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The Job Search Intensity Supply Curve: How Labor Market Conditions Affect Job Search Effort

Upjohn Institute Working Paper No. 14-215

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August 20, 2014

ABSTRACT

During the Great Recession of 2007, unemployment reached nearly 10 percent and the ratio of unemployment to open positions (as measured by the Help Wanted OnLine Index) more than tripled. The weak labor market prompted an unprecedented extension in the length of time in which a claimant can collect unemployment insurance (UI) to 99 weeks, at an expense to date of $226.4 billion. While many claim that extending UI during a recession will reduce search intensity, the effect of weak labor market conditions on search remains a mystery. As a result, policymakers are in the dark as to whether UI extensions reduce already low search effort during recessions or perhaps decrease excessive search, which causes congestion in the labor market. At the same time, modelers of the labor market have little empirical justification for their assumptions on how search intensity changes over the business cycle. This paper develops a search model where the impact of macro labor market conditions on a worker's search effort depends on whether these two factors are substitutes or complements in the job search process. Parameter estimates of the structural model using a sample of unemployment spells from the National Longitudinal Survey of Youth 1997 indicate that macro labor market conditions and individual search effort are complements and move together over the business cycle. The estimation also reveals that more risk-averse and less wealthy individuals exhibit less search effort.

JEL Classification Codes: D1, D9, E2, E3, J6

Key Words: Job search, search models, structural estimation, search methods

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Jeremy Schwartz [*†]

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Abstract

During the Great Recession of 2007, unemployment reached nearly 10 percent and the ratio of unemployment to open positions (as measured by the Help Wanted OnLine Index) more than tripled. The weak labor market prompted an unprecedented extension in the length of time in which a claimant can collect unemployment insurance (UI) to 99 weeks, at an expense to date of $226.4 billion. While many claim that extending UI during a recession will reduce search intensity, the effect of weak labor market conditions on search remains a mystery. As a result, policymakers are in the dark as to whether UI extensions reduce already low search effort during recessions or perhaps decrease excessive search, which causes congestion in the labor market. At the same time, modelers of the labor market have little empirical justification for their assumptions on how search intensity changes over the business cycle. This paper develops a search model where the impact of macro labor market conditions on a worker's search effort depends on whether these two factors are substitutes or complements in the job search process. Parameter estimates of the structural model using a sample of unemployment spells from the National Longitudinal Survey of Youth 1997 indicate that macro labor market conditions and individual search effort are complements and move together over the business cycle. The estimation also reveals that more risk-averse and less wealthy individuals exhibit less search effort.

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Introduction

During the Great Recession of 2007, the U.S. unemployment rate reached nearly 10 percent and the ratio of the number of individuals unemployed to the number of open positions more than tripled.[1] In reaction to the weak labor market, Congress increased the number of weeks one can collect unemployment insurance (UI) benefits from the standard 26 weeks to a maximum of 99 weeks, at a cost of $226.4 billion (Whittaker and Isaaces 2014). It is generally understood that unemployment insurance may negatively affect the exit rate from unemployment (Katz and Meyer 1990; Meyer 1990). While this has led to claims that extended UI decreases search intensity, we have little evidence on how the recession itself influences job search effort. As a result, policymakers are in the dark as to whether UI extensions may exacerbate already-low search effort or, more benignly, reduce excessive search during downturns, which causes congestion in the labor market. At the same time, modelers of the labor market have little empirical justification for their assumptions on how search intensity changes over the business cycle. This paper seeks to inform policymakers and enhance our knowledge of the business cycle by answering the question, "Does search intensity rise or fall with labor market conditions?"

Understanding how search intensity varies over the business cycle is critical to developing models of the labor market and for policy evaluation. Mortensen's (1976) and Pissarides's (1991) search frameworks have been the basis for much of the research in this area. In standard search models, exerting job search effort is more likely to yield employment during good times than during bad times. As a result, worker's search intensity is procyclical.

Kiley (2003), Sanchez (2008), and Schwartz (2013b) rely on these models to determine how UI should optimally adjust to macroeconomic conditions. Veracierto (2002), however, shows that procyclical effort is not consistent with the empirical regularities of a countercyclical unemployment rate. This is because greater effort in expansions decreases the unemployment rate, but more entrants into the labor force increases the unemployment rate. The model implies that unemployment is acyclical, which puts into doubt whether models that include the procyclical effort assumption should be used for policy analysis. This also motivates Shimer (2004), who addresses the technical aspects of how search influences the job-finding rate and shows that search intensity is positively related to macro conditions only for those with less than an 80 percent probability of finding a job during their search period.

[1] The number of open positions is based upon the Help Wanted OnLine Index.

To address how search intensity varies with labor market conditions, I develop a search model that differs from the existing literature in two important ways. First, the model assumes workers make binding consumption decisions. Only once consumption levels are chosen do workers then receive information on whether they have had success in the labor market (in which case they earn a market wage) or whether they failed to find a job (in which case they receive a lower government benefit). As a result, the unemployed base their budget on expected future income, which they can increase by exerting more effort, thus increasing the likelihood of finding a job and earning a wage. Second, the model allows for labor market conditions either to have a very positive impact on how productive search intensity is on finding work (a relation I refer to as job search complements) or to have no impact at all (a relation I refer to as job search substitutes). The flexible nature of the model allows me to identify how search intensity moves with changing labor market conditions, as well as to inform the intuition on why these movements occur.

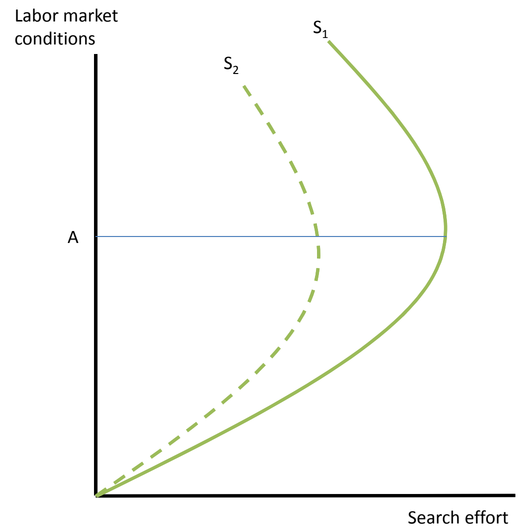
The assumption that workers make binding consumption decisions is meant to reflect the intuition that a job seeker may not reduce her consumption if she sees a high likelihood of getting back to work quickly. For instance, in a booming economy, a recently graduated computer science major, who correctly perceives that she has a high chance of landing a job quickly, may commit to a downtown apartment while seeking work. On the other hand, in a slumping economy, such a graduate may perceive she has little chance of finding a job and may commit to moving in with her parents or taking several roommates. Although this assumption represents a significant departure from the current literature, almost two-thirds of a household's budget relates to housing, transportation, and health care, areas that are difficult to immediately adjust when one's employment status changes.[2]

The model implies that the effect of macro labor market conditions on search intensity consists of two parts. First, similar to the classical income effect, an improvement in the labor market makes finding a job more likely, raising expected income. This leads to an increase in consumption, as workers are more confident they will find employment, as well as a decline in effort as workers focus on leisure activities. Second, similar to the classical substitution effect, when labor market conditions improve, effort has a greater impact on expected income. This increases the opportunity cost of not searching, and workers choose to implicitly substitute away from leisure activities toward searching for work.

[2]This two-thirds figure is derived from the 2011 Consumer Expenditure Survey.

The model implies that when labor market conditions and search intensity are perfect job-finding complements in the process of finding a job, the substitution effect always dominates, and individuals increase job search intensity as the labor market improves. However, if these factors are perfect job search substitutes, search intensity always decreases with an improving labor market, as the income effect dominates. Figure 1 indicates the relationship between labor market conditions and search intensity when they are neither perfect complements nor perfect substitutes. When labor conditions are poor (below point A) the substitution effect dominates and labor market conditions are positively related to search intensity. The reverse is true for very good labor market conditions (above point A). This suggests that the supply of search intensity with respect to labor market conditions may form a backward-bending curve, as pictured in Figure 1.

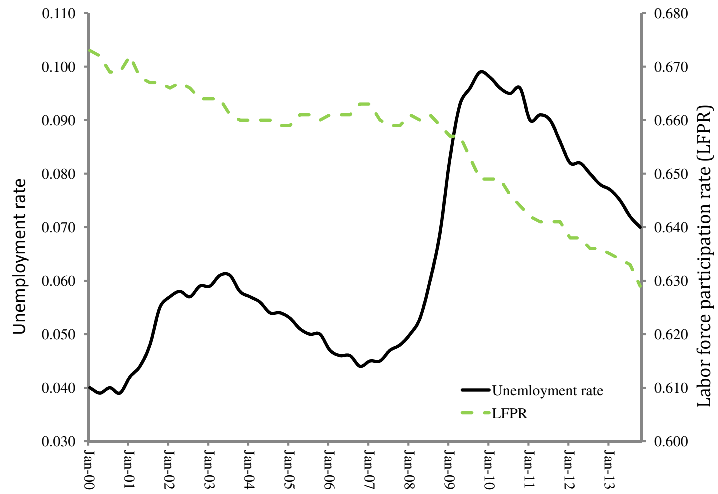
Figure 1 Search Intensity Supply Curve



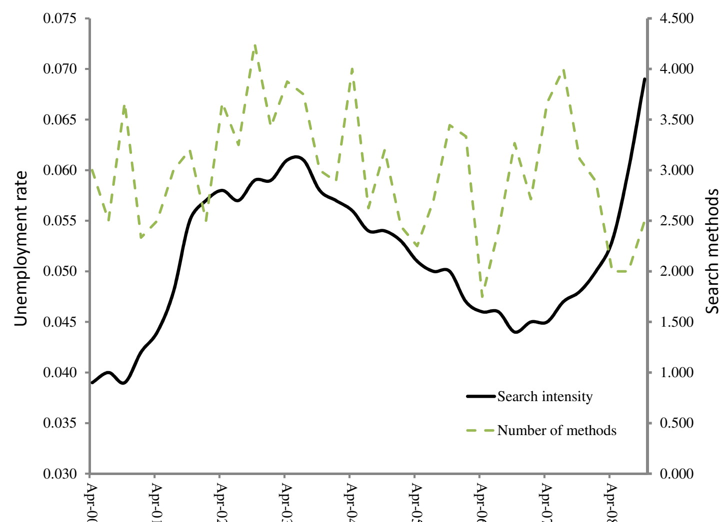
One of the obstacles present in the literature is the lack of availability of high-quality measures of search intensity. Figure 2 plots the two most common measures. The first, in Panel Panel A, is the labor force participation rate (LFPR), which provides a measure of the extensive margin, whether workers decide to search or not. LFPR appears to be slightly procyclical, but it fails to measure how intensively individuals search. The second measure, shown in Panel Panel B, presents the average number of job search methods used by unemployed workers, as determined by the National Longitudinal Study of Youth 1997 (NLSY97). Search methods include activities like sending out resumes or contacting employers. At best, the number of search methods appears to be weakly procyclical and very noisy during the period for which this measure is available. While the number of search methods may be positively related to search intensity, it is not clear that there is a strictly linear relationship. For instance, sending out resumes may have a bigger marginal impact on the probability of finding work than going to a union placement office. As a result, the number of search methods may be only a weak proxy of search intensity.

Similar to the theoretical literature, empirical studies that use these measures are mixed as to whether search is pro- or countercyclical. An early descriptive paper from Finegan (1981) examines the extensive

Figure 2 Measures of Search Intensity over the Business Cycle



Panel A Unemployment rate and labor force participation rate



Panel B Unemployment rate and number of search methods

NOTE: Search methods are the average number of methods used by the unemployed in the National Longitudinal Survey of Youth 1997 (NLSY97), conditional on using at least one method.

margin of whether to search or not and finds that it is procyclical. More recently, Bloemen (2005) estimates an empirical search model and shows that the elasticity of search intensity with respect to the exogenous portion of the unemployment exit rate is positive, indicating procyclical search intensity.

Studies that use the search methods of job seekers as proxies for search intensity also yield conflicting results. Böheim and Taylor (2001), using the British Household Survey, use the number of search methods employed by job seekers and determine that search intensity is inversely related to local unemployment rates. Bachmann and Baumgarten (2012) examine data on a variety of search methods using international data and also find a negative correlation between search intensity and the unemployment rate. Kuhnen (2010) confirms these findings with a micro data set of MBA graduates, who are shown to apply for fewer jobs during bad versus good labor markets. In contrast however, Doiron and Gorgens (2009), using a data set of Australian graduate students, finds search intensity decreases with improving labor market conditions.

To provide further evidence on the effect of labor market conditions on search intensity, this paper estimates the structural parameters of the search model. I use the NLSY97, which provides detailed work histories for 9,000 individuals. In addition to questions relating to various demographics (age, gender, education, etc.), the survey asks questions about risky behaviors and attitudes toward risk, which allows me to determine how risk aversion affects search intensity. To identify whether search intensity increases or decreases with labor market conditions I use variations in labor market conditions, across time and occupation.

To estimate the model, I use an approach similar to Lentz (2009), where a structural model determines unobserved search intensity for each nonemployment spell and then relates the predicted probability of finding a job to the spell length. Furthermore, similar to Bloemen (2005), I assume that the likelihood of an individual reporting a specific search method increases with the unobserved search intensity predicted by the model. Thus, rather than assuming a direct linear relationship between the number of search methods and search intensity, the method I employ allows the data to determine the relationship between search methods and job search intensity, only assuming a strictly increasing monotonic relationship. As a byproduct of this approach, the estimates reveal which methods have the highest marginal impact on the job-finding rate.

The estimation indicates that individual search intensity and macro labor conditions are strong complements in the job search process. While the model allows for a backward-bending supply of search intensity, search intensity is always increasing for the plausible range of labor market conditions. This should give modelers of the labor market, and those determining labor policy, more confidence when assuming that search intensity moves procyclically. Furthermore, the estimates indicate that those with greater risk aversion and less wealth have higher levels of job search effort. Finally, I find that sending out resumes and looking at advertisements have the largest effect on the exit rate from unemployment, while contacting placement centers, unions, or schools and other miscellaneous methods have the lowest marginal impact on the probability of finding a job.

The remainder of the paper proceeds as follows: Section Two, "A Two-Period Model," provides the intuition for the infinitely lived agent model I estimate, using a simplified two-period setting. Section Three, "A Dynamic Search Model," describes the dynamic model I use to estimate unobserved search intensity, and Section Four, "Estimation Strategy," discusses the estimation approach. I describe the data sources in Section Five, followed by the results in Section Six. Section Seven makes concluding remarks.

A Two-Period Model

To provide some intuition for the dynamic model in the next section, I first discuss a simplified two-period model of job search. The variable and parameter definitions can be found in Table 1. I assume that workers enter the world unemployed, live two periods, and have preferences given by

$$U(c_1, c_2, x) = u(c_1) - Gx + \beta u(c_2) \tag{1}$$

where c_i is consumption in period i, x is the effort one exerts to secure employment in period 2, and all take values on $\mathbf{R}_+$. Preference for consumption is given by a constant absolute risk aversion (CARA) utility function:

$$u(c) = -exp(-\delta c) \tag{2}$$

While unemployed, workers receive disposable income b. Workers have perfect foresight and face a stochastic process governing a positive employment shock in the second period that yields disposable income $w > b$. Specifically, the following equations determine the probability of transitioning to employment:

Table 1 Parameters and Descriptions

Parameter	Description	Parameter	Description
c	Consumption	δ	Coefficient of absolute risk aversion
$u(c) = -exp(-\delta c)$	Preferences over consumption		
x	Job search effort	G	Scale parameter for disutility of effort
b	Income while unemployed	w	Income while employed
m	Exogenous wealth	k	Savings
EI	Expected income	β	Discount rate
α	Measure of labor market conditions	κ	Scale parameter for x in $p(x, \alpha)$
ρ	Elasticity of substitution parameter	C	Scale parameter for $p(x, \alpha)$
$p(x, \alpha)$	Probability of employment		

$$p = p(x, \alpha) = 1 - exp(-f(x, \alpha)) \tag{3}$$

$$f = C[\alpha^{-\rho} + (\kappa x)^{-\rho}]^{\frac{-1}{\rho}} \tag{4}$$

where α is a measure of the strength of labor market conditions and is exogenous to the worker. The function f can be thought of as representing effective search units that are produced using a constant elasticity of substitution (CES) production function of the Ventura (1997) form, with search intensity, x, and macro labor market conditions, α, as the inputs. The elasticity of substitution between these two factors is given by $\sigma = \frac{1}{1+\rho}$.

The CES form of f accommodates a large degree of variation in the relationship between x and α. Intuition may suggest that an improving labor market, with more plentiful jobs, would make workers' search efforts more productive ($f_{x\alpha} > 0$). In other words, knocking on doors has a better chance of success when more of those doors have jobs behind them. I refer to such a situation as a case where x and α are job search complements. In the extreme, when $\rho = \infty$, f converges to a Leontief production function and x and α are perfect job search complements. The CES function also allows for $f_{x\alpha} = 0$, ($\rho = -1$), in which case there is no interaction between x and α in the job search process. One could either look for a job or, instead, have a job come to them. In this case a worker could substitute her own search effort for more favorable labor market conditions. I refer to this situation as a case where x and α are perfect job search substitutes.

In the first period, workers receive income, b, and have exogenous wealth, m, which they may save, k_1, or consume in period 1, c_1. This yields the first-period constraint:

$$b + m = c_1 + k_1 \tag{5}$$

Workers must commit to period 2 consumption prior to observing whether or not they have successfully found a job. In period 1, workers sign binding contracts for their second-period consumption, which has an analog to the majority of household expenditures, such as rent or mortgage payments, health insurance, and car payments, etc.

In the second period, workers earn a return on savings equal to $\beta^{-1} - 1$. While this assumption is not explicitly modeled, one can imagine that workers wish to use all of their resources during their two periods of life and receive no utility from providing assets to their heirs, nor do they wish to pass on debt. In expectation terms, the worker's period 2 budget constraint is

$$EI + \beta^{-1}k_1 = Ek_2 + c_2 \tag{6}$$

$$EI = p(x,\alpha)w + (1 - p(x,\alpha))b \tag{7}$$

where EI is expected income in the second period and Ek_2 is expected savings that would be left to a worker's heirs. Solving for c_2 using Equations (5), (6), and (7), and the assumption that the worker wishes to set $Ek_2 = 0$, the worker's problem is

$$U = \max_{c_1,c_2,x} u(c_1) - Gx + \beta u(c_2) \tag{8}$$

subject to

$$c_2 = p(\alpha, x)w + (1 - p(a, x))b + \beta^{-1}(m + b - c_1) \tag{9}$$

Proposition 1: Workers will smooth consumption perfectly over the two periods.

Proof: Implied by the first-order condition for c_1, $u'(c_1) - u'(c_2) = 0$.

The implication of Proposition 1 is that

$$c = c_1 = c_2 = \frac{p(\alpha, x)(w - b) + (1 + \beta^{-1})m}{2 + \beta^{-1}} + b \tag{10}$$

The first-order condition for x is

$$\psi = \beta U'(c) p_x (w - b) - G = 0 \tag{11}$$

Proposition 2: Search intensity (x) is 1) inversely related to labor market conditions, α, for all α, when $\rho = -1$; is 2) positively related to α, for all levels of α, when $\rho = \infty$; and is 3) positively related at low levels of α and negatively related at high levels of α when $-1 < \rho < \infty$.

Proof: Implicitly differentiating ψ with respect to α after substituting Equation (10) gives

$$\frac{\partial x}{\partial \alpha} = [-\frac{\beta(w - b)}{\psi_x}][p_x p_\alpha U'(c)][\frac{p_{x\alpha}}{p_x p_\alpha} - \delta \frac{(w - b)}{1 + \beta^{-1}}] \tag{12}$$

where $\psi_x < 0$ is the partial of ψ with respect to x. Using the functional form of $p(x, \alpha)$, $\frac{\partial x}{\partial \alpha} > 0$ if

$$\frac{1}{1 - p}[\frac{(1 + \rho)}{f} - 1] > \delta \frac{(w - b)}{1 + \beta^{-1}} \tag{13}$$

This condition will never hold with $\rho = -1$, proving part (1) of Proposition 2. This is the case when search effort and macro labor conditions are perfect job search substitutes. This condition will always hold if $\rho = \infty$, proving (2). This is the case of perfect job search complements.

For intermittent values of ρ, the condition will hold at low levels of α but will be violated as α approaches infinity. Note that totally differentiating the probability of finding work, p, gives $\frac{dp}{d\alpha} = p_\alpha + p_x \frac{dx}{d\alpha} > 0$. Although an increase in α may decrease search intensity, it will not totally offset the direct positive impact of α on p. Thus, $\lim_{\alpha \to 0} f(\alpha, x) = 0$, and the left-hand side of Equation (13) will approach infinity. As α

increases, f increases, and the left-hand side of Equation (13) will be negative when $f > 1 + \rho$.[3] Thus, one can also conclude that for intermittent values of ρ, x increases at low levels of α and decreases at high levels of α. However, without estimates of the parameters, it is unclear whether x and α would be both positively and negatively associated within a plausible range for α.

Proposition 3: Consumption levels increase with an improving labor market.

Proof: Implicitly differentiating Equation (10) gives $\frac{\partial c}{\partial \alpha} = \frac{(w-b)}{2+R}[p_\alpha + p_x x_\alpha] > 0$.

Figure 3 presents the intuition behind Propositions 1, 2, and 3. The first column in the figure presents a set of convex upward-sloping indifference curves in the effort (a bad) and consumption space, where the consumption level is common to periods 1 and 2. The figure also presents an upward-sloping, concave budget constraint that arises as more effort increases the unemployment exit rate, and expected income, but at a decreasing rate.

Each figure in the left column illustrates the effect of an increase in α on the budget constraint and, ultimately, on the choices of x and c. The figures can be understood in terms of two effects that are analogous to the classical income and substitution effects. Note that in the discussion to follow a "substitution effect" always refers to the individual's choice of consumption and search effort, while the term "job search substitutes" refers to the relation between search intensity and labor conditions in the production of f. First, the income effect results from an increase in α increasing expected income for all levels of x and is given by x^I_α:

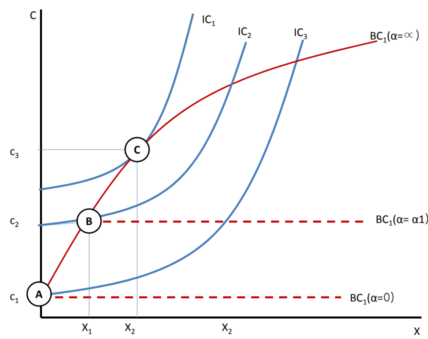
$$x^I_\alpha = [-\frac{\beta(w-b)}{\Delta_x}][-\delta C(\alpha)^{-\rho-1}[(Kx)^{-\rho} + \alpha^{-\rho}]^{-1/\rho-1}(1-p)\frac{G}{\beta+1}] \leq 0 \quad (14)$$

In addition, an increase in α changes the marginal effect of greater search effort on the probability of finding work. In other words, it changes the opportunity cost of not searching. This results in a substitution effect, x^s_α, which can be derived from minimizing expenditures subject to a given level of utility:

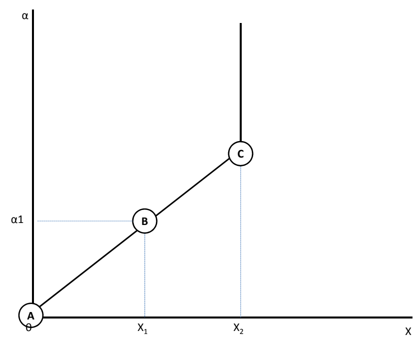
$$x^s_\alpha = x[\frac{-\beta(w-b)}{\Delta_x}]\frac{G\alpha^{-\rho-1}[(Kx)^{-\rho} + \alpha^{-\rho}]^{-1}[(1+\rho) - f]}{\beta(w-b)} \quad (15)$$

[3] Although Equation (13) could be violated before, when $f < 1 + \rho$, $f > 1 + \rho$ is a sufficient condition for Equation (13) not holding.

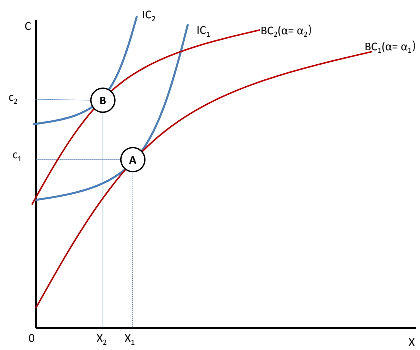
Figure 3 Utility Maximization and Supply of Search Intensity



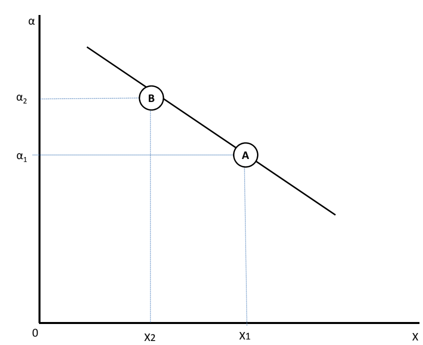
Panel A Perfect complements ($\rho = \infty$)



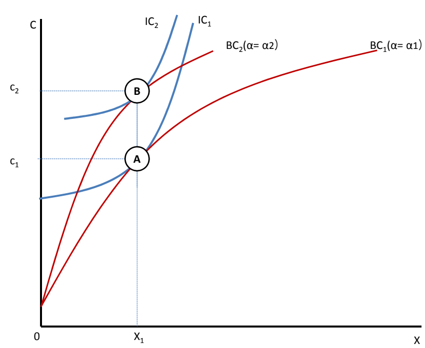
Panel B Supply curve: perfect complements ($\rho = \infty$)



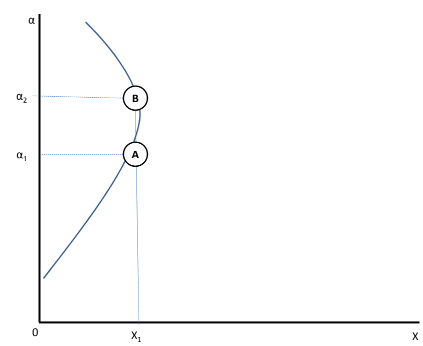
Panel C perfect substitutes ($\rho = -1$)



Panel D Supply curve: perfect substitutes ($\rho = -1$)



Panel E Intermittent values ($-1 < \rho < \infty$)



Panel F Supply curve: intermittent values ($-1 < \rho < \infty$)

The last term in x_α^s, $(1+\rho)-f$, indicates that the substitution effect could be negative or positive. In this term, $1+\rho$ relates to α's effect on f_x, $(f_{x\alpha})$, which depends on whether x and α are job-finding substitutes or complements. The stronger is the complementarity of these factors, the more one would wish to substitute towards searching for work (and, implicitly, away from leisure) when labor market conditions improve. When x and α are perfect job search complements, the substitution effect is always positive. The second part of the last term, $-f$, captures the diminishing returns of f on the probability of finding work ($p_{ff} < 0$). An increase in α increases f, reducing the marginal effect of increasing f through an increase in search intensity. This influences workers to substitute *away* from search intensity when α increases. In the extreme, when x and α are perfect job-finding substitutes ($\rho = -1$), this latter effect results in x_α^s being less than zero for all α.

Panel Panel A of Figure 3 presents the assumption that x and α are perfect job search complements, with $\rho = \infty$ and f converging to a Leontief production function. The figure also presents the budget constraint when $\alpha = \infty$. In this case, the optimal level of x, denoted as x_2, is given by the tangency between the budget constraint and the highest indifference curve. When $\alpha < \infty$, p is determined by x only up to $\alpha = \kappa x$. In this case, the budget constraint is the same as that for $\alpha = \infty$ when $\alpha > \kappa x$, and is a horizontal line when $\alpha \leq \kappa x$, since further increases in x have no effect on the probability of finding a job. Thus, as α increases, the optimal x always occurs at the kink in the budget constraint, until a tangency occurs between the indifference curve and budget constraint, after which x is constant.

In terms of income and substitution effects, examining Equation (15) shows that when $\alpha > \kappa x$, the substitution effect is positive and individuals face a large opportunity cost for not increasing search intensity with α. As a result, the substitution effect dominates the income effect. Panel Panel B presents the supply of search effort as a function of α under the perfect complements assumption. Search effort is given by α/κ until x_2 is optimal, after which further increases in α have no impact on x.

Next, Panel Panel C presents the indifference curves and budget constraints under the assumption that x and α are perfect substitutes in the search process, ($\rho = -1$). In this scenario, there is a positive probability of finding work even without searching at all. An increase in α represents a shift leftward in the budget constraint, resulting in less effort and more consumption. This occurs for two reasons. First, the greater α increases the probability of finding work and expected income, so x falls because of the income effect. Second, in the case of substitutes, $f_{x\alpha} = 0$. As a result, the substitution effect is also negative, resulting in a downward-sloping supply of search effort, as pictured in Panel Panel D.

The bottom two panels of Figure 3 depict situations where $\rho \in (-1, \infty)$. For these intermittent values of ρ, when α is low the substitution effect dominates, while at high levels of ρ the income effect dominates. In particular, examination of Equation (13) indicates that, given $\lim_{\alpha \to 0} f(\alpha, x) = 0$ and $\lim_{f \to 0} p(f) = 0$, when α is small the left-hand side of Equation (13) must be positive. As α increases, the left-hand side of Equation (13) becomes negative at some level of α and the income effect dominates. As a result, the supply of effort bends backward above a certain level of α as indicated in Panel Panel F.

Proposition 4: For consumption levels below $\hat{c} = \frac{1}{\delta}$, more risk-averse workers will search more intensively than less risk-averse workers. For consumption levels above $\hat{c}$, more risk-averse workers will search less intensively than less risk-averse workers.

Proof: Implicitly differentiating ψ yields $sign(x_\delta) = sign(\exp(-\delta c)(1 - c\delta))$, which is positive for values of $c < \frac{1}{\delta}$ and negative when $c > \frac{1}{\delta}$.

Proposition 4 can be interpreted as follows: When consumption is lower than $\hat{c}$, and a large income shock occurs from being out of work, more risk-averse individuals would wish to mitigate this shock by increasing their future expected income. This manifests itself in terms of greater search intensity. For workers who have a high level of consumption (above $\hat{c}$), the benefit of transitioning to employment will be low. More risk-averse workers in this range are unwilling to trade the certain reduction of utility that comes with greater search intensity for the relative small additions to utility that come from the higher expected income and consumption that greater search intensity generates.

The choice of the utility function, which allows for risk aversion to have positive or negative effects on search intensity, was deliberate. Ultimately, the data will determine if $\hat{c}$ is small or large and the corresponding relationship between search intensity and risk aversion.

A Dynamic Search Model

This section generalizes the two-period model to a dynamic setting of infinitely lived, utility-maximizing agents who may be either employed or nonemployed. The choice of modeling nonemployment spells rather than unemployment spells is done so that spells only end in employment rather than in exits from the labor force. As in the last section, the nonemployed make two choices in discrete time: 1) how much to consume next period and 2) how much to search.

Workers face a degenerate wage distribution, in which their skill set, experience, occupation, and other factors determine their market wage. This assumption is made to eliminate both the possibility of on-the-job search for the employed and the possibility of refusing wage offers. As a result, workers influence their nonemployment duration only through their choice of search intensity, and not through their choice of a reservation wage.

Heterogeneity among workers comes in part from the amount of savings held entering a nonemployment spell. To keep the state space manageable, as in Lentz (2009), I do not model life-cycle motivations for savings. While this may be an important consideration, the data set this paper uses consists of a fairly young group of individuals who are less likely to consider the implications of their financial decisions on retirement or on assistance with college expenses for children. Consequently, the lack of a life-cycle motive for savings likely does not materially influence the results.

Employed workers must choose their next-period consumption plan. Their problem can be represented by the following Bellman equation:

$$\begin{aligned}
V^e(c,k) &= \max_{c'} u(\tilde{c}) + \beta[(1-s)V^e(c',k') + sV^u(c',k')] \qquad (16)\\
&\text{s.t.:}\\
k' &= \begin{cases} w + k(1+r) - c \text{ if } w + k(1+r) - c \in (\underline{k}, \bar{k}) \\ \underline{k} \text{ if } w + k(1+r) - c \leq \underline{k} \\ \bar{k} \text{ if } w + k(1+r) - c \geq \bar{k} \end{cases}\\
\tilde{c} &= w + k(1+r) - k'\\
Ek'' &= sw + (1-s)b + k'(1+r) - c'\\
Ek'' &\in [\underline{k}, \bar{k}]
\end{aligned}$$

where the value of a variable y, next period, is denoted as y', r is the riskless return on savings, and, as in the two-period model, $u(c) = -\exp(-\delta c)$.

Equation (16) is instructive of the timing of the model. The employed enter the period with a consumption plan, c, and savings, k. Workers realize they have not incurred an averse employment shock and know they will be collecting a wage, w. If k is unbounded, it would be possible to calculate k' mechanically as $k' = w + k(1+r) - c$. Workers then choose their consumption plan for the next period considering a constant probability s of becoming nonemployed and probability $1-s$ they will continue to be employed.

Capital markets are not perfect, however, and k is restricted to $k \in [\underline{k}, \overline{k}]$. The consumption plan, which is based on expected income, may result in k lying outside its upper or lower bounds when true income is realized. In these cases, I assume that consumption adjusts to $\tilde{c}$, so k does not violate its bounds. This is captured in the first two sets of constraints in Equation (16). The second two sets of constraints indicate that the worker cannot set her next-period consumption so that she expects savings to violate its bounds at the end of the next period once the consumption plan is implemented.

Given the agent's observed state, consumption for this period, and stock of savings, the nonemployed choose both the next period's consumption plan and the effort they wish to exert to find work. The Bellman equation is

$$
\begin{aligned}
V^u(c,k) &= \max_{x,c'} u(\tilde{c}) - Gx + \beta[p(x,\alpha)V^e(c',k') + (1-p(x,\alpha))V^u(k',c')] \\
&\text{s.t.:} \\
k' &= \begin{cases} b + k(1+r) - c \text{ if } b + k(1+r) - c \in (\underline{k}, \bar{k}) \\ \underline{k} \text{ if } b + k(1+r) - c \leq \underline{k} \\ \bar{k} \text{ if } b + k(1+r) - c \geq \bar{k} \end{cases} \\
\tilde{c} &= b + k(1+r) - k' \\
Ek'' &= p(x,\alpha)w + (1-p(x,\alpha))b + k'(1+r) - c' \\
Ek'' &\in [\underline{k}, \overline{k}]
\end{aligned}
\tag{17}
$$

The nonemployed begin each period with a stock of savings and a consumption plan. Workers then choose the level of search effort they wish to exert, which influences the probability, p, of finding work and subtracts from utility. The probability of a finding a job, p, is given by Equation (3), and the CES production is given by Equation (4).

After workers make their consumption plan for the next period, along with their search effort, uncertainty is resolved in the labor market. With probability p, workers transition to employment, earning a wage, w, and with probability $1-p$, they continue their unemployment spell. Savings evolves in the same way as for employed workers.

Estimation Strategy

The estimation strategy augments that of Lentz (2009), who uses the implied hazard rates from his model to predict the observed durations of nonemployment spells. I use a similar approach to investigate the structural parameters of the dynamic model the last section describes. This approach requires three things: 1) a method for incorporating individual heterogeneity, 2) a strategy to relate the model's prediction of search intensity to observed proxies, and 3) a numerical means for solving or approximating the model solution for each observed unemployed spell. To illustrate the approach, I use the following indexing convention: i indicates the individual, j the individual's nonemployment spell, and τ the quarter within the individual nonemployment spell.

Beyond differences in wealth, I incorporate worker heterogeneity in the model in two ways. First, I allow δ_i to vary based on a linear combination of observed characteristics, Δ_i, so that $\delta_i = \theta_1 \Delta_i$, where θ_1 is a vector of parameters to be estimated. Second, I allow C_{ij} to be a linear function of observed traits, Γ_{ij}, so that $C_{ij} = \theta_2 \Gamma_{ij}$, where Γ_{ij} varies by unemployment spell and θ_2 is a vector of parameters to be estimated.

I depart from Lentz (2009), who takes search intensity to be entirely unobservable, by leveraging the methods individuals use to find work. Implicitly, I assume that while $x_{ij\tau}$ captures the aggregate degree of effort one exerts to find work, exerting effort to search involves undertaking a variety of different methods. In particular, I observe whether M different methods are employed during a nonemployment spell, but I do not observe when in the spell they are undertaken. I follow Bloemen (2005), who assumes that individual search methods are reported to a surveyor if $x_{ij\tau}$ exceeds a certain threshold, subject to reporting error. Let X_{ij}^m be one if method m is employed and zero otherwise, and let the unobserved factors influencing reporting of a method be ϵ_{ij}. I assume the following process governs the reporting of method m:

(18)
$$\begin{aligned} \tilde{X}_{ij}^m &= \overline{x}_{ij\tau} - (\gamma^m + \epsilon_{ij}), \epsilon_{ij}^m \sim N(0,1) \\ X_{ij}^m &= 1 \text{ if } \tilde{X}_{ij}^m > 0 \\ X_{ij}^m &= 0 \text{ if } \tilde{X}_{ij}^m \leq 0 \end{aligned}$$

where $\overline{x}_{ij\tau}$ is the mean optimal search intensity within a nonemployment spell. One can think of γ^m as the mean threshold, so that if the aggregate measure of search intensity, $\overline{x}_{ij\tau}$, is above the threshold, the worker employs method m in her job search. The term ϵ_{ij}^{m} can then be thought of in two ways. First, it may be the degree to which this threshold varies from the mean for an individual spell. Alternatively, it could also be thought of as a reporting error, where workers employ a method once search intensity is greater than γ^{m}, but where they may mistakenly report the method at $\gamma^{m} + \epsilon_{ij}^{m}$. The parameters, $\gamma^{1}, ...\gamma^{M}$ are collected in a vector γ.

Because of the computational complexity of the model, I do not estimate β, r, and s. I use three-month periods and accordingly set β to $0.95^{(1/4)}$ and set r to zero to ensure that savings is stationary. I take the separation rate from the Job Opening and Labor Turnover Survey (JOLTS), which has averaged 3.5 percent a month since 2000. I translate this into a 10.1 percent chance of losing a job at any point during a three-month period.[4]

I collect the remaining parameters, ρ and κ, in a vector θ_3 with $\theta = [\theta_1, \theta_2, \theta_3]$. For each individual in each spell I observe $\omega_{ij} = [w_{ij}, b_{ij}, \alpha_{ij}, k_{ij}^{0}, \Delta_i, \Gamma_{ij}]$, where k_{ij}^{0} is savings at the beginning of an unemployment spell. I use the fixed data across individuals, ω, to explain random variables t_{ij}, the length of an unemployment spell, and $X_{ij}^{1}, ..., X_{ij}^{M}$, the reported search methods. A remaining key variable, $x_{ij\tau}$, remains unobserved but recoverable using predicted values from the structural model.

To make estimation feasible, I use two approximations. The first is a cubic spline approximation of the value functions, V^{e} and V^{u}. For each observation, this allows one to calculate the value functions at a smaller set of grid points in the k and c state space and interpolate the value functions between these grid points.[5]

The second approximation is borrowed from the discrete choice literature. Keane and Wolpin (1997) confront the problem of calculating value functions at a large set of observables, N. They suggest determining the full specific solutions at a subset, $\tilde{N}$, of the N observations and then interpolating to derive the specific solutions at all possible combinations of the observed data. I take this approach by only calculating V^{u}, V^{e}, and $x_{ij\tau}$ at a small subset of the observables. Then I use this subset to interpolate values of $x_{ij\tau}$ for the remaining observations. Unlike Keane and Wolpin (1997), I use a nonparametric linear interpolation rather than a parametric interpolation. The strategy allows one to significantly reduce the computational burden of solving dynamic structural models.[6] One may naturally be concerned with a trade-off between

[4]The monthly separation rate, s^{m}, is aggregated to a quarterly period using $s = s^{m} + (1 - s^{m})s^{m} + (1 - s^{m})^{2}s^{m}$.

[5]I use a 25-point grid in the k and c space.

[6]In this context, this method reduces the computational time by approximately 90 percent, allowing for estimation of the pa-

speed and accuracy. As a result, at specific points within the algorithm I calculate the full solutions for V^u, V^e, and $x_{ij\tau}$ for an additional subset of observables and compare them to the interpolated approximation. In this way I can determine the degree to which the approximations influence the results and increase $\tilde{N}$ as needed for the desired precision.

The estimation algorithm can be summarized by the following steps:

1. First, I create a grid of H points across each of the variables in the state space (c and k).
2. I draw $\tilde{N} < N$ observations at random from ω to form subsample $\tilde{\omega}$.
3. The algorithm is initialized with a guess for θ.
4. For each nonemployment spell within $\tilde{\omega}$, the dynamic programming problem is solved using the following:
   a) I construct an initial value for functions $V_{ij}^e(c,k)$ and $V_{ij}^u(c,k)$ at each grid point and set of observables using the Ching et al. (2012) approach.[7]
   b) I interpolate the value functions using a cubic spline across the H grid points.
   c) I then update initial values of $V_{ij}^e(c,k)$ and $V_{ij}^u(c,k)$ at each grid point using Equations (16) and (17).
   d) I repeat the prior two steps until the value functions converge.[8]
5. I determine search intensity for each quarter of each spell by the following:
   a) Given the solution to the dynamic programming problem, I simulate x, $\tilde{c}$, and k for the each unemployment spell in $\tilde{\omega}$.
   b) Using the data set generated from this simulation, I determine policy functions $x(k,c,\omega)$ and $c'(k,c,\omega)$ using a linear nonparametric interpolation.
   c) Next, for $\tau = 0$ and initial conditions c_{ij0} and k_{ij0}, $x_{ij0} = x(k_{ij0}, c_{ij0}, \omega_{ij})$ and $c'_{ij\tau} = c'(k_{ij0}, c_{ij0}, \omega_{ij})$.

rameters within a week.

[7]Ching et al. (2012), in another context, show that initial values can be determined as a weighted average of past iterations' estimates of the value functions. The weights are based on a Gaussian kernels.

[8]To speed convergences, the algorithm alternates between a function evaluation step, where the algorithm determines optimal policy functions $x_{ij}(k,c)$, $c'_{ij}(k,c)$, and $k'_{ij}(k,c)$ and a policy iteration step, where the policy functions are kept fixed and only the value functions are updated.

d) For $\tau > 0$, I set $c_{ij\tau} = c_{ij(\tau-1)}$ and determine $\tilde{c}$, $k_{ij\tau}$, given the constraints that Equation (17) details. Then the linear interpolated policy functions again determine the search intensity and the next period's consumption plan.

6. The final portion of the algorithm constructs the likelihood function:

a) Using the values of x_{ij1}, I calculate $p_{ij\tau}$.

b) I construct the likelihood contribution for each individual-spell observation in the following way:

$$
\begin{aligned}
(19) \qquad L_{ij}(\theta) &= \prod_m t_{ij}[\phi(\tilde{X}_{ij})^{X^m_{ij}} \times \\
&\quad (1-\phi(\tilde{X}_{ij}))^{1-X^m_{ij}}] \times \\
&\quad \prod_\tau (1-p(x_{ij\tau},\alpha_{ij}))^{1-z_{ij\tau}} \times p(x_{ijt},\alpha_{ij})^{z_{ij\tau}}
\end{aligned}
$$

where $z_{ij\tau}$ is one if the worker receives a job in that period. The first term in Equation (19) indicates the probability that the worker reports undertaking method m, and the second is the probability of observing an unemployment spell of length t. Given the data requirements of the model, namely the wage the individual earns subsequent to the unemployment spell, I do not include any censored spells.

c) The full likelihood across all observations for given parameters θ and γ is calculated by accumulating the contribution to the likelihood of each function across individuals and spells:

$$
(20) \qquad L(\theta,\gamma) = \prod_j \prod_i L_{ij}(\theta)
$$

d) The parameter, vector γ, which relates to thresholds for reporting various search methods, does not affect optimal search intensity given θ, nor the probability of finding work. Thus, these parameters can be set for a given θ after determining that the preceding steps have found the optimal $x_{ij\tau}$ across all observations, and the final likelihood function can be calculated as $L(\theta) = \max_\gamma \prod_j \prod_i L_{ij}(\theta,\gamma)$.

Given this approach, I use standard algorithms to maximize the likelihood function with respect to θ. Once a maximum is found, for a subset of unemployment spells I compare the interpolated values of $x_{ij\tau}$ to the value of search intensity when fully determining the value functions. Unemployment spells that are more than 4 percent from the "true" solution are added to $\tilde{\omega}$, and the algorithm is repeated. For the 2000–2008 and 2005–2008 samples that the next section describes, this procedure yields an R^2 between the interpolated values and full solutions of 0.98 and 0.99, which involves fully determining value functions for 8 percent and 30 percent of observations for each of the two samples.

Data

The main data set is the National Longitudinal Survey of Youth 1997. The NLSY97 is a survey of approximately 9,000 U.S. residents that were between the ages of 12 and 16 at the end of 1996. Annual interviews of respondents have been conducted since 1997.

The NLSY97 was chosen for several reasons. First, respondents provide a complete diary of their work history, which allows one to calculate length of nonemployment spells. In addition, for each nonemployment spell, respondents are asked which methods they use to search for work. Finally, the survey includes questions on activities that involve taking risks as well as explicit questions about workers' willingness to take on risk.

I put several restrictions on our sample. First, I remove all individuals who find work in the agriculture sector or the military. I exclude spells that last less than one month, which may indicate short periods of voluntary time off before starting another position. In addition, while the sample is still younger than the general population, I eliminate spells that begin when workers are younger than 20 years of age. I am concerned with misreporting of spells that end in very low wages, in many cases less than $1.00 per hour. In addition, the NLSY97 top-codes income and both bottom- and top-codes assets. To deal with these two issues, I eliminate the bottom and top 1 percent of observations by income and assets. The final restriction is that spells must have a complete set of responses to all the variables in the model. This leaves 1,532 unique spells from 1,192 respondents from 2000 to 2008, and 499 unique spells from 457 respondents from 2005 to 2008. Table 2 summarizes the data sources, and Table 3 provides descriptive statistics for the 2000–2008 and 2005–2008 periods. The two periods are both presented since one of the measures of labor market conditions that is based upon the Help Wanted OnLine Index is not available prior to 2005. In all cases, nominal amounts are converted to real dollars using the CPI.

The state space requires data on wealth and the consumption plan at the beginning of an unemployment

Table 2 Data Sources

Variable	Data set	Source
Fixed parameters		
β		$0.95^{1/4}$
r		Set to zero to ensure savings is stationary
s		0.101 based on JOLTS data
G		Not identified, set to one
State space		
k_0	NLSY97	Imputed net worth[a]
k'	Model	Values determined by simulating model
c_0	Model	Determined by $c = EI$
c'	Model	Values determined by simulating model
Labor market variables		
α_1	NLSY97	Maximum occupational unemployment rate minus unemployment rate within individual's occupation at the beginning of nonemployment spell
α_2	HWOL	Maximum supply and demand ratio minus occupational supply and demand ratio divided by 100
w	NLSY97	Next position's wage[a]
b	NLSY97	Average UI benefit during spell[a]
Risk, demographics, and search		
C_i	NLSY97	Linear function of: gender, age, highest grade completed, spouse's income[a], number of children
δ_i	NLSY97	A linear function of: body mass index, substance abuse index, job lottery, general risk attitude, risk at work
X^j	NLSY97	Methods used to find work

[a] Normalized by the maximum wage.

spell. The NLSY97 asks respondents for their net worth at the ages of 18, 20, 25, and 30, and I impute net worth linearly in between these periods. On average, respondents enter a nonemployment spell with a net worth of $8,000, which is about one-and-a-half times the average quarterly wage. The range for net worth extends from –$12,000 to $65,000. Note that these also serve as the upper and lower bounds of k. I determine the the value of k beyond the initial period of nonemployment using the predictions of the model.

Unfortunately, the data set does not allow one to observe workers' consumption plans, and consequently an assumption must be made. I assume that in the prior employment spell, a respondent's wealth reached a fixed point, so that $k = k'$. In this case, the consumption plan at the beginning of the unemployment spell is set to the expected income while employed. The model determines c' after the first period of nonemployment.

Table 3 Summary Statistics

	Sample: 2000–2008				Sample: 2005–2008			
Description	Min	Max	Mean	Std. dev.	Min	Max	Mean	Std. dev.
Spell duration	1.000	12.000	1.667	1.463	1.000	8.000	1.640	1.328
Number spells per person	1.000	5.000	1.285	0.624	1.000	3.000	1.093	0.317
Beginning assets ($)	-11,686	65,053	8,810	11,720	-11,685	65,052	7,586	11,615
Labor market variables								
Unemployment rate	0.000	0.233	0.096	0.037	0.015	0.181	0.074	0.025
Supply-demand ratio	—	—	—	—	0.630	25.330	4.528	4.306
Wage ($)	3,097	8,969	5,020	1,262	3,108	8,646	5,056	1,325
UI benefits ($)	0	3,218	69	278	0	3,218	63	286
Demographics								
Female	0.000	1.000	0.411	0.492	0.000	1.000	0.469	0.500
Age	20.083	28.833	22.859	1.994	20.583	28.750	24.300	1.696
Highest grade completed	6.000	18.000	11.376	1.949	6.000	18.000	11.705	2.190
Spouse income ($)	0	72,723	3,657	10,277	0	72,723	4,769	12,070
Children	0.000	4.000	0.501	0.847	0.000	4.000	0.672	1.011
Risk								
Body mass index	10.286	98.478	23.248	5.852	12.456	98.478	23.022	6.759
Substance abuse index	0.000	3.000	1.218	1.118	0.000	3.000	1.078	1.093
One-third cut	0.000	1.000	0.218	0.413	0.000	1.000	0.229	0.421
Risk in general	0.000	10.000	5.625	2.766	0.000	10.000	5.764	2.828
Risk in work	0.000	10.000	4.258	3.275	0.000	10.000	4.483	3.277
Search methods								
Number of methods	1.000	6.000	3.136	1.414	1.000	6.000	3.066	1.467
Contacted employer	0.000	1.000	0.625	0.484	0.000	1.000	0.616	0.487
Placement center	0.000	1.000	0.418	0.494	0.000	1.000	0.424	0.495
Friends and relatives	0.000	1.000	0.561	0.497	0.000	1.000	0.520	0.501
Sent out resumes/applications	0.000	1.000	0.679	0.467	0.000	1.000	0.686	0.465
Looked at ads	0.000	1.000	0.685	0.465	0.000	1.000	0.620	0.486
Other	0.000	1.000	0.169	0.375	0.000	1.000	0.199	0.400

Note: —= data not available.

Turning to the labor market variables, I define two measures of labor market conditions, α_1 and α_2. First, I assign a worker an occupation from the Census Bureau's major Standard Occupational Classification (SOC) groupings, based upon the position obtained after each nonemployment spell. I first calculate the occupational unemployment rate for every month in the sample, using the NLSY97 data. This data, given the cohort structure of the panel, allows me to measure labor market conditions facing a worker among a group of peers.[9] The first measure of labor market conditions is given by the maximum occupational unemployment rate in the sample minus the unemployment rate within an individual's occupation at the beginning of her unemployment spell. The average unemployment rate for the entire period is 9.6 percent, and it is 7.4 percent for the 2005–2008 period. While this is larger than one would expect for the general population, it is expected, given the younger age of the sample.

The second measure, α_2, is constructed from the supply-and-demand ratio for workers in a specific occupation taken from the Help Wanted OnLine Index, and is available beginning in 2005. The Help Wanted OnLine Index counts the number of on-line advertisements and disaggregates them by occupation. The supply-and-demand ratio provides the number of unemployed workers for each advertisement. In the sample, the average ratio is about 4.5 unemployed workers per advertisement. I set α_2 equal to the maximum supply-and-demand ratio in the sample minus the supply-and-demand ratio at the beginning of each spell for the worker's occupation. I then divide by 100 as a convenience for ensuring that the scale of α_1 and α_2 are similar. Note that an increase in both α_1 and α_2 reflects improving labor market conditions.

Given the assumption of a degenerate wage distribution, w is the quarterly wage earned at the worker's next position. The average quarterly salary is slightly above \$5,000. For income outside of work, b, I use unemployment insurance income. Because of the limitation of the model to only accept one benefit amount per spell, I take the average reported UI benefit during the spell. The average b unconditional on whether the individual collects UI or not is about \$70. This reflects the large number of individuals that receive no unemployment benefits.

The next group of variables is demographic in nature. These variables are all measured at the start of a nonemployment spell and include an indicator variable for female, age, highest grade completed, income from a spouse, and number of children. About half the sample is female, and the average respondent is 23 (24 for the 2005–2008 sample), has a high school degree, and has 0.5 children (0.7 for the 2005–2008

[9] I group "engineers, architects, and surveyors," "engineer and related technicians," "physical scientists, social scientists, and related workers," and "life, physical, and social science technicians" into one occupation labeled "Professional" since the number of observations in each separate category is too small for the unemployment rate to be an accurate reflection of labor market conditions.

sample). I include these variables in a matrix, Γ, and use this, along with a constant term and the parameter estimates for θ_2, to determine C_{ij}.

I take two different approaches to measuring a worker's risk aversion; both have advantages and disadvantages. The first uses risky behaviors that workers engaged in before the age of 20, when they are initially included in the sample. Using Anderson and Mellor (2008) as a guide to inform me as to which behaviors relate to risk-taking, I include body mass index (BMI) and the substance abuse index (SAI); the SAI is the count of the number of substances used from among alcohol, cigarettes, and marijuana. Anderson and Mellor indicate that both of these variables are related to a greater willingness to take risk. Respondents in the sample report an average BMI of 23.2, just under the measure of being overweight, which is 25. The mean SAI is 1.2.

My second approach to measuring risk is to use a series of questions regarding risk preferences that respondents were asked in 2010. Specifically, workers were asked whether they would rather accept a job that would be guaranteed for life and that would either double their current salary or decrease it by 30 percent, or choose to keep their current job for life. A little more than 20 percent of the sample were willing to take such a risk. The survey also asks respondents to rank how likely they were to take risks in general and in a variety of aspects of their life. Respondents use a scale ranging from 0 (indicating not very likely to take risks) to 10 (very likely to take risks). I include the questions regarding general risk-taking and risk-taking at work.

The final vector of variables, Δ_i, includes these five measures of risk-taking and a constant term. An additional identification issue arises when estimating θ_1, which together with Δ_i determines δ_i. As indicated in Proposition 4, for a specific level of consumption, at very low levels of risk aversion an increase in δ increases search intensity, and at high levels of risk aversion an increase in δ decreases search intensity. To illustrate the issue, let us assume that the variables described above are indeed associated with greater risk-taking and that the true relationship between risk-taking and search intensity is positive. Without further restrictions, this could be accomplished in either of two ways: either by parameter estimates for a high constant term in θ_1 and risk-taking variables that decrease δ, or by estimates of a low constant term and positive effects of the risk-taking measures. As a result, an additional restriction is needed. I restrict each risk-taking variable to have a negative effect on δ. Consequently, more risk-averse workers will decrease search intensity when the constant term is large and will increase search intensity when the constant term is small.

Table 4 Parameter Estimates

	2000–2008 Sample α_1 (unemployment rate)		2005–2008 Sample α_2 (supply-demand ratio)	
	Estimates	Std. err.	Estimates	Std. err.
ρ	0.6312	0.0483	0.7645	0.1715
κ	18.9735	1.6783	5.9720	1.5133
$C - estimates$				
Constant	1.4607	0.0617	-7.1049	0.7571
Female	-0.1705	0.0698	0.5752	0.1679
Age	0.1309	0.0055	0.4196	0.0560
Education	0.2262	0.0510	0.2106	0.1086
Children	-0.5066	0.0662	-0.3793	0.1687
Spouse Income	0.0361	0.0673	-0.0490	0.0123
$\delta - estimates$				
Constant	0.0500	0.0101	0.2078	0.0916
Body Mass Index	0.0000	0.0007	-0.0006	0.0031
Substance Abuse Index	0.0000	0.0067	-0.0164	0.0194
One-third Cut	0.0000	0.0182	-0.0035	0.0052
Risk in General	0.0000	0.0014	-0.0040	0.0089
Risk at Work	-0.0002	0.0015	0.0000	0.0067
$\gamma - estimates$				
Contacted Employer	-0.2379	0.0191	-0.1723	0.0344
Contacted Placement Center	0.2858	0.0189	0.4160	0.0340
Contacted Friends and Relatives	-0.1483	0.0186	0.0613	0.0353
Sent out resumes	-0.4286	0.0127	-0.3010	0.0356
Looked at Ads	-0.3730	0.0127	-0.2570	0.0359
Other	1.0840	0.0229	1.1719	0.0426

The final set of variables consists of methods that workers report using to find work. I include six different methods from the NLSY97, which are listed in Table 3.[10] On average, workers use slightly more than three methods, with the most frequent being looking through want ads followed by sending out resumes. The least frequently used methods are "other" and checking with a placement center.

Results

Parameter Estimates

Table 4 presents the key parameter estimates. The first two columns relate to the sample that defines labor market conditions using occupational unemployment rates, which I refer to as the α_1 sample. The third and fourth columns of the table present results for the shorter sample, which defines labor market conditions based upon the HWOL supply-and-demand index for individual occupations. I refer to this as the α_2 sample. Of particular importance are the estimates for ρ, which under both definitions for α indicate that search intensity and labor market conditions are job-finding complements. The measures of elasticity of substitution for the two samples are 0.61 and 0.57. The degree that these elasticities result in α and x being positively related, and even perhaps negatively related at high levels of α, is explored in the next subsection. The estimates for κ are precisely estimated but have little economic meaning.

Turning to factors that influence the unemployment exit rate through C, we see that the results yield some consistent and some conflicting findings. For the α_1 sample, while not significant, the findings show that females have lower unemployment exit rates, holding all other factors constant, while for the α_2 sample the impact is positive and significant. The two estimates do agree, however, on the positive effects of age and education. This contrasts with Lentz's (2009) results, which find that both of these variables reduce the unemployment exit rate, although education does not appear to be statistically significant in those results. This could be explained in part by the younger sample Lentz uses, as well as societal differences between the U.S. and the Danish sample he uses. The presence of children has a negative effect on the unemployment exit rate, likely because it raises the value of time away from work. The support provided by spousal income is typically thought to reduce the probability of finding work. Curiously, however, it has a positive effect on the unemployment exit rate in the α_1 sample, although it is not estimated precisely. However, as expected, it has a negative effect in the α_2 sample.

Identifying heterogeneity in individuals' risk aversion proves to be difficult using α_1, where only the question regarding an individual's willingness to take risks at work, "Risk at work," is nonzero but not significant. In the case of α_2, however, all variables except "Risk at work" are nonzero but still not statistically

[10] While the question on search methods do change over time, I have conformed the methods to be the same across years. In cases where a worker indicates she has used a method to find work that was not asked about in prior years, I indicate that she used an "other" method. In addition, the NLSY asks separately if a worker contacted a private placement agency, union placement agency, or university office. I define another variable, "Placement center," as having a value of 1 if a worker used any of these methods.

significant. The average risk aversion in the α_1 sample is 0.050 with a standard deviation of 0.001. The average δ is 0.151 with a standard deviation of 0.023. The point estimates for δ are less important than the direction and magnitude of how more risk-averse individuals change their search intensity. The next subsection discusses these effects.

The last set of rows in Table 4 presents the estimates for γ, the mean threshold values for reporting a given method. In other words, each estimate gives the amount of search intensity, x, that corresponds to a 50 percent probability of an individual reporting the corresponding search method. In several cases this is a negative amount of search, implying that those with very little search intensity have a greater than 50 percent chance of reporting the method.

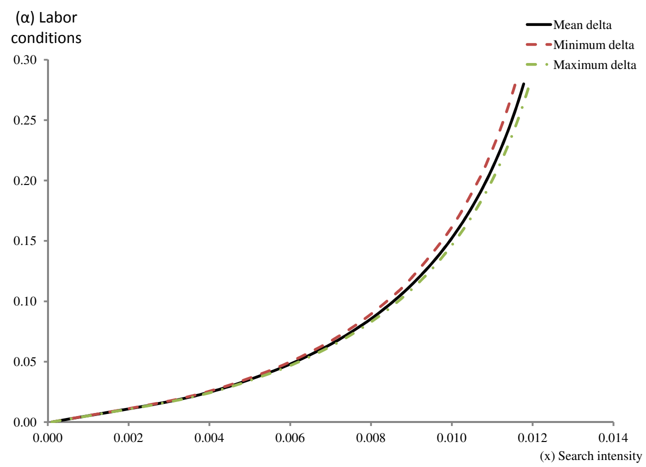
These estimates could be interpreted in a couple of ways. First, under both definitions of α, for someone who has a search effort near zero, sending out resumes has the highest chance of being used, followed by looking at ads, contacting an employer, contacting friends and relatives, contacting a placement center, and, last, the "other" category. Second, as x increases, this remains the same order in which these methods would be reported to the surveyor, with near certainty. Thus, one could also interpret the results as the order in which these methods would be employed as one increases search intensity. Given the concavity of f, this means that methods that are employed first, such as looking at ads and contacting employers, have the highest marginal effect on f, and that those employed later, such as contacting placement agencies and the "other" category, have the smallest marginal effect.

Supply of Search Intensity

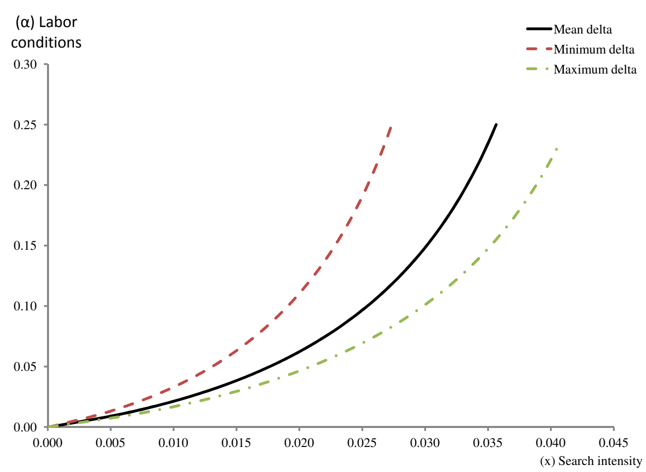
The strong positive estimates for ρ indicate that search intensity is positively related to α for some range of α, but could be negative at high levels. Figure 4 graphs the supply of search intensity as a function of α for the mean level of δ in the data set as well as for the maximum and minimum. All other variables are at their average. Panel A presents the results for the α_1 sample and Panel B for the α_2 sample. The range of α's in each data set are displayed. For all three values of δ and in both samples, search intensity is always increasing in α. Each curve is convex and would eventually have a negative slope, but not in the range of α's in the data set, nor for any realistic level of α. As a result, the supply of search intensity with respect to labor market conditions is upward-sloping.

Proposition 4 states that it is possible that more risk-averse workers could have either higher or lower search intensity, depending the level of risk aversion relative to consumption levels. However, the estimates

Figure 4 Supply of Search Intensity for Mean, Minimum and Maximum of δ



Panel A α_1 (defined by unemployment) sample



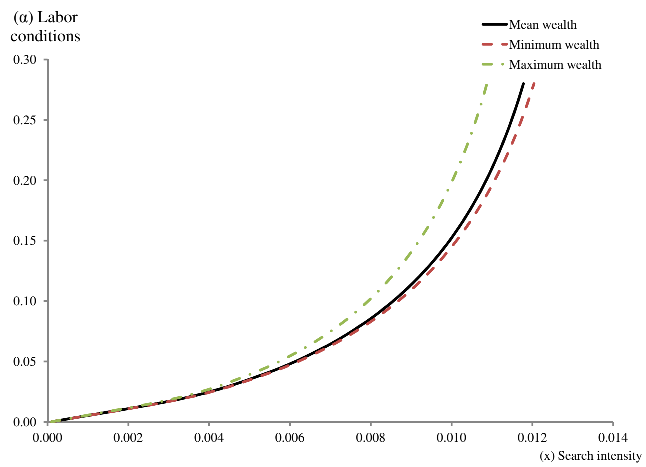
Panel B α_2 (defined by supply-demand ratio) sample suggest that more risk-averse individuals increase their search intensity. Thus, more risk-averse workers appear to mitigate the effect of income shock by increasing their expected income through greater search intensity.

The difference in search effort from the minimum to the maximum, δ, in the α_1 sample is quite small, reflecting the small estimated range of δ in this sample. For the α_2 sample, however, search intensity differs more significantly between the minimum and maximum levels of risk aversion. For the maximum level of α, an individual with the maximum level of risk aversion exerts 50 percent more search effort than an individual with the minimum risk aversion. It appears that more risk-averse individuals do try to avoid shocks to income by exerting more search effort.

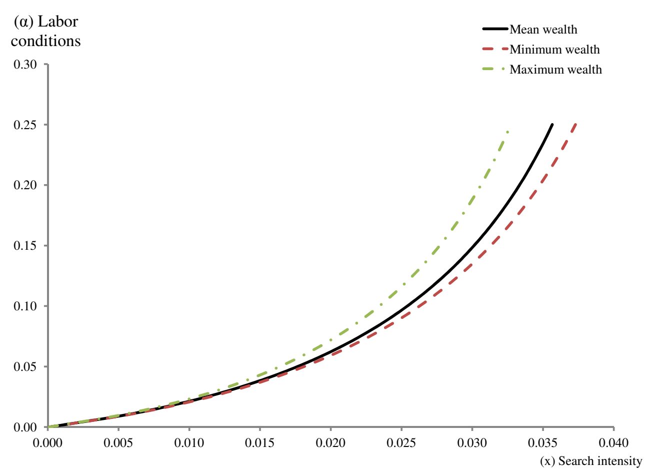
The gap between the search intensity of those with the minimum and maximum levels of risk aversion grows with α. The intuition for the growing gap comes from the two-period model in the case where x and α, are perfect job search complements. In this case, for a low level of α, the optimal level of x is determined simply by α. Given that x and α are estimated to be strong complements in the search process, this is why search intensity is largely the same for all three levels of risk aversion presented in Figure 4 when α is small. Under the perfect complements scenario, when α is larger than x, optimal search is determined by the tangency between the indifference curves and the budget constraint, which is influenced by the degree of risk aversion. As a result, in the case of a higher level of α, Figure 4 shows that the level of risk aversion has an effect on the optimal level of search intensity.

The same logic accounts for the increasing gap in search intensity among those with the maximum and minimum level of assets, which is pictured in Figure 5. The figure shows how the supply of search effort changes with different levels of wealth. Again, search effort is plotted at all levels of α, and Panel Panel A corresponds to the α_1 sample whereas Panel Panel B corresponds to the α_2 sample. In each panel, the supply of effort is plotted for the mean, minimum, and maximum levels of wealth in the sample. Confirming the results in Lentz (2009), search effort decreases with assets, as a worker is not able to smooth consumption using her own resources. In both samples, the supply of search effort with respect to labor market conditions shifts to the right as assets fall. At the maximum level of α, for both samples, search intensity is a fairly modest 12 percent higher for a worker with the maximum versus the minimum level of assets. The small effect is likely due to workers choosing a consumption plan based on expected income, which is higher than actual income for the unemployed, at least among those who exert positive search intensity. This allows those with assets that are close to the lower bound to still smooth consumption.

Figure 5 Supply of Search Intensity for Mean, Minimum and Maxmimum Wealth



Panel A α_1 (defined by unemployment) sample



Panel B α_2 (defined by supply-demand ratio) sample

Search Intensity during Nonemployment Spell

Figure 6 shows how search intensity varies during the first five quarters of a nonemployment spell under different levels of labor market conditions, risk-aversion, and wealth. Since the results are consistent under both samples, only the α_2 sample results are presented. The α_2 measure is also likely superior, since it considers both the supply and demand of labor, rather than just the supply, as is the case for α_1. Each figure shows the results for a worker at the average of all variables as well as the mean, 25th percentile and 75th percentile for α, δ, and initial wealth. In all graphs, workers' search intensity increases during their spell as they exhaust their savings. By the fifth quarter of nonemployment, search intensity does not change. This reflects the point where wealth has reached its lower bound.[11]

Panel Panel A presents search intensity during a nonemployment spell for different levels of α. The graph indicates that α increases search intensity at every level of unemployment duration. Similarly, Panel Panel B indicates that δ increases search intensity at every quarter of nonemployment. Panel Panel C shows how search intensity changes during an unemployment spell for those with different levels of wealth. Those at the 25th percentile of assets have just 2 percent more search intensity than those at the 75th percentile of the wealth distribution. Those with few assets increase their search intensity for three quarters, and then their intensity levels off in the fourth quarter. For those at the top of the wealth distribution, their search intensity starts at a lower level and then increases until the fifth quarter.

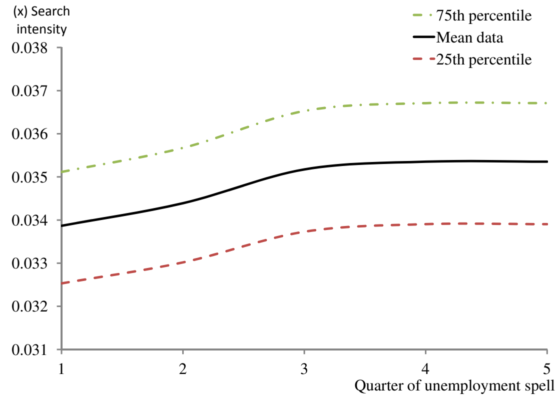
Search Intensity Across the Business Cycle

To illustrate how search intensity varies with the business cycle, Panel Panel A of Figure 7 graphs the unemployment rate since 2000, as well as the simulated search intensity from the α_1 sample, while Panel Panel B graphs the supply-and-demand ratio since 2005, as well as the simulated search intensity from the α_2 sample. In both cases, search intensity is generated using the sample parameters for an individual at the mean for all variables except α, which I assume to be consistent with the movements in these measures at the national level.

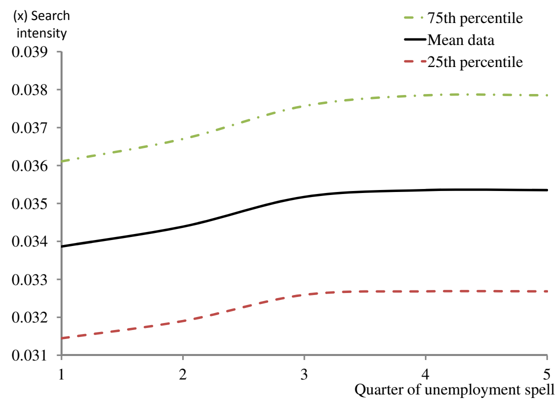
The figures reflect the estimate for ρ, which indicates that labor market conditions and search intensity are strong complements in the job search process. As a result, the figure shows that both the unemployment rate and the supply-and-demand ratio are mirror images of the corresponding simulated level of search

[11] Note that only 10 percent of observations have durations greater than five quarters.

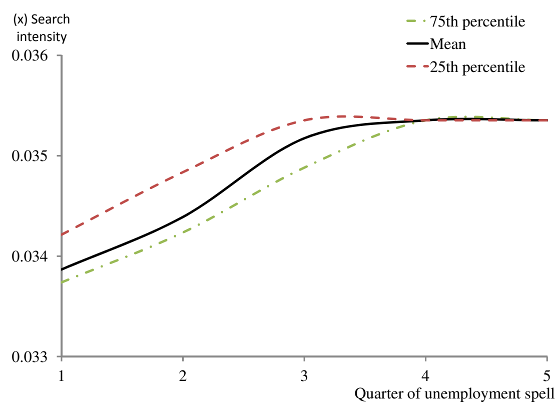
Figure 6 Search Intensity by Quarter of Nonemployment Spell



Panel A Different levels of labor market conditions

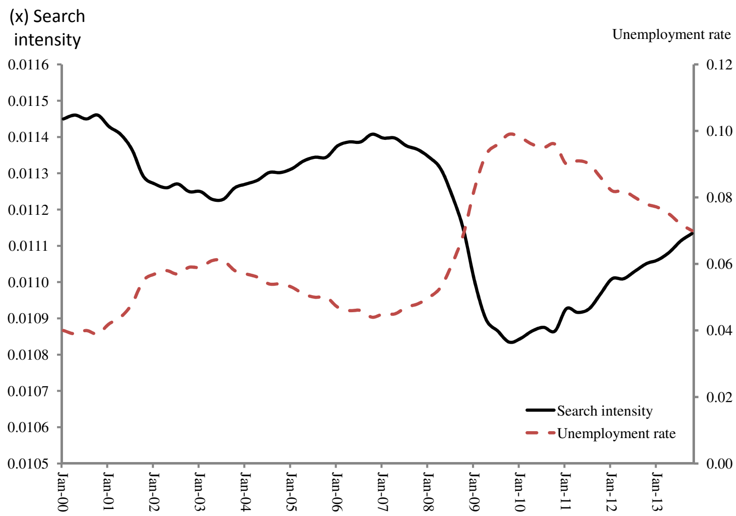


Panel B Different levels of risk aversion

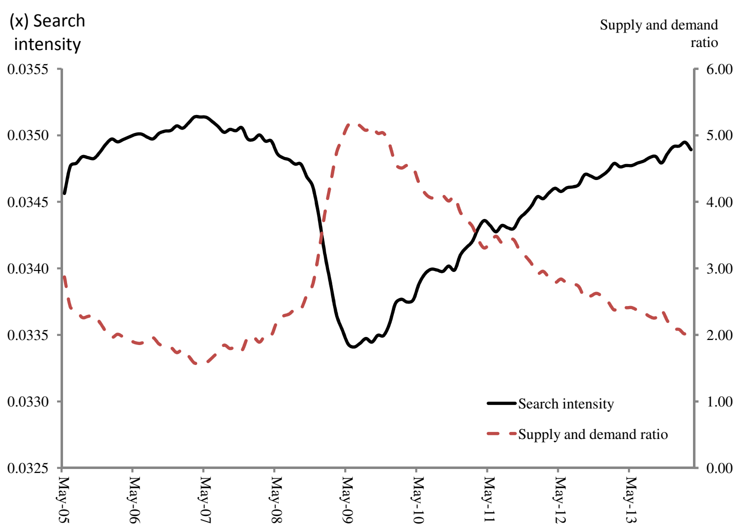


Panel C Different levels of initial wealth

Figure 7 Simulated Search Intensity over the Business Cycle



Panel A α_1 sample: unemployment rate



Panel B α_2 sample: supply-and-demand ratio intensity. The degree that search intensity changes during the business cycle, though, is fairly small in magnitude. Regressing the log of the simulated series for the α_1 sample on a constant and the log of the unemployment rate yields an elasticity of –0.06, and doing the same for the α_2 sample and the supply-and-demand ratio gives an elasticity of –0.04. This suggests that while search intensity and labor market conditions appear to be strong complements and move together, the magnitude by which search intensity adjusts over the business cycle is somewhat limited.

Conclusion

Much has been learned about how measures of the labor market vary across the business cycle, but one area that has remained a mystery has been the intensity of job search effort. This has remained an unknown despite its importance in understanding both how to model the labor market and how to design labor policy that adjusts to macro labor market conditions. Because of the lack of empirical consensus, modelers interested in endogenizing search intensity are left without strong support for the often-made assumption that search intensity is procyclical. Furthermore, policymakers that are interested in developing programs that could influence search intensity may be unsure whether search effort is already low during recessions or whether the unemployed are trying harder to find work, given that jobs are scarce. This paper attempts to fill this gap in our knowledge.

Determining how search intensity changes with macro conditions is made difficult by the inability to observe how much effort the unemployed exert. Often what one does observe is only the methods the unemployed utilize. To overcome this obstacle, this paper develops a search model that identifies search intensity. The predicted search intensity is used to explain both observed nonemployment spell length and methods that respondents report using during their search.

Estimates of the structural parameters of the model confirm the assumption, often made in theoretical research, that search intensity and labor market conditions are complements in the search process. An improving labor market is met with greater efforts to find work. While it is theoretically possible for a positive relationship to exist for poor labor market conditions and a negative one for good labor market conditions, for plausible values of α, as defined in this paper, the relationship is always positive. The degree, however, that search intensity changes over the business cycle is somewhat limited: a 10 percent decrease in the unemployment rate implies just a 0.6 percent increase in search intensity.

The results also shed light on the relationship between search intensity, risk aversion, wealth, and the degree to which different search methods contribute to finding work. First, while my model does not impose the condition that more risk aversion is associated with more search intensity, empirical estimates suggest this is the case. More risk-averse individuals avoid the income shock of unemployment by exerting more search intensity, which increases the probability of finding a job and the amount of expected income. In addition, I confirm the negative relationship between wealth and search intensity that is found in Lentz (2009), using an entirely different data set to do so. Finally, my results for job search method indicate that sending out resumes and looking at ads have the strongest effect on the job search process or are the methods that are most likely to be used first. My approach contrasts with other papers in the literature that simply rely on counting the number of methods used to find a job, implicitly assuming that each method is equally important in finding work.

The results should be interpreted in conjunction with the limitations of this paper. The first limitation is that computational complexity makes it infeasible to model the duration of unemployment benefits. However, given the low recipiency rate within the sample, and in the United States' at large, including the duration of UI benefits would likely not significantly change the results. The larger question is whether these results can be generalized to a sample constisting solely of UI recipients. Unfortunately, there are not enough UI recipients to undertake such an estimation. The second limitation is the age of the observations in my sample. The NLSY97 has many benefits, but one drawback is that it contains respondents who are generally younger than the population at large. As a result, others may wish to confirm the results in this paper with a population that is more representative, or with a sample of strictly older individuals.

Policymakers often make changes in social programs that are dependent on the phase of the business cycle. In particular, the United States has a history of extending unemployment insurance during recessions. The estimates in this paper suggest that recessions are periods of low search intensity. Thus, one may fear that extending unemployment insurance will further decrease search intensity. However, several researchers, including Schwartz (2013a) and Valletta and Kuang (2010), have found that the United States extended unemployment benefit programs do not meaningfully increase unemployment. This may be because lower search intensity during an economic downturn has already been reduced to such low levels that the additional effect of an unemployment insurance benefit extension in a recession is limited. It is left to future work to determine whether this is indeed the case.

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