J Labor Res (2018) 39:219–233
https://doi.org/10.1007/s12122-018-9263-1

On-the-Job Search, Mismatch and Worker Heterogeneity

Stephen B. DeLoach[1] · Mark Kurt[1]

Published online: 19 February 2018

Abstract This paper empirically examines the search behavior of currently employed workers to understand changes in on-the-job search across different types of employed individuals and varying labor market conditions. Using data from the American Time Use Survey, we estimate the responsiveness of workers with varying levels of productivity and job-match quality to regional labor market conditions. We find that those workers who are less-productive, mismatched in their current position, and high-productivity, mismatched workers are more likely to engage in search than other workers. These results have implications for models built on job mismatch, as well as for models seeking to explain increasing inequality and wage dispersion.

Keywords On-the-job search · Search intensity · Time use data · Mismatch

While theoretical models of on-the-job search (OJS) date back to Burdett (1978), little is known empirically known about the phenomenon. This is primarily due to the lack of high-quality data related to search activities of employed workers. Recent research by Carrillo-Tudela et al. (2015) underscores this point. Using data from the Contingent Worker Supplement to the Current Population Survey (CPS) for the years 1995, 1997, 1999, 2001, and 2005, they find that employed workers who make job-to-job transitions are often unlikely to report active search prior to taking a new job. Nevertheless, we know that OJS plays a significant role in the labor market as between one-third to one-half of all U.S. labor market movements in any given year job-to-job transitions (Bjelland et al. 2011).

OJS was first introduced by Burdett (1978) in a simple partial equilibrium reservation wage model to explain decreasing quit rates in worker age and job tenure. Since that time, the OJS model has been extended into a general equilibrium framework (Burdett and

✉ Stephen B. DeLoach
deloach@elon.edu

Mark Kurt
mkurt@elon.edu

[1] Department of Economics, Elon University, Elon, NC, USA

Mortensen 1998) and modified to allow for endogenous search (Pries 2008). Models with OJS have also been used to understand other important labor market phenomena including wage dispersion (Postel-Vinay and Robin 2002; Cahuc et al. 2006), differences in job-finding rates (Dolado et al. 2009; Chassamboulli 2011), job composition (Barlevy 2002), and the excess volatility in the vacancy-to-unemployment ratio, commonly referred to as the "Shimer puzzle" (Pries 2008; Krause and Lubik 2006, 2010).[1]

Most recent models of OJS assume some degree of mismatch between worker skill and job productivity. Job mismatch requires at least one type of heterogeneity in the labor market. Heterogeneity has been introduced at the firm level (Krause and Lubik 2006), at the worker level (Pries 2008), or both (Chassamboulli 2011). Heterogeneity adds increased volatility to the model that helps resolve the excess volatility puzzle noted by Shimer (2005). The key is that OJS is procyclical.

Chassamboulli (2011) offers an intuitive explanation for how this might work in the context of worker heterogeneity. In his model, job mismatch occurs when a high-quality worker is initially matched with a low-productivity firm. This may occur during recessions, where high-quality workers are more likely to accept low-age, low-productivity jobs, while low-quality workers are pushed into the ranks of the unemployed. Because the expected value of on-the-job search is relatively large for high-quality workers, they have more incentive to search than workers who are not mismatched. When the economy improves, high-quality workers search for a better job match. As a result, high-quality workers in a poor-quality match should respond relatively intensively to positive aggregate productivity shocks (i.e., increases in job vacancies), resulting in cyclical upgrading of jobs.

OJS models rely on critical assumptions about the decision to search and search intensity that have yet to be confirmed in the data. The main reason is that direct measures of search behavior by employed workers are notably lacking. For example, the CPS asks questions about different search activities, but only for the unemployed. The American Time Use Survey (ATUS) utilizes time-use diaries, allowing the econometrician to directly observe job search related activities for both unemployed and employed individuals. The downside of the ATUS is that it measures time use on one particular day, and time use is only recorded once per individual. The ATUS has been used recently to explain the search intensity of unemployed workers (Krueger and Mueller 2010; DeLoach and Kurt 2013; Gomme and Lkhagvasuren 2015).

While the current study focuses on employed search, the recent literature on unemployed search provides critical insights that inform our empirical model.[2]

[1] In his seminal work, Shimer (2005) showed that the canonical Diamond-Mortensen-Pissarides (DMP) random search model fails to explain the excess volatility of the vacancies to unemployment ratio over the business cycle. According to the DMP model, as new job offers arrive, vacancies and unemployment both decrease. The DMP model implies that changes in vacancies and in unemployment are relatively smooth. In fact, the data show that observed vacancies and unemployment are highly volatile over the business cycle. This inconsistency has led to a large body of empirical work and an entire class of theoretical search models that seek to resolve this puzzle. One way to explain this is to allow for on-the-job search. In its most simple form, increases in aggregate productivity raise the value of a match, inducing firms to post more vacancies. Of course, changes in wages dampen this amplification effect (Shimer 2005). One way to counter the wage-dampening effect is to allow for pro-cyclical search.

[2] Krueger and Mueller (2010) use the ATUS to estimate the responsiveness of unemployment benefits and duration on search intensity of unemployed workers. They find a negative relationship between the size of benefits and search intensity. They did not specifically consider cyclicality.

DeLoach and Kurt (2013) were the first to use ATUS data to investigate the responsiveness of unemployed search to changes the business cycle. They find that in aggregate, search intensity appears acyclical; however, after controlling for changes in wealth, unemployed search becomes procyclical. Gomme and Lkhagvasuren (2015) supplement ATUS data by exploiting job search data from the Current Population Survey. They also find evidence of procyclical search. In addition, they also provide evidence of the importance of worker heterogeneity. Specifically, they find that search is positively related to the unemployed workers' prior wage and hours worked. This suggests that high-productivity workers search more intensively when they become unemployed than their lower-productivity counterparts.

The purpose of this paper is to empirically examine job search behavior of employed workers. Our empirical model builds upon the previous work on unemployed search, specifically that of DeLoach and Kurt (2013). In addition to uncovering empirical facts regarding employed search behavior to inform future models, we are also able to directly test some of the critical assumptions upon which existing OJS models rely. Search activities are measured directly based on the daily search activities reported in the ATUS between 2003 and 2016. Following Hartog (2000), workers are classified as mismatched if their level of education exceeds the average education of workers in that occupation. Worker quality is measured as the residual between each individual's reported wage and their expected wage given their education, age, sex, occupation and industry.

Consistent with some predictions of recent models, the evidence suggests that mismatched workers are more likely to search than their peers. We also find that high-quality, mismatched workers are significantly more likely to engage in search. Of those not currently mismatched in their job, less productive workers are more likely to engage in search behavior. Finally, we find no evidence that search is related to changes in local labor market conditions.

The paper contributes to the literature by offering the first direct evidence of the factors that influence OJS. While these data have disadvantages, to date they are the only direct measure of search for employed workers. In addition, the results offer the first direct test of a number of key assumptions of an entire class of models relying on job mismatch. To our knowledge, these results offer the first empirical support for the class of endogenous on-the-job search models with both heterogeneous workers and firms.

Generalized Model of Search

Common in most models of OJS is the characterization of the job finding process as a two-sided matching problem. From the worker's point of view, it is worth engaging in search if the expected returns exceed the disutility of search. The disutility of search includes direct costs associated with job search as well as the opportunity costs associated with leisure. The expected returns to search are more complicated, as it involves a calculation of the probability of receiving an offer conditional on search multiplied by the difference between the expected wage offer and the current wage. The challenge, econometrically, is that an individual's potential new wage offer is unobservable, as it depends on both the individual's productivity and the potential employer's productivity.

Standard search theory predicts that search activity is positively related to the likelihood of receiving an offer conditional on search. This implies that search is procyclical, as the number of vacancies increases during expansions. However, without controlling for individual preferences for leisure, search is likely to appear acyclical (Shimer 2004). For example, Lammers (2014) argues that wealth raises reservations wages and decreases search. While the likelihood of receiving an offer may increase during expansions, the rising reservation wages of workers decreases the likelihood of accepting an offer. Recent empirical evidence appears to support this explanation. Using data from the ATUS, DeLoach and Kurt (2013) confirm that, without controlling for aggregate shocks to wealth (i.e., stock and housing prices), unemployed search appears acyclical. Once changes in wealth are included, however, unemployed workers increase search as the labor market improves as theory predicts.

Because employment is inherently a two-sided matching problem, a number of papers explicitly model OJS as a function of the existing match quality. For example, assume two types of workers and two types of job opportunities. In models such as Barlevy (2002), Cahuc et al. (2006), Dolado et al. (2009), and Chassamboulli (2011), high-quality (i.e., highly-productive) workers who are matched initially in low-productivity jobs, find themselves mismatched. As a result, their current wage is lower than their potential outside option. Naturally, these workers have an incentive to search for job opportunities that better match their abilities. In contrast, low-quality workers have less incentive to search on the job because firms will not hire these workers for high-productivity (high-wage) jobs.

The matching process may also be affected by the business cycle. For example, Moscarini and Vella (2008) find evidence that worker sorting across occupations appears to be more random during recessions. Specifically, Chassamboulli (2011) argues that in recessions, high-quality workers are more likely to accept low-wage jobs, causing some low-quality workers to be pushed into the ranks of the unemployed. High-quality workers are qualified for a broader range of job types than low-quality. Coupled with the possibility of OJS, high-quality workers are incentivized to accept a job with low skill requirements during economic downturns with the option to continue to search for a better job match. When the economy improves, the labor market loosens and high-quality workers search for better job matches. The implication is that workers in a poor-quality match will respond more intensively to positive aggregate productivity shocks (i.e., increases in job vacancies).

Data

To estimate the model described in the second section, data are pooled from several sources. All data on individual workers come from the ATUS 2003–16 (Bureau of Labor Statistics 2017c), a multi-year dataset is a pooled cross-section of its annual surveys. The ATUS is a sub-sample of the Current Population Survey (CPS). The sample consists of 86,186 full time workers, between the ages of 18 to 65. Because we are unable to calculate our productivity measure for some of these workers, our final sample consists of 73,497 workers. As will be discussed in more detail in the next section, women with children and rural workers will be excluded in some specifications in an attempt to minimize the bias caused by unobserved heterogeneity related to worker mobility.[3]

The data used to construct search come from the ATUS. Because the ATUS provides detailed data on time use, we are able to measure the time each individual spends searching during their diary day. In the 2003–16 multi-year dataset from the ATUS, activities related to job search include job search activities, job interviewing, waiting associated with job interviews, security procedures associated with search or interviews, and other job search activities not otherwise specified.[4]

Labor market tightness is measured by the VU ratio aggregated at the census region level. Regional job vacancies come from the Job Openings and Labor Turnover Survey (Bureau of Labor Statistics 2017b), while the regional unemployment rate comes from the Bureau of Labor Statistics (2017a). In standard search models, search is a positive function of the probability of obtaining a job offer conditional on search. This is a function of labor market tightness and the arrival rate conditional on searching, where the arrival rate is generally assumed constant. As a result, changes in the VU ratio will affect search. This is the key variable in our exercise because changes in the VU ratio are driven by exogenous changes in labor productivity.

To control for the quality of the existing job match, we use data on education levels from so-called realized matches and compare it to the education level of each individual (Hartog 2000). Our measure of match quality is analogous to being over- or under-educated for the current occupation. Specifically, using data from the CPS, we find the average level of education of worker currently employed in each occupation. This amounts to the realized level of education required in that occupation. If an individual has more education than the average, then that worker is considered to be over-educated, or mismatched, for that occupation.

Because we are using education to identify the quality of the job match, our measure of worker productivity (ε_{it}) should control for the level of education. Under perfect competition, a worker's wage will be determined by the marginal product of labor. The implication is that an individual worker's productivity can be proxied by the difference between the current wage and the expected wage, conditional on individual experience and education. Of course, the marginal product of labor is also dependent upon the occupation and industry in which workers are currently employed. As a result, our benchmark specification for the predicted wage includes controls for occupation and industry. Workers are defined as low-productivity workers if their wage is below their predicted wage. Workers are defined as high-productivity workers if their wage is equal to or above their predicted wage.

To estimate the predicted wage, we run regressions for all men and women who are employed full time using data from the CPS outgoing interview file for the period 2003–2016. This resulted in 265,399 full time workers between the ages of 18 and 65 who reported earnings and were not full-time students. To control for differences in costs of living, dummies for the state of residence are also included. The model is run separately for each sample year to generate the predicted wage for each worker. This

[3] Whether the worker resides in an urban or rural area is based on information in the GTMETSTA variable in the ATUS-CPS file.

[4] ATUS codes for these activities are t050481, t050403, t050404, t050405 and t050499.

allows for potential changes in the marginal returns to experience and education that may vary over time. It also controls for time-varying cost-of-living changes that affect market wages. The model includes age, age squared, dummies for the level of education, dummies for state of residence, and dummies for occupation and industry.

Unfortunately, the ATUS and CPS does not include data on wealth at the household level. We do know whether the worker owns a home and the state in which they live. This allows us some way to measure changes in wealth related to homeownership. For equity, we have to rely on changes in stock prices at the national level. Thus, proxies for wealth are the log of the average regional housing price, a dummy variable for whether the worker owns a home,[5] and the log of the S&P 500 index. Data proxying changes in household wealth come from Case and Shiller's index of housing market prices (Standard and Poor's 2017). These data are aggregated from city-level data into census regions. This way, our proxy for housing wealth is aggregated at the same level as the VU ratio. This is important because it allows us to separately identify the wealth effect from labor market tightness. In general, increases in household wealth decrease the returns to work, and thereby decreases searching.

In addition, controls for each individual's opportunity cost of search are proxied by household demographics. These include gender, race, marital status, the presence of children and state of residence. We also include the log of the real state maximum weekly unemployment benefits since unemployment is always an outside option for employed workers (Department of Labor 2017). Finally, because ATUS only asks respondents about their time use on one day, it is important to control for the day of the week, the month of the year, and whether it was a holiday when the time-use diary was conducted.

Summary Statistics

In Table 1 we report the proportion of active searchers and the average minutes per day of job-search activity reported by full-time workers across various sub-samples. These statistics have been weighted using the ATUS weights (TUFNWGTP). The data indicate that a relatively small number of full-time workers actually report engaging in search-related activities during their diary day. Part of this is due to the fact that the ATUS only observes activities during a single day. As with all self-reported data, there may also be a more general problem of under- or non-reporting. This weakness in the data is well-recognized in the literature. For example, recent research shows that employed workers who make job-to-job transitions are often unlikely to report active search prior to taking a new job (Carrillo-Tudela et al. 2015).

On average, the data show that search increases with education. Workers whose education level exceeds the average of that in their current occupation (mismatched) appear to search more on average than non-mismatched workers. Looking at our measure of productivity, it appears that workers are less likely to search as their productivity rises. However, conditional on search, higher-productivity workers appear to search more intensively. Overall, these data are suggestive of considerable worker heterogeneity in search. In the next section, we will examine the factors affecting workers' decision to search.

[5] Home ownership is based on HETENURE variable in the ATUS-CPS file.

Table 1 Average minutes per day workers report engaging in search-related activities

	Observations	Weighted mean conditional on search	Proportion of active searchers
Sample			
Full-time workers aged 18–65	73,487	103.91	0.004
Education levels			
No High School	4611	102.44	0.002
High School Diploma	17,829	81.24	0.003
Some College	20,966	90.27	0.004
College Degree	18,777	112.56	0.004
Graduate Education	11,314	140.85	0.005
Job mismatch (Hartog 2000)			
Mismatched	15,182	118.74	0.005
Not mismatched	58,315	98.83	0.004
Productivity			
Lowest productivity	36,748	101.82	0.005
High productivity	36,749	108.00	0.003

Weighted means and proportions are generated using the ATUS weights. Workers are classified as mismatched if their education level exceeds the average of that of their current occupation (Hartog 2000)

Econometric Model

The general theoretical model introduced in the second section is formalized in the following benchmark model:

$$s_{ijt} = \beta_0 + \beta_1\mu_i + \beta_2\varepsilon_i + \beta_3(\mu_i{*}\varepsilon_i) + \beta_4 VU_{jt} + \Gamma W_{jt} + \Pi\phi_i + \xi_i + e_{ijt} \qquad (1)$$

The overall quality of the match, μ, is proxied by a dummy variable equal to 1 if the worker has an education level above the average of that in their occupation. Productivity,, is proxied by the wage residual based on Mincer determinants along with occupation and industry. Labor market tightness is proxied by the regional *VU* ratio and whether they live in an urban area. Controls for household wealth, *W*, are proxied by homeownership along with changes in regional housing prices. The opportunity cost of search, ϕ, is proxied by whether the individual is married, has children, the maximum weekly unemployment benefits in the state in which they live, and controls for the month, day and year of their ATUS diary survey. In addition, existing theory suggests that high productivity workers who are currently mismatched should be the ones most likely to search, assuming the expected value from search is higher than low-productivity workers. We test this theoretical result by including an interaction, ($\mu_i * \varepsilon_i$). All regressions include state fixed effects, ξ_j. Standard errors are weighted and clustered by state of residence.

The decision to search is examined both the extensive and intensive margins. At the extensive margin, we use Probit regression. The choice of the appropriate model for estimation of search intensity is somewhat trickier. Estimation at the intensive margin is complicated due to the fact that a small fraction of employed workers report spending time on job search activities. It is unknown what proportion of these observations are true zeros (workers who are not actively searching for jobs) and what proportion are the mismeasured observations (workers engaged in search but not reporting search minutes on that particular day). Thus, with time spent searching censored at zero, there is some question about how to best estimate the model to address this kind of potential measurement error. The classical censoring model would be one in which the latent variable, s^*, may take on negative values, but that the observed, s, is censored at zero. In time use surveys, this is not the case. Because the observations are bounded by zero, many researchers have chosen to use Tobit to deal with this econometric issue. However, the implementation of Tobit assumes that the factors determining the likelihood that a respondent reports zero minutes of a given activity on a given day are the same as those determining total time spent, conditional on the respondent engaging in that activity on that day.

Recent work by Stewart (2013) shows that when this assumption is violated, the bias in Tobit estimates is large and that the size of this bias increases with the proportion of censored observations. As a result, he strongly recommends the use of OLS over Tobit in cases with data-generating processes such as this. In the context of unemployed search intensity, DeLoach and Kurt (2013) confirm that Tobit significantly biases the estimates towards zero, as predicted by Stewart (2013). Nevertheless, measurement error is a significant challenge in time use, especially when there is a large proportion of observations at zero. Because of this, many argue that the best strategy is to examine the extensive margin via Probit and examine the intensive margin using OLS conditional on search (Burda et al. 2017; Stewart 2013). We follow this approach.

Unlike with search intensity for unemployed workers, there is no reason to suspect reverse causality between in employed search and the regional VU ratio. If unemployed workers become discouraged and drop out of the labor force, this could affect the measure of unemployment and the VU ratio. However, employed workers are in the labor force regardless of whether they engage in search. Changes in employed search do not cause changes in the VU ratio. Hence, reverse causation does not present a challenge to identification.

The main challenge to identification involves unobserved heterogeneity. Because the ATUS is a pooled cross-section, it is not possible to control for unobserved heterogeneity using fixed effects. For this unobserved heterogeneity to bias our estimates of the effects of aggregate shocks on search intensity, such factors would have to be correlated with changes in the business cycle and search intensity. One example involves individual's unobserved geographical mobility. Suppose workers who are less mobile are concentrated in a region of the country hit worse by the recession. This would cause the coefficient on the VU ratio to be biased downward.

Alternatively, unobserved heterogeneity due to worker immobility may be simultaneously correlated with search intensity and factors such as productivity or job mismatch. Because they are immobile, such workers may be more prone to becoming employed in jobs in which they are over-educated on average (mismatched). This would cause the coefficient on job mismatch to be biased downward. To address these concerns, we test alternative specifications where married workers, those living in rural areas, and workers who own home are excluded from the sample.

Results

The model in Eq. 1 is estimated via OLS and Probit with standard errors clustered at the state level. Clustering at the state level allows us to control for arbitrary correlation across time by workers in each state.[6] Results are summarized in Tables 2 (Conditional OLS) and 3 (Probit). The OLS results in Table 2, reveal the difficulty in trying to estimate search intensity. Conditional on search, the sample sizes are rather small, resulting in partial effects that are estimated imprecisely.

In contrast, the Probit results in Table 3 are much more promising, and largely consistent with the predictions of many existing models of OJS. On average, workers living in state with more generous unemployment benefits and those in urban areas are more likely to engage in OJS. More productive and older workers are less likely to search. As theory predicts, workers who are mismatched in their current job are more likely to engage in search. Interestingly, when less mobile workers are excluded (married or homeowners) the coefficient on mismatch increases significantly. This makes intuitive sense as it implies that more mobile workers are substantially more likely to engage in search when mismatched. Whereas, less-mobile workers are relatively unresponsive to being mismatched.

We find higher-productivity mismatched workers are significantly more likely to search than other mismatched workers (Table 3). This is consistent with several models such as Barlevy (2002), Cahuc et al. (2006), and Dolado et al. (2009). In these models, high-productivity workers have a greater incentive to engage in search when they find themselves in a poor job match because the value of the outside option is relatively large. As with mismatched workers in general, mobility appears to play a role in determining the relative responsiveness (i.e, size of the coefficient) of search to being mismatched for highly-productive workers.

In general, it appears that unobserved heterogeneity is likely to be biasing these coefficients downward. Specifically, mismatched workers are typically not exogenously mismatched, as theory assumes. In reality, there is unobserved worker heterogeneity that is likely to be simultaneously correlated with search and the likelihood of being mismatched. Examples include lack of ambition, mobility and risk aversion. For example, a risk-averse worker may be simultaneously less likely to search for a new job and is more likely to become mismatched. This would bias the coefficient on mismatch downward. Ambition and mobility have similar effects. A more ambitious worker is simultaneously more likely to engage in OJS and be less likely to be mismatched.

Evidence of this bias is seen in Table 3. When we exclude married workers, the coefficients on *mismatch* and *productivity*mismatch* double. The omission of these factors could account for the lack of evidence that mismatched workers as a whole do not increase their search intensity as the economy improves. Logically, we expect that the top-wage earners (ones with large wage residuals) are more likely to be ambitious, mobile and open to new opportunities. These workers should be more responsive to improving local labor market conditions.

While there is no evidence that changes in regional labor market conditions amplify this effect, caution must be taken when drawing inferences based on these estimates. First, it is likely that the small proportion of workers who report searching limits the

[6] Results are not significantly different without clustering.

Table 2 Summary of OLS Regressions of search intensity conditional on search

`	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se	(7) b/se	(8) b/se	(9) b/se
Worker productivity	−15.922	−18.157	−25.077	−12.524	−41.312	−25.505	−29.576*	−2.023	25.911
	(18.170)	(16.557)	(16.521)	(27.173)	(32.568)	(16.348)	(16.374)	(27.557)	(32.894)
Currently mismatched	23.496	26.882	28.219	22.876	44.479	28.309	31.823	61.165**	28.248
	(22.387)	(21.484)	(20.092)	(21.441)	(32.330)	(20.120)	(21.032)	(28.185)	(39.606)
Productivity*mismatched	7.432	18.047	39.965	23.333	145.667*	88.603	46.672	5.447	39.337
	(46.504)	(43.930)	(44.954)	(51.968)	(80.966)	(117.102)	(44.133)	(67.023)	(84.926)
VU ratio	37.338	27.051	238.937*	593.919***	−32.237	242.129*	178.552	125.842	−30.629
	(117.279)	(120.722)	(136.048)	(170.046)	(266.111)	(134.113)	(150.727)	(257.158)	(201.291)
Max weekly UI benefits	31.416	30.061	42.483	76.218*	2.916	42.405	36.987	25.004	9.738
	(35.690)	(35.355)	(32.956)	(41.055)	(61.306)	(32.310)	(38.140)	(60.991)	(74.887)
Age		1.042*	0.981	1.177	1.051	0.974	1.074	0.188	1.319
		(0.604)	(0.592)	(0.828)	(0.878)	(0.607)	(0.687)	(1.042)	(0.848)
Urban		−2.200	−7.124	−16.127	−3.158	−7.705		25.946	−28.011
		(19.433)	(21.406)	(22.772)	(32.277)	(21.465)		(40.124)	(38.577)
Productivity*mismatched*VU						−98.530			
						(194.622)			
Sample size	253	253	253	132	121	253	228	140	98
Survey date controls	x	x	x	x	x	x	x	x	x
Non-age demographics		x	x	x	x	x	x	x	x
Wealth controls			x	x	x	x	x	x	x
2003–2008					x				
2009–2016						x			
Excluding married								x	
Excluding rural							x		
Excluding homeowners									x

Table 3 Summary of Probit regressions of the likelihood of search

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se	(7) b/se	(8) b/se	(9) b/se
Worker productivity	−0.372***	−0.372***	−0.371***	−0.371***	−0.383***	−0.364***	−0.390***	−0.434***	−0.386***
	(0.057)	(0.058)	(0.059)	(0.059)	(0.076)	(0.085)	(0.062)	(0.100)	(0.107)
Currently mismatched	0.141**	0.139**	0.137*	0.136*	0.143	0.138	0.155**	0.310***	0.295***
	(0.064)	(0.070)	(0.071)	(0.072)	(0.117)	(0.109)	(0.072)	(0.087)	(0.098)
Productivity*mismatched	0.154*	0.154*	0.151*	0.390**	0.120	0.170	0.174*	0.322**	0.260
	(0.089)	(0.090)	(0.088)	(0.178)	(0.198)	(0.132)	(0.090)	(0.150)	(0.216)
VU ratio	−0.042	−0.071	−0.391	−0.399	−0.405	−0.545	−0.393	−0.608	−1.262
	(0.426)	(0.437)	(0.527)	(0.535)	(0.569)	(1.090)	(0.566)	(0.606)	(0.817)
Max weekly UI benefits	0.289	0.262	0.273*	0.271*	0.482***	0.131	0.282*	0.492**	−0.130
	(0.182)	(0.176)	(0.164)	(0.163)	(0.130)	(0.174)	(0.170)	(0.199)	(0.120)
Age		−0.011***	−0.011***	−0.011***	−0.007**	−0.014***	−0.011***	−0.015***	−0.013***
		(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Urban		0.246**	0.235**	0.235**	0.119	0.386***		0.328**	0.341***
		(0.098)	(0.097)	(0.097)	(0.136)	(0.113)		(0.139)	(0.132)
Productivity*mismatched*VU				−0.512					
				(0.452)					
Sample size	73,497	73,497	73,497	73,497	37,465	36,032	61,343	32,304	19,400
Survey date controls	x	x	x	x	x	x	x	x	x
Non-age Demographics		x	x	x	x	x	x	x	x
Wealth controls			x	x	x	x	x	x	x
2003–2008					x				
2009–2016						x			
Excluding married								x	
Excluding rural							x		
Excluding homeowners									x

ability to estimate the effect of the business cycle on search. This underscores the weakness of relying solely on the ATUS measure of search. Second, the sign on the VU ratio is opposite of what we expect, suggesting a problem with the measurement of local labor market conditions itself.

To test this, we use state-level unemployment rather than the regional VU ratio (see Table 4 in the Appendix). Our results are largely consistent with either measure of regional labor market conditions. The sign on unemployment is typically positive, suggesting that OJS increases as the unemployment rate rises. As with the VU ratio, this is the opposite of what theory predicts. In addition to our inability to accurately measure local labor market conditions, our inability to control for changes in household wealth could play a part here. This is because the increases in wealth that come with improving labor market conditions theoretically reduces the incentive to search, while improving labor market conditions increases the incentive to search.

Conclusion

The purpose of this paper has been to examine factors that affect the decision to search on the job. Because we implicitly test some key assumptions of several existing theoretical models of OJS, these results have implications for future research in the field. First, there is strong evidence that the likelihood of search is negatively related to worker productivity in general. Second, mismatched workers appear more likely to engage in search than non-mismatched workers. Third, high-productivity workers who are currently mismatched in their job are more likely to search than other mismatched workers.

While the results appear promising, there are a number of cautions that should be taken seriously by future researchers. The first involves the measure used in this study to proxy OJS. Because such a small fraction of workers report job search on any particular day, we are identifying the model from a small sample of workers. As recent research by Carrillo-Tudela et al. (2015) demonstrates, employed workers who make job-to-job transitions are often unlikely to report active search prior to taking a new job. This represents a significant challenge for labor economists tying to study OJS. The second involves our inability to control for unobserved heterogeneity that is likely to bias the responsiveness of mismatched workers downward. Unfortunately, the nature of the ATUS makes it impossible to deal with this issue directly. The best solution is to utilize panel data so that fixed effects can be used to estimate the model. While such panel datasets exist, none have direct measures of search intensity. However, recent papers such as Mukoyama et al. (2014) offer some innovative alternatives to measuring search intensity that may be worth pursuing in this context.

Compliance with Ethical Standards

Conflicts of Interest The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Appendix

Table 4 Summary of Probit regressions of the likelihood of search with state unemployment

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se	(7) b/se	(8) b/se	(9) b/se
Worker productivity	−0.372***	−0.372***	−0.371***	−0.371***	−0.383***	−0.365***	−0.390***	−0.435***	−0.388***
	(0.057)	(0.057)	(0.059)	(0.059)	(0.076)	(0.086)	(0.062)	(0.101)	(0.107)
Currently mismatched	0.141**	0.139**	0.138*	0.136*	0.143	0.138	0.155**	0.312***	0.301***
	(0.064)	(0.069)	(0.070)	(0.071)	(0.117)	(0.107)	(0.072)	(0.086)	(0.097)
Productivity*mismatched	0.154*	0.154*	0.151*	−0.129	0.118	0.170	0.174*	0.321**	0.264
	(0.090)	(0.092)	(0.089)	(0.292)	(0.200)	(0.134)	(0.091)	(0.152)	(0.214)
State unemployment rate	0.012	0.005	0.009	0.009	0.053	−0.013	0.001	0.013	0.058**
	(0.020)	(0.021)	(0.023)	(0.023)	(0.035)	(0.025)	(0.024)	(0.030)	(0.024)
Max weekly UI benefits	0.295	0.268	0.292*	0.291*	0.508***	0.144	0.298*	0.523**	−0.072
	(0.194)	(0.187)	(0.173)	(0.172)	(0.138)	(0.195)	(0.179)	(0.218)	(0.137)
Age		−0.011***	−0.011***	−0.011***	−0.007**	−0.014***	−0.011***	−0.015***	−0.013***
		(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Urban		0.244**	0.234**	0.234**	0.115	0.395***	0.000	0.324**	0.304**
		(0.096)	(0.095)	(0.096)	(0.134)	(0.115)	(.)	(0.139)	(0.133)
Productivity*mismatched*VU				0.043					
				(0.038)					
Sample size	73,497	73,497	73,497	73,497	37,465	36,032	61,343	32,304	19,400
Survey date controls	x	x	x	x	x	x	x	x	x
Non-age demographics		x	x	x	x	x	x	x	x
Wealth controls			x	x	x	x	x	x	x

Table 4 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
2003–2008					x				
2009–2016						x			
Excluding married								x	
Excluding rural							x		
Excluding homeowners									x

References

Barlevy G (2002) The Sullying Effect of Recessions. Rev Econ Stud 69(1):65–96

Bjelland M, Fallick B, Haltiwanger J, McEntarfer E (2011) Employer-to-Employer Flows in the United States: Estimates Using Linked Employer-Employee Data. Journal of Business & Economic Statistics 29(4):493-505

Burda M, Genadek KR, Hamermesh D (2017) Non-Work at Work, Unemployment and Labor Productivity, No 12087, CEPR Discussion Papers. C.E.P.R, Discussion Papers

Burdett K (1978) A theory of employee job search and quit rates. Am Econ Rev 68(1):212–220

Burdett K, Mortensen D (1998) Wage Differentials, Employer Size, and Unemployment. Int Econ Rev 39(2): 257–273

Bureau of Labor Statistics (2017a) American Time Use Survey 2003–2016. http://www.bls.gov/578tus/datafiles_0311.htm

Bureau of Labor Statistics (2017b) Current Population Survey. http://www.bls.gov/cps/

Bureau of Labor Statistics (2017c) Job Openings and Labor Turnover Survey. http://www.bls.gov/jlt/

Cahuc P, Postel-Vinay F, Robin JM (2006) Wage bargaining with on-the-job search: Theory and evidence. Econometrica 74(2):323–364

Carrillo-Tudela C, Hobijn B, Perkowski P, Visschers L (2015) Majority of Hires Never Report Looking for a Job. FRBSF Econ Lett:2015–2010

Chassamboulli A (2011) Cyclical upgrading of labor and employment differences across skill groups. BE J Macroecon 11(1)

DeLoach SB, Kurt M (2013) Discouraging workers: Estimating the impacts of macroeconomic shocks on the search intensity of the unemployed. J Lab Res 34(4):433–454

Department of Labor (2017) State Unemployment Benefits. http://ows.doleta.gov/unemploy/583uifactsheet.asp

Dolado JJ, Jansen M, Jimeno JF (2009) On-the-Job Search in a Matching Model with Heterogeneous Jobs and Workers. Econ J 119(534):200–228

Gomme P, Lkhagvasuren D (2015) Worker search effort as an amplification mechanism. J Monet Econ 75: 106–122

Hartog J (2000) Over-education and earnings: where are we, where should we go? Econ Educ Rev 19(2):131–147

Krause MU, Lubik TA (2006) The cyclical upgrading of labor and on-the-job search. Labour Econ 13(4):459–477

Krause MU, Lubik T (2010) On-the-job search and the cyclical dynamics of the labor market. Federal Reserve Bank of Richmond Working Paper No. 10-12

Krueger AB, Mueller A (2010) Job search and unemployment insurance: New evidence from time use data. J Public Econ 94(3-4):298-307

Lammers M (2014) The effects of savings on reservation wages and search effort. Labour Econ 27:83–98

Moscarini G, Vella F (2008) Occupational Mobility and the Business Cycle. NBER Working Paper No. 13819. Cambridge: National Bureau of Economic Research

Mukoyama T, Patterson C, Sahin A (2014) Job search behavior over the business cycle. FRB of New York Staff Report

Postel-Vinay F, Robin JM (2002) Equilibrium wage dispersion with worker and employer heterogeneity. Econometrica 70(6):2295–2350

Pries MJ (2008) Worker heterogeneity and labor market volatility in matching models. Rev Econ Dyn 11(3): 664–678

Shimer R (2004) Search Intensity. Unpublished paper

Shimer R (2005) The cyclical behavior of equilibrium unemployment and vacancies. Am Econ Rev 95:25–49

Standard and Poor's (2017) Case-Shiller Housing Index. http://www.standardandpoors.com/indices/sp-case-shiller-home-price-indices/en/us/?indexId=spusa-cashpidff–p-us

Stewart J (2013) Tobit or not tobit? J Econ Soc Meas 38(3):263–290