Unknown Wage Offer Distribution

and Job Search Duration

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Abstract

If job searchers don't know the wage offer distribution they are facing, they might take the wage structure in their last firm as a prior. Doing so, reservation wages will be biased which will also bias unemployment duration. Using data for Austrian workers it is shown that workers seem to have good knowledge on expected mean wages, but less so for higher moments of the wage offer distribution.

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1. Introduction

Job search theory has gained widespread acceptance for the explanation of individual unemployment spells. Unemployed workers search sequentially for the best offer they can get. If offers arrive at random and the distribution of offers is known to the worker, the so-called reservation-wage property applies. For the searcher it turns out optimal to accept the first offer which is at or above the reservation wage. This strategy balances search costs and possible increases in lifetime income by further search.

The existence of an optimal reservation wage depends crucially on the assumption of a known wage offer distribution. Failing this, workers could make incorrect acceptance decisions and the resulting equilibrium unemployment rate may be far from optimal. In special situations - if the searcher's prior beliefs follow a Dirichlet distribution and the searcher is updating her priors according to Bayes's 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, p 694) mentions himself, ,,(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". Burgess (1992) extends the job-search framework to include search on-the-job. Once this restriction is relaxed, an individual ignorant of the true wage offer distribution will nevertheless make the optimal job acceptance/rejection decisions. This result depends on equal offer arrival rates for search off and on-the-job. If these arrival rates differ, the knowledge of the distribution is necessary to calculate the correct reservation wage.

Given these rather difficult and unrealistic conditions, the assumption of a known wage offer distribution seems problematic in assessing the optimality of actual search durations. It is especially troublesome that very little empirical results are available to judge the importance of this problem. Björklund and Holmlund (1981) investigate the impact of unexpected wage inflation as a measure of workers' misperceptions of the wage offer distribution. Using aggregate data for Swedish and U.S. exit rates from unemployment, they found small positive effects of unexpected inflation in both countries. On the other hand, there is some information on self-reported reservation wages and its impact on unemployment duration (e.g. Holzer, 1986) which goes half way in explaining the

relationship between wage offer distributions, reservation wages and job-search duration.¹ Several authors (Dominitz and Manski, 1996, Betts, 1996) have asked students about their expectations of the income they would earn after completing school. Betts (1996) finds that the median student makes an absolute error of

20 %, but the error declines with year of study.

In this paper I use information on the wage structure of previous employers². Lacking good knowledge about the actual wage offer distribution a searcher faces, he might take the wage distribution of the past firm as a prior. As soon as more information comes in, the searcher will update his prior.

2. Data and empirical results

I use date from a sample of workers from Austrian social security records. The sample design is particularly suitable for my purposes. Initially 2 % of firms were randomly chosen, in a second stage information on all the workers who ever worked (back to 1972) in these firms was collected. For these workers, information on employment spells is available back to 1972, information on unemployment spells is available from 1976 - 1991. Unfortunately coding for educational attainment is incomplete. Furthermore wages are top-coded at the social security contribution ceiling, which applies to approximately 9 % of workers.

To construct measures for the perceived (prior) wage offer distribution I analyse the wage distribution in the firm, the job searcher was working before falling unemployed. Mortensen (1988, p. 863) shows that a rise in mean and variance of the wage offer distribution will increase the reservation wage.³ A searcher coming from a firm with a high mean wage or a highly dispersed wage structure will have relatively high reservation wages. As the perceived wage structure does not match the actual wage offer distribution unemployment duration is expected to be larger.

¹ Van den Berg (1995) analyses the impact of wage dispersion on job mobility.

 $^{^{2}}$ Leonard and Van Audenrode (1995) use similar data on the wages in the previous firm in Belgium. They find that past wages of unemployed workers persist in the new job, even though unemployment duration in Belgium is very high.

³ See also Burdett and Ondrich (1985) on the impact of changes in labor demand on reservation wages.

To calculate meaningful wage distribution measures, I concentrate on workers below age 60 who come from firms with at least 20 employees. These restrictions result in a sample of approximately 19,000 unemployment spells. To tackle the problem of top-coding I follow Fichtenbaum and Shahidi (1988) and fit a Pareto distribution to the upper tail of each firm's wage distributions and approximate the missing values.⁴ Two proxies for income levels can be obtained, thus: mean and median income. The median has the advantage of being unaffected by top-coding problems. One measure for wage dispersion is the Gini-coefficient, constructed separately for each firm. Another approach is to look at a productivity-corrected wage distribution within firms. To this end I estimate firm-specific wage regressions of the form

(1)
$$\ln w_{ik} = \mathbf{a}_{k} X_{ik} + \mathbf{e}_{ik}$$
 $i = 1....I, k = 1...K$

for all *K* firms. Top-coding is considered in this specification by a Tobit model. X_{ik} contains typical human-capital variables: gender, citizenship, blue-collar, age and job tenure. The standard error of e_{ik} , "Sigma", can be interpreted as the remaining wage dispersion in the firm, after having controlled for human capital characteristics of the workers.

Unemployment duration itself is modeled with a Weibull hazard rate h(t):

(2)
$$h(t) = \frac{1}{q} \exp(-\mathbf{b}' Z_j) \left[\exp(-\mathbf{b}' Z_j) t \right]^{\frac{1}{q}-1} \dots j = 1 \dots J$$

The hazard rate in the short interval d + dt gives the probability of leaving unemployment in this period of time, provided the individual is still unemployed at time t. The shape parameter q determines whether the hazard function decreases (q < 1) over time. Covariates Z_j include human capital variables as well as past labor market performance indicators. Results are presented in Table 1. Columns 1 and 2 show results using different indicators for the unknown wage offer distribution. As the knowledge of workers of labor market opportunities might evolve over time, the analysis is also repeated for a sub-sample of young workers under age 26. As can be seem in Column 3, the

⁴ See Gusenleitner et al (1996) for a closer description of this procedure along with sensitivity tests.

results are not much different for the young. In general, there is not much evidence, that job-search duration is reacting to the "perceived wage offer distribution". Mean and median wages in the last firm are never significant and generally have the wrong sign. The results are mixed for wage dispersion indicators: unemployment duration is higher for workers coming from firms with high unconditional wage dispersion (Gini); residual wage dispersion after controlling for productivity characteristics has no effect (Sigma).

Other explanatory variables have generally the expected influence and are highly significant. Older, more tenured, better educated and female workers face higher, foreign citizens, blue-collars and workers in seasonal occupations lower unemployment duration. Workers who have experienced significant unemployment spells in the past years tend to stay unemployed longer as well as those who are able to collect unemployment benefits for a longer period.⁵

There may be several reasons for the inconclusive results concerning indicators for perceived wage offer distribution. The most obvious one is that workers do in fact have complete knowledge of the relevant wage offer distribution and therefore characteristics of the past firm's wage structure should be irrelevant. The consistent results for mean and median wages speak for a general availability of information on expected wages. On the other hand, measurement problems on the part of the researcher as well as assessment problems on the part of the workers might hinder empirical identification of these effects. E.g. workers could be unable to assess correctly the complete wage dispersion in the firm as well as the distribution of skills necessary to calculate the Gini-coefficient as well as Sigma.⁶ A less restrictive information requirement would assume that workers know some cornerstones of the compensation structure such as: Are women underpaid? What about age- and seniority-profiles in the firm, etc?

In a second step I rerun Weibull hazard rate models of the type (2) using the estimated firm-specific wage components \hat{a}_k as wage structure indicators. Each indicator was entered in a separate hazard

⁵ Potential unemployment benefit duration was constructed using legal requirements concerning age and insured work experience. These requirements have been changed over time, see Winter-Ebmer (1998) for a more thorough analysis. Actual benefit amounts are not available in the data.

⁶ Dominitz and Manski (1996) interactively asked students to report quantiles of their subjective earnings distribution. While having no problem with the concept of median, many subjects (up to 47 % in the first rounds) made logical errors, e.g.

rate regression and allowed to differ for the respective sub-group, i.e. it is to be expected that women coming form a firm with a high male-female differential to have low duration and vice versa for men. Results in Table 2 confirm the hypothesis that these indicators are more visible to the workers than the complete wage structure, they have often the expected impact. Men who are used to higher gender differentials stay unemployed longer, but women don't react. Overpaid white-collar workers search longer, underpaid blue-collars search a shorter period of time. There is no reaction to a high native-foreigner differential. Overpaid older and more-tenured workers search longer, on the other hand only the coefficient for low-tenured, but not for young workers is significant. Interestingly, the results for the sub-sample of young workers are similar but lower and less significant.

violating monotonicity of the cumulative distribution function. Furthermore, the respondents systematically overestimated the actual degree of earnings inequality in the U.S.

3. Conclusions

Under realistic conditions search behavior of workers should be different if the workers have complete knowledge of the relevant wage offer distribution or not. In this note a first attempt is made to investigate this relation empirically. Under the assumption that the prior wage offer distribution - which will be updated by later information - is built by the wage structure of the past firm, this structure should influence job-search duration of unemployed workers.

It turns out that mean wages in the previous firm have no influence on unemployment duration, but specific wage differentials, like returns to tenure, age and qualification, do. These results can be interpreted in the following way: Workers are able to build good estimates about expected mean wages, but less so for the whole wage offer distribution they are facing.

	1	2	Young workers only (<26)	Mean (all workers)
Ago	0.021	0.021	0.053	32.5
nge	(21.3)	(20.9)	(6.56)	(11.1)
Schooling (years)	0.012	0.011	-0.034	9.32
	(2.42)	(2.20)	(3.99)	(1.46)
Experience (years)	-0.005	-0.005	0.001	6.57
	(1.67)	(1.60)	(0.05)	(4.74)
Tenure (years)	0.034	0.029	0.111	1.76
	(2.92)	(2.50)	(5.67)	(0.69)
Previous wage ('000 ATS)	-0.007	-0.006	-0.019	8.36
	(2.12)	(1.80)	(3.51)	(2.88)
Female (0,1)	0.151	0.161	0.132	0.33
	(8.38)	(8.88)	(4.73)	
Blue-collar workers (0,1)	-0.159	-0.171	-0.067	0.85
	(6.93)	(7.32)	(2.01)	
Foreign citizen (0,1)	-0.279	-0.285	-0.131	0.06
	(8.96)	(1.86)	(1.86)	
Indiv. unemployment rate $_{t-1}$ (%)	0.005	0.005	0.003	10.86
	(10.0)	(9.86)	(2.84)	(15.8)
Indiv. unemployment rate	0.002	0.002	0.002	9.52
x v <i>t</i> -2	(3.78)	(3.66)	(2.04)	(17.0)
Indiv. unemployment rate $_{t-3}$	0.002	0.002	0.001	7.89
	(2.88)	(2.88)	(1.11)	(15.9)
Seasonal occupation (0,1)	-0.330	-0.322	-0.121	0.41
	(18.7)	(17.8)	(4.600)	
# of previous jobs	-0.002	-0.002	-0.002	13.3
	(5.50)	(5.42)	(4.38)	(8.5)
Potential benefit duration ('00 days)	0.011	0.012	-0.022	191.7
	(1.96)	(2.12)	(1.42)	(107.3)
Firm size	0.0001	0.0001	0.0001	425.5
	(8.80)	(8.78)	(5.13)	(681.2)

Table 1: Unemployment duration (Weibull model)

Wage offer distribution indicators

Mean wage last firm ('000 ATS)	-0.008 (0.93)		-0.009 (1.49)	9.85 (2.07)
Median wage last firm ('000 ATS)		-0.002 (0.48)		8.99 (1.92)
Gini last firm (%)	0.264 (2.35)		0.339 (1.98)	0.18 (0.07)
Sigma of firm-specific wage regression last firm		-0.037 (0.34)		0.19 (0.07)
\boldsymbol{q} (Standard error)	0.977 (0.005)	0.991 (0.013)	0.8853 (0.002)	
Log L	-28674.3	-27942.7	-9874.4	
Ν	19210	18670	6959	

The regressions include also flags for education unknown, experience censored before 1972 and 4 regional indicators as well as a time trend, t-values in parentheses.

only (<25) 1) Male -Female Differential (0.398) impact on men 0.061 0.025 impact on women 0.02 -0.018 (1.43) (0.30) (0.70) impact on women 0.02 -0.018 (0.277) (0.277) (0.277) impact on white-collars 0.202 0.074 (0.277) (0.81) (0.277) impact on blue-collars -0.283 -0.141 (0.422) (1.83) (0.63) 3) Native-Foreigner Differential (0.15) (0.06) impact on natives -0.019 0.023 impact on foreigners 0.028 0.028 (0.15) (0.06) (0.323) impact on odd(>40) 0.011 $ (0.131)$ $ (0.12)$ impact on odd(>40) 0.011 $ (0.100)$ (0.11) $-$ impact on odd(>40) 0.011 $ (0.100)$ (0.53) (0.13) impact on odd(>40) 0.011 $-$ </th <th></th> <th>All workers</th> <th>Young workers</th> <th>Mean (std. dev.)</th>		All workers	Young workers	Mean (std. dev.)
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Table 2: The impact of firm wage differentials on job search duration *

* Weibull duration model includes the same control variables as in Table 1. Wage differential indicators are included separately.

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