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.Changes in the composition of workers or displacing firms have explain little of the cyclicality. This suggests an important role of labor market conditions at job loss in shaping the long-term outcomes of job losers.

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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; Davis and von Wachter, 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 reaching ten to fifteen percent of employment in large recessions,[2] this implies that a substantial fraction of workers suffers large permanent reductions in their life-time earnings.

A growing literature has sought to uncover the channels leading to large costs of job loss. A common hypothesis has been that displaced workers lose job, industry, or occupation specific skills (e.g., Neal 1995; Poletaev and Robinson 2008). It has also been suggested that part of earnings losses could be explained by losses in rents (Topel 1990). Early papers indeed found displaced worker lose industry wage effects, a finding indicative of persistent industry differentials in wage setting (e.g., Katz and Dickens 1987; Krueger and Summers 1988). Based on Abowd et al. (1999), an increasing number of papers have argued that the labor market is characterized by persistent firm-wage differentials (e.g., Card et al. 2013; Song et al. 2016; Kline et al. 2019; Bonhomme et al. 2019). Yet, the study of how such firm wage differentials influence the cost of job loss is in its infancy (e.g., Lachowska et al. 2017; Moore and Scott-Clayton 2019).[3]

Even though job displacement is a much more common and costly phenomenon in reces-

[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)).

[3]See Carrington and Fallick (2015) for a survey of the literature on the cost of job loss.

sions, fewer studies examine how the the sources of the cost of job loss vary over the business cycle. Recessions have been interpreted to be periods of increased rate of potential costly job switches across sectors and occupations, or of reallocation of marginally productive jobs (e.g., Schumpeter 1942; Barlevy 2002). It has also been long hypothesized that recessions are periods of cyclical downgrading (Okun 1973; McLaughlin and Bils 2001), because high-wage sectors have more cyclical job creation (e.g., Reynolds 1953; Reder 1955). A small but growing number of studies suggest a similar phenomenon occurs at the firm level (e.g., Haltiwanger et al. forthcoming), and hence could explain cyclical wage losses at job displacement. In addition, during recessions longer unemployment spells could lead to lower reemployment wages through skill depreciation (e.g., Schmieder et al. 2016; Nekoei and Weber 2017).

In this paper, we study the determinants of displaced workers' earnings and wage losses over the business cycle using three decades worth of detailed data from Germany. Our data and a new empirical approach to study job loss allow us to analyze the role of losses in firm-wage premiums together with potential other channels such as losses in occupation- and industry-specific skills over the business cycle. At the same time, we are able to control for changes in worker composition and lengthening unemployment spells over the business cycle. The results allow us to connect the longstanding and hard-to-explain results from the job loss literature with the recently re-emerged literature on the role of employers in wage setting (e.g., Card et al. 2013; Song et al. 2016; Kline et al. 2019; Bonhomme et al. 2019). In light of this literature and our findings, large, persistent, and cyclical costs of job loss may be less of a puzzle than in more standard models of the labor market (e.g., Davis and von Wachter 2011).

The German social security data we use covers three decades of job displacements with a detail on daily employment transitions, wages and employment, and firm and worker characteristics not typically available in the U.S. over a long period of time. 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 comparable data from the U.S. used in Davis and von Wachter (2011), among others. We then assess whether earnings

losses and their cyclicality are simply due to lower employment rates, or whether wage losses themselves are cyclical as well, a crucial question for understanding the cost of job loss that is hard to answer with U.S. data.

In a final step, we analyze key sources of cyclical movements in wage losses highlighted in the literature, including changes in displaced workers' firm characteristics over the business cycle, indicators of specific skills, nonemployment duration, and changes in worker composition. To 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 us to effectively account for composition changes along several dimensions and to directly analyze various channels behind the cyclicality of the cost of job loss in a unified regression model.

Using a sample of male workers from West Germany, we obtain several key findings. First, as in 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 as in Germany. Also consistent with U.S.-based findings, we find that there is a high degree of cyclicality in earnings losses in Germany, with losses in recessions more than double the losses in booms.

Our second main finding is that the patterns of longer-term earnings losses after job displacement are entirely explained by cyclical wage losses. Temporary reductions in employment rates explain an important part of the initial reductions in earnings. While cyclicality in the incidence of nonemployment among displaced workers is expected, cyclical variation in reemployment wages are typically harder to explain.

Our third main finding is that losses in establishment fixed effects and establishment size are substantially larger in recessions than in expansion. In light of the recent literature examining the properties of establishment fixed effects estimated by the AKM model (e.g., Kline et al. 2019; Bonhomme et al. 2019), we subject our analysis to a thorough sensitivity analysis.

To assess potential role of a bias in the estimates of establishment effects, we introduce split-sample IV estimates, re-estimate our the IV analysis using a rolling window of fixed effects, and following the spirit of Bonhomme et al. 2019 we generate comparable findings based on firm-clusters. Our findings are robust to these and other sensitivity checks.

Our fourth main finding is that losses in establishment wage premiums explain the majority of the cyclicality in wage losses in our data. We first establish that changes in the composition of job losers or displacing firms cannot explain cyclical wage losses. We then show that displaced workers experience substantial reductions in establishment size and establishment wage premiums at job loss, and that these reductions are larger in recessions. Our accounting regressions suggest that the majority of average wage losses and a large part of their cyclicality appear to be driven by reductions in establishment wage premiums at job loss alone. We also find that duration of nonemployment, and various measures of changes in industry or occupation matter for explaining the average cost of job loss. However, only nonemployment has explanatory power for the cyclicality of wage losses, partly by being correlated with losses in establishment wage effects.[4] Again, these findings are robust to a range of in-depth sensitivity checks, and are very similar for women and when we include all of Germany.

These findings make several contributions to the literatures on the effects of job loss and on the wage structure. Our result that a majority of average wage losses at job loss, and a substantial portion of the cyclicality of wage losses, can be explained by losses in establishment fixed effects increases our understanding of the sources of the cost of job loss and its cyclicality. In terms of the level of the cost of job loss, our paper expands findings of the earlier literature that displaced workers lose industry- and occupation-specific rents (Krueger and Summers 1988; Katz and Dickens 1987). As in the earlier literature, our results underscore the importance of firm-specific components in wage setting found in recent studies (e.g., Card et

[4]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.

al. 2013; Song et al. 2016; Kline et al. 2019; Bonhomme et al. 2019).[5] While large wage losses at job loss are hard to explain without a substantial degree of frictions in the labor market, they are not a puzzle in the context of pervasive firm-specific rents in the labor market. Our findings are also consistent with work in Goldschmidt and Schmieder (2017), who demonstrate that wage losses at outsourcing are chiefly driven by reductions in establishment wage effects in Germany. Our paper expands on the recent studies by Lachowska et al. (2017) and Moore and Scott-Clayton (2019) for Washington and Ohio state, respectively. These papers find a more moderate role of firm wage effects in explaining the cost of job loss, something we return to in our discussion section.

In terms of the cyclicality of the cost of job loss, we are the first paper to systematically analyze the multitude of potential sources behind the cyclicality of the cost of job displacement found in Davis and von Wachter (2011) and in Farber (2016). After explicitly accounting for composition changes and the role of employment changes, our results imply that changes in the composition of firms hiring job losers in recessions can explain about one half to two thirds of the cyclicality of the wage losses we find. This is consistent with a growing recent literature showing that job creation shifts to less attractive firms in recession (e.g., Haltiwanger et al. forthcoming), which echoes similar early findings on industry composition (e.g., Reynolds 1953; Reder 1955). Our results are also reminiscent of findings that cyclical downgrading occurs for young labor market entrants (e.g., Okun 1973; Oreopoulos et al. 2012), and that workers' careers partly evolve by climbing up a job ladder towards high-paying firms (e.g., Topel and Ward 1992). In contrast to younger workers studied in these papers, average job mobility of the more mature workers we study is low, and hence downgrading appears permanent.

An important feature of the role of establishment wage effects we study is that on average, low-wage workers tend to experience larger and more cyclical wage losses. They also suffer

[5]The literature is still debating the extent of the variance in wages explained by firm or establishment fixed effects. Recent work by in Kline et al. (2019) and Bonhomme et al. (2019) suggests that the total variance may be smaller than what indicated by Abowd et al. (1999)Card et al. (2013), and Song et al. (2016), among others. As discussed in the paper, we replicated the approach in Bonhomme et al. (2019) in our data, and confirmed that the variance of total wages explained by establishment fixed effects is reduced but still important. Hence, we are confident that the role of establishment effects in explaining the wage distribution is consistent with our findings of their importance for explaining job losses.

larger losses in establishment effects than higher-wage workers, even when exiting the same establishment. While these findings are consistent with presence of outsourcing in normal times as found for Germany by Goldschmidt and Schmieder (2017), consistent with other recent work we do not find evidence that losses in establishment wage effects for low-wage workers intensify in recessions (e.g., Schmieder et al. 2018). This is further evidence that a key driver of the cost of job loss we find is the change in the type of firms that are hiring over the business cycle, not the type of firms that experiences layoffs. It also confirms evidence from the literature suggesting low-wage workers are more strongly affected by recessions (e.g., Cutler and Katz 1991; Hines et al. 2001). Overall, these findings further extend the stylized facts on the cost of job loss presented by Davis and von Wachter 2011, and job search and job ladder models aiming at explaining these results would benefit from incorporating worker heterogeneity.

Our paper is also able to connect our analysis of the role of losses in establishment wage effects directly to two other key strands of literature on the cost of job loss focusing on unemployment duration, and on industry and occupation attachment, respectively.

The most salient source for wage losses that emerges from our study besides establishment wage effects is the duration of nonemployment after job loss. Nonemployment duration explains an important part of the remainder of average wage losses once we control for establishment wage effects, and it has a substantial independent effect on the cyclicality of the cost of job loss. While nonemployment duration may be correlated with unobserved worker attributes, findings in Schmieder et al. (2016) suggests the effect is likely to be causal. This provides direct empirical evidence for presence of hysteresis due to long-term unemployment and shows that it amplifies the cost of business cycles (e.g., Song and von Wachter 2014). A key finding here is that about half of the total effect of nonemployment duration on wage losses is likely to be due to losses in establishment wage effects. This provides further evidence on cyclical downgrading, and important insights into the sources of hysteresis in recessions.

Finally, we also confirm that changes in industry or occupation at job loss tends to raise the cost of job loss, especially for workers that had longer industry or occupation tenure, as

found in a range of prior studies that did not have access firm-specific information (e.g., Neal 1995; Poletaev and Robinson 2008). Once we include such information, we find that industry and occupation changes and tenure are highly correlated with changes in establishment wage effects both on average and over the cycle. As a result, establishment wage effects explain a substantial fraction of the role of industry or occupation variables for average wage losses. While a precisely estimated effects of industry and occupation switches and industry and occupation tenure on average wage losses remains, it contributes little to explaining the cyclicality of wage losses at job displacement. This is consistent with a large empirical literature showing that reallocation between industries or occupation is unlikely a major source of employment fluctuations over the business cycle (e.g., Abraham and Katz 1986; Aaronson and Christopher 2004; Rothstein 2017). Overall, as hypothesized by Topel (1990)'s early contribution, both losses in rents and specific skills are likely to matter to explaining the cost of job loss, but losses in establishment effects and nonemployment duration are more important in recessions.

Last but not least, our approach provides a convenient, two-step estimation procedure that allows for an integrated treatment of a range of potential explanatory factors of the cost of job loss. Beginning with Jacobson et al. (1993)'s seminal contribution, most studies have focused on studying differences in the cost of job loss by worker and establishment characteristics by estimating large interacted distributed lag models. Here, we have taken cues from the large literature on heterogeneous treatment effects emerged since then and regressed individual-level wage losses with respect to a control observation as a function of workers and establishment variables. While the two approaches can be made isomorphic, our parsimonious approach allows us to better focus on the relative contribution of various explanatory factors, especially when analyzing the effect of job loss over the business cycle.

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, and in Section 7 we discuss potential mechanisms behind our findings. 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.[6] The data also contains basic demographic characteristics including education, as well as information on occupation, industry and receipt of unemployment insurance benefits. In addition, the worker-level data has been merged with information on employers on the establishment level (obtained from the *Betriebshistorikdatei*) to create a linked employer-employee panel spanning over 30 years from 1975 to 2009.

2.2 Measuring Job Displacement at Mass-Layoffs

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. In particular, availability of daily information on earnings and employment allows us to better date job separations, to separately analyze daily wages and time worked, and to analyze the role of several measures of career histories for explaining the effects of job loss over the business cycle. The data also allows us to compute various measures of employer characteristics, as further explained below.

Like similar administrative datasets in the U.S. and other countries, our data contains

[6] Self employment and civil servants are not covered in this data. The lack of self-employment is comparable to other papers studying job displacement using administrative data, while the lack of information on civil servants is unlikely to matter for job losers.

no direct information regarding the reason of a job separation. We follow the existing U.S. literature based on administrative data and define a job displacement as the event that a worker with at least 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. It also helps with establishing a counterfactual outcome, since most of these workers would likely have remained in covered employment absent a job loss.

We work with two common definitions of a mass-layoff event. First, we define a mass-layoff to occur either when the establishment's employment permanently declines by thirty or more percent over a short period of time. Second, we also consider the case when establishments 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 quite closely. Smaller establishments are subject to larger percentage employment fluctuations, such that these measures of mass-layoff are less meaningful.[7]

A key step in measuring mass-layoff events is to distinguish between actual permanent reductions in employment and events such as mergers, takeovers, outsourcing, or changes in employer 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 in 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,

[7] Moreover, Davis et al. (2016) show that at least in the U.S., at a 30% employment loss the majority of workers leaving the firm are laid off rather than voluntary quitters. Thus, this cutoff further helps in reducing measurement error from the presence of voluntary movers among the displaced. We are not aware of similar evidence being available in Germany.

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.[8]

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. It is important to bear in mind that these definitions exclude many job losers, and our study does not intend to capture the experiences of these other job losers. Analyses in von Wachter et al. (2011) and Hildreth et al. (2009) have shown that in the U.S., these estimates are robust to the restrictions on job tenure, and moderate variations in the restrictions on firm size and size of the mass layoff. However, changes in the composition of job losers and firms displacing them over the business cycle may affect comparisons of the effects of job loss over time and over the business cycle. We address such potential composition changes explicitly in our analysis of the role of worker and employer characteristics in explaining the costs of job loss over the cycle.

2.3 Constructing a sample of displaced workers and a control group

Baseline restrictions We construct our analysis sample in two steps. First, we denote the year prior to displacement the "baseline year" c and we choose for each baseline year all workers that satisfy the following restrictions on June 30th for that year: the individual is male, is between age 24 and 50, and works full time at a West German establishment with at least 50 employees, and has at least 3 years of tenure.[9] Furthermore we exclude individuals employed in the following sectors: mining, public administration, defense, activities of private households and extra-territorial organizations.[10] Within this sample, we define an individual as displaced (between year c and $c+1$) if a) the individual leaves the establishment between c and $c+1$ and is not employed at the year c establishment in any of the years $c+1$, $c+2$, ..., $c+10$

[8]For an exploration of these cutoffs in the context of Germany seeHethey-Maier and Schmieder (2013)

[9]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.

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

and b) the establishment has a mass-layoff (or plant closing) between year c and $c+1$.

We focus our main analysis in this paper on men for two reasons: First, to facilitate comparisons with the earlier literature that 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.

Propensity Score Matching Displaced and non-displaced workers differ in many ways that make them difficult to compare. While differences in average outcomes are easily controlled for using worker fixed effects, controlling for differential trends among treatment and control groups is more difficult. We use propensity score matching to obtain a comparison group that provides the appropriate counterfactual earnings trends for the displaced workers in our design. We implement the matching estimator as follows. 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 2 step-matching estimator where we match within baseline year and 1-digit industries based on a number of matching variables. Specifically for each baseline year and 1 digit industry, we estimate the propensity of being displaced using establishment size in year c, the worker's log wage in year $c-1$ and $c-2$, as well as education, tenure and age in year c 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 c and $c+1$, nor that they cannot be displaced in future years. Table 1 displays average worker characteristics (Panel a) and employer characteristics (Panel b) of our sample of displaced workers, a random sample of (unmatched) non-displaced workers, and the matched sample of non-displaced workers. Even absent matching, Table 1 shows observable characteristics between displaced

and non-displaced workers prior to displacement are very similar. While there is a small difference in pre-displacement daily wages, possibly due to lower job tenure, in the Appendix we show the two groups exhibit almost identical pre-displacement trends in wages, earnings and employment (Figure A-10). Table 1 and Figure 1 show that pre-displacement differences in wages, earnings, and job tenure disappear in our matched sample. In the robustness section, we show that the results do not hinge on the use of propensity score matching, and hold also in typical distributed lag models often used in the literature on the long-term effect of job loss.[11]

2.4 Empirical Approach

2.4.1 Event study Analysis

We first provide estimates of the effects of job loss on a variety of outcomes using an event study analysis. Let y_{itc} be the outcome of interest for a worker i, with baseline year c observed in year t. Furthermore let Disp_i be an indicator variable for whether worker i is a displaced worker or belongs to the control group. We estimate the following regression model:

$$y_{itc} = \sum_{k=-5}^{15} \delta_k \times I(t = c+1+k) \times \text{Disp}_i + \sum_{k=-5}^{15} \gamma_k \times I(t = c+1+k) + \pi_t + \alpha_i + X_{it}\beta + \varepsilon_{itc} \quad (1)$$

The main coefficients of interest are δ_k, which measure the change in earnings of displaced workers with respect to the baseline year *(c), relative* to the evolution of earnings of non-displaced workers.[12] As we discuss in the appendix, it is important to control for "year relative to baseline year" fixed effects (coefficients γ_k), since the tenure restriction in the baseline year leads to hump-shaped earnings profiles around the baseline year even for the control group that cannot be captured by year effects (included as π_t) alone. In addition we control for year effects π_t, individual effects α_i and time-varying control variables (x_{it}), chiefly worker age.

[11] 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.

[12] 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 $t^* - 5$.

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 thex_{it} make little difference to the estimates.

2.4.2 Decomposing the Sources of Cyclical Wage Losses using a Matched Diff-in-Diff Design

In order to study whether various factors, such as losses in establishment effects, can explain the wage losses at displacement, we construct an individual level measure of the wage loss after displacement.

To do so, 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 displacement:

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

where $\Delta_d w_{ic}$ is the short-term individual wage change before (-5 to -1 years) and after (1 to 3 years) job displacement (and$\Delta_{nd} w_{ic}$ is the wage change for the matched control individual) for a displaced worker i with baseline year cOne can think of $\Delta_{dd} w_{ic}$ as an estimate of the individual 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:

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

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 establishment composition we control for $\hat{\alpha}_i$ (the estimated individual FE) and $\hat{\psi}_{J(i,c)}$ (the estimated establishment FE *before* displacement).

Finally, in order to assess the role played by the loss in establishment FE we add to this model the change of the establishment effect at job loss relative to the control group $\Delta_{dd}\hat{\psi}_{J(i,t)}$.
:

$$\Delta_{dd}w_{ic} = \beta\, UR + \gamma\, \hat{\psi}_{J(i,c)} + \delta\, \hat{\alpha}_i + \xi\, \Delta_{dd}\hat{\psi}_J + X_i\theta + c\pi_1 + c^2\pi_2 + \varepsilon_{ic} \tag{3}$$

Comparing the coefficient estimate with and without controlling for losses in establishment effects will indicate to what extent losses in establishment 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 establishment 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 replicated the main result using purely annual variation in average changes in earnings and establishment characteristics, which are not affected of selective entry into establishments. Second, systematic wage differences across establishments 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 establishment or firm effects as signifying desirable employers.

2.5 Outcome Variables and the AKM Model

To be comparable with U.S. studies of job loss over the business cycle, we begin by analyzing the effect of job displacement on total annual earnings. Our measure of annual earnings is constructed to be comparable with the Social Security Data used in Davis and von Wachter (2011). A key advantage of our data is that it contains detailed information on daily wages (as recorded on June 30th each year) and days worked, which is typically not available in

administrative U.S. data sources. We use this data to decompose earnings losses over the business cycles into losses in daily wage and losses in the total number of days worked per year. We then analyze the effect of job loss on changes in employer attributes, chiefly the estimated establishment fixed effect, and decompose the wage loss over the business cycle into a range of factors as further discussed in Section 6. Although we focus on losses in earnings, wage and days worked, the German UI data can provide a richer picture of what happens during non-employment than is typically possible. We assess the effect of job loss on a range of additional outcomes, including total annual income (consisting of earnings plus payments form unemployment insurance), 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.

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.[13]

To obtain estimates of persistent differences in employer earnings, access to the universe of worker-firm records during our sample period allows us to estimate the canonic error-components model popularized by Abowd et al. (1999) [henceforth AKM]. We follow the

[13]Here, we depart fromvon 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.

implementation for Germany by Card et al. (2013) [henceforth CHK]. However, since we need to compare establishment effects over time, and the AKM model estimates the effects relative to an omitted baseline establishment, as in Goldschmidt and Schmieder (2017) we estimate the model jointly for the entire time period. The regression model we estimate is

$$\ln(w_{it}) = \psi_{J(i,t)} + \alpha_i + \theta_t + x'_{it}\beta + \epsilon_{it}, \tag{4}$$

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$m_{iJ(i,t)}$.

For our baseline measure of establishment effects, we estimate the AKM model pooling 30 years of data (1979 to 2009). A possible concern is that job losers themselves would contribute to the estimates of the establishment effect in the AKM model if we included them in the estimation and if job losers have wage losses for reasons outside the AKM model this might bias the estimates. To avoid this endogeneity, we exclude all post-displacement event observations for each worker who was displaced (and corresponding control worker) and for each establishment that mad a mass lay-off.

One concern about pooling 30 years of data for the AKM model is that the real establishment effects may not be constant over this long time horizon. For example, some firms may become more successful over time leading to more profit sharing and a higher establishment effect, while others may be on a downward trend with shrinking wage premiums. As an alternative to our main approach we therefore also employ a "rolling window" approach where we estimate a different AKM model for each cohort c of displaced workers, where we only use observations from year $c-5$ to year c (a 6 year window). These estimated establishment effects are then assigned to all future observations of workers in cohort c, so that we can assess post displacement outcomes. This has the advantage that establishment effects can vary over time across cohorts, while holding them constant within cohorts. It also has the advantage that the establishment effects are estimated entirely on pre-displacement data, thus fully alleviating

concerns of endogeneity.

Several papers have pointed out the problem of "limited mobility bias" in estimates of the AKM model.[14] The establishment effects are only identified by movers between establishments and while the total number of workers is large, the number of movers is typically relatively small. This leads to an upward bias in the estimated variance of establishment/firm effects and a downward bias in the covariance between worker and establishment effects. Recent papers have shown that the bias can be substantial (Bonhomme et al. 2019; Kline et al. 2019), especially in short panels and when small employers are included. We use several strategies to deal with limited mobility bias.

First, limited mobility bias is one motivation for estimating the AKM model over the full 30 window. Since over this long time horizon establishments have significantly more movers, this substantially reduces the problem of limited mobility bias. Furthermore since we focus on job losers separating from medium to large establishments, the establishment effects for the pre-displacement establishment is likely quite precisely estimated.

Our second strategy is to estimate these equations using a "split-sample IV" approach as a robustness check when estimating equation (2) and (3) Since the main concern is measurement error in the employer effect on the right hand side of these regressions, this approach should in principle work well. For this we randomly split the full data on which the AKM model is estimated on the person identifier and estimate the AKM model separately for each of the two samples. We then estimate the regression models (2) and (3) by using the estimated establishment effect from the first sample instrumented with the estimated establishment effect from the second sample, which corrects for the bias from measurement error. We use this strategy both for the long-AKM model which pools 30 years and for the rolling window AKM model (in which case we estimate a separate split sample AKM model for each cohort).

As our third strategy we use an idea inspired by Bonhomme et al. (2019), where we partition establishments with less than 50 employees into a small number of clusters of establishments with a similar wage structure. Like Bonhomme et al. (2019), we use the Kmeans

[14] E.g. Abowd et al. (2004); Andrews et al. (2008, 2012); Bonhomme et al. (2019); Kline et al. (2019).

clustering algorithm using the discretized empirical CDF of log wages as the measure of closeness and grouping all establishments into 20 distinct clusters. We then estimate the AKM model replacing the establishment FE with cluster FE (essentially assuming that within clusters establishments have the same establishment FE). Since the clusters are very large, there are many movers between clusters and limited mobility bias does not represent a problem. We discuss this further in the robustness section.

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 or establishment components into traditional earnings regressions. Despite well-known limitations, we believe that there is sufficient support for the model to treat the estimated establishment fixed effects as useful measures of employer characteristics. To benchmark our findings, we also use more common measures, such as establishment size and average establishment turnover rates.

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

3.1 Average labor market outcomes of displaced workers

We begin by providing benchmark estimates of the long-term effects of job displacement on earnings, wages, employment and unemployment up to 15 years after job loss. The results imply that a job displacement leads to long-lasting earnings losses that have not faded 15 years after job loss. Strikingly, both the patterns and magnitudes confirm existing findings based on comparable data in the U.S. What is new here is that we also find that job displacement leads to a very long-term effects on wages. In contrast, effects on employment and unemployment, are large but fade five years after job displacement.

The first step is to confirm that our matching strategy produces comparable control groups for displaced workers in our sample. 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 effects, 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. (Note that we are matching based only 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.)

Comparing the evolution of earnings for treatment and control groups, Figure 1 (a) 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 relative to average earnings prior to displacement. While subsequent years show some recovery, it is slow and even after 10 years, displaced workers still have about 5,000 Euro lower earnings then non-displaced workers, a 10% reduction relative to the pre-displacement mean. Note that 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 earnings 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:

$$y_{it} = \sum_{j=-4}^{14} \delta_j I(t = t^* + j) I(disp) + \alpha_t + \theta_i + x_{it}\beta + \varepsilon_{it} \tag{5}$$

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.[15] Theα_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 thex_{it} make little relatively difference to the estimates.

Figure 2 shows estimates of the effects of job displacement from 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

[15]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 $t^* - 5$.

visible 15 years after job loss.[16] From the results for daily wages (Panel (b)) and employment (Panel (c)), 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. Yet, the long-term earnings effect appears to be chiefly driven by a permanently reduction in wages, as we will formally show in the next section.

The effect on wages shows a large immediate effect and exhibits little in terms of recovery. It it important to note that since this figure is conditional on having found employment, it could understate the wage decline if high-wage workers are more likely to self-select into employment. To assess the potential role of sample selection, we compared the difference in median log wages across treatment and control groups and find it to be very similar to that shown in Figure 2 (Appendix Figure A-7).[17] Finally, the causal effect of job displacement on UI income shown in the final panel of Figure 2 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 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. The results are also consistent with findings in the empirical literature that the wage structure in the two countries exhibits important similarities, for example in the role of education and experience (e.g., Kane and Harhoff 1997), the role of job mobility in wage growth (e.g., Giuliano and von Wachter 2008), and the role of firms in wage setting (e.g., Card et al. 2013). On the other hand, much has been speculated about how the U.S., with

[16]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 establishment in the year before a separation.

[17]In Appendix Figure A-7, we also show that only the bottom decile of the distribution of days worked experiences a reduction in employment. Hence, the median regression yields an unbiased estimate of the change in median wages upon job loss.

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. 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 different institutional settings.

3.3 Decomposing Earnings Losses into Wage and Employment Losses

The previous results clearly showed that displaced workers experience both large employment losses - especially over the short run -, as well as sizable and long-lasting wage losses. In this subsection we investigate directly what share of earnings losses after displacement are explained by those two channels using a straightforward decomposition. The main finding is that long-run earnings losses are entirely explained by long-run wage losses, whereas in the short run both employment losses and selection into employment play an important role.

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:

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

Denotey_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:$\Delta = y_t^S - y_t^D$. Omitting the t subscript, we show in Appendix X that the earnings loss of a displaced worker relative to the control worker can be written as:

$$E[\Delta] \quad = \quad \Delta E[N_d]E[w^S] + E[N_d^D]\, \Delta E[w] + \Delta Cov(N_d, w) \qquad (6)$$

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 job losers with larger losses in days worked have lower wages while workers who work more have the highest wages.

Figure 3 shows the results of the decomposition in equation (6) over a 14-year period post-displacement.[18] In the first two years after job loss the employment losses explain a substantial share of earnings losses. Wage losses become more important than employment losses in explaining earnings in year three and onwards. Finally, the covariance term is quite striking: it is positive and large in the years following job loss. In the short run, 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 explaining 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

We next document a strong counter-cyclical pattern in earnings, employment, and wage losses at job displacement. Figure 4 Panel (a) shows earnings losses of displaced workers separately by year of displacement obtained by replication the regression in equation (5) for each displacement year. For presentation purposes, we only the first two years after job displacement. Vertical bars indicate recession years in Germany (defined as a year of negative GDP growth).

The figure reveals a strong cyclical pattern in the loss of annual earnings 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

[18] To implement the decomposition we have to drop those worker-year observations where workers are not working at all from this analysis. While the earnings losses are therefore slightly lower than before, the figure still shows very large earnings losses in the first year (t=0) after displacement of more than 35% and a similar recovery pattern.

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 (sometimes termed 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 2003 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 4 Panel (b) shows again 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. This indicates that an important part of the cyclicality of earnings losses at displacement are driven by employment losses. Figure 4 Panel (b) shows that wage losses are cyclical as well, though somewhat less so than earnings losses, especially during the early 1980s.

4.1 Decomposition of Cyclical Component of Earnings Losses

Figure 5 and Table 2 explore the cyclicality of the effects of job loss further. Figure 5 Panel (a) plots the short-term effects of job loss on annual earnings for each displacement year directly against the prevailing national unemployment rate. The coefficients from a univariate regression corresponding to the displayed fitted line in Panel (a) of Figure 5 is shown in Table 2 (row 2 of column 1). 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.[19] 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.

To explore 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 (6) above for each

[19]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.

cohort of job losers for earnings within three years after job loss, shown in the remaining panels of Figure 5. The scale of the y-axis in Panels (a) to (d) is identical and the units are comparable. The results in Panels (b) and (c) of Figure 5 and Table 2 confirm that earnings, wage losses are all strongly countercyclical. For each point increase in the unemployment rate, Table 2 shows the earnings loss rises by about 2% (row 2), whereas wages are reduced by 1.5% (row 3). It is clear from Figure 5 and Table 2 that the relationships are very precisely estimated. The decomposition shows that employment losses and wage losses both play an important role for explaining the overall cyclicality of earnings losses in the short run. In the longer run, most of the earnings loss is explained by wage losses as the employment gap fades. Interestingly, the covariance term in Panel (d) 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 6.

4.2 The Role of UI Benefits in Buffering Earnings Losses Over the Cycle

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, Table2, 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 Table2, 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 and 5. The high-quality information on workers' employers before and after job displacement available in our data allows us to make inference about several potential channels. In this Section, we explore one core hypothesis in detail, namely that displaced workers lose quasi-rents provided by the firm or establishment. 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.

Using these insights, we proceed in two steps. In this section, 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 (5) with two measures of establishment 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 Section 6 we assess directly whether such changes in establishment characteristics can help to explain the effect of job displacement on wages and its cyclicality. We then compare the role of changes in establishment characteristics with other channels behind the cost of job loss commonly studied in the literature.

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

In this section we show that workers coming from establishments with high fixed effects have much larger short- and long-term losses in both establishment fixed effects and daily wages. This is shown in various panels of Figures A-9 and 7.

Figure A-9 shows a clear pattern of mean reversion in establishment effects occurring at job loss. Panel (a) of Figure A-9 shows the average loss in establishment fixed effects for different quintiles of the (worker weighted) pre-displacement distribution of establishment fixed effects among the population of displaced workers. The bottom 20% among job losers experiences little change and the middle 20% experience a persistent loss of 5%. Only the bottom five percent of workers experience an increase (Figure A-9 Panel (b)). Panel (b) of Figure A-9 shows the relationship of the pre-displacement establishment fixed effects and the change in establishment fixed effects by vintiles of the distribution of pre-displacement establishment effects. The figure shows that the change in establishment fixed effects at job loss is close to linear and negative. However, at -0.35 the regression coefficient is far from one, implying that the initial advantage in establishment fixed effects is not lost.

Our data allows us to take a closer look at what happens to establishment fixed effects at job loss. To do so, it is helpful to put job losers in the context of the wider population of workers. The remainder of Figure A-9 displays several figures showing how job losers' position changes with respect to the distribution of establishment fixed effects among all workers.

Overall, the results again show a pattern of mean reversion. Panel (c) and Panel (d) of Figure A-9 replicate the first two figures but cut the sample by percentiles of the establishment fixed effects distribution among all workers. Panel (c) shows that job losers that were at the bottom of the overall establishment fixed effects distribution experience permanent increases in establishment fixed effects, whereas those who were at the top experience a permanent decline. Panel (d) of Figure A-9 shows mean reversion is again proportional, such that the two extremes experience larger increases and reductions relative to the middle of the distribution.

It is clear however, that despite mean reversion job losers have higher establishment fixed effects than the average worker even after job loss. That job losers come from the top of

the overall distribution of establishment fixed effects is clearly apparent when we directly compare the distributions of establishment fixed effects among job losers before and after job loss relative to the population in Panel (e) of Figure A-9. As a result, the correlation in the level of pre- and post-displacement establishment fixed effects is relatively high at 0.64 (Figure A-9, Panel (f)).

Figure 7 shows that losses in establishment fixed effects play an important role in explaining wage losses for displaced workers in Germany. Panel (a) of Figure 7 plots the average loss in daily wages for the same quintiles of the pre-displacement distribution of establishment fixed effects among job losers that were used in Figure A-9, Panel (a) to assess losses in establishment fixed effects. Comparing the two figures, it is immediately apparent that losses in establishment effects closely correlate with losses in wages. This is shown directly in Panel (b) of Figure 7, which shows the scatter plot of 3-year losses in wages and 3-year losses in establishment fixed effects. The two losses are proportional with a slope coefficient roughly 0.8. This result is consistent with our findings in Table 3, and suggests that losses in establishment fixed effects are a strong determinant of losses in wages.

Figure 7 Panel (b) also contains important information about how recovery patterns differ by establishment effects of job losers' old employers. Overall, the long-term loss in wages appears to reflect the loss in establishment fixed effects, while in the short run other factors appear to play an additional role (something we come back to in the next section). Job losers at the bottom of the pre-displacement distribution of establishment fixed effects (among job losers) do not experience a loss in establishment fixed effects, and no permanent reduction in wages. They do experience a short-term loss that fades after about seven years. (Interestingly, those few lucky displaced workers that do experience increases in establishment fixed effects also experience increases in wages.) It is notable that for the middle 20% of the pre-displacement establishment fixed effects distribution experience a short-run loss that is larger than their average loss in establishment fixed effects (Figure A-9 Panel (a)), but that for them, too, the long-run loss in equal to the loss in establishment fixed effects. In contrast, workers from the top 20% of the pre-displacement establishment fixed effect distribution experience a

permanent loss in wages without much of a recovery, and this loss is slightly larger than the loss in establishment fixed effects.

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

Losses in establishments characteristics at job displacement are more pronounced during recessions. Figure 8 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 9 and Table2, Panel B show that both of these effects correlate systematically with the unemployment rate at job loss, particularly the reduction in mean establishment wages. The cyclicality in the loss of establishment characteristics is partly due to a rise in job displacement from high-wage firms during recessions.[20] However, as we show in the next section, the key of the cyclicality of losses in establishment characteristics over the business cycles is a reduction in the quality of the post-displacement employer.

To complement our analysis of the role of changes in establishment fixed effects for explaining wage losses over the business cycle, we also analyzed the cyclical behavior of some of the key alternative channels highlighted in the literature. We do find that several of the channels are highly pro-cyclical (shown in the Appendix). Not surprisingly, the average duration of nonemployment spells increases sharply in recessions. The incidence of changing industry (3 digit) or occupation (2 digit) also increases in recession, but to a lesser degree. Average nonemployment durations more than double for job losses in recession compare to expansions (from a base of a little over two months). The incidence of industry and occupation switches increases by 35% and 30% from expansions to recessions (from a base of 23 and 44 percentage points, respectively). We also examined whether the type of worker displaced and

[20] Appendix Figure A-2 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 A-2 Panel (a) shows that the mass layoff rate is higher and more cyclical for establishments with fixed effects above the median, while Panel (b) shows that the same is true for plant closings.

establishment displacing changes over the cycle, and we find no noticeable correlation with the business cycle, something that will be relevant for our findings in the next section.

6 Sources of Earnings Losses for Job Losers Over the Business Cycle

6.1 Employer-Level Determinants of the Average Cost of Job Loss

The findings in Section 5 suggest that the large wage losses at job loss and their cyclicality documented in Sections 3 and 4 could be partly explained by losses in establishment characteristics. As a benchmark, we first show that when we pool all displacement years as in Section 3, losses in establishment effects appear to explain the majority of earnings losses, and seem to be closely correlated with other changes in job characteristics. Panel (a) of Figure 10 shows a series of estimates for the effect of job loss on log daily wages, in which we sequentially 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, changes in establishment size, or the length of nonemployment after job loss when included separately have a non-negligible effect. However, losses in establishment fixed effects alone explain the vast majority of the earnings loss, substantially more than each of the other changes. This finding suggests that losses in establishment effects are a key driver of job losses in our sample, and is of course consistent with the assumptions underlying the AKM model, according to which conditional on the worker effect, changes in the establishment effect explain all changes at job loss. They are also consistent with a direct assessment of this assumption based on flows between firm effect classes in Card et al. (2013) and Song et al. (2016). The finding also suggests that changes in industry, occupation, establishment size, and nonemployment duration appear to be correlated with losses in firm effects, something we return to below. An important caveat throughout the analysis is that the associations in the depicted regressions do not necessarily imply causal relationship if workers with larger or smaller wage losses tend to select different employers after job loss.

6.2 Employer-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 year-to-year change in Panel A and the level 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), 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.

We next use our framework to examine the role of worker composition. The overall finding is that changes in worker composition has very little effect on the cyclicality of job loss. Column (2) confirms that workers coming from high-wage firms experience higher wage losses (see Section 5). In addition, we find that lower wage workers experience larger wage losses as well, independently of whether we use pre-displacement fixed effects (Column 2) or completed years of education (Column 4) as a measure of worker type. However, controlling for changes in worker and establishment composition (Columns 3 or 5) does not affect our main coefficient, suggesting that composition changes are not responsible for explaining the cyclicality of job loss we find.

We next show that a sizable portion of cyclicality is explained by changes in employer characteristics at job loss. Combined with our finding of little role for changes in the composition of displacing firms, this implies that it is changes in post-displacing employers that drive a substantial portion of cyclicality. When we include the change in establishment fixed effects as a control variable in Column (6), our estimates of the cyclicality of job loss decline by around one half relative to the basic result in Column (1). As a sensitivity check, in column (7) we control for the change in the establishment fixed effect, but force the coefficient on the establishment fixed effect to be equal to 1, in which case the change in the establishment fixed effect can explain even more of the cyclicality. These findings are also visible in Panel (b) of Figure 10, which shows the corresponding scatter plot – the strong correlation with the

unemployment rate present in Panel b) of Figure 4 is substantially reduced once we control for the change in employer fixed effect at job loss. Overall, these results confirm the visual impression from Section 5 that losses in establishment wage premiums are a key driver of the variation in the cost of job loss over the business cycle.

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

Overall, Section 6.2 finds that losses in establishment fixe effects can explain 80-90% of the level of wage losses, and about half of the cyclical variability. In this section, we examine a range of other potential mechanisms behind the cyclical variation in the cost of job loss and their correlation with losses in establishment fixed effects. From an empirical point of view, analyses of variation in the costs of job displacement in the previous literature can be grouped into roughly 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., establishment size, establishment fixed effect); c) variation in pre-displacement career outcomes, such as job tenure, occupation tenure, 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.

We have explored including a range of variables from each of these categories in our regression model outlined in Section 2.4.2. While we found several of these characteristics to matter in expected ways for explaining the cost of job loss, most do not help to further explain its cyclicality. 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 do not help to explain variation in the cost of job loss over the business cycle. Hence, we focused our main analysis on the role of 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.

Table4 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 both the average cost of job loss and its cyclicality. This is consistent with findings in Schmieder et al. (2016) that show that nonemployment duration has a negative causal effect on reemployment wages. Controlling for pre-displacement establishment effects does not affect this 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 of nonemployment duration (two thirds if we set the coefficient to one to address the concern of measurement error). This suggests that an important part of the loss in wages due to nonemployment duration found in Schmieder et al. (2016) is due to entry into lower paying firms.

Turning to changes industry and occupation affiliation, these have a substantial effect on the average 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 changes in industry and occupation 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 establishment effects, factors such as changes in industry or occupation, explain only a moderate amount of the variation of wages.

6.4 Sensitivity Analysis

Our main findings are very robust to variation in samples, refinements of methodology, or in the way we measure the business cycle. Here we discuss a number of important robustness checks to our main analysis, some of which are shown in Table 6. In this table we focus on the main specifications of the cyclicality results, that correspond to Table 3 columns (1), (2) and

(5). Panel A shows the relationship of the change in the unemployment and the log wage loss, Panel B adds the pre-displacement establishment effect, worker effects as well as experience and tenure to control for composition changes, Panel C adds the change in the establishment effect. Column (1) of Table 6 shows the baseline results form Table 3 for reference.

Robustness to Limited Mobility Bias

As discussed in section 2, we estimate the AKM model pooling all years from 1979 to 2009 in order to maximized the precision of the estimated establishment fixed effects and to reduce the problem of limited mobility bias. A concern with this approach is that it may be implausible that establishment effects are constant over such a long time horizon. Column (2) of Table 6 therefore shows the results based on the rolling AKM model, where AKM model is estimated using only observations within 6 years prior to the displacement event. In this model adding the change in establishment FE appears to explain slightly less in the cyclicality (the coefficient on the Change in the UR is now -0.016 as opposed to -0.014 in column 1). Furthermore the coefficient on the change in the establishment effect is slightly smaller (0.70 as opposed to 0.74).

Note that we lose almost 12,000 observations in the rolling AKM model since we lose displaced workers who move to employers that did not exist prior to the baseline year (and thus are not in the AKM model). Furthermore in this shorter panel we expect limited mobility bias to be significantly more problematic and the resulting measurement error is likely biasing the coefficient on the change in the establishment effect towards 0.

Another way to address limited mobility bias is to correct for the measurement error bias using a split sample IV, where we randomly split the data that is used in the AKM estimation into two equal sized samples (keeping person histories together) and estimate the AKM model separately. We then use the establishment effects estimated on one sample as instruments for the establishment effects from the other sample, in particular instrumenting for the level and change in the establishment effect in these specifications. This is shown in column (3) for the long AKM model. The number of observations drops slightly since using a smaller sample

makes the largest connected group smaller and we lose some small establishments where we do not get estimates of the establishment effect in both samples. The results of the split sample IV are very much in line with our expectations: the change in the establishment effect coefficient increases to 0.78 (consistent with measurement error bias) and it now explains slightly more of the cyclicality.

We use the same split sample IV for the rolling AKM model strategy, where we now split the AKM data for each 6 year window. The results, shown in column (4), suggest that for the shorter AKM window the split sample IV matters more, consistent with the hypothesis that limited mobility bias should be worse in the smaller AKM window. In particular the coefficient on the change in the establishment effect increases from 0.70 (in column 2) to 0.90 in the split sample IV. The cyclicality that is explained in this model is essentially identical as in the long AKM window without split sample IV.

As another way of dealing with the limited mobility bias, we use a hybrid Kmeans clustering approach, where we estimate separate establishment FE for establishments with at least 50 employees, but divide all smaller establishments (less than 50 employees) into 20 clusters using the Kmeans clustering approach of Bonhomme et al., 2019. We then estimate the AKM model on the rolling window (6 years prior to job loss) by essentially treating each of the 20 clusters of small establishments as a single establishment. This is useful since limited mobility bias is much more problematic for small establishments that may have only few movers especially in a short panel. It dramatically reduces the number of estimated establishment (or rather "cluster") fixed effects. For example in 2009 the long AKM model estimates 1.02 million establishment effects, while the Hybrid Kmeans clustering AKM model only estimated 47,699 establishment effects plus 20 clusters effects (for the small firms). As one would expect from limited mobility bias, the resulting AKM decomposition of the variance of log wages (Appendix Table A-4) shows that the Kmeans model does attribute a smaller share to the variance of establishment effects (in 2009 about 15.5% as opposed to 27.6% in the long AKM model) but a larger share to the covariance term.[21] Yet it appears substantial heterogeneity

[21]Interestingly, the result from Card et al., 2013 that a large part of the increase in the variance of log wages in Germany can be attributed to the rise in the variance of establishment effects and the covariance term

in establishment/cluster effects remains. indeed column (5) of Table 6 shows that using this approach establishment effects still explain a very similar share of the cyclicality, with a coefficient on the change in the unemployment rate of -0.016 Panel C. It is also reassuring that the estimated coefficient on the change in the establishment / cluster effect effect is substantially larger than in columns (1) and (2), as one would expect if the Kmeans approach reduces limited mobility bias.

Other Robustness Checks

We also conducted a number of other robustness checks to see whether our results are driven by specific methodological choices or our sample.

In column (6) we show results where the control group is not constructed using a matching algorithm, but instead where the each worker is simply assigned a random control observation with the only restriction that this control worker satisfies the same baseline restrictions (tenure, establishment size, etc). The results are very similar to column (1).

Our baseline results use a 3 year post-displacement window. A longer window has the downside that we cannot use as many cohorts of displaced workers and thus have less variation from the business cycle. Nevertheless if we do use a 10 year post-displacement window, as shown in column (7), the results are qualitatively very similar with slightly smaller cyclicality in the raw correlation but a similar decline when controlling for composition and the change in the establishment effect.

Column (8) shows the results for women. Women's wage losses actually exhibit stronger cyclicality (-0.039 in the raw correlation) but again controlling for composition and the change in the establishment effect reduces this coefficient by a a similar amount.

Finally column (9) shows that the results are virtually identical if we pool displaced workers from East and West Germany.

Appendix Table A-8 shows a number of additional robustness checks where we control for a wide range of additional pre-displacement characteristics (such as detailed occupation

still appears to hold in the Kmeans model in Table A-4, though the weight is shifted a bit more towards the covariance term.

and industry codes, or occupation and industry tenure), displacement characteristics (such as whether it was a plant closing or mass-layoff), and post-displacement characteristics, such as changes in establishment size, part-time status, or the establishment turnover rate. Conditional on the establishment effect variables, none of these additional controls have a significant impact on the cyclicality of wage losses.

We also redid our entire analysis using the level of the unemployment rate instead of the change in the unemployment rate. The results are shown in the appendix and qualitatively similar. The level of the unemployment rate is less informative in Germany as the 1990s had high levels of long-term unemployment rates even at times when the labor market was doing relatively well and the economy was growing. This longer term trends lead to a relatively weak correlation between the business cycle (as measured by GDP growth) and the level, while the change in the unemployment rate is much more tightly linked.

7 Discussion of Findings

7.1 Employer Wage Effects and the Average Cost of Job Loss

A key finding of our analysis is that changes in establishment wage effects can explain an important part of large and persistent wage losses at job displacement. This finding is consistent with recent research that has reexamined the extent to which firm-specific wage components help explain the cross-sectional distribution of wages (e.g., Abowd et al. 1999; Card et al. 2013; Kline et al. 2019; Bonhomme et al. 2019; Song et al. 2016). A long literature in labor economics has tried to understand the puzzle of large losses in earnings and wages at job displacement. In light of the new literature on the role of firms in wage setting the large and permanent wage losses of job losers are less of a puzzle, the presence of such firm-specific wage components can naturally explain large and persistent costs of job loss. Since displaced workers are typically more stable workers coming from larger, more stable firms, they are likely to have settled at firms with higher wages. Upon job loss, they obtain job offers from a broader set of firms, and hence are more likely to move to lower-paying employers.

That changes in establishment wage components can explain a large fraction of wage

changes at job mobility is of course implied by the basic statistical model of wages on which Abowd et al. (1999) (AKM) is based. Analysis of job changes across firm types in Card et al. (2013) (CHK) and Song et al. (2016) (FUI), among others suggest that changes in firm wage components play an important role in explaining wage changes. Losses in such firm wage effects have been used to explain large wage changes in the course of domestic outsourcing (e.g., Goldschmidt and Schmieder 2017). Here we extend this finding to job losers affected to mass-layoffs and over the business cycle.

The contribution of establishment wage components to explain wage changes is bounded by the variance of establishment fixed effects. To a lesser degree, it is also related to the share of the total variance in wages explained by establishment fixed effects. While CHK and FUI suggested establishment fixed effects could explain approximately 20% and 10% of the variance in daily wages or annual earnings, respectively, more recent studies suggest that adjusting for biases in the calculation of the variance in firm fixed effects the total contribution may be smaller. Findings based on Bonhomme et al. (2019) and Kline et al. (2019) suggest the correction could reduce the contribution of firm fixed effects substantially. For Germany, as described in Section 6.4 we use a hybrid Kmeans clustering approach inspired Bonhomme et al. (2019), and found that the share of total variance in wages explained by establishment fixed effects is about 0.16, compared to about 0.2 in CHK's original study (Table III). Overall, the findings in this paper confirm that the variance in establishment wage effects is substantial enough to play an important role in explaining the cost of job loss.

Another important finding of our analysis is that changes in establishment fixed effects are closely correlated with other potential channels of the cost of job loss highlighted in the previous literature, including changes in industry and occupation, industry and occupation tenure, and nonemployment duration. Hence, introducing of establishment wage effects does not only help to rationalize wage losses at job loss, it also sheds new light on other core potential explanations of the cost of job loss. For example, our findings suggest that the the causal effect of nonemployment duration on reemployment wages is likely to be partly explained by an increasing likelihood to switch to lower-paying employers over the nonemployment spell.

Our results also suggest that the importance of industry and occupation changes and industry and occupation tenure partly reflect changes in establishment type in addition to losses of specific skills.

We are not the only paper that has studied the role of employer wage effects for explaining the cost of job loss. Recent studies by Lachowska et al. (2017) and Moore and Scott-Clayton (2019) use administrative data from the state of Washington and the state of Ohio, respectively, to examine this question. While both papers find that displaced workers lose employer wage effect, they disagree on the magnitude of this effect. Relative to these papers, a key difference of our study that we are able to study the role of firm-wage effects over the business cycle, as discussed next. Our detailed data and large sample sizes also allowed us to explore the interaction of firm-wage effects with other classic channels in more detail.

Another difference in our analysis is that we explored differences in outcomes by worker type. The work on outsourcing of low wage workers, as well as findings of an increasing covariance in worker and establishment wage effects in CHK and FUI suggest potential differences in role of establishment wage effects by worker skill levels. We exploited our data to learn more about the role of worker skill in the cross-section and and over the business cycle. To do so we used our estimated worker fixed effects as proxy for permanent human capital and examined differences in the role of establishment fixed effects for wage losses for job losers with high and low worker fixed effects.[22]

The results of this exercise are shown in Figure 11 (a) and Table 5 and contain two additional important findings. The loss in establishment wage effects matters more for low worker types. In fact, for high worker types there us little loss in establishment wage effects at job displacement. This may occur either because low types are more likely to lose jobs at high wage firms, or because they have higher losses in establishment wage effects conditional on coming from same the establishment. Figure 11 (b) shows clearly that low fixed effect workers have higher losses in firm wage effects coming from the same establishment. This result essentially replicates the outsourcing result for the broad sample of low-wage job losers.

[22] To make sure that the job loss event itself does not affect our measure of permanent skill, we use worker fixed effects that were estimated based on wage data prior to the displacement event.

As a result from these changes, the correlation between worker and establishment fixed effects goes up in our sample of job losers. However, we do not find that 'over-placed' low-wage workers that experienced the largest losses. We defined 'over-placed' workers as those whose firm wage effect at the displacing firm was above average than then mean establishment wage effect for workers with similar worker fixed effects. Yet, this measure neither predicted a higher likelihood of job loss nor a larger loss in establishment wage effects upon displacement.

Besides helping to better understand the cost of job loss, our findings also provide information on potential models of the labor market that could be used to develop models of job displacement. A model in which workers search for better employers over time off and on the job, and lose their search 'rent' at displacement would be a natural starting point (e.g., Burdett 1978; Manning 2003; Moscarini and Postel-Vinay 2018). Yet, models of frictionless job mobility could have similar implications, such as the monopsony model in Card et al. (2013). In either case, our findings by worker type suggest that incorporating both worker and firm heterogeneity would yield a better fit in the data.

7.2 Employer Wage Effects and the Cost of Job Loss Over the Business Cycle

Another main finding of our analysis is that losses in establishment fixed effects play an important role in explaining the cyclicality of the cost of job loss. A key advantage of our approach is that we can show that this result is not driven by composition of job losers, but by changes in the types of employers hiring job losers over the business cycle.

Despite important work on the incidence of job loss and cost of job loss over the business cycle (e.g., Farber 2016; Davis and von Wachter 2011), few papers have analyzed the relative importance of different sources of the cost of job loss over the cycle. Yet, the theoretical and empirical literature suggests several potential explanations for the cyclicality of cost of job loss. A range of studies have emphasized what can be called (labor) 'supply side' explanations that evolve around the worker. These include the loss in the value of industry and occupation specific skills, perhaps due to structural change in recessions (e.g., Neal 1995; Poletaev and Robinson 2008; Topel 1990), as well as losses in match effects, as for example in cleansing

or sullying views of the business cycle (e.g., Schumpeter 1942; Barlevy 2002). Another set of explanations of the cost of job loss are based on change in labor demand. For example, nonemployment durations typically increase in recessions because of a lack of job creation. Similarly, the type of firms that are hiring in recessions can change and thereby affect the cost of job loss.

In this rough and arguably imperfect classification, our results point to a potentially important role of demand side factors. A classic pattern of job mobility in recessions is that workers lose jobs in more cyclical, high-wage durable goods producing sectors and obtain jobs in less cyclical, lower-wage service sectors (e.g., McLaughlin and Bils 2001; Oreopoulos et al. 2012). This pattern is sometimes referred to as cyclical downgrading (e.g., Okun 1973). An increasing number of empirical studies suggests that job creation from high-wage firms slows in recessions even within sectors (e.g., Haltiwanger et al. forthcoming). Our findings complement these firm-based analyses and show that reduction in firm-wage effects of firms hiring job losers play a larger role in recessions.

Again, we also assessed the role of other factors for explaining the cyclicality of job loss. As discussed in the previous section, only nonemployment duration helps to explain the degree of cyclicality in wage losses above and beyond changes in employer wage effects. This is consistent with lack of jobs playing an important role during recessions. The fact that changes in industry or occupation cannot explain cyclicality of the cost of job loss is perhaps not surprising given the extended literature assessing the role of structural changes in recessions, and its finding that these do not appear to play a major role in explaining increased unemployment rates and labor reallocation (e.g., Abraham and Katz 1986; Aaronson and Christopher 2004; Rothstein 2017).

Davis and von Wachter (2011) had explored the ability of several models of unemployment fluctuations to explain the cyclicality of the cost of job loss. Our results on the importance of employer wage effects can be used to further calibrate models of job mobility and unemployment. As suggested in the previous section, a basic sequential search or job ladder model with cyclical distributions of firm types would be a good point of departure in explaining these

patterns. Given we found an important role of differences in worker types in the cross section, we also analyzed differences in cyclical explanatory power of firm wage effects and other factor for wage losses by worker fixed effect.

We proceeded as in the cross-section by replicating our main findings for groups of high and low worker effect, where the worker effect again proxied for permanent differences in skills and was calculated based on earnings data prior to the job loss. The main results are shown in Table 5. Wage losses of low fixed effect workers are more cyclical than for high wage workers. As for the full sample, cyclical wage losses are partly explained by larger role of the loss in establishment wage effects. Interestingly, there is a similar effect of including change in firm-wage effect on the cyclicality of wage losses. The difference with respect to high-wage workers is partly due to a larger role of pre-displacement establishment wage effects. In other words, low-wage workers are more likely to lose high-wage jobs in recessions than high-wage workers. Yet, conditional on coming from the same employer, the loss in establishment wage effects is stable over the cycle. This is shown directly in Figures 11 (c) and (d). There appears to be no increase in the effect of outsourcing on wage losses during recessions.

We also checked the differential effects of other potential channels by worker type over the business cycle, shown in the Appendix. For low wage workers, losses in firm wage effects play a more important role in explaining the negative effect of nonemployment duration on wages after job loss. Perhaps not surprisingly, low wage workers also tend to experience larger earnings losses at industry and occupation changes.[23] Overall, these additional findings are very plausible, and confirm the importance of considering differences by worker type.

Overall, our findings paint a rich picture of the effects of job displacement over the business cycle. There appears to be a clear role of changes in hiring patterns of higher wage employers in recessions, consistent with the recent literature based on firm-worker flows. In addition, some of the patterns we document indicate a clear role of differences by worker type. An important task for future work will be to build a model based on these findings. Our results

[23] There is no differential effect of the amount of occupation or industry tenure by worker type. This is consistent with the flexibility of general skills giving high type workers an advantage rather than the accumulation of specific skills.

suggest a job ladder model with a role for worker skills may be a good place to start.

8 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, Matched Control Sample, West Germany, Men

	(1) Non-displaced workers	(2) Displaced mass lay-off	(3) Displaced plant closing	(4) Displaced mass lay-off or plant closing	(5) Random Sample of non-disp. workers with same baseline restrictions
Panel A: Individual Characteristics					
Non-German	0.1	0.2	0.1	0.1	0.1
	[0.3]	[0.4]	[0.3]	[0.3]	[0.3]
Real wage	93.0	92.3	91.0	91.6	99.1
	[25.9]	[26.7]	[25.4]	[26.0]	[25.6]
Parttime	0	0	0	0	0
	[0]	[0]	[0]	[0]	[0]
Female	0	0	0	0	0
	[0]	[0]	[0]	[0]	[0]
West Germany	1	1	1	1	1
	[0]	[0]	[0]	[0]	[0]
Years of education	11.0	11.1	10.8	10.9	11.0
	[2.3]	[2.4]	[2.1]	[2.2]	[2.4]
Potential experience	21.2	20.8	21.7	21.3	21.1
	[7.4]	[7.4]	[7.3]	[7.4]	[7.4]
Tenure with current Employer	9.6	9.2	9.8	9.5	10.3
	[5.1]	[5.1]	[5.3]	[5.2]	[5.4]
Actual experience, but censored 1975	13.1	12.8	13.3	13.1	13.4
	[6.0]	[6.0]	[6.2]	[6.1]	[6.2]
Total yearly earnings	33823.4	32604.1	32154.7	32354.1	36072.7
	[9573.2]	[10298.1]	[9811.6]	[10032.9]	[9464.1]
Total yearly income	33848.0	32885.2	32518.7	32681.3	36084.6
	[9548.0]	[10058.4]	[9543.4]	[9776.9]	[9450.5]
Days per year working fulltime	363.6	352.2	352.7	352.5	364.0
	[17.8]	[37.1]	[35.8]	[36.4]	[16.1]
Wage on June 30th of year	93.0	92.3	91.0	91.6	99.1
	[25.9]	[26.7]	[25.4]	[26.0]	[25.6]
Log of wage in June	4.5	4.5	4.5	4.5	4.6
	[0.3]	[0.3]	[0.3]	[0.3]	[0.3]
Panel B: Establishment Characteristics					
Number of employees	435.3	477.2	416.3	443.3	3297.0
	[760.6]	[791.5]	[768.3]	[779.3]	[8287.8]
Share of fulltime employees	0.9	1.0	1.0	1.0	0.9
	[0.09]	[0.08]	[0.08]	[0.08]	[0.1]
Establishment FE	2.2	2.2	2.2	2.2	2.2
	[0.1]	[0.1]	[0.1]	[0.1]	[0.1]
Avg. years of education in estab.	10.8	10.9	10.7	10.8	10.9
	[1.0]	[1.1]	[0.9]	[1.0]	[1.1]
Number of Spells	95478	42375	53103	95478	102468

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 sample of workers in Column (1) are matched to displaced workers using propensity score matching within year and industry cells. Non-displaced sample of workers in Column (5) is a random sample of workers (one per displaced worker, including workers for whom no match could be found in Col 1) that satisfy the same baseline restrictions.

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

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 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% Change UR	Mean of dependent variable
Outcome:	Coefficient	Std. Err.	$\Delta UR = -1\%$	$\Delta UR = +1\%$		
Annual Earnings (in Euro)	-1896.2	[422.1]	-4256.2	-8048.6	-3792.4	-6626.4
Annual Earnings (Log points)	-0.063	[0.0099]	-0.13	-0.25	-0.12	-0.21
Log Wage Change	-0.030	[0.0073]	-0.036	-0.096	-0.060	-0.074
Annual Days Worked	-12.6	[2.18]	-24.8	-50	-25.2	-40.6
Change in Estab FE	-0.020	[0.0044]	-0.031	-0.071	-0.040	-0.056
Annual Income (in Euro)	-1627.3	[392.5]	-3706.4	-6961	-3254.6	-5740.5
Annual UI Receipt (in Euro)	268.9	[43.0]	549.8	1087.6	537.8	885.9
Change in Log Estab. Size	-0.15	[0.040]	-0.56	-0.86	-0.30	-0.75
Panel B: 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	Mean of dependent variable
Outcome:	Coefficient	Std. Err.	UR=4%	UR=9%		
Annual Earnings (in Euro)	-624.2	[157.2]	-4542.1	-7663.1	-3121	-6626.4
Annual Earnings (Log points)	-0.013	[0.0050]	-0.16	-0.23	-0.070	-0.21
Log Wage Change	-0.011	[0.0025]	-0.037	-0.092	-0.055	-0.074
Annual Days Worked	-2.29	[1.08]	-33.0	-44.4	-11.4	-40.6
Change in Estab FE	-0.0056	[0.0018]	-0.036	-0.064	-0.028	-0.056
Annual Income (in Euro)	-583.9	[137.8]	-3791	-6710.5	-2919.5	-5740.5
Annual UI Receipt (in Euro)	40.3	[22.8]	751.1	952.6	201.5	885.9
Change in Log Estab. Size	-0.017	[0.017]	-0.69	-0.77	-0.080	-0.75

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

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage
Change in UR t-1 to t	**-0.030**	**-0.028**	**-0.014**	**-0.0095**	**-0.014**	**-0.0085**
	(0.0030)**	(0.0037)**	(0.0022)**	(0.0022)**	(0.0022)**	(0.0022)**
Establishment FE		-0.30			-0.020	0.079
		(0.030)**			(0.014)	(0.016)**
Worker effect		0.16			0.071	0.038
		(0.011)**			(0.010)**	(0.012)**
Change in Estab FE			0.77	1	0.74	1
			(0.017)**		(0.019)**	
Potential experience		-0.0085	-0.0088	-0.0084	-0.0081	-0.0080
		(0.00082)**	(0.00065)**	(0.00065)**	(0.00068)**	(0.00069)**
Experience squared		0.000085	0.00011	0.00011	0.000099	0.00010
		(0.000018)**	(0.000016)**	(0.000016)**	(0.000016)**	(0.000017)**
Pre-disp Tenure		-0.0044	-0.0048	-0.0047	-0.0048	-0.0050
		(0.00099)**	(0.00070)**	(0.00065)**	(0.00071)**	(0.00068)**
Tenure squared		0.00010	0.00012	0.00011	0.00011	0.00012
		(0.000030)**	(0.000022)**	(0.000022)**	(0.000023)**	(0.000023)**
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.077	-0.077		-0.077	-0.077	-0.077
R^2	0.016	0.10	0.33	0.034	0.34	0.039
N	80905	80905	80905	80905	80905	80905

Notes: The sample is men displaced between 1980 and 2005. The dependent variables is the wage loss 3 years post displacement. Regressions control for year and year squared. The change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Columns (5) and (6) 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: The Cyclicality of Log Wage Losses controlling for Individual characteristics

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage	
Change in UR t-1 to t	**-0.028**	**-0.022**	**-0.010**	**-0.013**	**-0.011**	**-0.014**	**-0.0098**
	(0.0037)**	(0.0032)**	(0.0021)**	(0.0022)**	(0.0021)**	(0.0022)**	(0.0020)**
Establishment FE	-0.30	-0.30	-0.030	-0.030	-0.036	-0.027	-0.049
	(0.030)**	(0.028)**	(0.013)*	(0.016)	(0.014)*	(0.013)	(0.015)**
Change in Estab FE			0.71	0.70	0.68	0.73	0.65
			(0.018)**	(0.016)**	(0.017)**	(0.018)**	(0.015)**
Worker FE	0.16	0.13	0.057	0.058	0.060	0.070	0.048
	(0.011)**	(0.0093)**	(0.0099)**	(0.011)**	(0.0097)**	(0.010)**	(0.010)**
Nonemp. Duration (post Disp)		-0.092	-0.052				-0.033
		(0.0078)**	(0.0041)**				(0.0035)**
Occ. change				-0.023			-0.00012
				(0.0033)**			(0.0030)
Ind. change				-0.029			-0.013
				(0.0025)**			(0.0024)**
Change in Industry Tenure					0.0042		0.0031
					(0.00021)**		(0.00021)**
Change in Occupation Tenure					0.0029		0.0022
					(0.00023)**		(0.00017)**
Parttime - Diff-Diff						-0.36	-0.34
						(0.039)**	(0.042)**
Pre-disp Tenure	-0.0044	-0.0050	-0.0052	-0.0049	-0.0033	-0.0048	-0.0039
	(0.00099)**	(0.00093)**	(0.00069)**	(0.00077)**	(0.00074)**	(0.00071)**	(0.00079)**
Tenure squared	0.00010	0.00013	0.00013	0.00011	0.00011	0.00011	0.00012
	(0.000030)**	(0.000028)**	(0.000022)**	(0.000027)**	(0.000026)**	(0.000022)**	(0.000028)**
Potential experience	-0.0085	-0.0088	-0.0083	-0.0086	-0.0080	-0.0081	-0.0084
	(0.00082)**	(0.00075)**	(0.00065)**	(0.00068)**	(0.00067)**	(0.00067)**	(0.00071)**
Experience squared	0.000085	0.00010	0.00011	0.00010	0.00011	0.000098	0.00011
	(0.000018)**	(0.000017)**	(0.000015)**	(0.000016)**	(0.000016)**	(0.000016)**	(0.000017)**
Mean of dep. var	-0.077	-0.077	-0.077	-0.077	-0.077	-0.077	-0.077
R^2	0.10	0.14	0.35	0.34	0.36	0.35	0.37
N	80905	80905	80905	68213	80905	80905	68213

Regressions Control for year and year squared. Columns (2) - (7) also control for tenure dummies
Change UR are measured in percentage points

Table 5: The Cyclicality of Log Wage Losses with and without controlling for establishment effects - High vs. Low Worker FE Sample

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage
Panel A: High Worker FE (above median)						
Change in UR t-1 to t	**-0.017**	**-0.016**	**-0.0073**	**-0.00011**	**-0.0071**	**0.000056**
	(0.0025)**	(0.0027)**	(0.0023)**	(0.0031)	(0.0023)**	(0.0030)
Establishment FE		-0.18			-0.0051	0.13
		(0.025)**			(0.017)	(0.023)**
Worker effect		0.088			0.030	-0.016
		(0.015)**			(0.013)*	(0.015)
Change in Estab FE			0.57		0.57	
			(0.016)**		(0.015)**	
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.028	-0.028		-0.028	-0.028	-0.028
R^2	0.076	0.095	0.25	0.060	0.25	0.065
N	33141	33141	33141	33141	33141	33141
Panel B: Low Worker FE (below median)						
Change in UR t-1 to t	**-0.036**	**-0.037**	**-0.018**	**-0.015**	**-0.018**	**-0.015**
	(0.0047)**	(0.0045)**	(0.0024)**	(0.0022)**	(0.0023)**	(0.0023)**
Establishment FE		-0.43			-0.031	0.047
		(0.034)**			(0.015)*	(0.013)**
Worker effect		0.27			0.13	0.10
		(0.018)**			(0.014)**	(0.015)**
Change in Estab FE			0.85		0.84	
			(0.017)**		(0.018)**	
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.11	-0.11		-0.11	-0.11	-0.11
R^2	0.040	0.079	0.37	0.024	0.38	0.027
N	47764	47764	47764	47764	47764	47764

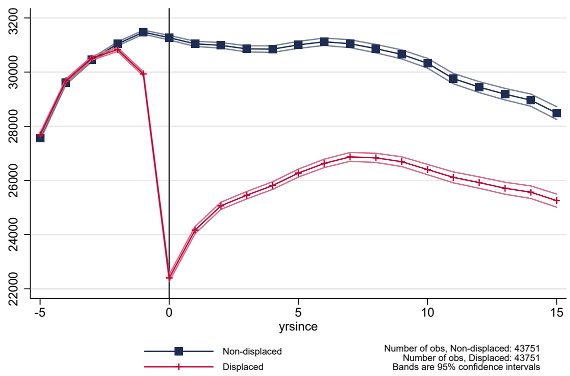
Notes: Regressions control for year. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Columns (5) and (6) regresses the log wage loss on the unemployment rate (change in UR) controlling for the change in the establishment effect, where the coefficient on the establishment effect is forced to be equal to 1.

Table 6: Robustness Checks

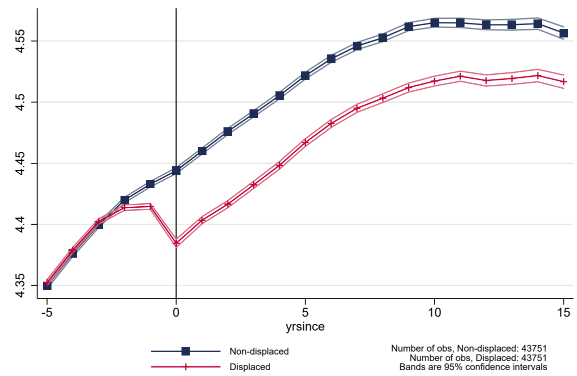
	(1) Baseline West-Ger. Men	(2) Rolling Window AKM Model West Men	(3) Split Sample IV West Men	(4) Rolling Window & Split Sample IV West Men	(5) Kmeans Clustering West Men	(6) Random Control Group West Men	(7) 10 year Horizon West Men	(8) Women West-Germany	(9) Men, Pooling West & East Germany
Panel A: Raw correlation (controlling for year and year squared only)									
Change in UR t-1 to t	**-0.030**	**-0.030**	**-0.030**	**-0.027**	**-0.030**	**-0.032**	**-0.023**	**-0.039**	**-0.030**
	(0.0030)**	(0.0030)**	(0.0030)**	(0.0029)**	(0.0030)**	(0.0032)**	(0.0025)**	(0.0058)**	(0.0030)**
Observations	80905	80905	79968	65207	80905	86423	61219	24702	99442
R^2	0.016	0.016	0.016	0.016	0.016	0.015	0.011	0.008	0.014
Panel B: Controlling for composition effects (incl. expericence and tenure polynomial)									
Change in UR t-1 to t	**-0.028**	**-0.027**	**-0.028**	**-0.022**	**-0.027**	**-0.029**	**-0.019**	**-0.038**	**-0.027**
	(0.0037)**	(0.0036)**	(0.0036)**	(0.0031)**	(0.0037)**	(0.0037)**	(0.0036)**	(0.0061)**	(0.0038)**
Establishment FE	-0.30	-0.35	-0.31	-0.44	-0.38	-0.30	-0.39	-0.17	-0.23
	(0.030)**	(0.022)**	(0.032)**	(0.018)**	(0.027)**	(0.033)**	(0.028)**	(0.048)**	(0.019)**
Worker effect	0.16	0.17	0.16	0.17	0.18	0.17	0.18	0.22	0.18
	(0.011)**	(0.011)**	(0.011)**	(0.011)**	(0.011)**	(0.013)**	(0.011)**	(0.014)**	(0.0099)**
Observations	80905	80897	79968	65207	80905	86423	61219	24702	99442
R^2	0.103	0.108	0.104	0.122	0.110	0.114	0.116	0.057	0.098
Panel C: Controlling for change in estab FE and composition effects									
Change in UR t-1 to t	**-0.014**	**-0.016**	**-0.013**	**-0.014**	**-0.016**	**-0.014**	**-0.0100**	**-0.024**	**-0.013**
	(0.0022)**	(0.0025)**	(0.0023)**	(0.0026)**	(0.0025)**	(0.0022)**	(0.0028)**	(0.0047)**	(0.0027)**
Worker effect	0.071	0.11	0.066	0.097	0.096	0.076	0.088	0.13	0.070
	(0.010)**	(0.0079)**	(0.010)**	(0.0081)**	(0.0083)**	(0.011)**	(0.012)**	(0.015)**	(0.010)**
Establishment FE	-0.020	-0.025	-0.018	0.018	0.077	-0.021	0.020	0.077	-0.012
	(0.014)	(0.016)	(0.014)	(0.016)	(0.026)**	(0.018)	(0.017)	(0.030)*	(0.0082)
Change in Estab FE	0.74	0.70	0.78	0.90	0.85	0.75	0.82	0.68	0.75
	(0.019)**	(0.021)**	(0.018)**	(0.020)**	(0.020)**	(0.019)**	(0.021)**	(0.023)**	(0.016)**
Observations	80905	68470	79968	65207	68726	86423	61219	24702	99442
R^2	0.340	0.300	0.297	0.230	0.298	0.357	0.373	0.165	0.359

Notes: Each column in each panel represents a separate regression of the log wage loss of job losers (based on the individual diff-in-diff estimate) change in the national unemployment rate. All regressions control for year and year squared. Panel (A) does not include other controls, Panel (B) controls for the worker effect and the pre-displacement establishment effect as well as tenure and experience polynomials. Panel (C) is the same as Panel (B) but adds the (diff-in-diff) change in the establishment effect. Column 2, uses establishment effects that are estimated using an AKM model that only uses observations within 5 years prior to the displacement event. Column 3, Panel (B) and (C) uses a split sample IV estimator to instrument for the establishment FE and the change in the establishment FE. Column 4, combines the split sample IV with the rolling AKM window. Column 5 uses the hybrid kmeans clustering approach described in the text.

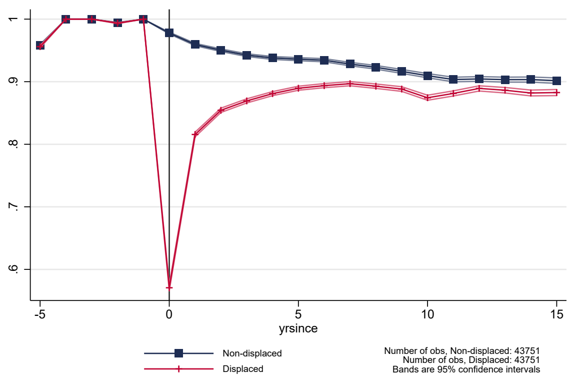
Figure 1: Labor Market Outcomes of Displaced Workers before and after Job Loss - Comparing Raw Means of Displaced Workers and Control Group



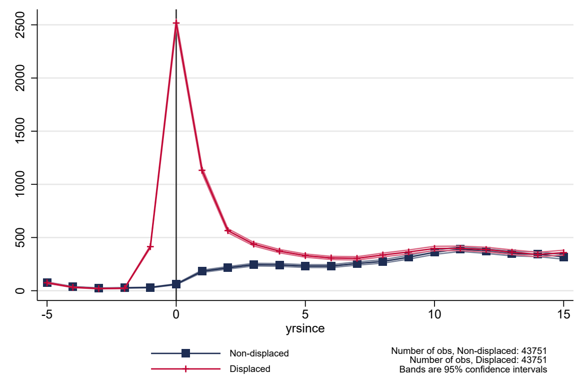
(a) Total Earnings in Year



(b) Log Wage



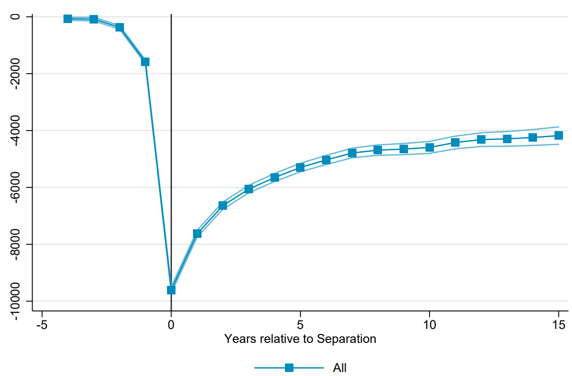
(c) Employed on June 30th of Year



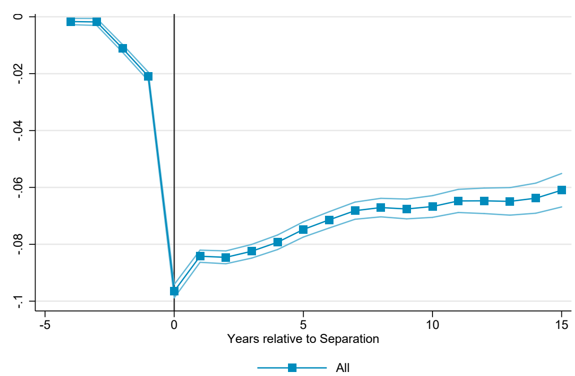
(d) Income from Unemployment Insurance Benefits

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.

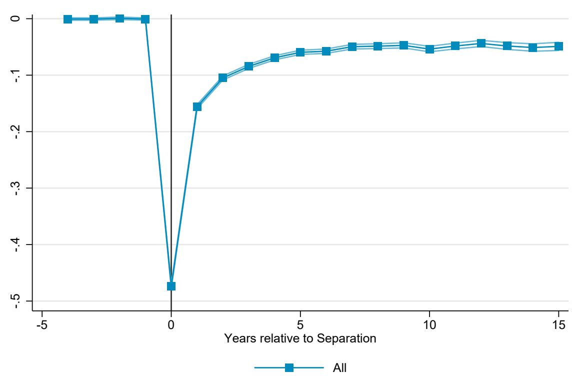
Figure 2: Labor Market Outcomes of Displaced Workers before and after Job Loss - Eventstudy Regression Estimates



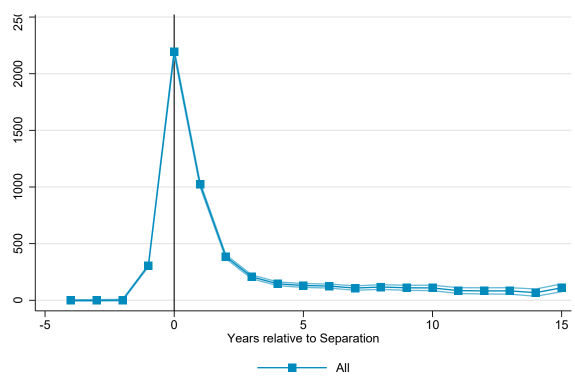
(a) Total Earnings in Year



(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

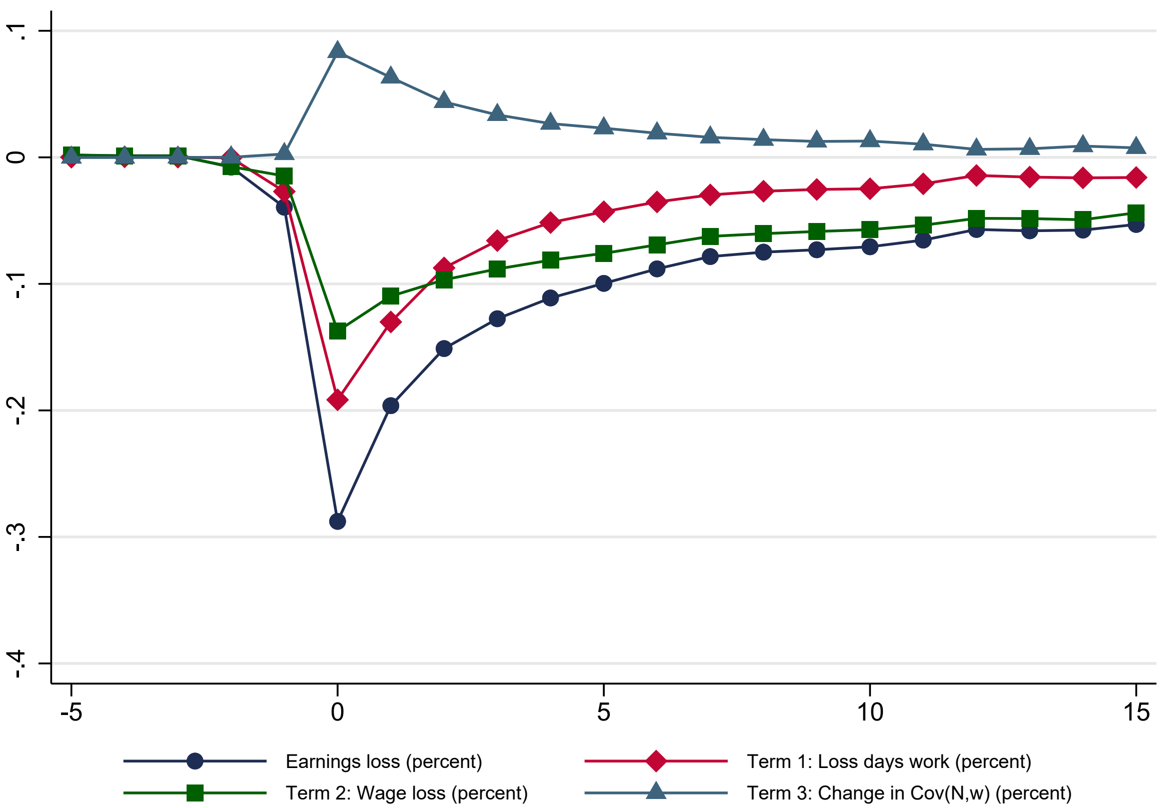
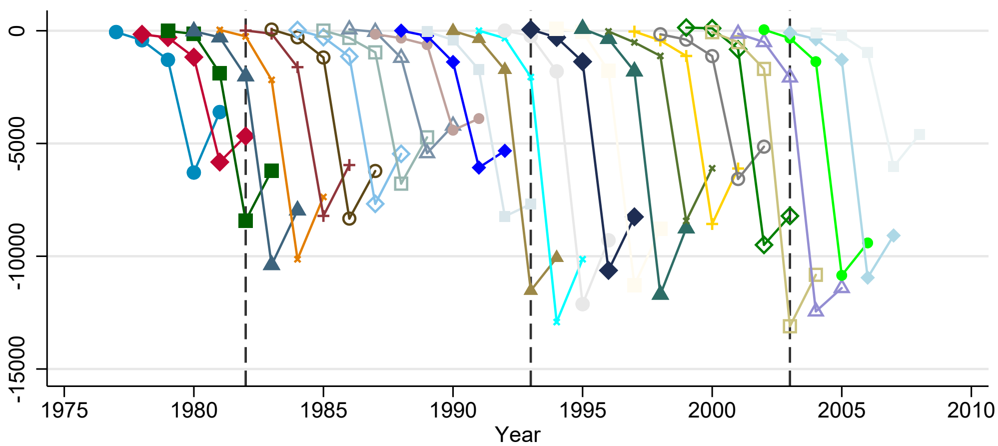
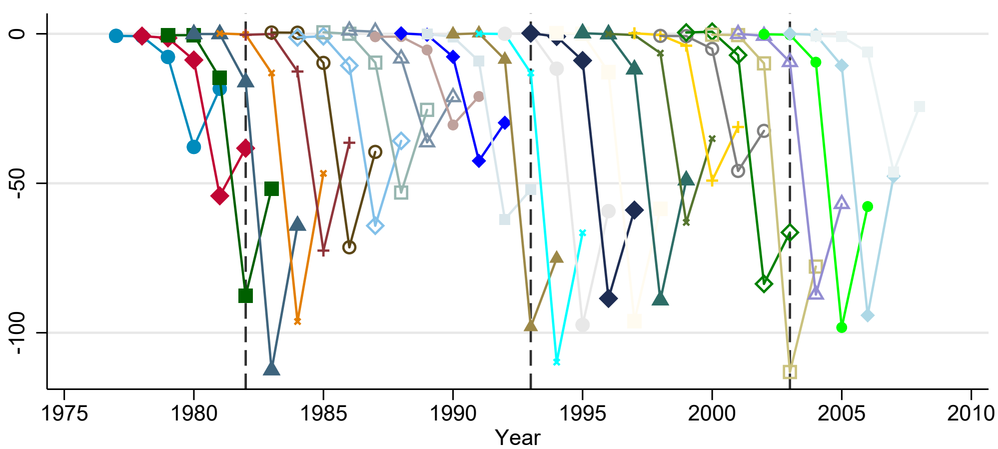


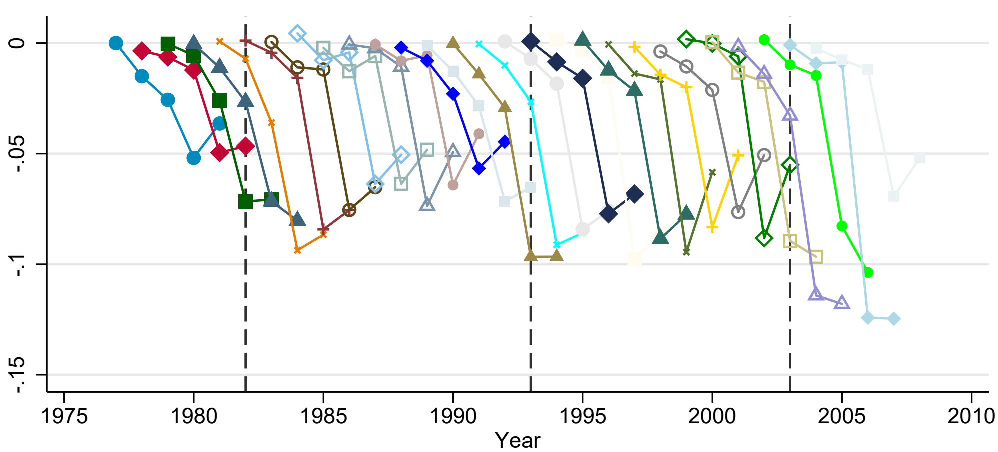
Figure 4: Labor Market Outcomes of Displaced Workers by Year of Job Loss



(a) Earnings Losses by Year

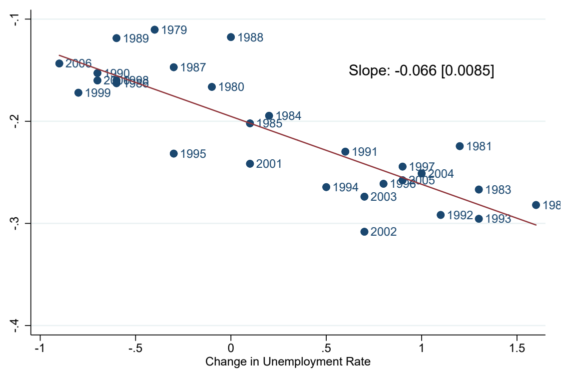


(b) Days Worked Losses by Year

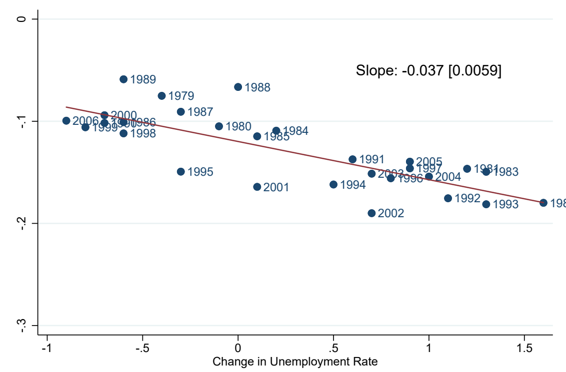


(c) Wage Losses by Year

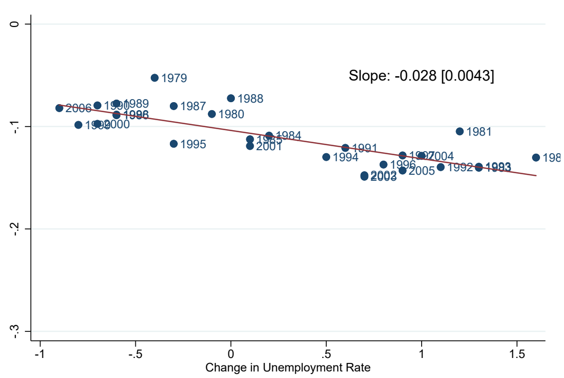
Figure 5: Decomposition of 3 Year Earnings Loss into Wage and Employment Losses, by State of Labor Market



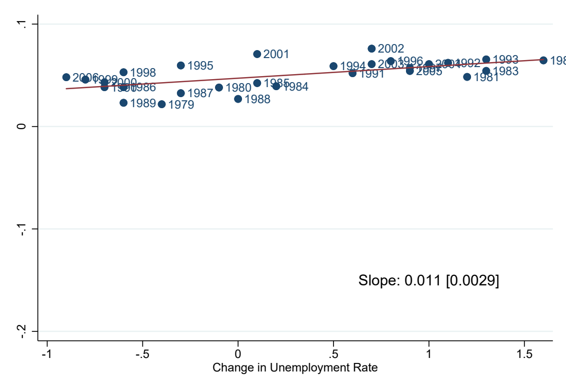
(a) Earnings loss



(b) Earnings loss due to days work

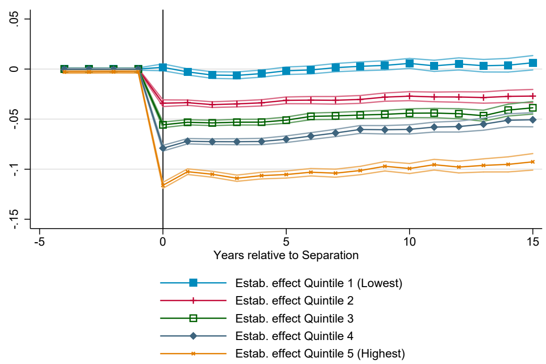


(c) Earnings loss due to wage loss

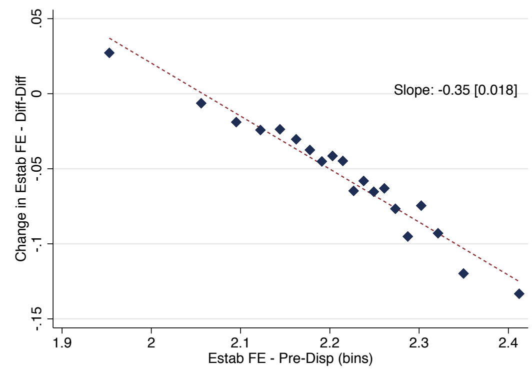


(d) Earnings loss due to change in covariance

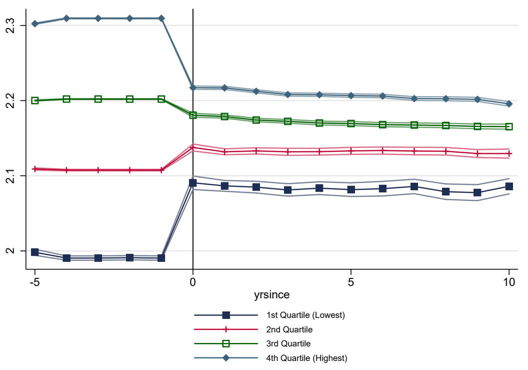
Figure 6: The Relationship between Estab FE Losses and Wage Losses - Alternative: Quintiles



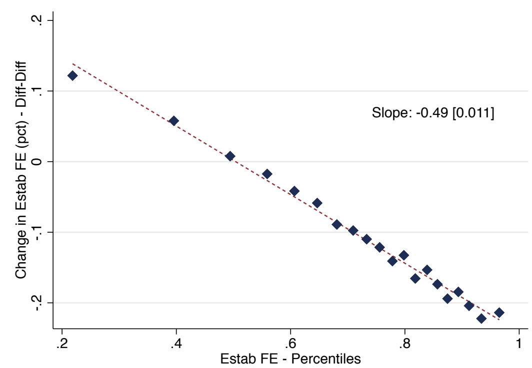
(a) Loss of Estab FE by Quartile of Displacing Estab FE - Quartiles based on analysis Smpl



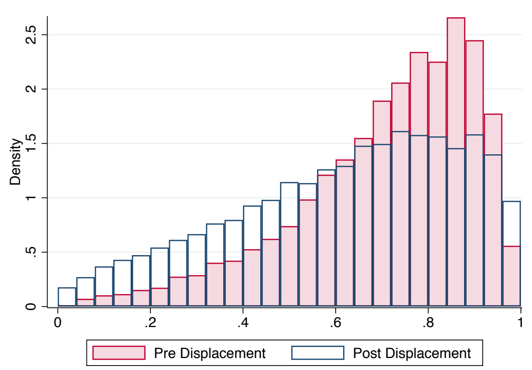
(b) Loss of Estab FE by Pre-Disp Estab FE



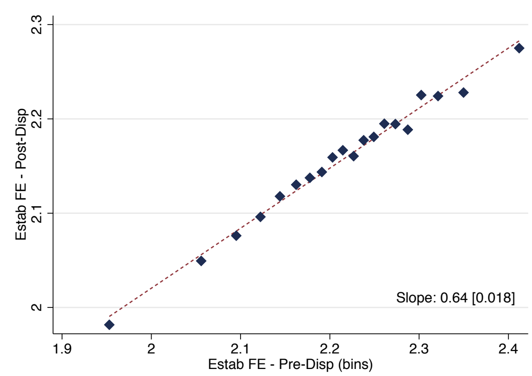
(c) Loss of Estab FE by Quartiles of Pre-Disp Estab FE



(d) Change in Estab FE pctile by Pre-Disp Estab FE pctile

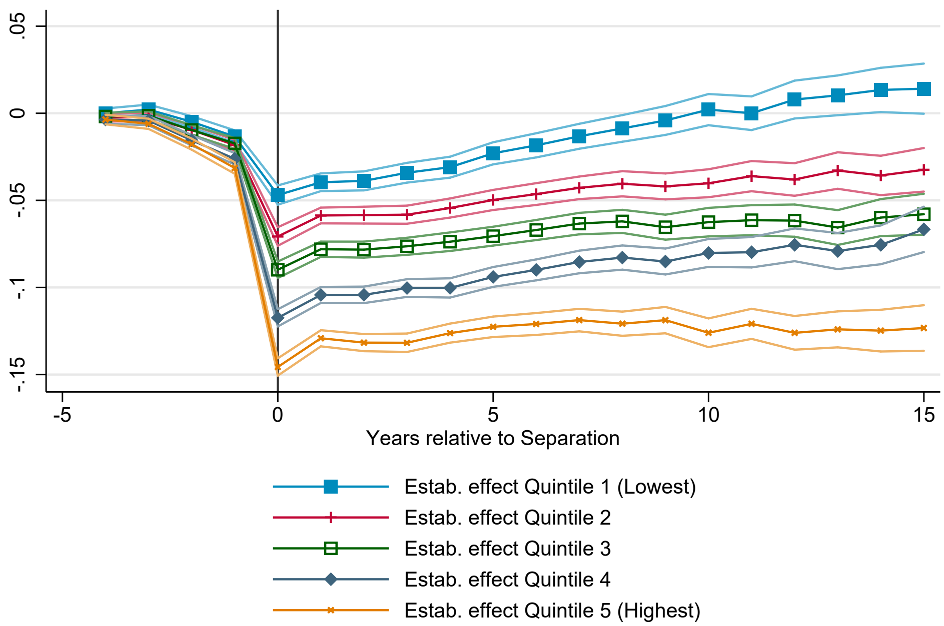


(e) Histogram of Estab FE pctile pre and post disp.

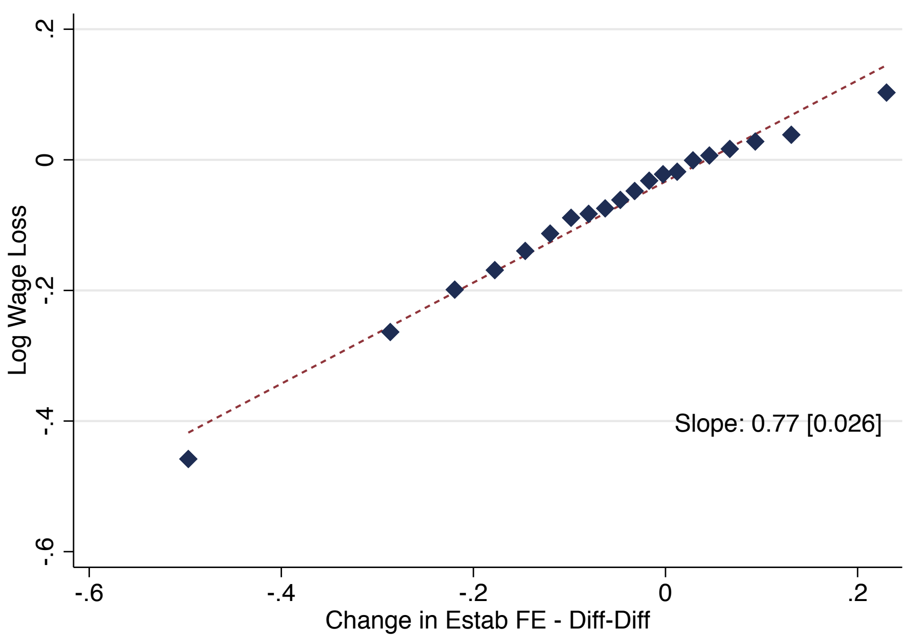


(f) Post-Disp. Estab FE by Pre-Disp Estab FE

Figure 7: The Relationship between Estab FE Losses and Wage Losses

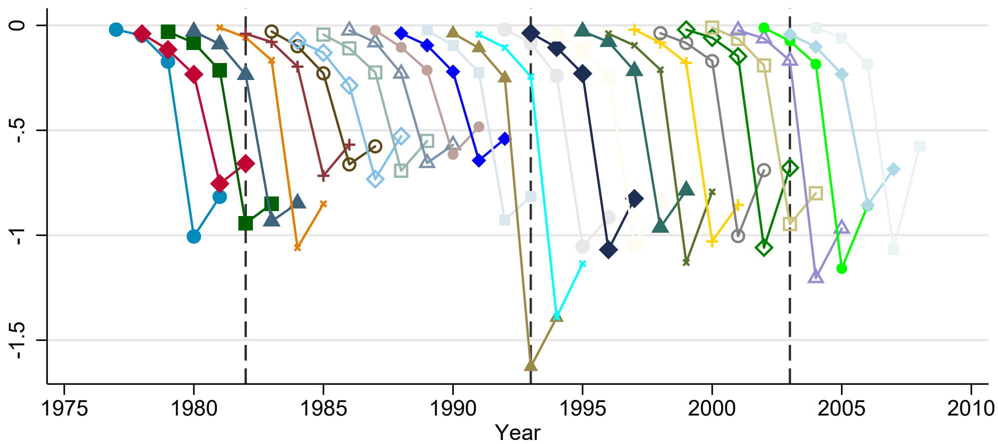


(a) Wage Loss by Quartile Displacing Estab FE - Quartiles based on analysis Smpl

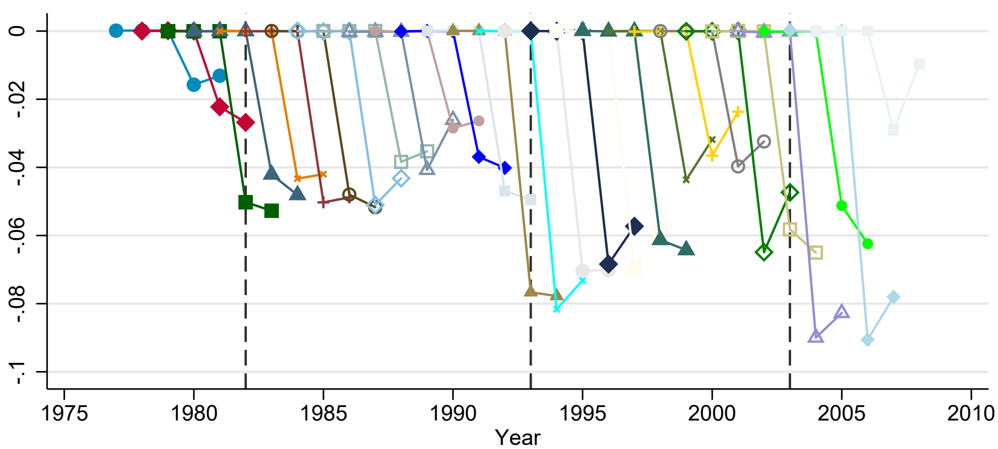


(b) Wage Loss by Estab FE Loss

Figure 8: Employer Characteristics (Number of Employees and Establishment Effect of Displaced Workers by Year of Job Loss

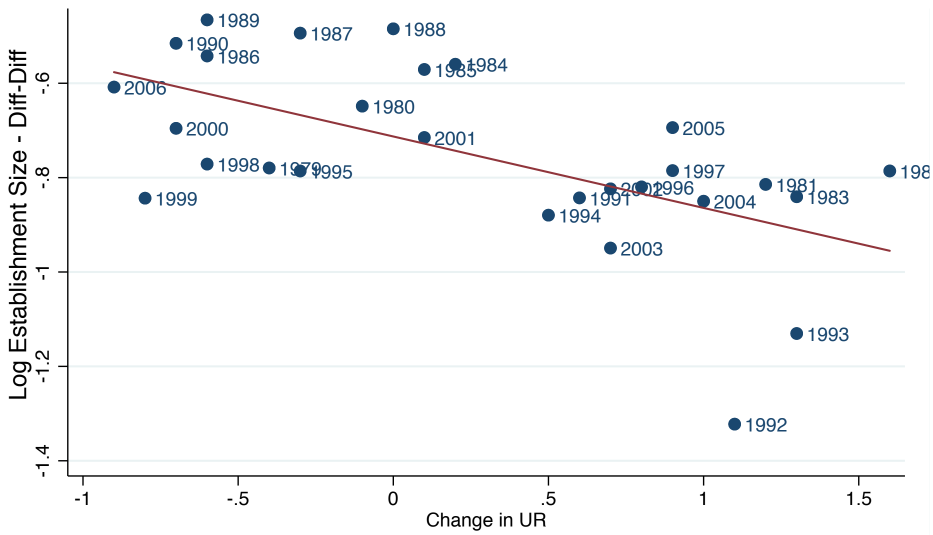


(a) Log Number of Employees at Establishment

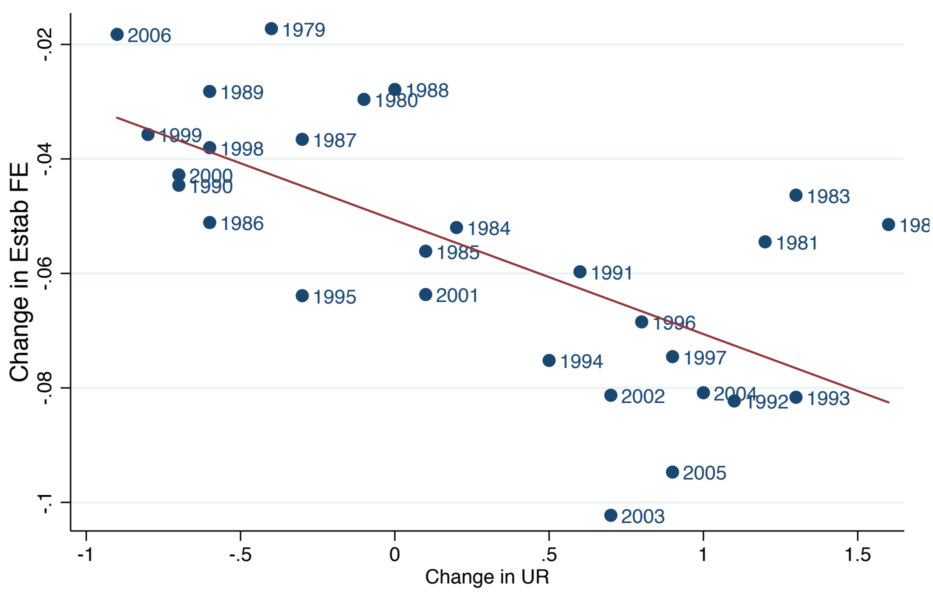


(b) Establishment Effect

Figure 9: 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



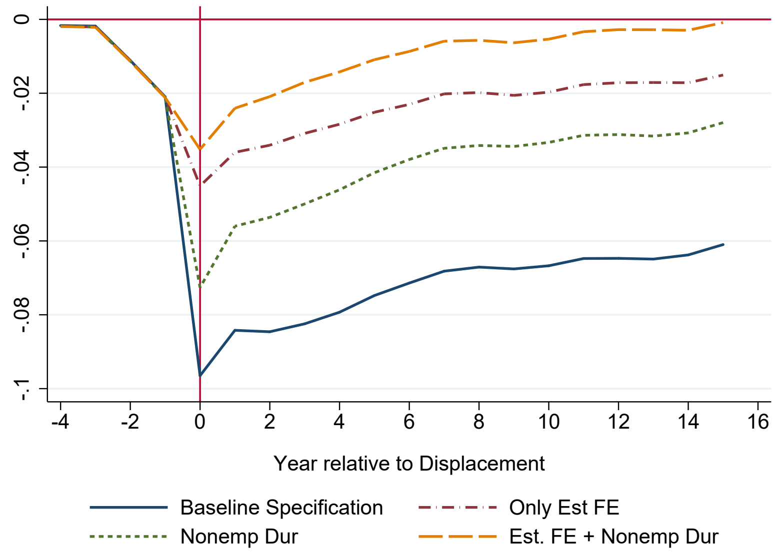
(a) Log Number of Employees at Establishment



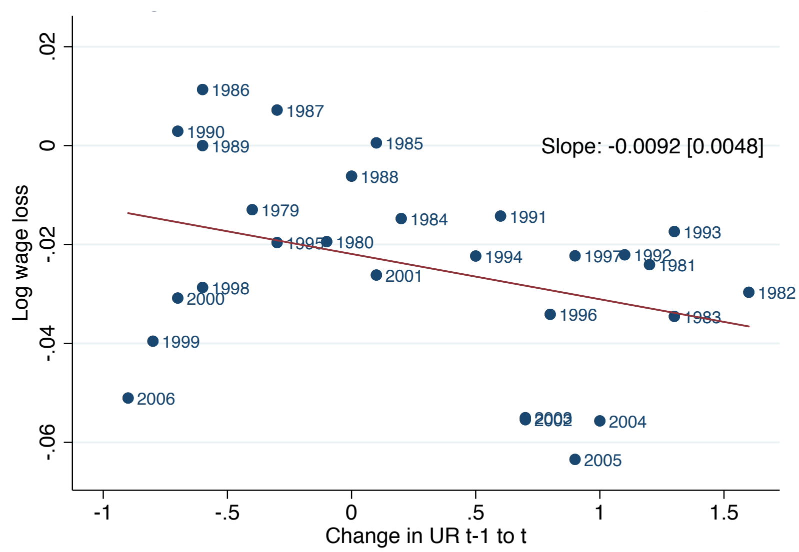
(b) Establishment FE

Notes: The figure shows scatterplots of the earnings and wage losses of job losers collapsed to the year level relative to the year over year change in the unemployment rate. The top figure shows the change in log establishment employment, where the slope of the regression line is -0.15 [SE: 0.040]. The bottom figure shows the change in the establishment FE, where the slope of the regression line is -0.020 [SE: 0.0044].

Figure 10: Effect of Job Loss on Log Daily Wages 3 Years After Displacement With Controls for Employer Characteristics



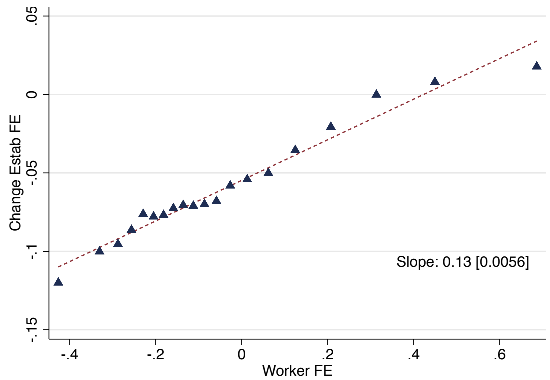
(a) Average Over All Displacement Years



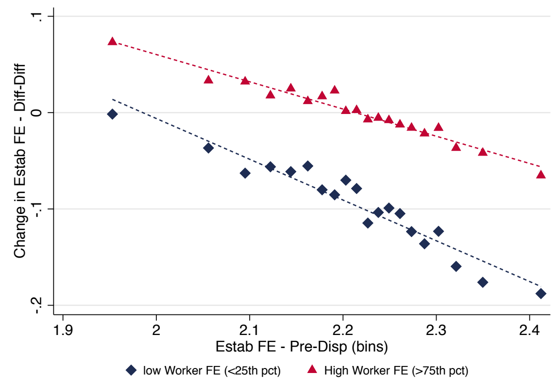
(b) By Year of Job Loss vis-a-vis Rate of Unemployment

Notes: The top figure shows eventstudy regressions of the effects of job loss on log wages pooling all years and controlling for year effects and individual effects (baseline specification) and additional controls. The bottom figure shows the estimated year effects from a regression of the log wage loss on year dummies, the worker FE, the pre-displacement establishment FE, the change in the establishment FE (pre-post job loss) and the nonemployment duration.

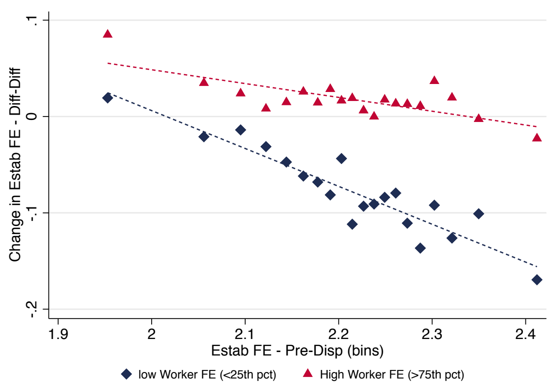
Figure 11: The Role of Jobloss in Reallocating Low Skill Workers to Low Estab FE Firms



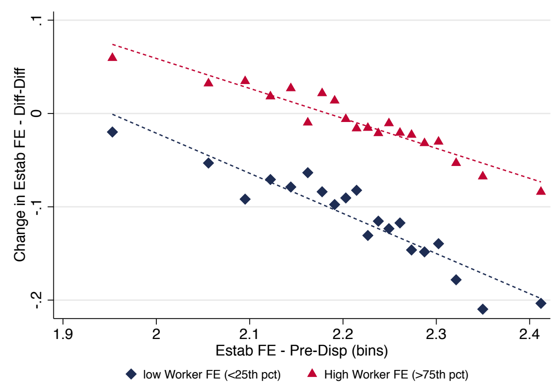
(a) Changes in Estab FE by Worker FE



(b) Changes in Estab FE by Pre-Disp Estab FE



(c) Changes in Estab FE by Pre-Disp Estab FE, Change UR<-0.5 (Expansions)



(d) Changes in Estab FE by Pre-Disp Estab FE, Change UR>0.5 (Recessions)

Table A-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	0.1	0.2	0.1	0.1
	[0.3]	[0.4]	[0.3]	[0.3]
Real wage	93.0	92.3	91.0	91.6
	[25.9]	[26.7]	[25.4]	[26.0]
Parttime	0	0	0	0
	[0]	[0]	[0]	[0]
Female	0	0	0	0
	[0]	[0]	[0]	[0]
West Germany	1	1	1	1
	[0]	[0]	[0]	[0]
Years of education	11.0	11.1	10.8	10.9
	[2.3]	[2.4]	[2.1]	[2.2]
Potential experience	21.2	20.8	21.7	21.3
	[7.4]	[7.4]	[7.3]	[7.4]
Tenure with current Employer	9.6	9.2	9.8	9.5
	[5.1]	[5.1]	[5.3]	[5.2]
Actual experience, but censored 1975	13.1	12.8	13.3	13.1
	[6.0]	[6.0]	[6.2]	[6.1]
Total yearly earnings	33823.4	32604.1	32154.7	32354.1
	[9573.2]	[10298.1]	[9811.6]	[10032.9]
Total yearly income	33848.0	32885.2	32518.7	32681.3
	[9548.0]	[10058.4]	[9543.4]	[9776.9]
Days per year working fulltime	363.6	352.2	352.7	352.5
	[17.8]	[37.1]	[35.8]	[36.4]
Wage on June 30th of year	93.0	92.3	91.0	91.6
	[25.9]	[26.7]	[25.4]	[26.0]
Log of wage in June	4.5	4.5	4.5	4.5
	[0.3]	[0.3]	[0.3]	[0.3]
Panel b: Establishment Characteristics				
Number of employees	435.3	477.2	416.3	443.3
	[760.6]	[791.5]	[768.3]	[779.3]
Share of fulltime employees	0.9	1.0	1.0	1.0
	[0.09]	[0.08]	[0.08]	[0.08]
Establishment FE	2.2	2.2	2.2	2.2
	[0.1]	[0.1]	[0.1]	[0.1]
Avg. years of education in estab.	10.8	10.9	10.7	10.8
	[1.0]	[1.1]	[0.9]	[1.0]
Number of Spells	95478	42375	53103	95478

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 A-2: 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 C: Industry (percent)				
C Manufacturing	62.9	61.8	63.8	62.9
	[48.3]	[48.6]	[48.0]	[48.3]
D Energy supply	0.9	0.9	0.9	0.9
	[9.4]	[9.3]	[9.4]	[9.4]
E Water supply and other utilities	0.5	0.5	0.4	0.5
	[6.7]	[7.3]	[6.3]	[6.7]
F Construction	12.8	10.8	14.5	12.8
	[33.5]	[31.0]	[35.2]	[33.5]
G Wholesale and retail trade, Vehicle repair	10.0	10.1	9.8	10.0
	[29.9]	[30.2]	[29.8]	[29.9]
H Transport and storage	3.2	4.4	2.3	3.2
	[17.7]	[20.5]	[15.1]	[17.7]
I Hotels and restaurants	0.09	0.08	0.10	0.09
	[3.0]	[2.7]	[3.2]	[3.0]
J Information and communication	2.4	2.9	2.1	2.4
	[15.4]	[16.7]	[14.3]	[15.4]
K Financial and insurance services	1.9	1.7	2.0	1.9
	[13.6]	[12.9]	[14.2]	[13.6]
L Real estate, renting and business activities	0.06	0.07	0.05	0.06
	[2.5]	[2.7]	[2.3]	[2.5]
M Personal, technical and scientific services	2.1	2.7	1.7	2.1
	[14.4]	[16.2]	[12.8]	[14.4]
N Other business services	1.1	1.2	1.0	1.1
	[10.3]	[10.8]	[10.0]	[10.3]
P Education	0.05	0.07	0.03	0.05
	[2.2]	[2.7]	[1.7]	[2.2]
Q Health and social work	0.5	0.6	0.4	0.5
	[7.0]	[7.6]	[6.5]	[7.0]
R Arts and recreation	0.002	0.005	0	0.002
	[0.5]	[0.7]	[0]	[0.5]
S Other services	1.4	2.3	0.8	1.4
	[11.9]	[14.9]	[8.9]	[11.9]
Number of Spells	95478	42375	53103	95478

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 A-3: The Correlation of Explanatory Variables with the Business Cycle

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 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% Change UR	Mean of dependent variable
	Coefficient	Std. Err.	$\Delta UR = -1\%$	$\Delta UR = +1\%$		
Outcome:						
Nonemp. Duration (Years)	0.12	[0.016]	0.19	0.43	0.24	0.35
Occupation change	0.037	[0.0096]	0.23	0.31	0.080	0.28
Industry change	0.072	[0.025]	0.44	0.58	0.14	0.53
Change in Establishment FE	-0.020	[0.0047]	-0.031	-0.071	-0.040	-0.056
Estab FE	-0.0012	[0.0046]	2.23	2.23	0	2.23
Worker FE	-0.021	[0.0093]	-0.0070	-0.049	-0.042	-0.033
Panel B: 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	Mean of dependent variable
	Coefficient	Std. Err.	UR=4%	UR=9%		
Outcome:						
Nonemp. Duration (Years)	0.015	[0.0088]	0.29	0.36	0.070	0.35
Occupation change	-0.010	[0.0042]	0.31	0.26	-0.050	0.28
Industry change	-0.026	[0.0069]	0.62	0.49	-0.13	0.53
Change in Establishment FE	-0.0056	[0.0019]	-0.036	-0.064	-0.028	-0.056
Estab FE	-0.0042	[0.0016]	2.24	2.22	-0.020	2.23
Worker FE	-0.014	[0.0031]	0.013	-0.057	-0.070	-0.033

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 year over year change in the national unemployment rate (Panel A). and the level of the national unemployment rate (Panel B). The model is estimated on the yearly level.

Table A-4: Decomposing the Variance of Log Daily Wages into AKM Components (West German Fulltime Men)

	(1) Long AKM 1980	(2) Rolling AKM 1980	(3) Kmeans 1980	(4) Long AKM 2009	(5) Rolling AKM 2009	(6) Kmeans 2009
Panel A: Mean of Log Wages						
Log wage	4.3053	4.3323	4.3248	4.3955	4.4168	4.4001
Panel B: AKM Decomposition						
Var of Log Wage	0.1345	0.1138	0.1204	0.2736	0.2613	0.2711
Var[Estab. FE]	0.02685	0.02227	0.01370	0.07373	0.05560	0.04288
Var[Worker FE]	0.1051	0.08745	0.07845	0.09009	0.1524	0.1373
Cov[Worker FE; Estab FE]	-0.007350	-0.01303	0.009515	0.04357	0.03498	0.07021
SD of Estab. FE	0.1639	0.1492	0.1170	0.2715	0.2358	0.2071
SD of Worker effect	0.3241	0.2957	0.2801	0.3001	0.3903	0.3705
Number of Establishments	768,541	619,450	796,804	1,017,976	749,850	1,041,313
Number of Workers	11,262,108	10,556,274	10,805,596	11,271,573	10,661,523	11,156,323
Number of Clusters			39,233			47,719

Notes: The decomposition in columns (1) and (4) is based on the pooled AKM model pooling all years from 1979 to 2009. The decomposition in columns (2) and (5) is based on the rolling AKM model that uses only observations from the previous 6 years (up to and including the year in the column heading). Columns (3) and (6) use a hybrid kmeans clustering approach also using the 6 years up to the year in the column heading, where we allow for an establishment fixed effect for establishments with at least 50 employees (in any of the previous 6 years) but classify all establishments with less than 50 employees into 20 clusters using the Bonhomme, Lamadon and Manresa (2019) kmeans-clustering approach. The number of clusters in the last line is then the number of establishments with at least 50 employees plus the 20 clusters. Other wage components, like the role of experience and the respective covariance terms are included in the AKM model but not shown in the table.

Table A-5: The Cyclicality of Log Wage Losses with and without controlling for establishment effects - Alternative Year Controls

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage
Panel A: Linear Year Control						
Change in UR t-1 to t	-0.030	-0.028	-0.014	-0.0093	-0.013	-0.0082
	(0.0011)**	(0.0011)**	(0.00092)**	(0.00093)**	(0.00092)**	(0.00093)**
Establishment FE		-0.31			-0.021	0.075
		(0.0078)**			(0.0069)**	(0.0068)**
Worker effect		0.17			0.071	0.040
		(0.0029)**			(0.0026)**	(0.0026)**
Change in Estab FE			0.78		0.75	
			(0.0042)**		(0.0044)**	
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.077	-0.077		-0.077	-0.077	-0.077
R^2	0.016	0.070	0.31	0.0042	0.32	0.0087
N	80905	80905	80905	80905	80905	80905
Panel B: Cubic Year Controls						
Change in UR t-1 to t	-0.031	-0.028	-0.014	-0.0093	-0.013	-0.0082
	(0.0011)**	(0.0011)**	(0.00092)**	(0.00093)**	(0.00092)**	(0.00093)**
Establishment FE		-0.31			-0.026	0.069
		(0.0078)**			(0.0069)**	(0.0068)**
Worker effect		0.17			0.072	0.040
		(0.0029)**			(0.0026)**	(0.0026)**
Change in Estab FE			0.78		0.75	
			(0.0042)**		(0.0044)**	
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.077	-0.077		-0.077	-0.077	-0.077
R^2	0.016	0.071	0.31	0.0062	0.32	0.011
N	80905	80905	80905	80905	80905	80905

Notes: Regressions control for year. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Columns (5) and (6) 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 A-6: The Cyclicality of Log Wage Losses with and without controlling for establishment effects - Level of Unemployment Rate

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage
Panel A: Unemployment Rate - Quadratic Year Controls						
Unemployment rate	-0.0073	-0.0050	-0.0038	-0.0028	-0.0035	-0.0031
	(0.00083)**	(0.00080)**	(0.00069)**	(0.00070)**	(0.00069)**	(0.00070)**
Establishment FE		-0.30			-0.019	0.072
		(0.0078)**			(0.0069)**	(0.0068)**
Worker effect		0.17			0.073	0.041
		(0.0029)**			(0.0026)**	(0.0026)**
Change in Estab FE			0.78		0.76	
			(0.0042)**		(0.0044)**	
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.077	-0.077		-0.077	-0.077	-0.077
R^2	0.0077	0.063	0.31	0.0050	0.32	0.0097
N	80905	80905	80905	80905	80905	80905
Panel B: Unemployment Rate - Cubic Year Controls						
Unemployment rate	-0.0091	-0.0069	-0.0052	-0.0042	-0.0049	-0.0043
	(0.00088)**	(0.00086)**	(0.00074)**	(0.00075)**	(0.00074)**	(0.00075)**
Establishment FE		-0.30			-0.020	0.072
		(0.0078)**			(0.0069)**	(0.0068)**
Worker effect		0.17			0.073	0.041
		(0.0029)**			(0.0026)**	(0.0026)**
Change in Estab FE			0.78		0.76	
			(0.0042)**		(0.0044)**	
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.077	-0.077		-0.077	-0.077	-0.077
R^2	0.0081	0.063	0.31	0.0053	0.32	0.0100
N	80905	80905	80905	80905	80905	80905

Notes: Regressions control for year. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Columns (5) and (6) 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 A-7: 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	(6) log wage
Panel A: Change in Unemployment Rate - 10 Year Horizon						
Change in UR t-1 to t	-0.023	-0.018	-0.0100	-0.0079	-0.0083	-0.0064
	(0.0014)**	(0.0014)**	(0.0012)**	(0.0012)**	(0.0012)**	(0.0012)**
Establishment FE		-0.41			0.0072	0.091
		(0.011)**			(0.0093)	(0.0090)**
Worker effect		0.18			0.087	0.069
		(0.0037)**			(0.0032)**	(0.0031)**
Change in Estab FE			0.86		0.83	
			(0.0050)**		(0.0053)**	
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.066	-0.066		-0.066	-0.066	-0.066
R^2	0.011	0.072	0.33	0.0041	0.34	0.013
N	61219	61219	61219	61219	61219	61219
Panel B: Level of Unemployment Rate - 10 Year Horizon						
Unemployment rate	-0.0027	0.00059	-0.000032	0.00040	0.00042	0.00039
	(0.0011)*	(0.0010)	(0.00087)	(0.00088)	(0.00087)	(0.00087)
Establishment FE		-0.41			0.0074	0.091
		(0.011)**			(0.0093)	(0.0090)**
Worker effect		0.18			0.089	0.070
		(0.0037)**			(0.0031)**	(0.0031)**
Change in Estab FE			0.86		0.83	
			(0.0050)**		(0.0053)**	
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.066	-0.066		-0.066	-0.066	-0.066
R^2	0.0065	0.069	0.33	0.0034	0.34	0.013
N	61219	61219	61219	61219	61219	61219

Notes: Regressions control for year. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Columns (5) and (6) 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 A-8: Effect of Unemployment Rate on Outcomes for Job Losers over 3 years after Job Displacement

	(1) Baseline West-Germany Men	(2) Control for Occupation and Industry	(3) Control for Occupation and Industry Tenure	(4) Control for MLF and PCL	(5) Control for Parttime after Jobloss	(6) Control for Change in Estab. Size	(7) Control for Change in Estab. Turnover and Sep. rate	(8) All Controls Simultaneously
Panel A: Raw correlation (controlling for year and year squared only)								
Change in UR t-1 to t	**-0.030**	**-0.030**	**-0.030**	**-0.030**	**-0.030**	**-0.030**	**-0.030**	**-0.030**
	(0.0030)**	(0.0030)**	(0.0030)**	(0.0030)**	(0.0030)**	(0.0030)**	(0.0030)**	(0.0030)**
R^2	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016
Panel B: Controlling for composition effects (incl. expericence, tenure polynomial and variables in column heading)								
Change in UR t-1 to t	**-0.028**	**-0.027**	**-0.028**	**-0.028**	**-0.029**	**-0.028**	**-0.027**	**-0.024**
	(0.0037)**	(0.0034)**	(0.0037)**	(0.0035)**	(0.0037)**	(0.0036)**	(0.0035)**	(0.0030)**
Establishment FE	-0.30	-0.35	-0.30	-0.30	-0.31	-0.30	-0.27	-0.33
	(0.030)**	(0.031)**	(0.031)**	(0.029)**	(0.030)**	(0.030)**	(0.030)**	(0.027)**
Worker effect	0.16	0.16	0.17	0.17	0.16	0.17	0.15	0.15
	(0.011)**	(0.013)**	(0.011)**	(0.011)**	(0.011)**	(0.011)**	(0.0096)**	(0.012)**
Pre-disp. occupation tenure			-0.0015					-0.0017
			(0.00044)**					(0.00033)**
Pre-disp. industry tenure			-0.00036					-0.00071
			(0.00037)					(0.00033)*
Plant closing				0.020				0.016
				(0.0027)**				(0.0027)**
Parttime - Diff-Diff					-0.41			-0.40
					(0.049)**			(0.047)**
Establishment Size - Diff-Diff						0.0000052		0.0000040
						(0.00000058)**		(0.00000038)**
Turnover rate - Diff-Diff							-0.15	-0.15
							(0.017)**	(0.017)**
Separation rate - Diff-Diff							0.0036	0.0068
							(0.020)	(0.021)
R^2	0.103	0.109	0.103	0.104	0.121	0.106	0.133	0.162
Panel C: Controlling for change in estab FE and composition effects								
Change in UR t-1 to t	**-0.014**	**-0.014**	**-0.014**	**-0.013**	**-0.014**	**-0.014**	**-0.014**	**-0.014**
	(0.0022)**	(0.0023)**	(0.0023)**	(0.0022)**	(0.0022)**	(0.0023)**	(0.0022)**	(0.0023)**
Worker effect	0.071	0.083	0.075	0.072	0.070	0.070	0.071	0.086
	(0.010)**	(0.012)**	(0.010)**	(0.010)**	(0.010)**	(0.010)**	(0.010)**	(0.012)**
Establishment FE	-0.020	-0.036	-0.018	-0.021	-0.027	-0.017	-0.022	-0.039
	(0.014)	(0.018)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.017)*
Change in Estab FE	0.74	0.75	0.74	0.74	0.73	0.74	0.72	0.73
	(0.019)**	(0.018)**	(0.019)**	(0.019)**	(0.018)**	(0.018)**	(0.018)**	(0.016)**
Pre-disp. occupation tenure			-0.0014					-0.0014
			(0.00028)**					(0.00023)**
Pre-disp. industry tenure			-0.00070					-0.0010
			(0.00029)*					(0.00023)**
Plant closing				0.014				0.012
				(0.0020)**				(0.0020)**
Parttime - Diff-Diff					-0.36			-0.35
					(0.039)**			(0.039)**
Establishment Size - Diff-Diff						-0.0000020		-0.0000020
						(0.00000027)**		(0.00000026)**
Turnover rate - Diff-Diff							-0.045	-0.043
							(0.0071)**	(0.0075)**
Separation rate - Diff-Diff							0.032	0.030
							(0.011)**	(0.011)*
R^2	0.340	0.346	0.341	0.341	0.354	0.341	0.339	0.361

Notes: Each column in each panel represents a separate regression of the log wage loss of job losers (based on the individual diff-in-diff estimate) change in the national unemployment rate. All regressions control for year and year squared. Panel (A) does not include other controls, Panel (B) controls for the worker effect and the pre-displacement establishment effect as well as tenure and experience polynomials. Panel (C) is the same as Panel (B) but adds (diff-in-diff) change in the establishment effect. Column 5, Panel (B) and (C) uses a split sample IV estimator to instrument for the establishment FE and the change in the establishment FE

Table A-9: The Cyclicality of Log Wage Losses with and without controlling for establishment effects - Rolling AKM Model

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage
Panel A: Change in Unemployment Rate						
Change in UR t-1 to t	-0.028	-0.024	-0.018	-0.014	-0.016	-0.013
	(0.0012)**	(0.0011)**	(0.0010)**	(0.0010)**	(0.0010)**	(0.0010)**
Establishment FE		-0.40			-0.023	0.12
		(0.0083)**			(0.0079)**	(0.0075)**
Worker effect		0.18			0.12	0.095
		(0.0031)**			(0.0028)**	(0.0028)**
Change in Estab FE			0.75	1	0.72	1
			(0.0051)**		(0.0054)**	
Year	-0.0028	0.000027	-0.0012	-0.00073	-0.00069	-0.00097
	(0.00013)**	(0.00014)	(0.00012)**	(0.00012)**	(0.00012)**	(0.00012)**
year2	-0.000086	-0.00021	-0.00013	-0.00014	-0.00014	-0.00011
	(0.000016)**	(0.000015)**	(0.000014)**	(0.000014)**	(0.000014)**	(0.000014)**
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.079	-0.079		-0.079	-0.079	-0.079
R^2	0.017	0.086	0.25	0.0061	0.27	0.027
N	69960	69960	69960	69960	69960	69960
Panel B: Level of Unemployment Rate						
Unemployment rate	-0.0069	-0.0026	-0.0020	-0.00042	-0.0017	-0.0014
	(0.00088)**	(0.00085)**	(0.00076)**	(0.00078)	(0.00076)*	(0.00077)
Establishment FE		-0.40			-0.022	0.12
		(0.0083)**			(0.0079)**	(0.0075)**
Worker effect		0.18			0.12	0.097
		(0.0031)**			(0.0028)**	(0.0028)**
Change in Estab FE			0.76	1	0.73	1
			(0.0051)**		(0.0054)**	
Year	-0.00070	0.0011	-0.00046	-0.00039	-0.000020	-0.00043
	(0.00024)**	(0.00023)**	(0.00021)*	(0.00021)	(0.00021)	(0.00021)*
year2	-0.00012	-0.00022	-0.00014	-0.00015	-0.00015	-0.00012
	(0.000016)**	(0.000016)**	(0.000014)**	(0.000014)**	(0.000014)**	(0.000014)**
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.079	-0.079		-0.079	-0.079	-0.079
R^2	0.0095	0.080	0.25	0.0035	0.27	0.025
N	69960	69960	69960	69960	69960	69960

Notes: Regressions control for year. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Columns (5) and (6) 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 A-10: The Cyclicality of Log Wage Losses with and without controlling for establishment effects - Controlling for Parttime

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage
Panel A: Change in Unemployment Rate						
Change in UR t-1 to t	-0.030	-0.028	-0.014	-0.0092	-0.013	-0.0083
	(0.0011)**	(0.0011)**	(0.00091)**	(0.00092)**	(0.00091)**	(0.00092)**
Establishment FE		-0.31			-0.031	0.066
		(0.0077)**			(0.0068)**	(0.0067)**
Worker effect		0.17			0.070	0.038
		(0.0029)**			(0.0025)**	(0.0025)**
Change in Estab FE			0.77	1	0.74	1
			(0.0042)**		(0.0044)**	
Parttime - Diff-Diff	-0.42	-0.41	-0.36	-0.35	-0.36	-0.34
	(0.010)**	(0.010)**	(0.0088)**	(0.0089)**	(0.0087)**	(0.0089)**
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.077	-0.077		-0.077	-0.077	-0.077
R^2	0.035	0.088	0.32	0.024	0.33	0.028
N	80905	80905	80905	80905	80905	80905
Panel B: Level of Unemployment Rate						
Unemployment rate	-0.0073	-0.0050	-0.0038	-0.0028	-0.0035	-0.0031
	(0.00082)**	(0.00080)**	(0.00068)**	(0.00069)**	(0.00068)**	(0.00069)**
Establishment FE		-0.31			-0.025	0.069
		(0.0077)**			(0.0068)**	(0.0067)**
Worker effect		0.17			0.071	0.039
		(0.0029)**			(0.0025)**	(0.0025)**
Change in Estab FE			0.78	1	0.75	1
			(0.0041)**		(0.0043)**	
Parttime - Diff-Diff	-0.42	-0.41	-0.36	-0.35	-0.36	-0.34
	(0.011)**	(0.010)**	(0.0088)**	(0.0089)**	(0.0088)**	(0.0089)**
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.077	-0.077		-0.077	-0.077	-0.077
R^2	0.026	0.081	0.32	0.023	0.33	0.027
N	80905	80905	80905	80905	80905	80905

Notes: Regressions control for year. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Columns (5) and (6) 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 A-11: The Cyclicality of Log Wage Losses with and without controlling for establishment effects - Split Sample IV

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage	(7) log wage	(8) log wage	(9) log wage
Panel A: Change in Unemployment Rate									
Change in UR t-1 to t	-0.030	-0.028	-0.028	-0.014	-0.013	-0.0091	-0.013	-0.012	-0.0080
	(0.0011)**	(0.0011)**	(0.0011)**	(0.00091)**	(0.00094)**	(0.00092)**	(0.00091)**	(0.00094)**	(0.00092)**
Establishment FE		-0.32					-0.024		0.070
		(0.0077)**					(0.0069)**		(0.0068)**
Establishment FE (IV)			-0.32					-0.023	
			(0.0081)**					(0.0074)**	
Change in Estab FE				0.79		1	0.76		1
				(0.0044)**			(0.0046)**		
Change in Estab FE (IV)					0.82			0.79	
					(0.0050)**			(0.0053)**	
Worker effect		0.17	0.17				0.070	0.066	0.039
		(0.0029)**	(0.0029)**				(0.0026)**	(0.0026)**	(0.0025)**
Change in Estab FE coef = 1						1			1
Mean of dep. var	-0.075	-0.075	-0.075	-0.075	-0.075	-0.075	-0.075	-0.075	-0.075
R^2	0.016	0.072	0.071	0.30	0.26	0.0061	0.31	0.27	0.011
F-stat 1st stage excl. instr.			526142.0		239781.5				
N	79968	79968	79968	79968	79968	79968	79968	79968	79968
Panel B: Level of Unemployment Rate									
Unemployment rate	-0.0073	-0.0050	-0.0049	-0.0037	-0.0033	-0.0028	-0.0035	-0.0031	-0.0030
	(0.00082)**	(0.00079)**	(0.00079)**	(0.00069)**	(0.00070)**	(0.00070)**	(0.00068)**	(0.00070)**	(0.00069)**
Establishment FE		-0.31					-0.017		0.073
		(0.0078)**					(0.0069)*		(0.0068)**
Establishment FE (IV)			-0.31					-0.017	
			(0.0082)**					(0.0074)*	
Change in Estab FE				0.79			0.76		
				(0.0043)**			(0.0046)**		
Change in Estab FE (IV)					0.83	1		0.80	1
					(0.0050)**			(0.0053)**	
Worker effect		0.17	0.17				0.071	0.067	0.040
		(0.0029)**	(0.0029)**				(0.0026)**	(0.0026)**	(0.0025)**
Change in Estab FE coef = 1						1			1
Mean of dep. var	-0.075	-0.075	-0.075	-0.075	-0.075	-0.075	-0.075	-0.075	-0.075
R^2	0.0076	0.064	0.063	0.30	0.26	0.0051	0.31	0.27	0.0098
F-stat 1st stage excl. instr.			524825.0		242195.0				
N	79968	79968	79968	79968	79968	79968	79968	79968	79968

Notes: Regressions control for year. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Columns (5) and (6) 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 A-12: Pre-displacement worker characteristics by displacement status – Random Control Group (No Matching)

	(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	0.1	0.2	0.1	0.1
	[0.3]	[0.4]	[0.3]	[0.4]
Real wage	99.1	92.3	91.0	91.6
	[25.6]	[27.1]	[25.5]	[26.2]
Parttime	0	0	0	0
	[0]	[0]	[0]	[0]
Female	0	0	0	0
	[0]	[0]	[0]	[0]
West Germany	1	1	1	1
	[0]	[0]	[0]	[0]
Years of education	11.0	11.1	10.8	10.9
	[2.4]	[2.5]	[2.1]	[2.3]
Potential experience	21.1	20.8	21.6	21.2
	[7.4]	[7.5]	[7.4]	[7.4]
Tenure with current Employer	10.3	9.0	9.7	9.4
	[5.4]	[5.1]	[5.3]	[5.2]
Actual experience, but censored 1975	13.4	12.7	13.2	13.0
	[6.2]	[6.0]	[6.2]	[6.1]
Total yearly earnings	36072.7	32588.9	32166.0	32355.0
	[9464.1]	[10444.1]	[9858.2]	[10126.3]
Total yearly income	36084.6	32867.6	32525.2	32678.2
	[9450.5]	[10207.8]	[9592.1]	[9873.4]
Days per year working fulltime	364.0	351.9	352.7	352.4
	[16.1]	[37.7]	[35.8]	[36.7]
Wage on June 30th of year	99.1	92.3	91.0	91.6
	[25.6]	[27.1]	[25.5]	[26.2]
Log of wage in June	4.6	4.5	4.5	4.5
	[0.3]	[0.3]	[0.3]	[0.3]
Panel B: Establishment Characteristics				
Number of employees	3297.0	482.8	481.3	482.0
	[8287.8]	[809.4]	[1181.1]	[1031.6]
Share of fulltime employees	0.9	1.0	1.0	1.0
	[0.1]	[0.09]	[0.08]	[0.08]
Establishment FE	2.2	2.2	2.2	2.2
	[0.1]	[0.1]	[0.1]	[0.1]
Avg. years of education in estab.	10.9	11.0	10.7	10.8
	[1.1]	[1.2]	[1.0]	[1.1]
Number of Spells	102468	45790	56678	102468

Notes: Average characteristics of establishments with at least 50 employees depending on whether they have a PCL or MLF the following year. Data 1978 to 2008, West Germany. Standard deviations in brackets.

Table A-13: Pre-displacement worker characteristics by displacement status – Random Control Group (No Matching)

	(1) Non-displaced workers	(2) Displaced mass lay-off	(3) Displaced plant closing	(4) Displaced mass lay-off or plant closing
Panel C: Industry (percent)				
A Agriculture, fishing, hunting and forestry	0.08	0.3	0.09	0.2
	[2.8]	[5.1]	[3.0]	[4.1]
C Manufacturing	61.5	58.8	62.0	60.6
	[48.7]	[49.2]	[48.6]	[48.9]
D Energy supply	2.4	1.1	0.9	1.0
	[15.4]	[10.3]	[9.6]	[9.9]
E Water supply and other utilities	1.0	0.7	0.5	0.6
	[9.7]	[8.4]	[7.0]	[7.7]
F Construction	5.7	10.4	14.2	12.5
	[23.2]	[30.6]	[34.9]	[33.1]
G Wholesale and retail trade, Vehicle repair	7.9	9.8	9.6	9.7
	[27.0]	[29.7]	[29.4]	[29.6]
H Transport and storage	5.2	4.8	2.5	3.5
	[22.2]	[21.3]	[15.7]	[18.4]
I Hotels and restaurants	0.3	0.4	0.3	0.3
	[5.2]	[6.0]	[5.6]	[5.8]
J Information and communication	1.8	3.0	2.3	2.6
	[13.2]	[17.1]	[15.1]	[16.0]
K Financial and insurance services	4.5	1.7	2.1	1.9
	[20.8]	[13.0]	[14.2]	[13.7]
L Real estate, renting and business activities	0.4	0.3	0.3	0.3
	[6.0]	[5.7]	[5.3]	[5.5]
M Personal, technical and scientific services	2.5	2.9	1.8	2.3
	[15.7]	[16.8]	[13.2]	[15.0]
N Other business services	0.7	1.7	1.3	1.5
	[8.3]	[12.9]	[11.4]	[12.1]
P Education	0.7	0.3	0.05	0.2
	[8.4]	[5.7]	[2.3]	[4.2]
Q Health and social work	3.6	0.7	1.1	0.9
	[18.6]	[8.2]	[10.2]	[9.4]
R Arts and recreation	0.5	0.2	0.04	0.10
	[7.2]	[4.1]	[2.0]	[3.1]
S Other services	1.3	2.9	1.0	1.8
	[11.2]	[16.8]	[9.8]	[13.4]
Number of Spells	102468	45790	56678	102468

Notes: Average characteristics of establishments with at least 50 employees depending on whether they have a PCL or MLF the following year. Data 1978 to 2008, West Germany. Standard deviations in brackets.

Table A-14: The Cyclicality of Log Wage Losses with and without controlling for establishment effects - Random Control Group (No Matching)

	(1) log wage	(2) log wage	(3) log wage	(4) log wage	(5) log wage	(6) log wage
Panel A: Change in Unemployment Rate						
Change in UR t-1 to t	-0.032	-0.028	-0.014	-0.0097	-0.013	-0.0085
	(0.0011)**	(0.0010)**	(0.00089)**	(0.00090)**	(0.00089)**	(0.00090)**
Establishment FE		-0.32			-0.030	0.057
		(0.0072)**			(0.0064)**	(0.0063)**
Worker effect		0.18			0.078	0.048
		(0.0028)**			(0.0024)**	(0.0024)**
Change in Estab FE			0.80	1	0.77	1
			(0.0040)**		(0.0042)**	
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.086	-0.086		-0.086	-0.086	-0.086
R^2	0.015	0.076	0.32	0.0046	0.33	0.010
N	86423	86423	86423	86423	86423	86423
Panel B: Level of Unemployment Rate						
Unemployment rate	-0.011	-0.0084	-0.0072	-0.0063	-0.0068	-0.0064
	(0.00081)**	(0.00079)**	(0.00067)**	(0.00068)**	(0.00067)**	(0.00068)**
Establishment FE		-0.31			-0.023	0.062
		(0.0073)**			(0.0064)**	(0.0063)**
Worker effect		0.18			0.079	0.049
		(0.0028)**			(0.0024)**	(0.0024)**
Change in Estab FE			0.80		0.77	
			(0.0040)**		(0.0042)**	
Change in Estab FE coef = 1				1		1
Mean of dep. var	-0.086	-0.086		-0.086	-0.086	-0.086
R^2	0.0067	0.070	0.32	0.0042	0.33	0.010
N	86423	86423	86423	86423	86423	86423

Notes: Regressions control for year. The unemployment rate and the change in the unemployment rate is measured in percentage points and is the unemployment rate for West Germany. Columns (5) and (6) 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

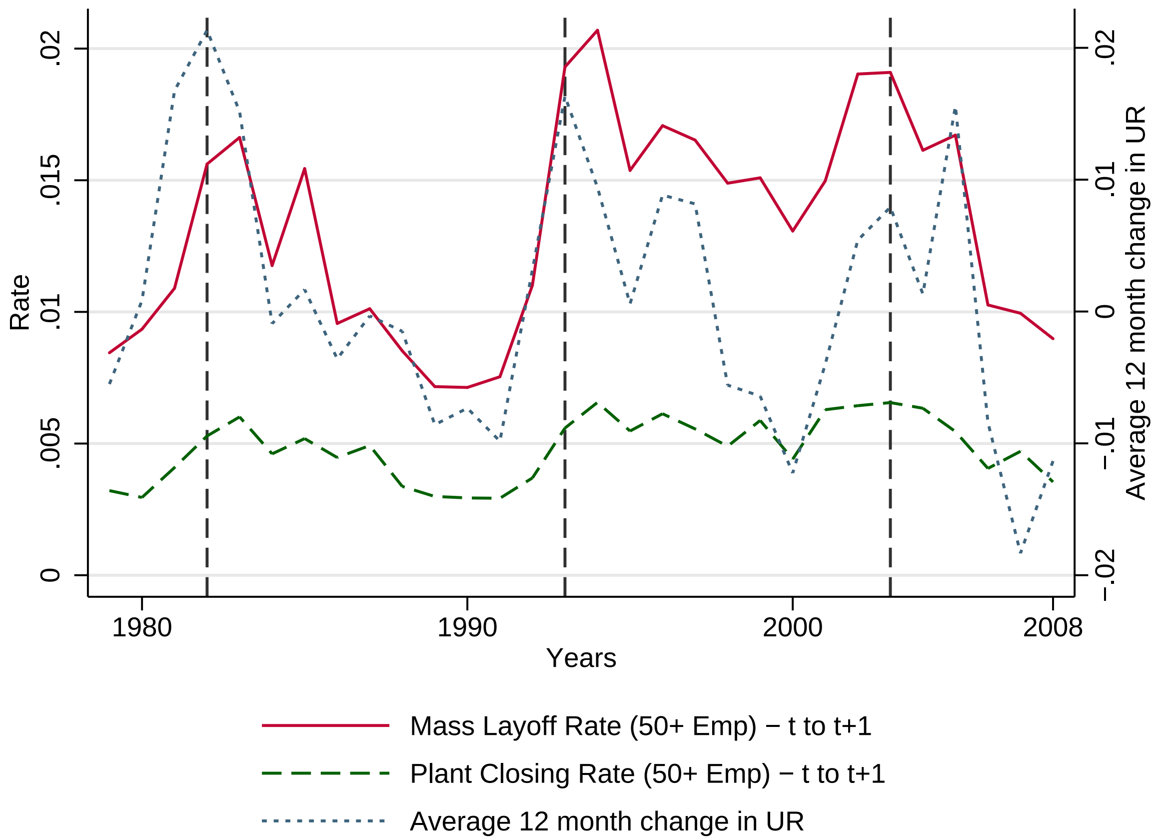
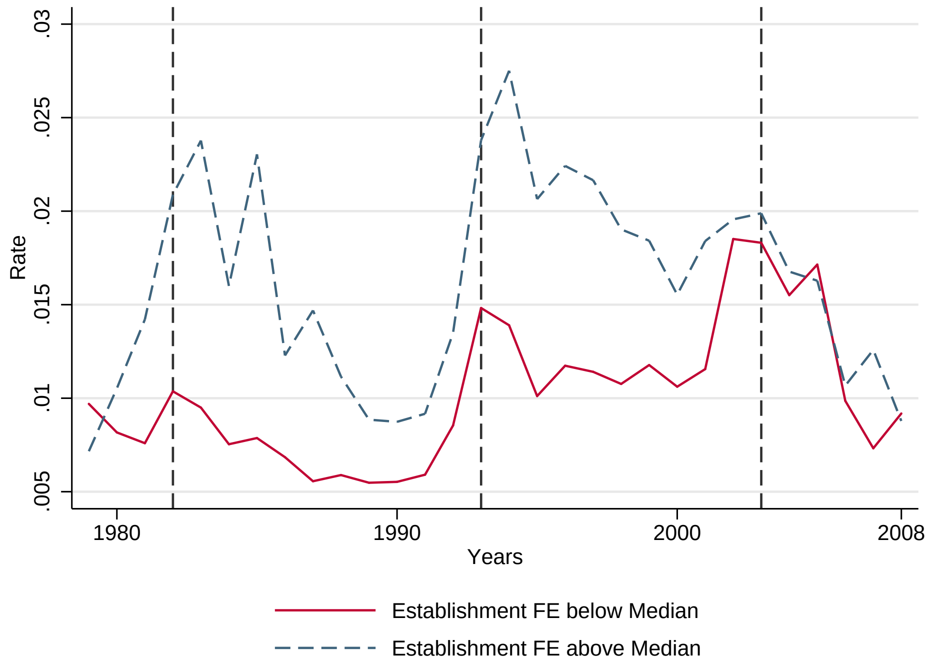
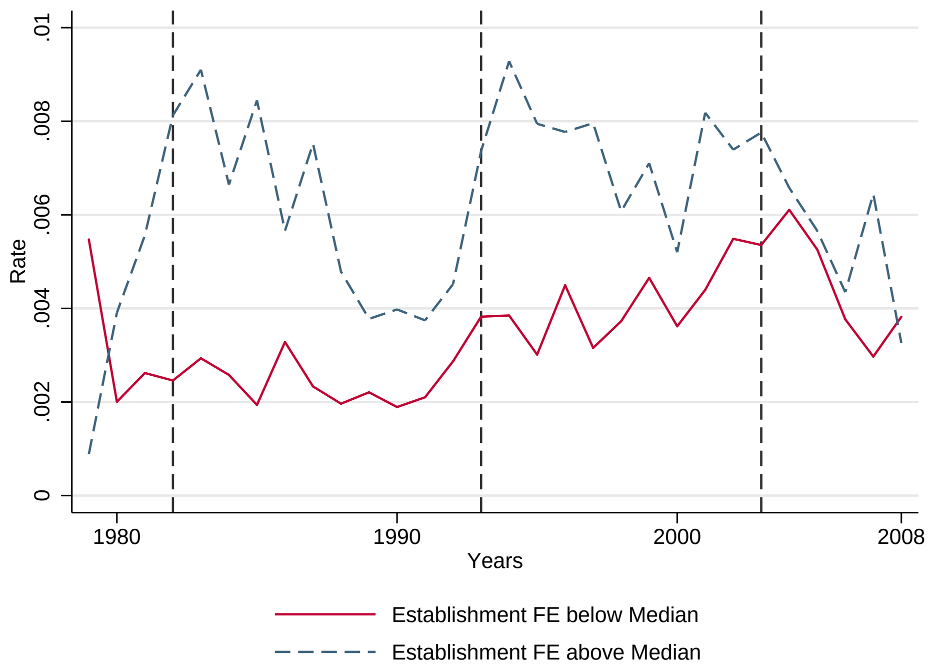


Figure A-2: Incidence of Job Loss by Establishment Fixed Effect

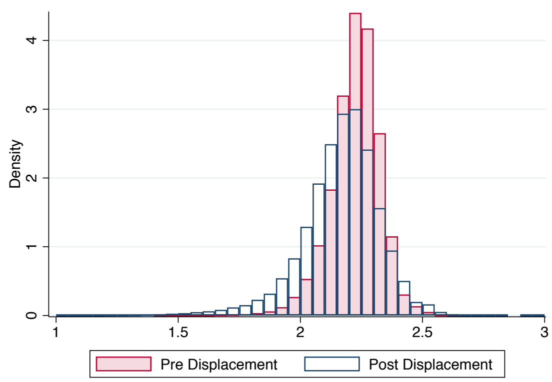


(a) Mass Layoff Rate by Year

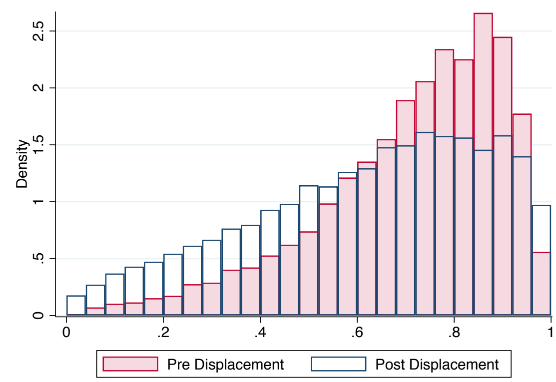


(b) Plant Closing Rate by Year

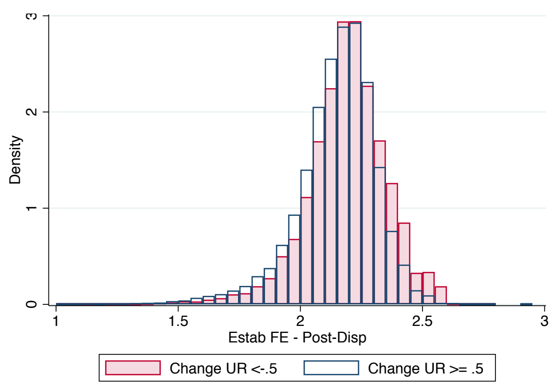
Figure A-3: The Effects of Job Loss On Distribution of Establishment Fixed Effects



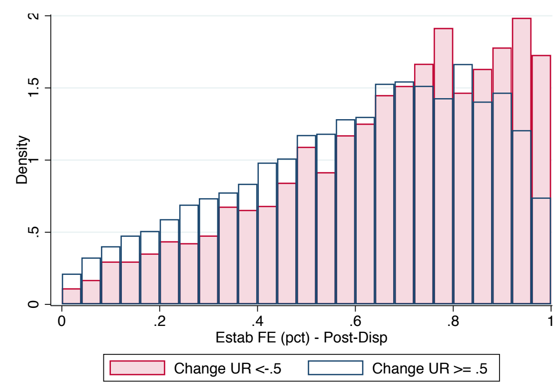
(a) Distribution of Estab FE Job Losers vs. Controls



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

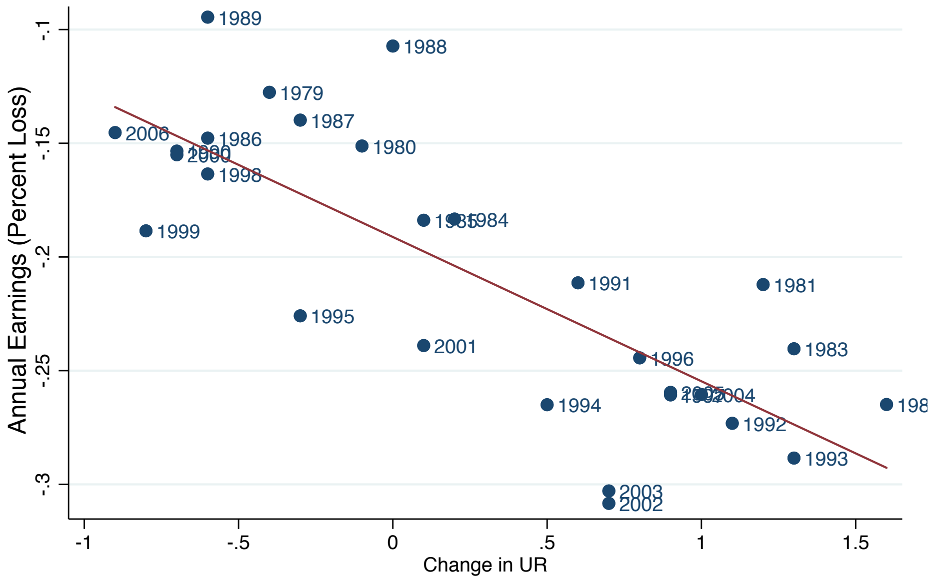


(c) Distribution of Estab FE Job Losers vs. Controls

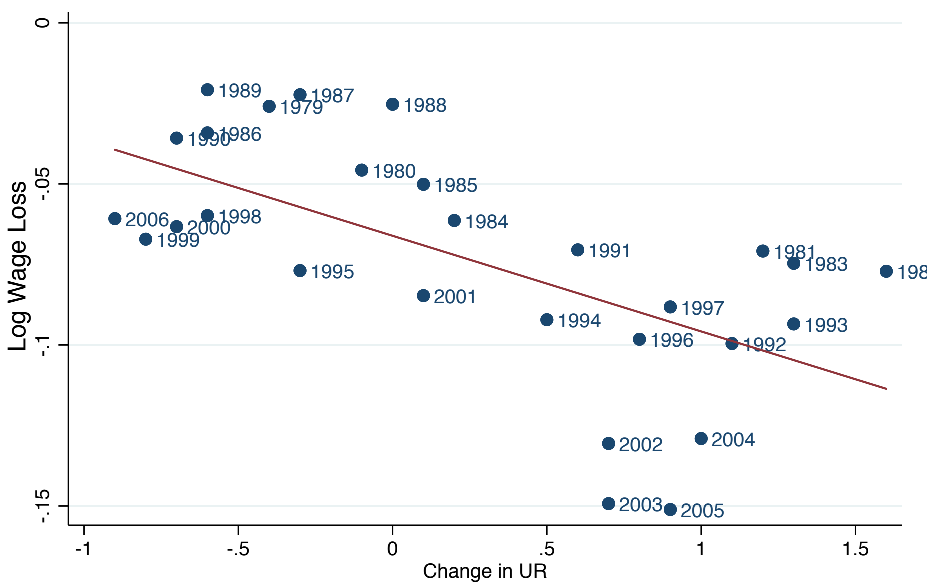


(d) Distribution of Estab FE Job Losers vs. Controls in Percentiles

Figure A-4: 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

Notes: The figure shows scatterplots of the earnings and wage losses of job losers collapsed to the year level relative to the year over year change in the unemployment rate. THe top figure shows the percent change in average annual earnings, where the slope of the regression line is -0.063 [SE: 0.0099]. The bottom figure shows the change in average log wages, where the slope of the regression line is -0.030 [SE: 0.0073].

Figure A-5: Decomposition of Earnings Loss by Year

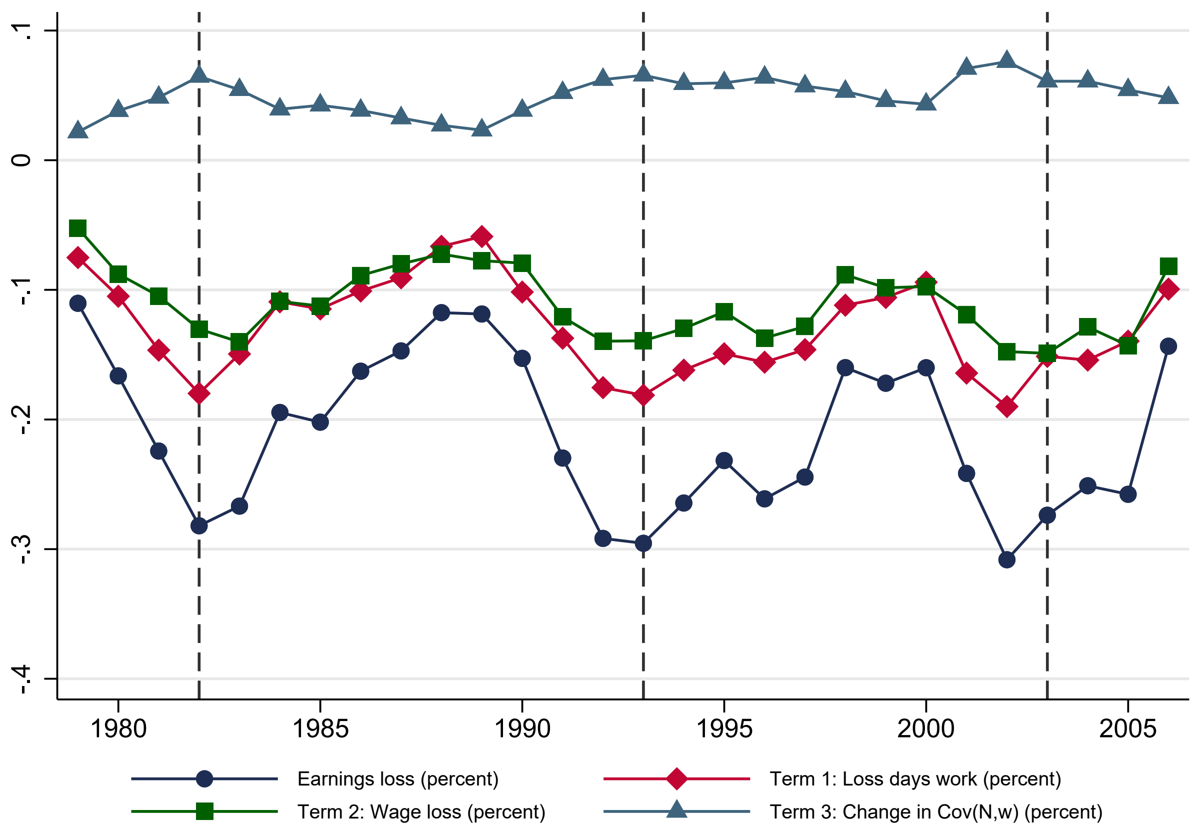
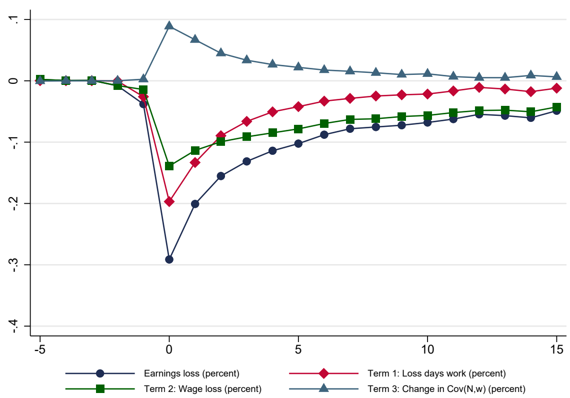
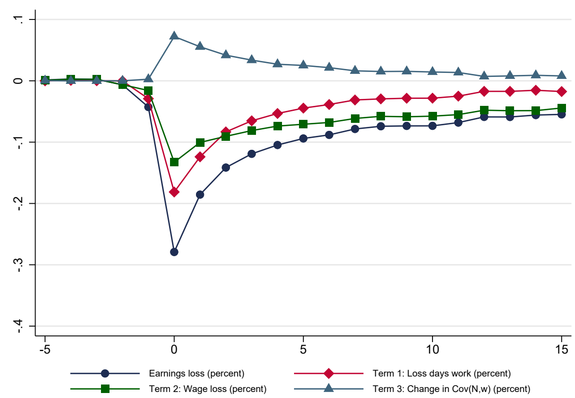


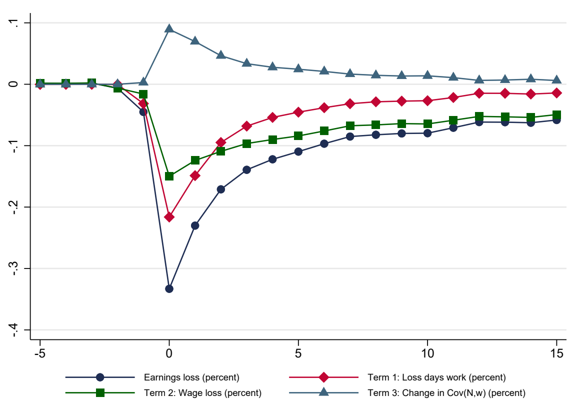
Figure A-6: Decomposition of Earnings Loss by State of Labor Market



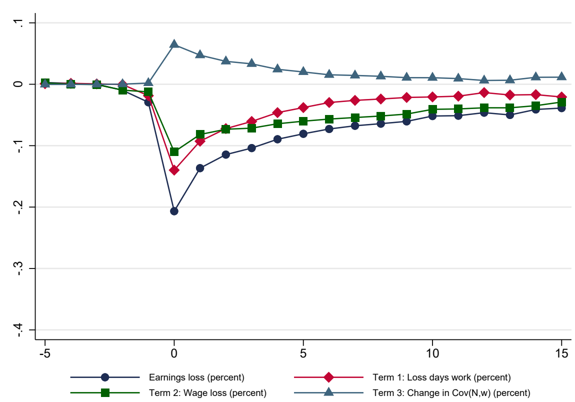
(a) Unemployment Rate >=7%



(b) Unemployment Rate <7%

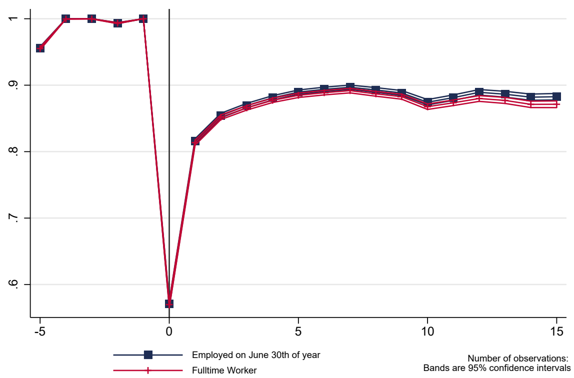


(c) Change Unemployment Rate >=0%

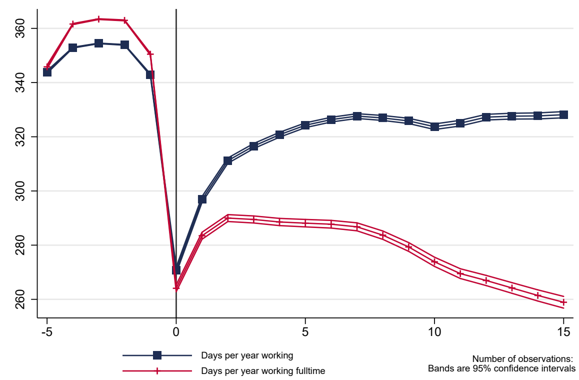


(d) Change Unemployment Rate <0%

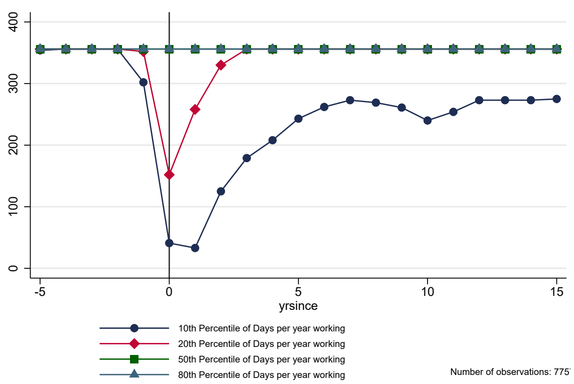
Figure A-7: The Effect of Job Displacement on Fulltime / Parttime, Days worked and Median Wages - Men



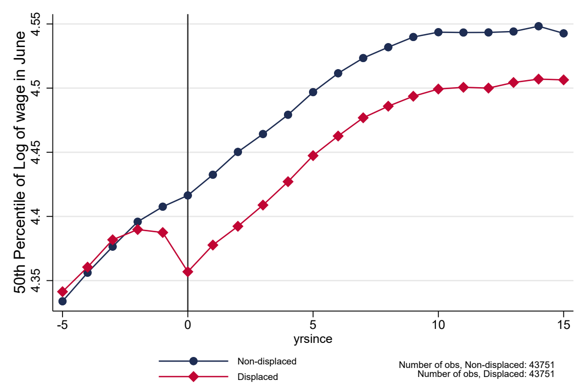
(a) Employed and Employed Fulltime



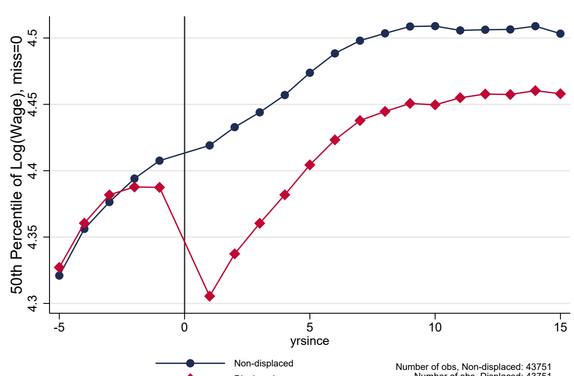
(b) Days Employed and Days Employed Fulltime



(c) Quantiles of Days Worked



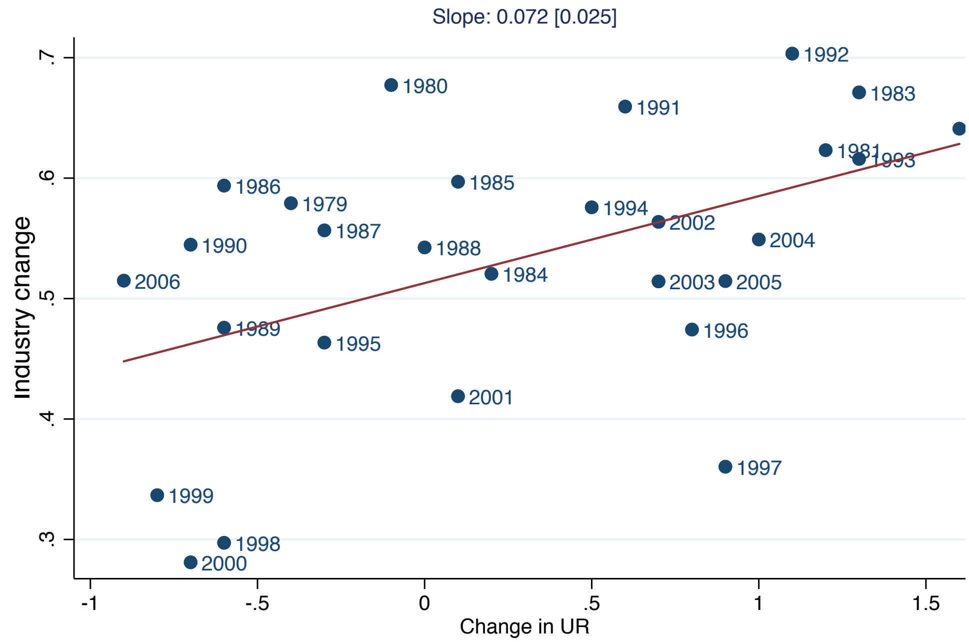
(d) Log Wage Median, not incl. missings



(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.

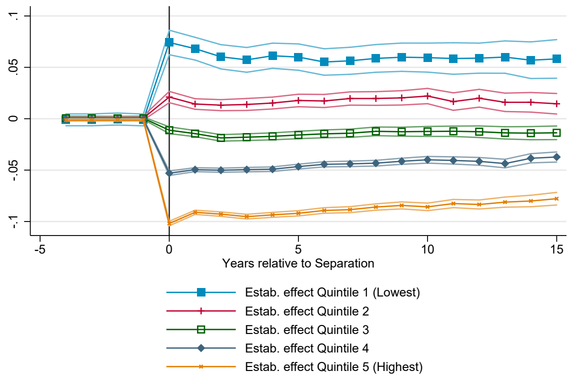
Figure A-8: Probability of Changing 2-Digit Industry After Job Loss by Year of Job Loss



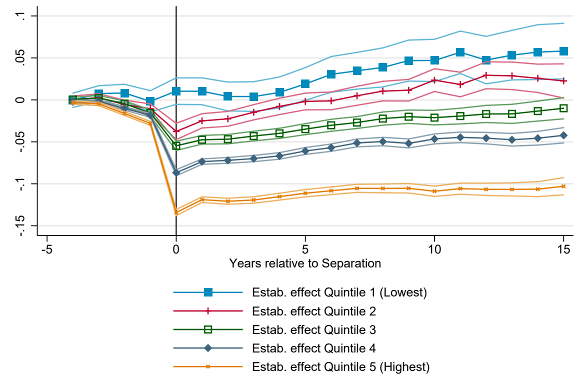
(a) Prob. Industry Change vs Change UR

(b) Prob. Industry Change vs Change UR

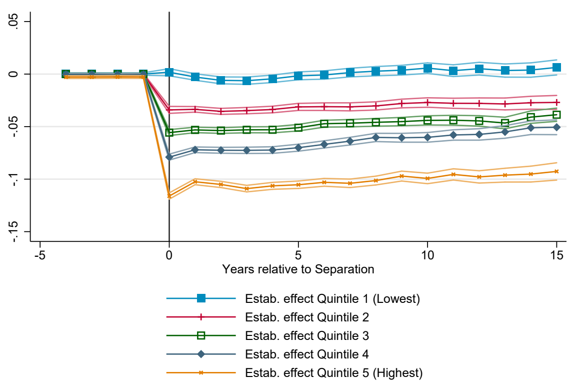
Figure A-9: The Relationship between Estab FE Losses and Wage Losses



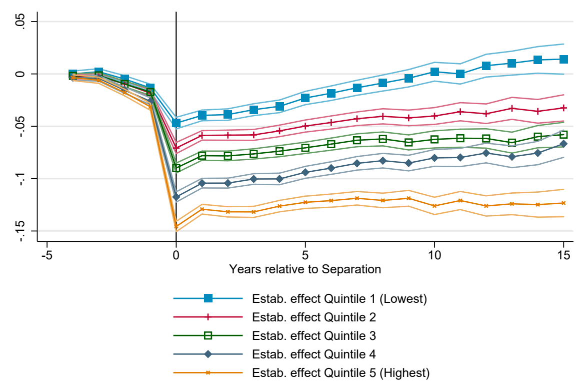
(a) Loss of Estab FE by Quartile of Displacing Estab FE - Quintiles based on full pop.



(b) Wage Loss by Quartile Displacing Estab FE - Quintiles based on full pop.

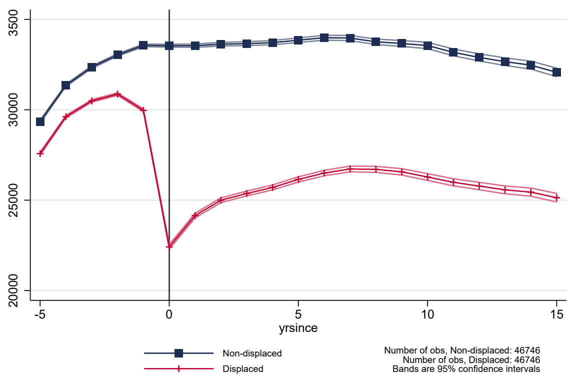


(c) Loss of Estab FE by Quartile of Displacing Estab FE - Quintiles based on analysis Smpl

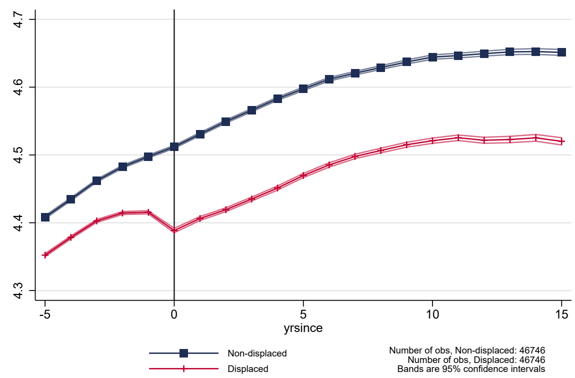


(d) Wage Loss by Quartile Displacing Estab FE - Quintiles based on analysis Smpl

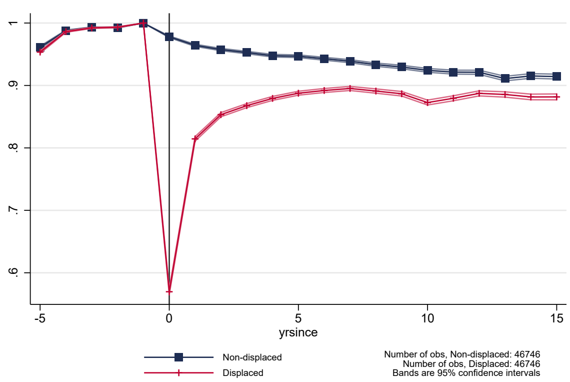
Figure A-10: Labor Market Outcomes of Displaced Workers before and after Job Loss - Comparing Raw Means of Displaced Workers and Control Group - Random Control Group (No Matching)



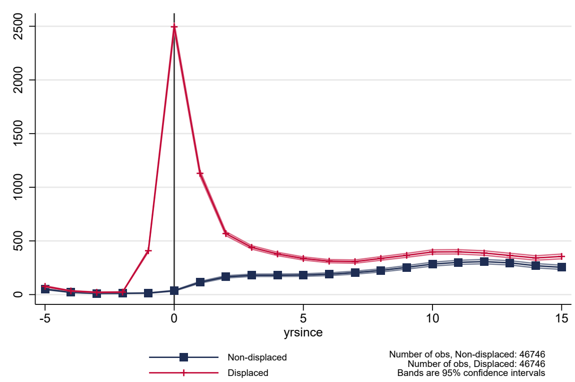
(a) Total Earnings in Year



(b) Log Wage



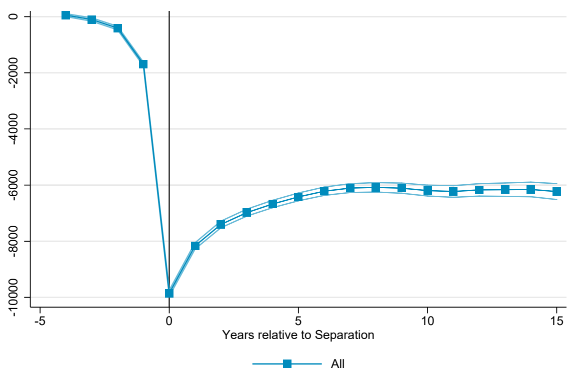
(c) Employed on June 30th of Year



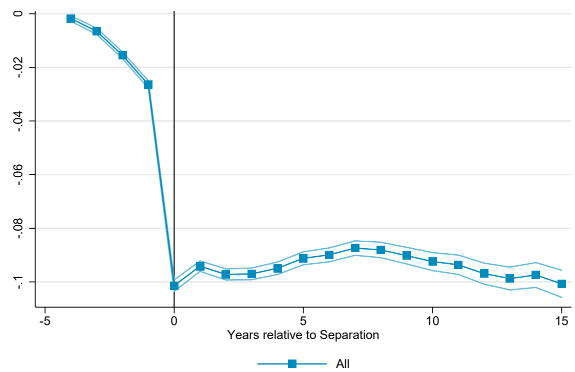
(d) Income from Unemployment Insurance Benefits

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.

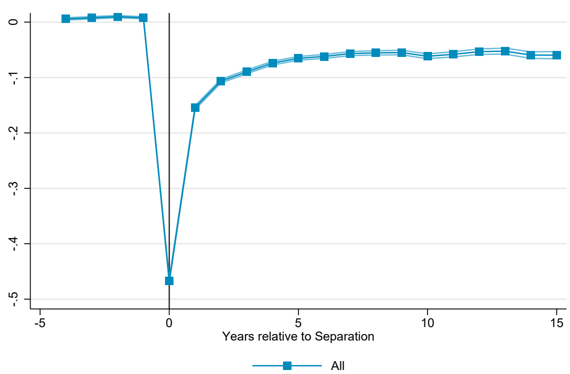
Figure A-11: Labor Market Outcomes of Displaced Workers before and after Job Loss - Eventstudy Regression Estimates - Random Control Group (No Matching)



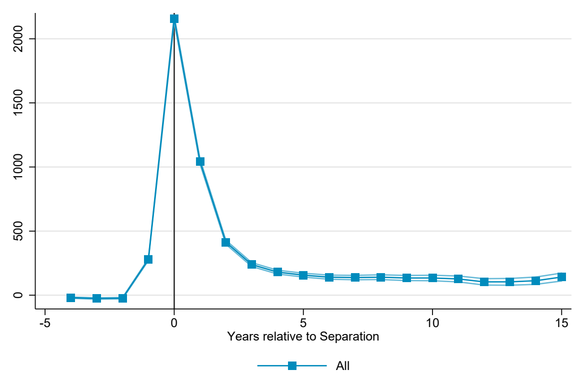
(a) Total Earnings in Year



(b) Log Wage



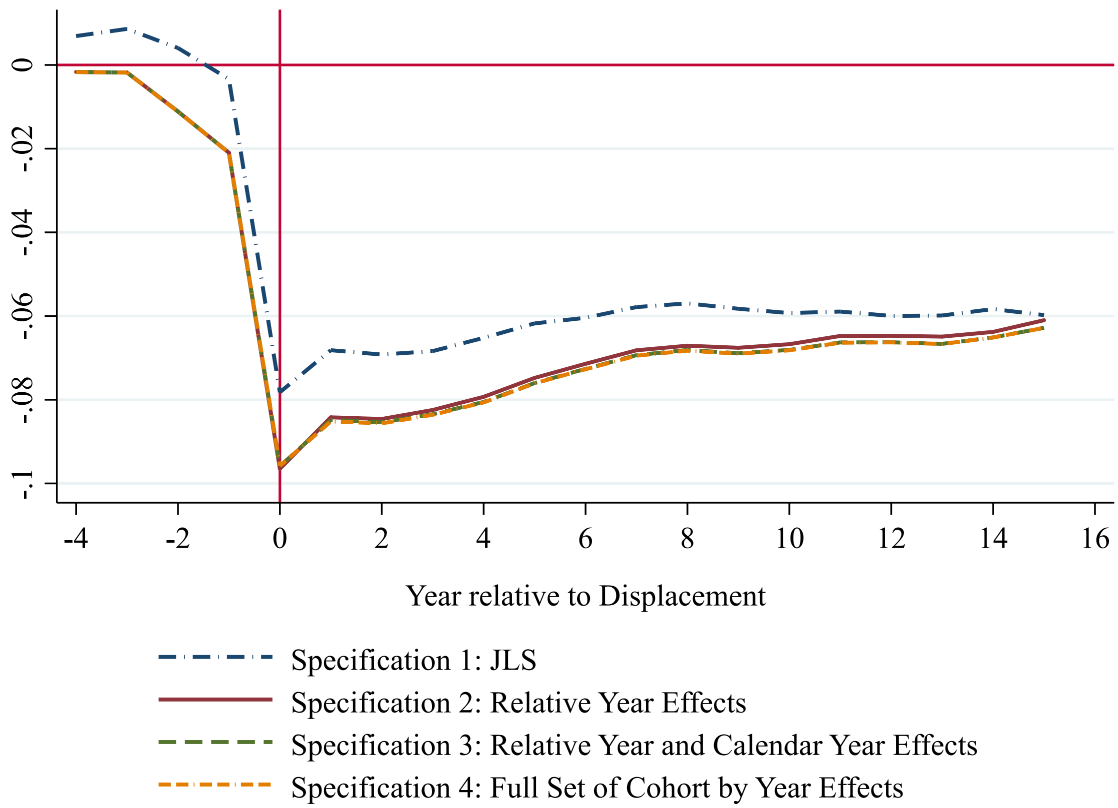
(c) Employed on June 30th of Year



(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-12: Comparing Alternative Job Loss Eventstudy Specifications



Notes: The figures shows evenstudy estimates of the effects of job loss on log wages comparing alternative regression specifications. The sample is the baseline sample from the main paper (West-German Men, Pooling all displacement years). See Appendix Section 2 for details of the regression specifications.