Comments and Discussion

COMMENT BY
STEVEN J. DAVIS  Alan Krueger and Andreas Mueller present new evidence on job search activity, job finding, life satisfaction, mood, and reservation wages among unemployed workers. Notably, they exploit high-frequency longitudinal data to estimate how individual search time responds to unemployment spell duration (measured as weeks receiving unemployment benefits). Another noteworthy aspect of the Krueger-Mueller study is the setting: a period of high unemployment and historically low job-finding rates.

The authors’ survey instrument yields two measures of search time. On average, unemployed workers devote 65 minutes per day to job search activity according to time diary data and 98 minutes per day according to weekly recall data. Over three decades ago, John Barron and Wesley Mellow (1979) reported that unemployed persons spend on average about 7 hours per week searching for a job, remarkably similar to what Krueger and Mueller find in their time diary data.

Krueger and Mueller find large negative effects of unemployment spell duration on job search time. In a regression specification that controls for individual fixed effects, they estimate that 10 additional weeks of unemployment reduces search time by 27 minutes per day in the time diary data and by 22 minutes per day in the weekly recall data (table 2). This estimated effect drops to about 16 minutes when they add controls for whether an individual’s benefits lapsed or ended and a dummy for observations after November 8, 2009, when the federal government extended the maximum benefit duration from 79 weeks to 99 weeks. Given the wide variation in spell duration, its estimated effect is very large relative to mean search time.

This finding is important for at least two reasons. First, standard theoretical models of job-seeking behavior imply that search intensity is constant or increasing with respect to unemployment spell duration. This implication
is at odds with the Krueger-Mueller evidence, assuming that search time serves as a reasonable proxy for search intensity. Second, the large theoretical and empirical literatures that use matching functions to explain labor market flows, job-finding rates, and Beveridge curve behavior routinely assume that average search intensity per unemployed worker is stable over time. As I explain below, the Krueger-Mueller evidence challenges this assumption. Some of my recent work with Jason Faberman and John Haltiwanger (Davis, Faberman, and Haltiwanger 2010) challenges the analogous assumption of stable recruiting intensity per vacancy on the employer side of the market.

My remarks below treat three issues related to Krueger and Mueller’s finding that search time falls with spell duration. First, do reporting errors impart a bias to this estimated relationship? Second, why might search time fall with the duration of unemployment? Third, does the estimated effect of spell duration on search time have important macroeconomic implications? In particular, can it shed light on the cyclical behavior of average job-finding rates among the unemployed? Although the paper has many other interesting aspects, I confine my remarks to these issues.

**DO REPORTING ERRORS BIAS THE ESTIMATED EFFECT OF SPELL DURATION ON SEARCH TIME?** The authors’ weekly survey instrument triggers several additional questions if the respondent reports searching for a job. These additional questions seek to elicit information about time spent in specific search activities, self-assessed mood during various search activities, the types of jobs to which the respondent applied, the farthest distance traveled to look for a job, and whether and how the respondent used the Internet to search for a job. Thus, the respondent can lessen the inconvenience of completing the questionnaire by reporting that he or she did not search for a job. A given respondent completes the questionnaire up to 24 times. So there is ample opportunity to learn that affirmative responses to questions about job search trigger additional questions. If respondents become more likely to falsely report no job search as they gain familiarity with the questionnaire, they also become more likely to falsely report zero search time as spell duration increases. This pattern of reporting errors imparts a negative bias to the estimated effect of spell duration in search-time regressions fit to longitudinal data.

Two aspects of the empirical results reported suggest that this source of bias is at work. First, across cohorts defined by the timing of job loss in the authors’ figure 3, reported search time in the first application of the survey instrument does not fall with spell duration—despite a range of more than 70 weeks in the initial spell duration. Krueger and Mueller refer
to this phenomenon as a “curious” pattern of parallel search-time profiles across cohorts. They argue, persuasively in my view, that calendar time effects do not explain this curious pattern. They also argue that differences in average characteristics across cohorts influence the levels of the cohort-specific search-time profiles. However, they do not quantify whether and to what extent these differences help reconcile their preferred estimates for the spell duration effect with the cross-cohort pattern of search-time profiles. I suspect that differences in average cohort characteristics do not go very far in this direction. In short, it appears that neither calendar time effects nor cohort effects explain the curious pattern in figure 3. Reporting errors that vary with the number of previous interviews provide an alternative explanation.

Second, the top panel of the authors’ figure 4 shows that reported participation in job search activity declines sharply with spell duration for each cohort. This graph also exhibits the same curious pattern as figure 3. These two aspects are consistent with the reporting error story described above. However, the bottom panel of the figure shows that reported search time falls with spell duration among those who report job search activity on the previous day. This graph also exhibits the same curious pattern of roughly parallel search-time profiles across cohorts. The reporting error story described above does not imply these patterns in the bottom panel.

In practice, the number of previously completed interviews does not advance in lockstep with spell duration because respondents skip many of the weekly interviews. This makes it possible to estimate the effect of spell duration conditional on the number of previous interviews. Krueger and Mueller kindly supplied me with search-time regression results for specifications that include controls for the number of previous interviews. My table 1 reports the estimated effect of spell duration on search time with and without these controls. The first column reproduces results from the authors’ table 2. The second column allows for a reporting error effect that is linear in the number of previous interviews, and the third relaxes the linearity restriction.1

Adding a linear control attenuates the estimated spell duration effect in the time diary data but not in the weekly recall data. Adding a vector

1. Specifically, the third column adds to the regression in the first column a vector of dummy variables for 1, 2, 3, 4, 5, and 6 or more previous interviews. This specification adequately controls for the reporting error effect discussed in the text if there are no material differences in conditional mean reporting errors by cohort and by number of previous interviews greater than 6.
of controls for number of previous interviews has a much stronger impact on the character of the results. As the third column of table 1 shows, the estimated spell duration effect is now modest and statistically insignificant in the time diary data. It remains negative and statistically significant in the weekly recall data, but the point estimate is much smaller than in the first column.

I read table 1 and my observations about the authors’ figures 3 and 4 as strong indications that the estimates reported in the rightmost three columns of their table 2 overstate the true effect of spell duration on search time. My table 1 suggests that the bias results from reporting errors that become more severe with repeated applications of the survey instrument. However, these results and my remarks about figure 4 indicate that reporting errors do not fully explain the decline in search time as an individual’s unemployment spell lengthens. In other words, the overall weight of the evidence supports the claim that search time declines with spell duration. As I remarked at the outset, I see this result as an important finding.

There is a need for additional research into the relationship between spell duration and search time. As Krueger and Mueller point out, it would be useful to randomly vary the time interval between interviews to deal more

### Table 1. Regressions Explaining Job Search Time with Unemployment Spell Duration and the Number of Survey Interviews

<table>
<thead>
<tr>
<th>Regression specification</th>
<th>No. of previous interviews</th>
<th>Vector of controls for previous interviews</th>
</tr>
</thead>
<tbody>
<tr>
<td>..........................</td>
<td>None(^b)</td>
<td></td>
</tr>
<tr>
<td>Dependent variable: time spent on job search yesterday (minutes per day)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Krueger and Mueller,</td>
<td>–2.73</td>
<td>−0.44</td>
</tr>
<tr>
<td>table 2, fourth column</td>
<td>(0.25)</td>
<td>(0.32)</td>
</tr>
<tr>
<td>Krueger and Mueller,</td>
<td>–1.62</td>
<td>−0.45</td>
</tr>
<tr>
<td>table 2, fifth column</td>
<td>(0.31)</td>
<td>(0.36)</td>
</tr>
<tr>
<td>Dependent variable: time spent on job search in last 7 days (minutes per day)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Krueger and Mueller,</td>
<td>–2.25</td>
<td>−0.96</td>
</tr>
<tr>
<td>table 2, fourth column</td>
<td>(0.29)</td>
<td>(0.39)</td>
</tr>
<tr>
<td>Krueger and Mueller,</td>
<td>–1.54</td>
<td>−0.90</td>
</tr>
<tr>
<td>table 2, fifth column</td>
<td>(0.33)</td>
<td>(0.40)</td>
</tr>
</tbody>
</table>

Source: Krueger and Mueller, this volume, and regressions conducted by Krueger and Mueller not reported in the paper.

a. Table reports estimated coefficients on the unemployment spell duration variable in the indicated regression specification. Standard errors are in parentheses.
b. As reported in Krueger and Mueller, this volume, table 2.
c. Vector consists of dummy variables for 1, 2, 3, 4, 5, and 6 or more previous interviews.
conclusively with the effects of reporting errors that vary with the number of interviews.

**WHY MIGHT SEARCH TIME FALL WITH UNEMPLOYMENT SPELL DURATION?** One possibility is that individuals become more efficient searchers with practice: for example, they may become faster at scanning help-wanted advertisements and assessing which ones offer suitable matches. If search efficiency improves in this sense, optimal search time per period declines with spell duration under mild assumptions about the costs and benefits of job search.2 A second possibility is that job search activity becomes increasingly painful psychologically as an unemployment spell lengthens. Psychological effects of this sort could raise the marginal cost of searching and reduce individually optimal search time. Yet another possibility is that lack of success in job hunting leads to negative revisions in the worker’s assessment of his or her own skills and capabilities. Revisions of this sort imply inward shifts in the schedule describing the perceived marginal benefit of search time. As a result, individually optimal search time falls. A fourth possibility is that persons negatively revise their judgments about the availability of suitable job opportunities as an unemployment spell lengthens. This possibility involves revisions to perceived market opportunities rather than one’s own skills, but it, too, produces an inward shift in the perceived rewards to search activity. All four of these possibilities warrant attention in future research.

Krueger and Mueller interpret some of their findings as evidence that the psychological costs of job search may rise with spell duration, and that such costs could discourage job search after an extended period of unemployment. I am sympathetic to this concern, but the relationship between subjective well-being and search intensity is likely to be complex. Even if deteriorations in mood or life satisfaction raise the psychological costs of job search, the overall effect on search intensity is unclear because of a countervailing effect on the psychological reward to finding a job.

Previous research suggests that this countervailing effect is empirically relevant and large. Using British data, Andrew Clark (2003) finds that persons who experience larger drops in subjective well-being on becoming unemployed are more likely to search actively for a new job if still unemployed 1 year later. Using German data, Anne Gielen and Jan van Ours (2010) find much higher job-finding rates for persons who experience

---

2. Marginal costs that rise with search time in the period and marginal benefits that fall with efficiency units of search are sufficient conditions at an interior optimum.
larger drops in life satisfaction on becoming unemployed. They also find that postunemployment wages are unrelated to the drop in life satisfaction, which suggests that higher job-finding rates result from greater search intensity, not from lower reservation wages.

Evaluating the impact of psychological effects on job search activity and, more generally, investigating why spell duration negatively affects search time are important topics for future research. Krueger and Mueller’s study adds to the impetus for additional research in this area.

**IMPLICATIONS FOR THE CYCICALITY OF AVERAGE JOB-FINDING RATES** My figure 1 plots the mean unemployment spell duration in the United States from January 2001 to February 2011. The figure shows a dramatic rise in mean duration from 17 weeks in July 2008 to 34 weeks in May 2010 and 37 weeks in January 2011. If one applies the spell duration effect estimated by Krueger and Mueller to this 20-week rise in mean spell duration, it implies that average search time per unemployed worker fell by 31 to 55 minutes per day over this period.\(^3\) That is a very large drop relative to

\(^3\) These search-time responses reflect the estimated coefficients on spell duration in the last two columns of Krueger and Mueller’s table 2, reproduced in the first column of my table 1.
the mean search time of 60 to 100 minutes per day reported by Krueger and Mueller and by Barron and Mellow (1979), and large enough to have important macroeconomic consequences.

To appreciate this point, consider the cyclical behavior of job-finding rates for unemployed workers, an object of intensive research efforts in recent years (for example, Hall 2005 and Shimer 2005). My figure 2 compares a standard empirical measure of the job-finding rate since 2001 with the rate implied by a standard Cobb-Douglas matching function for aggregate hires, \( H = \mu U^{\alpha} V^{1-\alpha} \). In computing the implied job-finding rate, I set \( \alpha = 0.6 \). This value lies in the middle of the range of elasticity estimates produced by matching function studies that use unemployment outflows as the dependent variable (Petrongolo and Pissarides 2001).

As figure 2 shows, the actual and implied job-finding rates track each closely over most of the sample period, but there is a large and persistent divergence in recent years. The nature of the divergence is interesting: the empirical job-finding rate declines more sharply than implied by the standard

**Figure 2.** Empirical Job-Finding Rate and Rate Implied by a Standard Job-Matching Function, January 2001–February 2011

Source: Author’s calculations using data from the Current Population Survey (CPS) and the Job Openings and Labor Turnover Survey (JOLTS).

- Unemployment exit rate calculated using CPS data on unemployment by duration. See, for example, section II.B in Davis, and Haltiwanger (2010) for a description of the calculation.
- Calculated by substituting CPS data on unemployment and JOLTS data on job vacancies into the matching function \( H = \mu U^{\alpha} V^{1-\alpha} \), where \( \mu \) is chosen to equate the means of the empirical and implied job-finding rates from 2001 to 2007 and \( \alpha = 0.6 \).
matching function beginning in 2007. Moreover, it has yet to recover to levels implied by the standard matching function.

The standard matching function includes no role for variations in average search intensity per unemployed worker. The evolution of the gap between empirical and implied job-finding rates in figure 2 and its rough similarity to the path of mean spell duration in figure 1 suggest that the standard matching function breaks down because it neglects the role of cyclical movements in search intensity. Davis, Faberman, and Haltiwanger (2010) present an analogous comparison for the job-filling rate of vacant job positions. They obtain a pattern very similar to that in figure 2: the empirical and implied job-filling rates track each other closely until the end of 2007, after which a large and persistent divergence arises. Thus, it is unlikely that the path of the residual gap in figure 2 reflects some deficiency in the empirical measure of the job-finding rate. Instead, the deficiency more likely lies in the specification of the matching function.

The evidence presented by Krueger and Mueller, taken together with figure 1, suggests that one deficiency is the omission of movements in average search intensity per unemployed worker. Davis, Faberman, and Haltiwanger (2010) develop evidence that another deficiency is the omission of movements in recruiting intensity per vacancy. Following the approach in my work with Faberman and Haltiwanger, I now generalize the standard matching function to encompass these two intensity margins. I will use the generalized function to provide a first-pass quantification of what the Krueger-Mueller evidence implies for the cyclical behavior of job-finding rates.

To draw out the implications of the Krueger-Mueller evidence, I must take a partial stand on what drives the estimated effect of spell duration on search time. I treat search time as a measure of effective search units supplied by an individual unemployed worker. This approach is a natural one and consistent with standard extensions of Mortensen-Pissarides models to incorporate variable search intensity (see, for example, chapter 5 in Pissarides 2000). However, my approach here is not suitable if individual search efficiency per unit of search time varies substantially with individual spell duration.

Consider a generalized matching function for new hires in period $t$ given by

$$H_t = \mu [s U_t]^{\alpha} [q V_t]^{1-\alpha},$$

where $U$ and $V$ are the numbers of unemployed workers and vacant jobs, $s$ is average search intensity per unemployed worker, $q$ is average recruiting intensity per vacancy, and the elasticity parameter $\alpha$ lies between
0 and 1. This matching function yields the following expression for the job-finding rate:

$$JF_t = \mu \left[ s_t \right]^{\alpha} \left[ q_t \left( \frac{V_t}{U_t} \right) \right]^{1-\alpha}.$$

To operationalize this expression, I need measures for vacancies, unemployment, the two intensity indexes, and the elasticity parameter. I obtain data on vacancies and unemployment from the Bureau of Labor Statistics’ Job Openings and Labor Turnover Survey and the Current Population Survey (CPS), respectively. I set the elasticity parameter $\alpha = 0.6$, as before. The recruiting intensity index I borrow from Davis, Faberman, and Haltiwanger (2010).

To construct a search intensity index, I combine the Krueger-Mueller estimation results with CPS data on mean unemployment spell duration. Specifically, I treat search intensity per unemployed worker as a linear function of search time per unemployed worker:

$$s_t = A - \beta \left( \text{weeks} \right),$$

where $\text{weeks}$ is the mean spell duration of unemployed workers and $\beta$ is the marginal effect of spell duration on search time. From the last column of Krueger and Mueller’s table 2 (bottom panel), I set $\beta = 1.54$. I set $A = 97.6 + 1.54(27.4)$, where 97.6 is mean search time in minutes per week in the Krueger-Mueller sample and 27.4 is mean spell duration in weeks at the sample start. Substituting these values into the search intensity index and feeding through the aggregate time series for mean spell duration yields a time series for $s$. In light of my earlier remarks about bias in the Krueger-Mueller estimates, I repeat the construction of the search intensity index using $\beta = 0.90$ from the third column of my table 1.4

Figure 3 plots the resulting index of search intensity alongside the index of recruiting intensity. Both intensity measures fall sharply in recent years, which depresses the job-finding rate at any given vacancy-unemployment ratio. The recent behavior of the two indexes also differs in important respects. The recruiting intensity index falls by about 20 percent over 2007 and 2008, then stabilizes and recovers slightly. The search intensity index holds steady until the middle of 2008 but then falls nearly 25 percent by the middle of 2010. The big swings in these two indexes suggest that attention to search and recruiting intensity can improve our

4. In this case I should also adjust the mean search time in the Krueger-Mueller sample for measurement error. For simplicity, I ignore this issue in my calculations.
understanding of fluctuations in job-finding rates, job-filling rates, and related phenomena.

Table 2 reports the results of a simple exercise along these lines: a decomposition of the change in the job-finding rate from 2006 to 2010. As reported in the first row, the empirical job-finding rate fell by 81 log points over this period, an enormous drop. As the next row shows, the standard matching function predicts a drop of only 50 log points. In other words, the fall in the vacancy-unemployment ratio from 2006 to 2010 accounts for only 62 percent of the drop in the observed job-finding rate. This calculation confirms the visual impression given by the path of the residual gap in figure 2.

The second and third panels in table 2 report the log change in the job-finding rate implied by the generalized matching function. In constructing the search intensity index, the second panel draws on Krueger and Mueller’s table 2 to obtain the effect of spell duration on search time. The third panel draws on the estimated spell duration effect in the specification that includes a vector of controls for number of previous interviews. I use estimates based on the weekly recall data in both cases, because they are more robust to the treatment of the reporting error effect.
Table 2. Decomposing the Change in the Job-Finding Rate from 2006 to 2010

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Empirical job-finding rate, monthly, from CPS data</td>
<td>0.474</td>
<td>0.211</td>
<td>-0.811</td>
<td></td>
</tr>
<tr>
<td>Rate implied by standard matching function with $\alpha = 0.6$</td>
<td>0.480</td>
<td>0.291</td>
<td>-0.500</td>
<td></td>
</tr>
<tr>
<td>Vacancy-unemployment ratio</td>
<td>0.647</td>
<td>0.186</td>
<td>-1.250</td>
<td>-0.500</td>
</tr>
<tr>
<td>Rate implied by generalized matching function with $\alpha = 0.6$ and $\beta = 1.54$</td>
<td>0.481</td>
<td>0.235</td>
<td>-0.716</td>
<td></td>
</tr>
<tr>
<td>Recruiting intensity per vacancy</td>
<td>1.057</td>
<td>0.891</td>
<td>-0.167</td>
<td>-0.067</td>
</tr>
<tr>
<td>Search intensity per unemployed worker</td>
<td>113.9</td>
<td>88.8</td>
<td>-0.248</td>
<td>-0.149</td>
</tr>
<tr>
<td>Rate implied by generalized matching function with $\alpha = 0.6$ and $\beta = 0.90$</td>
<td>0.481</td>
<td>0.250</td>
<td>-0.655</td>
<td></td>
</tr>
<tr>
<td>Recruiting intensity per vacancy</td>
<td>1.057</td>
<td>0.891</td>
<td>-0.167</td>
<td>-0.067</td>
</tr>
<tr>
<td>Search intensity per unemployed worker</td>
<td>107.1</td>
<td>92.5</td>
<td>-0.147</td>
<td>-0.088</td>
</tr>
</tbody>
</table>

Source: Author’s calculations.

a. Figures reported for 2006 and 2010 are 12-month averages of monthly values. For each matching function, $\mu$ is normalized so as to equate the average values of the empirical and implied job-finding rates from 2001 to 2007. See the text for matching function specifications and a description of the inputs to the calculations.

b. Contribution is the same for all three matching functions shown.
The generalized matching function performs much better in explaining the observed drop in the job-finding rate from 2006 to 2010. Using the higher value of $\beta = 1.54$ and comparing the first and fourth rows of table 2, I find that the generalized matching function accounts for 88 percent of the log change in the observed job-finding rate. The last two rows in the second panel show that the recruiting intensity margin accounts for a decline in the job-finding rate of 6.7 log points over this period, and the search intensity margin for a decline of 14.9 log points. Taken together, the two intensity margins erase 70 percent of the residual gap between the observed and the implied job-finding rates that emerges over this period (figure 2). The contribution of the search intensity margin is smaller when the generalized matching function is constructed using $\beta = 0.90$ (bottom panel), but the contribution of the intensity margins remains sizable.

To sum up, the results in table 2 point to important roles for variation in search intensity per unemployed worker and recruiting intensity per vacancy in the recent behavior of U.S. job-finding rates. As a corollary, the intensity margins also have important effects on the rate at which employers fill vacant job positions, the evolution of the unemployment rate, and the behavior of the Beveridge curve. I conclude that Krueger and Mueller’s estimated effect of spell duration on individual search time has important macroeconomic implications. There is high value to additional research that seeks to more precisely pin down the size of the spell duration effect and to identify the factors that influence its magnitude and possible variation over time. There is also high value to research that explicitly incorporates search and recruiting intensity margins into macroeconomic models of fluctuations in the labor market.

REFERENCES FOR THE DAVIS COMMENT


**COMMENT BY**

**AYŞEGÜL ŞAHİN** In this paper Alan Krueger and Andreas Mueller study job search behavior and the emotional well-being of unemployed workers in New Jersey during the period from fall 2009 to winter 2010. The authors designed and conducted a survey of unemployment insurance (UI) claimants in New Jersey, collecting high-frequency longitudinal data on search activity. More than 6,000 unemployed workers were interviewed every week for up to 24 weeks. The strength of the paper is its use of longitudinal data that track search intensity for the same individuals over the course of their unemployment spell. Since workers with different durations of unemployment can be quite different in their characteristics, this type of analysis is superior to examining cross-sectional patterns of job search across those with different durations.

The authors’ analysis of their survey findings reveals some interesting patterns regarding job search and emotional well-being among these unemployed workers. Perhaps the most striking finding is that job search time declines sharply over the spell of unemployment: average daily search time falls by 30 minutes over a 12-week period, about a third of the average search time at the start of an unemployment spell. The study also finds that an unemployment spell is a stressful period for workers. Unemployed workers express dissatisfaction and unhappiness with their lives, and their unhappiness rises the longer they are unemployed.

These and other findings make this a very interesting and timely paper. With more than 13 million workers still unemployed, unemployment remains a major issue for the U.S. labor market. How unemployed workers search for employment opportunities, how their behavior changes depending on unemployment insurance (UI) policy, and their emotional state during the
spell of unemployment are all important issues that need to be better understood. Krueger and Mueller report some striking facts about unemployment and job search. It will probably take a long time before the patterns they have uncovered in their carefully designed survey are fully understood. Nevertheless, I will attempt to interpret their findings in light of well-known labor market models.

**JOB SEARCH BEHAVIOR** The first part of the paper focuses mostly on the job search behavior of UI claimants. What should one expect to see in light of existing job search models? Krueger and Mueller mostly focus on the implications of Dale Mortensen’s 1977 study. Mortensen’s model implies that the amount of time devoted to searching for a job should be constant or rising over the spell of unemployment. The intuition is clear: as the unemployment spell progresses, an unemployed worker’s savings become depleted and the expiration of UI benefits gets closer, leading the unemployed worker to search harder. However, various other forces, absent in the standard model, can affect job search time in the opposite direction over the unemployment spell. Human capital depreciation is one of these. As modeled by Lars Ljungqvist and Thomas Sargent (1998), skill depreciation during unemployment could cause a decline in reemployment wages. Consequently, the value of a job to the unemployed worker falls, inducing a decline in job search effort as unemployment duration gets longer. Another possible rationale for declining search effort can be found in stock-flow matching models of the labor market. In that class of models, newly unemployed workers face a pool of job vacancies for which they can apply. Those who exhaust this initial stock of job openings without finding a job then start to monitor the flow of new openings. This stock-flow nature of matching causes a decline in job search time. A third possibility is “learning by searching.” Unemployed workers may become more efficient in job search as they gain experience in monitoring, identifying, and applying for job openings. Depending on the quantitative importance of all these factors, search effort could go down or up over the spell of unemployment.

Using their unique survey of UI claimants, Krueger and Mueller provide estimates of job search time over the spell of unemployment. Their figure 4 reveals two striking patterns. First, search effort falls as the unemployment spell progresses. Second, the search time profiles of cohorts of workers who enter the survey at different times in their unemployment spell are approximately parallel lines, with the exception of the very long term unemployed. The question is what might explain these patterns. Are they at odds with what one would expect? I will discuss three potential
explanations: calendar time effects, stock-flow matching, and the use of a sequential search strategy. In doing so, I will make use of Help Wanted OnLine (HWOL) data from the Conference Board, which are targeted to cover the full universe of all online advertised vacancies posted directly on Internet job boards or through newspaper online ads.¹ The reason for focusing on job openings is that, as Krueger and Mueller show in their figure 6, almost two-thirds of job search time is spent looking at job advertisements, placing or answering advertisements, and sending out applications. Consequently, the number of job openings is likely to be an important determinant of search time. The HWOL data are ideal for examining the link between job openings and job search time, since they provide information about the location, occupation, required education level, and other aspects of each job listing.

CALENDAR TIME EFFECTS Before discussing calendar time effects, it will be worth recalling a few details about the timing and the administration of the authors’ survey. Individuals selected for the study were invited to participate for 12 consecutive weeks. Most of the interviews took place between September 2009 and January 2010. In early January 2010, individuals with 60 weeks or more of UI paid at the start of the study were invited to participate in an extended study. Consequently, two cohorts (the two rightmost cohorts in the authors’ figure 4) were interviewed for an additional 12 weeks from January to April 2010. If unemployed workers are spending a great deal of their search time reviewing job listings, the time series of the number of job openings in New Jersey during that period should be an important determinant of job search time. In particular, if there was a decline in the number of job listings, it could explain the declining search time profiles observed in the survey.

To investigate this issue, my figure 1 shows the number of job openings in New Jersey from the HWOL data between September 2009 and May 2010, the period during which all the interviews were conducted. Job openings did decline during the first wave of the survey but recovered after January 2010. The decline is likely to have affected all cohorts, possibly having a calendar time effect on search time profiles. Moreover, for the long-term unemployed who were interviewed for the additional 12 weeks, search time profiles flatten during that period. Such a flattening is consistent with the pickup in job listings that took place in New Jersey in the first 5 months of

¹. The HWOL data provide monthly measures of advertised vacancies at the national, regional, state, and metropolitan area levels since July 2005. For more details see www.conferenceboard.org/data/helpwantedonline.cfm.
I argue therefore that calendar time effects are potentially important in affecting the observed job search behavior, since there is pronounced time variation in job openings.

**STOCK-FLOW MATCHING** Another potential explanation for the decline in job search time is stock-flow matching, which can be described as follows. Imagine a worker who has recently lost her job. She first observes the current stock of vacancies in the market in which she is searching and applies for a set of jobs drawn from this initial stock. If she finds a suitable vacancy, she can quickly leave unemployment. If not, she must wait for the inflow of new vacancies coming onto the market. Since the stock of job listings generally exceeds the flow, this phenomenon of stock-flow matching is consistent with workers spending more time searching in the early part of the unemployment spell, then reducing their search effort after they exhaust this stock and can only monitor the inflow of new vacancies.

Using the HWOL data, one can examine the stock and the flow of vacancies at a monthly frequency. Before doing so, however, it is important to try to define the labor markets within which individuals are searching, since

---

**Figure 1.** Online Job Vacancies, New Jersey, September 2009–May 2010

Thousands of listings


---

workers care only about job listings that are potentially relevant for them. Unemployed workers most likely limit their search to a certain geographic area and a particular occupation category. The HWOL data report the occupations of vacancies using the Standard Occupational Classification (SOC) coding system, which at the 5- or 6-digit level defines a reasonable market for job searchers. (For example, at the 5-digit level, the code 21101 stands for counselors, and at the 6-digit level, the code 211013 stands for marriage and family therapists.) Assuming that unemployed workers limit their search to a single 5- or 6-digit occupation classification in their home state, I will therefore examine the stock and flow of vacancies in New Jersey at the 5- and 6-digit SOC levels.

The left panel of my figure 2 shows the stock of job listings for the median 5- and 6-digit SOC codes during the authors’ survey period in New Jersey. The stock of job openings for the median 5-digit occupation was around 40 to 50, implying that for the median unemployed worker there were 40 to 50 relevant job listings. The right panel shows that the flow of vacancies for the median 5-digit occupation is around 25 to 30: every month there are about 25 to 30 suitable new job listings. This difference between the stock and the flow of vacancies may help explain Krueger and Mueller’s finding

**M A S T E R S**
of a drop in search time from 65 minutes per day to 35 minutes per day over a 12-week period.

SEQUENTIAL JOB SEARCH STRATEGY Both calendar time effects and stock-flow matching are consistent with declining search time profiles. However, they do not explain why the search time profiles approximate parallel lines for different cohorts, with the exception of the very long-term unemployed. This feature of the data seems rather puzzling. One possibility is that the different cohorts differ in their characteristics, and Krueger and Mueller show that this is indeed the case. Their figure 7 shows that, possibly because of differences in the timing of layoffs in different industries, cohorts differ markedly in earnings and other characteristics such as industry and education. I expect that unemployed workers with different characteristics will have different average job search times simply because of differences in the number of suitable job vacancies. For example, as my figure 3 shows, from November 15 to December 15, 2009, 53 percent of 5-digit occupations had fewer than 50 job listings, 13 percent had between 50 and 99 listings, 21 percent had 100 to 499 listings, and 13 percent had 500 listings or more. This wide dispersion in the distribution of vacancies suggests that if different cohorts vary in their characteristics and thus in their suitability for

**Figure 3.** Distribution of Total Listings for 5-Digit SOCs, New Jersey, September 2009–May 2010

jobs in different occupations, this could generate differences in job search time that are independent of the duration of unemployment.

If this is so, then another potential explanation for the parallel lines for different cohorts is one that combines stock-flow matching with the idea that unemployed workers pursue a sequential job search strategy: they search first within the stock of job listings in their preferred labor market in terms of occupation and location; if unsuccessful, they continue to monitor the flow of new listings in the preferred labor market. At some point they also start searching in a less preferred labor market, again looking first at the existing stock of vacancies, and then monitoring new listings in both the preferred market and the new market. The very long term unemployed, finding that all stocks related to their occupations of interest have been depleted, will simply monitor the new listings in various occupations. This sequential strategy would thus lead to a flat search time profile over time.

UNEMPLOYMENT AND HAPPINESS Another important contribution of Krueger and Mueller’s survey is their examination of trends in the well-being and happiness of unemployed workers over time and during various activities. They find that only a small fraction of UI recipients say they are very satisfied with their lives, compared with almost half of employed workers. Moreover, unemployed workers grow increasingly unhappy the longer they are unemployed. These findings are consistent with the findings of a growing literature that links economic conditions and happiness and finds that high unemployment lowers happiness and life satisfaction (see, for example, Di Tella, MacCulloch, and Oswald 2003, Wolfers 2003, and Stevenson and Wolfers 2008). However, in standard macroeconomic models where unemployment is modeled as a temporary loss of wage income, unemployment does not appear to be very costly for the individuals in the model (as discussed by Mukoyama 2010). The reason is that the median unemployment duration in the United States is generally less than 3 months, so that individuals can maintain their consumption during a typical unemployment spell by using their savings. But what are the costs of unemployment that go beyond temporary loss of income? And what is the link between the perceived cost of unemployment and the cost of unemployment implied by economic models?

3. Krueger and Mueller’s survey was conducted during the most depressed labor market conditions in the postwar era. The unemployment rate was around 10 percent, and approximately 40 percent of the unemployed had been unemployed for more than 6 months. It is likely that these adverse labor market conditions aggravated the pain of unemployment, with the unemployed becoming increasingly pessimistic about their job-finding prospects as they observed the dismal aggregate labor market conditions.
An abundance of evidence indicates that displaced workers who had previously enjoyed long job tenure experience large and enduring earnings losses upon reemployment (see Couch and Placzek 2010, Jacobson, LaLonde, and Sullivan 1993, Neal 1995, and Farber 2005). Workers losing jobs in a depressed labor market experience especially large losses (Jacobson, LaLonde, and Sullivan 1993). Unemployment also has long-lasting effects on young workers. The evidence surveyed by Till von Wachter (2010) suggests that the consequences of entering the labor market in a recession are severe in both the short and the long run. In the short run, labor market entrants and young workers suffer more from larger increases in unemployment and layoffs than the average worker. According to Philip Oreopoulos, von Wachter, and Andrew Heisz (2008), part of the decline in earnings arises because young workers entering the labor market in a recession accept jobs that they otherwise would reject. Lisa Kahn (2010) finds in addition that cohorts who graduate from college during poor economic conditions tend to find work in occupations that pay lower wages than the occupations they would otherwise enter, which suggests that these workers find it difficult to shift into better jobs after the economy picks up. As a result, some individuals never recover from the initial shock and experience persistent negative effects. In addition to these earnings losses, Daniel Sullivan and von Wachter (2009) find major health consequences for displaced workers: high-seniority male workers who were displaced in Pennsylvania in the 1970s and 1980s had 10 to 15 percent higher mortality rates than would otherwise have been expected, even 20 years after displacement. Models of unemployment that abstract from these long-lasting earnings or health consequences are naturally likely to underestimate the costs of unemployment.

It is important to emphasize that the costs of unemployment go beyond economic costs. Loss of a job is often associated with loss of one’s identity, self-esteem, self-confidence, and sense of security. Unemployment can also cause stress in the household by causing a shift in the allocation of household responsibilities. As discussed by Krueger and Mueller, job search assistance might be helpful for the unemployed in overcoming feelings of anxiety and sadness associated with job search.

To conclude, Krueger and Mueller’s paper uncovers new information about the job search behavior of the unemployed. Their unique dataset can be useful in improving our understanding of unemployment and potentially devising ways of helping unemployed workers in their job search. For example, one potential intervention that could be very beneficial in improving the job search and matching process would be to link UI records
with the HWOL data. The UI records provide an estimate of the number and characteristics of unemployed workers searching for jobs, whereas the HWOL data give an estimate of the composition and number of job listings. Providing the unemployed with an estimate of their job finding prospects in a particular location and occupation would help them direct their search. Moreover, using the HWOL data in combination with the UI records could help in directing training into particular fast-growing occupations.

REFERENCES FOR THE ŞAHİN COMMENT

