DEPARTMENT OF ECONOMICS
JOHANNES KEPLER UNIVERSITY OF LINZ

Great Expectations: Past Wages and Unemployment Durations

by

René BÖHEIM
Gerard Thomas HORVATH
Rudolf WINTER-EBMER*)

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Johannes Kepler University of Linz
Department of Economics
Altenberger Strasse 69
A-4040 Linz - Auhof, Austria
www.econ.jku.at

rudolf.winterebmer@jku.at
phone +43 (0)70 2468 -8236, -8217 (fax)

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René Böheim
Rene.Boeheim@jku.at

Gerard Thomas Horvath
Gerard_Thomas.Horvath@jku.at

Rudolf Winter-Ebmer
Rudolf.WinterEbmer@jku.at

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Abstract

Decomposing wages into worker and firm wage components, we find that firm-fixed components (firm rents) are sizeable parts of workers' wages. If workers can only imperfectly observe the extent of firm rents in their wages, they might be mislead about the overall wage distribution. Such misperceptions may lead to unjustified high reservation wages, resulting in overly long unemployment durations. We examine the influence of previous wages on unemployment durations for workers after exogenous lay-offs and, using Austrian administrative data, we find that younger workers are, in fact, unemployed longer if they profited from high firm rents in the past. We interpret our findings as evidence for overconfidence generated by imperfectly observed productivity.

Keywords: Unemployment, Job Search, Overconfidence.
JEL classification: J3, J6

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*Department of Economics, Johannes Kepler University Linz, Austria; Austrian Center for Labor Economics and the Analysis of the Welfare State. René Böheim is also affiliated with the Austrian Institute of Economic Research, and IZA, Bonn. Rudolf Winter-Ebmer is also affiliated with the Institute for Advanced Studies, Vienna, and IZA, Bonn. Thanks to Holger Bonin, David Card, Julian Messsina, Tim Hatton, Andrea Weber and participants at seminars in Linz, London (EALE), Essen (ESPE) and at the IZA summer school 2010. This research was supported by the Austrian Science Funds (FWF).

1 Introduction

Job search theory offers a framework to explain the duration of unemployment spells. In this framework, unemployed workers search sequentially for a job. If job offers arrive at random and the distribution of offers is known, it is optimal for the searcher to accept the first offer which is at or above the reservation wage. This strategy balances search costs and expected gains from further search.

Knowing or learning about the distribution of wage offers is a non-trivial task for job-seekers. While the job searcher is learning over time — updating prior beliefs with recently sampled job offers — the choice of an initial prior is important.[1] A job searcher may use his or her past wage as a prior for the wage offer distribution. If the past wage equals the worker's productivity, it will be a perfect starting point. If, however, the wage was greater than the worker's productivity, e.g., because of seniority wages, this may result in an overly high reservation wage due to a distorted perception of the worker's productivity. In consequence, the overly high reservation wage will result in the rejection of wage offers the worker would have accepted had the reservation wage been based on the correct wage distribution. Empirically, this will translate into relatively longer unemployment durations, which are being determined by how quickly the searcher updates his or her prior of the wage

[1] In special situations, e.g., if the searcher's prior beliefs follow a Dirichlet distribution and the searcher is updating her priors according to Bayes' rule, this does not matter: even if the wage offer distribution is unknown, the qualitative properties of optimal search strategies remain the same (Rothschild, 1974). But as Rothschild (1974) points out, "(the results) are still quite special, as the proofs depend on the process of revising beliefs to accommodate new information having a particular—and not terribly natural—local property" (p. 694).

offer distribution.[2]

We study workers who exogenously lost their jobs due to plant closures and analyze their unemployment durations. A random sample of unemployed workers would be problematic for two reasons: workers dismissed for a cause might be negatively selected and, more importantly, workers who quit their job voluntarily typically do so because they are looking for a better(-paid) job. These workers will bias the analysis. Using unemployed workers from plant closures solves this problem, because plant closures hit all workers alike.

Because wages may contain components which are not related to a worker's productivity, such as rents, seniority pay or efficiency wage components, we decompose past wages into worker-specific, human-capital specific and firm-specific components. The decomposition separates wage components which reflect a worker's productivity, including unobservable productivity components (fixed effects), from a firm-specific part of the wage. The firm-specific component — we use the term "rent" from now on — are normalized to reflect deviations from the industry average. Our data cover all Austrian workers for more than three decades, which allows us to reliably decompose the last wage before the plant closures and to study the unemployed workers' subsequent labor market spells. Using the same decomposition procedure, Gruetter and Lalive (2009) show that firm fixed effects indeed play an important role in the wage determination in Austria. Their estimates suggest that around 27% of total variation in wages can be explained by

[2]Winter-Ebmer (1998) studies the relation between the wage distribution in the last firm and unemployment durations and finds that average wages have no association with unemployment durations, while other parameters of the wage distribution, e.g., inequality in the old firm, do.

unobserved firm effects, i.e. firm rents.

These considerations are related to recent discussions in behavioral economics about overconfidence (Della Vigna, 2007). Workers who judge their productivity correctly will base their expectations of the wage offer distribution only on those parts of the wage which reflect their productivity. Overconfident workers might mistake (parts of) the firm rent for their own productivity and attribute the firm rent to their own effort and ability. While there is field evidence on overconfidence in e.g., trading patterns of individuals (Barber and Odean, 2001) or in CEO behavior (Malmendier and Tate, 2005), there is little direct evidence on labor market or search behavior. Hoch (1985) found that MBA students overestimate the number of job offers they will receive and the magnitude of their salary.[3]

Our analysis is also relevant for the discussion of the employment patterns of older workers. For example, Saint-Paul (2009) argues that Continental European labor markets are rigid, especially because of age- and tenure-related wage schedules, and in addition to earnings-related (Bismarckian) welfare state benefits, older workers might easily become too expensive, given their productivity. If older workers receive wages that are in excess of their productivity due to seniority-based wages and they, on becoming unemployed, mistakenly assume that such wages reflect their true productivity, they will have reservation wages that are too high and end up with long unemployment durations. Our analysis can shed some light on this discussion.

[3]Dubra (2004) assumes in a theoretical model that searchers are overconfident and explores search behavior and corresponding welfare effects. There is also a larger experimental literature on bargaining behavior, e.g., Babcock and Loewenstein (1997).

We find that only young workers can be described as overconfident. Workers who previously had a high firm rent tend to search longer for a new job than those who had a low firm rent. They presumably expect to find high-paying jobs and turn down more realistic job offers at the start of their unemployment spells. We explore that the pattern might be caused by misconceptions of the true wage distribution, e.g., because workers have not been actively searching for new employment in the past. Our analyses along such lines suggest that overconfidence is the more probable explanation for the relatively longer unemployment durations of workers who had high firm rents. In addition, we do not find evidence that older workers remain unemployed because they systematically misjudge potential wages, given their productivity.

2 Empirical Strategy

We model unemployment durations with proportional discrete time hazard rate models. We use the Prentice and Gloeckler (1978) model, augmented with a discrete mixture distribution to account for unobserved individual heterogeneity, as proposed by Heckman and Singer (1984).[4]

Suppose there are $i = 1, ..., N$ workers who become unemployed at time $t = 0$ and are observed for s time periods. At each point in time, the worker either remains unemployed or finds new employment. The discrete hazard

[4]We use Jenkins' (2004) Stata module to estimate the hazard models.

rate in period t is (Prentice and Gloeckler, 1978):

$$h_t = 1 - \exp(-\exp(\beta_0 + X_{it}\beta)), \tag{1}$$

where β_0 is an intercept and the linear index function, $X_{it}\beta$, incorporates the impact of the covariates. (See also Jenkins (1995).) Workers who leave the sample for other reasons, e.g., retiring, are treated as censored.

Suppose that each worker belongs to a group of an unobserved type, e.g., low or high ability in obtaining a job. This can be parameterized by allowing the intercept term β_0 to differ across types (Heckman and Singer, 1984). In a model with types $z = 1, ..., Z$, the hazard function for worker belonging to type z is:

$$h_{z,t} = 1 - \exp(-\exp(m_z + \beta_0 + X_{it}\beta)), \tag{2}$$

and the probability of belonging to type z is p_z. The m_z are the mass points of a multinomial distribution where m_1 is normalized to equal zero and $p_1 = 1 - \sum_{z=2}^{z=Z} p_z$. The z-th mass point equals $m_z + \beta_0$.

This econometric specification allows for time-varying covariates and to investigate the importance of unobserved heterogeneity for leaving unemployment. The vector of characteristics, X_{it}, includes time-invariant characteristics, e.g., the firm size at the start of the unemployment spell, and time-varying characteristics, such as e.g., the benefit replacement rate of the unemployed. In addition to these (standard) controls, we also control for whether the worker enjoyed above-average firm rents or not, estimated from a decomposition of the wages. We expect that workers who had received above-average firm rents to remain unemployed longer, all other things equal.

3 Data

We use linked employer-employee data from the Austrian Social Security Database (ASSD) which contains detailed information on all workers covered by the Austrian social security system from 1972 to 2009.[5] Because of strong seasonality in employment (Del Bono and Weber, 2008), we exclude construction and tourism workers. We also limit our sample to workers with a minimum tenure of six weeks in the last firm.

Typically, a sample of job searchers is composed of workers who were fired in their old job due to inadequate performance, workers who were fired due to labor demand volatility and workers who quit voluntarily. Both workers fired for cause and those quitting voluntarily pose a problem for an analysis of wage expectations, because their separation from the firm is an endogenous event. We therefore concentrate on workers from plant closures where the cause of unemployment is an exogenous event. Our sample consists of workers who were laid off due to plant closures between 1990 and 1996 and who were between 20 and 55 (50 for females) years of age at that time.

Plant closures are not directly observed in the data, but identified indirectly by the disappearance of a firm's identifier. To ensure these disappearances are true plant closures, and not merely caused by e.g., administrative

[5] See Zweimüller et al. (2009) for a description of the data.

recoding, we define firms as closing firms only if one of the following requirements is fulfilled. First, the majority of workers is not immediately employed after the disappearance of the identifier, (2) the majority of workers is employed in a single firm with a different identifier, but the workers account for less than 50% of the new firm's workforce, or (3) the majority of workers is spread out over different firms.

In total, we observe 28,078 female and 37,432 male workers being laid off from 31,704 closing firms within 60 days before plant closure.[6] From these, we exclude workers for whom we cannot decompose the wages, which reduces our estimating sample to 24,424 female and 34,746 male workers in 30,192 closing firms.[7] The unemployment duration is the number of days starting from the day the worker is laid off until the worker starts a new job. Unemployment spells that last longer than 1,500 days are censored. Spells that end with death, self employment, maternity leave, or subsidized employment and sick leave lasting for more than 6 months are also censored.

3.1 Decomposition of wages

Following Gruetter and Lalive (2009) we derive our proxy for the distortion of the reservation wage by decomposing wages into worker-specific, human-capital specific and firm-specific components. For this we use the universe of all blue-collar workers for the years 1980 to 2000 (and not only our sample of

[6]To check for robustness, we follow Schwerdt (2008) and also sample early leavers: workers who were laid off up to 180 days before plant closure. See below.

[7]Notice that firm-fixed components in the wages are only identified if we observe at least one worker moving in or out of a firm. Similarly, worker-fixed components are only identified for workers who are observed in at least two different firms.

workers who worked in firms that closed down). These are 3,818,508 workers in 459,144 firms after deleting observations where we cannot identify the wage components. (Summary statistics of the sample that we use for the decomposition of the wages are shown in the Appendix, Table 8.)

The wages are decomposed following Abowd et al. (1999):

$$\begin{aligned} \underbrace{y_{ijt}}_{\log(\text{wage})} = & \underbrace{\phi_j}_{\text{firm-fixed component}} + \underbrace{\theta_i}_{\text{person-fixed component}} \\ & + \underbrace{X'_{ijt}\beta}_{\text{returns to productivity}} + \epsilon_{ijt}, \end{aligned} \tag{3}$$

where

$$E\left[\epsilon_{it}|\theta_i, \phi_j, t, X_{ijt}\right] = 0. \tag{4}$$

The parameter ϕ_j in equation (3) gives the difference in earnings in firm $j = 1, ..., J$, relative to the average firm. This is our indicator of firm rents as it indicates a relatively low or high wage in the past job, controlling for observed and unobserved worker heterogeneity. The parameter θ_i captures all (unobserved) time-invariant differences between workers and may be seen as a proxy for ability. The parameter vector β captures economy wide returns to productivity and experience for the time-varying characteristics of worker i in firm j at time t, X_{ijt}.[8]

It is important to stress that the identifying assumption behind equa-

[8]We use Ouazad's (2008) Stata module. Standard errors are obtained via bootstrapping. Detailed estimation results are shown in the appendix.

tion (4) requires the error term to be independent of any observable effects in X_{ijt}, the person-fixed component θ_i or the firm-fixed component ϕ_j. In other words, it assumes exogenous mobility. If there is positive assortative matching, i.e., good firms employ good workers, then the correlation between θ_i and ϕ_j should be positive (and large).[9] Here, in contrast, we find that firm and worker fixed components are weakly negatively correlated, the correlations are -0.01 for male and -0.006 for female workers. However, Abowd et al. (2004) caution that the mere examination of the correlation between person and firm components is not sufficient to provide evidence for or against sorting in the labor market. We therefore follow De Melo (2008) and additionally calculate the correlation between a worker's fixed component, θ_i, and the mean of the co-workers' fixed components, $\bar{\theta}_{-i}$. This correlation is small, $\mathrm{corr}(\theta_i, \bar{\theta}_{-i}) = 0.095$, and indicates that there is little sorting in our data.[10]

Because we normalize the firm rent to reflect deviations from the industry average, we characterize workers by whether they worked in firms that paid above the average, "high-rent firms", and those that paid below the average. Table 1 tabulates summary statistics of our sample of unemployed workers, dividing the sample into persons coming from firms with below and above average firm rents. 54% of the men who became unemployed after a plant closure had below average firm rents. In contrast, 71% of women had below average rents. Workers who received low rents had on average lower

[9]Shimer (2005) shows that a model with coordination frictions may lead to positive but imperfect correlation between workers' productivity and firms' types. Abowd et al. (2004), in a simulation of Shimer's (2005) results, obtain a negative correlation between person and firm components.

[10]We bootstrap the correlation using 50 replications.

wages than those with high rents, the difference in means was greater for men (about €14/day) than for women (€10/day). Consistent with our arguments above, we observe longer unemployment durations with high rents than for those with low rents if we consider male workers - 128 vs. 117 days. For women, however, the mean duration of 123 days for high rent workers is slightly shorter than for low rent workers (126).

Although post-unemployed wages were on average higher for high rent workers than for low rent workers, we see that high rent workers experienced a relative wage loss and low rent workers a relative wage gain. High rent workers were slightly older than workers coming from low rent firms, and they had on average shorter tenures.

Table 2 tabulates mean unemployment durations for different groups of workers in more detail. Overall, men were unemployed for some 121 days and women for about 127 days. On average, workers with a low person-fixed component remain unemployed much longer than those with a high person-fixed component, 135 vs. 107 days for men and 135 vs. 112 days for women. This is consistent with interpreting the person-fixed component as an indicator of ability where workers who are more adept in the workplace are also more skilled in obtaining new employment. We also see that unemployment durations are on average longer for older workers.

If our decomposition of wages is valid, firm rents are random and workers who worked in high-rent firms should lose the rent, and vice versa. This is, in fact, what we find. For both males and females, workers who worked in low-rent firms have on average higher wages in their new jobs, and workers from high-rent firms have lower wages in their new jobs. Figure 1 looks at this pattern in more detail. For each elapsed unemployment duration, we plot the average wage change between the old and new job, distinguishing between workers who earlier had worked in low-rent or high-rent firms. Workers who had enjoyed positive firm-rents in the past clearly have lower wages in their new jobs, independent of elapsed unemployment duration. In contrast, workers who had worked in low-rent firms experience wage increases at shorter unemployment durations. For longer unemployment durations, they also experience a wage loss, however, this is less pronounced than for workers who had worked in high-rent firms.[11] Overall, workers who remain unemployed longer than about 20 weeks face a negative trend in wages, which is probably a combination of selection and stigma effects.

Figure 2 indicates that the convergence in wages is, in fact, driven by a convergence in firm rents. We see large increases in firm rents — up to 25% — for workers who had worked in low-rent firms and losses of about 10% for those from high-rent firms. These patterns are confirming once more the validity of the wage decomposition procedure.

4 Results

We present results from non-parametric discrete-time hazard rate models, estimated separately for men and women, in Table 3. The explanatory variables in all specifications include the replacement rate, the worker's age at

[11] Due to smaller sample sizes at longer unemployment durations, the confidence intervals are large at durations longer than 30 weeks.

the time of plant closure, the (old) firm's size at the time of plant closure, and indicator variables for year, industry and region. The specification presented in columns (1) and (4) does not contain the wage components and serves as a benchmark for our specifications below. The estimates indicate that the higher the replacement rate, the lower the hazard of finding employment, a finding that is consistent with previous research on unemployment durations (e.g., Meyer, 1990). Older workers search somewhat longer than younger workers.

The specification in columns (2) and (5) augments the benchmark specification with the estimated firm- and person-fixed wage components which are introduced as dummy variables indicating below or above average values. Workers who had high firm rents in their previous employment have lower hazard rates, indicating that they search longer than comparable workers who had low firm rents. The result holds both for men and women; however, for women, the coefficient is not statistically significant at conventional levels. The resulting longer unemployment durations for workers from high-rent firms are compatible with our hypothesis that these workers base their wage expectations not only on their person-specific component, but also on the firm rent.

These workers could be characterized as being overconfident of their own abilities and productivity. In other words, they appear to attribute the wage they earned in the past firm largely towards their own capabilities and disregard the randomness which might have played a role in the rent they enjoyed in the last firm. In addition, we find that individuals with high person-specific components leave unemployment earlier, in particular men. This variable is a proxy for fixed personal traits, such as ability, productivity or work effort, and the positive association with the hazard rate is therefore to be expected.

The specification in columns (3) and (6) additionally controls for unobserved heterogeneity in the search process by estimating two mass points for the distribution of abilities.[12] In addition to heterogeneity captured by the fixed person effects, which indicate differences in unobserved productivity, the mass points control for unspecific differences in job finding (and accepting) probabilities. It turns out that the inclusion of mass points does not change our estimated estimated coefficients to a large extent. The only exception is the coefficient for the high firm component for females, which is now more precisely estimated. Interestingly, the estimates imply only minor differences for male and female workers, and especially the associations between high rents and the hazard rate are virtually identical.

4.1 Age differences

Results from the psychological literature suggests that older adults have greater insight into the limitations of their knowledge than younger ones (Musiélak et al., 2006; Pliske and Mutter, 1996); in other words, overconfidence might be related to age and the associated differences in postformal cognitive development (Pliske and Mutter, 1996).

[12]When we include more than two mass points, all additional mass points are not statistically significant at conventional levels.

We split our population into young, prime-age and old workers. The results are tabulated in Table 4 using the comprehensive specification with mass points. While all other coefficients—in particular the person fixed effect and the benefit replacement rate—have almost exactly the same influence across age groups, the effect of the firm rent differs across age groups. Only for workers below the age of 30 we find a negative and significant effect of high rents on the hazard of leaving unemployment. This is consistent with other patterns of overconfidence by young people as know e.g., from traffic accidents.[13]

More importantly perhaps, we do not see any evidence for distorted wage expectations for prime-age workers and, in particular, for older workers. It seems that these workers do not have excessive wage expectations which were caused by firm rents; Saint-Paul's (2009) argument for the unemployability of older workers due to misguided reservation wages is not supported by our evidence.

4.2 Overconfident or inexperienced?

In our interpretations above we stressed overconfidence, i.e., attributing spurious wage components to one's own ability or effort, as the cause for the differences in unemployment durations. However, our empirical results could also be driven by systematic errors in deriving the reservation wages, for example, because workers with long tenures are less informed about the state

[13]Young drivers' higher probability of being involved in car accidents is found to be linked to young drivers being overconfident in their own driving abilities. See e.g., Brown (1982) and Rumar (1985).

of the labor market than workers who have short tenures. Workers with long tenures may not have good knowledge of the relevant wage offer distribution and they therefore might put too much emphasis on past wages. Workers who are new in a firm might have a better understanding of the outside opportunities, which they faced when they searched for the current job, and might therefore have less distorted views about the wage offer distribution and their own productivity. To investigate this issue, we separate our sample into workers with short and long tenure in the previous firm.[14] A tenure is short if it lasted up to 500 days.

The results are tabulated in Table 6. For males, we do not see any difference between short- and long-tenured workers. Young workers do search longer if they came from a high-rent firm, regardless of their tenure; prime-age and old workers do not search differently with respect to low-rent or high-rent firms. This is strong evidence against the misconception argument. For females, the results are similar: while we do find firm-rent effects for young short-tenured workers, the effect is smaller and insignificant for females with a longer job tenure in the past. If long tenures had caused the misconception, we would have expected the opposite result. Again, there is no effect for prime-age or old women.

A similar test concerns the number of previous jobs, where workers who were more exposed to *realized* rather than *offered* wages might have a more realistic perception of the wage offer distribution. We proxy this exposure by the number of previous jobs and define a worker who had 5 or more

[14] Due to small sample sizes, we pool prime age and older workers.

previous jobs as a "job hopper" and one with fewer than 5 previous jobs as a "stayer". The lower panel in Table 6 reports the estimated coefficients for these groups of workers, interacted with age. Again, we obtain large negative coefficients for young male workers, regardless whether they were stayers or hoppers, indicating that high firm rents have a distortive effect on their wage expectations. While the coefficient for stayers is somewhat higher as compared to hoppers, the difference is not statistically significant. For females, the results are similar; both young job hoppers as well as stayers face longer unemployment durations in case of higher previous firm rents—but the effect for stayers is statistically insignificant. Overall these tests imply that our results are not driven by young workers' lack of job search experience.

4.3 Are plant closures random (enough)?

Because we use workers who are remaining with the firm until the very end of the firm, we may have a selected sample of workers who have below average characteristics of the unemployed. ("Good" workers may have had other opportunities and left prior to the firm's closing-down.) This aspect has been studied with similar Austrian data by Schwerdt (2008), who suggests that an analysis that uses plant closures to obtain an unbiased sample of the unemployed should experiment with different sampling periods prior to plant closure.

We therefore repeat the analysis including all employees who have been laid off from the firm within six months before plant closure. Extending the sampling period from two to six months increases out sample size to 26,315 male and 13,363 female workers experiencing at least one day of unemployment after lay-off.

Table 5 shows that our results are remarkably stable and, again, young males and females have significant longer unemployment durations if they had high firm rents. The coefficients are similar in size to the ones in Table 4. It is therefore unlikely that our result of a negative impact of high firm rents on unemployment durations for younger workers is caused by workers who left the plants early.

5 Conclusion

Assessing one's own productivity is important for job search and matching in the labor market. A realistic perception of one's productivity will enable the job search to match efficiently with an employer. According to psychological research workers often attribute (excessively) high wages to their own abilities rather than to pure luck in obtaining employment with a firm that pays high rents. Such a distorted assessment could result in a systematic misjudgement of the wage offer distribution a job searcher faces with corresponding repercussions for the job search process.

We study job search behavior of workers who were made redundant due to plant closures in Austria and find that young workers can be characterized as being overconfident: high firm rents in the past job lead to significantly longer unemployment durations. We do not find such a pattern for prime-age or older workers. These results challenge the view that the high unemployment rates of older workers in Europe are due to excessive wage claims.

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6 Tables and Graphs

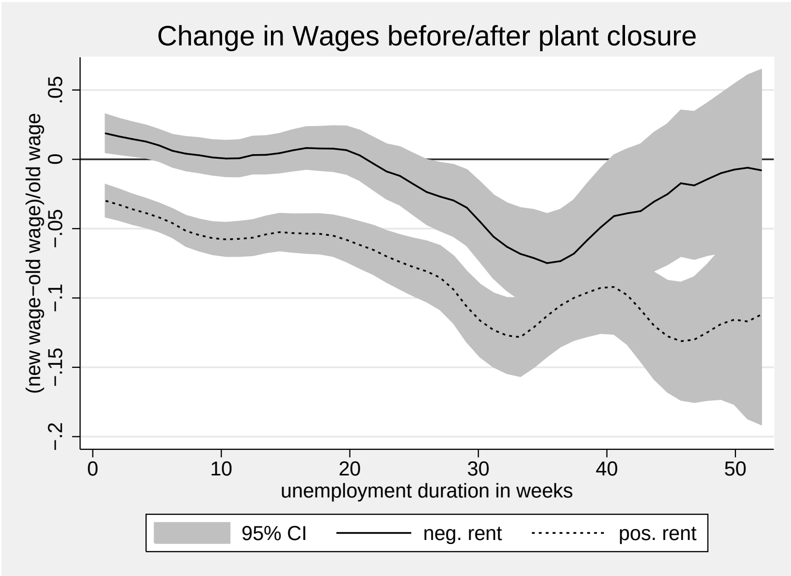

Figure 1: Relative change in wages before and after plant closure by level of firm wage components (firm rent)

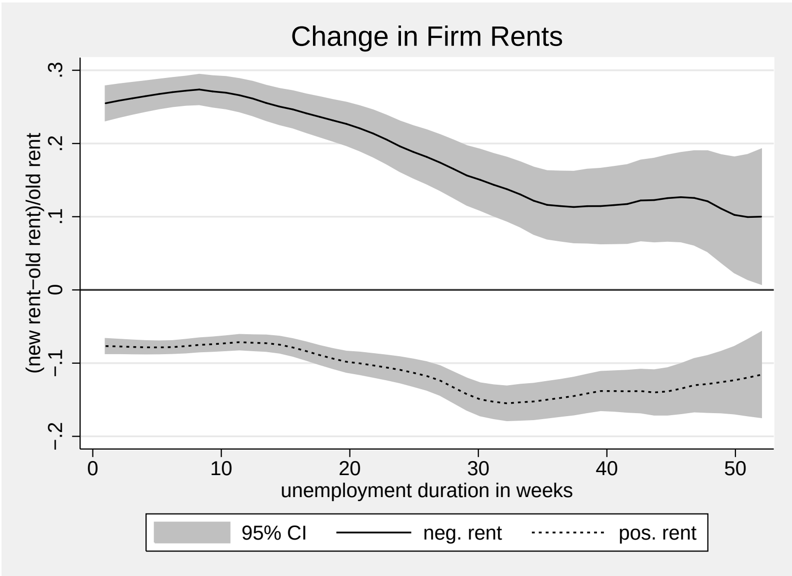

Figure 2: Relative change in firm rents before and after plant closure by level of pre-displacement firm rent

Table 1: Descriptive statistics by gender and firm rent category.

	Male		Female	
	Low Rents	High Rents	Low Rents	High Rents
Daily wage old job	40.8	55.0[a]	25.9	35.4[a]
	(12.8)	(14.4)	(8.9)	(11.4)
Unemployment duration	117	128[a]	126	123[a]
	(128)	(130)	(134)	(115)
Daily wage new job	41.1	49.1[a]	28.8	32.8
	(14.5)	(15.0)	(10.8)	(12.1)
Age	33.6	34.7[a]	32.5	32.7
	(9.7)	(10.1)	(8.8)	(9.1)
Tenure (days)	1308	1267	1226	1219
	(1820)	(1822)	(1563)	(1610)
Workers with high person effect (%)	52.5	55.4	38.2	30.2
% of workers	54.6	45.4	70.9	29.1[a]

NOTES: Means (standard deviations in parentheses). Wages are deflated to prices of 1990. [a] difference between low and high rent statistically significant at the 5% level.

Table 2: Average unemployment durations (days), by gender and wage components.

	male		female	
	mean	N	mean	N
All	121	16574	127	10448
Low person component	135	8156	135	6914
High person component	107	8418	112	3534
Young (20-30)	113	6785	118	4460
Prime age (30-45)	117	6994	131	4609
Old (45+)	149	2795	143	1379

Table 3: Estimated hazard rates from unemployment to employment, by gender.

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
High firm component (0/1)	-	-0.057***	-0.054**	-	-0.024	-0.055*
	-	(0.022)	(0.027)	-	(0.025)	(0.030)
High person component (0/1)	-	0.184***	0.217***	-	0.099***	0.098***
	-	(0.017)	(0.022)	-	(0.024)	(0.029)
Replacement rate	-0.032***	-0.024***	-0.032***	-0.031***	-0.025***	-0.031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.015***	-0.013***	-0.013***	-0.008***	-0.005***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
masspoint	1.334***	-	1.329***	1.244***	-	1.247***
	(0.028)	-	(0.028)	(0.049)	-	(0.049)
P(masspoint)	0.647	-	0.659	0.724	-	0.729
	0.0181	-	0.0182	0.0487	-	0.0494
Obs.	16574	16574	16574	10448	10448	10448

NOTES: Discrete-time proportional hazard rate models. Additional variables are log(firmsize), 5 year, 9 region and 15 industry dummy variables. ***, ** and * indicate significance at the 1, 5 and 10% level.

Table 4: Estimated hazard rates from unemployment to employment, by gender and age group.

	male workers			female workers		
	$20-30$	$30-45$	45+	$20-30$	$30-45$	45+
	(1)	(2)	(3)	(4)	(5)	(6)
high firm component (0/1)	-0.145***	0.016	0.007	-0.103**	-0.028	0.063
	(0.042)	(0.041)	(0.074)	(0.048)	(0.045)	(0.083)
high person component (0/1)	0.202***	0.257***	0.263***	0.152***	0.028	0.202**
	(0.033)	(0.033)	(0.059)	(0.042)	(0.045)	(0.087)
replacement rate	-0.032***	-0.032***	-0.033***	-0.033***	-0.029***	-0.030***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
age	0.004	-0.001	-0.107***	-0.034***	0.005	-0.080***
	(0.006)	(0.004)	(0.007)	(0.007)	(0.004)	(0.020)
masspoint	1.233***	1.287***	1.471***	1.375***	1.077***	1.010***
	(0.044)	(0.045)	(0.078)	(0.066)	(0.084)	(0.145)
P(masspoint)	0.669	0.697	0.538	0.714	0.738	0.609
	0.0301	0.0294	0.0541	0.0347	0.0576	0.189
Obs.	6785	6994	2795	4460	4609	1379

NOTES: Discrete-time proportional hazard rate models corresponding to columns (2) and (5) inTable 3. Additional variables as in Table 3.***, ** and * indicate significance at the 1, 5 and 10% level.

Table 5: Estimated hazard rates from unemployment to employment, including early leavers.

	male workers			female workers		
	$20-30$	$30-45$	45+	$20-30$	$30-45$	45+
	(1)	(2)	(3)	(4)	(5)	(6)
high firm component (0/1)	-0.109***	0.002	-0.040	-0.112*	0.012	-0.059
	(0.032)	(0.030)	(0.050)	(0.066)	(0.039)	(0.046)
high person component (0/1)	0.226***	0.222***	0.213***	0.130***	-0.016	0.065
	(0.029)	(0.026)	(0.044)	(0.040)	(0.043)	(0.079)
replacement rate	-0.033***	-0.032***	-0.033***	-0.035***	-0.030***	-0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age	0.020***	0.000	-0.109***	-0.025***	-0.001	-0.077***
	(0.005)	(0.003)	(0.006)	(0.007)	(0.004)	(0.017)
masspoint	1.321***	1.403***	1.538***	1.460***	1.244***	1.054***
	(0.034)	(0.036)	(0.056)	(0.053)	(0.055)	(0.128)
P(masspoint)	0.633	0.733	0.597	0.666	0.712	0.686
	(0.0216)	(0.0189)	(0.0364)	(0.0312)	(0.0343)	(0.109)
Obs.	10125	11152	5038	5208	6192	1963

NOTES: Discrete-time proportional hazard rate models corresponding to columns (2) and (5) inTable 3. Additional variables as in Table 3.***, ** and * indicate significance at the 1, 5 and 10% level.

Table 6: Estimated effect of *high firm rent (0/1)* on the hazard rates from unemployment to employment for male and female workers, by pre-displacement tenure and number of pre-displacement jobs.

	(1)	(2)	(3)	(4)
	male		female	
	young	prime age/old	young	prime age/old
short tenure[1]	-0.146***	-0.018	-0.128***	0.054
	(0.051)	(0.049)	(0.062)	(0.059)
long tenure[1]	-0.167***	0.038	-0.051	-0.050
	(0.075)	(0.053)	(0.075)	(0.052)
hopper[2]	-0.136***	0.029	-0.093*	-0.005
	(0.053)	(0.042)	(0.053)	(0.044)
stayer[2]	-0.173***	-0.106	-0.123	-0.066
	(0.072)	(0.069)	(0.104)	(0.088)

NOTES: Discrete-time proportional hazard rate models corresponding to column (3) in Table 3. Only the coefficients for high firm rent are reported, additional variables as in Table 3. [1] A tenure is short if it was shorter or equal to 500 days. [2] Workers with less/more than 4 different previous jobs are defined as stayers/hoppers. ***, ** and * indicate significance at the 1, 5 and 10% level.

A Appendix

Table 7: Transitions after Plant Closure.

	male	female
status after plant closure:		
job to job transition	18,172 (52.3%)	13,976 (57.3%)
unemployed after plant closure	16,574 (47.7%)	10,448 (42.7%)
transition after unemployment:		
reemployed	14,998 (90%)	8,862 (85%)
retired after unemployment	185 (1%)	69 (1%)
censored	1,401(9%)	1,517 (14%)

Note: 34,746 male and 24,424 female blue-collar workers.

Table 8: Summary statistics, decomposition sample.

Total Number of Observations	36,745,258
Total Number of Workers	3,818,508
# Males	2,333,789
Total Number of Firms	459,144
# Firms w. firmsize 10 to 100	90,158
# Firms w. firmsize 101 to 1000	7,574
# Firms w. firmsize>1000	274
Total Number of Years	21
Average age[1]	35.1 (11.1)
Average wage (€per day)[1]	41.0 (16.1)
Average tenure(years)[1]	9.5 (8.9)
Average experience (years)[1]	11.4 (6.4)

NOTES: [1] Calculated for the year 1990. Standard deviation in parentheses.

Table 9: Estimation results from wage decomposition.

	Coef.	Std. Err.[1]
log(tenure)	0.0145	0.0006
Experience (years)		
1-3[2]	0.0194	0.0014
4-5	0.0318	0.0024
6-8	0.1133	0.0024
9-12	0.1319	0.0023
13-17	0.1475	0.0030
17+	0.1662	0.0042
Age	0.0231	0.0001
Age^2	-0.0220	0.0001
Firmsize	-0.0001	0.0001

NOTES: Additional explanatory variables: year, region, industry dummies. [1] Standard errors obtained via bootstrapping (20 repetitions). [2] Baseline: 0-1 years of experience.

Table 10: Complete Table 6 A

	male				female			
	young		prime age / old		young		prime age / old	
	short tenure	long tenure	short tenure	long tenure	short tenure	long tenure	short tenure	long tenure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
high firm component (0/1)	-0.146***	-0.167**	-0.018	0.038	-0.128**	-0.051	0.054	-0.050
	(0.051)	(0.075)	(0.049)	(0.053)	(0.062)	(0.075)	(0.059)	(0.052)
high person component(0/1)	0.166***	0.235***	0.178***	0.292***	0.089*	0.271***	0.050	0.051
	(0.040)	(0.058)	(0.040)	(0.042)	(0.054)	(0.067)	(0.060)	(0.053)
replacement rate	-0.032***	-0.033***	-0.028***	-0.036***	-0.028***	-0.040***	-0.026***	-0.031***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
age	-0.003	0.016	-0.017***	-0.035***	-0.024**	-0.058***	-0.006	-0.010***
	(0.007)	(0.010)	(0.003)	(0.003)	(0.009)	(0.011)	(0.004)	(0.004)
log(firmsize)	0.085***	0.157***	0.135***	0.150***	0.095***	0.218***	0.208***	0.242***
	(0.015)	(0.023)	(0.015)	(0.017)	(0.023)	(0.030)	(0.023)	(0.021)
masspoint	1.100***	1.435***	1.120***	1.604***	1.167***	1.798***	0.842***	1.283***
	(0.055)	(0.080)	(0.059)	(0.052)	(0.081)	(0.158)	(0.099)	(0.113)
P(masspoint)	0.640	0.724	0.680	0.631	0.645	0.830	0.611	0.791
	0.0472	0.0388	0.0493	0.0268	0.0589	0.0354	0.137	0.0489
Obs.	4134	2651	4487	5302	2588	1872	2353	3635

NOTES: A tenure is short if it was shorter or equal to 500 days. Discrete-time proportional hazard rate models corresponding to column (2) in Table 3.Additional variables as in Table 3.

Table 11: Complete Table 6 B

	male				female			
	young		prime age / old		young		prime age / old	
	stayer	hopper	stayer	hopper	stayer	hopper	stayer	hopper
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
high firm rent (0/1)	-0.173**	-0.136***	-0.106	0.029	-0.123	-0.093*	-0.066	-0.005
	(0.072)	(0.053)	(0.069)	(0.042)	(0.104)	(0.053)	(0.088)	(0.044)
high pers. comp.(0/1)	0.274***	0.167***	0.340***	0.248***	0.411***	0.078*	0.009	0.072
	(0.053)	(0.042)	(0.054)	(0.034)	(0.093)	(0.046)	(0.089)	(0.045)
replacement rate	-0.029***	-0.034***	-0.032***	-0.032***	-0.036***	-0.032***	-0.035***	-0.028***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
age	0.004	-0.001	-0.041***	-0.019***	0.034**	-0.056***	-0.025***	-0.001
	(0.009)	(0.008)	(0.003)	(0.002)	(0.017)	(0.008)	(0.006)	(0.003)
logfirmsize	0.090***	0.122***	0.076***	0.162***	0.092**	0.157***	0.253***	0.220***
	(0.020)	(0.015)	(0.021)	(0.013)	(0.037)	(0.021)	(0.038)	(0.017)
masspoint	1.170***	1.218***	1.228***	1.364***	1.148***	1.358***	1.218***	1.099***
	(0.071)	(0.061)	(0.077)	(0.045)	(0.145)	(0.090)	(0.327)	(0.081)
P(masspoint)	0.605	0.723	0.595	0.676	0.462	0.772	0.835	0.742
	0.0563	0.0392	0.0727	0.0289	0.131	0.0389	0.101	0.0525
Obs.	2752	4033	2927	6862	926	3534	1191	4797

NOTES: A tenure is short if it was shorter or equal to 500 days. Discrete-time proportional hazard rate models corresponding to column (2) in Table 3.Additional variables as in Table 3.