Routine Tasks and Recovery from Mass Layoffs

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Abstract

We analyze the effect that an occupation's degree of routine intensity has on the long-term costs of job loss. To this end we identify workers who experienced displacement as a result of a mass layoff in Germany between 1980 and 2010. We use detailed information on these individuals' employment biographies before and after the mass layoff in order to control for institutional differences as well as individual self-selection into occupations. Our results show that conditional on covariates the employment biographies of workers in occupations with a high and a low extent of routine intensity do not differ prior to the mass layoff. However, we find that after the event the negative effect on subsequent employment and earnings is significantly more severe for former employees of routine-intensive occupations. A possible explanation for this finding is that the human capital accumulated in routine-intensive occupations has become less valuable. Moreover, we show that the effect of routine-intensity varies across age, sex and qualification groups as well as with population density and time of the mass layoff.

JEL-Classification: J24, J63 O33

Keywords: routine replacing technological change, work biographies, mass layoffs, Germany

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1. Overview

This paper analyses the effect that technological change during the past three decades had on the employment biographies of incumbent workers. Specifically, we focus on workers active in the German labour market, who were displaced during a mass-layoff between 1980 and 2010 and thus face an exogenous break in their employment history. After controlling for individual and workplace characteristics, those workers differ only in terms of the extent to which they performed routine tasks in their previous job. We show that the adverse effects of job loss on earnings and subsequent employment increase with the extent of an occupation's routine-intensity.

We argue that occupations which are characterized by a high degree of routine intensity face a larger risk of experiencing substitution of human labour by machines and are therefore more likely to be affected by technological change than occupations which are less routine-intensive. It is known that computer technology is especially suitable to substitute routine jobs because computers are good at algorithms, i.e. fixed sets of rules, which especially characterize routine tasks (Autor, Levy, Murnane 2003, Spitz-Oener 2006). Therefore, profit-oriented firms use "routine-biased technical progress" (Goos, Manning, Salomons 2014) to increase productivity.

From an aggregate perspective, this form of technical progress is associated with a polarization of the labour market (Autor, Dorn 2013) because the most routine intensive jobs in the US and in other countries are mostly placed in the middle of the income distribution. Since modern technology is complementary to high skilled occupations and neutral to non-routine manual occupations, there are gains at both ends end of this distribution, relative to the middle ranks. Empirical evidence supporting this hypothesis in Germany is provided by Goos, Manning, Salomons (2014).

In this paper, we take a complementary look at the individual perspective. However, a simple comparison of randomly chosen workers in routine occupations versus non-routine occupations is problematic in several regards. First, our major concern is that workers have selected into occupations for various reasons that may be correlated with subsequent labour market outcomes. If routine-intensive jobs require fewer formal skills and offer smaller wages than non-routine jobs (in our data set the correlation coefficients between routine intensity and indicators for high, medium and low skills are -0.29, -0.18 and 0.4, respectively; the correlation coefficient between routine intensity and earnings is -0.33), workers with lower (observed and unobserved) skills select into those jobs. It is thus not clear how much of the difference in labour market outcomes between both groups can actually be attributed to routine replacing technological change and how much to selection on unobserved skills. Our second concern is that incumbent workers might be shielded from the effects of technological change. Even if new technology could potentially replace human labour, institutions might prevent employers from actually using this technology. Job protection makes it costly for employers to simply replace workers with machines. Depending how easily they can be re-trained, incumbent workers will either be moved to a different function or even be kept at their original job. Especially in European countries, this is amplified by the tendency of labour unions and work councils to protect insiders from labour-saving technological changes (see Lommerud, Straume, 2012). This creates an insider/outsider distinction on how technological change will affect workers.

We contribute to the literature on the effects of technological change on individuals by focusing on a group of workers that face an exogenous break in their working lives. By looking at workers who are displaced during a mass-layoff event, we ensure that workers do not differ with respect to institutional job protection.[4] In our econometric analysis, we condition on observable characteristics including plant

[4] In Germany, larger firms that do not lay off their entire workforce in a mass-layoff must develop a social plan which essentially sort workers according to their tenure and not according to their skills.

fixed effects and one-digit occupations. This means that we compare observationally similar workers who were displaced from similar jobs in the same firm and differ only with regard to the routine intensity of their specific job. While we cannot rule out that there is any selection bias left, we show that the evolution of their careers ex-ante does not vary systematically with the routine-intensity of their occupation. We use this identification strategy to examine if workers who accumulated human capital in routine jobs adjust differently compared to their colleagues in non-routine jobs. Will they be able to find new jobs as quickly? And are these effects mediated by other characteristics such as age, education, or place of residence?

Our results indicate that the occupational paths of the workers in our sample prior to the mass layoff do not vary with the routine-intensity of the original job. This supports the identifying assumption that earnings and employment would have evolved along similar trajectories if the mass-layoff had not happened. This means that, after conditioning on either plant fixed effects and 1-digit industries or worker fixed effects, the workers with different routine intensities in the population under study are valid counterfactuals for each other. After the layoff, we find a negative relationship of earnings and employment losses and routine intensity: routine intensity aggravates the long term costs of displacement. Therefore, otherwise similar workers have more difficulties in adjusting to a negative employment shock. Technological change has made the human capital accumulated on their previous job redundant.

Our paper is most closely related to other studies that assess the consequences of the current form of technical progress for individual workers. Cortes (2015) finds that workers, who stay in routine occupations have smaller wage growth compared to those who leave. In addition, Maczulskij, Kauhanen (2017) look at the connection to migration. However, because there are only a few studies available, we aim at a relevant research gap: Whereas in other studies the development of industries or of regions (Autor, Dorn 2013 and Autor, Salomons 2017) is the focus of interest, we concentrate on the fate of people. We look at the fate of the losers of modernization, at those who are set free by routine biased technical progress.

We do not aim to identify the reason for the bad position of workers involved in routine tasks. Many will be made redundant by measures of (computer) technology. Autor, Dorn and Hanson (2015) test international trade versus technology as reasons for job losses. Industries affected most by imported goods are working with a relatively high share of routine labour. And there is the additional possibility of offshoring to a foreign country. Profit-oriented firms will slice the value chain in a way that the simpler jobs will be carried out elsewhere (Hummels, Munch, Xiang 2016).

We discuss our empirical strategy in Section 2. In Section 3, we introduce our dataset and explain in detail our procedure to identify workers who were displaced in a mass-layoff. Section 4 presents the Benchmark results of the overall costs of job displacement while Section 5 analyzes if these costs depend on routine intensity of the previous job. In Section 6, we examine if this effect varies across age, education, and location of the workers and whether they changed over our observation period of more than three decades. Section 7 concludes.

2. Empirical Strategy

We follow the literature on mass layoffs to measure the long-term effects of being displaced during a mass layoff. Our baseline model is:

$$\ln(y_{it}) = \alpha + \sum_{k=-12}^{24} \delta_k I(t = t^* + k)_t + \tau_t + \alpha_i + u_{it} \qquad (1)$$

The dependent variable *ln(y_it)* represent the natural logarithm of total wage earnings and the number of days in employment of worker i in quarter t, respectively.[5] $I(t = t^* + k)_t$ are the time-to-event dummies that indicate whether i is observed $k = -12, -11, \ldots, 24$ quarters before/after the layoff. We omit $k = -1$ as the reference category, so the coefficients δ_k are interpreted as conditional earnings or employment days relative to the time before the layoff. These coefficients will indicate the costs of a job loss in the long run and how long it takes the average worker to recover to levels of employment and earnings comparable to before the layoff. τ_t is a vector of calendar quarter dummies that capture macroeconomic conditions that affect the labor market outcomes of all workers laid off at the same quarter in different plants and α_i are worker fixed effects. As we are primarily interested in whether the speed of recovery differs with a worker's occupation prior to the layoff, we may expect that the error terms are correlated among workers with the same occupation. We compute standard errors that are clustered at the level of the occupation before the layoff.

In order to assess whether workers employed in a routine job take longer to recover, we let the coefficients of the time-to-event dummies vary with the routine intensity of the job before the layoff:

$$\ln(y_{it}) = \alpha + \sum_{k=-12}^{24} [\beta_k routine_i \times I(t = t^* + k)_t + \delta_k I(t = t^* + k)_t] + \mathrm{\tau_t} + \mathrm{\alpha_i} + u_{it} \qquad (2)$$

The variable $routine_i$ is the measure of routine intensity in the occupation that an individual was employed in during the quarter before the mass-layoff. This variable varies only across occupations and across the decades during which the mass layoff took place. We include this variable in the list of control variables in vector $\boldsymbol{x_{it}}$ and also generate interaction terms of this variable with the time-to-event dummies. The coefficients β_k are the differential employment/earnings losses due to a mass-layoff caused by an additional percentage-point in routine intensity.

In the baseline specification we include the following control variables: linear and squared measures of an individual's work experience, which are given by the time since the worker's first entry into the labor market, the time since the worker started working at the establishment at which the mass layoff was later experienced and the time since the start of the job held at the time of the mass layoff; dummy variables for a worker's level of qualification, as well as dummy variables for sex, German nationality and year of birth. At the level of the establishment we control for the number of employees, the sector (1-digit level) and for whether an establishment was located in East Germany (all at the time of the mass layoff). All of those variables are measured at the time of the mass layoff and are thus time invariant. Finally, we include dummy variables for the year and the calendar quarter of the mass-layoff.

In addition, we use dummy variables to control for the occupation the worker was employed in during the quarter preceding the mass layoff (measured at the 1-digit level). And we use the within transformation to control for either fixed effects for the establishment at which the mass layoff occurred (model 1) or for worker fixed effects (model 2).

Instead of controlling for individual fixed effects, we could also control for worker and plant characteristics measured in the quarter before the layoff. This could even include 1-digit occupation dummies and plant fixed effects. The estimates would then be tightly identified by the variation of the routine intensity within each 1-digit occupation. Controlling for the layoff-plant means that we only compare workers from similar occupations who were laid-off at the same time from the same plant. Using individual fixed effects means that all these characteristics in $t = t^* - 1$ are accounted for and drop out of the model. In addition, the fixed effects should also account for many unobservable

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[5] The value of 1 is added to these variables to prevent that an observation drops out of the sample when wage earnings or days in employment are zero.

characteristics. Even if the levels of wages and employment prior to the layoff depend on the routine intensity of an occupation, we argue that it is much more plausible to assume that those worker's employment biographies would have at least evolved along similar trajectories if the layoff had not happened. This is an assumption that we can test by looking at the trends before the layoff.

3. Data

3.1. Mass layoffs

In this section, we explain how we prepare our dataset of workers who experienced a mass layoff. We do this by following several papers from the related mass-layoff literature, e.g. Davis, von Wachter (2011) and Schmieder, von Wachter, Bender (2010). First, we identify plants where a mass layoff occurred. For this step, we use the Establishment History Panel (BHP) of the IAB. This dataset contains aggregated plant level information on all employees subject to security contributions of all German plants on June 30.[6]

The panel structure of this dataset allows us to follow the changes in the size of each plant over time. We then look for plants that had a rather stable size and then permanently contract by a large fraction of their initial size within one year. Specifically, we select all plant/year-observations that meet the following criteria:

- a plant has 50 or more employees on June 30 of year t^*
- the number of employees contracts by 30 to 100 percent until June 30 of year $t^* + 1$
- the number of employees on June 30 of year t^* is not less than 80 percent and not more than 120 percent of the number in $t^* - 1$ and $t^* - 2$
- the number of employees does not recover by more than 50 percent of the initial drop by June 30 $t^* + 2$ or $t^* + 3$

For those plants, June 30 of year t^* is the onset of a drastic event. However, since the id in our data identifies plants and not firms, the above criteria might also reflect restructuring of workers across plants within a multi-establishment firm. This is discussed in length by Hethey-Maier, Schmieder (2010). They also propose an approach to discriminate those cases from true mass-layoffs. We create a mobility matrix of worker flows between each pair of plants for each year using the full worker level information on June 30 of each year from the Employee History (BEH, Version V10.01.00 - 160816) of the IAB. This matrix reveals how many workers move from one plant to the same new plant. Hethey-Maier, Schmieder (2010) use similar data to show that the incidence of cases where less than 25 percent of the total outflow move to the same new plant is correlated to the business cycle, whereas this correlation vanishes for larger clustered outflows. Cases where more than 25 percent move to the same new plant are thus less likely to reflect true layoffs rather than firm-restructuring. We follow this argument and restrict our sample to cases where less than 25 percent of all movers show up at the same new employer in the next year. Our final sample then comprises 9,287 plants in the manufacturing and service sectors that plausibly has a mass layoff in a year between 1980 and 2010.

The second step is to select those workers who experienced one of those mass-layoffs. The Integrated Labor Market Biographies (IEB V12.00.00 - 2015.05.15) is the universe of all German workers subject to social security. This dataset is maintained at the department DIM at the IAB. We requested an excerpt of this dataset that contains the full employment biographies of all workers who held their main job in one of the affected plants on June 30 of year t^*. Following the mass-layoff literature, we only consider workers who were highly attached to the plant before the event. We hence restrict the

[6] A detailed description can be found in Spengler (2008).

sample to workers aged 24 to 50 who had a regular full-time job for at least three years and left the plant anytime between June 30 of year t^* and June 29 of year $t^* + 1$. The final sample consists of 359,264 workers.

For each of those workers, we observe the times of employment and receipt of unemployment insurance benefits with daily precision. Each spell contains information on the start and end date, the average daily wage, demographic characteristics such as sex, age, and education, as well as some employer characteristics including industry, location, and size.

To fit our regression models, we transform the spell data into a dataset containing individual information at the quarterly level. We restrict the analysis to a period of up to 12 quarters before and 24 quarters after the mass layoff. The dependent variables of the analysis are total labor earnings and the number of days spent in employment within a given quarter.

3.2. Measuring Routine Intensity of Occupations

In our empirical analysis, we analyzes whether workers in routine intensive occupations have more difficulties recovering from a layoff compared to otherwise identical workers in less routine intensive occupations. There are various ways to gauge the task content of an occupation. In the US, information on occupations is provided by *O*NET*. In Germany, similar information is provided by *BERUFENET ("Berufe" is the German word for occupations)*. For our purpose, the usefulness of the latter is limited since occupational information stems from interviews of experts conducted in 2011 onwards. This means that the task composition of jobs might be the result of technological change rather than reflect its potential. An occupation that used to be routine intensive in the past might have endogenously changed due to technological change. Workers who held this occupation in the past might then look like non-routine workers according to *BERUFENET* but might have actually suffered particularly strongly from technological change. This would bias our results towards zero.

It is therefore essential to measure the task content of occupations ex ante, that is, at the moment of the layoff or at the beginning of the observation period. This data is provided by the surveys of employees conducted by the Federal Institute for Vocational Education and Training BIBB and the IAB in 1985, 1991, and 1999. In each those surveys, more than 20,000 employees were asked detailed question on the contents and requirements of their occupations. Most questions changed from one wave to the next, but there are two suitable questions that were asked every time:

1) Are the contents of a job minutely described by the employer?
2) Does the job sequence repeat itself regularly?

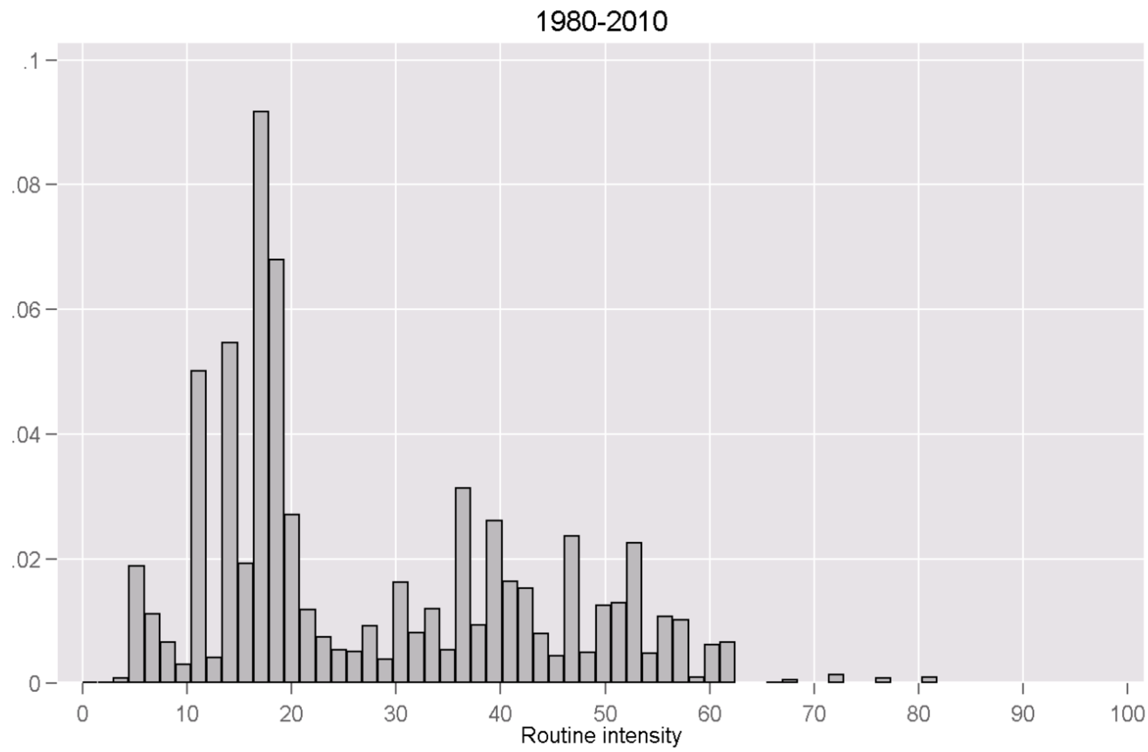
Our measure of routine intensity is defined as the share of individuals within an occupation (defined at the 2-digit level of the *Klassifikation der Berufe 1988* - classification of occupations, 86 groups) who report either of these items to be the case often. Occupations with high measures of this variable are, in our view, more likely to experience substitution of labour by capital as the comparative advantage of machines rests in tasks that follow a pre-described process.

Given that the job contents within occupations are likely to change with time, we construct the routine-intensity variable using data from each of the three surveys. When then proceed to match workers who experienced a mass layoff between 1980 and 1989 with the routine-intensity variable from the 1985 survey, while the variable from the 1991 and the 1999 survey are merged with the employment biographies of individuals who experienced a mass layoff between 1990 and 1999 and between 2000 and 2010, respectively.

3.3. Descriptive statistics

Appendix Table A.1 reports summary statistics of all workers in the quarter before the layoff. In total, 359,264 workers meet the criteria set out in section 3.1. Due to the restriction of the sample, to workers with high labor force attachment, the employment rate is high: on average workers were employed 91 days in the quarter before the layoff. The average quarterly earnings conform to annual earnings of 38,955.48 Euros (deflated to constant 2010 Euros). The main variable of interest is the routine-intensity measure. This varies markedly from 0 (pastors) to 81.82 percent (textile refiners), with an average of 27.68 percent. Figure 1 displays the distribution of this variable for all individuals measured in the quarter before the layoff.

Figure 1: Distribution of routine intensity



Note: The figure displays the distribution of the routine intensity measure in the quarter before the mass-layoff

4. The long-term costs of mass-layoffs

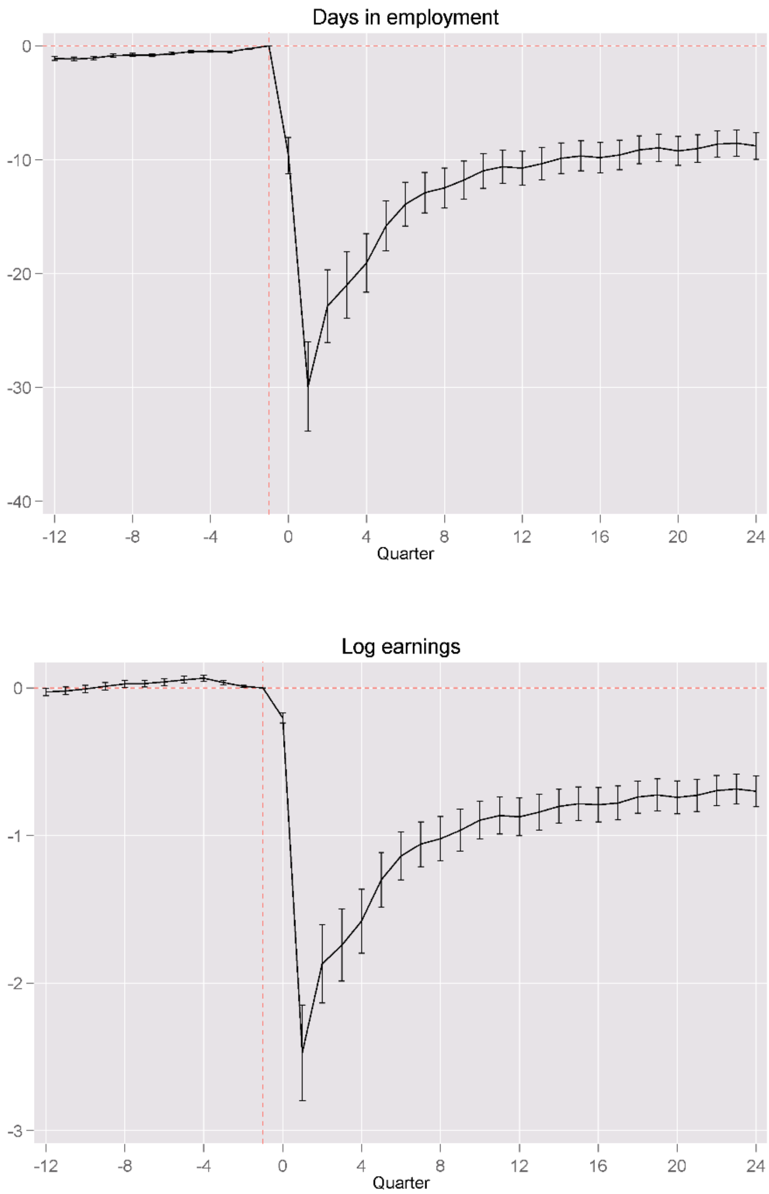
As a benchmark, we start by estimating equation (1) to calculate the average long-term costs of being displaced during a mass layoff following Jacobson, LaLonde, Sullivan (1993). Figure 2 displays the coefficients of the time-to-event dummies. We see that both the employment rate and earnings increase steadily in the 20 quarters prior to the layoff. In the case of earnings, there is a slight Ashenfelter's dip, which indicates that firms were already in trouble before the event and already reduced wages. Columns 1 and 2 of Table A.2 report the coefficient of a linear trend estimated for the pre-event period only. In both cases, a t-test does not reject the null hypothesis that the trend is zero.

In the quarter of the event, employment and earnings decline sharply and reach a minimum in the quarter after the event.[7] Then workers begin to recover and their outcomes level off about 10 quarters

[7] This arises by construction of the sample: the event can occur on any day during a calendar-quarter.

after the event but never fully recover to the pre-event level. This is because some workers become either long-term unemployed or discouraged and drop out of the labour force. In both cases, they drop out of the dataset and we count their employment and earnings as Zero. Columns 3-5 of Table A.2 report the averages and sums of the quarters-to-event dummies in both models. The average decline in employment is 12 days and the average earnings-decline is 0.95 log points per quarter, which conforms to around 4774 Euros ($= exp(8.96) - exp(8.96 - 0.95)$). This amounts to a total loss of 310 days and 114,586 Euros over the six years after the mass-layoff.

Figure 2: Baseline event study results

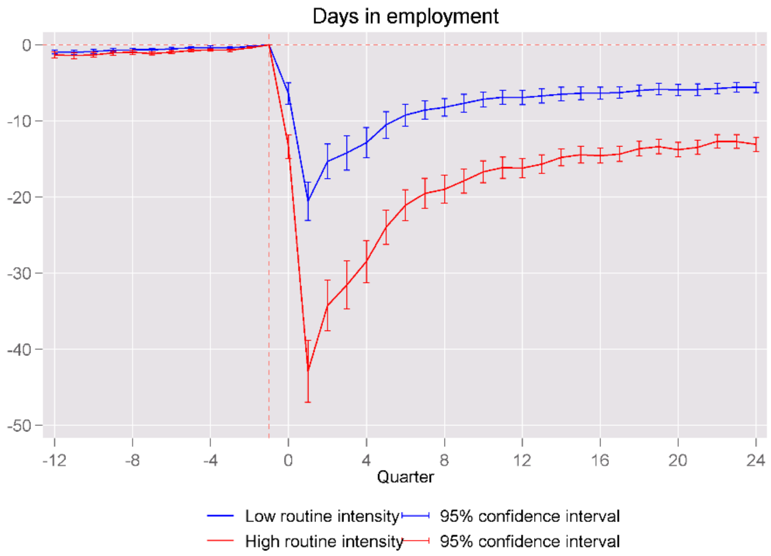


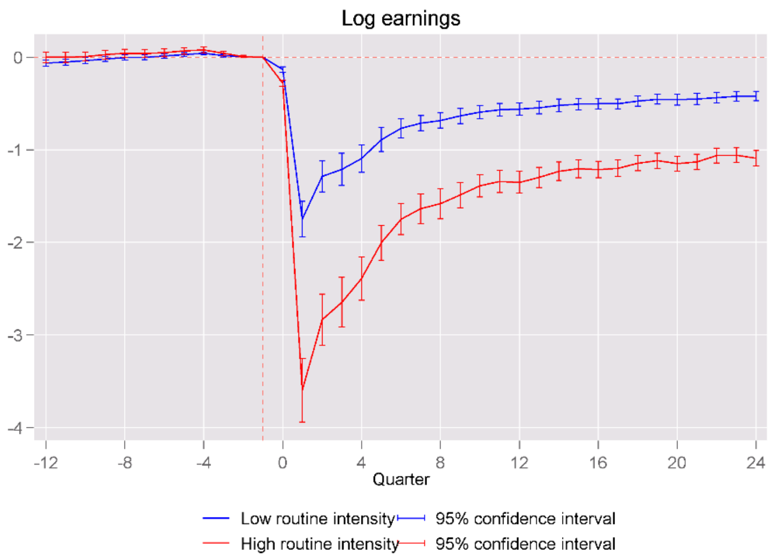
Notes: The figures show the coefficients of the time-to-event dummies indicating the quarters before/after the mass-layoff event. Number of individual workers: 359,624. The vertical bars represent 95% confidence intervals, constructed from standard errors clustered by 86 2-digit occupations.

We can now ask if those long-run effects differ for different occupations. To this end, we re-estimate equation (1) only for the occupations below the 25th and above the 75th percentile of routine intensity, respectively. As can be seen, the careers of the workers in both occupation look very similar before the event. So even in absence of a counterfactual, we may assume that both groups' careers would have evolved similarly if the mass-layoff had not happened. After the event, there is a clear difference: workers in the less routine-intensive occupations have a much less severe drop in employment and earnings immediately after the event. They also recover more quickly at first and have considerably higher earnings and employment by the end of the observation period. In the long run, the earnings loss of workers in the most routine intensive occupations is 19.8 log points larger than that of the least routine intensive occupations. In terms of employment, both groups differ by 246 days.

This may be regarded as an indication that routine workers have more difficulties to adapt after a negative shock. They might have accumulated skills that can be more easily substituted by machines and after leaving their previously stable job, employers seem to be more reluctant to hire them. At the same time, they might have more difficulties to acquire new skills that would make them employable in a different occupation compared to workers in less routine intensive jobs. In the next section, we examine this more systematically.

Figure 3: Event study results for exemplary routine and non-routine occupations





Notes: The figures show the coefficients of the time-to-event dummies indicating the quarters before/after the mass-layoff event from to separate regressions occupations below the 25th (blue line, 90,371 individuals) and above the 75th percentile of routine intensity (red line, 92,551 individuals). The vertical bars represent 95% confidence intervals, constructed from standard errors clustered by 86 2-digit occupations.

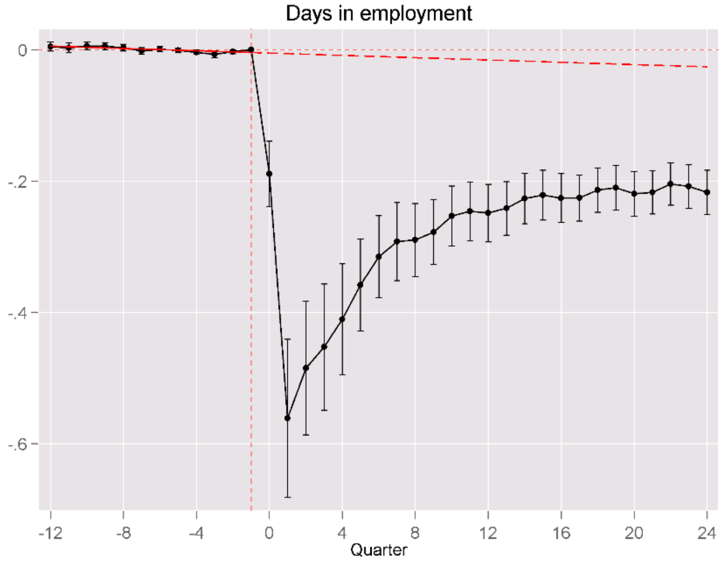
5. Routine tasks and the recovery from mass-layoffs

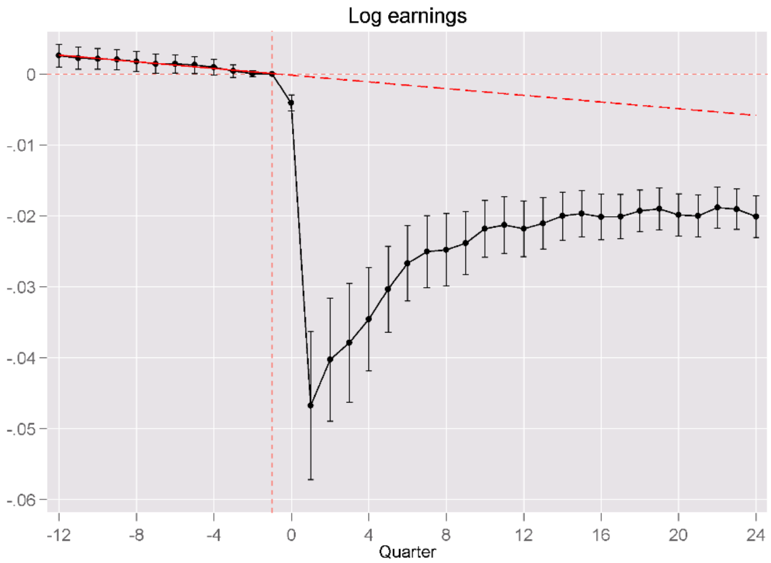
In a next step, we analyze if the long-run costs of a mass-layoff depend systematically from the routine intensity of the last job. We again control for observable characteristics of the workers as well as fixed effects for the previous employer and the 1-digit occupation. This ensures that we do not compare workers with entirely different jobs. Instead, by controlling for the previous employer we identify our main coefficients from the differences between workers who were previously employed in the same environment, under the same institutions and working towards the same goal. Similarly, by controlling for the previous 1-digit occupation, our coefficients will be identified by the differences among workers in the same or related parts of the value chain.

Our estimation approach according to equation (2) is essentially a difference-in-differences estimator. We compare the earnings and employment differences after versus before a mass-layoff for workers in jobs with different routine intensities. The interpretation of this difference as a causal effect requires the identifying assumption that the careers of workers would have evolved along the same trajectories if the layoff had not happened. We can check the plausibility of this assumption by looking at the pre-trends. Columns 1 and 2 of Panel B of Table A.2 report the coefficient of the interaction term of a linear trend interacted with the routine intensity share. The null hypothesis that the trend does not vary with routine intensity is rejected at any significance level. However, while it is precisely estimated, the pre-trend is virtually flat: Each additional percentage point of routine intensity reduces pre-employment by 0.0003 days and earnings by 0.00018 log points per quarter, which means that a one standard deviation difference of routine intensity results in a difference of 0.004 days or 0.28 percent in earnings per quarter in the pre-period. So in economic terms, after conditioning on worker fixed effects, the pre trends do not depend in routine intensity.

Figure 4 reports the coefficients of the interactions between routine intensity and the time-to-to-event dummies. The coefficients before the layoff are mostly not significantly different from zero, which confirms that the careers paths of the observed workers do not systematically differ with respect to the routine intensity of their previous jobs. After the layoff, however, there are large and significant differences. In the quarter after the layoff, when the immediate effect is largest, each additional percentage point of routine intensity increases the employment loss by 0.273 days and the earnings loss by 2.1 percentage points. Over the subsequent six years, this adds up to a substantial loss of 6.8 days and 3,923 ($= exp(8.96) \times 4 \times 6 \times 0.021$) Euros, respectively.

Figure 4: Event study results: Additional loss per percentage point of routine intensity





Notes: The figures show the coefficients of interaction terms of routine intensity and the time-to-event dummies indicating the quarters before/after the mass-layoff event. Each point is the additional employment or earnings loss for each additional percentage point of routine intensity in the job before the layoff. Number of individual workers: 359,624. The vertical bars represent 95% confidence intervals, constructed from standard errors clustered by 86 2-digit occupations.

6. Heterogeneous coefficients

In the previous section, we have shown that the costs of job displacement increase with the job's routine intensity. However, estimating equation (2) for all workers implies that the effect of routine intensity is constant for different groups of workers. This is not necessarily the case: Younger workers might find it easier to adjust and change to a different occupation. The same should apply to high skilled workers who might possess more general human capital that can be applied in various jobs. The effects might also vary with the size of the local labor market. On the one hand, workers who are laid off in a very specialized smaller city could find it even more difficult to adjust because the whole region is affected by the mass layoff. On the other hand, routine replacing technological change might be even faster in larger cities and thus reducing the chances of finding a job in the original occupation even further. Finally, the effect of routine intensity could also vary over time: the machines introduced in the 1980ies replaced a different kind of routine jobs compared to the 1990ies or 2000s. We thus re-estimate equation (2) but split our sample along different dimensions.

In order to assess whether the estimated effects differ across age we split the sample into two groups consisting of individuals who were below and above the median age at the time of the mass layoff. Figure A.1 in the appendix shows that while the initial effect of having been employed in an occupation that was more routine-intensive has a similarly sized effect on the earnings and days in employment for both age groups, the recovery over the subsequent period is less pronounced for older individuals. For members of the older age group having been employed in an occupation in which the routine intensity was higher by one standard deviation implies an accumulated loss of employment over the following 6 years of approximately 115 days. The corresponding value for members of the younger age group stands at 97 days. Similarly, in terms of wage loss the effects amount to -9.1 and -7.3 log points. We proceed by splitting the sample by sex. It can be seen from Figure A.2 that the negative impact of having been employed in a more routine-intensive occupation is larger for females than for males. An increase in routine intensity by one standard deviation leads to an accumulated loss of approximately 123 days in employment for females, but only 96 days for men, while the corresponding wage effects stand at -9.8 and -7.6 log points, respectively. Figure A.3 compares the estimated treatment effects for mass layoffs that took place in urban districts with those occurring in rural areas. The point estimates suggest that the effect of an increase in routine intensity leads to an accumulated employment loss of 112 days in urban regions compared to 84 days in rural areas with the corresponding earnings effects being -9.0 and -5.7 log points.

We next estimate equation (2) separately for three different qualification groups. We define those individuals who at the time of the mass layoff did not have a completed apprenticeship as low skill, those with an apprenticeship as medium skill and individuals with completed tertiary education as high skill. The results, as shown in Figure A.4, suggest that a higher level of qualification reduces the negative wage and employment effects of having formerly been employed in a routine-intensive occupation. The accumulated employment losses stand at 78 days for low-skilled workers, 73 days for medium-skilled workers and 70 days for high-skilled workers. The corresponding earnings losses are 6.7, 5.5 and 4.5 log points, respectively. Finally, we assess whether there has been a change in the magnitude of the negative effects associated with having been employed in a routine-intensive occupation. As indicated by the results shown in Figure A.5, the implications of job loss have become more severe over time. The accumulated loss of employment is given by 92 days for mass layoffs that occurred between 1980 and 1989, 109 days for the period 1990-1999 and 114 days for the period 2000-2010. The corresponding earnings effects are -6.7 log points, -7.7 log points and -10.0 log points.

7. Conclusion

This paper contributes to the research about the effects of technological change by analyzing its effects on the employment biographies of incumbent workers during the past three decades. Specifically, we focus on workers who were displaced during a mass layoff between 1980 and 2010 and thus face an exogenous break in their working lives. After controlling for individual and workplace characteristics, those workers differ only in terms of the extent to which they performed routine tasks in their previous job. We show that adjusting to this shock is more difficult the more routine intensive the previous job was.

The problems of routine workers might be caused by routine biased technological change. Routine operations characterized by a fixed set of rules could be replaced by computer technology relatively easily. However, there are other possibilities: These operations could be relocated to a foreign country.

Either, the relevant products or intermediate products are simply imported from abroad or there is a relocation of the relevant departments of a domestic firm to a foreign country. In both cases it can be expected that routine jobs are affected more by these replacements, because it will be easier to produce routine operations elsewhere than performing more variable or more complicated production steps.

Our results indicate that the occupational paths prior to the mass layoff of the workers in the population under study do not vary with the routine intensity of the original job. This supports the identifying assumption that earnings and employment would have evolved along similar trajectories if the mass-layoff had not happened. The consequence is that, after conditioning on either plant fixed effects and 1-digit industries or worker fixed effects, the workers in our sample with different routine intensities are valid counterfactuals for each other. We find, that after the layoff there is a negative relationship of wages and employment losses and routine intensity: routine intensity aggravates the long term costs of displacement. This indicates that otherwise similar workers have more difficulties in adjusting to a negative employment shock. Technological change has made the experiences and qualifications accumulated in their previous jobs less valuable.

Literature

Autor, David H.; Dorn, David (2013): "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market." *American Economic Review* 103(5), pp. 1553-1597

Autor, David H.; Dorn, David; Hanson, Gordon H. (2015): "Untangling Trade and Technology: Evidence from Local Labour Markets." *Economic Journal* 125(584), pp. 621-646.

Autor, David H.; Levy, Frank; Murnane, Richard J. (2003): "The Skill Content of Recent Technological Change. An Empirical Exploration." *Quarterly Journal of Economics* 118(4), pp. 1279-1333.

Autor, David H.; Salomons, Anna (2017): "Does Productivity Growth Threaten Employment?" Paper presented at the 4th Annual ECB Forum on Central Banking, Sintra, Portugal.

Cortes, Guido Matias (2015): "Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data." *Journal of Labor Economics* 34(1), pp. 63-105.

Davis, Steven J; von Wachter, Till (2011). “Recessions and the costs of job loss”. In: *Brookings Papers on Economic Activity* Fall 2011(1), pp. 1–55.

Goos, Maarten; Manning, Alan; Salomons, Anna (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review* 104(8), pp. 2509-2526.

Hethey-Maier, Tanja and Johannes F. Schmieder (2010). “Does the use of worker flows improve the analysis of establishment turnover: Evidence from German administrative data.” *FDZ-Methodenreport 06/2010.*

Hummels, David; Munch, Jacob R.; Xiang, Chong (2016). „Offshoring and Labor Markets.“ In: *Journal of Economic Literature*, forthcoming.

Jacobson, Louis S.; LaLonde, Robert J.; Sullivan, Daniel G. (1993). “Earnings losses of displaced workers”. In: American Economic Review 83(4), pp. 685-709.

Lommerud, Kjell E.; Straume, Odd R. (2012). "Employment Protection Versus Flexicurity: On Technology Adoption in Unionised Firms." *Scandinavian Journal of Economics 114(1), pp. 177-199*.

Maczulskij, Terhi; Kauhanen, Merja (2017). "Where do workers from declining routine jobs go and does migration matter." *Työpapereita Working Papers* 314.

Schmieder, Johannes; von Wachter, Till; Bender, Stefan (2010). "The long-term impact of job displacement in Germany during the 1982 recession on earnings, income, and employment". *IAB-Discussion Paper 1/2010.*

Spengler, Anja (2008). “European data watch: The establishment history panel”. In*: Schmollers Jahrbuch - Journal of Applied Social Science Studies* 128(3), pp. 501–509.

Spitz-Oener, Alexandra (2006): "Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure." *Journal of Labor Economics* 24(2), pp. 235-270.

Appendix

A. Appendix Tables

Table A.1 Descriptive Statistics

	Obs	Mean	St dev	Min	Max
Routine intensity	359,264	27.68	15.63	0.00	81.82
Earnings	359,264	9,738.87	7,054.77	0.00	456,468.81
Employment duration	359,264	90.95	5.49	1.00	92.00
Earnings (log)	359,264	8.96	1.10	0.00	13.03
Years since labour-market entry	359,264	13.60	6.47	3.00	36.00
Years since entry into establishment	359,264	9.77	5.47	0.00	36.00
Years since start of job	359,264	9.22	5.07	0.00	35.00
Female	359,264	0.30	0.46	0.00	1.00
German nationality	359,264	0.88	0.32	0.00	1.00
Year of birth	359,264	1,956.39	10.47	1930	1986
Qualification					
No apprenticeship	67,471	0.19			
Apprenticeship	263,442	0.73			
Tertiary education (university of applied science)	12,972	0.04			
Tertiary education (university)	15,379	0.04			
Occupation (1-digit)					
0	680	0.00			
1	30,862	0.09			
2	52,998	0.15			
3	50,677	0.14			
4	12,981	0.04			
5	28,504	0.08			
6	69,680	0.19			
7	101,444	0.28			
8	4,856	0.01			
9	6,582	0.02			
Establishment in East Germany	359,264	0.13	0.33	0.00	1.00
Year of mass layoff					
1980-89	100,556	0.28			
1990-99	144,900	0.40			
2000-10	113,808	0.32			
Number of employees	359,264	880.06	2,933.05	50.00	17,341.00
Sector					
1	49,111	0.14			
2	127,660	0.36			
3	54,460	0.15			
4	11,397	0.03			
5	56,275	0.16			
6	30,342	0.08			
7	26,918	0.07			
9	3,101	0.01			

Notes: This table shows summary statistics of the main variables, measured in the quarter before the mass-layoff.

Table A.2: Summary of results

	(1)	(2)	(3)	(4)	(5)	(6)
	Pre-treatment		**Post-treatment**			
	ln(earnings)	**Employment**	**ln(earnings)**		**Employment**	
			Sum	Mean	Sum	Mean
[A] Model 1	**Linear trend**		**Quarter dummies**			
Full sample	-0.00351 (.)	-0.00739 (1.68408)	-23.867*** (1.781)	-0.954*** (0.071)	-310.944*** (21.362)	-12.438*** (0.854)
Low routine	-0.00205 (0.00168)	-0.05250 (0.04464)	-15.917*** (0.962)	-0.637*** (0.038)	-190.700*** (13.627)	-7.628*** (0.545)
High routine	-0.00760*** (0.00103)	-0.01374 (0.00859)	-35.735*** (1.551)	-1.429*** (0.062)	-463.562*** (18.949)	-18.542*** (0.758)
[B] Model 2	**Trend x routine intensity**		**Quarter dummies x routine intensity**			
Full sample	-0.00018*** (0.00004)	-0.00033*** (0.00012)	-0.529*** (0.053)	-0.021*** (0.002)	-6.819*** (0.625)	-0.273*** (0.025)
Below median age	-0.00021** (0.00009)	-0.00027 (0.00019)	-0.470*** (0.046)	-0.019*** (0.002)	-6.224*** (0.612)	-0.249*** (0.024)
Above median age	-0.00016*** (0.00003)	-0.00040*** (0.00009)	-0.581*** (0.068)	-0.023*** (0.003)	-7.369*** (0.707)	-0.295*** (0.028)
Female	-0.00011 (0.00007)	-0.00020 (0.00017)	-0.625*** (0.106)	-0.025*** (0.004)	-7.882*** (1.190)	-0.315*** (0.048)
Male	-0.00017*** (0.00003)	-0.00030*** (0.00009)	-0.487*** (0.044)	-0.019*** (0.002)	-6.137*** (0.488)	-0.245*** (0.020)
Urban	-0.00017*** (0.00005)	-0.00034*** (0.00013)	-0.575*** (0.050)	-0.023*** (0.002)	-7.147*** (0.572)	-0.286*** (0.023)
Rural	-0.00022*** (0.00007)	-0.00031 (0.00022)	-0.3644*** (0.085)	-0.015*** (0.003)	-5.396*** (0.990)	-0.216*** (0.040)
Low skill	-0.00006* (0.00004)	-0.00010 (0.00023)	-0.429*** (0.068)	-0.017*** (0.003)	-5.003*** (0.676)	-0.200*** (0.027)
Medium skill	-0.00014** (0.00007)	-0.00023 (0.00015)	-0.353*** (0.059)	-0.014*** (0.002)	-4.700*** (0.738)	-0.188*** (0.030)
High skill	-0.00014* (0.00008)	0.00039 (0.00030)	-0.285*** (0.097)	-0.011*** (0.004)	-4.465*** (1.070)	-0.179*** (0.043)
1980-89	-0.00020*** (0.00005)	-0.00019 (0.00024)	-0.426*** (0.047)	-0.017*** (0.002)	-5.863*** (0.614)	-0.235*** (0.025)
1990-99	-0.00030*** (0.00008)	-0.0053*** (0.00017)	-0.492*** (0.089)	-0.020*** (0.004)	-6.956*** (0.999)	-0.278*** (0.040)
2000-10	-0.00005 (0.00003)	-0.00020 (0.00013)	-0.641*** (0.080)	-0.026*** (0.003)	-7.312*** (0.904)	-0.292*** (0.036)

Notes: The table summarizes the results of the event studies. Columns 1 and 2 report the coefficient of a linear trend in the pre-treatment period. Columns 3-5 report the coefficients of quarter-to-event dummies. In panel B, the numbers are the coefficients of interaction terms of those variables with the routine intensity of the occupation one quarter before the layoff.

Figure A.1: Event study results for different age groups

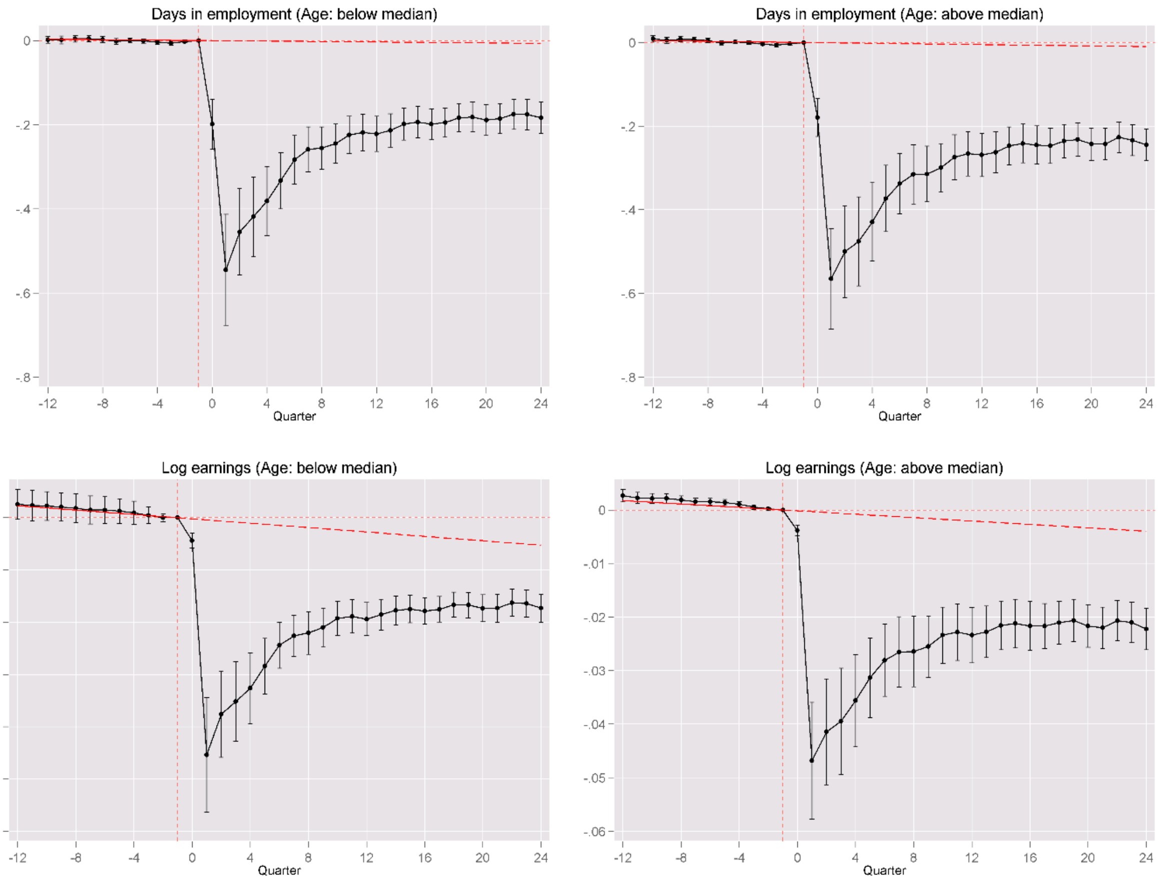
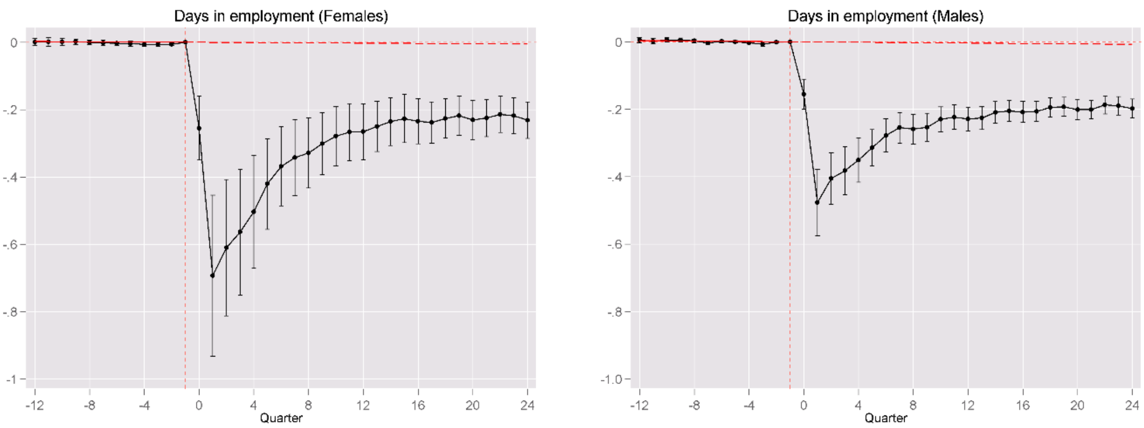


Figure A.2: Event study results by sex



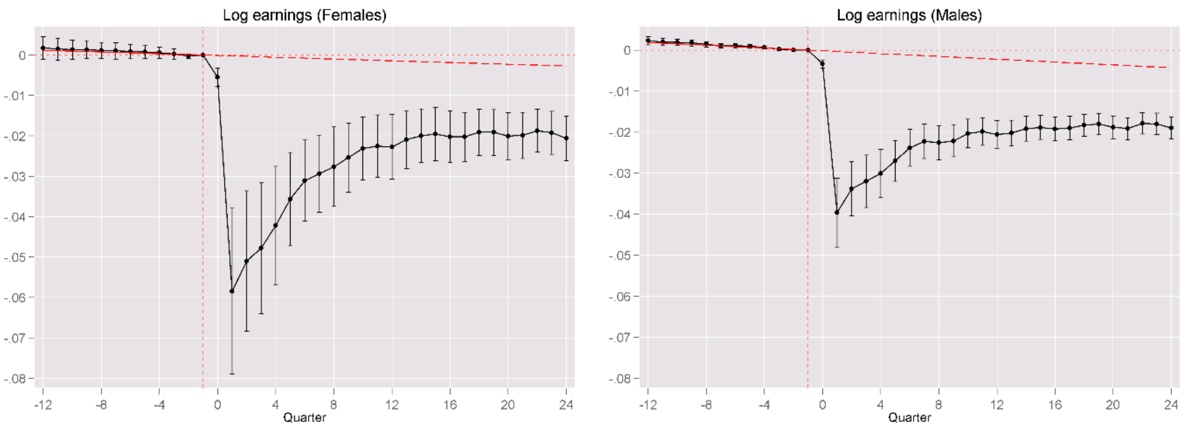


Figure A.3: Event study results by district type

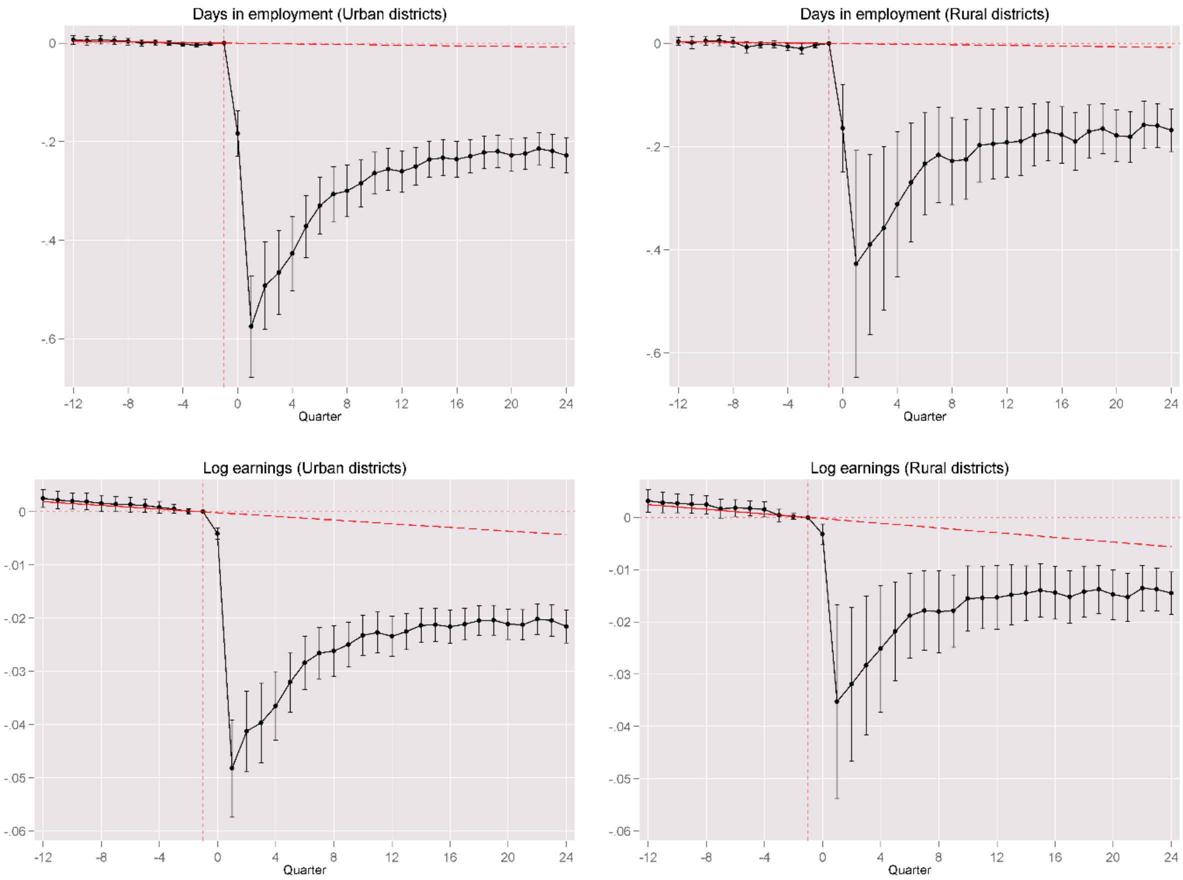


Figure A.4: Event study results by qualification groups

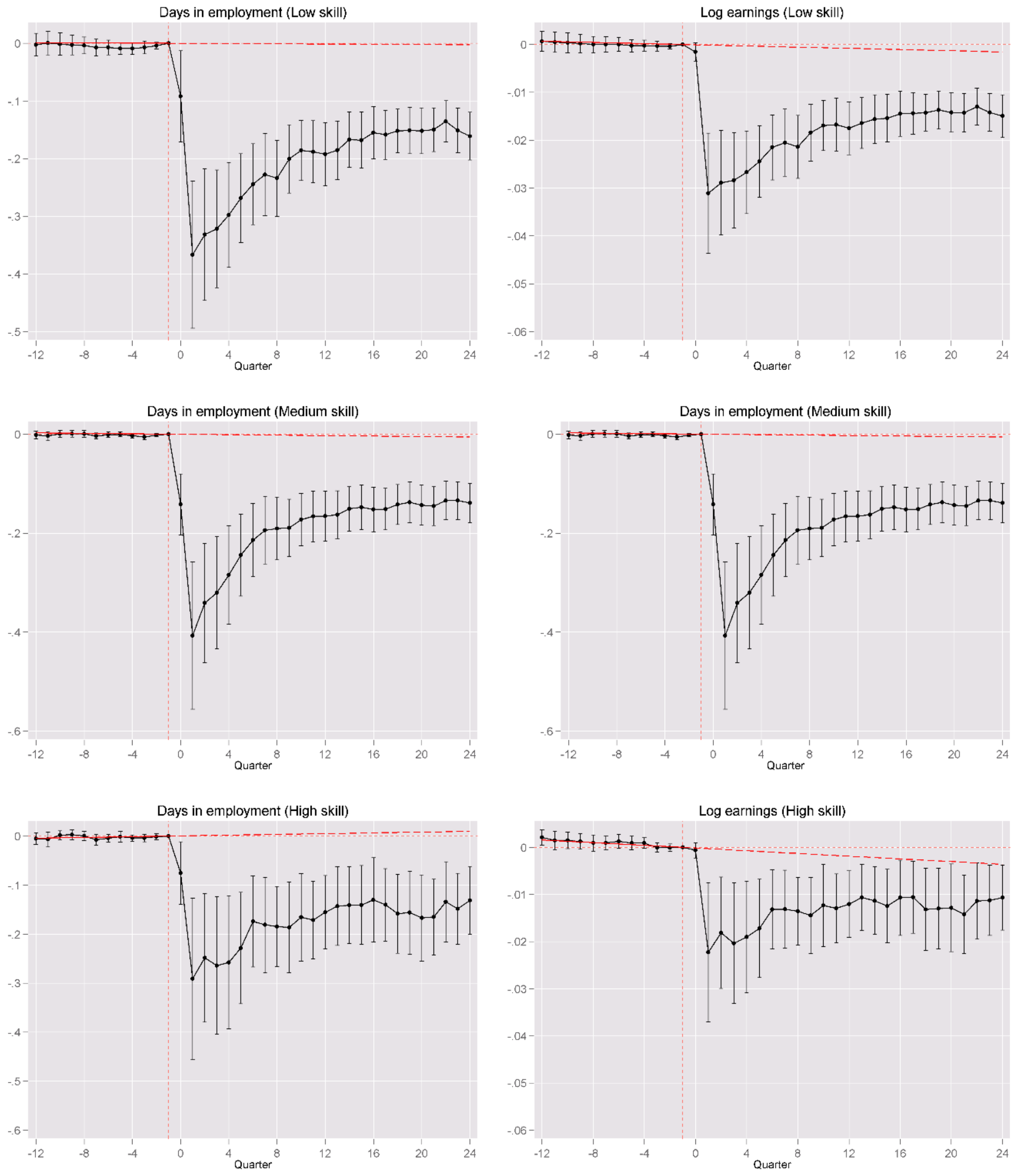


Figure A.5: Event study results by decade of mass layoff