment and losses in wages. Second, we can assess the contribution of employer characteristics in determining the losses in wages we find. Finally, we can establish the role of unemployment insurance in buffering the large and cyclical losses we find.

We obtain four main findings. First, earnings losses at job loss in Germany are large, persistent, and strongly countercyclical. The magnitude and cyclicality of the losses we find are surprisingly similar as comparable estimates from the U.S. Second, while losses in employment play an important role, the majority of the longterm earnings losses are driven by reductions in wages. These wage reductions are again countercyclical. Third, we find that a large part of the wage losses and a substantial degree of their cyclicality can be explained by reduction of the wage levels of new employers. While displaced workers tend to come from large firms, and this pattern is countercyclical, the majority of our finding is driven by changes in the characteristics of new employers over the business cycle.

These findings are consistent with an increasing literature documenting the existence of firm-specific wage components, the variation of firm characteristics over the business cycle, and their role in explaining career trajectories of young workers. Our findings confirm a substantial role in firm-specific wage components in explaining wage dynamics. It appears that access to a labor market with a high quality of jobs plays a crucial role in determining the wage losses of displaced workers, another indicator of the important and persistent role of luck in the labor market.

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Table 1: Worker characteristics by displacement status the following year – 1980-2007

	(1) Non-displaced workers	(2) Displaced mass lay-off	(3) Displaced plant closing	(4) Displaced mass lay-off or plant closing
Panel A: Individual Characteristics				
Non-German	0.09	0.1	0.1	0.1
	[0.3]	[0.3]	[0.3]	[0.3]
Real wage	84.5	84.1	82.3	83.1
	[27.3]	[28.2]	[27.1]	[27.6]
Parttime	0	0	0	0
	[0]	[0]	[0]	[0]
Female	0.3	0.3	0.3	0.3
	[0.5]	[0.5]	[0.4]	[0.5]
West Germany	0.9	0.8	0.8	0.8
	[0.3]	[0.4]	[0.4]	[0.4]
Years of education	10.9	11.1	10.8	10.9
	[2.3]	[2.4]	[2.1]	[2.2]
Potential experience	21.1	20.7	21.4	21.1
	[7.6]	[7.5]	[7.5]	[7.5]
Tenure with current Employer	8.9	8.5	9.0	8.8
	[4.7]	[4.8]	[5.0]	[4.9]
Actual experience, but censored 1975	12.1	11.7	12.1	11.9
	[6.0]	[5.9]	[6.1]	[6.0]
Total yearly earnings	30725.0	29610.1	28998.5	29275.0
	[10080.3]	[10769.5]	[10379.2]	[10561.8]
Total yearly income	30739.7	29891.6	29351.2	29595.6
	[10068.3]	[10559.7]	[10145.8]	[10338.4]
Days per year working fulltime	363.3	350.0	350.7	350.4
	[18.3]	[39.7]	[38.1]	[38.8]
Wage on June 30th of year	84.5	84.1	82.3	83.1
	[27.3]	[28.2]	[27.1]	[27.6]
Log of wage in June	4.4	4.4	4.4	4.4
	[0.3]	[0.3]	[0.3]	[0.3]
Panel B: Establishment Characteristics				
Number of employees	506.4	519.8	512.2	515.6
	[1408.2]	[870.7]	[1460.2]	[1229.2]
Share of fulltime employees	0.9	0.9	0.9	0.9
	[0.1]	[0.1]	[0.1]	[0.1]
Establishment effect	2.0	2.0	2.0	2.0
	[0.1]	[0.1]	[0.1]	[0.1]
Avg. years of education in estab.	10.9	11.0	10.8	10.9
	[1.1]	[1.2]	[1.0]	[1.1]
Number of Spells	171619	77598	94021	171619

Notes: Characteristics of displaced and non-displaced workers in year prior to displacement year. Workers satisfy the following restrictions: age 24 to 50, working fulltime in pre-displacement year, have at least 3 years of tenure and establishment has at least 50 employees. Non-displaced workers are matched to displaced workers using propensity score matching algorithm.

Table 2: Effect of Unemployment Rate on Outcomes for Job Losers over 3 years after Job Displacement

	(1)	(2)	(3)	(4)	(5)
Panel A: Regression of Effect of Job Loss on National Unemployment Rate					
	Estimated Effect of Unemployment Rate		Predicted Effect of Unemployment Rate		Difference going from 4% to 9% UR
	Coefficient	Std. Err.	UR=4%	UR=9%	
Outcome:					
Annual Earnings (Loss in Euro)	-734.2	[164.0]	-4833.5	-8504.5	3671
Annual Earnings (Percent Loss)	-0.019	[0.0053]	-0.17	-0.27	0.10
Log Wage Loss	-0.015	[0.0027]	-0.043	-0.12	0.077
Annual Days Worked Loss	-4.87	[1.56]	-44.5	-68.8	24.3
Change in Estab FE	-0.0024	[0.0015]	-0.070	-0.082	0.012
Annual Income (Loss in Euro)	-662.5	[141.4]	-4076.3	-7388.8	3312.5
Annual UI Receipt (Loss in Euro	71.7	[24.5]	757.1	1115.6	-358.5
Panel B: Regression of Effect of Job Loss on Year over Year Change in National Unemployment Rate					
	Estimated Effect of Change in UR		Predicted Effect of Change in UR		Difference going from -1% to +1%
	Coefficient	Std. Err.	$\Delta UR = -1\%$	$\Delta UR = +1\%$	
Outcome:					
Annual Earnings (Loss in Euro)	-1917.5	[488.2]	-4888.6	-8723.6	3835
Annual Earnings (Percent Loss)	-0.064	[0.013]	-0.16	-0.28	0.12
Log Wage Loss	-0.029	[0.0097]	-0.055	-0.11	0.055
Annual Days Worked Loss	-18.0	[3.77]	-38.3	-74.3	36
Change in Estab FE	-0.015	[0.0034]	-0.059	-0.089	0.030
Annual Income (Loss in Euro)	-1649.9	[435.3]	-4226.2	-7526	3299.8
Annual UI Receipt (Loss in Euro	267.6	[60.0]	662.3	1197.5	-535.2

Notes: Each row represents a separate regression of the mean losses in the outcome variable over a three year period after job loss on the national unemployment rate (Panel A). and the year over year change in the national unemployment rate (Panel B). The model is estimated on the yearly level.

Table 3: The Cyclicality of Log Wage Losses with and without controlling for establishment effects – 3 Year Horizon - Men

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage	(7) log wage
Panel A: Change in Unemployment Rate							
Change in UR t-1 to t	-0.028		-0.029		-0.029	-0.016	-0.013
	(0.0014)**		(0.0014)**		(0.0014)**	(0.0012)**	(0.0012)**
Establishment effect		-0.32	-0.33	-0.34	-0.35		
		(0.012)**	(0.011)**	(0.012)**	(0.012)**		
Worker effect		0.18	0.18				
		(0.0030)**	(0.0030)**				
Education years				0.017	0.016		
				(0.00055)**	(0.00054)**		
Change in Estab FE						0.79	1
						(0.0054)**	
Mean Dep. Var.	-0.087	-0.087	-0.087	-0.087	-0.087		-0.087
N	43512	43512	43512	43512	43512	43512	43512
R^2	0.020	0.10	0.11	0.047	0.057	0.34	0.018
Panel B: Unemployment Rate - Level							
Unemployment rate	-0.0095		-0.0061		-0.0069	-0.0052	-0.0040
	(0.0011)**		(0.0010)**		(0.0011)**	(0.00088)**	(0.00089)**
Establishment effect		-0.32	-0.32	-0.34	-0.33		
		(0.012)**	(0.012)**	(0.012)**	(0.012)**		
Worker effect		0.18	0.18				
		(0.0030)**	(0.0030)**				
Education years				0.017	0.016		
				(0.00055)**	(0.00055)**		
Change in Estab FE						0.79	1
						(0.0054)**	
Mean Dep. Var.	-0.087	-0.087	-0.087	-0.087	-0.087		-0.087
N	43512	43512	43512	43512	43512	43512	43512
R^2	0.014	0.10	0.10	0.047	0.048	0.34	0.016

Notes: Regressions control for year and year squared. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Column 7 regresses the log wage loss on the unemployment rate (change in UR) controlling for the change in the establishment effect, where the coefficient on the establishment effect is forced to be equal to 1.

Table 4: Log Wage Loss - Diff-Diff

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	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage	(7) log wage	(8) log wage
Change in UR t-1 to t	-0.018	-0.018	-0.012	-0.0095	-0.018	-0.018	-0.012	-0.0095
	(0.0015)**	(0.0015)**	(0.0013)**	(0.0014)**	(0.0015)**	(0.0015)**	(0.0013)**	(0.0014)**
Establishment effect		-0.34				-0.33		
		(0.012)**				(0.012)**		
Change in Estab FE			0.69				0.70	
			(0.0060)**				(0.0060)**	
Worker FE (Std)	0.14	0.12	0.075	0.056				
	(0.0042)**	(0.0045)**	(0.0039)**	(0.0040)**				
Nonemp. Dur. (Years)	-0.11	-0.11	-0.058	-0.037	-0.12	-0.11	-0.063	-0.042
	(0.0024)**	(0.0025)**	(0.0022)**	(0.0023)**	(0.0023)**	(0.0025)**	(0.0022)**	(0.0022)**
Potential experience	-0.0049	-0.0056	-0.0062	-0.0062	-0.0080	-0.0081	-0.0084	-0.0083
	(0.00083)**	(0.00088)**	(0.00076)**	(0.00078)**	(0.00084)**	(0.00088)**	(0.00076)**	(0.00078)**
exp2	0.00012	0.00012	0.00012	0.00012	0.000091	0.000093	0.00012	0.00013
	(0.000019)**	(0.000020)**	(0.000018)**	(0.000018)**	(0.000020)**	(0.000021)**	(0.000018)**	(0.000018)**
Occ. change		-0.033	-0.016	-0.0086		-0.041	-0.022	-0.014
		(0.0024)**	(0.0020)**	(0.0021)**		(0.0024)**	(0.0020)**	(0.0021)**
Ind. change		-0.045	-0.024	-0.015		-0.049	-0.025	-0.015
		(0.0025)**	(0.0022)**	(0.0022)**		(0.0025)**	(0.0022)**	(0.0023)**
edyrs== 13.0000					0.032	0.030	0.014	0.0084
					(0.0053)**	(0.0056)**	(0.0048)**	(0.0050)
edyrs== 16.0000					0.066	0.064	0.023	0.0087
					(0.0050)**	(0.0053)**	(0.0046)**	(0.0047)
edyrs== 18.0000					0.053	0.053	-0.0043	-0.024
					(0.0057)**	(0.0060)**	(0.0052)	(0.0053)**
Mean Dep. Var.	-0.088	-0.088	-0.088	-0.088	-0.088	-0.088	-0.088	-0.088
N	43136	36555	36555	36555	43329	36734	36734	36734
R^2	0.14	0.17	0.38	0.057	0.12	0.16	0.37	0.052

Regressions Control for year and year squared as well as tenure dummies and experience polynomial
UR and Change UR are measured in percentage points

Table 5: The Cyclicality of Log Wage Losses with and without controlling for establishment effects - 10 Year Horizon

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage
Panel A: Change in Unemployment Rate					
Change in UR t-1 to t	-0.027		-0.027	-0.020	-0.017
	(0.0015)**		(0.0015)**	(0.0013)**	(0.0013)**
Establishment effect		-0.20	-0.20		
		(0.012)**	(0.012)**		
Worker effect		0.069	0.069		
		(0.0031)**	(0.0030)**		
Change in Estab FE				0.76	1
				(0.0060)**	
Mean of dep. var.	-0.081	-0.081	-0.081	-0.081	-0.081
Number of Obs.	39314	39314	39314	39314	39314
R^2	0.0098	0.022	0.030	0.30	0.012
Panel B: Unemployment Rate - Level					
Unemployment rate	-0.0070		-0.0058	-0.0046	-0.0038
	(0.0011)**		(0.0011)**	(0.00091)**	(0.00093)**
Establishment effect		-0.20	-0.19		
		(0.012)**	(0.012)**		
Worker effect		0.069	0.069		
		(0.0031)**	(0.0031)**		
Change in Estab FE				0.76	1
				(0.0060)**	
Mean of dep. var.	-0.081	-0.081	-0.081	-0.081	-0.081
Number of Obs.	39314	39314	39314	39314	39314
R^2	0.0027	0.022	0.023	0.29	0.0076

Notes: Regressions control for year and year squared. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Column 5 regresses the log wage loss on the unemployment rate (change in UR) controlling for the change in the establishment effect, where the coefficient on the establishment effect is forced to be equal to 1.

Table 6: The Cyclicality of Log Wage Losses with and without controlling for establishment effects – 3 Year Horizon - Women

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage
Panel A: Change in Unemployment Rate					
Change in UR t-1 to t	-0.033		-0.033	-0.027	-0.025
	(0.0027)**		(0.0027)**	(0.0025)**	(0.0025)**
Establishment effect		-0.17	-0.17		
		(0.019)**	(0.019)**		
Years education		0.012	0.012		
		(0.0016)**	(0.0015)**		
Change in Estab FE				0.70	
				(0.010)**	
Mean Dep. Var.	-0.13	-0.13	-0.13		-0.13
N	28933	28933	28933	28933	28933
R^2	0.012	0.011	0.016	0.15	0.011
Panel B: Unemployment Rate - Level					
Unemployment rate	-0.0066		-0.0063	-0.0026	-0.00098
	(0.0020)**		(0.0020)**	(0.0018)	(0.0019)
Establishment effect		-0.17	-0.16		
		(0.019)**	(0.019)**		
Years education		0.012	0.013		
		(0.0016)**	(0.0016)**		
Change in Estab FE				0.71	
				(0.010)**	
Mean Dep. Var.	-0.13	-0.13	-0.13		-0.13
N	28933	28933	28933	28933	28933
R^2	0.0075	0.011	0.012	0.15	0.0073

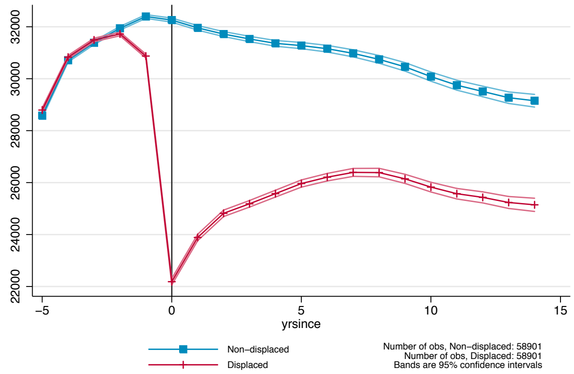
Notes: Regressions control for year and year squared. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Column 5 regresses the log wage loss on the unemployment rate (change in UR) controlling for the change in the establishment effect, where the coefficient on the establishment effect is forced to be equal to 1.

Table 7: The Cyclicality of Log Wage Losses with and without controlling for establishment effects - Restricted to Workers who are not switching Industries - Men

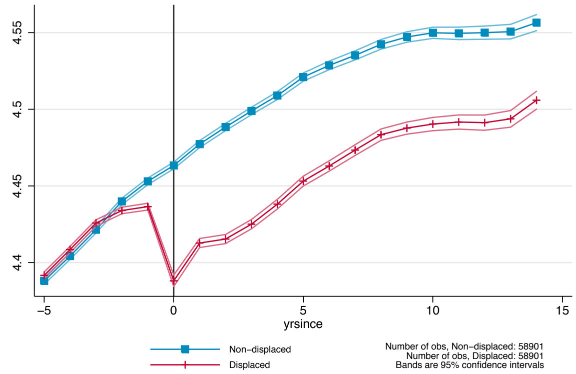
	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage	(7) log wage
Panel A: Change in Unemployment Rate							
Change in UR t-1 to t	-0.0093		-0.0099		-0.011	-0.0073	-0.0064
	(0.0022)**		(0.0021)**		(0.0021)**	(0.0019)**	(0.0020)**
Establishment effect		-0.11	-0.11	-0.11	-0.12		
		(0.017)**	(0.017)**	(0.017)**	(0.017)**		
Worker effect		0.12	0.12				
		(0.0046)**	(0.0046)**				
Education years				0.0093	0.0094		
				(0.00085)**	(0.00085)**		
Change in Estab FE						0.69	1
						(0.014)**	
Mean Dep. Var.	-0.037	-0.037	-0.037	-0.037	-0.037		-0.037
N	11533	11533	11533	11533	11533	11533	11533
R^2	0.0054	0.064	0.065	0.017	0.019	0.19	0.014
Panel B: Unemployment Rate - Level							
Unemployment rate	-0.0026		-0.0022		-0.0021	-0.0016	-0.0011
	(0.0016)		(0.0016)		(0.0016)	(0.0015)	(0.0015)
Establishment effect		-0.11	-0.10	-0.11	-0.11		
		(0.017)**	(0.017)**	(0.017)**	(0.017)**		
Worker effect		0.12	0.12				
		(0.0046)**	(0.0046)**				
Education years				0.0093	0.0093		
				(0.00085)**	(0.00085)**		
Change in Estab FE						0.69	1
						(0.014)**	
Mean Dep. Var.	-0.037	-0.037	-0.037	-0.037	-0.037		-0.037
N	11533	11533	11533	11533	11533	11533	11533
R^2	0.0040	0.064	0.064	0.017	0.017	0.19	0.013

Notes: Regressions control for year and year squared. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. The sample is restricted to individual who do not switch 3 digit industries after job loss. Column 7 regresses the log wage loss on the unemployment rate (change in UR) controlling for the change in the establishment effect, where the coefficient on the establishment effect is forced to be equal to 1.

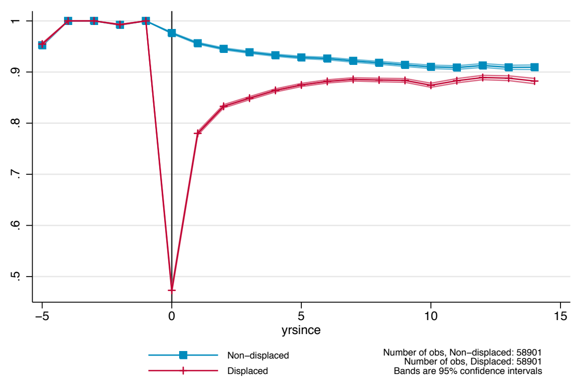
Figure 1: Labor Market Outcomes of Displaced Workers before and after Job Loss - Comparing Raw Means of Displaced Workers and Control Group - Men



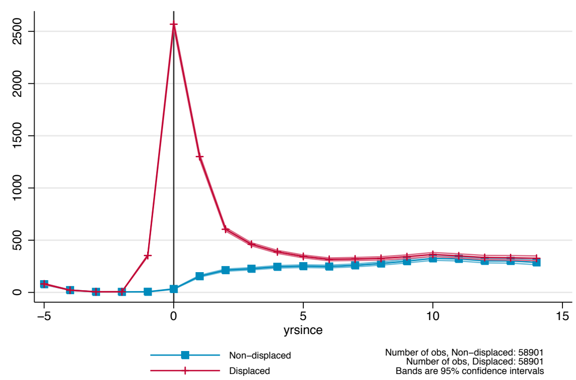
(a) Total Earnings in Year



(b) Log Wage



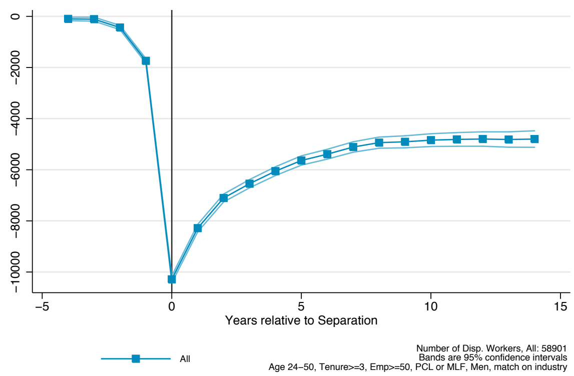
(c) Employed on June 30th of Year



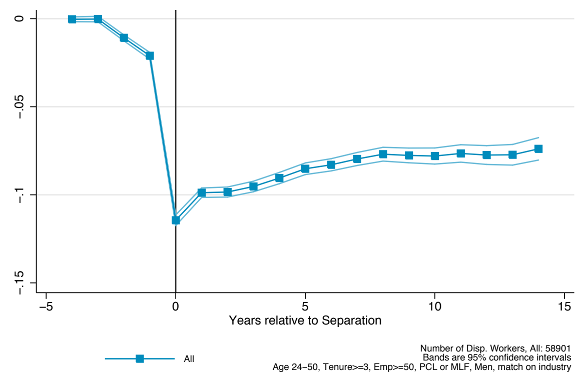
(d) Income from Unemployment Insurance Benefits

Notes: The figures shows labor market outcomes for displaced and non-displaced workers. The red line corresponds to workers who are displaced from year -1 to 0, while the blue line corresponds to the matched control group that is constructed of non-displaced workers via propensity score matching. Each point represents the average value in the respective worker group. The figure is constructed pooling workers displaced between 1979 and 2008, while the outcome data spans 1975-2009.

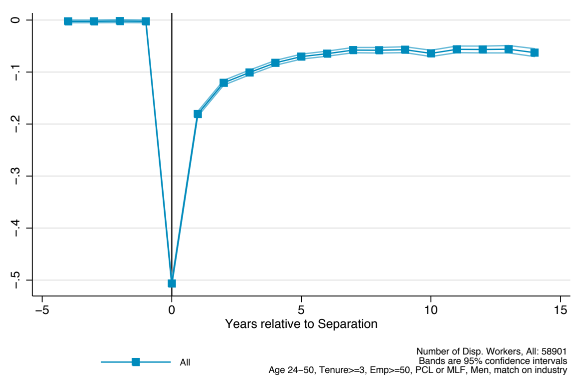
Figure 2: Labor Market Outcomes of Displaced Workers before and after Job Loss - Eventstudy Regression Estimates - Men



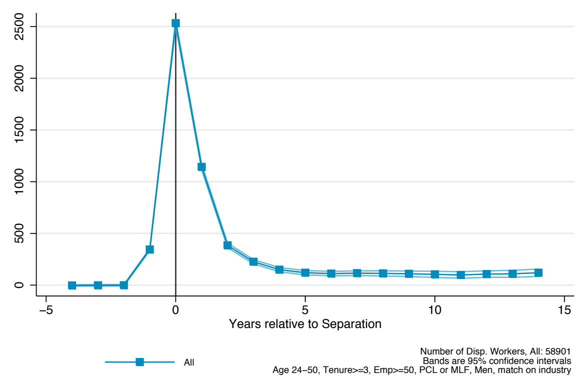
(a) Total Earnings in Year



(b) Log Wage



(c) Employed on June 30th of Year



(d) Income from Unemployment Insurance Benefits

Notes: The figures shows labor market outcomes for displaced and non-displaced workers. The red line corresponds to workers who are displaced from year -1 to 0, while the blue line corresponds to the matched control group that is constructed of non-displaced workers via propensity score matching. Each point represents the average value in the respective worker group. The figure is constructed pooling workers displaced between 1979 and 2008, while the outcome data spans 1975-2009.

Figure 3: Decomposition of Earnings Loss into Wage Loss, Loss in Days Worked and Covariance

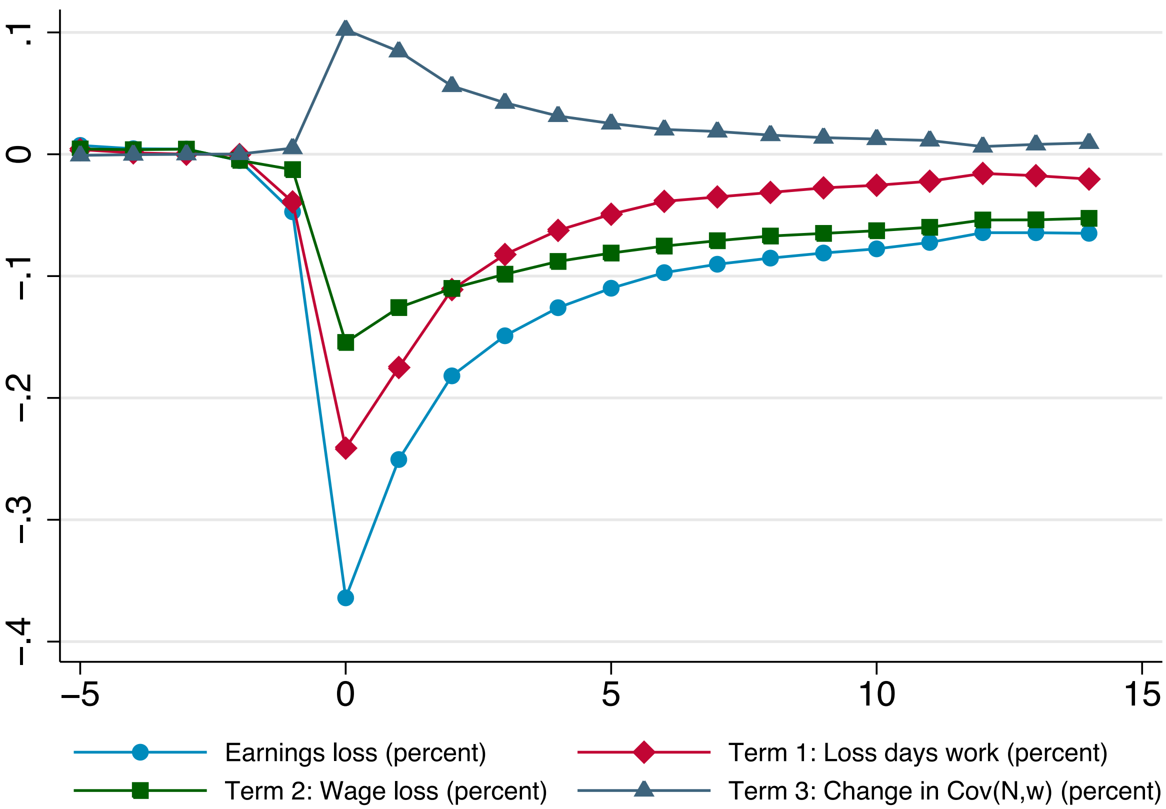


Figure 4: Earnings Losses of Displaced Workers by Year of Job Loss - Men

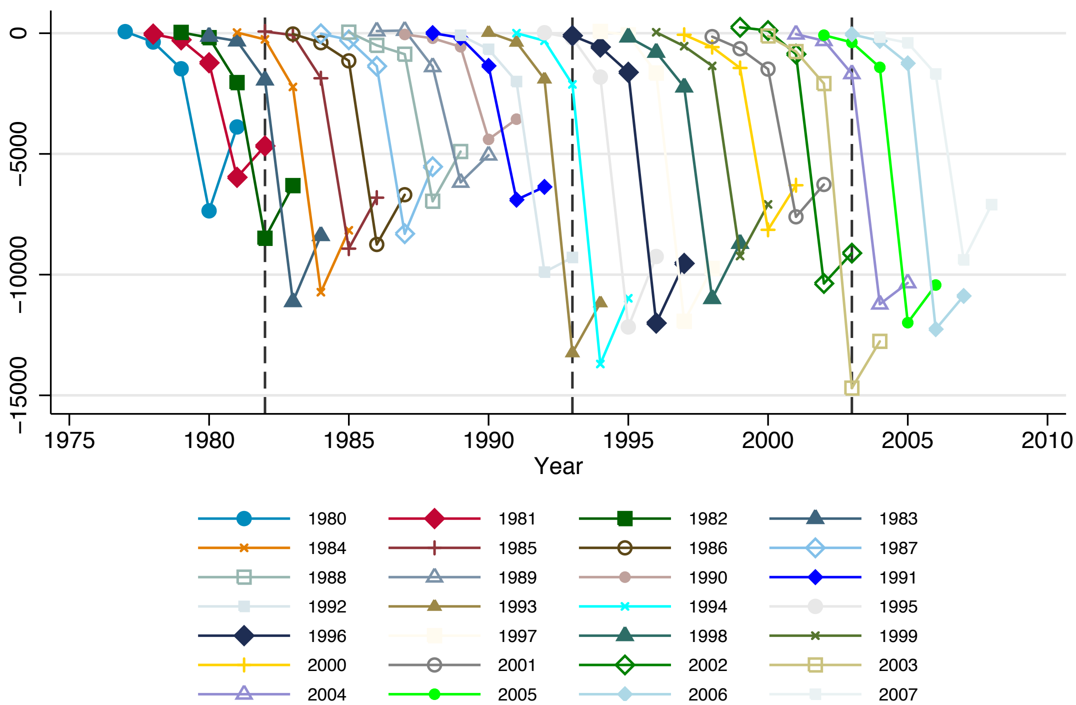


Figure 5: Days Worked of Displaced Workers by Year of Job Loss - Men

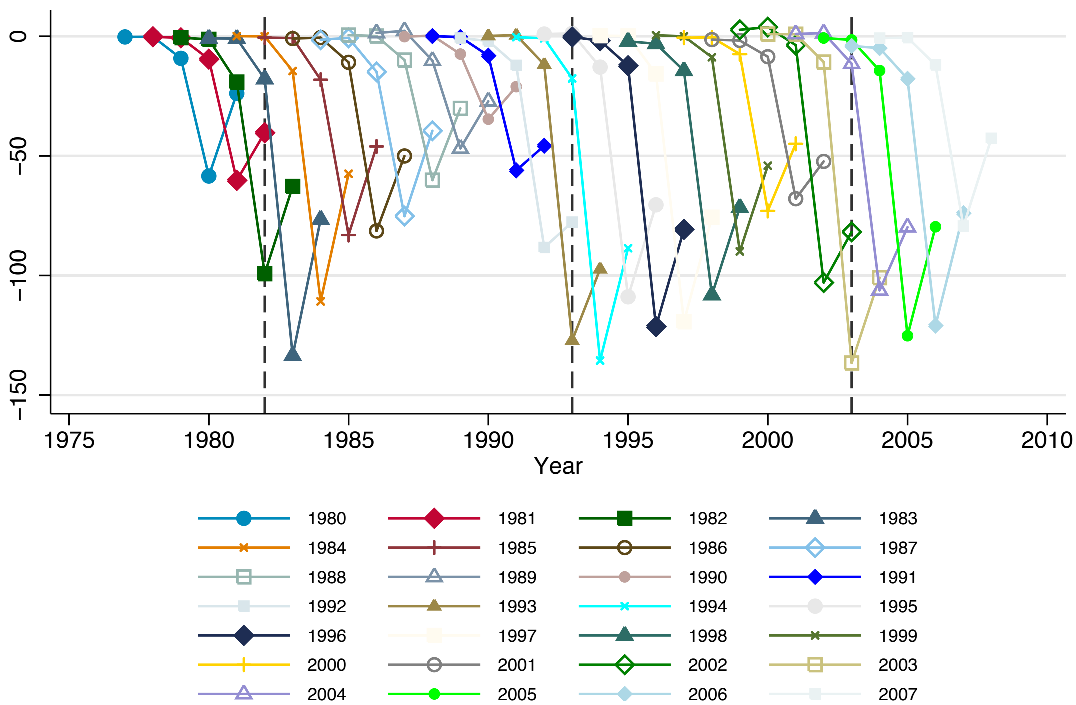


Figure 6: Wages of Displaced Workers by Year of Job Loss - Men

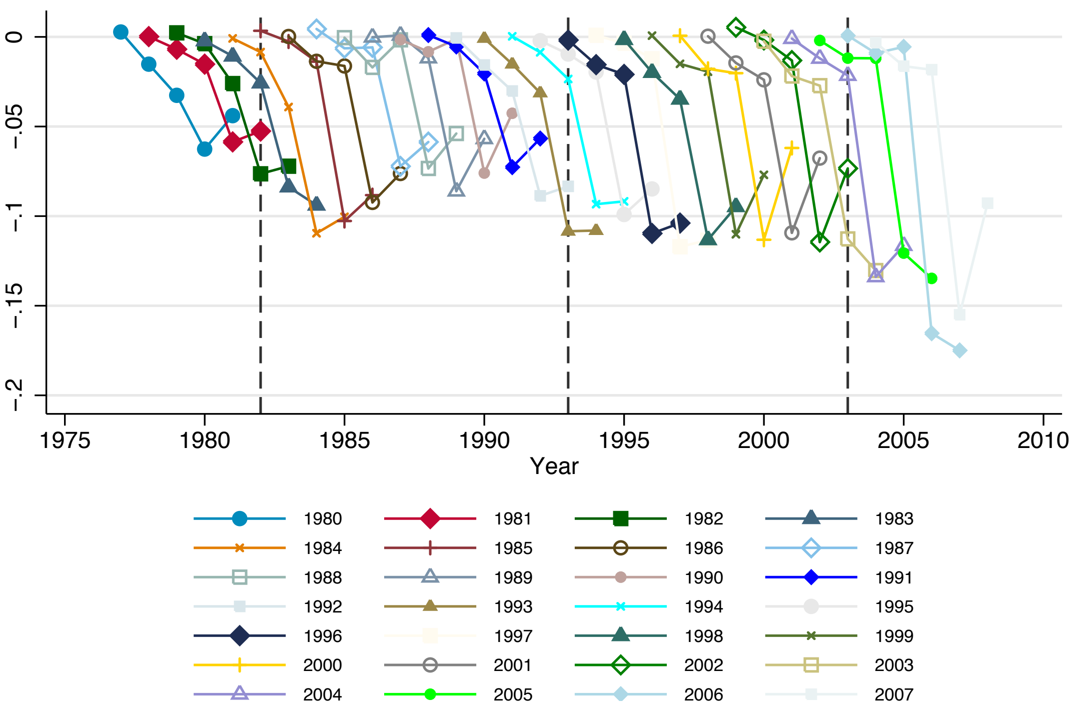
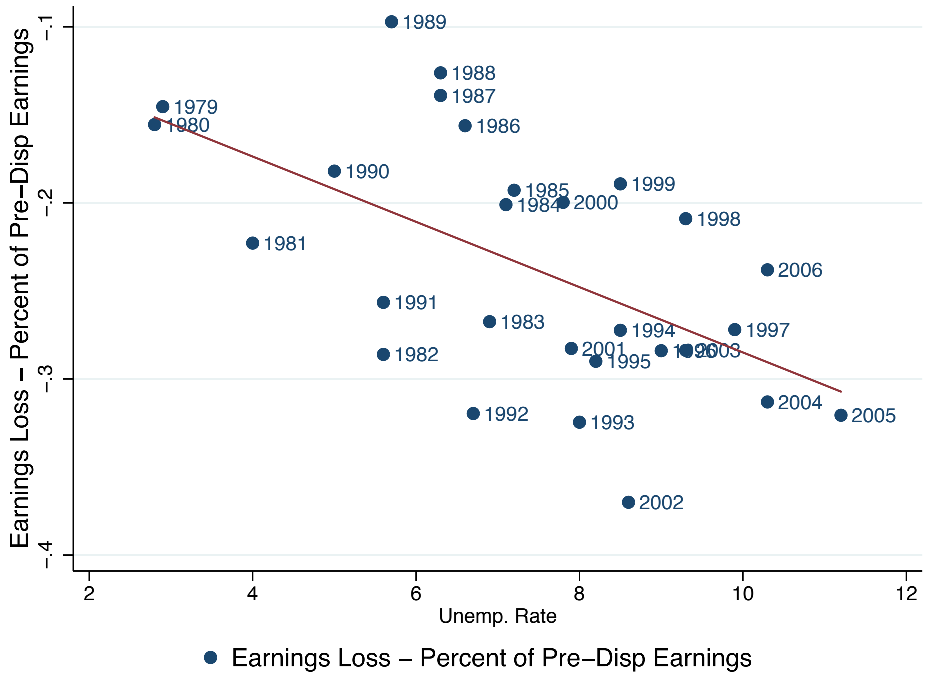
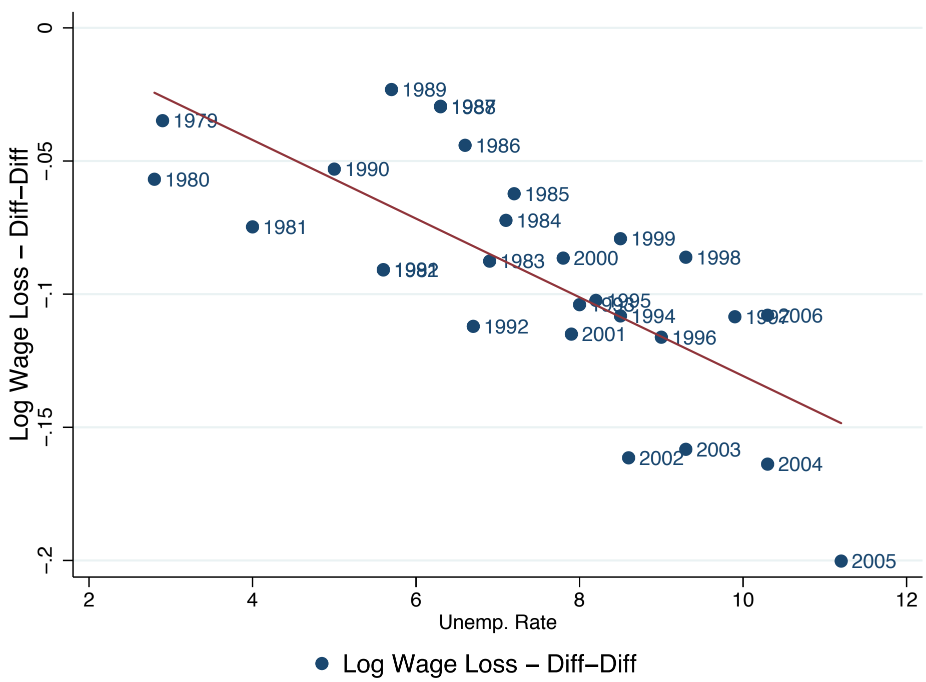


Figure 7: Effect of Job Loss on Annual Earnings and Log Daily Wages 3 Years After Displacement by Year of Job Loss vis-a-vis National Unemployment Rate at Job Loss - Men

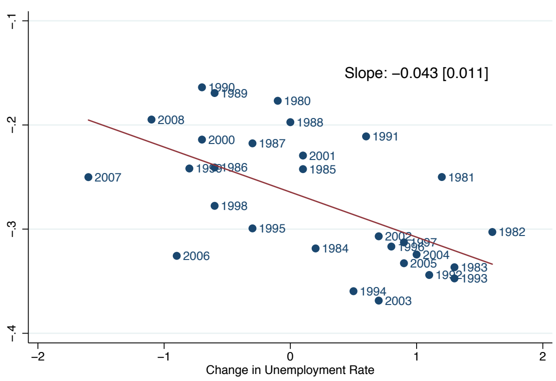


(a) Annual Earnings

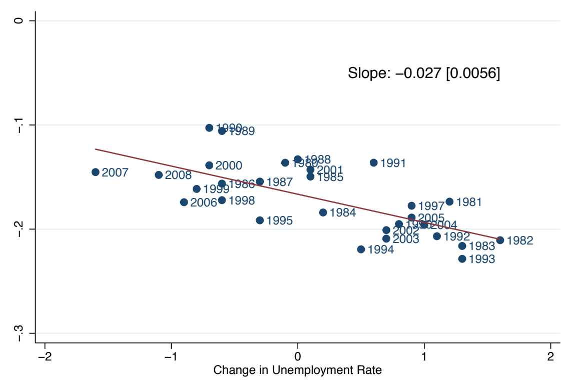


(b) Log Daily Wage

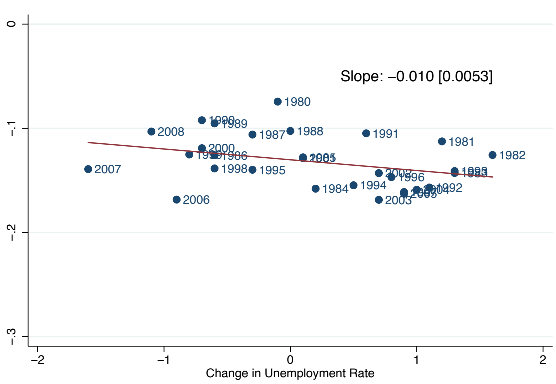
Figure 8: Decomposition of 3 Year Earnings Loss into Wage and Employment Losses, by State of Labor Market



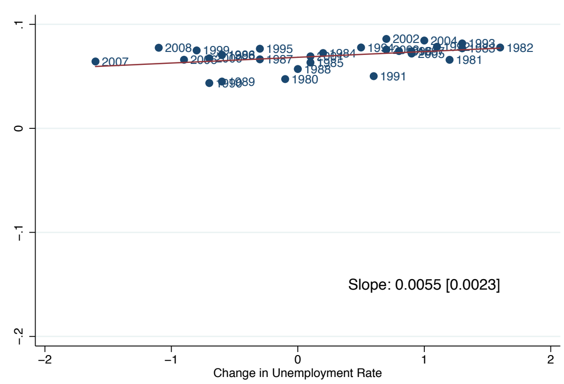
(a) Earnings loss



(b) Earnings loss due to days work



(c) Earnings loss due to wage loss



(d) Earnings loss due to change in covariance

Figure 9: Decomposition of Earnings Loss by Year

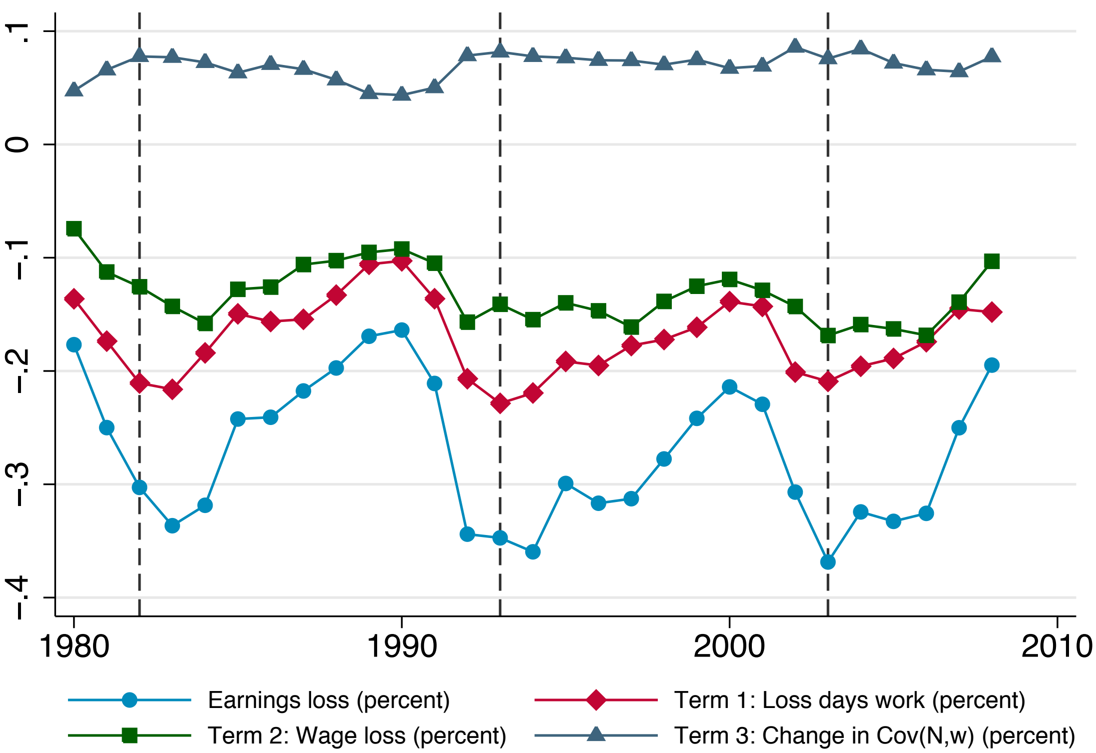
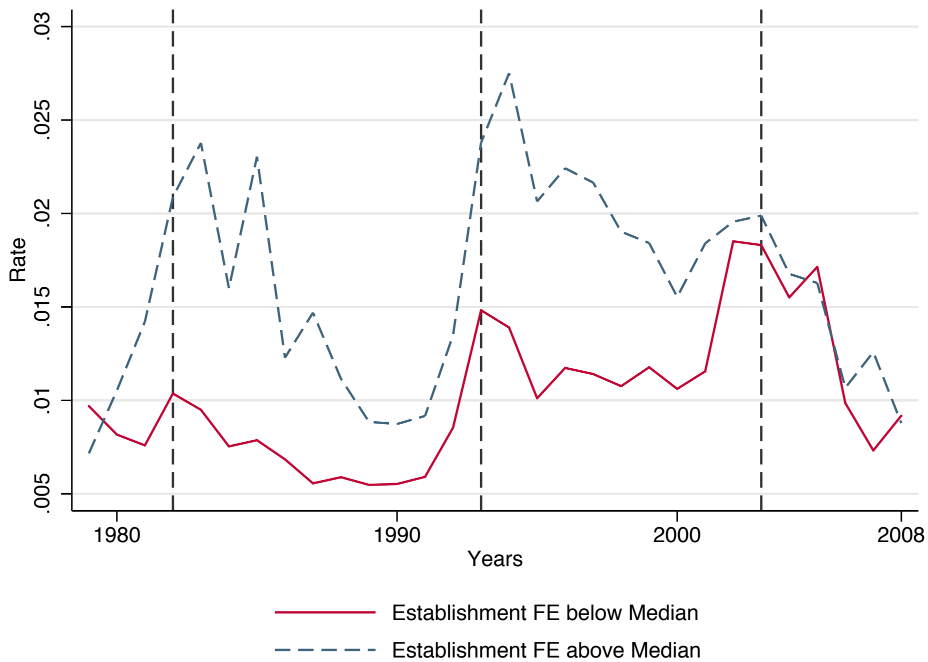
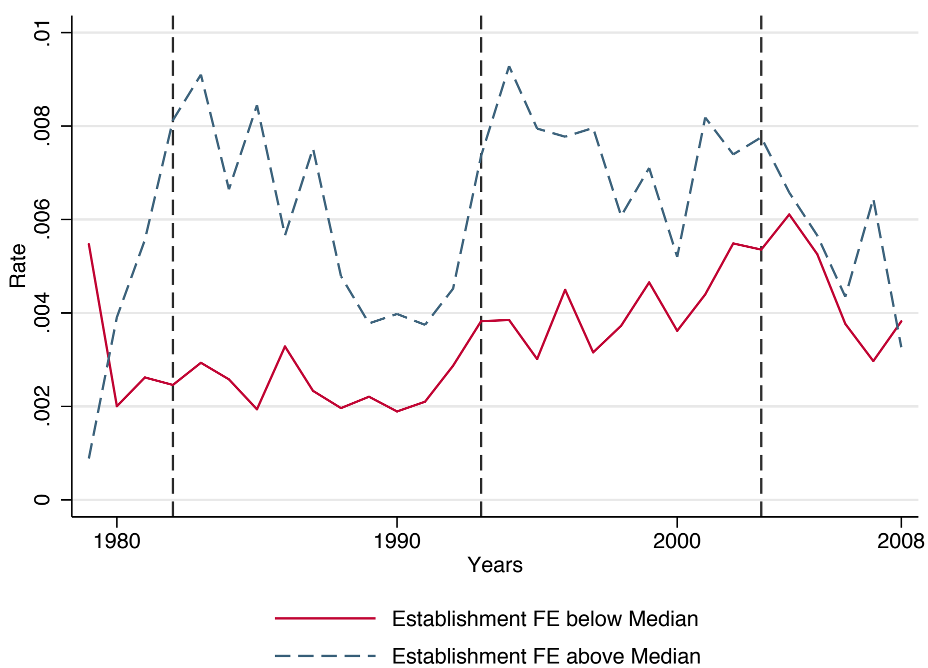


Figure 10: Incidence of Job Loss by Establishment Fixed Effect

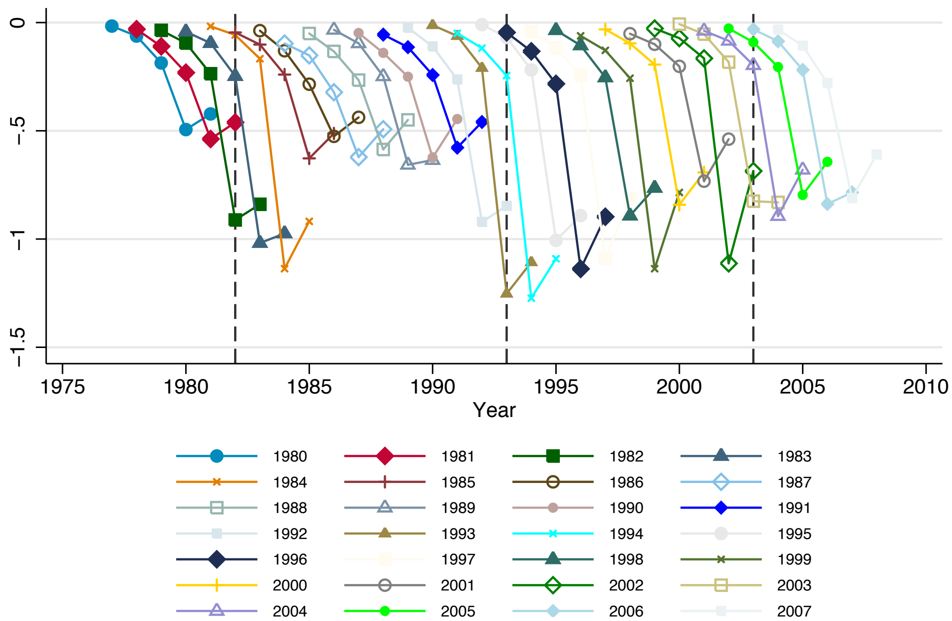


(a) Mass Layoff Rate by Year

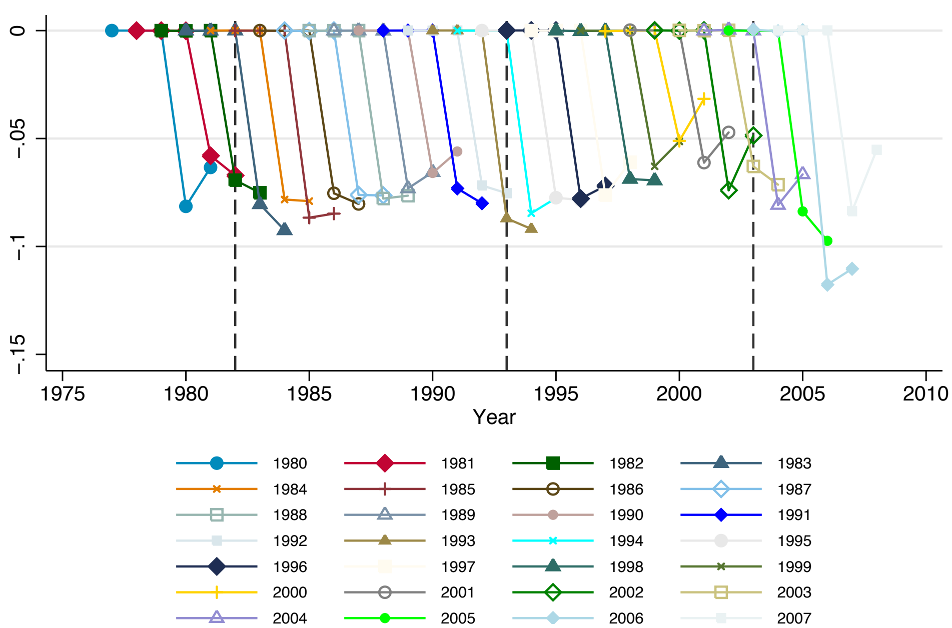


(b) Plant Closing Rate by Year

Figure 11: Employer Characteristics (Number of Employees and Establishment Effect of Displaced Workers by Year of Job Loss - Men

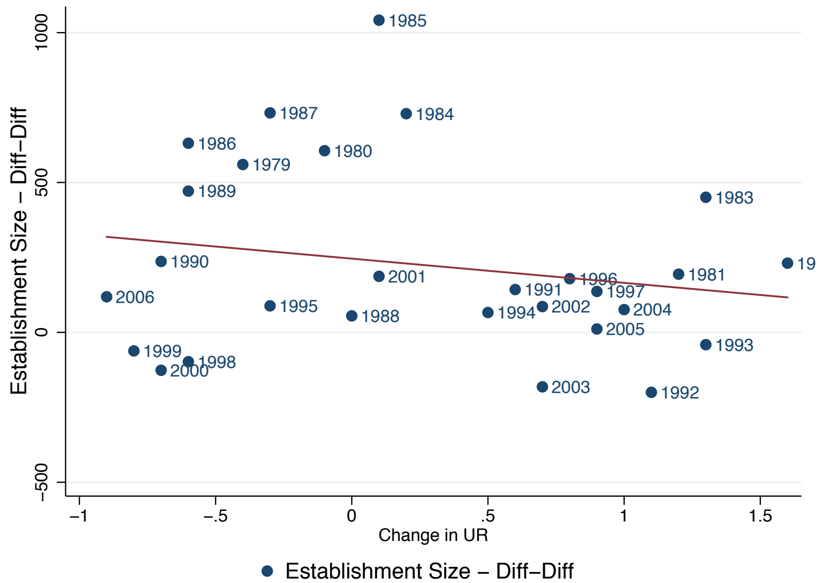


(a) Log Number of Employees at Establishment

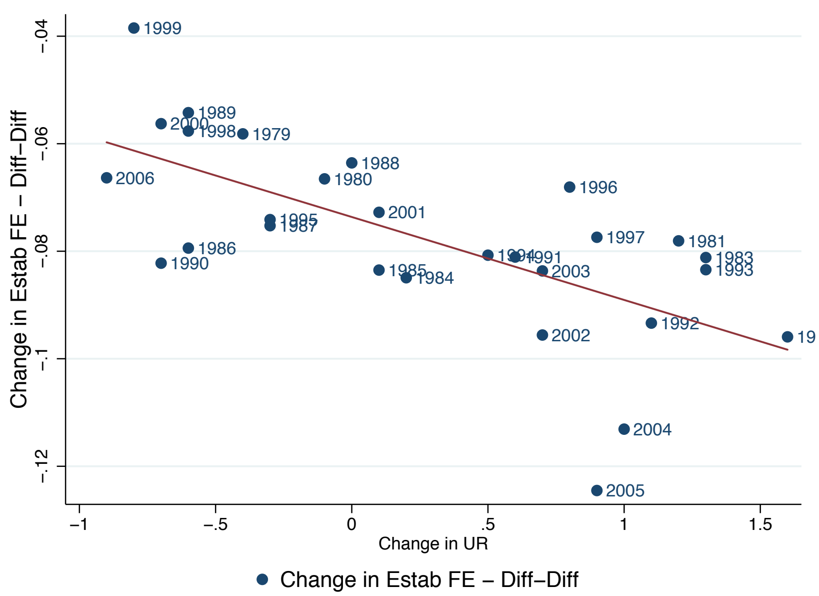


(b) Establishment Effect

Figure 12: Effect of Job Loss on Employer Characteristics 3 Years After Displacement by Year of Job Loss vis-a-vis National Unemployment Rate at Job Loss - Men

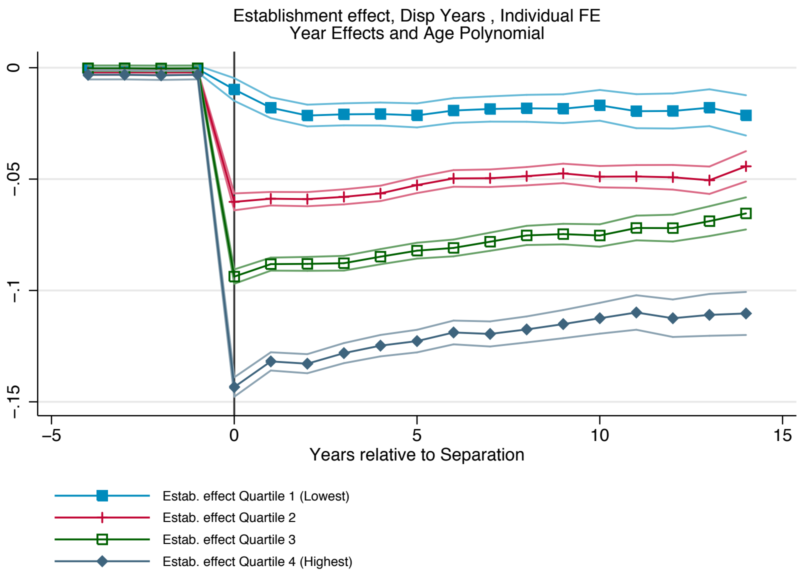


(a) Number of Employees at Establishment

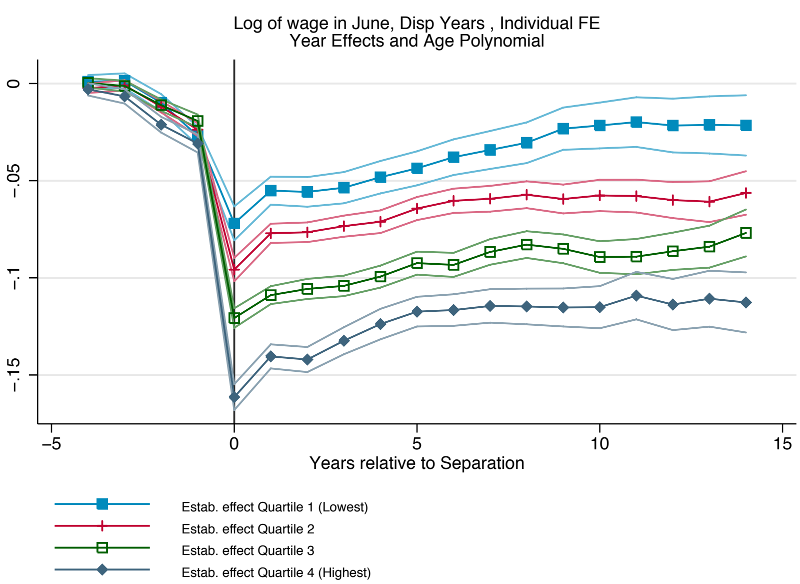


(b) Establishment FE

Figure 13: The Effects of Job Loss by Estab FE of Displacing Establishment

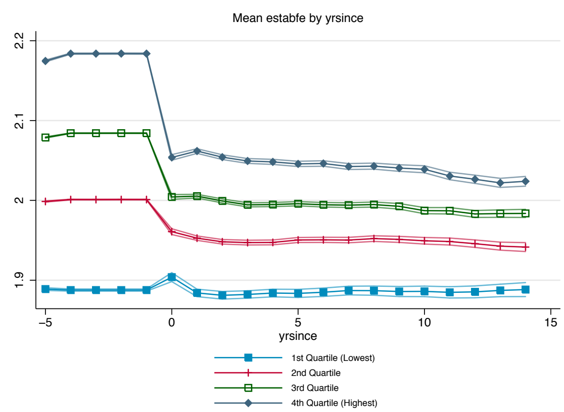


(a) Loss of Estab FE by Quartile of Displacing Estab FE

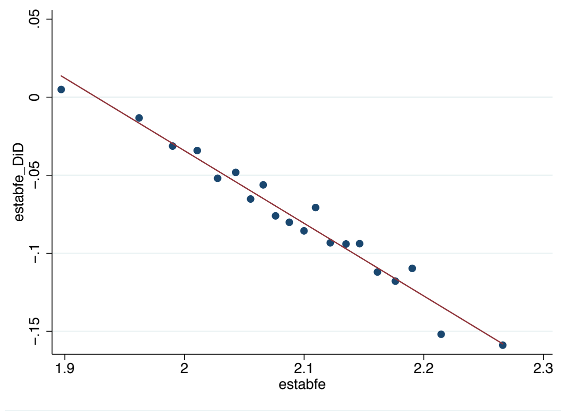


(b) Wage Loss by Quartile Displacing Estab FE

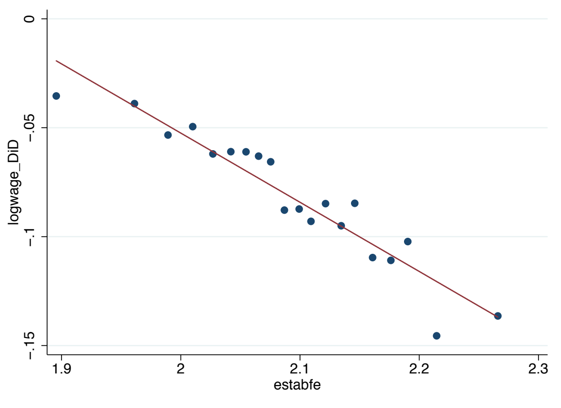
Figure 14: The Effects of Job Loss by Estab FE of Displacing Establishment



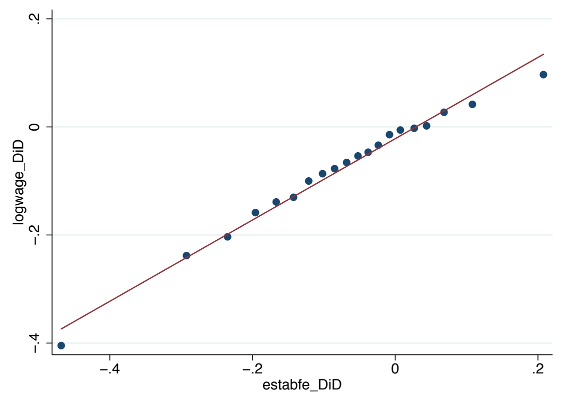
(a) Loss of Estab FE by Displacing Estab FE



(b) Loss of Estab FE by Displacing Estab FE

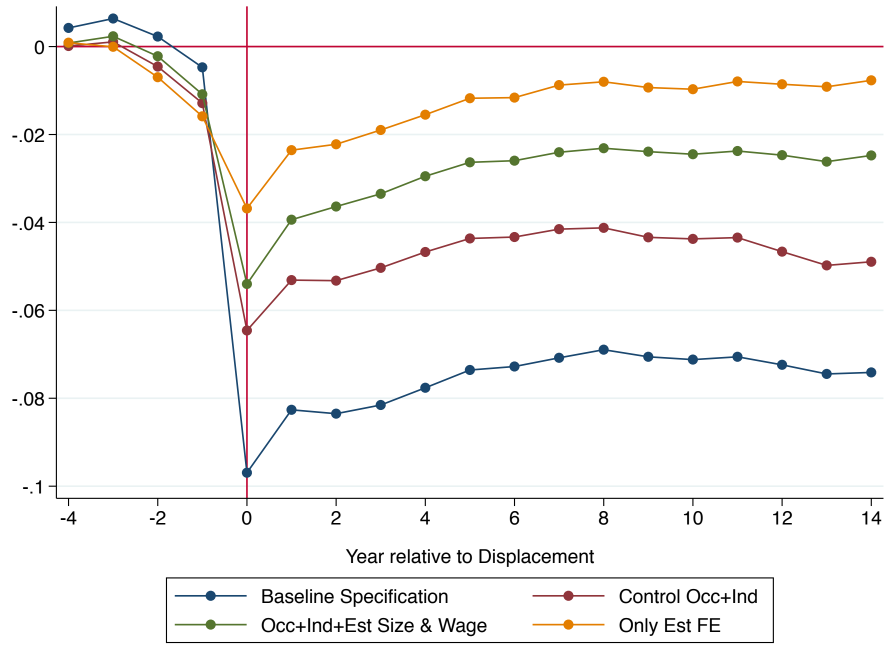


(c) Wage Loss by Displacing Estab FE

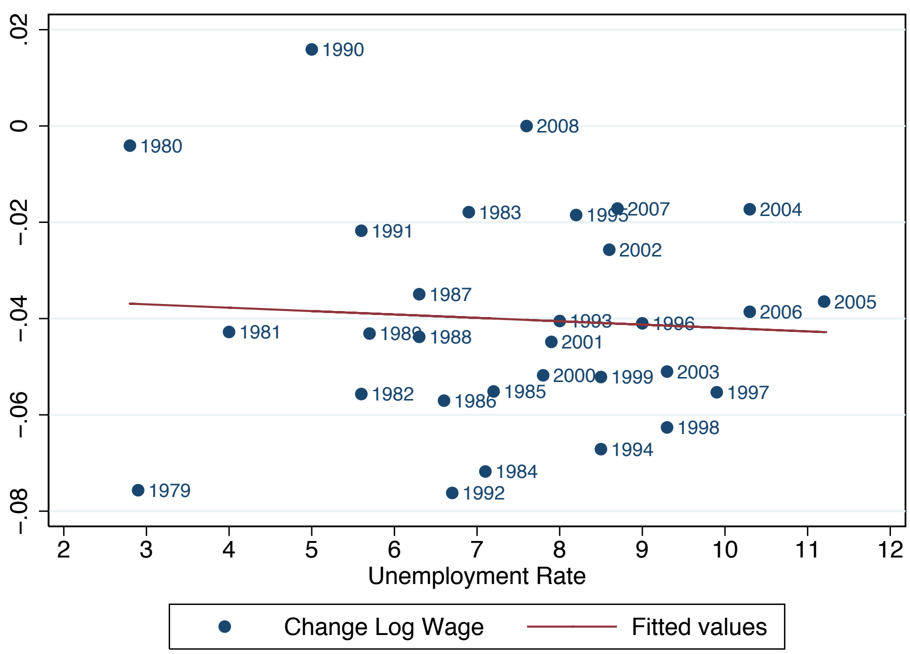


(d) Wage Loss by Estab FE Loss

Figure 15: Effect of Job Loss on Log Daily Wages 3 Years After Displacement With Controls for Employer Characteristics – All Job Losses and by Year of Job Loss



(a) Average Over All Displacement Years



(b) By Year of Job Loss vis-a-vis Rate of Unemployment

Appendix

In order to identify mass-layoffs and plant closings in the German administrative data we used the following approach. After merging the establishment history panel with information on all year to year cross establishment worker flows, we defined mass layoffs as a drop in employment from one year to the next of at least 30 percent in an establishment with at least 50 employees in the year before the employment drop. To assure that these establishments were relatively stable prior to the drop and that the drop did not constitute just temporary fluctuations, we also required that employment did not increase by more than 30 percent in either of the two years before the employment drop and did not re-bounce in the two years after the drop. Furthermore to avoid identifying restructuring of the firm (such as outsourcing of larger parts) as a mass-layoff, we required that not more than 20 percent of the leaving workers were re-employed together at a single establishment in the following year (thus the leaving workers are either unemployed or dispersed over many different establishments). Similarly we defined a plant-closing as a drop in employment of at least 80 percent, again requiring that not more than 20 percent of the leaving workers were re-employed together in the following year.

The establishment history panel and the flow data provide information on the workforce of the establishments on June 30th of each year. We thus consider a mass-layoff as happening in 1982 if a plant loses 30 percent of its workforce between 1981 and 1982. We consider a worker as displaced in 1982 if he permanently left an establishment in 1982 and this establishment had a mass-layoff either in 1982 or 1983.

In order to get precise estimates we use a 20 percent random sample of all male workers in the German administrative data who we follow over the entire time period 1975 to 2009. In order to be in our main analysis sample of displaced workers and the control group, workers had to be continuously employed for at least 3 years at an establishment that was at risk of a mass-layoff. Furthermore we only selected male workers age 24 to 50 in the displacement year.

Yearly earnings were calculated as the sum of all wages during that year measured Euro and deflated to prices of 2000. For these calculations we only used workers who in a given year had at least one observation (either because they were employed for at least one day or they received unemployment benefits

Table A-1: The Cyclicality of Log Wage Losses with and without controlling for establishment effects – 3 Year Horizon - Men and Women

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage
Panel A: Unemployment Rate - Level					
Unemployment rate	-0.0086		-0.0077	-0.0041	-0.0029
	(0.00095)**		(0.00094)**	(0.00079)**	(0.00081)**
Establishment effect		-0.18	-0.17		
		(0.010)**	(0.010)**		
Worker effect		0.076	0.076		
		(0.0027)**	(0.0027)**		
Change in Estab FE				0.79	
				(0.0049)**	
mean_v	-0.091	-0.091	-0.091		-0.091
N	61983	61983	61983	61983	61983
r2	0.010	0.026	0.027	0.30	0.010
Panel B: Change in Unemployment Rate					
Change in UR t-1 to t	-0.028		-0.028	-0.017	-0.013
	(0.0013)**		(0.0013)**	(0.0011)**	(0.0011)**
Establishment effect		-0.18	-0.18		
		(0.010)**	(0.010)**		
Worker effect		0.076	0.075		
		(0.0027)**	(0.0027)**		
Change in Estab FE				0.79	
				(0.0049)**	
mean_v	-0.091	-0.091	-0.091		-0.091
N	61983	61983	61983	61983	61983
r2	0.016	0.026	0.033	0.31	0.012

Notes: Regressions control for year and year squared. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Column 5 regresses the log wage loss on the unemployment rate (change in UR) controlling for the change in the establishment effect, where the coefficient on the establishment effect is forced to be equal to 1.

Figure A-1: Mass Layoff and Plant Closing Rates by Year

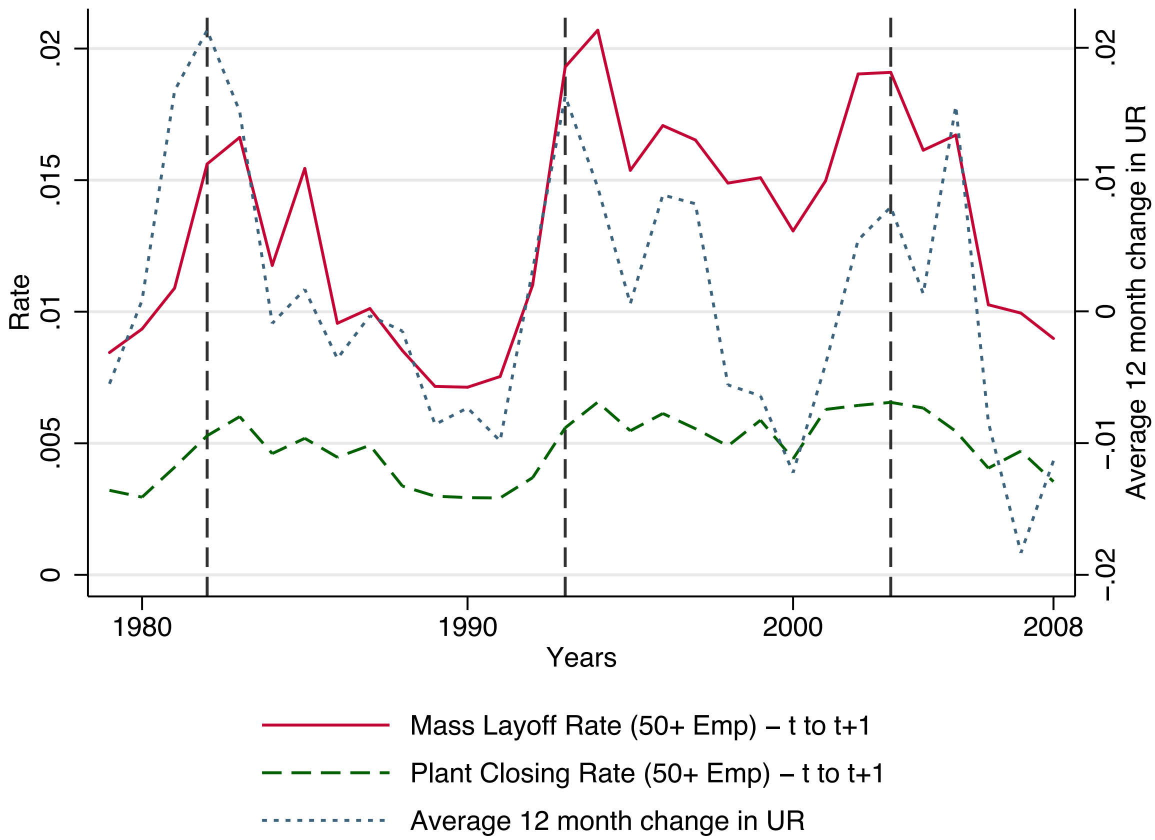
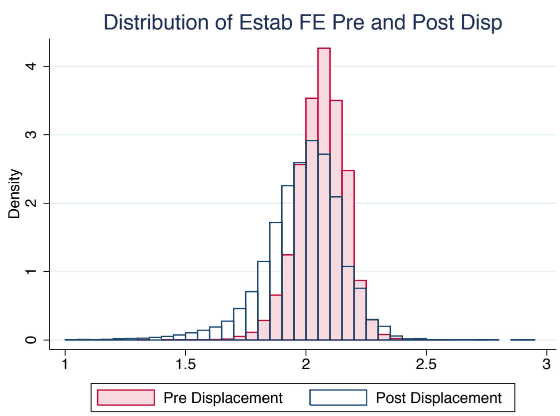
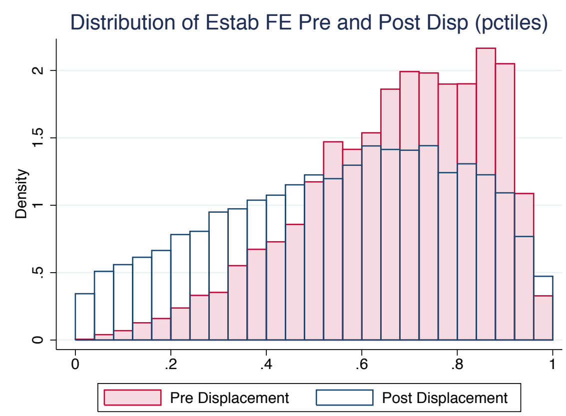


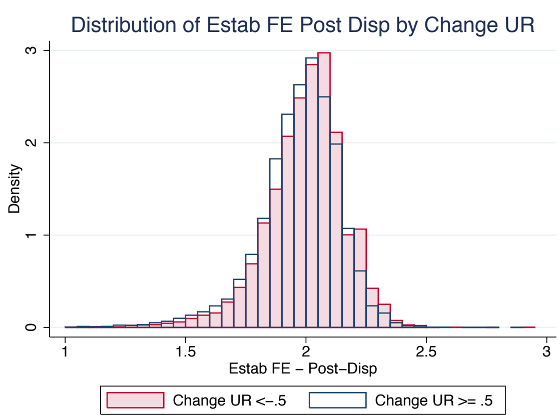
Figure A-2: The Effects of Job Loss On Distribution of Establishment Fixed Effects



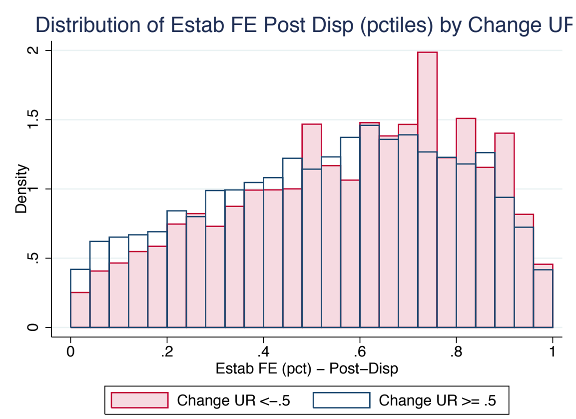
(a) Distribution of Estab FE Job Losers vs. Controls



(b) Distribution of Estab FE Job Losers vs. Controls in Percentiles

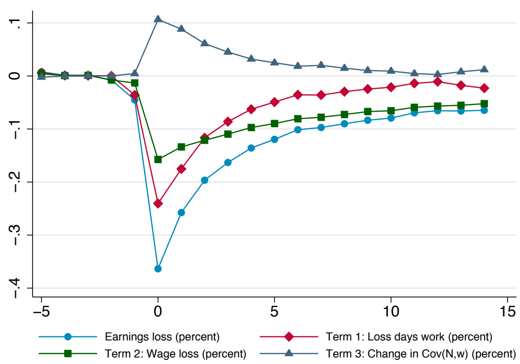


(c) Distribution of Estab FE Job Losers vs. Controls

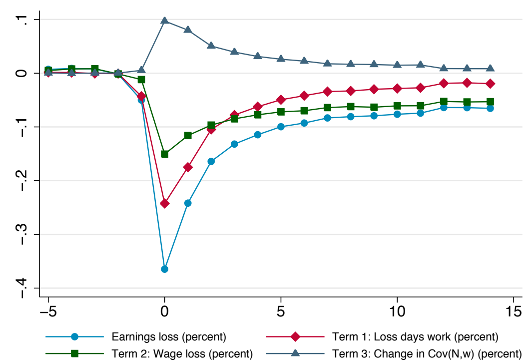


(d) Distribution of Estab FE Job Losers vs. Controls in Percentiles

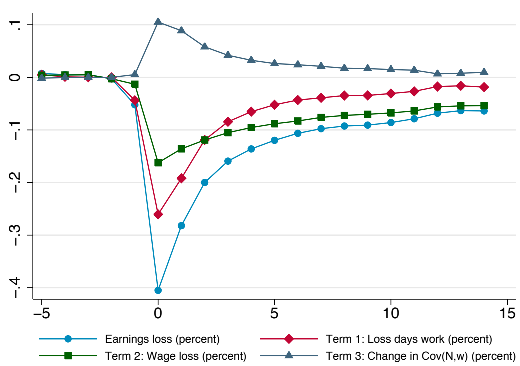
Figure A-3: Decomposition of Earnings Loss by State of Labor Market



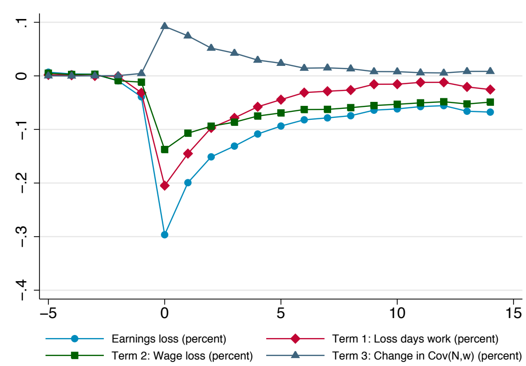
(a) Unemployment Rate >=7%



(b) Unemployment Rate <7%

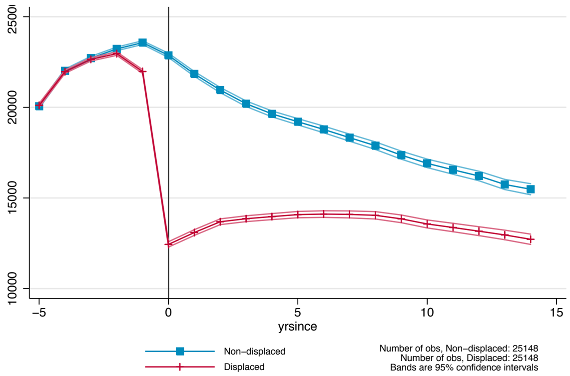


(c) Change Unemployment Rate >=0%

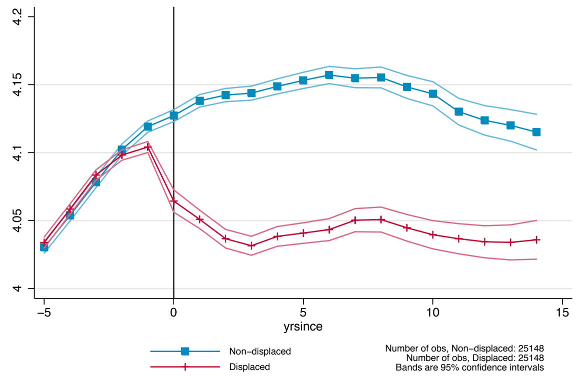


(d) Change Unemployment Rate <0%

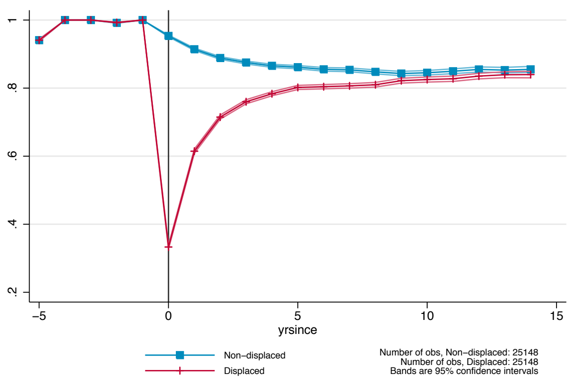
Figure A-4: Labor Market Outcomes of Displaced Workers before and after Job Loss - Comparing Raw Means of Displaced Workers and Control Group - Women



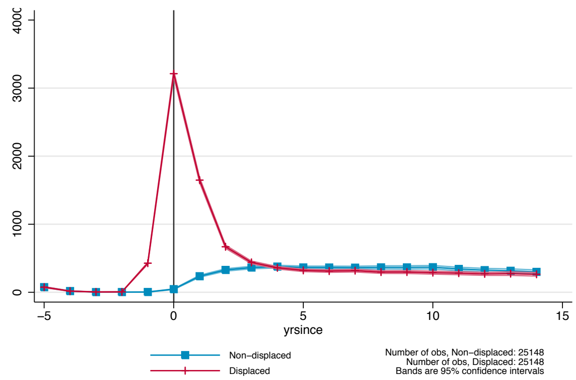
(a) Total Earnings in Year



(b) Log Wage



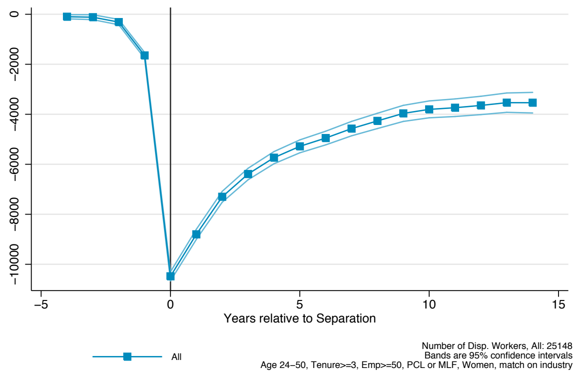
(c) Employed on June 30th of Year



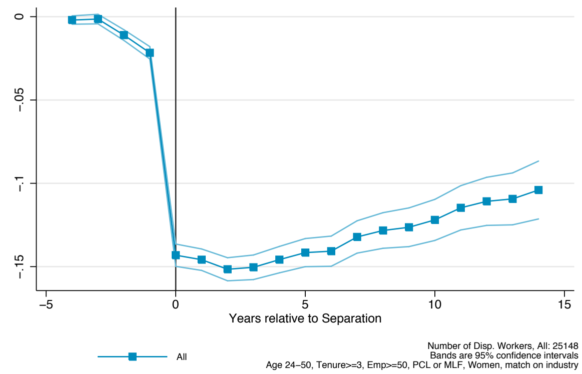
(d) Income from Unemployment Insurance Benefits

Notes: The figures shows labor market outcomes for displaced and non-displaced workers. The red line corresponds to workers who are displaced from year -1 to 0, while the blue line corresponds to the matched control group that is constructed of non-displaced workers via propensity score matching. Each point represents the average value in the respective worker group. The figure is constructed pooling workers displaced between 1979 and 2008, while the outcome data spans 1975-2009.

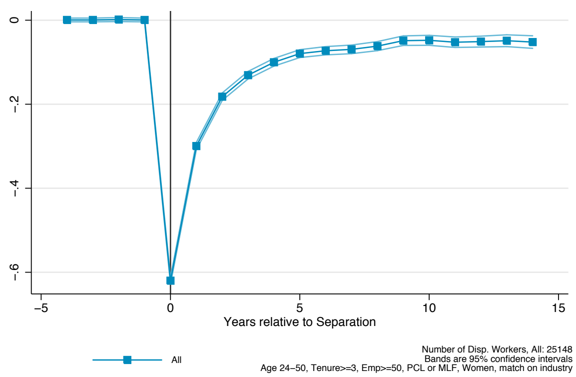
Figure A-5: Labor Market Outcomes of Displaced Workers before and after Job Loss - Eventstudy Regression Estimates - Women



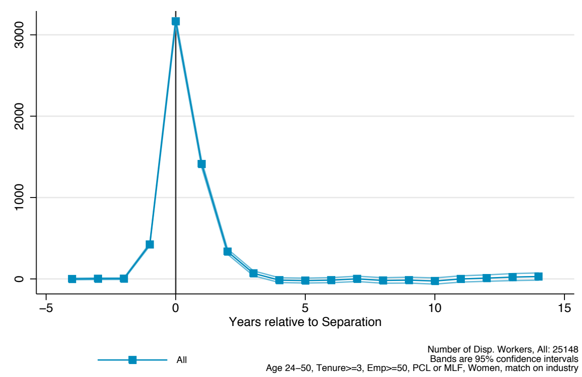
(a) Total Earnings in Year



(b) Log Wage



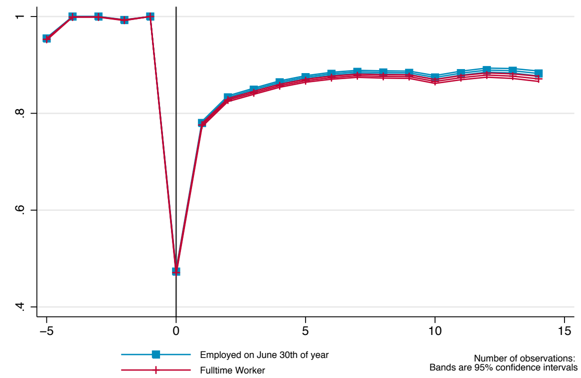
(c) Employed on June 30th of Year



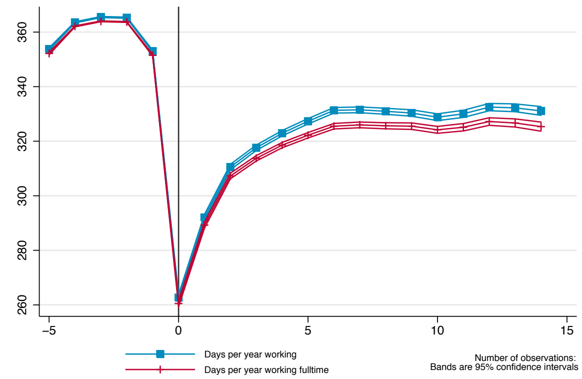
(d) Income from Unemployment Insurance Benefits

Notes: The figures shows labor market outcomes for displaced and non-displaced workers. The red line corresponds to workers who are displaced from year -1 to 0, while the blue line corresponds to the matched control group that is constructed of non-displaced workers via propensity score matching. Each point represents the average value in the respective worker group. The figure is constructed pooling workers displaced between 1979 and 2008, while the outcome data spans 1975-2009.

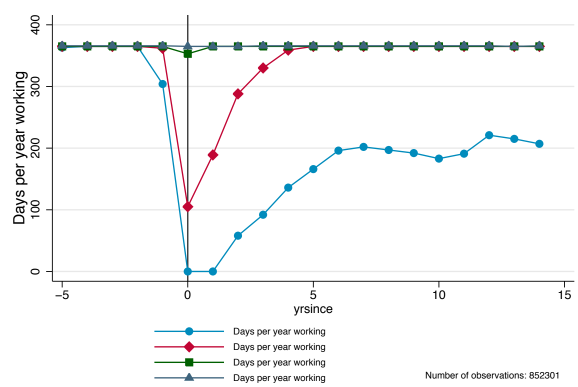
Figure A-6: Labor Market Outcomes of Displaced Workers before and after Job Loss - Raw Means - Men



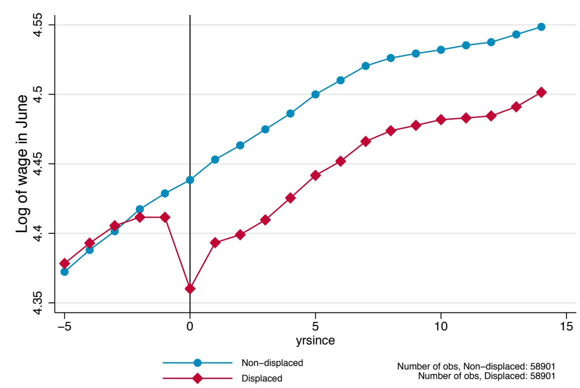
(a) Employed and Employed Fulltime



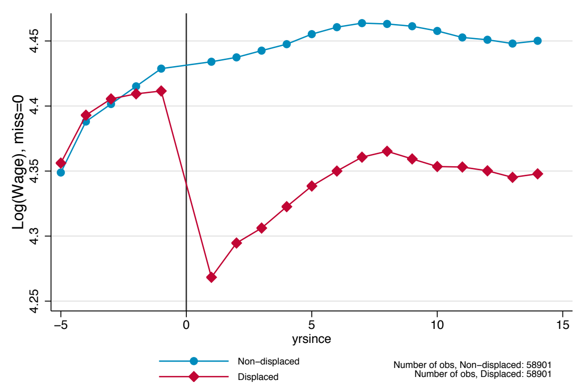
(b) Days Employed and Days Employed Fulltime



(c) Quantiles of Days Worked



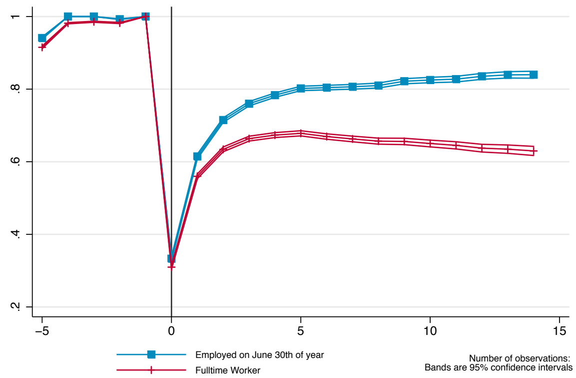
(d) Log Wage Median, not incl. missings



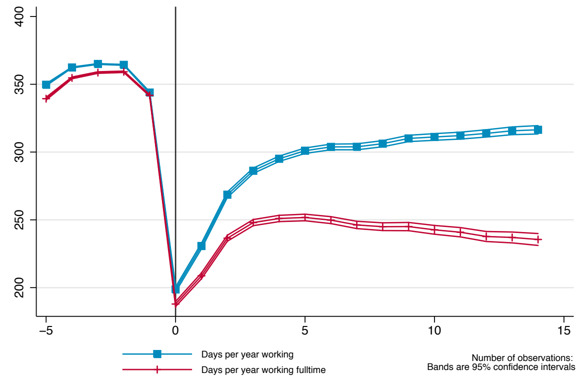
(e) Log Wage Median, missings set to 0

Notes: The figures shows labor market outcomes for displaced and non-displaced workers. The red line corresponds to workers who are displaced from year -1 to 0. Each point represents the average value in the respective worker group. The figure is constructed pooling workers displaced between 1979 and 2008, while the outcome data spans 1975-2009.

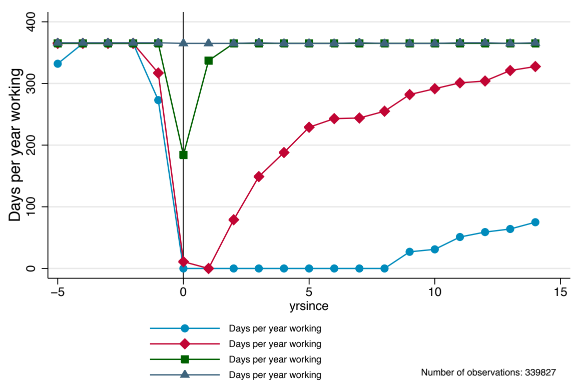
Figure A-7: Labor Market Outcomes of Displaced Workers before and after Job Loss - Raw Means - Women



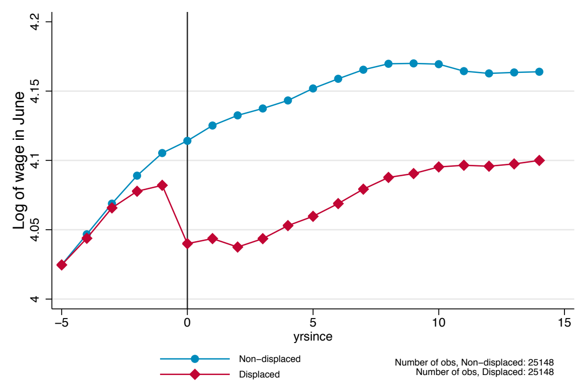
(a) Employed and Employed Fulltime



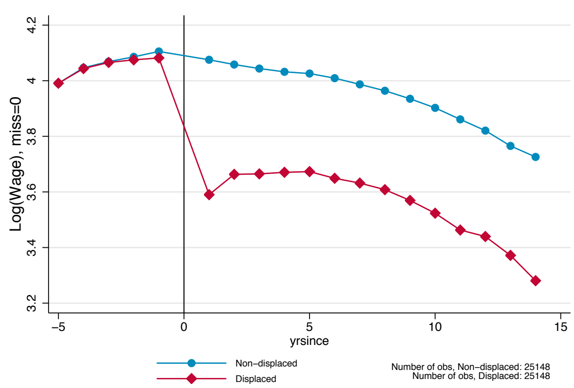
(b) Days Employed and Days Employed Fulltime



(c) Quantiles of Days Worked



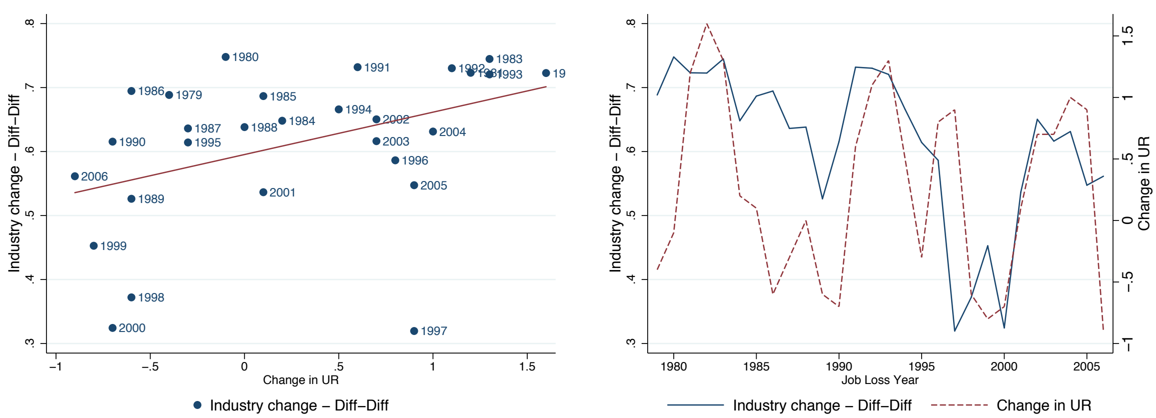
(d) Log Wage Median, not incl. missings



(e) Log Wage Median, missings set to 0

Notes: The figures shows labor market outcomes for displaced and non-displaced workers. The red line corresponds to workers who are displaced from year -1 to 0. Each point represents the average value in the respective worker group. The figure is constructed pooling workers displaced between 1979 and 2008, while the outcome data spans 1975-2009.

Figure A-8: Probability of Changing 2-Digit Industry After Job Loss by Year of Job Loss



(a) Prob. Industry Change vs Change UR

(b) Prob. Industry Change vs Change UR