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On-the-job search and wage dispersion: New evidence from time use data

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ABSTRACT

This paper provides new evidence on time devoted to job search by the employed in the U.S. I find that search effort decreases with the current wage, with an elasticity between −0.7 and −1.3.

1. Introduction

The U.S. labor market features large employer-to-employer (EE) flows. As recently emphasized by Fallick and Fleischman (2004), around 2.6% of employed persons change employment each month without going through a spell of unemployment. Why do so many employed workers change jobs each month? One explanation is that in the face of wage dispersion, employed workers search for better paying jobs. Christensen et al. (2005), e.g., provide a search model of the labor market with on-the-job search, wage dispersion and endogenous search effort. Their model predicts that search effort decreases with the wage since returns to search for a better job are higher the further down the worker is in the wage ladder. In Danish labor market data, they find that the job separation rate is decreasing in the wage, supporting the model's prediction.

The present paper provides direct evidence on job search intensity of the employed in the U.S., modeling job search intensity as time allocated to job search activities. I use data from the American Time Use Survey (ATUS) and find a highly significant effect of the wage on job search intensity, with an elasticity between −0.7 and −1.3.

2. Model

I briefly sketch a partial equilibrium model of on-the-job search, similar to Christensen et al. (2005),[1] where the employed worker allocates a fraction s of her total available time (normalized to 1) to job search activities and faces a known wage offer distribution $F(w)$. There are no savings, so consumption is equal to the wage. The Bellman equation of the employed worker is:

$$W(w) = \max_{s}\left\{u(w, 1-s) + \beta\left[W(w) + \alpha(s)\int_{w}(W(x)-W(w))dF(x)-\delta(W(w)-U)\right]\right\} \tag{1}$$

where $W(w)$ is the value of an employed worker with wage w, $u(.,.)$ is the utility derived from consumption and leisure, β the discount factor, $\alpha(s)$ the probability of receiving a job offer for a given search effort s, δ the separation rate and U the value of being unemployed. I make the standard assumption of diminishing marginal utility of leisure ($u_{22}<0$). Note that the employed worker never accepts a job offer that pays less than her current wage w. The first order condition for s is:

$$u_2(w, 1-s) = \alpha'(s)\,\beta\int_{w}(W(x)-W(w))dF(x) \tag{2}$$

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[1] The main deviation from Christensen et al. is that I model search costs as forgone leisure whereas they assume a search cost function of the form $c(s)=gs^{\lambda}$.

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Table 1
Descriptive statistics ATUS 2003–2008, by labor force status.

	# of respondents	% of total	Job search per day, in min	Fraction searching on diary day	Job search (conditional on searching), in min
Employed	50,444	76.5%	0.65	0.6%	106.7
Unemployed	2580	3.9%	34.99	20.0%	175.2
Not in labor force	12,954	19.6%	0.83	0.5%	154.7

Notes: Averages and participation rates are computed with survey weights. Universe: civilian, noninstitutional population, age 20–65.

The optimal amount of time devoted to job search trades off the marginal cost of foregone leisure against the marginal increase in the probability of receiving a job offer (times the discounted expected gain from such an offer).

Proposition. *If the marginal utility of leisure is independent of consumption ($u_{12}=0$) and the returns to search are constant ($\alpha''=0$), then s is decreasing in the wage w.*

Proof. If $u_{12}=0$, then the left hand side of (2) is independent of w and increasing in s because of diminishing marginal utility of leisure. Moreover, if $\alpha''=0$, then the right hand side is decreasing in w since the worker will accept fewer job offers. Therefore, at a higher wage w, s has to be lower for (2) to hold[2]. □

3. Data and Descriptive Statistics

I use data from six consecutive years (2003–08) of the ATUS, which is a nationally representative time use survey, drawn from the 8th outgoing rotation group of the Current Population Survey (CPS). The ATUS collects detailed information on the amount of time respondents devoted to various activities on the previous day, including job search activities such as contacting a potential employer, calling or visiting an employment agency, job interviewing, etc.[3]

Table 1 provides descriptive statistics of time allocated to job search by labor force status. The average employed searches 0.65 min per day or 20 min per month, which is 54 times less than the average unemployed. Moreover, only 0.6% of the employed reported positive minutes of job search on the diary day. However, those who search on the diary day tend to spend a lot of time on job search activities. Fig. 1 shows the Kernel density of time spent on job search conditional on searching on the diary day. The average duration of search is more than 100 min and 70% of employed job searchers spend 1 h or more searching for a job on the diary day.

Despite very little average time allocated to job search by the employed, there are large EE flows in the U.S. labor market: Fallick and Fleischman (2004) report that 2.6% of workers in the CPS change employer each month,[4] compared with 28.3% of unemployed persons who find employment each month. In other words, monthly unemployment-to-employment (UE) flows are 11 times larger than EE flows. This suggests that on-the-job search is almost five times more effective in terms of time allocated to job search. As already emphasized by Blau and Robins (1990), a higher efficiency of search on-the-job could be driven either by differences in search technology

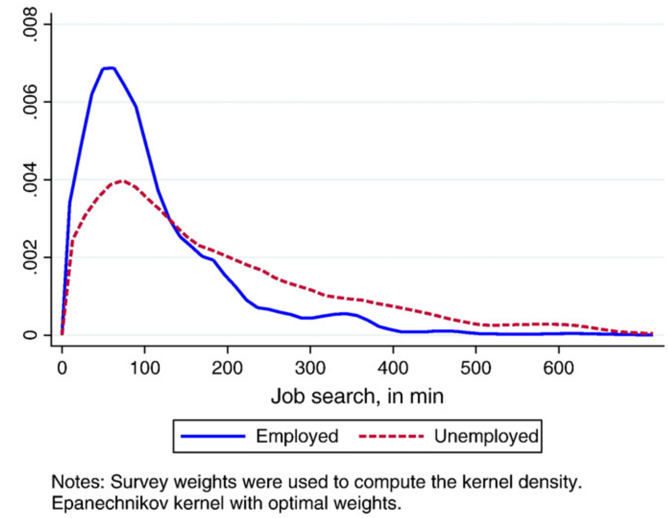

Fig. 1. Kernel density: Job search (conditional on non-zero search).

(e.g., through better contacts) or unobserved heterogeneity between employed and unemployed workers in terms of job search efficiency. Also, job search activities such as defined in the time use data might be less relevant for employed workers (e.g., every lunch is a job interview).

4. Estimation

In order to test the prediction of the model outlined above, I carry out a reduced form regression relating time devoted to job search s_i to the log hourly wage[5]:

$$s_i = \beta_0 + \beta_1 \log(\text{hourly wage}_i) + \beta_2 X_i + \varepsilon_i \tag{3}$$

where X_i includes controls for sex, age, education, race, martial status, children, interaction terms, a dummy for whether the diary day was a weekend day, a dummy for whether the person was absent from work in the reference week (for reasons other than layoff) as well as dummies for month and year of interview and state of residence. I restrict the sample to private-sector employees of age 20–65 who were not enrolled in high school, college or university at the time of the survey. I also trim the sample in terms of the hourly wage, excluding all observations with a wage of less then \$1 or more than \$100.[6] The sample size is 33,628. Standard errors are robust to heteroskedasticity.

One open question is whether one should include occupation and industry dummies in the regression model. Note that the assumption here is that – at given observable characteristics of the worker – the observed wage reflects the position of the worker in the wage ladder. It makes sense to include occupational dummies as they mainly reflect workers characteristics such as human capital. However, there is good reason to exclude industry dummies from the specification because

[2] See Mortensen (1977) for a similar analysis in the case of the unemployed worker. Note also that one can generalize the proposition to the case where consumption and leisure are complements ($u_{12}>0$) and where returns to search are non-increasing ($\alpha''\leq 0$). When consumption and leisure are substitutes, however, job search could be increasing in the wage because at higher wages the marginal cost of search is lower.

[3] See the Appendix Table in Krueger and Mueller (2010) for a detailed description of job search activities in the ATUS.

[4] They use data from the CPS 1994 and 1996–2003.

[5] Hourly wages for non-hourly workers are computed by dividing weekly earnings by usual hours. Hours were imputed for those who indicated "varying hours" from regressions of hours on age and dummies for race, education, foreign born and citizenship for four different samples (full-time men, part-time men, full-time women, part-time women), as suggested by Schmitt (2003). To adjust for top-coding of weekly earnings (the top code is \$2885), I assumed a Pareto distribution and used the 90th percentile of the observed distribution to estimate the mean above the top-code (see Schmitt, 2003, for a discussion of adjustment for top-coding in the CPS). Hourly wages for those who work by the hour are adjusted for overtime earnings. Moreover, wages are deflated with the implicit deflator for hourly earnings in the private non-farm business sector from the BLS productivity and costs program.

[6] I also excluded those who reported zero usual hours (3 observations).

Table 2
Results of regressions.

Dependent variable: time allocated to job search, in minutes per day	Linear model						Tobit model (marginal effects) (1)	
	Mean (Std)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean of dependent variable		0.680	0.680	0.680	0.680	0.680	0.680	0.680
Log (hourly wage)	2.69	−0.912	−0.938	−0.858	−0.865	−0.845	−0.473	−0.384
	(0.61)	(0.231)***	(0.231)***	(0.251)***	(0.251)***	(0.253)***	(0.078)***	(0.072)***
Log (usual hours)	3.69				−1.457			−0.439
	(0.35)				(0.480)***			(0.083)***
Age/10	4.04	−0.964	−0.994	−0.982	−0.721	−0.931	−0.32	−0.157
	(1.16)	(0.614)	(0.617)	(0.631)	(0.620)	(0.610)	(0.220)	(0.199)
Age^2/100		0.097	0.102	0.1	0.066	0.093	0.023	0.004
		(0.069)	(0.069)	(0.071)	(0.070)	(0.068)	(0.028)	(0.025)
Some college or associate degree (2)	0.27	0.69	0.691	0.707	0.716	0.687	0.382	0.371
		(0.270)**	(0.274)**	(0.277)**	(0.278)***	(0.269)**	(0.152)**	(0.141)***
College degree (BA, MA or PhD)	0.29	0.983	0.984	0.994	0.994	0.959	0.689	0.634
		(0.231)***	(0.234)***	(0.281)***	(0.280)***	(0.286)***	(0.196)***	(0.178)***
Female	0.45	−0.539	−0.556	−0.601	−0.627	−0.653	−0.202	−0.168
		(0.347)	(0.351)	(0.350)*	(0.353)*	(0.369)*	(0.132)	(0.118)
Female*partner	0.29	0.439	0.442	0.318	0.121	0.308	0.058	−0.062
		(0.365)	(0.365)	(0.350)	(0.338)	(0.349)	(0.181)	(0.147)
Female*children	0.21	−0.776	−0.764	−0.652	−0.775	−0.687	−0.163	−0.19
		(0.348)**	(0.349)**	(0.336)*	(0.341)**	(0.343)**	(0.133)	(0.112)*
Partner	0.67	−0.418	−0.406	−0.21	−0.147	−0.199	−0.212	−0.118
		(0.335)	(0.326)	(0.317)	(0.313)	(0.314)	(0.169)	(0.146)
Children	0.46	0.74	0.736	0.658	0.652	0.69	0.268	0.237
		(0.298)**	(0.297)**	(0.288)**	(0.287)**	(0.294)**	(0.157)*	(0.144)*
Black (3)	0.10	0.488	0.607	0.588	0.594	0.532	0.089	0.095
		(0.398)	(0.423)	(0.433)	(0.432)	(0.440)	(0.128)	(0.119)
Hispanic	0.15	−0.371	−0.444	−0.559	−0.535	−0.573	−0.15	−0.127
		(0.239)	(0.285)	(0.309)*	(0.305)*	(0.319)*	(0.092)	(0.086)
Asian or other	0.05	−0.765	−0.827	−0.793	−0.826	−0.8	−0.275	−0.244
		(0.139)***	(0.167)***	(0.164)***	(0.169)***	(0.174)***	(0.080)***	(0.073)***
Absent from work last week	0.03	0.419	0.422	0.372	0.34	0.36	0.266	0.239
		(0.450)	(0.447)	(0.473)	(0.474)	(0.472)	(0.236)	(0.216)
Weekend	0.29	−0.368	−0.369	−0.415	−0.401	−0.447	−0.225	−0.193
		(0.150)**	(0.151)**	(0.154)***	(0.153)***	(0.159)***	(0.065)***	(0.060)***
Year and month dummies		x	x	x	x	x	x	x
State dummies			x	x	x	x		
Occupation dummies (3-digit)				x	x	x		
Industry dummies (3-digit)						x		
Observations		33,628	33,628	33,628	33,628	33,628	33,628	33,628
(Pseudo-) R-squared		0.01	0.01	0.06	0.06	0.07	0.06	0.07
Robust standard errors in parentheses		* significant at 10%; ** significant at 5%; *** significant at 1%						

Notes: Regressions are weighted using survey weights. Universe: private-sector employees of age 20–65 who were not enrolled in high school, college or university at the time of the survey. I also trim the sample in terms of the hourly wage, excluding all observations with a wage of less then $1 or more than $100. (1) For dummy variables the discrete change from 0 to 1 is reported. (2) The base group consists of those with a high school degree or less. (3) The base group is White.

they may capture features of the wage distribution faced by similar workers rather than differences in individual characteristics (see, e.g., Krueger and Summers, 1988).

Table 2 reports the results for a linear regression model: the models in column 1–3 and 5 differ only in whether state, occupation and industry dummies are included or not. The effect of the log hourly wage is negative and significant at the 1% level in all 4 columns and the coefficients are of similar size. For my preferred specification (column 3), which includes state and occupation dummies, the implied elasticity of time devoted to job search with respect to the wage is −1.3.

Column 4 in Table 2 also includes the log of usual hours of work on the current job. The effect is highly significant and negative, with an elasticity of −2.1. This suggests that workers allocate more time to job search when they have more time on their hands. One may argue, however, that working hours are endogenous to the hourly wage and thus should be excluded from the regression model. It is reassuring that the estimated coefficient on the log wage changes only little between column 3 and 4.

In results not presented here, I included the monthly U.S. unemployment rate to control for the business cycle (and I excluded the month and year dummies from that specification). The estimated coefficient was positive but not significant and the coefficient on the log wage was unaffected. As a further robustness check, I restricted the sample to those of age 25–59. The implied elasticity of job search with respect to the wage was smaller (−1.0) but still significant at the 1% level. Moreover, I re-estimated column 3 without trimming the sample at the hourly wages of $1 and $100. The coefficient remained significant at the 1% level but the implied elasticity was smaller (−1.0). Finally, I included dummies for whether the person was unemployed or out of the labor force in the CPS interview 2–5 months prior to the ATUS interview. Those unemployed in the CPS searched 3.1 min more per day than those employed in the CPS, but the estimated coefficient on the log wage was virtually unaffected and remained significant at the 1% level.

I also estimate a Tobit model to account for the mass of workers with 0 min of job search on the diary day. Unfortunately, the log likelihood procedure did not converge when re-estimating the specifications of the linear model reported in columns 2–5. The likely reason is that the log likelihood is not well behaved due to multicollinearity in the presence of many state, industry and/or occupation dummies. Therefore, I estimate the Tobit model without state, industry and occupation effects. The results of the linear model suggest that this is innocuous, as the estimated coefficients change only little between column 1 and columns 2–5. Columns 6 and 7 report the marginal effects for the Tobit model where the latter also includes the log of usual hours. The effect of the log wage is negative and highly statistically significant in both specifications (with *t*-stats in excess of 5). The estimated coefficients, however, are only about half as large as in the linear model. For column 6, the implied elasticity of time devoted to job search w.r.t. the wage is −0.7. I also confirm the significant negative effect of log hours on time devoted to job search, but with a substantially lower elasticity (−0.6).

Finally, to gauge the magnitude of the estimated effect of the wage on job search, consider the effect of reducing the log wage by one standard deviation. Decreasing the log wage by 0.61 points, increases the job search intensity by 16 min per month in the linear model (column 3) and 9 min in the Tobit model (column 6). Given that the average time allocated to job search is only 20 min per month this suggests an economically important effect of the wage on job search intensity.

5. Conclusion

The results presented suggest that on-the-job search effort, modeled as time allocated to job search activities, is decreasing in the wage of the current job with an elasticity of −0.7 to −1.3. One word of caution is warranted, however, as a potential bias might arise because of unobserved heterogeneity among employed workers: high ability workers might search harder because of higher returns to search, which will lead the estimated coefficient of the wage to be biased towards 0. Nevertheless, the evidence presented above supports models where similar workers face wage dispersion and invest time in order to find better paying jobs.

One open question is why job search is so much more effective on-the-job than when unemployed. In future surveys, it would be useful to collect time use data in connection with job transitions to shed further light on this issue.

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