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What Are The Returns To Regional Mobility? Evidence From Mass Layoffs

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What Are The Returns To Regional Mobility? Evidence From Mass Layoffs *

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Abstract

This paper estimates the effects of regional mobility on individual employment prospects and wages, exploiting rich German social security data spanning over 30 years. Our focus is on unemployed workers with strong labor force attachment who search for employment after being exposed to a mass layoff. By that we concentrate on a group of individuals who are plausibly searching for employment for exogenous reasons. Comparing individuals who stay in the local labor market to movers, we find that employment rates are around 15 percentage points higher for movers three years after the layoff. Large differences in employment rates persist even 10 years after the layoff. In contrast, there are no effects of regional mobility on wages conditional on finding employment.

JEL-classification: J61, J63, R23

Keywords: mass-layoffs, regional mobility, earnings, employment

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1 Introduction

This paper estimates the effects of regional mobility on individual employment prospects and wages. Our focus is on unemployed workers with strong labor force attachment who search for employment after being exposed to a mass layoff. By that we concentrate on a group of individuals who are plausibly searching for employment for exogenous reasons.

Strikingly large differences in unemployment rates and employment prospects of searching workers persist across places within countries. In 2009 in the midst of the Great Recession, the unemployment rate in Detroit was 18 percent. In Iowa City, about 500 miles west, the unemployment rate only stood at 4.5 percent (Moretti, 2012). Given these enormous disparities even across relatively closely located labor market, should we conclude there is a lack of mobility, especially among unemployed individuals? The answer to this question will depend on the social and private benefits and costs of regional mobility. Unfortunately, the literature has accumulated very little empirical knowledge about the size of those parameters. We try to make progress by shedding light on the return side.

There exists ample evidence that places and local labor markets are closely associated with individual wages and employment outcomes (Glaeser, Ponzetto, and Tobio, 2014). Much less is understood, in contrast, about the short-term and long-term consequences of regional mobility. Concentrating on unemployed job seekers we ask what are the economic consequences for individuals from moving from a depressed labor market to a booming one? Do potential positive employment and wage effects kick in on impact? Are potential gains persistent? Do the effects materialize through changes in job stability or by changing the sector of employment?

Our research design exploits job displacements caused by mass layoffs, plausibly giving rise to a situation in which workers become unemployed and are forced to search for exogenous reasons. This follows the established literature on the consequences of job displacement (?, among others). Our baseline analysis is of the event study type, comparing the outcomes of laid-off workers who leave the local labor market *after the layoff* (movers) to workers who decide to stay in the region (stayers). We present graphical evidence that before the a mass layoff conditional on standard individual control variables, movers and stayers share indistinguishable outcomes in terms of employment and earnings. After the layoff, the labor market outcomes of stayers and movers start to drastically diverge.

Our study is most closely related to Huttunen, Møen, and Salvanes (2015), who study the mobility of Norwegian workers after layoff in Norway. They find substantial income losses of mobile people, that stem almost exclusively from people who leave urban areas to move back to their parents at the countryside. One major difference between Norway and Germany is that the former has only two urban areas. Unlike in Norway, mobility of German city dwellers does not inevitably mean moving to rural areas. With its multi-central regional structure, the German economic geography is more similar to the majority of industrialized countries such as the United States, most Western European countries, or Japan. Moving within Germany would

mean moving between different agglomeration but not necessarily mean moving to a tighter labor market.

2 Data

2.1 Data source and preparation

Our data stems from the full universe of records from the German social security system, assembled by the Institute for Employment Research into the Integrated Employment Biographies (IEB) data file. The IEB covers all spells of private sector employment subject to social security as well as recieption of unemployment insurance benefits with daily precision. The data include spell duration, daily wage, a plant identifier, as well as information on location, education, occupation, industry, and employment status. With the exception of civil servants and self-employed workers, this data covers about 80% of the total German workforce. Wages are censored at social security contribution ceiling but imputed following (Card, Heining, and Kline, 2013).

We first aggregate this data at the level of plants to identify mass layoffs: Following Schmieder, Wachter, and Bender (2010), we select all plants with at least 50 employees as of June 30 in a given year that either closed down or reduced their workforce by at least 33 percent by June 30 in the next year.

Our base sample consists of the whole employment biographies of every male full-time worker who was employed in one of these plants before the mass layoff and had at least one unemployment spell after the mass layoff between 1980 and 1999. Our next step is to convert this spell dataset into a panel. We therefore generate a discrete time variable that takes the value of zero at the day of layoff and the value t at $t \times 365$ days before or after the layoff. We then count the days in employment and earnings within moving 1-year windows. E.g.: earnings at $time = 0$ is cumulative earnings in 365 days before the layoff. Earnings at $time = t$ is cumulative earnings in $t - 1 \times 365 < \text{days} \leq t \times 365$ before/after layoff. All control variables are measured at the end of each 365 days window. We distinguish two different states: employed if the daily wage is above the marginal part-time income threshold (€13.15 in 2010) and unemployed otherwise. The latter category thus includes periods for which we have no observations in the original data because people left the labor force to receive disability insurance benefits, early retirement pensions or leave for unknown reasons up until the age of 65. Only if people leave for the following reasons do we stop counting earlier: death, move to another country, or self employment. We restrict the dataset to people who were at least 24 years old when they were laid off and at most 65 years old in 2010, our last year of observation. This leaves us with 395,888 cross sectional observations.

Following Jacobson, LaLonde, and Sullivan (1993), we next ensure that our panel is balanced by keeping only workers who continuously appear in the panel at least 5 years before and 10

years after being laid off (dropping 103,463 individuals). We further drop workers who move back to their very first working place, as this is most likely due to private and non-economic reasons (19,272), who have not been employed full time in the layoff firm for 4 years prior to the layoff (171,889), and who at any point in time have earned more than the 99th percentile of all contemporaneous wages, which is most likely due to an imputation error (5,781). This leaves us with a final sample of 93,620 cross sectional units.

Our main dependent variable is the employment rate during the time window t , defined as the days in employment with a wage above the marginal-job wage divided by 365 (or 366 if the window includes a leap day). Our second dependent variable is the cumulative earnings during each time window. The main explanatory variable is a dummy that takes the values of one if the first job after the mass layoff is in a different labor market region (delineated by commuting flows)¹

2.2 Descriptive Statistics

Table 1: Means and standard deviations of main variables at time of layoff

	stayers				movers			
	total	low skill	med. skill	high skill	total	low skill	med. skill	high skill
yearly earnings	32.277 (9.028)	28.816 (6.449)	33.396 (9.171)	46.295 (15.691)	34.434 (9.942)	29.249 (6.147)	35.228 (9.862)	46.561 (14.133)
average daily wage	88.442 (24.732)	78.957 (17.666)	91.507 (25.123)	126.836 (42.990)	94.356 (27.240)	80.141 (16.841)	96.530 (27.020)	127.577 (38.715)
dummy, prev. mobile	0.158 (0.365)	0.106 (0.307)	0.174 (0.379)	0.435 (0.496)	0.305 (0.460)	0.173 (0.379)	0.326 (0.469)	0.591 (0.492)
dummy, married	0.727 (0.445)	0.752 (0.432)	0.719 (0.450)	0.651 (0.477)	0.737 (0.440)	0.785 (0.411)	0.730 (0.444)	0.613 (0.487)
age	41.467 (8.113)	41.830 (8.237)	41.320 (8.088)	41.438 (6.524)	39.971 (7.641)	39.606 (7.934)	40.072 (7.622)	39.627 (5.967)
experience	13.522 (5.318)	12.741 (5.318)	13.856 (5.294)	12.762 (4.739)	13.331 (5.354)	12.044 (5.178)	13.697 (5.365)	11.733 (4.550)
tenure in layoff-firm	10.756 (5.022)	10.861 (5.036)	10.747 (5.027)	9.091 (4.164)	10.196 (4.774)	10.202 (4.739)	10.272 (4.805)	8.124 (3.539)
dummy, low skilled	0.285 (0.452)				0.188 (0.390)			
dummy, med. skilled	0.700 (0.458)				0.784 (0.412)			
dummy, high skilled	0.015 (0.120)				0.029 (0.168)			
observations	78240	22329	54767	1144	15380	2884	12051	445

Note: Variables measured at time of layoff. Standard deviations in parentheses.

Table 1 reports summary statistics for all workers in the year before the layoff, by skill group and mobility. It is obvious, that movers and stayers differ in a number of observable

¹We cannot observe moves within unemployment spells before 1999. Yet, a shorter sample of workers laid off between 2000 and 2005 allows us to confirm that our results do not change if these moves are included.

characteristics even before the layoff. Movers earn almost 10 percent higher wages, even within skill groups. Movers are also more mobile per se, the percentage of workers who had already been mobile before is twice as large among movers. They are a little younger, less experienced and more often have a university degree. Interestingly, movers are more often married. This might point towards the mechanism uncovered by Huttunen, Møen, and Salvanes (2015), where recently laid off workers tend to move back to their parents and siblings. People might also tend to search for jobs close to their spouses if they work at different places. Unfortunately, our data do not allow us to identify family ties.

These differences suggest that a naive comparison of outcomes between movers and stayers will most likely yield upwards biased results on the effects of mobility. Our empirical strategy will therefore be twofold: first, we use a simple propensity score estimator to control for observed heterogeneity. The tangible results of this estimator will come at the cost of being an upper bound at best. Our second approach will therefore control for individual fixed effects in an event study design. We will then focus on the divergent development over time within stayers and movers while allowing for differences in levels.

3 Long term labor market outcomes of stayers and movers

3.1 Matching estimates

We begin by comparing the cumulative labor market outcomes of people who stay in their original region versus people who move to another region within two years. We use a simply propensity score matching estimator to condition on observable characteristics at the time of layoff and 5 years before. Since this framework does not allow us to hold constant any unobserved characteristics, our estimates are likely to be upwards biased, if movers are positive selected of all people in our mass-layoff sample. This exercise is still useful in two ways: first, we analyze which of the observed characteristics are related to the probability to take up a job elsewhere after a layoff. Second, repeating the matching procedure for groups of workers with the same occupational field, who were laid off in the same region and year, helps us to narrow down the control group of non-movers in the subsequent event study analysis.

Table 2 reports marginal effects of probit models, where the mobility dummy is regressed on the observable characteristics before the layoff. The findings corroborate the impression from the summary statistics: the likelihood to move within 3 years after the layoff decreases with age, experience, and low qualification. Workers with higher earnings before the layoff are more likely to move. Married men are about 1 percentage point more likely to move, while the likelihood to move increases by about 10% points for workers who were mobile before.

Models in table 3 report average treatment effects on the treated from matching models. The propensity scores have been determined from the models shown above, separately for each

Table 2: Observable determinants of mobility, marginal effects of probit models

	Dependent variable: dummy, 1= moves within 3 years after layoff			
	total	low skill	med. skill	high skill
age	-0.0482*** (0.014)	-0.0475** (0.021)	-0.0464*** (0.017)	-0.3584** (0.168)
age ²	0.0015*** (0.000)	0.0014** (0.001)	0.0014*** (0.000)	0.0093** (0.004)
age ³	-0.0000*** (0.000)	-0.0000*** (0.000)	-0.0000*** (0.000)	-0.0001** (0.000)
exper	-0.0214*** (0.003)	-0.0092** (0.004)	-0.0268*** (0.003)	-0.0218 (0.015)
exper ²	0.0006*** (0.000)	0.0002 (0.000)	0.0007*** (0.000)	0.0005 (0.001)
tenure	0.0067*** (0.002)	0.0032 (0.003)	0.0084*** (0.002)	-0.0021 (0.014)
tenure ²	-0.0002*** (0.000)	-0.0001 (0.000)	-0.0003*** (0.000)	0.0001 (0.001)
dummy, married	0.0129*** (0.003)	0.0193*** (0.005)	0.0125*** (0.004)	-0.0142 (0.023)
dummy, prev. mobile	0.1055*** (0.004)	0.0602*** (0.006)	0.1195*** (0.004)	0.1171*** (0.024)
dummy, low skilled	-0.0432*** (0.004)			
dummy, high skilled	-0.0057 (0.009)			
earnings _{t=-0}	0.0007* (0.000)	-0.0015* (0.001)	0.0011*** (0.000)	-0.0005 (0.001)
earnings _{t=-1}	-0.0000 (0.001)	0.0031** (0.002)	-0.0003 (0.001)	-0.0005 (0.002)
earnings _{t=-2}	0.0015*** (0.000)	-0.0000 (0.002)	0.0018*** (0.001)	-0.0011 (0.002)
earnings _{t=-3}	0.0008 (0.001)	-0.0004 (0.002)	0.0008 (0.001)	0.0031* (0.002)
earnings _{t=-4}	0.0012** (0.000)	0.0016 (0.001)	0.0012** (0.001)	-0.0001 (0.002)
obs	93620	25208	66818	1580
pseudo R ²	0.048	0.032	0.043	0.063

Note: Variables measured at time of layoff, unless otherwise noted. Standard errors clustered within mass-layoff events in parentheses. Levels of significance: *** 1 %, ** 5 %, * 10 %.

outcome. The first outcome is the annual employment rate, cumulated over the observation period. This variable takes the value of 10 if a worker found a job right after the layoff and was employed for the whole observation period. We see that the average employment rate is substantially smaller for both groups. Movers are employed for about 7.5 years during the decade after the layoff, which is still 1.3 years longer than comparable stayers.² There is also a substantial drop in cumulative earnings. For low and medium skilled workers, the mobility-premium is around €48,000 over 10 years. Compared to the annual earnings 4 years before the layoff, the effect of mobility amounts to around 14 percent of pre-layoff earnings. Differences in average wages are much more modest. Apparently, differences in earnings are driven more strongly by differences in the employment rate rather than wages.

Table 3: Propensity score matching estimates of cumulative long term outcomes

total		low skilled		med. skilled		high skilled	
movers	ATT	movers	ATT	movers	ATT	movers	ATT
A) Dependent variable: cumulative employment rate $0 < t \leq 10$							
7.476	1.282	7.075	1.574	7.577	1.162	7.326	2.336
	(0.042)		(0.098)		(0.047)		(0.293)
B) Dependent variable: cumulative earnings $0 < t \leq 10$							
243,479	47,812	199,265	44,999	251,131	46,086	322,822	122,214
	(1,643)		(3,186)		(1,844)		(14,624)
C) Dependent variable: average daily wage $0 < t \leq 10$							
86.675	3.315	74.032	1.804	88.533	4.148	118.287	7.199
	(0.317)		(0.515)		(0.356)		(3.004)
D) Dependent variable: cumulative earnings $0 < t \leq 10$ relative to $10 \times$ earnings in $t = -4$							
0.768	0.138	0.713	0.174	0.779	0.131	0.824	0.295
	(0.006)		(0.012)		(0.006)		(0.044)
E) Dependent variable: average daily wage $0 < t \leq 10$ relative to wage in $t = -4$							
0.993	0.041	0.969	0.031	0.996	0.048	1.087	0.092
	(0.004)		(0.008)		(0.005)		(0.034)

Note: Average treatment effects on the treated, control group determined from propensity scores of probit models as in table 2. Abadie-Imbens robust standard errors in parentheses.

3.2 Event study design

The matching estimates of the previous chapter are an upper bound of the mobility effect at best. If the selection into mobility is correlated to unobserved but time-constant factors such as innate motivation and ability or individually perceived costs of moving, controlling for fixed effects will yield more conservative estimates. We use an event study type of design in

²While this effect is much larger for high skilled workers, this result should be regarded with caution due to the small size of this group in our sample.

the vein of Jacobson, LaLonde, and Sullivan (1993) to exploit the time structure of our data and to control for unobserved heterogeneity between workers. The difference to their classical event study design is that everyone in our sample is “treated” with a layoff, but not everybody is “treated” with regional mobility. So instead of comparing laid-off to retained workers, we compare regional stayers and movers within the population of workers hit by a mass layoff.

To construct the graphs, we run regressions of the form:

$$y_{ikm} = \alpha_i + \gamma_t + X'_{ik}\beta + \sum_{k=\underline{C}}^{\bar{C}} \delta_k^S S_{ik} + \sum_{k=\underline{C}}^{\bar{C}} \delta_k^M M_{ik} + u_{ik}. \quad (1)$$

i is the individual, k the years relative to the layoff and m indicates the firm at which the mass layoff occurred for person i . M_{ik} and S_{ik} represent the interactions between the migration decision for movers/stayers and the number of periods relative to the layoff. We set $\underline{C} = -4$ and $\bar{C} = 10$. We work with a balanced set in event time units for the treatment effect of mobility, following (McCrary, 2007) we bin the endpoints. For all individuals with more than 10 post-layoff periods, we impose $M_{ik}^{\bar{C}} = I [k \geq \bar{C} \wedge m_i = 1]$, where m_i is an indicator if the person moved after the layoff. Analogously, we bin pre-layoff observations of more than 5 years always, for those individuals with the information available, as $M_{ik}^{\underline{C}} = I [t \geq L_{ik} \wedge m_i = 1]$. Finally, we normalize $\delta_{t-4}^S = 0$ for both groups. Each event-time coefficient δ_k^S (δ_k^M) can thus be interpreted as the difference of outcome y_{ikm} between 4 years before the layoff and period k , for the average stayer (mover). α_m and γ_t are individual and calendar year fixed effects.

3.3 Baseline Results

Figure 1 reports our baseline results for the total sample.³ All five panels show that the evolution of stayers and movers is extremely similar before the layoff. Since our sample is restricted to workers with high firm attachment prior to the layoff, this is not surprising in the left picture. But it is reassuring to see that also earnings and wages, that are not fixed by construction, follow the same trend before the layoff. In both cases, a more or less pronounced downwards trend can be observed, which points towards an Ashenfelter’s (1978) dip, as firms were already doing bad before the layoff.⁴

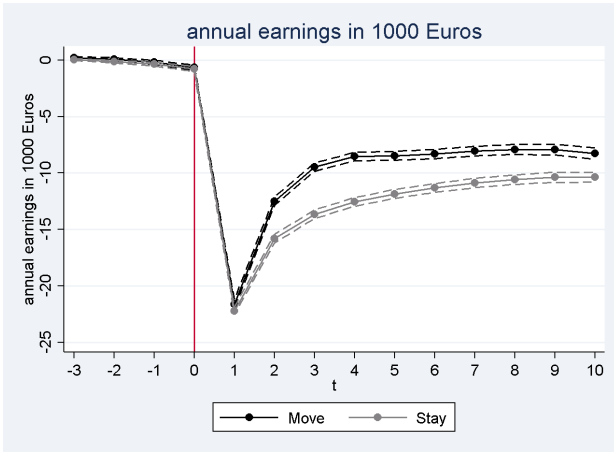
One year after the layoff, the employment rate and earnings of movers and stayers are virtually indistinguishable. Four years after the layoff, however, the difference in terms of employment rates is around 14 percent. The differential earnings losses between movers and stayers are about the same size. Mover’s earnings losses after four years are about €4,000 smaller than stayer’s losses, which again corresponds to 14 percent of pre-layoff earnings. Even

³The same results are tabulated in table A1 in the appendix.

⁴One might wonder whether this makes our sample selective. However, we do not observe workers who left the firm at one exact date, but rather those who left within a 365 days period in which a firm reduced its size or disappeared.



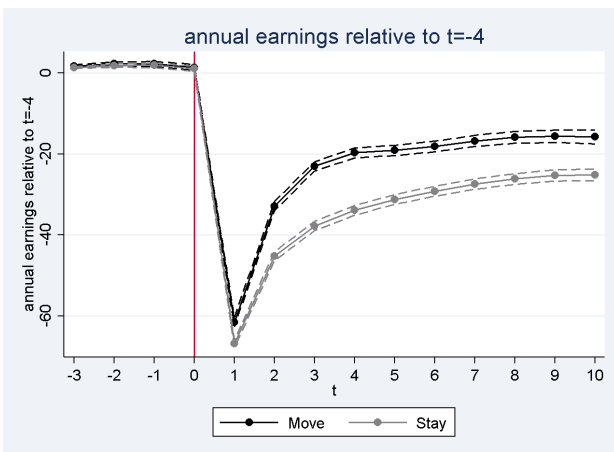
(a) employment rates



(b) annual earnings



(c) average daily wages



(d) relative annual earnings in %



(e) relative average daily wages in %

Figure 1: Event studies, baseline results: all movers and stayers

after 10 years, those differences never disappear. We also observe that both movers and stayers have a permanent decline in average wages after the layoff of about 15 percent, conditional on finding a job. Yet, movers have slightly smaller losses. They are compensated for possible mobility costs in terms of a wage premium of around 2.7 percent in terms of the average wage 4 years before the layoff. Given the much smaller differences in conditional wages, the differential earnings thus stem almost exclusively from differences in the employment probability.

Summing up over the whole observation window, movers have lost around €29,000 less in earnings, which corresponds to a relative difference of around 11 percent, both in terms of employment rates and relative earnings.

3.4 Robustness Checks

One caveat of our main data set is that we can only observe mobility if people change their place of work, which necessarily means that they take up a new job. Yet, some people might first relocate and then start searching for a job in their new place of residence. Since we can only observe the place of residence after 1999, we repeat our event study with a similar sample of all workers who lost their job in a mass layoff between 2000 and 2005 and observe their biographies for the following 5 years. We now change the definition of our mobility variable to include all changes of residence as well as changes of working place, but not if someone changes his place of residence to the former working place, which might be an artefact of a deferred notification of a previous move.⁵

Figure 2 in the appendix shows that adding the mobility during unemployment does not alter our main findings. Interestingly, the mobility premium becomes even larger: after four years, the annual employment rate now differs by 17 rather than 14 percentage points. This supports our belief that mobility measured by a change of working place is a good indicator for unemployed who search for a new job outside of their original region. We cannot disentangle whether the larger effect stems from unemployed job seekers being an even better selection of all unemployed or if the latter time period was more dynamic. But we can reason that omitting unemployed movers does not reduce the validity of our results.

3.5 Effects By Skill Groups

Figures 3-5 display results from the benchmark specification of the pre-2000 layoff sample, separated by skill groups. The general conclusions hold for each skill group individually, both in terms of employment and earnings. However, high skilled movers are the group that recovers best. After 10 years, there is no significant difference in employment rates compared to before the layoff, while there are still substantial losses for high skilled stayers. The other two skill groups have more modest mobility premia of 13 (medium) and nine (low) percent, respectively.

⁵All other data cleaning procedures are analogous to the main sample.

3.6 Effects Among Previously Mobile

Previous mobility is by the far the strongest predictor of mobility after the layoff. There might be two reasons, why these people are more likely to move a second time: first, they might have moved away from their families earlier. Being laid off might be a motive to move back to their families. Second, these people might have unobserved characteristics that make them more mobile. If the former reason is more important, focusing on previously mobile movers should yield results in line with Huttunen, Møen, and Salvanes (2015): the mobility premium should shrink as these people might be willing to accept lower earnings or employment prospects just to be with their families (and possibly save costs in housing etc.). If the later reason prevails, the mobility premium should shrink as well. As those people are a positive selection out of all workers, stayers and movers in this particular group should be more similar. Since we dropped all workers who moved back to their very first place of work, a reduction of the mobility premium is likely to stem from the second mechanism.

In appendix figure 6 and 7, we focus on those workers who have been mobile before. The results show an interesting pattern. The difference in average wages indeed decreases, both after three years and over the whole period. But the effect on employment and earnings becomes slightly larger by around two percentage points for the group of previously mobile workers. It appears as if movers and stayers are more similar in terms of ability, but searching for a job in another region gives those people an even larger edge in the probability to find a job more quickly. This effect becomes even larger by one additional percentage point if only unmarried workers are considered.

3.7 Industry mobility

Finally, we benchmark our results against mobility between industries, as another form of mobility. A mass layoff means that there is a large supply shock or work in a local labor market. It is unlikely that this supply is absorbed fully within the same local industry. While some workers seek employment in another region, a second mechanism of adjustment might be to work in another industry, despite the the loss of specific human capital. In figure 8, we repeat the event study but redefine mobility. Mobile workers now have changed into another 2-digit industry within three years after the layoff. The mobility premium increases substantially, both in terms of employment and earnings. The pattern in subfigure (c) is particularly striking: industry movers have significantly higher wage losses up until four years. After eight years, they earn higher wages than industry stayers. Apparently, it takes time to accumulate specific human capital in the new industry. Employment gains are more immediate. If a large firm closes or lays off a large share of its workers, it might do so because the whole sector is declining. Moving to another sector is thus a dominant strategy, regardless of whether it is in the original region or elsewhere.

4 Conclusion

Our study uses a comprehensive administrative dataset on the employment biographies of workers who were laid off during a mass layoff event. Even after controlling for observable and unobservable individual heterogeneity, we find that the negative long term effects of being fired are substantially reduced if people search for jobs out of their original region. Over the period of ten years after the layoff, mobile workers are more than one year more employed than those who prefer to stay in the original region.

The effects of regional mobility are smaller than those of moving between industries. Nonetheless, a mass layoff often affects a whole local labor market. Moving away can be a sensible strategy to avoid the rat race among job seekers for the remaining jobs in the home region.

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Appendix

A Table Appendix

Table A1: Baseline results, all movers and stayers

	Dependent variables:				
	employment rate	annual earnings	avg. daily wage	earnings relative to $t = -4$	avg. wage
mover, 3 yrs before layoff	-0.0024*** (0.001)	0.2176*** (0.050)	0.5666*** (0.121)	1.7073*** (0.171)	0.8971*** (0.155)
mover, 2 yrs before layoff	-0.0031*** (0.001)	0.0838 (0.068)	0.0872 (0.155)	2.2687*** (0.236)	0.5887*** (0.208)
mover, 1 yrs before layoff	-0.0022 (0.002)	-0.2023** (0.092)	-0.8757*** (0.210)	2.2130*** (0.307)	-0.3594 (0.268)
mover, year of layoff	-0.0104*** (0.002)	-0.6510*** (0.118)	-1.0925*** (0.270)	1.3348*** (0.389)	-0.5614* (0.341)
mover, 1 yrs after layoff	-0.5589*** (0.005)	-21.6053*** (0.203)	-15.2229*** (0.340)	-61.5110*** (0.567)	-14.9879*** (0.416)
mover, 2 yrs after layoff	-0.2553*** (0.004)	-12.4991*** (0.189)	-15.4099*** (0.353)	-32.9098*** (0.574)	-15.2433*** (0.432)
mover, 3 yrs after layoff	-0.1549*** (0.004)	-9.4807*** (0.185)	-15.3400*** (0.380)	-23.0865*** (0.585)	-15.2150*** (0.464)
mover, 4 yrs after layoff	-0.1295*** (0.004)	-8.5447*** (0.191)	-14.6760*** (0.396)	-19.7329*** (0.616)	-14.5150*** (0.492)
mover, 5 yrs after layoff	-0.1300*** (0.005)	-8.4727*** (0.199)	-14.3296*** (0.417)	-19.1283*** (0.642)	-14.1872*** (0.521)
mover, 6 yrs after layoff	-0.1260*** (0.005)	-8.3164*** (0.210)	-14.1388*** (0.447)	-18.1500*** (0.675)	-14.0240*** (0.559)
mover, 7 yrs after layoff	-0.1191*** (0.005)	-8.0561*** (0.216)	-13.8511*** (0.470)	-16.7643*** (0.703)	-13.6567*** (0.594)
mover, 8 yrs after layoff	-0.1162*** (0.006)	-7.9114*** (0.227)	-13.3729*** (0.493)	-15.8813*** (0.744)	-13.1518*** (0.625)
mover, 9 yrs after layoff	-0.1144*** (0.006)	-7.9267*** (0.240)	-13.2924*** (0.525)	-15.6494*** (0.778)	-13.1764*** (0.653)
mover, 10 yrs after layoff	-0.1225*** (0.007)	-8.2721*** (0.259)	-13.3551*** (0.562)	-15.8058*** (0.859)	-13.2242*** (0.725)
stayer, 3 yrs before layoff	-0.0012**	0.0513	0.0553	1.3282***	0.4137***

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	(0.001)	(0.042)	(0.101)	(0.135)	(0.121)
stayer, 2 yrs before layoff	-0.0007	-0.1321**	-0.6142***	1.7818***	-0.1013
	(0.001)	(0.061)	(0.143)	(0.193)	(0.175)
stayer, 1 yrs before layoff	0.0018	-0.3617***	-1.5018***	1.8475***	-1.0530***
	(0.002)	(0.084)	(0.184)	(0.265)	(0.226)
stayer, year of layoff	-0.0047**	-0.7826***	-1.7283***	1.0863***	-1.2772***
	(0.002)	(0.109)	(0.235)	(0.342)	(0.289)
stayer, 1 yrs after layoff	-0.6139***	-22.2111***	-16.3070***	-66.8457***	-17.4758***
	(0.004)	(0.161)	(0.252)	(0.460)	(0.311)
stayer, 2 yrs after layoff	-0.3833***	-15.8139***	-16.4573***	-45.2393***	-17.5501***
	(0.005)	(0.192)	(0.273)	(0.565)	(0.336)
stayer, 3 yrs after layoff	-0.3060***	-13.6431***	-16.3135***	-37.7787***	-17.3822***
	(0.006)	(0.195)	(0.302)	(0.586)	(0.375)
stayer, 4 yrs after layoff	-0.2690***	-12.5598***	-16.1894***	-33.9048***	-17.1928***
	(0.006)	(0.199)	(0.324)	(0.606)	(0.404)
stayer, 5 yrs after layoff	-0.2448***	-11.8468***	-16.1002***	-31.2302***	-17.0423***
	(0.006)	(0.200)	(0.341)	(0.616)	(0.432)
stayer, 6 yrs after layoff	-0.2277***	-11.3212***	-15.9959***	-29.1875***	-16.9221***
	(0.006)	(0.203)	(0.368)	(0.631)	(0.466)
stayer, 7 yrs after layoff	-0.2147***	-10.8824***	-15.8322***	-27.4257***	-16.6736***
	(0.006)	(0.210)	(0.397)	(0.654)	(0.502)
stayer, 8 yrs after layoff	-0.2064***	-10.5817***	-15.6547***	-26.1747***	-16.4323***
	(0.006)	(0.215)	(0.423)	(0.672)	(0.534)
stayer, 9 yrs after layoff	-0.2007***	-10.3813***	-15.5564***	-25.3021***	-16.2996***
	(0.006)	(0.226)	(0.449)	(0.710)	(0.564)
stayer, 10 yrs after layoff	-0.2056***	-10.3673***	-15.7004***	-25.1297***	-16.5138***
	(0.006)	(0.228)	(0.484)	(0.731)	(0.616)
obs	1932725	1932725	1426125	1932700	1426101
groups	93620	93620	93620	93619	93619
R ²	0.484	0.459	0.128	0.429	0.114
difference after 4 yrs	0.140	4.015	1.513	14.172	2.678
total difference	1.045	28.523	1.712	10.960	2.810

Note: Fixed effects regressions. Standard errors clustered within mass-layoff events in parentheses.

Levels of significance: *** 1%, ** 5%, * 10%.

B Figure Appendix

B.1 Layoffs after 2000

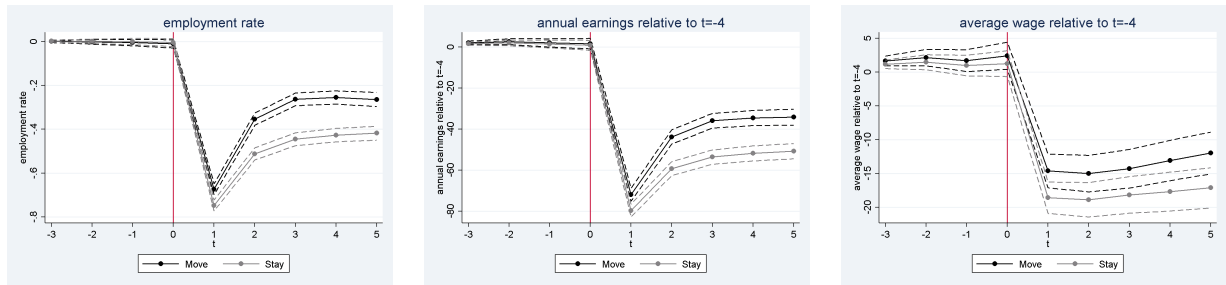


Figure 2: Layoffs after 2000

B.2 Different skill groups

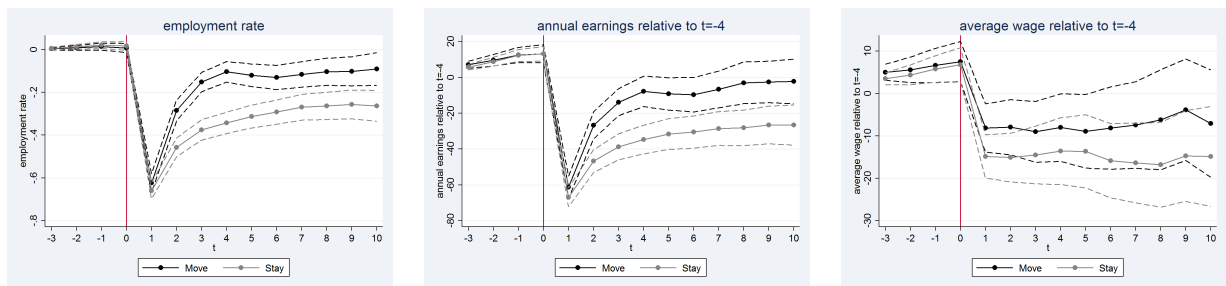


Figure 3: Event studies, high skilled only

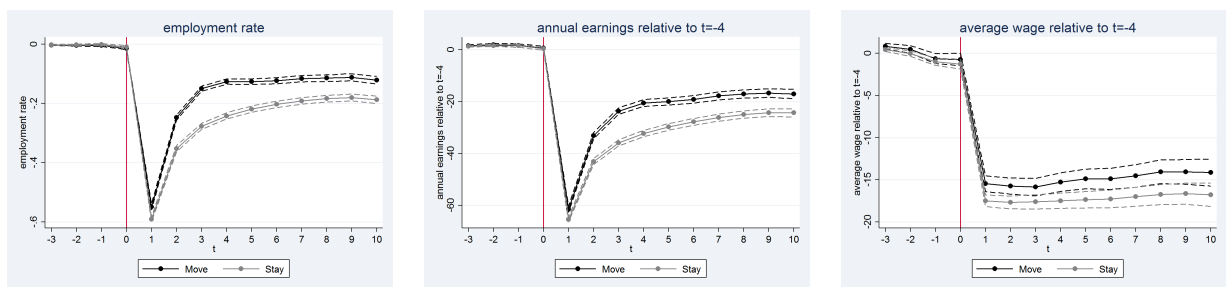
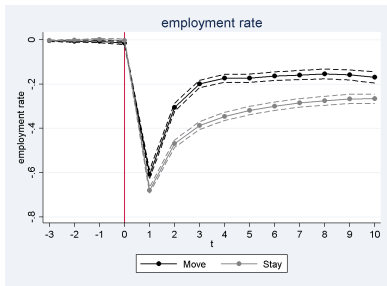
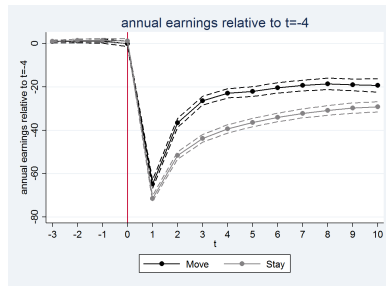


Figure 4: Event studies, medium skilled only



(a) employment rates



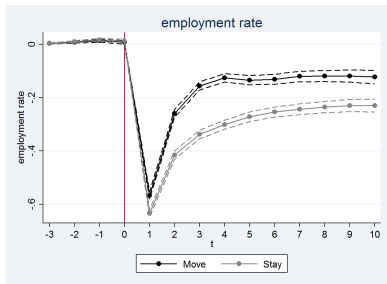
(b) relative annual earnings in %



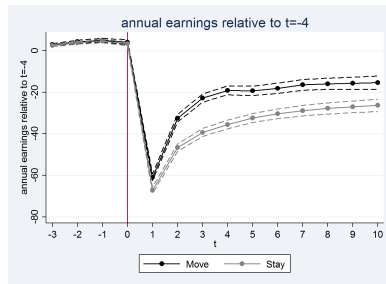
(c) relative avg. daily wages in %

Figure 5: Event studies, low skilled only

B.3 Only previously mobile people



(a) employment rates

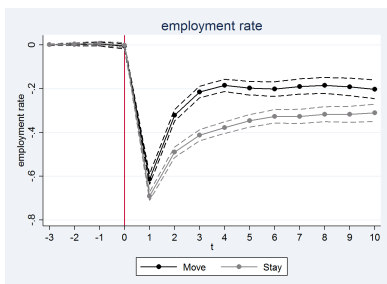


(b) relative annual earnings in %

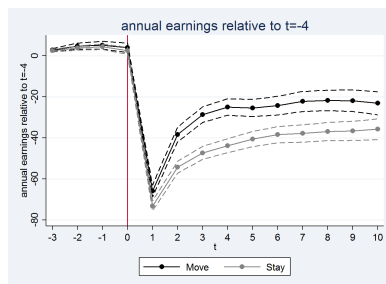


(c) relative avg. daily wages in %

Figure 6: Event studies, previously mobile only



(a) employment rates



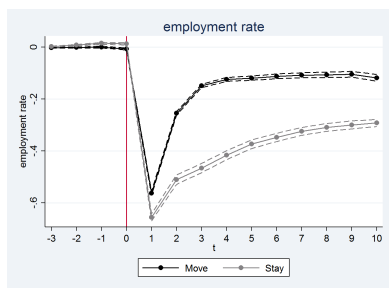
(b) relative annual earnings in %



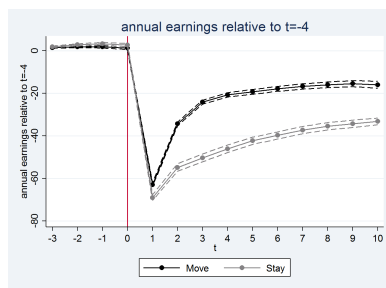
(c) relative avg. daily wages in %

Figure 7: Event studies, previously mobile, unmarried only

B.4 Industry mobility



(a) employment rates



(b) relative annual earnings in %



(c) relative avg. daily wages in %

Figure 8: Event studies, industry mobility