Occupational routine intensity and the adjustment to job loss: evidence from mass layoffs

Uwe Blien[1]

Institute for Employment Research (IAB); University of Bamberg; IZA

Wolfgang Dauth[2]

University of Würzburg; Institute for Employment Research (IAB); IZA

Duncan Roth[3#]

Institute for Employment Research (IAB)

Abstract

Against the background of falling employment shares in routine-intensive occupations, this paper empirically assesses how differences in the degree of occupational routine intensity affect the impact of job loss on a worker's subsequent employment biography. Using data on mass layoffs in Germany between 1980 and 2010, we find that experiencing a mass layoff persistently reduces earnings for all affected workers, but that this effect increases with the degree of initial routine intensity. Decomposing the change in earnings reveals that this effect is driven by similarly sized reductions in the number of days in employment and the level of wages. Moreover, we find that a higher degree of routine intensity reduces employment in higher-quality jobs, while being associated with increased sectoral and reduced regional mobility.

JEL-Classification: J24, J63 O33

Keywords: routine replacing technological change, labour market biographies, mass layoffs, Germany, difference-in-differences

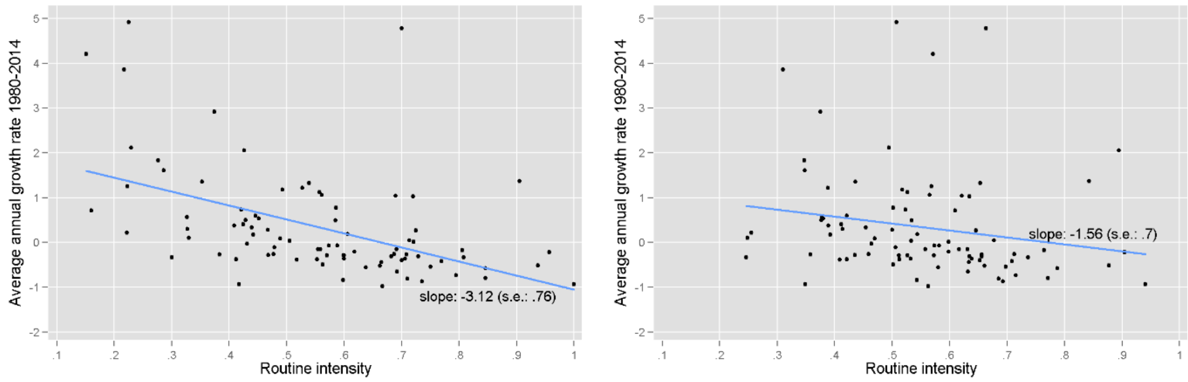
[1] Regensburger Straße 104, 90478 Nürnberg, Germany. E-mail: uwe.blien@iab.de
[2] Sanderring 2, 97070 Würzburg, Germany. E-mail: wolfgang.dauth@uni-wuerzburg.de
[3] Josef-Gockeln-Straße 7, 40474 Düsseldorf, Germany. E-mail: duncan.roth@iab.de
[#] Corresponding author.

1 Introduction

In recent years, technological progress has raised concerns about its effect on employment. On the one hand, these concerns refer to the general level of employment (Autor and Salomons (2018)) which are commonly discussed under the label of 'technological unemployment' – an expression initially termed by Keynes (1933). On the other hand, certain groups of workers appear to be at a larger risk of job loss than others. As computer technology is particularly suited to executing algorithms, i.e. repeatedly following a fixed set of rules, it is potentially able to substitute workers whose jobs primarily consist of performing routine tasks (Autor, et al. (2003), Spitz-Oener (2006)). In this context, profit-oriented firms have been shown to make use of 'routine-biased technological progress' in order to increase productivity (Goos, et al. (2014)).

Empirical evidence suggests that the share of routine jobs is falling (Autor and Dorn (2013), Biagi, et al. (2018)). From an aggregate perspective, this form of technical progress is associated with a polarisation of the labour market (Autor and Dorn (2013), Adermon and Gustavsson (2015), Fonseca, et al. (2018), Ikenaga and Kambayashi (2016), Ross (2017)) in many countries, because most routine-intensive jobs in the US and elsewhere are usually located in the middle of the income distribution. In contrast to the majority of the extant literature, which has focussed on the effects of technological progress at an aggregated level, such as task groups, occupations, sectors or regions (Autor and Dorn (2013), Autor and Salomons (2017)), we adopt a complementary perspective by focussing on individual outcomes. Figure 1 shows that also in Germany the growth of employment has been slower among routine-intensive occupations. Based on this evidence, this paper addresses the question how the degree of routine intensity affects the employment biographies of workers following job loss.

Figure 1: Correlation of occupational employment growth and routine intensity



Panel A: unconditional

Panel B: conditional

<u>Notes:</u> Panel A shows the correlation of employment growth between 1980 and 2014 and the routine intensity of the 83 German 2-digit occupations. In Panel B, both variables have been purged of the occupation's average wage, age, and shares of women and college graduates in 1980. The solid line represents the slope of the regression coefficient.

Incumbent workers, however, may 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 replace workers with machines. Depending on how easily they can be re-trained, incumbent workers are either assigned to a different function or 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 (Lommerud and Straume (2011)). This creates an insider/outsider distinction on how technological change will affect workers. We therefore focus on a group of workers that is particularly vulnerable: Workers who have lost their job during a mass layoff. Those workers face an exogenous shock to their employment biography and previous research has shown that this causes a large and persistent earnings loss (see Jacobson, et al. (1993), Davis, et al. (2011)). We analyse if the magnitude of this loss is systematically related to the routine intensity of the occupation performed before the layoff.[4]

A further major concern is that workers select into occupations for various reasons that are potentially correlated with subsequent labour market outcomes. If routine-intensive jobs require fewer formal skills and offer smaller wages than non-routine jobs, workers with lower (observed and unobserved) skills select into those jobs. It is therefore not clear how much of the difference in labour market outcomes between routine and non-routine workers can actually be attributed to routine replacing technological change and how much to selection on observable or unobservable skills.

To address this concern, we employ an event study design in the spirit of Jacobson, LaLonde and Sullivan (1993) and Davis, Von Wachter, Hall and Rogerson (2011) to analyse if the routine intensity of a worker's previous job affects the chances to subsequently return to the previous earnings level. This allows us to compare workers with similar earnings profiles before the layoff that only differ with regard to the routine intensity of their previous jobs. Indeed, we find that workers initially employed in more routine-intensive occupations do not display largely different developments of the outcome variables during the period before the mass layoff.

Our results indicate that on average mass layoffs severely and persistently reduce earnings, but that this effect becomes more pronounced as the degree of routine intensity increases. In order to identify the mechanisms underlying he earnings effect, we show that routine intensive workers face similarly sized negative effects on the number of days in employment and on wages. Moreover, we find that the initial degree of routine intensity reduces the extent of subsequent employment in higher-quality jobs, increases employment in a different occupation and reduces regional mobility. A possible explanation of these findings is that technological progress has reduced the demand for routine-intensive labour, which increases the costs of adjusting to job loss for workers initially employed in such occupations.

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 move to other occupations. In addition, Maczulskij and Kauhanen (2017) look at the connection to migration. While we emphasis the role of technological progress as the driving force behind the developments described in this paper, we acknowledge that other factors may also be relevant in explaining the fact that the costs of job loss are larger among routine-intensive workers. Autor, et al. (2015) assess the relative importance of technological progress and international trade and find that those sectors that are most affected by imports also employ a relatively high share of routine labour. Moreover, if routine tasks can also be performed abroad, firms may have an incentive to off-shore parts of their employment (Hummels, et al. (2018), Oldenski (2014)).

The structure of the remainder of the paper is as follows. Besides introducing the dataset, Section 2 explains how we identify workers who experienced mass layoff and compares the characteristics of these workers with workers not involved in a mass layoff. Moreover, we discuss our measure of occupational routine intensity. The empirical model and the identification of the treatment effects are the topics of Section 3. The results of our analysis are presented in Section 4. After showing the estimated average impact of mass layoff on earnings, we discuss how these effects differ depending on the initial degree of routine intensity and decompose these effects to identify the underlying

[4] In Germany, larger firms that do not lay off their entire workforce must develop a social plan for a mass-layoff, which essentially sorts workers according to their tenure and not according to their skills. The probability of job loss during a mass layoff is therefore unlikely to be correlated with the routine intensity of the previous job.

mechanisms. In addition, we analyse the transitions into different forms of employment after the mass layoff as well as effect heterogeneity across different groups of workers. Section 5 concludes.

2 Data and variables

The purpose of this section is to describe the dataset and to introduce the main variables of empirical analysis. The first subsection documents how we identify the establishments that experienced mass layoff and how we match information on the workers that were employed at those establishments before the mass layoff. We then proceed to provide information about establishment and worker characteristics and compare them with a random sample of workers who were not involved in a mass layoff. The second subsection introduces our measure of occupational routine intensity.

2.1 Identification of mass layoffs

To construct a dataset of workers who experienced mass layoff first requires identifying those establishments in which such an event occurred. To this end, we adopt the approach set out in established contributions to the mass layoff literature (in particular Davis and von Wachter, 2011). We use the Establishment History Panel (BHP), which includes annual information on all establishments in Germany.[5] This database contains the number of workers subject to social security employed by the establishment on 30 June of a given year. The panel structure of the BHP allows us to identify those establishments that initially have a sufficiently large and stable workforce which then contracts sharply from one year to the next and does not recover to its initial level in the following years. Specifically, for an establishment to be defined as having experienced a mass layoff, we impose the conditions that there must have been at least 50 workers employed on 30 June of year t and the size of the workforce must not have been below 80 percent or above 120 percent of that level in the two preceding years. Between the years t and t+1 the establishment's workforce has to fall by between 30 and 100 percent and must not recover by more than 50 percent of the initial drop within the next two years.

Since the data in the BHP is at the establishment level, it is possible that large changes in the size of the workforce represent restructuring within multi-establishment firms rather than genuine mass layoffs. To remove such cases we follow the approach of Hethey-Maier and Schmieder (2010) who show that the incidence of less than 25 percent of an establishment's initial workforce moving to the same new establishment is highly correlated with the business cycle. By contrast, flows containing more than 25 percent of the initial employment level do not display such a correlation and therefore are more likely to be the result of restructuring. We use the Employment History (BeH), which covers the universe of employees in Germany (except for civil servants and the self-employed), in order to construct a mobility matrix that shows the size of worker flows between any two establishments from 30 June of one year to the next. According to the above argument, we discard establishments that potentially experienced a mass layoff if the size of the worker flows to a single different establishment exceeds 25 percent of the initial size of that workforce.

In the next step, we turn to the workers who experienced a mass layoff. For this purpose, we use the Integrated Employment Biographies (IEB, version 13.00.01-171010), which contain individual-level information on all labour-market participants in Germany (except for civil servants and the self-employed). We then compile the full labour-market biographies of all workers whose main employment on 30 June was at one of the establishments in which a mass layoff took place in the corresponding year. From this group we only retain those individuals who were aged between 25 and 50 at the time of the mass layoff and who had been in regular full-time employment for the three years before leaving the establishment between 30 June of that year and 29 June of the following year. We

[5] Establishments must have at least one worker subject to social security contributions or, from 1999 onwards, at least one marginally employed workers. See Spengler (2008) for further details on the BHP.

motivate these restrictions by the fact that a mass layoff should have a larger impact on individuals who, in the absence of such an event, would be expected to continue working at the establishment; moreover, workers in this age group are unlikely to go straight into retirement after the mass layoff.

The IEB contains spell data corresponding to periods of employment and unemployment with exact start and end dates for each so-identified individual. Moreover, it provides individual-level information associated with these spells such as age, sex, level of education, occupation and average daily earnings as well as information on the establishment such as sector affiliation, size of the workforce and location. Based on this data we construct an employee panel data set at quarterly frequency containing the number of days in employment as well as total earnings per quarter. Each worker in the dataset is observed for 12 quarters before and for up to 24 quarters after the mass layoff.

Our dataset contains 9,365 establishments that experienced mass layoff between 1980 and 2010 and a total of 342,045 affected workers. Table A1 in the Appendix contains information on different characteristics of these establishments that refer to the quarter before the mass layoff. The number of establishments and workers is larger during the last two decades reflecting an increase in the workforce following German re-unification. Initially, mass layoffs occur predominantly in manufacturing with 66% of establishments in the decade 1980-89 and 73% of workers being accounted for by that sector.[6] Though manufacturing remains the largest single sector in terms of mass layoffs, these shares have fallen to 43% and 56%, respectively, in the last decade. At the same time, mass layoffs have become more common in the service sectors with increases in *K – Real estate, renting and business activities*, *I – Transport, storage and communication* as well as *G – Wholesale and retail trade*. Taken together, these sectors account for 49% of the affected establishments and 37% of workers during the decade 2000-2010. More than half of the establishments in the sample employ between 50 and 99 workers, while more than 80% have workforces below 199 employees. The differences between the size groups are considerably smaller in terms of employment shares. During the second and third decade, less than one fifth of establishments are located in East Germany.

The establishments that experienced a mass layoff do not represent the entirety of establishments in Germany. Table A2 in the Appendix compares the employment shares from Table A1 (Panel B) with the corresponding values from a randomly drawn sample of 1 million workers per decade who did not experience mass layoff.[7] Certain sectors that account for non-negligible shares of employees such as *L- Public administration and defence* or *N – Health and social workers* are not present in the mass layoff sample while other sectors (*D – Manufacturing*, *G – Wholesale and retail trade*) are over-represented. In terms of workforce size, workers that experienced mass layoff are more likely to have been in establishments with less than 500 employees, whereas larger establishments account for a considerably smaller fraction of workers. The share of workers in East German establishments, however, is comparable in both samples. Mass layoffs therefore do not appear to be concentrated within one part of the country.

To allow for a better assessment of the individual characteristics of the workers in the mass layoff sample, we compare them to a sample of randomly drawn workers for which the distribution of establishment characteristics is identical to that displayed in Table A1 (Panel B).[8] Table 1 shows that quarterly earnings are lower for workers that experienced a mass layoff during the 1980s, while they

[6] Sector definitions follow the *German Classification of Economic Activities (edition 1993)*. We do not consider mass layoffs that occurred in sector *O – Other community, social and personal service activities*.

[7] We apply the same restrictions to this sample as described in the identification of workers who experienced a mass layoff (e.g. age and minimum level of tenure).

[8] For each combination of decade, sector, workforce size and East/West-location we draw twice the number of observations compared to the mass layoff sample.

are actually larger for the subsequent two decades. The number of days in employment per quarter is very similar in both samples, while the pattern of average daily wage earnings resembles that of quarterly earnings. In terms of the outcome variables there appears to be no evidence that the workers who experienced mass layoff represent a negatively selected sample. The share of females is smaller among those who experienced a mass layoff, while the fraction of foreigners is larger. Moreover, workers in the mass layoff sample have on average two more years of tenure, are more likely to have lower levels of qualification and more often work in manufacturing occupations and less often in service occupations.

Table 1: Worker characteristics

	1980-1989		**1990-1999**		**2000-2010**		**1980-2010**	
	ML	Random	ML	Random	ML	Random	ML	Random
Earnings (quarterly)	8536.50	8787.09	9893.81	9671.34	11134.60	10642.98	9908.63	9732.84
	(3966.27)	(4369.54)	(6281.68)	(5938.22)	(9389.24)	(8148.71)	(7021.06)	(6414.53)
Days in employment (quarterly)	91.04	90.59	91.08	90.65	91.11	90.66	91.08	90.64
	(4.84)	(4.72)	(4.89)	(4.32)	(4.56)	(4.23)	(4.77)	(4.41)
Average daily wage	93.72	96.91	108.54	106.58	122.07	117.23	108.69	107.26
	(43.12)	(47.78)	(68.41)	(65.10)	(102.57)	(89.42)	(76.59)	(70.33)
Female	27.79	30.80	30.54	33.56	27.18	29.21	28.70	31.41
	(44.80)	(46.17)	(46.06)	(47.22)	(44.49)	(45.47)	(45.24)	(46.41)
Foreign	16.13	12.40	11.59	8.92	8.25	7.97	11.80	9.59
	(36.78)	(32.96)	(32.01)	(28.51)	(27.51)	(27.09)	(32.26)	(29.45)
Age	38.20	39.76	37.61	37.13	39.09	37.08	38.24	37.85
	(7.45)	(8.08)	(7.12)	(7.89)	(6.53)	(7.37)	(7.06)	(7.87)
Tenure	7.91	6.87	9.49	7.41	10.14	7.35	9.26	7.24
	(2.80)	(2.72)	(5.39)	(4.69)	(5.98)	(4.77)	(5.10)	(4.27)
Skill: low	28.45	26.39	15.98	13.80	13.22	9.39	18.59	15.92
	(45.12)	(44.08)	(36.65)	(34.49)	(33.87)	(29.17)	(38.90)	(36.58)
Skill: medium	68.15	68.41	75.93	77.08	75.17	75.65	73.52	74.21
	(46.59)	(46.49)	(42.75)	(42.03)	(43.20)	(42.92)	(44.12)	(43.75)
Skill: high	3.40	5.19	8.08	9.13	11.60	14.96	7.89	9.88
	(18.13)	(22.19)	(27.26)	(28.80)	(32.03)	(35.67)	(26.97)	(29.84)
Agriculture/Fishing	0.11	0.15	0.07	0.15	0.11	0.19	0.09	0.17
	(3.28)	(3.91)	(2.73)	(3.92)	(3.29)	(4.39)	(3.08)	(4.07)
Mining/Quarrying	0.13	0.15	0.09	0.07	0.01	0.02	0.08	0.08
	(3.61)	(3.85)	(2.92)	(2.71)	(1.18)	(1.47)	(2.75)	(2.79)
Manufacturing	57.00	51.57	49.40	46.49	41.96	40.25	49.16	45.93
	(49.51)	(49.98)	(50.00)	(49.88)	(49.35)	(49.04)	(49.99)	(49.83)
Technical occupations	9.80	10.33	11.59	10.46	12.13	10.94	11.26	10.57
	(29.73)	(30.43)	(32.01)	(30.60)	(32.64)	(31.21)	(31.61)	(30.75)
Services	32.96	37.80	38.85	42.82	45.80	48.59	39.41	43.25
	(47.01)	(48.49)	(48.74)	(49.48)	(49.82)	(49.98)	(48.87)	(49.54)
Observations	95,529	191,058	137,929	275,858	108,587	217,174	342,045	684,090

__Notes:__ The table shows the share of workers in percentage points as well as the corresponding standard deviations for various individual-level characteristics. The columns 'ML' show the values for those workers who experienced a mass layoff (measured *at the quarter directly preceding the mass layoff). The columns 'Random' show the values for a randomly chosen group of workers who did not experience mass layoff, but who satisfy the same conditions as the workers in the mass layoff sample (e.g. age and minimum level of tenure).*

2.2 Construction of the routine-intensity measure

The objective of this paper is to assess whether the degree to which an employee's occupation contains routine components affects how workers can adjust to unexpected job loss. In order to analyse this relationship, a measure of occupational routine intensity is required. Related studies from the US have made use of information provided by the Dictionary of Occupational Titles (DOT) or the Occupational Information Network (O*NET) to construct corresponding measures (see Autor (2013) for a description of these datasets).

While a comparable source of information about the contents of occupations is available in the form of BERUFENET[9], it does not lend itself to the analysis of this paper because it is constructed from interviews with experts from the year 2011 onwards. Due to changes in occupational contents, the current prevalence of routine components within an occupation might not reflect the situation several decades ago. Specifically, the current state of an occupation's contents might already be an outcome of technological change.

To avoid this problem, we extract information from a contemporaneous data source which should better provide information about the prevalence of routines within an occupation at the time of the mass layoff. The 'employee survey' ('*Erwerbstätigenbefragung'*), which has been conducted by the Federal Institute for Vocational Education (BIBB) and the Institute for Employment Research (IAB) in the years 1985, 1991 and 1999, contains detailed questions about the contents and requirements of a job and contains about 20,000 individuals per survey. Machines are especially able to perform processes that follow well-defined routines. We argue, therefore, that the use of technology is particularly suited in occupations in which such processes are common. To capture this idea, we make use of the following two survey items:

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

We define our measure of routine intensity as the share of workers within an occupation who report both items to be the case *'almost always'*.[10] The advantage of these items is that they are coded consistently across the different survey waves that we use and therefore do not suffer from changes in the wording of the questions or in the answer options as is the case with the information about the different tasks that workers perform (for example, Spitz-Oener (2006) or Antonczyk, et al. (2009)). Moreover, our measure avoids the need for an ad-hoc assignment of tasks into broader groups, but instead provides a measure of potential exposure to the implementation of technological capital.

Routine intensity is computed for each of 83 occupations corresponding to the third level (*'*Berufsgruppen') of the 1988 occupational classification scheme (*'Klassifikation der Berufe 1988'*).[11] The occupational code provides the link between the survey and the administrative data. Specifically, we assign each worker the routine intensity of the occupation performed during the quarter directly preceding the mass layoff. In doing so, we match the measure derived from the 1985 survey with

[9] 'Beruf' is the German word for occupation (see www.berufenet.arbeitsagentur.de).

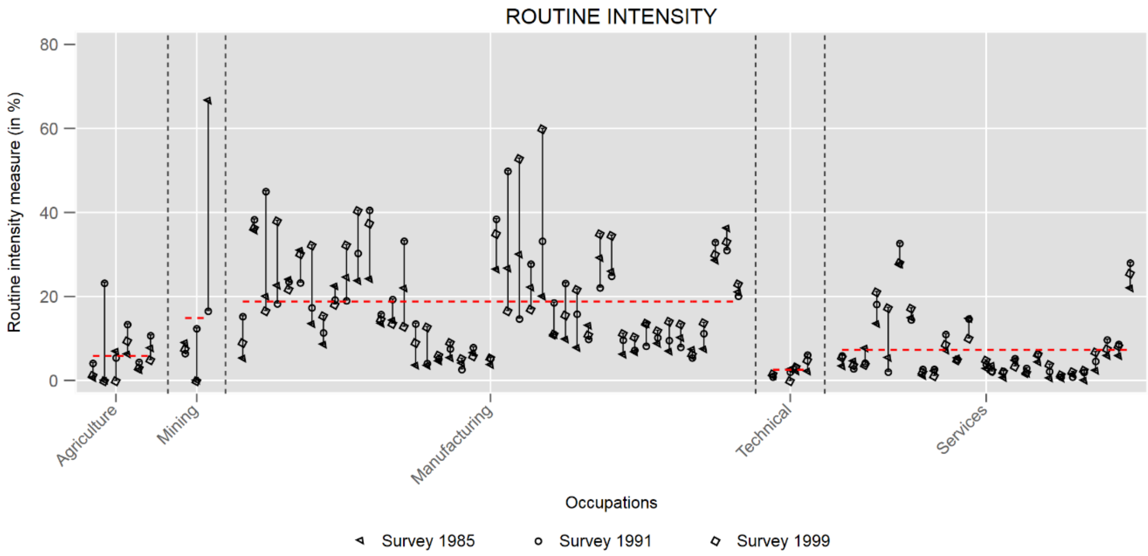
[10] The remaining answer options are *'often'*, *'occasionally'*, *'rarely'* and *'hardly anytime'*. Table 6 shows that our findings are robust to using the share of workers reporting both items to be the case either *'almost always'* or *'often'*.

[11] We do not consider the group *'Other occupations'* (*'Andere Arbeitskräfte'*).

individuals who experienced mass layoff during the decade 1980-89. We use the 1991 and 1999 survey in the same way for mass layoffs that occurred during the period 1990-99 and 2000-10, respectively.

Figure 2 shows the routine intensity of each occupation as estimated from the employee surveys of the years 1985, 1991 and 1999. The highest value of routine intensity for a single occupation applies to *'mineral preparers'* in the 1985 survey. However, within broad occupational groups average routine intensity is highest among manufacturing occupations. *'Spinners'*, *'textile makers'* and *'textile refiners'* display particularly high values of routine intensity, as do *'ceramics workers'*, *'moulders'* and *'metal moulders'*. In contrast, routine intensity is considerably smaller on average within technical occupations[12] and service occupations, although higher values are also to be found in the latter group for *'communication occupations'* and *'cleaning occupations'*. The average routine intensity for agriculture and mining occupations falls between the values found in technical and manufacturing occupations, but, as shown in Table 1, the former two groups only account for a very small share of employees in the mass layoff sample.

Figure 2: Occupational routine intensity



Notes: The graph shows the estimated routine intensity measure of each occupation separately for the surveys from the years 1985, 1991 and 1999. The solid vertical lines display the range of occupational routine intensity over the three survey years. The dashed vertical lines delineate broader occupational groups ('Berufsbereiche'), while the dashed horizontal lines represent the average routine intensity within these groups.

For many occupations the share of workers reporting both of the above-mentioned items to be the case *'almost always'* takes on a comparable magnitude across the different survey years. This is especially the case for technical occupations and service occupations, whereas larger discrepancies occur for some manufacturing occupations. On the one hand, these differences may represent genuine changes in occupational contents. On the other hand, they may also reflect an imprecise estimation of routine intensity. Indeed, the average number of observations in the survey for each of the previously mentioned manufacturing and mining occupations, which not only display large values but also large differences across survey years, are also comparatively small.

In the empirical analysis, we relate subsequent changes in outcome variables, such as quarterly earnings, to the level of routine intensity at the time of the mass layoff. Changes in the routine intensity of an occupation over time that do not reflect genuine changes in occupational contents could bias the

[12] Among other occupations, this group includes engineers, architects, chemists, physicists.

estimated effects if these differences were related to changes in the severity of mass layoffs for all or several occupations. To address this concern, we assign each individual the value of occupational routine intensity from a single survey. As a result, we rule out that for any given individual the estimated effects are driven by an association between changes in outcomes and changes in routine intensity. Moreover, we purge the effect of average shifts in the routine intensity measure across survey years through the inclusion of calendar fixed effects.

To further validate the robustness of our findings, we show that similar results are obtained if the analysis is restricted to observations from a single decade (and hence using routine intensity measures from a single survey year, see Table 5). Moreover, we find that the estimated effects of routine intensity are not only restricted to mass layoffs in manufacturing but that they also apply to mass layoffs occurring outside of manufacturing (see Table 5). Finally, we show that the estimated effects are not driven by the discrepancies in the routine intensity measures across survey years by using the routine intensity derived from a single survey for the whole period (see Table 6).

Analogous to Table 1, we show descriptive statistics for the routine intensity measure for individuals who experienced a mass layoff and compare them with the corresponding values for a randomly chosen group of workers who did not experience mass layoff. Table 2 shows that average routine intensity in the mass layoff sample takes on similar values in each of the three decades of the analysis and that these values do not appear to differ materially from those of the randomly chosen sample. We conclude, that, as was the case for the three outcome variables, the employees in the mass layoff sample do not represent a negatively selected sample characterised by unusually high levels of routine intensity.

Table 2: Worker characteristics (routine intensity)

	1980-1989		1990-1999		2000-2010		1980-2010	
	ML	Random	ML	Random	ML	Random	ML	Random
Routine intensity	12.03	11.56	13.48	13.03	12.33	12.33	12.71	12.40
	(9.69)	(9.73)	(11.61)	(11.18)	(10.66)	(10.87)	(10.82)	(10.71)
Observations	95,529	191,058	137,929	275,858	108,587	217,174	342,045	684,090

Notes: The table shows mean values of routine intensity as well as the corresponding standard deviations. The columns 'ML' show the values for those workers who experienced a mass layoff (measured at the quarter directly preceding the mass layoff). The columns 'Random' show the values for a randomly chosen group of workers who did not experience mass layoff, but who satisfy the same conditions as the workers in the mass layoff sample (e.g. age and minimum level of tenure).

3 Empirical strategy

We first analyse the effects that a layoff has on an individual's labour market outcome by using an event study design typically used in the literature on mass layoffs (see Jacobson, LaLonde and Sullivan (1993) and Davis, Von Wachter, Hall and Rogerson (2011)). Specifically, we estimate the following difference-in-differences specification:

$$\ln(y_{it}) = \sum_{k=-12}^{k=24} \delta_k \, I(t = t' + k) + \varphi_t + \alpha_i + u_{it} \tag{1}$$

The dependent variable y_{it} represents an outcome variable (quarterly earnings, number of days in employment per quarter, average daily earnings) of individual *i* during quarter *t*.[13] $I(t = t' + k)$ stands for a set of time-to-event dummies which indicate the timing of quarter *t* relative to the quarter of the mass layoff *t'*. The baseline period is the quarter directly preceding the mass layoff ($k = -1$). The coefficients δ_k provide information about the change in the value of the outcome between quarter *t*

[13] We add the value of 1 to these variables in order to prevent that an observation drops out of the sample during a spell of non-employment.

and the quarter of the mass layoff. They therefore shed light on the average development of outcomes following the mass layoff. In addition, the model includes a set of calendar fixed effects at the quarterly level, which account for unobserved time-specific effects. α_i represents individual fixed effects that allow us to control for unobserved, time-invariant worker characteristics and u_{it} is a random error term.

In order to assess how the effect of job loss varies with the prevalence of routine components in an individual's occupation, we extend the model shown in Equation (1) by including interactions between our treatment measure, i.e. the degree of routine intensity, RI_i, measured during the quarter before the mass layoff, and the time-to-event indicators:

$$\ln(y_{it}) = \sum_{k=-12}^{k=24} [\beta_k I(t = t' + k) + \gamma_k RI_i \times I(t = t' + k)] + \psi_t + \eta_i + v_{it} \quad (2)$$

The coefficients γ_k show how an increase in occupational routine intensity by one percentage point affects the magnitude of the change in the outcomes from the quarter of the mass layoff (*k = -1*) and the quarter *k*. The corresponding coefficient estimates therefore provide the basis for evaluating whether workers in more routine-intensive occupations suffer larger costs as a result of job loss and whether this effect is persistent.

It is possible that in the absence of a mass layoff the outcomes of workers in more routine-intensive occupations would have developed differently to those of workers with a lower degree of routine intensity. In such a case, the coefficient estimate of γ_k would provide an incorrect estimate of the treatment effect. In order to address this concern we compute a linear extrapolation of the estimated coefficients of γ_k from the pre-treatment period which we argue provide us with a counterfactual against which we can evaluate the impact of the treatment variable (see Ahlfeldt, et al. (2018)). To this end, we regress the coefficient estimates of γ_k on a constant and a linear trend:

$$\hat{\gamma}_{k|k\leq-1} = \pi_0 + \pi_1 k + w_k \quad (3)$$

The estimated coefficients of the above equation form the basis for computing the counterfactual for the post-treatment period:

$$\hat{\tau}_{k|k>-1} = \hat{\gamma}_k - (\hat{\pi}_0 + \hat{\pi}_1 k) \quad (4)$$

In order to quantify the impact that changes in the degree of routine intensity have on the adjustment to job loss, we compute three forms of treatment effects. First, we compute the proportional change in the outcome that is due to an increase in the degree of routine intensity by *ΔRI* for the first quarter after the mass layoff:

$$r_1 = exp(\hat{\tau}_1 * \Delta RI) - 1 \quad (5)$$

On average, the outcome of a worker whose degree of routine intensity is higher by *ΔRI* will, ceteris paribus, be lower by $100*r_1$% in quarter k = 1. Second, as the magnitude of the treatment effect can vary across the quarters of the post-treatment period, we also compute an average measure for the proportional change:

$$\bar{r} = exp\left(\bar{\hat{\tau}}_k * \Delta RI\right) - 1 \quad (6)$$

Third, for each quarter we compute an estimate of the difference in the outcome that is due to an increase in the initial level of routine intensity by an amount *ΔRI*. We then proceed to compute the estimated cumulated difference by summing the quarter-specific effects over the post-treatment period:

$$a_k = \left[exp(\hat{\beta}_k) exp(\hat{\tau}_k RI) y_{it|k=-1}\right] * \left[exp(\hat{\tau}_k * \Delta RI) - 1\right] \quad (7)$$

$$a = \sum_{k=1}^{24} a_k \quad (8)$$

When computing this effect, we set the routine intensity variable to its median value and use the mean value of the outcome from the quarter before the mass layoff.

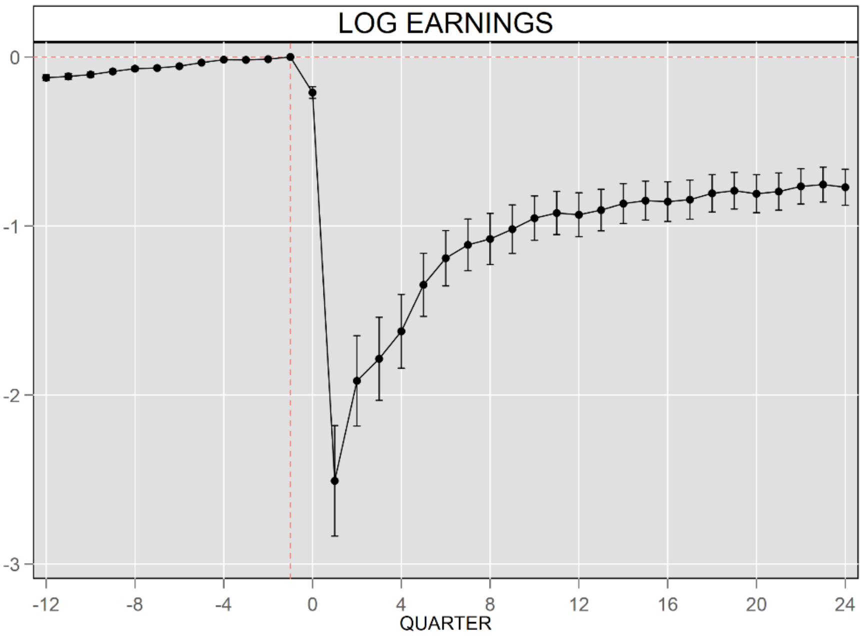
Through the inclusion of individual fixed effects we control for the influence of time-invariant factors such as individual-level and establishment-level characteristics measured at the time of the mass layoff. In an alternative specification, we use these characteristics as control variables instead of the individual fixed effects. Table 6 shows that the results are similar to those of the fixed effects specification. As the routine intensity measure does not vary within occupations, standard errors are clustered at the occupational level.

4 Results

4.1 Effects of mass layoffs

This subsection illustrates the impacts of experiencing a mass layoff by estimating Equation (1) using log quarterly earnings as the dependent variable. Figure 3 shows that up to the quarter preceding the mass layoff quarterly earnings tended to grow on average. The incident of the mass layoff then stipulates a rather different development as there is a sharp decline in earnings by an average of 2.5 log points during the first quarter after the mass layoff. While earnings subsequently recover during the post-treatment period, they stagnate well below the pre-treatment level. Since earnings are the product of the days in employment per quarter and the average daily wage earned during employment, this development suggests that experiencing a mass layoff is followed by a transition into unemployment and/or transitions into lower-paying jobs.

Figure 3: The impact of mass layoffs on earnings



Notes: The graph is based on the results from estimating a fixed effects model of individual log quarterly earnings regressed on time-to-event dummies and calendar dummies. Dots represent the estimated coefficients of the time-to-event dummies that indicate the quarter relative to that during which the mass layoff occurred (baseline: the quarter directly preceding the mass layoff). Vertical bars indicate the estimated 95% confidence interval derived from standard errors that are clustered at the level of 83 occupations.

Panel A of Table 3 provides an overview of the immediate effect that a mass layoff has on the three outcome variables. Quarterly earnings fall by approximately 30% between the quarters directly preceding and following the mass layoff, while similarly sized effects are found for days in employment and average daily wages.

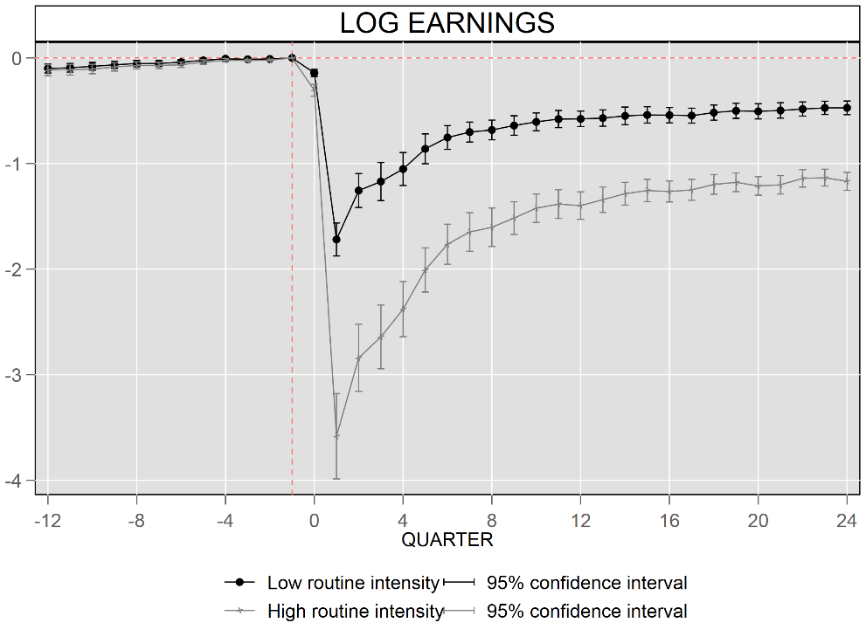
Table 3: Comparing outcomes immediately before and after the mass layoff

Outcome	(1) Quarter before mass layoff (k = -1)	(2) Quarter after mass layoff (k = 1)	(3) % change
Panel A – All workers			
Earnings (quarterly)	9908.63	7028.23	-29.07
Days in employment (quarterly)	91.08	61.72	-32.23
Average daily wage	108.69	82.03	-24.53
Panel B – Workers in low-routine occupations			
Earnings (quarterly)	13455.93	10657.21	-20.80
Days in employment (quarterly)	91.23	71.55	-21.57
Average daily wage	147.40	121.58	-17.52
Panel C – Workers in high-routine occupations			
Earnings (quarterly)	7299.28	3985.43	-45.40
Days in employment (quarterly)	90.89	49.01	-46.07
Average daily wage	80.27	48.88	-39.11

Notes: The table shows the average values of the outcome variables for the quarters directly preceding and following the mass layoff as well as the percentage change in these values. Low-routine occupations refer to the first quarter of the routine-intensity distribution during the quarter before the mass layoff, while high-routine occupations refer to the fourth quarter.

That the adjustment to job loss varies with the degree of routine intensity can already be seen from Figure 4, which contrasts the development of earnings of workers initially employed in occupations from the first and the fourth quarter of the routine intensity distribution. While the profile of earnings growth was remarkably similar in the period before the mass layoff, the initial earnings drop is considerably larger for workers from high-routine occupations. Although the initial recovery from job loss appears to be faster for this group, earnings losses are persistently larger. Panels B and C of Table 3 show that the initial drops are indeed greater for every outcome among workers from high-routine occupations.

Figure 4: The impact of mass layoffs on earnings by routine intensity



Notes: See Figure 3. Separate models are estimated based on individuals whose occupation during the quarter before the mass layoff had a routine intensity belonging to the first and the last quartile, respectively, of the routine intensity distribution of that quarter.

4.2 Baseline specification

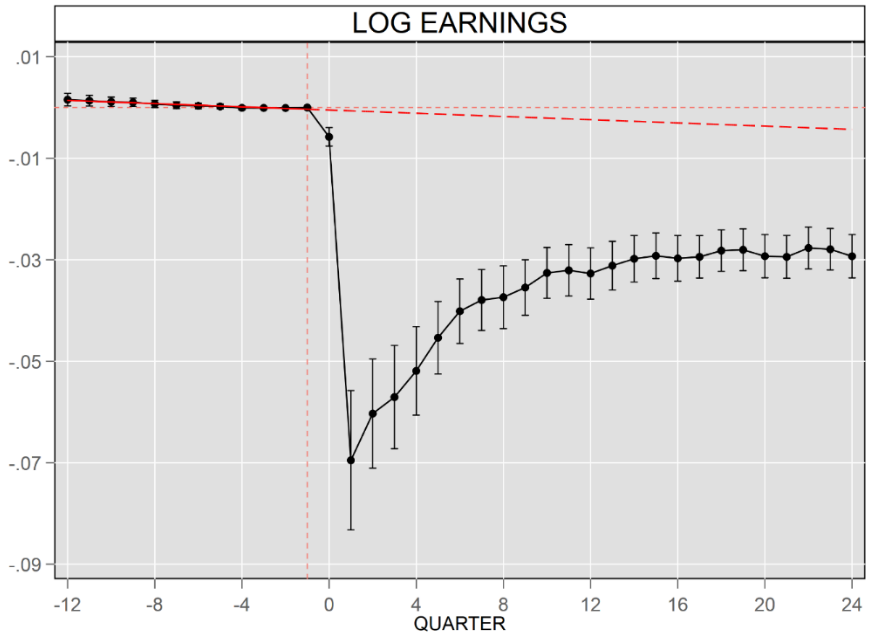
The previous results showed that the costs of job loss are larger and more persistent among workers in occupations with a high routine intensity compared to workers in occupations with a low routine intensity, even though their earnings profiles were remarkably similar before the layoff. However, one might object that workers in occupations at the extremes of the distribution of routine intensity are not comparable in many ways. We therefore estimate Equation (2), where the time-to-event indicators are interacted with a continuous measure of routine intensity. This allows comparing the long run effects of a layoff for otherwise equal workers who have similar jobs with routine intensities that differ only by a small extent.[14] Figure 5 reports the estimated coefficients of the interaction terms. The interpretation of these estimates is by how many log-points the earnings loss in the *k*th quarter (relative to the quarter before the layoff) is magnified due to a 1 percentage point increase in routine intensity. Alternatively, these coefficients indicate the proportional difference in the earnings in quarter k between the workers whose routine intensity differs by one percentage point.

Prior to the layoff, the coefficients drop from small and barely significant positive values to virtually zero in the quarters immediately before the layoff. This indicates that workers in more routine intensive jobs had a slightly smaller real wage growth compared to workers in less routine intensive jobs. We account for these ex-ante differences by linearly extrapolating the pre-treatment trend as shown by the dashed line. We then calculate the treatment effect of routine intensity as the difference between the coefficient of the interaction term and the extrapolated pre-treatment trend. This correction, however, is relatively small. For workers whose initial degree of routine intensity was higher by one percentage point, earnings are predicted to fall by 0.00016 log points each quarter relative to the quarter preceding the mass layoff.

[14] If the model contained fixed effects for the 1-digit occupation group a worker held prior to the layoff, then the coefficients would be identified only by the variation within this group. Since our model includes individual fixed effects, those occupation fixed effects are redundant, but this interpretation still holds.

After the layoff, all interaction terms have large negative coefficients, which does not change even after correcting for differences in pre-treatment trends. The negative sign of the treatment effect implies that workers who were initially employed in an occupation with a higher degree of routine intensity suffer larger earnings losses. While the proportional difference becomes smaller over time, it remains negative and stabilises at a value of around -0.03.

Figure 5: Treatment effects on log earnings



<u>Notes:</u> The graph is based on the results from estimating a fixed effects model of individual log quarterly earnings regressed on time-to-event dummies, interactions between treatment variable and time-to-event dummies and calendar dummies. Time-to-event dummies indicate the quarter relative to that during which the mass layoff occurred (baseline: the quarter directly preceding the mass layoff). The treatment variable is defined as the routine intensity of the occupation that an individual was employed in during the quarter before the mass layoff. Dots represent the estimated coefficients of the interaction terms. Vertical bars indicate the estimated 95% confidence interval derived from standard errors that are clustered at the level of 83 occupations. The solid part of the line shows the fitted values of a regression of the estimated coefficients of the interaction terms from the pre-treatment period on a constant and a linear trend; the dashed part represents the linear extrapolation of this relationship into the post-treatment period. The quarter-specific treatment effects are given by the vertical difference between the dots representing the coefficient estimate of the interaction term and the dashed line which represents the linear extrapolation of the pre-treatment trend.

Panel A of Table 4 quantifies the treatment effect – the difference in the change in earnings due to a difference in the degree of initial routine intensity – in three different ways. Column (1) shows that a difference in routine intensity by one percentage point on average further reduces the level of earnings in the first quarter after the mass layoff by approximately 7%, ceteris paribus. When we compare two workers who had jobs that differ by one standard deviation, their earnings difference is 53%. Comparing a worker at the 10th and one at the 90th percentile of the distribution of routine intensity results in an earnings difference of 84 percent. This effect is largest immediately after the mass layoff and decreases over time. The average proportional difference over 24 quarters after the layoff amounts to an additional reduction of 3% in the case of a difference in routine intensity by one percentage point. To obtain an intuition of the absolute magnitude of this effect, we evaluate the difference at the median routine intensity and benchmark it against the earnings of the average worker during the quarter before the mass layoff. Our results imply a cumulated additional earnings loss of 3,200 Euros for each additional percentage point of routine intensity. For a one standard deviation difference of routine intensity, the cumulated earnings difference will be approximately 30,000 Euros and even more than 43,000 Euros for two workers who differ by one interdecile range.

Table 4: Treatment effects of routine intensity on labour market outcomes after mass-layoffs

ΔRI	(1) Relative change (k = 1)	(2) Relative change (average)	(3) Absolute change (cumulative)
Panel A – Earnings (quarterly)			
Percentage point	-0.07	-0.03	-3,226.17
Standard deviation	-0.53	-0.31	-29,797.25
Interdecile range	-0.84	-0.60	-43,262.00
Panel B – Days in employment (quarterly)			
Percentage point	-0.04	-0.02	-24.79
Standard deviation	-0.33	-0.18	-244.72
Interdecile range	-0.63	-0.39	-443.35
Panel C – Average daily wage			
Percentage point	-0.03	-0.02	
Standard deviation	-0.29	-0.16	
Interdecile range	-0.57	-0.35	

Notes: The table contains different forms of treatment effects for each of the three outcome variables computed for different changes in the routine intensity variable. The second column shows the proportional difference in the change in the outcome variable for the first quarter after the mass layoff, while the third column shows an average effect across all quarters of the post-treatment period. The final column contains the sum of the absolute difference in the change of the outcome over all quarters of the post-treatment period. In the case of the absolute change, the initial degree of routine intensity takes on the median value of the quarter preceding the mass layoff for changes by one percentage point and by one standard deviation, while the value is set to the 10th percentile for a change by the interdecile range. Moreover, the outcomes are set to mean value of the quarter before the mass layoff.

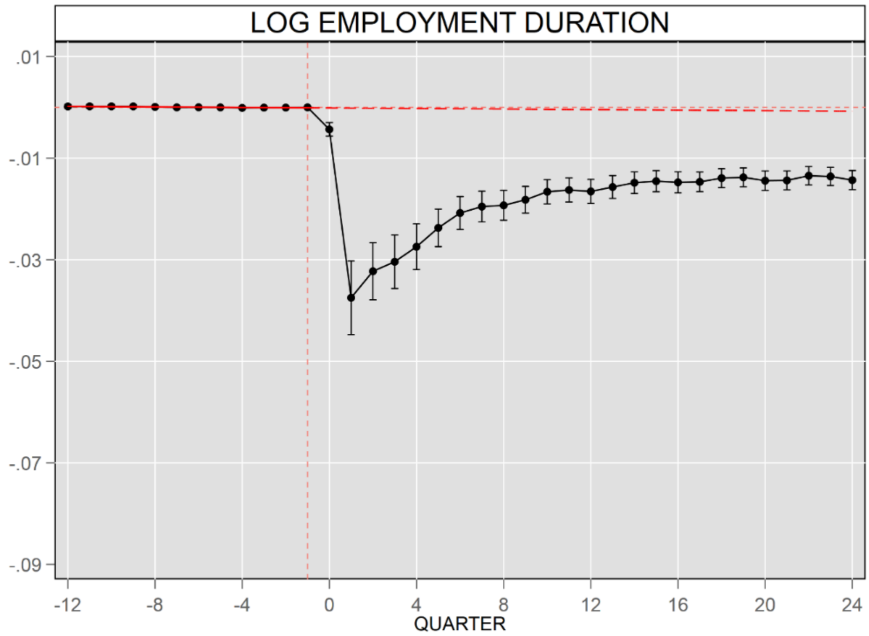
4.3 Decomposition

The previous sub-section showed that otherwise identical workers, on average, suffer a larger drop in earnings if they were initially employed in more routine intensive occupations. It is unclear, however, to what extend this finding is driven by routine intensive workers having more difficulties finding a new job or by them being re-employed in lower-paying jobs. Since quarterly earnings are the product of days in employment per quarter and average daily earnings, it is possible to discriminate between the channels underlying the impact on earnings.

In order to do so, we estimate Equation (2) separately for the natural logarithm of the number of days in employment per quarter and the average daily wage. Since these quantities add up to log earnings per quarter, the sum of the estimated coefficients is identical to the corresponding coefficient estimates from the earnings model which allows an assessment of the relative importance of both channels.[15] Figure 6 and Figure 7 show the estimated coefficients of the interaction term between time-to-event dummies and treatment variable. In both cases, the pattern is similar to that of Figure 5. A higher degree of initial routine intensity leads to a larger reduction in employment duration as well as daily wages. The effect is largest in the quarter directly following the mass layoff and while it decreases in magnitude, the effect remains negative throughout the post-treatment period.

[15] The adding of the value 1 as described in footnote 13, implies that the sum is not exactly identical.

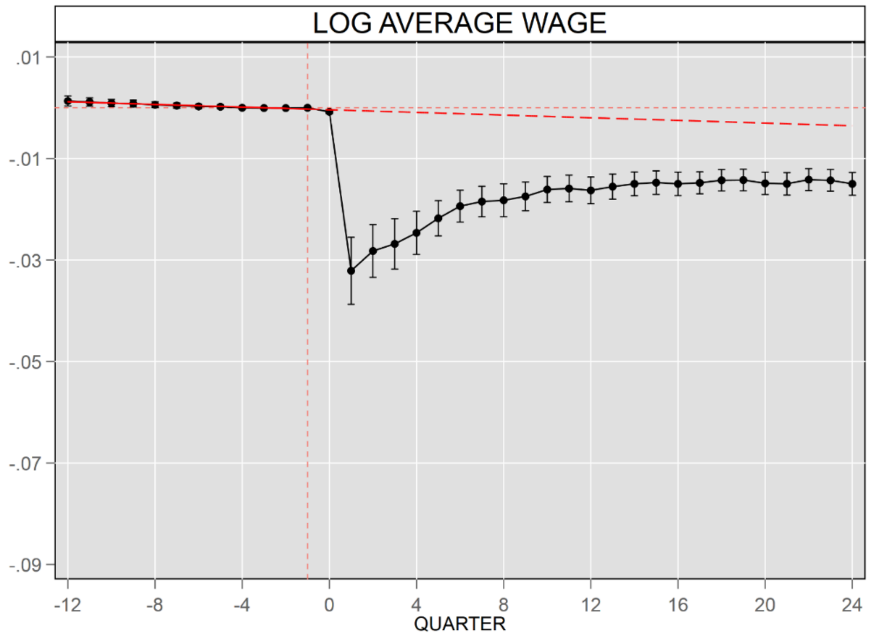
Figure 6: Treatment effects on the log employment duration



<u>Notes:</u> See Figure 5. The dependent variable is the log number of days in employment per quarter.

Panels B and C of Table 4 show the quantities of the treatment effects for the employment and the wage outcome, respectively. Specifically, we find that an increase in routine intensity by one percentage point reduces the number of days in employment during the first quarter after the mass layoff by an additional 4%, while the corresponding additional reduction in daily wages stands at 3%. We conclude that the larger negative earnings effect that workers in routine intensive occupations experience is driven to a similar extent by less time being spent subsequently in employment and by being employed in lower-paying jobs.

Figure 7: Treatment effects on the log average wage



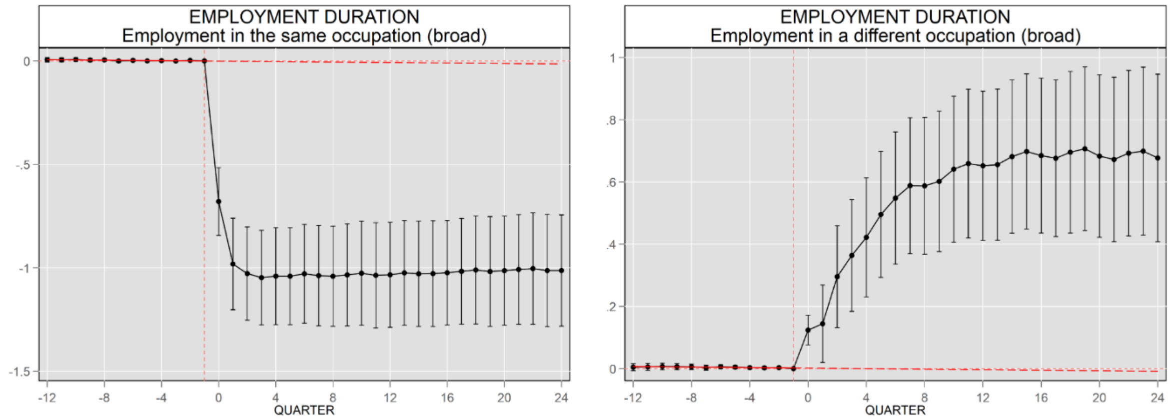
<u>Notes:</u> See Figure 5. The dependent variable is the individual log average daily wage.

4.4 Subsequent transitions into employment

We have shown that mass layoffs lead to large and persistent reductions in earnings for all workers, but that for workers who used to be employed in routine-intensive occupations, the costs of job loss are more severe and more persistent. In this sub-section we aim to analyse in more detail how the further employment biography is shaped by the routine intensity of the previous occupation. After having been employed in an occupation for a certain time, workers have a specific human capital either acquired by on-the-job learning or because they needed to have certain skills in order to get their specific job in the first place. The chances to find a new job and the quality of this job depend on how well the specific skills of the previous job can be transferred to a new job. For more routine intensive jobs the additional problem is that the demand for those decreased constantly during the past decades, as shown in Figure 1. While job protection measures might have shielded these workers to a certain degree while in employment, they are exposed to this development after job loss and when searching for a new job.

To shed further light on the adjustment processes of laid-off workers in times of technological change, we assess the impact of routine intensity on the ability of taking up employment in higher-quality jobs – as measured by average daily wages – as well as on occupational and regional mobility. To this end, we estimate three pairs of variations on Equation (2) which use the number of days in employment as the dependent variable. For the first pair, we differentiate quarterly employment during the post-layoff period according to whether a worker is employed in the same or an occupation within the same occupational group as before the layoff.[16] For example, when we are interested in the effect of routine intensity on employment chances in the worker's initial occupational group, we set the log employment duration to zero for all post-layoff observations where a worker is either unemployed or employed in a different occupational group. This way, the coefficients of the interaction terms that belong to post-layoff quarters add up to the overall effect on the number days in employment per quarter. In the same way, we differentiate employment in higher- or lower-paying occupations as well as between jobs in the same county as opposed to a different county.[17]

Figure 8: Treatment effects on the duration of employment by same vs. different occupational group



Panel A: Same occupational group — Panel B: Different occupational group

Notes: See Figure 5. For the pre-treatment period, the dependent variable is given by the number of days in employment per quarter; during the post-treatment period the dependent variable takes on non-zero values only in those quarters during which

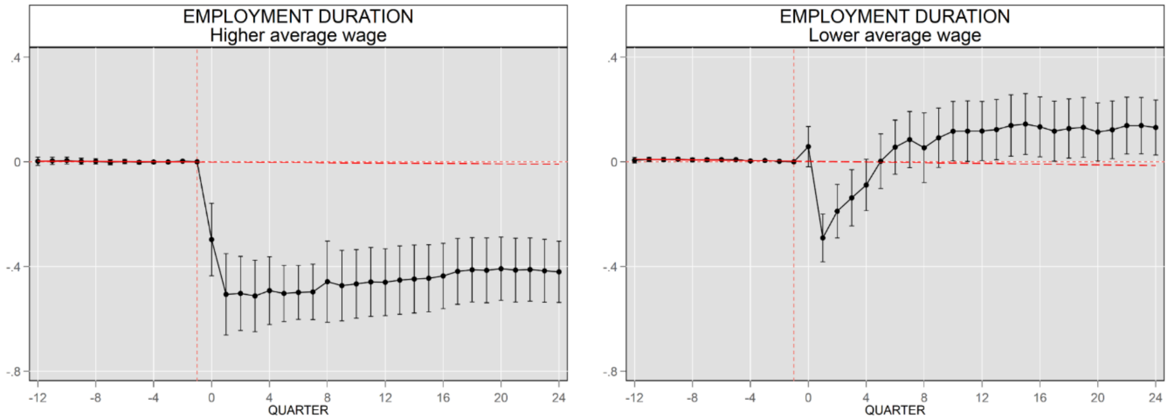
[16] We use the six values of the *'Berufsbereiche'* according to the '*Klassifikation der Berufe 1988*'.

[17] Similar results are obtained when using the 33 values of the *'Berufsabschnitte'*. Likewise, comparable patterns emerge when labour-market regions are used instead of counties. Results are available upon request.

a worker is employed in the same occupation as (Panel A) or a different occupation than (Panel B) during the quarter directly preceding the mass layoff.

Figure 8 displays the coefficients of the interaction terms of the time-to-event indicators with routine intensity. Panel A shows that the more routine intensive the last occupation was, the less likely it is that a worker will return into this or a similar occupation after the layoff. This corroborates the hypothesis that in times of declining demand for routine tasks, the job-specific skills of workers in routine intensive jobs lose value immediately in the case of a layoff. As Panel B shows, the more routine intensive the previous job was, the more likely it is that subsequent employment will be in a different occupation.

Figure 9: Treatment effects on the duration of employment by average daily earnings

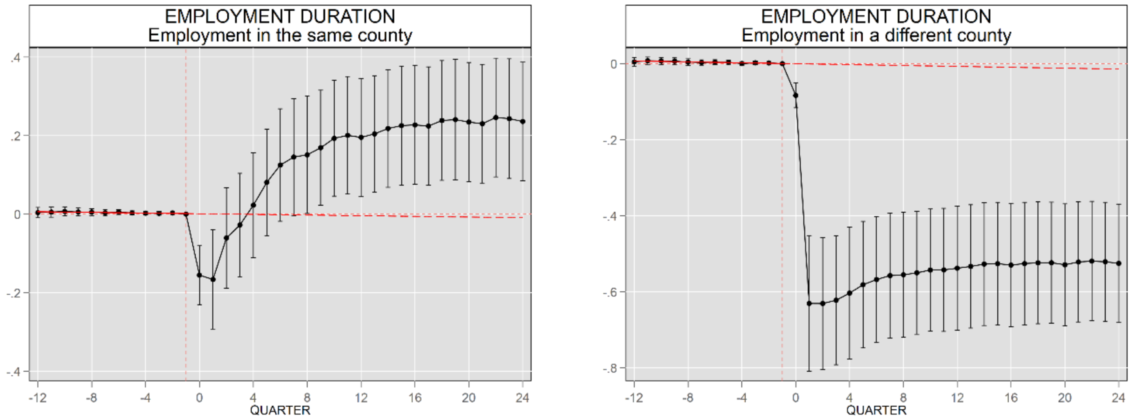


Panel A: Higher-paying occupations Panel B: Lower-paying occupations

<u>Notes:</u> See Figure 5. For the pre-treatment period, the dependent variable is given by the number of days in employment per quarter; during the post-treatment period the dependent variable takes on non-zero values only in quarters during which a worker holds an earns an average daily wage that was at least as high as (Panel A) or lower than (Panel B) that earned during the quarter directly preceding the mass layoff.

In Figure 9, we also look at occupational mobility, but from a different angle. Specifically, we compare a worker's average daily earnings during the pre-treatment period with the level obtained during the quarter before the layoff. One may suspect that this exercise is spoiled by a mechanical effect: If routine-intensive jobs pay lower wages, the probability of moving to a higher-paid job should increase with routine intensity in absence of any causal effect of routineness. However, Panel A of Figure 9 shows that the exact opposite holds true. The coefficients are negative throughout the entire post-layoff period. This means that workers in more routine intensive jobs find it more difficult to climb the occupational ladder after a layoff compared to workers in less routine jobs. In Panel B, the coefficients in the first year after the layoff are negative as well. This indicates that workers in previously more routine intensive jobs have more difficulties finding any job, regardless of whether it is paid more or less than the previous one. After 2.5 years, employment durations in lower paid jobs are significantly higher the more routine intensive the previous job was. To summarize, the likelihood to find a job immediately after a layoff declines with the routine intensity of the old job. When workers in previously more routine-intensive occupations find a new job eventually, it is likely less well paid than the old job. Figure 10 shows that a higher degree of routine intensity has a negative effect on subsequent employment in a different county. While employment in routine-intensive occupations is associated with subsequently finding employment in a different occupation, it also reduces regional mobility.

Figure 10: Treatment effects on the duration of employment by same vs. different county



Panel A: Same county

Panel B: Different county

<u>Notes:</u> See Figure 5. For the pre-treatment period, the dependent variable is given by the number of days in employment per quarter; during the post-treatment period the dependent variable takes on non-zero values only in quarter during which a worker is employed in the same county as (Panel A) or a different county than (Panel B) during the quarter directly preceding the mass layoff.

4.5 Effect heterogeneity and robustness checks

Finally, we are interested in whether the effects of having been employed in a more routine intensive occupation prior to a mass layoff varies across specific groups of the population. To analyse this, we split the sample into disjunctive groups and estimate the model of Equation (2) separately for each group.

Table 5: Treatment effects of routine intensity on earnings by population groups

	(1)	(2)	(3)	(4)
Dependent variable: log quarterly earnings				
	Relative change (k = 1)	Relative change (average)	Mean value (k = -1)	Absolute change (cumulative)
Panel A – By Education				
Unskilled	-0.04 (0.01)	-0.03	7,119.20	-698.46
Vocational training	-0.05 (0.01)	-0.02	9,425.62	-2,347.83
College degree	-0.04 (0.02)	-0.02	20,974.96	-7,109.84
Panel B – By age at layoff				
23-29 years	-0.06 (0.01)	-0.03	7,696.78	-2,410.99
30-44 years	-0.07 (0.01)	-0.03	10,211.55	-3,395.97
45-51 years	-0.07 (0.01)	-0.04	10,429.76	-2,883.65
Panel C – By decade of mass layoff				
1980-89	-0.08 (0.01)	-0.03	8,536.50	-2,542.40
1990-99	-0.06 (0.01)	-0.03	9,893.81	-2,710.34
2000-10	-0.07 (0.01)	-0.04	11,134.60	-4,010.17
Panel D – By sector of mass layoff				
Manufacturing	-0.06 (0.00)	-0.03	9,556.77	-2,557.83
Non-Manufacturing	-0.04 (0.02)	-0.03	10,557.75	-2,921.61
Panel E – East vs. West Germany				
East	-0.04 (0.02)	-0.02	8,249.54	-1,232.79
West	-0.07 (0.01)	-0.03	10,146.00	-3,513.42
Panel F – By share of the workforce laid-off				
Less than 90%	-0.07 (0.01)	-0.04	10,095.25	-3,476.72
More than 90%	-0.06 (0.01)	-0.03	9,555.29	-2,623.26

<u>Notes:</u> The table contains different forms of treatment effects computed for a one percentage point change in the routine intensity variable. Column (1) shows the proportional difference in the change in the outcome variable for the first quarter after the mass layoff and the standard error of the point estimate. Column (2) shows an average effect across all quarters of

the post-treatment period. Column (3) reports the average outcome of the respective group in the quarter before the mass layoff, and column (4) contains a measure for the absolute difference in the change of the outcome.

Table 5 shows the variation of the effect of an additional percentage point of routine intensity of the previous occupation on earnings by different sub groups. The first column again reports the effect of one additional percentage point of routine intensity on earnings in the quarter after the layoff. To asses the uncertainty of this estimate, we add the standard error of the interaction term in parentheses. Column 2 shows the average effect over the entire post-layoff period in relative terms and column 4 in absolute terms. In column 3, we report the average earnings of the respective group in the quarter before the layoff as a benchmark. In Panel A, workers are distinguished by educational degree. Over the entire post-layoff period, the least skilled workers suffer most from having worked in more routine intensive occupations. However, the confidence intervals of the effects of the different groups overlap, which indicates that the differences are not statistically significant. However, it is interesting to see that all estimates of the short run effects of routine intensity drop in magnitude. This indicates that the overall effect of 0.7 also reflects some systematic compositional differences in terms of skills. More routine intensive occupations typically require a lower education and the overall effect stems in part from the fact that less educated people have more difficulties finding a new job in general. Column 1 in Panel B shows that proportionally the additional initial earnings reduction is slightly smaller among younger workers, although the difference is not significant. We therefore do not find strong evidence that the negative impact of routine intensity is concentrated among older workers.

Splitting the sample also allows us to check the robustness of our results in several ways. The results in Panel C show that the effect of routine intensity varies only little over time. More interestingly, the short run effect is considerably larger in the manufacturing sector, as can be seen in Panel D. Most routine intensive occupations are related to manufacturing (see Figure 2). Workers laid off in this sector have the problem of a devaluation of their human capital because of technological change and the general trend of structural change of employment from the manufacturing to the service sector. In Panel E, we distinguish between East and West Germany. Somewhat puzzlingly, the effect of routine intensity is more pronounced for Westerners. One explanation might be that the labour market situation in East Germany is more difficult for all occupations, regardless of their routine intensity. Finally, one objection against our identification strategy might be that our definition of mass layoffs comprises closures of establishments as well as events in which establishments continue to exist but lay off only a fraction of their workforce. To check if this affects our results, we split the sample by whether an establishment laid off more or less than 90% of its workforce. In Panel E shows that there are only marginal differences between these cases.

Table 6 provides the results of a number of additional robustness checks for the estimated treatment effect of routine intensity on earnings. While the baseline specification employs worker fixed effects in order to control for the effects of individual- and establishment-level characteristics from the quarter preceding the mass layoff (as well as unobservable time-invariant influences), Panel A shows the results from a specification that uses these variables instead of the fixed effects. The estimated treatment effects are qualitatively similar, albeit slightly smaller as suggested by the smaller absolute change shown in column 4. The results in Panel B derive from the same empirical model as specified in Equation (2), but are based on different forms of the routine intensity measure. First, we assess the sensitivity of the results by extending the definition of routine intensity to the share of workers in an occupation reporting both items to be the case 'almost always' or 'often'. As expected, including workers for whom routines are not as common reduces the magnitude of the treatment effects, although the former remain negative. Finally, we use routine intensity measures that rely on a single wave of the 'employee survey'. The estimated treatment effects are negative in each case. However, the magnitude of the absolute change in column 4 is largest if the data from the 1985 survey is used and smallest for the 1999 survey suggesting that not taking into account changes in occupational job contents results in an over- or underestimation of the treatment effects.

Table 6: Treatment effects of routine intensity on earnings (robustness)

	(1)	**(2)**	**(3)**	**(4)**
Dependent variable: log quarterly earnings				
	Relative change (k = 1)	Relative change (average)	Mean value (k = -1)	Absolute change (cumulative)
Baseline specification	-0.07 (0.01)	-0.03	9,908.63	-3,226.17
Panel A – Alternative model specification				
Control variables	-0.07 (0.01)	-0.03	9,908.63	-2,683.31
Panel B – Alternative routine intensity measures				
Often or always almost	-0.04 (0.00)	-0.02	9,908.63	-1,938.27
Survey 1985	-0.08 (0.01)	-0.04	9,908.63	-3,395.67
Survey 1991	-0.06 (0.01)	-0.03	9,908.63	-2,848.79
Survey 1999	-0.06 (0.01)	-0.03	9,908.63	-2,594.28

Notes: See Table 5.

5 Conclusion

In the labour economics literature, there is a broad consensus that technological change is routine biased and has led to the secular decline of routine-intensive jobs. In this paper, we look at the individual perspective. We assess how individual workers adjust to this secular trend. We argue that in a country like Germany, labour market institutions shield workers to a certain degree from the immediate effects of technological change. Even if a firm would want to replace an employee in a routine-intensive occupation by a machine or by a different worker specialized in less routine-intensive tasks, job protection laws or works councils might prevent them from doing so. We hence concentrate on a group of individuals that are particularly vulnerable: workers who exogenously lost their job during a mass layoff event.

We find that with each additional percentage point of the routine intensity of the previous job, the earnings losses caused by the layoff increase both in the short run and persist over at least the subsequent six years. We estimate that the additional earnings associated with a one standard deviation difference in routine intensity amounts to almost 30,000 Euros in six years. This is driven in equal parts by a reduced probability of quickly finding a new job and a lower wage level in the new job. Workers who previously held a more routine-intensive occupation are less likely to find a new job in the same or similar occupation but rather change into a less well-paid occupational group.

These results highlight an additional channel on how routine biased technological change affects the labour market on the intensive margin. Once confronted with an exogenous shock to their career, workers in more routine-intensive occupations face persistently worse labour market outcomes for the rest or their working life. This fosters income inequality since routine-intensive jobs are typically located at the lower part of the wage distribution. Labour market policies targeted at routine workers should thus aim to improve the employability of those workers either at their original workplace even before a possible layoff or in different firms.

References

Adermon, A. and Gustavsson, M. (2015) Job polarization and task-biased technological change: Evidence from sweden, 1975–2005. *The Scandinavian Journal of Economics*, **117**, 878-917.

Ahlfeldt, G. M., Roth, D. and Seidel, T. (2018) The regional effects of germany's national minimum wage. *Economics Letters*, **172**, 127-130.

Antonczyk, D., Fitzenberger, B. and Leuschner, U. (2009) Can a task-based approach explain the recent changes in the german wage structure? *Jahrbücher für Nationalökonomie und Statistik*, **229**, 214-238.

Autor, D. H. (2013) The "task approach" to labor markets: An overview. *Journal for Labour Market Research*, **46**, 185-199.

Autor, D. H. and Dorn, D. (2013) The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, **103**, 1553-1597.

Autor, D. H., Dorn, D. and Hanson, G. H. (2015) Untangling trade and technology: Evidence from local labour markets. *The Economic Journal*, **125**, 621-646.

Autor, D. H., Levy, F. and Murnane, R. J. (2003) The skill content of recent technological change: An empirical exploration*. *The Quarterly Journal of Economics*, **118**, 1279-1333.

Autor, D. H. and Salomons, A. (2017) Does productivity growth threaten employment? *4th Annual ECB Forum on Central Banking*: Sintra, Portugal.

Autor, D. H. and Salomons, A. (2018) Is automation labor-displacing? Productivity growth, employment, and the labor share *Brookings Papers on Economic Activity*.

Biagi, F., Naticchioni, P., Ragusa, G. and Vittori, C. (2018) Routinization and the labour market: Evidence from european countries In: Pupillo, L., Noam, E. and Waverman, L., (eds.) *Digitized labor: The impact of the internet on employment*, Palgrave Macmillan.

Cortes, G. M. (2015) Where have the middle-wage workers gone? A study of polarization using panel data. *Journal of Labor Economics*, **34**, 63-105.

Davis, S. J., Von Wachter, T., Hall, R. E. and Rogerson, R. (2011) Recessions and the costs of job loss [with comments and discussion]. *Brookings Papers on Economic Activity*, 1-72.

Fonseca, T., Lima, F. and Pereira, S. C. (2018) Job polarization, technological change and routinization: Evidence for portugal. *Labour Economics*, **51**, 317-339.

Goos, M., Manning, A. and Salomons, A. (2014) Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, **104**, 2509-2526.

Hethey-Maier, T. and Schmieder, J. F. (2010) Does the use of worker flows improve the analysis of establishment turnover: Evidence from German administrative data. *FDZ-Methodenreport*, Institute für Arbeitsmarkt- und Berufsforschung: Nürnberg, Germany.

Hummels, D., Munch, J. R. and Xiang, C. (2018) Offshoring and labor markets. *Journal of Economic Literature*, **56**, 981-1028.

Ikenaga, T. and Kambayashi, R. (2016) Task polarization in the japanese labor market: Evidence of a long-term trend. *Industrial Relations: A Journal of Economy and Society*, **55**, 267-293.

Jacobson, L. S., LaLonde, R. J. and Sullivan, D. G. (1993) Earnings losses of displaced workers. *The American Economic Review*, **83**, 685-709.

Keynes, J. M. (1933) *The means to prosperity*, Macmillan and Co. Ltd, London.

Lommerud, K. E. and Straume, O. R. (2011) Employment protection versus flexicurity: On technology adoption in unionised firms*. *The Scandinavian Journal of Economics*, **114**, 177-199.

Maczulskij, T. and Kauhanen, M. (2017) Where do workers from declining routine jobs go and does migration matter? *Työpapereita Working Papers*.

Oldenski, L. (2014) Offshoring and the polarization of the u.S. Labor market. *ILR Review*, **67**, 734-761.

Ross, M. B. (2017) Routine-biased technical change: Panel evidence of task orientation and wage effects. *Labour Economics*, **48**, 198-214.

Spitz-Oener, A. (2006) Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics*, **24**, 235-270.

Appendix

Table A1: Establishment characteristics

Panel A – Establishment level	**1980-1989**		**1990-1999**		**2000-2010**		**1980-2010**	
	mean	sd	mean	sd	mean	sd	mean	sd
D – Manufacturing	65.81	(47.44)	58.98	(49.19)	43.32	(49.56)	55.19	(49.73)
E – Electricity, gas, and water supply	0.29	(5.42)	0.68	(8.21)	0.39	(6.27)	0.48	(6.92)
F – Construction	2.52	(15.69)	1.98	(13.93)	1.88	(13.58)	2.08	(14.28)
G – Wholesale and resale trade	19.09	(39.31)	18.60	(38.92)	21.79	(41.29)	19.85	(39.89)
H – Hotels and restaurants	1.18	(10.79)	1.82	(13.36)	2.61	(15.94)	1.93	(13.77)
I – Transport, storage and communication	3.99	(19.59)	7.78	(26.79)	9.79	(29.72)	7.53	(26.39)
J – Financial intermediation	1.51	(12.21)	1.76	(13.16)	2.36	(15.20)	1.91	(13.69)
K – Real estate, renting and business activities	5.59	(22.98)	8.41	(27.75)	17.85	(38.30)	11.02	(31.32)
50-99 employees	56.31	(49.61)	57.40	(49.46)	61.41	(48.69)	58.54	(49.27)
100-199 employees	26.41	(44.09)	26.49	(44.13)	25.16	(43.40)	26.00	(43.87)
200-499 employees	14.09	(34.80)	12.09	(32.61)	10.64	(30.84)	12.09	(32.60)
500 or more employees	3.20	(17.59)	4.01	(19.63)	2.79	(16.47)	3.37	(18.06)
East Germany	2.82	(16.55)	16.11	(36.76)	17.82	(38.28)	13.34	(34.00)
Observations	2378		3688		3299		9365	
Panel B – Worker level	**1980-1989**		**1990-1999**		**2000-2010**		**1980-2010**	
	mean	sd	mean	sd	mean	sd	mean	sd
D – Manufacturing	73.41	(44.18)	65.68	(47.48)	56.25	(49.61)	64.85	(47.74)
E – Electricity, gas, and water supply	0.34	(5.80)	2.81	(16.54)	0.89	(9.38)	1.51	(12.20)
F – Construction	2.64	(16.04)	1.20	(10.87)	1.40	(11.74)	1.66	(12.79)
G – Wholesale and retail trade	12.84	(33.45)	13.86	(34.55)	18.74	(39.02)	15.12	(35.83)
H – Hotels and restaurants	0.31	(5.60)	0.76	(8.67)	1.07	(10.28)	0.73	(8.53)
I – Transport, storage and communication	3.10	(17.34)	8.77	(28.29)	6.85	(25.27)	6.58	(24.79)
J – Financial intermediation	1.41	(11.79)	1.51	(12.18)	3.03	(17.15)	1.96	(13.87)
K – Real estate, renting and business activities	5.95	(23.65)	5.41	(22.63)	11.77	(32.23)	7.58	(26.47)
50-99 employees	25.09	(43.36)	28.08	(44.94)	32.20	(46.72)	28.55	(45.17)
100-199 employees	24.90	(43.24)	26.60	(44.19)	25.97	(43.85)	25.93	(43.82)
200-499 employees	28.60	(45.19)	25.54	(43.61)	21.15	(40.83)	25.00	(43.30)
500 or more employees	21.41	(41.02)	19.79	(39.84)	20.68	(40.50)	20.52	(40.39)
East Germany	2.41	(15.35)	17.86	(38.30)	14.61	(35.32)	12.52	(33.09)
Observations	95,529		137,929		108,587		342,045	

Notes: The table shows the share of establishments (Panel A) and workers (Panel B) in percentage points as well as the corresponding standard deviations for various establishment-level characteristics. The figures refer to the quarter directly preceding the mass layoff.

Table A2: Establishment characteristics (worker shares)

	1980-1989		1990-1999		2000-2010		1980-2010	
	ML	Random	ML	Random	ML	Random	ML	Random
A – Agriculture, hunting and forestry		0.20		0.60		0.45		0.42
		(4.44)		(7.74)		(6.72)		(6.45)
B – Fishing		0.00		0.00		0.00		0.00
		(0.68)		(0.52)		(0.37)		(0.54)
C – Mining and quarrying		2.02		1.04		0.45		1.17
		(14.08)		(10.14)		(6.68)		(10.76)
D – Manufacturing	73.41	48.37	65.68	39.27	56.25	37.58	64.85	41.74
	(44.18)	(49.97)	(47.48)	(48.83)	(49.61)	(48.43)	(47.74)	(49.31)
E – Electricity, gas, and water supply	0.34	1.75	2.81	1.72	0.89	1.28	1.51	1.58
	(5.80)	(13.11)	(16.54)	(13.02)	(9.38)	(11.22)	(12.20)	(12.48)
F – Construction	2.64	6.44	1.20	7.23	1.40	3.83	1.66	5.83
	(16.04)	(24.54)	(10.87)	(25.90)	(11.74)	(19.20)	(12.79)	(23.44)
G – Wholesale and retail trade	12.84	8.70	13.86	9.52	18.74	11.20	15.12	9.80
	(33.45)	(28.18)	(34.55)	(29.35)	(39.02)	(31.53)	(35.83)	(29.74)
H – Hotels and restaurants	0.31	0.43	0.76	0.70	1.07	1.11	0.73	0.75
	(5.60)	(6.55)	(8.67)	(8.32)	(10.28)	(10.49)	(8.53)	(8.61)
I – Transport, storage and communication	3.10	4.58	8.77	4.83	6.85	5.95	6.58	5.12
	(17.34)	(20.91)	(28.29)	(21.45)	(25.27)	(23.66)	(24.79)	(22.04)
J – Financial intermediation	1.41	5.11	1.51	5.88	3.03	5.52	1.96	5.50
	(11.79)	(22.01)	(12.18)	(23.52)	(17.15)	(22.83)	(13.87)	(22.80)
K – Real estate, renting and business activities	5.95	3.48	5.41	4.92	11.77	10.35	7.58	6.25
	(23.65)	(18.33)	(22.63)	(21.62)	(32.23)	(30.47)	(26.47)	(24.21)
L – Public administration and defence		8.53		9.84		7.41		8.59
		(27.93)		(29.78)		(26.19)		(28.02)
M – Education		1.78		2.80		2.92		2.50
		(13.20)		(16.50)		(16.84)		(15.61)
N – Health and social work		7.80		11.23		11.82		10.28
		(26.82)		(31.58)		(32.29)		(30.38)
P – Private households		0.01		0.00		0.00		0.00
		(0.82)		(0.49)		(0.49)		(0.62)
Q – Extraterritorial organisations		0.80		0.42		0.13		0.45
		(8.92)		(6.46)		(3.59)		(6.69)
50-99 employees	25.09	16.59	28.08	21.28	32.20	22.71	28.55	20.19
	(43.36)	(37.20)	(44.94)	(40.93)	(46.72)	(41.90)	(45.17)	(40.14)

100-199 employees	24.90	14.49	26.60	16.71	25.97	18.93	25.93	16.71
	(43.24)	(35.20)	(44.19)	(37.31)	(43.85)	(39.18)	(43.82)	(37.31)
200-499 employees	28.60	19.84	25.54	21.03	21.15	22.23	25.00	21.03
	(45.19)	(39.88)	(43.61)	(40.75)	(40.83)	(41.58)	(43.30)	(40.75)
500 or more employees	21.41	49.08	19.79	40.99	20.68	36.13	20.52	42.06
	(41.02)	(49.99)	(39.84)	(49.18)	(40.50)	(48.04)	(40.39)	(49.37)
East Germany	2.41	3.53	17.86	16.80	14.61	16.09	12.52	12.06
	(15.35)	(18.45)	(38.30)	(37.38)	(35.32)	(36.75)	(33.09)	(32.57)
Observations	95,529	1,000,000	137,929	1,000,000	108,587	1,000,000	342,045	1,000,000

Notes: The table shows the share of workers and the corresponding standard deviation for various establishment-level characteristics. The columns 'ML' show the values for those workers who experienced a mass layoff (measured at the quarter directly preceding the mass layoff). The columns 'Random' show the values for a randomly chosen group of workers who did not experience mass layoff, but who satisfy the same conditions as the workers in the mass layoff sample (e.g. minimum level of tenure).