Learning and Job Search Dynamics during the Great Recession*

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Abstract

Krueger and Mueller (2011) show that job seekers' search effort fell throughout unemployment during the Great Recession. Exploiting the longitudinal nature of their data, I show that variation in past search effort explains this decline. Furthermore, I document that search effort rises after a job offer is received. These facts are inconsistent with standard models of search. I introduce a tractable model of sequential search in which job seekers are uncertain about the process governing the arrival of job offers and learn through search. I use the model to show that beliefs influence search via two opposing channels: Failing to find work reduces search by reducing the perceived opportunity cost of leisure, but stimulates search by reducing the perceived option value of unemployment. I structurally estimate the model and show that learning can quantitatively account for the measured effects of job offers and cumulative past search in the data.

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1 Introduction

This paper articulates a theory of sequential job search informed by data from the Great Recession. The paper makes three substantive contributions: First, using high-frequency longitudinal data on individuals' search decisions, I show that falling search effort over the unemployment spell—as documented by Krueger and Mueller (2011)—is explained by variation in search effort since job loss. I provide evidence from data on job offers that this reflects job seekers learning about the stochastic process governing the arrival of offers. Second, I develop a theory of sequential search to rationalize the empirical results. The theory is analytically tractable and sheds new light on the mechanisms through which uncertainty and learning influence individuals' search decisions. Finally, I structurally estimate the model and show that learning can quantitatively account for the measured effect of job offers and cumulative past search, as well as several other features of the data.

The paper begins with an empirical study of job-search dynamics during the Great Recession. The jumping off point is an important study by Krueger and Mueller (2011). They use high-frequency longitudinal data on job search from the Survey of Unemployed Workers in New Jersey (SUWNJ) to document that job seekers' search effort fell over the unemployment spell during the Great Recession. I revisit their analysis and show that the decline in search effort over the unemployment spell is due to variation in individuals' search effort since job loss: When search effort is allowed to depend on both unemployment duration and cumulative search effort since job loss, the former drops out of the model while the latter enters with a highly significant and negative coefficient. To investigate the mechanism driving this result, I turn to data on job offers in the SUWNJ. These data show that search effort jumps discretely after a job offer is received, suggesting that the result is driven by uncertainty and learning about the stochastic process governing the arrival of offers.

These results are important for two principal reasons. First, they suggest that randomness inherent to the search process may induce systematic changes in behavior that impinge on subsequent job-finding prospects. Second, the results challenge a fundamental assumption underlying the canonical theory of sequential job search: that job seekers have complete information about the rate at which job opportunities will arrive during unemployment. In contrast, the findings in this paper suggest that job seekers are uncertain about the availability of work, and that search decisions are driven by learning from experience.

Motivated by this evidence, I introduce a theory of sequential search under uncertainty and learning. In the model, at the beginning of each week of unemployment, job seekers choose the amount of time for which a Poisson process with an unobservable arrival rate parameter will run. The amount of time allocated to the Poisson search process, as well as the number of job offers realized during that time, jointly comprise all of the relevant new information made available to job seekers through search. At the end of each week, job seekers update their beliefs to reflect this new information and, if no offer has arrived or if an offer has been rejected, proceed to the next week of unemployment and reoptimize in light of their updated beliefs. Search dynamics during unemployment are thus driven by the dynamic interaction between search decisions and beliefs: Beliefs respond rationally to the outcomes of past search, while search decisions are driven by endogenously evolving beliefs.

This model is the first to integrate learning about the arrival of job offers into a dynamic framework suitable for studying the contours of job search over the spell of unemployment. Its tractability enables transparent characterization of time devoted to job search and the reservation wage at any duration of unemployment in terms of cumulative past search and the stock of job offers received. Indeed, I show that a first-order approximation of the structural model implies the reduced-form regression equation described above, and I provide an explicit structural interpretation of the reduced-form parameters. I use the model to decompose the effect of learning on job search into two components: Failing to find work exerts a negative influence on search by reducing the perceived opportunity cost of leisure in the current period, but also stimulates search by reducing the option value of unemployment in future periods, akin to a reduction in the value of unemployment insurance benefits in standard models. Because the relative strength of these effects varies endogenously as unemployment progresses and job seekers observe the stochastic outcomes of their effort, the model generates rich—and potentially nonmonotonic—search dynamics over the unemployment spell.

Finally, I return to the data and structurally estimate the parameters of the model via a simulated minimum distance procedure. I identify key structural parameters—including those governing the distribution of beliefs at the time of job loss—using the reduced-form parameter estimates obtained in the first part of the paper, as well as average search effort, the average arrival rate of job offers, and the average acceptance rate of offers (among those receiving offers) from the SUWNJ data. The estimated model provides a strong account of the data, and in particular, is able to quantitatively account for the observed effect of cumulative past search and job offers on subsequent search effort. Interestingly, under the estimated model, I find that job seekers underestimate their job-finding prospects by roughly 40% at the time of job loss.

Understanding the determinants of individuals' search decisions is important. To the extent that search determines the likelihood of finding work, it is inextricably tied to the persistence of income loss associated with unemployment, and thus welfare. Labor-market policies that seek to address unemployment—such as the provision of unemployment insurance benefits, job-search-assistance programs, and employment subsidies—are necessarily predicated on assumptions about the factors that influence individuals' search decisions. This paper argues that the randomness intrinsic to the search process is itself essential to understanding individuals' search decisions and behavior throughout unemployment.

The remainder of the paper is organized as follows. Section 2 discusses related literature. Section 3 studies the empirics of job search during the Great Recession. Section 4 develops the theoretical model and characterizes search and reservation wage dynamics. Section 5 structurally estimates the model. Section 6 concludes.

2 Related Literature

This paper lies at the intersection of an empirical literature that seeks to understand the determinants of individuals' job-search decisions during unemployment and a theoretical literature that seeks to integrate learning into models of job search.

The paucity of high-frequency longitudinal data on job search has hampered attempts to study the determinants of individuals' job-search decisions during unemployment. Nonetheless, several recent papers have attempted to fill this void. Shimer (2004) uses Current Population Survey (CPS) data to study the determinants of job search in the United States prior to the Great Recession. He measures search effort as the number of reported search methods among actively searching respondents, and finds a hump-shaped profile of job search over the first year of unemployment, peaking at roughly 20 weeks. Mukoyama et al. (2014) update Shimer's analysis by exploiting overlap between the CPS and the American Time Use Survey (ATUS). They construct time-intensity weights for each of the search methods considered in the CPS and use the weights to impute search time for the full CPS sample. Their results corroborate Shimer's findings that search exhibits a hump-shaped profile over the spell of unemployment. Krueger and Mueller (2011) use the SUWNJ—the same data set used in this paper—to show that during the Great Recession, time devoted to job search fell monotonically over the course of unemployment.

This paper complements previous work by developing evidence that, at least during the Great Recession, search decisions were significantly influenced by individuals' experiences while searching for work. Moreover, the theoretical mechanism described herein provides a unified explanation for the fact that job-search effort declined monotonically during the Great Recession, but exhibited a hump-shaped profile in the years prior to the Great Recession: When job seekers' beliefs are sufficiently pessimistic, search declines monotonically throughout unemployment. In contrast, when beliefs are not too pessimistic—as may have been the case prior to the Great Recession—the model implies hump-shaped dynamics qualitatively similar to those documented by Shimer (2004) and Mukoyama et al. (2014).

The paper is also closely related to a literature that studies search in the context of learning. Early examples include Rothschild (1974) and Burdett and Vishwanath (1988), who study search when individuals have incomplete information about the distribution of prices or wages. In this paper, I study search when job seekers have incomplete information about the distribution of offer-arrival times. Falk et al. (2006a) present evidence from a laboratory experiment that job seekers exhibit substantial uncertainty about their job-finding prospects, and update beliefs based on search outcomes. In a companion paper, Falk et al. (2006b) develop an equilibrium model in which job seekers learn about their linear job-finding probability. Results from the laboratory experiment broadly conform to the message in this paper. However, their theoretical model only accommodates an extensive margin of search, and thus is constrained to focus only on the implications of learning for aggregate labor-market dynamics. This paper, by contrast, is concerned with the contours of the *intensive* margin of search throughout the course of unemployment and with clarifying the underlying mechanisms through which evolving beliefs govern search decisions.

3 Empirics of Job Search during the Great Recession

In this section I study some empirical aspects of job search during the Great Recession using high-frequency longitudinal data on the job search decisions of the unemployed from the SUWNJ.

3.1 Survey description and sample

The SUWNJ is a weekly longitudinal survey of unemployment insurance (UI) benefit recipients in New Jersey beginning in the fall of 2009 and continuing through early 2010. The survey was conducted by the Princeton University Survey Research Center and the data have been made publicly available. The survey covers 6,025 unemployed job seekers for up to 24 weeks for a total of 39,201 weekly interviews. Sampled individuals were asked to participate in a weekly online survey that lasted for a minimum of 12 weeks and, for the long-term unemployed, up to 24 weeks. The weekly survey consisted of questions pertaining to job-search activity, time use, job offers, and consumption. See Appendix A.1 for a more complete description of the survey, and Krueger and Mueller (2011) for a comprehensive description of methodology.

3.2 Evidence from search histories

Using SUWNJ data, Krueger and Mueller (2011) show that job seekers' search effort fell throughout the unemployment spell during the Great Recession. One possible explanation for this observation is that failed job search is discouraging: Repeatedly trying, and failing, to find work creates the impression that suitable work is not available, thus causing job seekers to give up looking. If this is driving the observed decline in search effort during the Great Recession, then search decisions should depend on total time spent searching for work since the time of job loss, not unemployment duration *per se*. I exploit the high-frequency longitudinal nature of the SUWNJ to examine this hypothesis.

3.2.1 Empirical strategy

Consider expressing time devoted to job search as a function of unemployment duration, a measure of aggregate labor market slack, and—reflecting the preceding intuition—the total time spent looking for work since job loss:

$$s_{it} = \iota + \kappa d_{it} + \pi \sum_{\tau=1}^{t-1} s_{i\tau} + \gamma u_t + \eta_i + \epsilon_{it}. \tag{1}$$

For individual i in interview week t, s_{it} denotes minutes per day spent on job search, d_{it} denotes unemployment duration, u_t is the (seasonally adjusted) New Jersey unemployment rate, and η_i is a person-specific fixed effect.[1] The coefficients of primary interest are κ and π, which

[1] Day-of-week indicators are included in the time diary regressions.

measure the impact of duration and cumulative past search, respectively, on time spent searching for work.

Because of the cohort structure of the data, no individuals in the sample are observed from the beginning of the unemployment spell. This implies that cumulative past search—the variable of interest—is only partially observed, so equation (1) cannot be estimated directly. Accordingly, I take first differences of (1) to clean out all unobservable person-specific terms:

$$\Delta s_{it} = \kappa \Delta d_{it} + \pi s_{it-1} + \gamma \Delta u_t + \Delta \epsilon_{it}. \tag{2}$$

The presence of the lagged-dependent variable on the right-hand side of (2) now gives rise to an endogeneity problem common to dynamic panel models: $\mathbb{E}\left[s_{it-1}\Delta\epsilon_{it}\right] \neq 0$. I address the endogeneity of s_{it-1} by instrumenting with its first lag, s_{it-2}. Under the assumption that ϵ_{it} is serially uncorrelated, $\Delta\epsilon_{it}$ is an MA(1) process, and thus s_{it-2} is a valid instrument for s_{it-1}. The Arellano-Bond test for serial correlation confirms that s_{it-2} is indeed a valid instrument.[2]

I refrain from including further lags of s_{it-1}, because doing so entails considerable loss of data, given that the average individual is observed for fewer than 6 weeks. In Appendix A.7, I estimate the model using the GMM estimator developed by Arellano and Bond (1991) to exploit additional available moment conditions while mitigating the data loss associated with differencing. Point estimates are consistent with those from the more parsimonious instrumenting strategy discussed above.[3]

3.2.2 Results

Table 1 reports results from two models: (i) a baseline specification that does *not* include as a regressor cumulative past search (Baseline), and (ii) an identical specification augmented with cumulative past search time as described above (Augmented).[4] For each specification, I report results for both the time diary and weekly recall measures of search time.[5]

Two principal results emerge from Table 1. First, the coefficient on cumulative past search is statistically significant and negative for both measures of search effort. Moreover, the augmented model provides a much better fit for the data as measured by the adjusted R^2. Second, when cumulative past search is included as a regressor, unemployment duration ceases to enter the model with a significant negative coefficient. Put differently, the observed decline in effort over the

[2]See Appendix A.4 for details.

[3]GMM estimation is implemented via first-differences and forward-orthogonal deviations.

[4]To emphasize the parameters of interest, κ and π, I exclude the estimated coefficient on the unemployment rate from Table 1. Results for the full model are available upon request.

[5]The baseline specification is intended to capture a model similar to that of Krueger and Mueller (2011), relating search effort to unemployment duration. However, their estimation strategy—using a within transformation to purge individual fixed effects—is not feasible in the Augmented model due to the inclusion of cumulative past search, which is partially unobserved. Table A.2 in Appendix A.3 reports results from fixed effects estimation of the Baseline model following Krueger and Mueller (2011). Results are similar to those presented in the fourth column of their Table 2.

Table 1: Job Search over the Unemployment Spell

	Time Diary		Weekly Recall	
	Baseline	Augmented	Baseline	Augmented
Duration (κ)	-5.460***	4.528***	-4.585***	6.085*
	(1.504)	(1.604)	(1.507)	(3.296)
Past Search (π)		-0.150***		-0.0906***
		(0.0282)		(0.0248)
Observations	5497	5497	5445	5445
Adjusted R^2	0.066	0.209	0.006	0.086

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

Notes: Regressions use survey weights. Standard errors are robust and clustered at the individual level. The sample consists of respondents ages 25-54 who have not yet accepted a job offer, are not currently employed, and who do not expect to be recalled by or return to their former employer.

unemployment spell documented by Krueger and Mueller (2011) can be attributed to variation in past search.

3.2.3 Robustness

I consider several modifications to the model and estimation strategy described above to ensure that the results presented in Table 1 are a robust feature of the data.[6] First, I estimate the model on the exact sample used in Krueger and Mueller (2011).[7] The results are not sensitive to this change. Second, I allow for the possibility that search depends nonlinearly on duration via a cubic polynomial. The results are not sensitive to this change. Third, to address the possibility that search declines over the spell because respondents learn to circumvent the litany of questions on job search by reporting that they have not searched, I restrict attention to individuals reporting strictly positive search effort.[8] The coefficient on cumulative past search for the time diary data is attenuated slightly but remains significant and negative; otherwise, the results do not change. Finally, to address the possibility that the decline in online vacancies between October 2009 and January 2011 in New Jersey is driving the results, I include the Conference Board's Help Wanted OnLine data from New Jersey for the period in question in the analysis.[9] The results are not sensitive to this change.

[6] Results for all robustness checks are reported in Appendix A.

[7] The sample used throughout the paper is the same as that used in Krueger and Mueller (2011), with two exceptions: I focus on individuals aged 25 to 54 and I restrict attention to individuals who do not expect to return to or be recalled from their last job.

[8] See Davis (2011) in Krueger and Mueller (2011). An alternative strategy would be to include in equation (1) a variable representing the interview number for a respondent. However, in first differences, the effect of the interview number could not be separately identified from the effect of duration. Because it is necessary to first-difference the data for reasons described above, this approach is not feasible, so I only report results for the intensive margin approach.

[9] See Sahin (2011) in Krueger and Mueller (2011).

3.3 Discussion

The results in Table 1 could plausibly be due to job seekers learning about the arrival rate of offers or stock-flow matching. I exploit data on job offers from the SUWNJ to test the learning hypothesis. I then consider a sample of individuals who have been unemployed for a relatively long period to test the stock-flow hypothesis.

3.3.1 Learning

The results in Table 1 could be explained by job seekers learning about the process governing the arrival of offers through their idiosyncratic search experiences. If this is the case, then the arrival of a job offer should affect subsequent search decisions. A number of subtle issues potentially impede studying the effect of job offers on search in the framework described above. I exploit the differential timing of job offers and search in the time-diary data to address these issues and examine learning as a potential explanation for the results in Table 1.

Consider augmenting (1) with a variable representing the total number of offers that an individual has received since job loss, analogously to the total search time since job loss:

$$s_{it} = \iota + \kappa d_{it} + \pi \sum_{\tau=1}^{t-1} s_{i\tau} + \phi \sum_{\tau=1}^{t} o_{i\tau} + \gamma u_t + \eta_i + \epsilon_{it} \tag{3}$$

where $o_{i\tau}$ represents the number of offers received by individual i in week τ of unemployment. I focus on the time diary data and therefore index the sum from $\tau = 1$ to t instead of $t-1$.[10] First differencing as before, we obtain

$$\Delta s_{it} = \kappa \Delta d_{it} + \pi s_{it-1} + \phi o_{it} + \gamma \Delta u_t + \Delta \epsilon_{it}. \tag{4}$$

The first column of Table 2 ("Offers") reports results from naïve estimation of (4). The effect of offers is positive and significant at the 5% level: An additional offer is associated with a 36-minute increase in search effort per day. As mentioned above, however, these point estimates are likely contaminated by two biases neglected in the naïve model. I consider these in turn below.

The first possibility is that, if search effort at time t or $t-1$ increases the likelihood of receiving a job offer at time t, then $Cov(o_{it}, \Delta\epsilon_{it}) \neq 0$. The former case is unlikely, as it is unlikely that search effort as measured by the time diary data will affect the likelihood of an offer in the same period, as discussed above. The latter case is more plausible, and will tend to attenuate the estimate of ϕ. To address this concern, I first regress an indicator for whether or not an offer was received in period t (o_{it}) on contemporaneous and past search effort, unemployment duration, individual fixed

[10] In a given week, job offers are likely to arrive *before* search is recorded in the time diary, whereas it is impossible to disentangle the timing of offers from the timing of search using the weekly recall data. I therefore restrict attention to time diary data. Results using the weekly recall measure are not generally significant.

effects and other controls. I then use the residuals from this regression—the component of the offer purged of the effects of past search—to instrument for o_{it} in (4). The second column of Table 2 ("Offers (residual)") reports the results. Consistent with attenuation resulting from the effect of search on offers, the coefficient on offers increases substantially and is now significant at the 1% level: An additional offer is now associated with a 51-minute increase in search effort per day.[11]

The second possibility is that offer quality may be driving these results: That is, perhaps individuals search more only after receiving particularly high offers that convey positive information about the offer quality distribution, and thus their earnings prospects. If data on individuals' wage expectations were available, one could restrict attention to offers below the expected wage, and thus rule out this possibility. Because such data are not available in the SUWNJ, I proceed by repeating the analysis described in the previous paragraph, restricting attention to individuals whose best offer is below their previously declared *reservation wage*.[12] While imperfect, this approach will successfully rule out offers inducing optimism about earnings prospects and stimulating search so long as search costs are relatively high: As discussed in Burdett and Vishwanath (1988), in this case the option value of unemployment will be relatively low, implying that no offers above the expected wage will be rejected, so that all individuals who reject offers will also become more pessimistic about their earnings prospects. If such offers affect search, it is unlikely that it is resulting from job seekers learning that better jobs are available; rather, it is consistent with offers affecting search by affecting the perceived availability of jobs in general. The third column of Table 2 ("Offers ($\leq \underline{w}_{t-1}$)") reports results from this final specification. The estimated effect of offers is similar in magnitude to the effect in the previous specification, and remains significant at the 5% level. If offer quality was driving the results, we would expect a significantly smaller coefficient.[13]

Thus, regardless of the specification, job offers appear to have an economically and statistically significant effect on subsequent search effort. These results are robust to inclusion of higher-order polynomials in duration, alternative approaches to controlling for macroeconomic effects, and using various demographic subsamples. Furthermore, the results hold when the total number of offers an individual received in a period is used instead of an indicator for whether or not at least one offer was received.[14] These results suggest an important role for learning about the process governing the arrival of offers in the job search process.

[11] Because the sample is restricted to individuals who have never accepted an offer, there is no concern that individuals are receiving part-time offers and continuing to search.

[12] Because the reservation wage is potentially affected by the arrival of a job offer, I use its lagged value.

[13] Note that this is a particularly conservative approach to purging the effect of learning about the offer quality distribution: By excluding all offers for individuals whose best offer exceeds their reservation wage, I am likely excluding individuals receiving multiple offers some of which are below the reservation wage—individuals whose behavior may in fact also reflect learning about the availability of jobs, not just the offer distribution. Unfortunately, however, this is necessary because data are only available on the wage of the best offer.

[14] Two interesting exceptions to the otherwise robust significance of offers are worth noting: First, inclusion of individuals who expect to be recalled by their former employer reduces the significance of cumulative past search in these regressions (although the signs remain negative and duration still becomes insignificant). Second, inclusion of older individuals—specifically, those 55 and above—reduces the significance of job offers (although the sign remains positive). These results are not surprising in the context of a model of learning: The salience of new information for search decisions is likely very different for individuals expecting to be recalled. Likewise, the information content of offers—and thus the effect of such information on search—is likely to be much smaller for older individuals who have been in the labor market for most of their working lives.

Table 2: The effect of job offers

	Offers	Offers (residual)	Offers ($\leq \underline{w}_{t-1}$)
Duration (κ)	3.096	2.748	3.122
	(2.325)	(2.371)	(2.357)
Past Search (π)	-0.0956**	-0.0961**	-0.0947**
	(0.0405)	(0.0403)	(0.0405)
Offers (ϕ)	36.23**	51.03***	44.56*
	(15.11)	(19.36)	(24.41)
Observations	3380	3380	3380
Adjusted R^2	0.153	0.152	0.148

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

Notes: Regressions use survey weights. Standard errors are robust and clustered at the individual level. The sample consists of respondents ages 25-54 who have not yet accepted a job offer, are not currently employed, and who do not expect to be recalled by or return to their former employer. I furthermore restrict the sample to individuals who have been in the survey for at least one month in order to consistently estimate the first stage regression in columns 2 and 3.

3.3.2 Stock-flow matching

Another possible explanation for the results in Table 1 is the presence of stock-flow matching (Coles and Smith, 1998; Ebrahimy and Shimer, 2006; Coles and Petrongolo, 2008).[15] Specifically, suppose that upon job loss, individuals observe a stock of relevant vacancies, and search time is devoted to applying to those jobs. Once that stock has been exhausted, subsequent search is limited by the flow of newly posted vacancies. In this environment, the time devoted to search at the beginning of the unemployment spell corresponds to the rate at which the initial stock is drawn down. Thus, individuals who devote more time to search early in the unemployment spell may more rapidly reduce their search.

As a simple test of whether stock-flow matching is driving the results in Table 1, I restrict the sample to individuals who have been unemployed for over one month. Because they have been unemployed for a relatively long period of time, in a stock-flow model these individuals are more likely to have already drawn down the initial stock of pre-existing vacancies, and thus their current search effort should be dictated by the flow of new vacancies, not their past effort. Table A.4 in Appendix A.5 reports the results. The measured effect of cumulative past search is nearly identical to that found in Table 1 for both measures of search time, suggesting that stock-flow matching is unlikely to be driving the results.

[15] Of course, stock flow matching is unlikely to be able to explain the results in Table 2.

4 A Theory of Sequential Search with Learning

In the canonical theory of sequential search, job offers either arrive every period or arrive stochastically at a known average rate. In this section, I develop a theory of search in which job seekers have incomplete information about the availability of work (precisely, the rate at which offers arrive) and learn from their experiences while searching. Specifically, I assume that: (i) Job seekers choose how much time to spend looking for work at the beginning of each period, and (ii) job seekers do not observe the rate at which job offers arrive per unit of time devoted to search. Because the arrival rate is unobserved, job seekers are endowed with a distribution of beliefs that evolves endogenously in response to the arrival of new information. In the model, search time and reservation-wage dynamics over the unemployment spell are driven by the evolution of beliefs, which in turn respond to the idiosyncratic outcomes of search.

In what follows, I present a stylized model of search to illustrate the mechanisms at work. See Appendix B for details of the more general model used for estimation in Section 5.

4.1 Environment

4.1.1 Timing

Unemployment duration is discrete and measured in weeks. Unemployed job seekers maximize the present discounted value of income net of search costs: $E_0 \sum_{t=0}^{\infty} \delta^t (y_t - \eta s_t)$. Search costs may be thought of as monetary costs or the imputed value of forgone leisure.

At the beginning of each week t, job seekers choose to devote fraction s_t of their week to searching for work. While searching, job offers arrive according to a Poisson process with true average rate parameter λ^T.[16] Letting $\tilde{\tau}_t$ denote the stochastic arrival time of the first offer, the *true* probability of a job offer arriving before search ends is given by

$$Pr(\tilde{\tau}_t \leq s_t) \equiv F(s_t; \lambda^T) = 1 - e^{-\lambda^T s_t}. \tag{5}$$

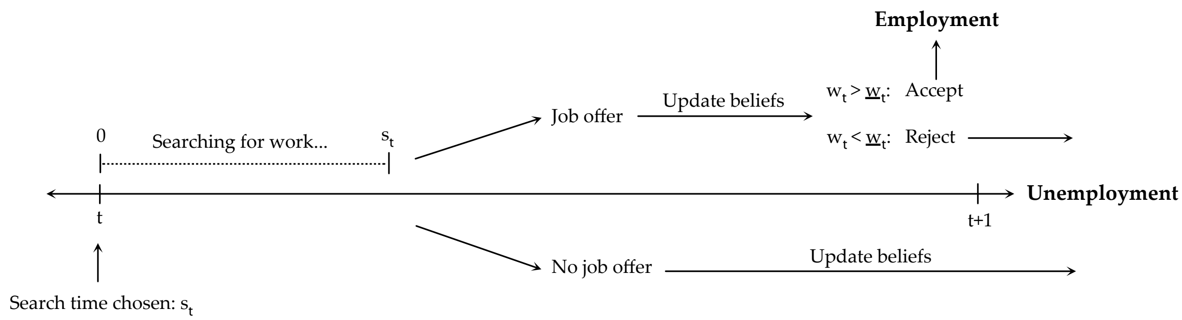
If a job offer arrives before search ends ($\tilde{\tau}_t \leq s_t$), the job seeker updates her estimate of λ^T and decides whether to accept the offer, as in a standard McCall (1970)-style search framework.[17] Offers are drawn from a known distribution $\Phi(\omega)$ with density $\phi(\omega)$. If the offer is accepted, the job seeker receives the wage offer for the rest of her life. If the offer is rejected, the job seeker receives flow value of unemployment b and continues searching in the next period. If no offer arrives before

[16] Unemployment duration is discrete, but offers arrive according to a continuous Poisson process within periods. When an offer arrives, I assume that job seekers must stop searching for the remainder of the period to update beliefs and evaluate the offer, so agents never receive more than one offer per week. This assumption could be relaxed by assuming that the number of offers arriving each period follows a Poisson distribution.

[17] The generalized model in Appendix B allows for an exogenously fixed component of the arrival rate, independent of time devoted to search. This is important when accounting for direct transitions from out-of-the-labor-force to employment, but does not fundamentally alter any of the analysis presented here.

search ends ($\tilde{\tau}_t > s_t$), the job seeker receives flow value of unemployment b and updates her estimate of λ^T to reflect the fact that searching for fraction s_t of the week yielded no offers. Figure 1 depicts the timing of the model.

Figure 1: Timing of events



4.1.2 Beliefs

I assume that job seekers do not know the true job offer arrival rate λ^T. Instead, they form beliefs about the value of λ^T, which take the form of a Gamma distribution, parameterized by α_t and β_t. The assumptions that observed arrival times follow a (right-censored) exponential distribution and that beliefs follow a Gamma distribution together imply that beliefs are time-invariant up to parameters α_t and β_t, which affords the model considerable tractability.[18]

The density of beliefs in week t is thus given by

$$Pr(\tilde{\lambda} = \lambda) \equiv \gamma(\lambda; \alpha_t, \beta_t) = \frac{\beta_t^{\alpha_t} \lambda^{\alpha_t - 1} e^{-\beta_t \lambda}}{\Gamma(\alpha_t)}. \tag{6}$$

The mean and variance of the distribution of beliefs in week t are

$$E_t(\tilde{\lambda}) = \frac{\alpha_t}{\beta_t} \qquad Var_t(\tilde{\lambda}) = \frac{\alpha_t}{\beta_t^2}. \tag{7}$$

The parameters of the belief distribution α_t and β_t evolve endogenously over the unemployment spell according to the following laws of motion:

$$\alpha_{t+1} = \begin{cases} \alpha_t + 1 & \text{if } \tau_t \leq s_t \text{ (offer)} \\ \alpha_t & \text{if } \tau_t > s_t \text{ (no offer)} \end{cases} \tag{8}$$

[18] See Appendix B.2 for a simple proof of this claim.

$$\beta_{t+1} = \begin{cases} \beta_t + \tau_t & \text{if } \tau_t \leq s_t \text{ (offer)} \\ \beta_t + s_t & \text{if } \tau_t > s_t \text{ (no offer).} \end{cases} \tag{9}$$

Note that α_t counts the number of job offers received since job loss and β_t measures accumulated search time since job loss. The endogeneity of beliefs arises from two sources: (i) the explicit presence of s_t in (8) and (9); and (ii) the fact that whether or not an offer is received implicitly depends on s_t.

Figure 2: Beliefs

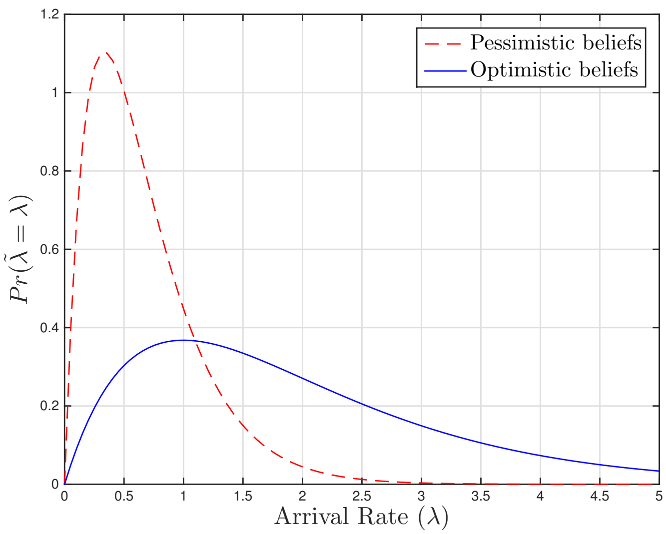


Figure 2 depicts two belief distributions associated with different values of α_t and β_t. As more job offers arrive, job seekers become optimistic, and the belief distribution shifts outward. Conversely, as more time is spent searching without receiving an offer, job seekers become pessimistic, and the belief distribution shifts inward.[19] Notice that this specification of beliefs is fairly flexible: Because the belief distribution is fully characterized by two parameters, α and β, which map into the mean and variance of beliefs via (7), any combination of optimism/pessimism (as measured by $\mathbb{E}[\tilde{\lambda}]$) and precision (as measured by $Var(\tilde{\lambda})$) can be accommodated via choice of α and β. This will be important when I turn to structural estimation of individuals' priors at the time of job loss in Section 5.

In keeping with much of the macroeconomic literature on learning, I assume that job seekers optimize within an anticipated-utility framework.[20] This assumption serves to simplify the exposition of the model, and provides a significant reduction in the computational burden associated with estimating the model in Section 5.

[19] Conditional on not receiving an offer, arrival time τ_t is not observed. See Appendix B.2 for discussion of this point as it pertains to conjugacy of the Gamma distribution.

[20] See Kreps (1998).

4.2 Recursive formulation

The value of entering week t unemployed with beliefs characterized by α_t and β_t may be written recursively as

$$V_t^U(\alpha_t, \beta_t) = \max_{s_t} \Bigg\{ E_t^{\lambda} \Big[F(s_t; \lambda) E_t^{\omega} \left[V_t^O(\omega, \alpha_t, \beta_t) \right] + (1 - F(s_t; \lambda))[b + \delta V_{t+1}^U(\alpha_t, \beta_t)] \Big] - \eta s_t \Bigg\} \tag{10}$$

where $V_t^O(\omega, \cdot)$ denotes the value of having offer ω in hand and is given by

$$V_t^O(\omega, \alpha_t, \beta_t) = \max \left\{ \frac{\omega}{1-\delta}, b + \delta V_{t+1}^U(\alpha_t, \beta_t) \right\}. \tag{11}$$

The value of entering week t unemployed is a probability-weighted average of the expected value of receiving a job offer and the value of receiving no offer and remaining unemployed into period $t+1$, less the cost of search. Because λ^T is unobserved, job seekers integrate over possible values of the underlying arrival rate according to the current state of their beliefs, as characterized by α_t and β_t.

4.3 Solution

I solve the model in two stages. First, I characterize behavior at the end of the period for job seekers who have received offers; optimal behavior takes the form of a familiar reservation-wage policy. Second, I determine optimal search time at the start of the period conditional on the reservation-wage policy determined in the first stage.

4.3.1 Reservation wage

Consider first the problem of an unemployed job seeker with a known offer ω in hand. Because the first argument in the max operator in equation (11) is strictly increasing in ω, while the second is constant, the optimal choice between accepting and rejecting the offer may be characterized by a standard reservation-wage policy:

$$V_t^O(\omega, \alpha_t, \beta_t) = \begin{cases} \dfrac{\omega}{1-\delta} & \text{if } \ \omega > \underline{w}_t \\ b + \delta V_{t+1}^U(\alpha_t, \beta_t) & \text{if } \ \omega \leq \underline{w}_t \end{cases} \tag{12}$$

where the reservation wage is defined by

$$\frac{\underline{w}_t}{1-\delta} = b + \delta V_{t+1}^U(\alpha_t, \beta_t). \tag{13}$$

Job seekers choose a threshold wage rate $\underline{w}_t$ such that the present discounted value of accepting an offer $\underline{w}_t$ is equated with the flow value of unemployment b plus the value of remaining unemployed.

4.3.2 Search effort

Consider next an unemployed job seeker at the beginning of week t who has not yet begun to search for work. Making explicit the belief distribution, (10) may be written as

$$V_t^U(\alpha_t, \beta_t) = \max_{s_t} \Bigg\{ \int_0^\infty \Big[F(s_t; \lambda) E_t^\omega \left[V_t^O(\omega, \alpha_t, \beta_t) \right] + (1 - F(s_t; \lambda))[b + \delta V_{t+1}^U(\alpha_t, \beta_t)] \Big] \gamma(\lambda; \alpha_t, \beta_t) d\lambda - \eta s_t \Bigg\}. \tag{14}$$

The first-order condition for the choice of s_t is given by

$$\eta = \int_0^\infty f(s_t; \lambda) \Big[E_t^\omega \left[V_t^O(\omega, \alpha_t, \beta_t) \right] - b - \delta V_{t+1}^U(\alpha_t, \beta_t) \Big] \gamma(\lambda; \alpha_t, \beta_t) d\lambda. \tag{15}$$

The expression in brackets is the expected net benefit from receiving an (unknown) offer. Making use of (12) and (13), this term may be written as

$$E_t^\omega \left[V_t^O(\omega, \alpha_t, \beta_t) \right] - b - \delta V_{t+1}^U(\alpha_t, \beta_t) = \frac{1}{1-\delta} \int_{\underline{w}_t}^\infty (\omega - \underline{w}_t) \phi(\omega) d\omega. \tag{16}$$

The first-order condition thus reduces to

$$\eta = \int_0^\infty f(s_t; \lambda) \left[\frac{1}{1-\delta} \int_{\underline{w}_t}^B (\omega - \underline{w}_t) \phi(\omega) d\omega \right] \gamma(\lambda; \alpha_t, \beta_t) d\lambda. \tag{17}$$

Job seekers equate the marginal cost of search η with the expected marginal benefit. The expected marginal benefit is the product of the marginal increase in the probability of finding an offer multiplied by the expected net value of an offer, integrated over the unobserved arrival rate λ.

4.3.3 Model dynamics

Using (14) to eliminate the value function from (13) and explicitly integrating over beliefs yields the two key equations that jointly characterize time devoted to job search and the reservation wage:

$$s_t = \beta_t \left[\left(\frac{1}{\eta(1-\delta)} \int_{\underline{w}_t}^B (\omega - \underline{w}_t) \phi(\omega) d\omega \left(\frac{\alpha_t}{\beta_t} \right) \right)^{\frac{1}{\alpha_t + 1}} - 1 \right] \tag{18}$$

$$\underline{w}_t - b + \delta \eta s_t = \left[1 - \left(\frac{\beta_t}{\beta_t + s_t} \right)^{\alpha_t} \right] \left(\frac{\delta}{1-\delta} \int_{\underline{w}_t}^B (\omega - \underline{w}_t) \phi(\omega) d\omega \right). \tag{19}$$

Model dynamics are governed by the optimality conditions in (18) and (19), together with the laws of motion for beliefs in (8) and (9).

4.4 Reservation wage

A large literature in empirical labor economics seeks to understand how reservation wages vary with unemployment duration. A robust finding in this literature suggests that reservation wages tend to decline over the course of unemployment (cf. Devine and Kiefer, 1991; Barnes, 1975; Feldstein and Poterba, 1984). Proposition 1 establishes that the model predicts monotonically declining reservation wages in the absence of job offers.

Proposition 1. *The reservation wage is monotonically declining in cumulative past search.*

Proof. See Appendix B. □

The intuition for this result is straightforward: Reductions in the perceived likelihood of finding work reduce the option value of remaining unemployed—thus making job seekers more willing to accept offers and reducing the reservation wage. In this sense, failing to find work in the model developed above is analogous to a progressive reduction in the level of unemployment benefits in terms of their implications for reservation wages.

4.5 Search effort

4.5.1 Decomposing the effect of beliefs on search

In the model, job seekers learn about the unobserved arrival rate of job offers through their experiences looking for work. The learning process induces changes in the distribution of beliefs through α_t and β_t, which in turn govern search decisions.

How exactly does learning affect search decisions? Consider a small increase in β_t, which corresponds to a week in which a small amount of time is devoted to search that yields no offers. When search ends and no offers have arrived, job seekers update their beliefs to reflect the failure to find work. This has two effects on subsequent search decisions. On the one hand, a lower perceived probability of finding work means that remaining unemployed is a less attractive option. Just as lower unemployment benefits reduce the option value of remaining unemployed in the standard McCall (1970) model of sequential search, a perceived reduction in the probability of finding work likewise reduces the option value of remaining unemployed in the model described above. On the other hand, a lower perceived probability of finding work reduces the opportunity cost of leisure. This induces a substitution away from time devoted to search.[21] I refer to the first effect as the

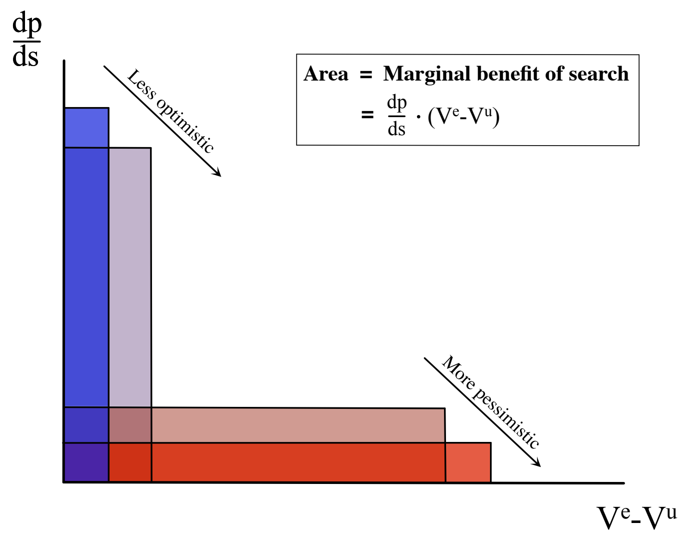
[21] In principle, if $s_t > \frac{\beta_t}{\alpha_t}$, a reduction in the perceived opportunity cost of leisure via an incremental increase in β_t will induce a substitution *toward* search instead of *away from* search. Estimation of the model in Section 5 indicates that the search productivity effect is indeed negative in the relevant portions of the parameter space.

option value effect and the second effect as the *search productivity effect*. Formally, the effect of failing to find work on subsequent search time is decomposed as follows:

$$\frac{\partial s_t}{\partial \beta_t} = \left[\frac{\beta_t + s_t}{\alpha_t + 1}\right] \cdot \Bigg[\underbrace{\frac{\alpha_t}{\beta_t} - \frac{\alpha_t + 1}{\beta_t + s_t}}_{\text{Search productivity effect}} \underbrace{- \frac{(1 - \Phi(\underline{w}_t))}{\int_{\underline{w}_t}^{B} (\omega - \underline{w}_t)\phi(\omega) d\omega} \frac{\partial \underline{w}_t}{\partial \beta_t}}_{\text{Option value effect}} \Bigg]. \tag{20}$$

Because α_t and β_t are endogenous, the relative strength of the two effects varies endogenously over time. The model is therefore capable of generating nonmonotonic search dynamics over the unemployment spell, even in the absence of job offers.[22]

Figure 3: Nonmonotonic search dynamics



Theoretically, the decomposition above sheds light on the channels through which evolving beliefs affect search effort: While crude intuition might lead one to believe that pessimism will necessarily depress search effort, the model illustrates that there is an important—and opposing—effect associated with the fact that job seekers are forward-looking. Indeed, for large regions of the belief space, failing to find a job actually *stimulates* search effort. The intuition for this result is illustrated in Figure 3. When job seekers are optimistic (blue rectangles), the perceived increase in the job-finding probability from an extra minute of search, $\frac{dp}{ds}$, is large (the rectangles are tall), while the gain from successful search, $V^e - V^u$, is small (the rectangles are narrow). This means that when a job seeker fails to find work and becomes less optimistic (darker to lighter blue), the *reduction* in the marginal benefit of search due to the fall in $\frac{dp}{ds}$ is small because it is scaled by a low value of $V^e - V^u$, whereas the *increase* in the marginal benefit of search due to the rise in $V^e - V^u$ is large because it is scaled by a high value of $\frac{dp}{ds}$. The net effect is thus an increase in the

[22]The stochastic arrival of job offers introduces yet another source of nonmonotonicity.

perceived marginal benefit of search (the light blue rectangle has greater area than the dark blue rectangle), and thus an increase in search effort. On the other hand, this argument is reversed when job seekers are pessimistic (red rectangles). In this case, the perceived increase in the job-finding probability from an extra minute of search, $\frac{dp}{ds}$, is small (the rectangles are short), while the gain from successful search, $V^e - V^u$, is large (the rectangles are wide). This means that when a job seeker fails to find work and becomes even more pessimistic (lighter to darker red), the *reduction* in the marginal benefit of search due to the fall in $\frac{dp}{ds}$ is large because it is scaled by a large value of $V^e - V^u$, whereas the *increase* in the marginal benefit of search due to the rise in $V^e - V^u$ is small because it is scaled by a small value of $\frac{dp}{ds}$. The net effect is thus a reduction in the perceived marginal benefit of search (the dark red rectangle has less area than the light red rectangle). Note that this argument is just a mechanical application of the "product rule" to differentiating the marginal benefit of job search, $\frac{dp}{ds}(\beta)(V^e - V^u(\beta))$, with respect to β.

Empirically, nonmonotonic search dynamics are a feature of pre-Great Recession data: Both Shimer (2004) and Mukoyama et al. (2014) independently document that search effort appears to exhibit a hump-shaped profile over the first two years of unemployment using CPS data. A credible theory of search should therefore be able to account for this feature of the data. Through the competing search productivity and option value effects described above, the model developed in this paper can do precisely that without relying on other mechanisms. Indeed, when beliefs are sufficiently optimistic at the time of job loss—as one might expect in pre-Great Recession data—the model implies a hump-shaped profile of search effort over the spell. Yet when beliefs are pessimistic, search will decline monotonically as during the Great Recession. I elaborate on this point more below.

4.5.2 Reduced-form analysis revisited

The model developed in this section was motivated by the fact that total search effort since job loss exerts a negative influence on subsequent search effort. Given that β_t is properly interpreted as total search effort since job loss, Equation (20) suggests a link between the motivating empirics in Section 3 and the search productivity and option value effects described above. Proposition 2 formalizes this connection.

Proposition 2. *Search effort is declining in cumulative past search iff the search productivity effect dominates the option value effect.*

Proof. See Appendix B. □

Thus, qualitatively, the model is capable of rationalizing the empirical results if and only if the search productivity effect of beliefs dominates the option value effect. Is it possible to more explicitly formalize this link between the reduced-form empirics and the structural model? Proposition 3 does so by deriving an explicit structural interpretation of the reduced-form parameter π from Section 3.

Proposition 3. *When (i) the wage offer distribution is degenerate, and (ii) $\alpha_0 = 1$, the coefficient on cumulative past search from the reduced-form regression has a closed-form representation in terms of structural parameters:*

$$\pi = \frac{1}{2}\left[\beta_0\left(\frac{w-b}{\eta}\right) + \delta\beta_0^2\right]^{-\frac{1}{2}}\left[\frac{w-b}{\eta} + 2\delta\beta_0\right] - 1. \tag{21}$$

Furthermore, $\pi < 0$ iff

$$\beta_0 > \underline{\beta}_0 \equiv \left(\frac{w-b}{2\delta\eta}\right)\left[\left(\frac{1}{1-\delta}\right)^{\frac{1}{2}} - 1\right]. \tag{22}$$

Proof. See Appendix B. □

The first part of Proposition 3 gives a structural interpretation of the reduced-form regression coefficient on cumulative past search from Section 3. The second part provides a condition on initial beliefs under which that reduced-form regression coefficient is negative in the structural model, consistent with the key empirical result documented in Section 3. The existence of a threshold level of beliefs, $\underline{\beta}_0$, indicates that search will decline in cumulative past search when beliefs at the time of job loss are sufficiently pessimistic. Interestingly, the threshold is increasing in the differential between the wage rate and the flow value of unemployment, and decreasing in the cost of search. Intuitively, when job seekers are roughly indifferent between employment and unemployment, or when the cost of searching is high, beliefs at the time of job loss need not be very pessimistic for past search to exert a negative influence on current search.

Proposition 3 also provides a set of testable implications of the theory developed in this section. In particular, one could imagine partitioning respondents in the SUWNJ according to measures of disutility from search (η), discount factors (δ), expected wages (w) or unemployment insurance benefits (b), re-estimating Equation (2) on various subsamples, and testing the restrictions implied by Equation (21). Such tests are beyond the scope of this paper, but should be of considerable interest for researchers seeking to understand the determinants of search behavior in future work.

5 Structural Estimation

This section structurally estimates the model developed in Section 4.[23] There are two principal goals of the exercise: (i) to evaluate the extent to which the simple structural search model described above is able to account for the reduced-form results in Section 3; and (ii) to characterize the distribution of beliefs about the job-finding rate in the data. To accomplish these goals, I identify key structural parameters—including those governing beliefs at the time of job loss—using the estimated parameters from the reduced-form analysis in Section 3, in addition to sample averages of search effort, the offer arrival rate, and the offer acceptance rate from the SUWNJ data.

[23]See Appendix B for details of the full model.

5.1 Empirical strategy

I use a simulated minimum distance procedure to estimate the model developed in the preceding section. Despite its considerable tractability, the likelihood function associated with the model is too cumbersome to permit taking the model directly to the data. I therefore estimate the model by choosing structural parameters to match a set of empirical moments. Specifically, I estimate the following five structural parameters:

$$\Theta = [\ \underbrace{\alpha_0, \beta_0, Bias}_{\text{Beliefs}}\ ,\quad \underbrace{\eta, b}_{\text{Physical}}\ ]' \tag{23}$$

where *Bias* is a measure of the distortion in individuals' beliefs about the likelihood of finding work (defined formally below). The remaining parameters are directly calibrated from estimates in the literature. Estimation then proceeds in three steps. First, I specify the auxiliary model; this is the lens through which I compare the model with the data. Next, I estimate the parameters of the auxiliary model—the auxiliary parameters—using the SUWNJ data. Finally, I choose the *structural* parameters Θ so as to minimize the distance between the auxiliary parameters generated by the SUWNJ data and the auxiliary parameters generated by simulating the structural model.

5.1.1 Identification and the auxiliary model

In order to identify the structural parameters Θ, I specify the auxiliary model as two vectors of moments:

$$\Omega = [\Omega_1, \Omega_2] \tag{24}$$

where

$$\Omega_1 = [\hat{\pi}, \hat{\phi}, \hat{\kappa}_1, \hat{\kappa}_2] \tag{25}$$

$$\Omega_2 = [\hat{s}, \hat{o}, \hat{a}]. \tag{26}$$

The first vector of moments, Ω_1, contains the four key reduced-form coefficients from Section 3:[24] $\hat{\pi}$ is the measured effect of cumulative past search from Table 2; $\hat{\phi}$ is the measured effect of job offers from Table 2; $\hat{\kappa}_1$ is the measured effect of duration in a fixed-effects specification in the spirit of Krueger and Mueller (2011) (without controlling for the effect of cumulative past search or job offers); and $\hat{\kappa}_2$ is the measured effect of duration from Table 2 (controlling for cumulative past search and job offers). The second vector of moments, Ω_2, contains sample averages of search time, the probability of receiving an offer, and the probability of accepting an offer conditional on having received an offer.

[24] In what follows, I measure search time as the fraction the day spent on job search. Thus, the targeted moments will, in some cases, appear different from the corresponding values in Section 3, although the underlying data are the same.

Letting Ω^e denote the vector of moments obtained from the SUWNJ and $\Omega^m(\Theta)$ denote the moments obtained from simulating the structural model at parameters Θ, we have:

$$\text{SUWNJ:} \quad \Omega^e \quad = [\hat{\pi}, \hat{\phi}, \hat{\kappa}_1, \hat{\kappa}_2, \hat{s}, \hat{o}, \hat{a}]' \tag{27}$$

$$\text{Model:} \quad \Omega^m(\Theta) = [\tilde{\pi}, \tilde{\phi}, \tilde{\kappa}_1, \tilde{\kappa}_2, \tilde{s}, \hat{o}, \tilde{a}]'. \tag{28}$$

The reduced-form parameters in Ω_1^e are taken directly from the estimates in Section 3, and thus the discussion of the treatment of the data elsewhere in the paper continues to apply. The sample averages in Ω_2^e are simply the predicted values from a linear regression model including as regressors an indicator for whether or not an individual was eligible for unemployment insurance benefits, an indicator for November 8, 2009 (the date when UI extensions came into effect in New Jersey) and the New Jersey unemployment rate, evaluated at the means of the explanatory variables. The sample is identical to the sample used elsewhere in the paper.

5.1.2 Implementation

Prior to estimation, I fix the weekly discount factor δ to 0.999 and the weekly separation rate ρ to 0.004 following Lentz (2009). I assume that the wage-offer distribution $\Phi(\omega)$ is lognormal with mean normalized to one. I then calibrate the variance ν to match the estimated standard deviation of log job values from Hall and Mueller (2018) of 0.38.

I assume that newly unemployed job seekers draw unobserved arrival rates λ^T from a Gamma distribution with arbitrary mean (to be estimated) and variance equal to the variance of job seekers' initial beliefs over arrival rates.[25] I directly estimate the bias in individuals' beliefs at the time of job loss, defined as the percentage difference between the *perceived* mean arrival rate (α_0/β_0) and the true population mean arrival rate ($E[\lambda^T]$):[26]

$$Bias \equiv \frac{\alpha_0/\beta_0 - E[\lambda^T]}{E[\lambda^T]}. \tag{29}$$

Structural parameters Θ are chosen to minimize the distance between the empirical auxiliary parameters Ω^e and the model-generated auxiliary parameters $\Omega^m(\Theta)$. Formally, the estimator is

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \left[\Omega^m(\Theta) - \Omega^e\right]' W \left[\Omega^m(\Theta) - \Omega^e\right], \tag{30}$$

where W is an identity weighting matrix.[27]

[25] Beliefs are thus restricted to be consistent with the underlying population distribution of arrival rates up to a bias term.

[26] Note that the true population mean arrival rate, $E[\lambda^T]$ can be backed out from estimates of α_0, β_0 and *Bias*.

[27] Use of alternative weighting matrices does not materially affect the results described below.

5.2 Results

Table 3 reports estimates of Θ. Standard errors are reported in parentheses. The model is well-identified by the seven moments described above. This is not surprising given the tight link between the structural model developed in Section 4 and the reduced-form results in Section 3, elucidated in Proposition 3.

Table 3: Parameter estimates

Parameter	Concept	Estimate (SE)
Beliefs		
α_0	Initial belief parameter (shape)	0.50 (0.01)
β_0	Initial belief parameter (rate)	4.17 (0.12)
$Bias$	$\frac{\alpha_0/\beta_0 - E[\lambda^T]}{E[\lambda^T]}$	-0.39 (0.01)
Physical		
η	Search cost	17.57 (1.71)
b	Flow value of unemployment	0.19 (0.06)

Standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey.

Notes: All auxiliary regressions use survey weights. The sample consists of respondents ages 20-65 who have not received a job offer, left their previous job involuntarily, and do not expect to return.

Perhaps most notably, the parameter estimates imply that beliefs are biased downward by roughly 40% relative to the true distribution of offer arrival rates in the economy. I discuss this point more below.

5.2.1 Discussion

Table 4 reports estimates of auxiliary parameters from the SUWNJ data and from the model simulated at the parameter values in Table 3. The moments in the "Data" column of Table 4 are not identical to the moments in Table 2 only because the former measures search time as the fraction of a day spent searching, whereas the latter measures search time in terms of minutes per day. The underlying data are identical. The model provides a good fit for the data, particularly in light of how parsimoniously it has been specified. It is notably successful in accounting for the data along the two dimensions emphasized in Section 3. In particular, the model-generated values of $\hat{\pi}$ (the measured effect of cumulative past search) and $\hat{\phi}$ (the measured effect of a job offer) are both quantitatively very close to their estimated values from the SUWNJ data. The model tends to underpredict the magnitude of the raw effect of duration on search effort ($\hat{\kappa_1}$), although, reassuringly, the sign remains negative. This likely also explains why the extent to which the effect of duration is attenuated by the presence of past search and job offers is also smaller than in the data. The model underpredicts average search effort fairly significantly, but does better in terms of the average arrival rate of offers ($\hat{o}$) and indeed does quite well in terms of the average acceptance rate offers ($\hat{a}$).

Table 4: Auxiliary Parameters/Moments

Aux. Parameter	Concept	Data	Model
Section 2			
$\hat{\pi}$	Coefficient on cumultive past search	-0.1052	-0.0986
$\hat{\phi}$	Coefficient on job offers	0.0227	0.0337
$\hat{\kappa}_1$	Duration coefficient (Baseline model, FE)	-0.0034	-0.0002
$\hat{\kappa}_2$	Duration coefficient (Augmented model, FD)	0.0026	-0.0000
Sample averages			
$\hat{s}$	Average search time (time diary)	0.0408	0.0115
$\hat{o}$	Average arrival rate	0.0202	0.0305
$\hat{a}$	Average acceptance rate	0.4828	0.4807

Standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey.

Notes: All auxiliary regressions use survey weights. The sample consists of respondents ages 20-65 who have not received a job offer, left their previous job involuntarily, and do not expect to return.

Perhaps the most interesting result in Table 3 is that the model implies individuals underestimate the arrival rate of offers by roughly 40%. This result could, at least in part, be driven by the fact that the data used in estimation are from a period of time after the economy had begun to recover from the recession (real GDP returned to growth in the fourth quarter of 2009), but during which the official (and well-publicized) unemployment rate reached 10% (October 2009). Then, to the extent that the unemployment rate is a lagging indicator of the state of the economy, it may not be too surprising that individuals' expectations about their prospects of finding work, as manifested through their search and acceptance decisions, reflect a somewhat undue degree of pessimism.

6 Conclusion

This paper articulates a theory of sequential job search informed by data from the Great Recession. The paper makes three substantive contributions: First, using high-frequency longitudinal data on individuals' search decisions, I show that falling search effort over the unemployment spell—as documented by Krueger and Mueller (2011)—is explained by variation in search effort since job loss. I provide evidence from data on job offers that this reflects job seekers learning about the stochastic process governing the arrival of job offers. Second, I develop a theory of sequential search to rationalize the empirical results. The theory is analytically tractable and sheds light on the mechanisms through which uncertainty and learning influence search decisions. Finally, I structurally estimate the model and show that learning quantitatively accounts for observed search behavior during the Great Recession.

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Appendices

A Data and Robustness

A.1 Sample selection

The Survey of Unemployed Workers in New Jersey (SUWNJ) was conducted by the Princeton University Survey Research Center starting in the fall of 2009 and lasting for up to 24 weeks. A stratified random sampling procedure was used to select participants from the universe of individuals receiving unemployment-insurance (UI) benefits in New Jersey as of September 28, 2009. The original data were stratified by unemployment-duration intervals interacted with the availability of an e-mail address, over-sampling the long-term unemployed and those with e-mail addresses on file. To account for the considerable nonresponse rates, sample weights were created from the underlying administrative records. Because these records contained comprehensive demographic information for the universe from which the sample was drawn, nonresponse weights could be created by comparing the demographic characteristics of respondents and the underlying population of UI-benefit recipients. For a comprehensive description of the survey methodology, the reader is referred to Krueger and Mueller (2011).

Empirical results throughout the paper correspond to a subset of the respondents from the SUWNJ. Unless otherwise noted, the sample includes all prime-age individuals (ages 25-54) who, at the time of the interview, (i) had not accepted a job offer, (ii) did not work for pay in the current week, and (iii) did not expect to be recalled or return to a previous job. The single exception to this is Table A.2, in which I use the sample considered by Krueger and Mueller (2011), who adopt a broader definition of prime age (20-65) and include individuals expecting to be recalled or to return to a previous job.

I likewise follow Krueger and Mueller (2011) in defining time spent on job search. In particular, I only include observations for which at least 14 out of 16 episodes from the time diary were completed and for which respondents indicated at least four different activities over the course of the day. When two activities are reported, each activity is assumed to take 30 minutes. Finally, I trim observations in which time spent on job search exceeds 80 hours per week, and in which time spent on a search method is missing. For further details on construction of search time variables in both papers, see p. 55 of Krueger and Mueller (2011).

A.2 Summary Statistics

Table A.1: Summary Statistics: Job Search

	Time Diary		Weekly Recall	
Duration (weeks)	Full Sample	Estimation Sample	Full Sample	Estimation Sample
1-10	65.12	80.18	111.21	127.48
11-20	56.12	70.73	95.88	123.71
21-30	67.87	77.06	116.57	133.42
31-40	67.60	78.20	119.25	136.17
41-50	70.43	78.02	121.34	140.48
51-60	70.23	86.06	120.17	142.51
61-70	72.12	83.51	118.82	134.99
71-80	67.02	75.08	118.89	131.37
81-90	50.13	57.65	100.12	119.13
91-100	41.80	50.71	85.98	109.95
101-110	30.13	39.22	70.48	93.76
111-120	20.85	66.00	42.79	46.71
Observations	36045	15731	36466	15916

Source: Survey of Unemployed Workers in New Jersey

Full Sample: All respondents.

Estimation Sample: Respondents ages 25-54 who have not yet accepted a job offer, are not currently employed, and who do not expect to be recalled by or return to their former employer.

A.3 Krueger and Mueller (2011): Fixed Effects (FE) and First Diff. (FD)

Table A.2: Job Search over the Unemployment Spell

	Time Diary		Weekly Recall	
	FE	FD	FE	FD
Duration	-3.310***	-3.568***	-2.637***	-2.912***
	(0.192)	(0.463)	(0.264)	(0.602)
Observations	25366	20537	25640	20486
Adjusted R^2	0.103	0.069	0.020	0.003

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

Notes: Regressions use survey weights. Standard errors are robust and clustered at the individual level. Following Krueger and Mueller (2011), the sample consists of respondents ages 20-65 who have not yet accepted a job offer and are not currently employed. Sample sizes are smaller in the first-differenced specification due to the necessity of dropping observations without an associated lag.

A.4 Serial correlation test

Table A.3 reports the tests for first- and second-order autocorrelation in the first-differenced residuals developed by Arellano and Bond (1991).[28] If the errors ϵ_{it} of Equation (1) in levels are serially uncorrelated we should expect to see no evidence of second-order autocorrelation in the differenced residuals.[29]

Table A.3: Tests for serial correlation

	Time Diary		Weekly Recall	
	Statistic	p-value	Statistic	p-value
Arellano-Bond test for AR(1)	$z = -7.21$	0.000	$z = -5.39$	0.000
Arellano-Bond test for AR(2)	$z = 0.49$	0.627	$z = -0.73$	0.4640

Source: Survey of Unemployed Workers in New Jersey.

H_0: No serial correlation.

The results in Table A.3 suggest that the disturbances ϵ_{it} are serially uncorrelated, and therefore that s_{it-2} is a valid instrument for s_{it-1}.

[28] The test was developed in the context of a GMM framework, but is nonetheless applicable to the simple 2SLS procedure used in the body of the paper.

[29] First-order autocorrelation in the first-differenced residuals results mechanically from the process of taking first differences.

A.5 Stock-Flow Matching

Table A.4: Job Search over the Unemployment Spell

	Time Diary		Weekly Recall	
	Baseline	Augmented	Baseline	Augmented
Duration (κ)	-5.297***	4.827***	-4.648***	6.040*
	(1.524)	(1.633)	(1.514)	(3.315)
Past Search (π)		-0.154***		-0.0908***
		(0.0290)		(0.0249)
Observations	5464	5464	5416	5416
Adjusted R^2	0.068	0.212	0.006	0.087

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

Notes: Regressions use survey weights. Standard errors are robust and clustered at the individual level. The sample consists of respondents ages 25-54 who have not yet accepted a job offer, are not currently employed, and who do not expect to be recalled by or return to their former employer. The smaple is furthermore restricted to individuals who have been unemployed for at least 4 weeks, as described in the body of the text.

A.6 Robustness

Table A.5: Krueger and Mueller (2011) sample

	Time Diary		Weekly Recall	
	Baseline	Augmented	Baseline	Augmented
Duration (κ)	-5.646***	3.791**	-5.330***	4.287**
	(1.180)	(1.715)	(0.952)	(1.956)
Past Search (π)		-0.138***		-0.0847***
		(0.0240)		(0.0187)
Observations	9542	9542	9387	9387
Adjusted R^2	0.064	0.196	0.004	0.080

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

Table A.6: Robustness: Duration trends

	Time Diary		Weekly Recall	
	Baseline	Augmented	Baseline	Augmented
Past Search (π)	-0.149***	-0.149***	-0.0918***	-0.0931***
	(0.0276)	(0.0278)	(0.0253)	(0.0254)
Duration (κ)	4.411**	5.670*	6.490**	0.276
	(1.845)	(2.902)	(3.185)	(3.989)
Log(Duration)	15.23		-26.94	
	(18.96)		(25.88)	
Duration^2		-0.0314		0.0652
		(0.0650)		(0.0883)
Duration^3		0.000293		0.0000145
		(0.000412)		(0.000563)
Observations	5497	5497	5445	5445
Adjusted R^2	0.207	0.207	0.087	0.089

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

Table A.7: Robustness: Intensive margin

	Time Diary		Weekly Recall	
	Baseline	Augmented	Baseline	Augmented
Duration (κ)	-5.143***	6.129	-3.986***	4.690***
	(1.302)	(4.693)	(0.935)	(1.728)
Past Search (π)		-0.0865**		-0.0559***
		(0.0379)		(0.0119)
Observations	2061	2061	4330	4330
Adjusted R^2	0.041	0.119	0.002	0.052

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

Table A.8: Robustness: Calendar time effects (HWOL data)

	Time Diary		Weekly Recall	
	Baseline	Augmented	Baseline	Augmented
Duration (κ)	-7.150***	3.385*	-6.916***	3.997
	(1.220)	(1.789)	(1.380)	(2.751)
Past Search (π)		-0.154***		-0.0908***
		(0.0268)		(0.0250)
Vacancies	-0.00212***	-0.00188***	-0.000880**	-0.000832**
	(0.000483)	(0.000470)	(0.000391)	(0.000367)
Observations	5497	5497	5445	5445
Adjusted R^2	0.073	0.217	0.006	0.087

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey and Conference Board Help Wanted OnLine

Notes: Regressions use survey weights. Standard errors are robust and clustered at the individual level. The sample consists of respondents ages 25-54 who have not yet accepted a job offer, are not currently employed, and who do not expect to be recalled by or return to their former employer.

A.7 GMM

There are two principal drawbacks to the 2SLS procedure used in the body of the text. First, it neglects the additional moment conditions implied by the exogeneity of s_{it-2}. Second, the process of first-differencing induces potential data loss due to missed interviews. I address both of these concerns using the GMM estimators for dynamic panels developed by Holtz-Eakin et al. (1988) and Arellano and Bond (1991).[30]

A.7.1 Differences

To exploit the additional available moment conditions, I estimate the model using the Difference GMM estimator developed by Arellano and Bond (1991). Table A.9 reports the results and Table A.10 reports the associated tests of instrument validity.

Table A.9: Robustness: Two-step GMM (Differences)

	Time Diary		Weekly Recall	
	Baseline	Augmented	Baseline	Augmented
Duration (κ)	-7.297***	-1.131	-3.836***	0.943
	(1.281)	(3.446)	(1.211)	(3.128)
Past Search (π)		-0.0808**		-0.0476**
		(0.0354)		(0.0206)
Observations	8752	6487	8728	6427

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

Table A.10: Tests of serial correlation and over-identifying restrictions (differences)

	Time Diary		Weekly Recall	
	Statistic	p-value	Statistic	p-value
Arellano-Bond test for AR(1)	$z = -8.66$	0.000	$z = -6.97$	0.000
Arellano-Bond test for AR(2)	$z = -0.38$	0.706	$z = -0.94$	0.346
Sargan test of over-ID restrictions	$\chi^2_8 = 94.67$	0.000	$\chi^2_8 = 48.20$	0.000
Hansen test of over-ID restrictions	$\chi^2_8 = 18.12$	0.020	$\chi^2_8 = 18.07$	0.021

Source: Survey of Unemployed Workers in New Jersey.

H_0 (AB): No serial correlation; H_0 (Sargan/Hansen): Instruments are jointly exogenous.

[30]Specifically, I focus on Difference GMM and Orthogonal Deviations GMM. A System GMM approach is ruled out because for most individuals, the stock variable of interest is itself partially unobserved.

A.7.2 Orthogonal deviations

To circumvent the potential data loss associated with differencing, I also estimate a version of the model in which individual effects are purged by taking forward-orthogonal deviations.[31] Table A.11 reports the results, and Table A.12 reports the associated tests of instrument validity.

Table A.11: Robustness: Two-step GMM (Orthog. deviations)

	Time Diary		Weekly Recall	
	Baseline	Augmented	Baseline	Augmented
Duration (κ)	-5.971***	0.235	-4.495***	-0.332
	(0.425)	(1.025)	(0.524)	(1.327)
Past Search (π)		-0.0971***		-0.0428***
		(0.0163)		(0.0132)
Observations	13078	9366	13186	9371

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

Table A.12: Tests of serial correlation and over-identifying restrictions (orthogonal deviations)

	Time Diary		Weekly Recall	
	Statistic	p-value	Statistic	p-value
Arellano-Bond test for AR(1)	$z = -9.28$	0.000	$z = -7.23$	0.000
Arellano-Bond test for AR(2)	$z = -0.30$	0.761	$z = -1.23$	0.220
Sargan test of over-ID restrictions	$\chi^2_8 = 115.07$	0.000	$\chi^2_8 = 67.06$	0.000
Hansen test of over-ID restrictions	$\chi^2_8 = 15.30$	0.053	$\chi^2_8 = 21.80$	0.005

Source: Survey of Unemployed Workers in New Jersey.

H_0 (AB): No serial correlation; H_0 (Sargan/Hansen): Instruments are jointly exogenous.

A.7.3 Discussion

The results above correspond to the two-step estimators with Windmeijer (2005)-corrected standard errors. To avoid instrument proliferation, which can overfit the model and weaken the Hansen test, I restrict attention to a "collapsed" instrument matrix.

Focusing first on parameter estimates in Tables A.9 and A.11, for both differencing and orthogonal deviations, the estimated coefficients on cumulative past search are highly significant and negative. Furthermore, in both cases, the coefficient on duration is attenuated dramatically

[31] The forward-orthogonal deviation of y_{it} is defined as $y^{\perp}_{it+1} \equiv c_{it}\left[y_{it} - \frac{1}{T_{it}}\sum_{s>t} y_{is}\right]$ where $c_{it} \equiv \sqrt{T_{it}/(T_{it}+1)}$.

by the presence of cumulative past search and becomes insignificant, consistent with the results in the body of the text and the claim that cumulative past search accounts for much of the decline in search over the unemployment spell.

Turning next to the tests of serial correlation and over-identifying restrictions in Tables A.10 and A.12, there is no significant evidence of serial correlation in the differenced errors. This suggests that the second lag and beyond of the dependent variable are valid instruments. The Hansen and Sargan tests, however, reject the null of joint validity for both measures of search time. While there is clearly some disrepancy in these results, Arellano and Bond (1991) use simulated panel data from an AR(1) model to demonstrate that their test for serial correlation has greater power than Hansen-Sargan tests to detect invalidity of lagged instruments due to serial correlation. Thus, to the extent that their analysis is applicable here, there is at least some reason to prefer the Arellano-Bond test of second-order serial correlation when assessing the validity of the instruments.

B Model Solution and Proofs

Appendix B presents a generalized version of the model described in Section 4. The model presented here allows for: (i) separations at the beginning of each period of employment, and (ii) a baseline arrival rate of job offers that is independent of the amount of time devoted to job search. The model in Section 4 is nested through two parameters.

B.1 Separations and the arrival of offers

I introduce separations by assuming that employed agents separate from their jobs at rate ρ at the beginning of each period of employment. Job seekers separated at the beginning of period t immediately enter the unemployment pool and choose search effort s_t. Beliefs are conditioned from the previous spell of unemployment. The timing of the model is otherwise identical to that described in Section 4.

I also introduce an exogenously fixed component of the arrival rate of offers that is independent of time devoted to job search. To do this, I express the offer-arrival probability as:

$$Pr(\tilde{\tau}_t \leq s_t + \xi) \equiv F(s_t + \xi; \lambda^T) = 1 - e^{-\lambda^T (s_t + \xi)}. \tag{B.1}$$

ξ enters the job-finding probability as a perfect substitute for search time. Accordingly, it can be thought of as the fixed time spent outside the home each week on non-search activities, during which time individuals may encounter job offers despite not actively searching.

The model described in the body of the text is nested by setting $\rho = \xi = 0$.

B.2 Posterior distribution of beliefs

This section demonstrates that the Gamma distribution is the conjugate prior for the right-censored exponential distribution, and derives the laws of motion for the parameters of the belief distribution with Bayesian updating. Consider an individual who has been unemployed for n weeks. For each week $t = 1, ..., n$ of the unemployment spell, the individual allocates s_t units of time for job search. Define $K \equiv \{t : \tau_t \leq s_t + \xi\}$ as the set of weeks in which an offer (below the reservation wage) arrives before search ends, $n^s \equiv \#K$ and $n^f \equiv n - n^s$. For weeks $t \in K$, individuals observe the exact arrival time $\tau_t \leq s_t + \xi$. For the remaining weeks $t \notin K$, individuals only observe that $\tau_t > s_t + \xi$.

Because offers arrive according to a Poisson process with unobserved rate parameter λ, arrival times are distributed according to a right-censored exponential distribution with distribution function F and density f. The corresponding likelihood function for λ is thus given by

$$\mathscr{L}(\lambda) = \mathscr{L}\left(\lambda | \{\tau_t\}_{t\in K}; \{s_t\}_{t\notin K}\right) \tag{B.2}$$

$$= \prod_{t\in K} f(\tau_t|\lambda) \prod_{t\notin K} \left(1 - F(s_t + \xi|\lambda)\right) \tag{B.3}$$

$$= \prod_{t\in K} \lambda e^{-\lambda\tau_t} \prod_{t\notin K} e^{-\lambda(s_t+\xi)} \tag{B.4}$$

$$= \lambda^{n^s} e^{-\lambda\left(\sum_{t\in K}\tau_t + \sum_{t\notin K}(s_t+\xi)\right)} \tag{B.5}$$

$$= \lambda^{n^s} e^{-\lambda(n^s\bar{\tau} + n^f(\bar{s}+\xi))} \tag{B.6}$$

where $\bar{\tau} \equiv \frac{1}{n^s}\sum_{t\in K}\tau_t$ and $\bar{s} \equiv \frac{1}{n^f}\sum_{t\notin K} s_t$.

Suppose now that prior beliefs over λ follow a Gamma distribution with hyperparameters α_0 and β_0, distribution function $G(\lambda|\alpha_0, \beta_0)$, and density $g(\lambda|\alpha_0, \beta_0)$. Applying Bayes' rule and using the expression for the likelihood function above, the posterior distribution of beliefs over λ is given by

$$p(\lambda) = \frac{\mathscr{L}(\lambda)g(\lambda|\alpha_0,\beta_0)}{\int \mathscr{L}(\lambda')g(\lambda'|\alpha_0,\beta_0)d\lambda'} \tag{B.7}$$

$$= \frac{\lambda^{n^s} e^{-\lambda(n^s\bar{\tau}+n^f(\bar{s}+\xi))}\beta_0^{\alpha_0}\lambda^{\alpha_0-1}e^{-\lambda\beta_0}/\Gamma(\alpha_0)}{\int (\lambda')^{n^s} e^{-\lambda'(n^s\bar{\tau}+n^f(\bar{s}+\xi))}\beta_0^{\alpha_0}(\lambda')^{\alpha_0-1}e^{-\lambda'\beta_0}/\Gamma(\alpha_0)d\lambda'} \tag{B.8}$$

$$= \frac{e^{-\lambda(\beta_0+n^s\bar{\tau}+n^f(\bar{s}+\xi))}\lambda^{\alpha_0+n^s-1}}{\int e^{-\lambda'(\beta_0+n^s\bar{\tau}+n^f(\bar{s}+\xi))}(\lambda')^{\alpha_0+n^s-1}d\lambda'} \tag{B.9}$$

$$= \frac{e^{-\lambda(\beta_0+n^s\bar{\tau}+n^f(\bar{s}+\xi))}\lambda^{\alpha_0+n^s-1}(\beta_0+n^s\bar{\tau}+n^f(\bar{s}+\xi))^{\alpha_0+n^s}}{\int e^{-\lambda'(\beta_0+n^s\bar{\tau}+n^f(\bar{s}+\xi))}(\lambda')^{\alpha_0+n^s-1}d\lambda'(\beta_0+n^s\bar{\tau}+n^f(\bar{s}+\xi))^{\alpha_0+n^s}} \tag{B.10}$$

Defining $x^{'} \equiv \lambda^{'}(\beta_0 + n^s\bar{\tau} + n^f(\bar{s}+\xi))$, we can rewrite the denominator of (B.10) in terms of $x^{'}$ as follows

$$\begin{aligned}
&\int e^{-x^{'}} \left(\frac{x^{'}}{\beta_0 + n^s\bar{\tau} + n^f(\bar{s}+\xi)}\right)^{\alpha_0+n^s-1} dx^{'}(\beta_0 + n^s\bar{\tau} + n^f(\bar{s}+\xi))^{\alpha_0+n^s-1} && \text{(B.11)}\\
&= \int e^{-x^{'}} \left(x^{'}\right)^{\alpha_0+n^s-1} dx^{'} && \text{(B.12)}\\
&= \Gamma(\alpha_0 + n^s). && \text{(B.13)}
\end{aligned}$$

Substituting (B.13) into (B.10) and defining $\alpha \equiv \alpha_0 + n^s$ and $\beta \equiv \beta_0 + n^s\bar{\tau} + n^f(\bar{s}+\xi)$, (B.10) reduces to

$$\begin{aligned}
p(\lambda) &= \frac{\lambda^{\alpha-1}e^{-\lambda\beta}\beta^{\alpha}}{\Gamma(\alpha)} && \text{(B.14)}\\
&= g(\lambda|\alpha,\beta). && \text{(B.15)}
\end{aligned}$$

Thus, as claimed in the text, the Gamma distribution with prior hyperparameters α_0 and β_0 is the conjugate prior for the right-censored exponential distribution. Moreover, the posterior hyperparameters α and β, which govern the evolution of beliefs in the model, are defined recursively as

$$\begin{aligned}
\alpha &= \alpha_0 + n^s && \text{(B.16)}\\
\beta &= \beta_0 + \sum_{t\in K}\tau_t + \sum_{t\notin K}(s_t+\xi). && \text{(B.17)}
\end{aligned}$$

Intuitively, the posterior hyperparameters net of their initial values measure the total number of job offers received and the total past time spent looking for work, respectively.

B.3 Model solution

This section solves the model and derives equations (18) and (19) in Section 4 for the general case in which $\rho \in [0,1]$ and $\xi \geq 0$.

Define $\tilde{s}_t \equiv s_t + \xi$. $\tilde{s}_t \in [\xi, 1+\xi]$. The value of entering week t unemployed with beliefs characterized by α_t and β_t may be written recursively as

$$\begin{aligned}
V_t^U(\alpha_t,\beta_t) = \max_{\tilde{s}_t}\Bigg\{ E_t^{\lambda}\Bigg[& F(\tilde{s}_t;\lambda)E_t^{\omega}\left[V_t^O(\omega,\alpha_t,\beta_t)\right]\\
& + (1-F(\tilde{s}_t;\lambda))[b+\delta V_{t+1}^U(\alpha_t,\beta_t)]\Bigg] - \eta\tilde{s}_t\Bigg\} && \text{(B.18)}
\end{aligned}$$

where $V_t^O(\omega, \cdot)$ denotes the value of having offer ω in hand and may be written as

$$V_t^O(\omega, \alpha_t, \beta_t) = \max\left\{\omega + \delta V_{t+1}^E(\omega, \alpha_t, \beta_t), b + \delta V_{t+1}^U(\alpha_t, \beta_t)\right\}. \tag{B.19}$$

The value of entering period $t+1$ employed at wage ω is given by

$$V_{t+1}^E(\omega, \alpha_t, \beta_t) = (1-\rho)\big[\omega + \delta V_{t+2}^E(\omega, \alpha_t, \beta_t)\big] + \rho V_{t+1}^U(\alpha_t, \beta_t). \tag{B.20}$$

Assuming that the wage rate during employment is expected to be constant and that no offers arrive during employment, $V^E(\cdot)$ is time-invariant, which implies that (B.19) and (B.20) reduce to

$$\begin{aligned} V_t^O(\omega, \alpha_t, \beta_t) = \max\Bigg\{&\omega + \frac{\delta}{1-\delta(1-\rho)}\Big[(1-\rho)\omega + \rho V_{t+1}^U(\alpha_t, \beta_t)\Big], \\ &b + \delta V_t^U(\alpha_t, \beta_t)\Bigg\}. \end{aligned} \tag{B.21}$$

The optimal choice between accepting and rejecting the offer is characterized by a standard reservation-wage policy:

$$V_t^O(\omega, \alpha_t, \beta_t) = \begin{cases} \omega + \dfrac{\delta}{1-\delta(1-\rho)}\Big[(1-\rho)\omega + \rho V_{t+1}^U(\alpha_t, \beta_t)\Big] & \text{if } \ \omega > \underline{w}_t \\ b + \delta V_{t+1}^U(\alpha_t, \beta_t) & \text{if } \ \omega \leq \underline{w}_t \end{cases} \tag{B.22}$$

where

$$\underline{w}_t = (1-\delta(1-\rho))b + (1-\delta)(1-\rho)\delta V_{t+1}^U(\alpha_t, \beta_t). \tag{B.23}$$

Next, observe that (B.18) may be written as

$$\begin{aligned} V_t^U(\alpha_t, \beta_t) = \max_{\tilde{s}_t}\Bigg\{&\int_0^\infty \Bigg[F(\tilde{s}_t; \lambda) E_t^\omega\left[V_t^O(\omega, \alpha_t, \beta_t)\right] \\ &+ (1 - F(\tilde{s}_t; \lambda))[b + \delta V_{t+1}^U(\alpha_t, \beta_t)]\Bigg]\gamma(\lambda; \alpha_t, \beta_t)d\lambda - \eta\tilde{s}_t\Bigg\}. \end{aligned} \tag{B.24}$$

The first-order condition for the choice of $\tilde{s}_t$ is given by

$$\eta = \int_0^\infty f(\tilde{s}_t; \lambda)\left[\frac{1}{1-\delta(1-\rho)}\int_{\underline{w}_t}^B (\omega - \underline{w}_t)\phi(\omega)d\omega\right]\gamma(\lambda; \alpha_t, \beta_t)d\lambda. \tag{B.25}$$

The model is tractable because the mixture of an Exponential distribution (according to which offer arrival times are distributed) and a Gamma distribution (according to which beliefs are distributed) is a Pareto distribution. In particular, we can write the *perceived* density and distribution functions for arrival times as

$$\int_0^\infty f(\tilde{s}_t;\lambda)\gamma(\lambda;\alpha_t,\beta_t)d\lambda = \frac{\alpha_t\beta_t^{\alpha_t}}{(\beta_t+\tilde{s}_t)^{\alpha_t+1}} \tag{B.26}$$

$$\int_0^\infty F(\tilde{s}_t;\lambda)\gamma(\lambda;\alpha_t,\beta_t)d\lambda = 1-\left(\frac{\beta_t}{\beta_t+\tilde{s}_t}\right)^{\alpha_t}. \tag{B.27}$$

These identities will be useful throughout the remainder of the derivation. Making use of (B.26), we see immediately that the first-order condition for $\tilde{s}_t$ reduces to

$$\eta = \frac{\alpha_t\beta_t^{\alpha_t}}{(\beta_t+\tilde{s}_t)^{\alpha_t+1}}\left[\frac{1}{1-\delta(1-\rho)}\int_{\underline{w}_t}^{B}(\omega-\underline{w}_t)\phi(\omega)d\omega\right]. \tag{B.28}$$

Rearranging and solving explicitly for $\tilde{s}_t$, we obtain (18) in the text:

$$\tilde{s}_t = \beta_t\left[\left(\frac{1}{\eta(1-\delta(1-\rho))}\int_{\underline{w}_t}^{B}(\omega-\underline{w}_t)\phi(\omega)d\omega\left(\frac{\alpha_t}{\beta_t}\right)\right)^{\frac{1}{\alpha_t+1}}-1\right]. \tag{B.29}$$

Next, using (B.27), the value of beginning the period unemployed can be written more concisely as

$$\begin{aligned} V_t^U(\alpha_t,\beta_t) = \max_{\tilde{s}_t}\Bigg\{&\left(1-\left(\frac{\beta_t}{\beta_t+\tilde{s}_t}\right)^{\alpha_t}\right)E_t^\omega\left[V_t^O(\omega,\alpha_t,\beta_t)\right] \\ &+\left(\frac{\beta_t}{\beta_t+\tilde{s}_t}\right)^{\alpha_t}\left[b+\delta V_{t+1}^U(\alpha_t,\beta_t)\right]-\eta\tilde{s}_t\Bigg\}. \end{aligned} \tag{B.30}$$

Rearranging, we obtain a more convenient form,

$$\begin{aligned} V_t^U(\alpha_t,\beta_t) = \max_{\tilde{s}_t}\Bigg\{&\left(1-\left(\frac{\beta_t}{\beta_t+\tilde{s}_t}\right)^{\alpha_t}\right)\left[E_t^\omega\left[V_t^O(\omega,\alpha_t,\beta_t)\right]-b-\delta V_{t+1}^U(\alpha_t,\beta_t)\right] \\ &+b+\delta V_{t+1}^U(\alpha_t,\beta_t)-\eta\tilde{s}_t\Bigg\}. \end{aligned} \tag{B.31}$$

The term in square brackets represents the expected value of the wage offer in (B.30) conditional on optimal reservation-wage behavior net of the option value of unemployment, which reduces to

$$E_t^\omega\left[V_t^O(\omega,\alpha_t,\beta_t)\right]-b-\delta V_{t+1}^U(\alpha_t,\beta_t) = \frac{1}{1-\delta(1-\rho)}\int_{\underline{w}_t}^{\infty}(\omega-\underline{w}_t)\phi(\omega)d\omega. \tag{B.32}$$

Combining (B.31) and (B.32) we obtain

$$V_t^U(\alpha_t,\beta_t) = \max_{\tilde{s}_t}\Bigg\{\left(1-\left(\frac{\beta_t}{\beta_t+\tilde{s}_t}\right)^{\alpha_t}\right)\left[\frac{1}{1-\delta(1-\rho)}\int_{\underline{w}_t}^{\infty}(\omega-\underline{w}_t)\phi(\omega)d\omega\right] + b + \delta V_{t+1}^U(\alpha_t,\beta_t) - \eta\tilde{s}_t\Bigg\}. \tag{B.33}$$

Observe that in (B.33), so long as the period $t+1$ value function is evaluated at α_t and β_t instead of α_{t+1} and β_{t+1} (i.e., so long as we impose anticipated utility), and assuming that there are no other non-stationarities in the model, the period t and $t+1$ value functions are identical. Therefore, we can solve explicitly for the value functions for use in (B.23). Solving (B.33) for the value function yields

$$V_t^U(\alpha_t,\beta_t) = \max_{\tilde{s}_t}\Bigg\{\frac{1}{1-\delta}\Bigg[\left(1-\left(\frac{\beta_t}{\beta_t+\tilde{s}_t}\right)^{\alpha_t}\right)\left[\frac{1}{1-\delta(1-\rho)}\int_{\underline{w}_t}^{\infty}(\omega-\underline{w}_t)\phi(\omega)d\omega\right] + b - \eta\tilde{s}_t\Bigg]\Bigg\}. \tag{B.34}$$

Substituting (B.34) into (B.23) and rearranging yields (19) from the text:

$$\underline{w}_t = b + \left[1-\left(\frac{\beta_t}{\beta_t+\tilde{s}_t}\right)^{\alpha_t}\right]\left(\frac{\delta(1-\rho)}{1-\delta(1-\rho)}\int_{\underline{w}_t}^{B}(\omega-\underline{w}_t)\phi(\omega)d\omega\right) - \delta(1-\rho)\eta\tilde{s}_t. \tag{B.35}$$

Together, (18) and (19) characterize the optimal values of $\tilde{s}_t$ and $\underline{w}_t$, and thus model dynamics.

B.4 Proof of Proposition 1

Proof. Using (B.29) to eliminate references to $\tilde{s}_t$ from (B.35), and applying the implicit function theorem,

$$\frac{\partial \underline{w}_t}{\partial \beta_t} = \frac{\delta(1-\rho)\eta - z\alpha_t\left(\beta_t^{-1}\int_{\underline{w}_t}^{B}(\omega-\underline{w}_t)\phi(\omega)d\omega\right)^{\frac{1}{\alpha_t+1}}}{1+(1-\phi(\underline{w}_t))\left(\frac{\delta(1-\rho)}{1-\delta(1-\rho)} - z\left(\beta_t\left[\int_{\underline{w}_t}^{B}(\omega-\underline{w}_t)\phi(\omega)d\omega\right]^{-1}\right)^{\frac{\alpha_t}{\alpha_t+1}}\right)} \tag{B.36}$$

where

$$z \equiv \frac{\delta(1-\rho)\eta}{(\eta(1-\delta(1-\rho)))^{\frac{1}{\alpha_t+1}}}\alpha_t^{-\frac{\alpha_t}{\alpha_t+1}}. \tag{B.37}$$

Making use of the optimality conditions for $\tilde{s}_t$ and $\underline{w}_t$, (B.36) reduces to

$$\frac{\partial \underline{w}_t}{\partial \beta_t} = -\left[\frac{\delta(1-\rho)\eta\left(\frac{\tilde{s}_t}{\beta_t}\right)}{1+(1-\Phi(\underline{w}_t))\left(\frac{\delta(1-\rho)}{1-\delta(1-\rho)}\right)\left[1-\left(\frac{\beta_t}{\beta_t+\tilde{s}_t}\right)^{\alpha_t}\right]}\right] < 0. \tag{B.38}$$

□

B.5 Proof of Proposition 2

Proof. The result follows immediately from (20). □

B.6 Proof of Proposition 3

Proof. Assume that (i) the wage offer distribution is degenerate at w, and (ii) $\alpha_0 = 1$. I begin by solving the model and deriving an analytical expression for time devoted to job search in terms of structural parameters and β_t.

Using (B.26) and (B.27) and observing that job seekers will accept all job offers when the wage distribution is degenerate (provided the wage is sufficiently high to warrant search), the value of entering a period unemployed is given by

$$\begin{aligned} V_t^U(\alpha_t, \beta_t) = \max_{\tilde{s}_t} \Bigg\{ & \left(1-\left(\frac{\beta_t}{\beta_t+\tilde{s}_t}\right)^{\alpha_t}\right)\frac{w}{1-\delta(1-\rho)} \\ & + \left(\frac{\beta_t}{\beta_t+\tilde{s}_t}\right)^{\alpha_t}\left(b+\delta V_{t+1}^U(\alpha_t,\beta_t)\right) - \eta\tilde{s}_t\Bigg\}. \end{aligned} \tag{B.39}$$

The associated first-order condition for search time is then

$$\eta = \frac{\alpha_t \beta_t^{\alpha_t}}{(\beta_t+\tilde{s}_t)^{\alpha_t+1}}\left[\frac{w}{1-\delta(1-\rho)} - b - \delta V_{t+1}^U(\alpha_t,\beta_t)\right]. \tag{B.40}$$

Together, these equations may be rearranged to write the first-order condition as

$$\tilde{s}_t = \left[\frac{\alpha_t \beta_t^{\alpha_t}}{\eta}\left(w - b + \delta(1-\rho)\eta\left(\frac{\beta_t}{\alpha_t} + \left(\frac{\alpha_t - 1}{\alpha_t}\right)\tilde{s}_t\right)\right)\right]^{\frac{1}{\alpha_t+1}} - \beta_t. \tag{B.41}$$

A few observations are warranted. First, when the offer distribution is degenerate, it must be that $\alpha_t = \alpha_0 = 1\ \forall t$, simply because all offers are accepted. Second, $\beta_t \equiv \beta_0 + \sum_{\tau=0}^{t-1} \tilde{s}_\tau$ for $t \geq 1$. As before, this follows from the fact that the first offer that arrives before search expires is accepted; search is never terminated prematurely by an offer that is subsequently rejected.

Imposing $\alpha_t = \alpha_0 = 1$, the first-order condition reduces to

$$\tilde{s}_t = \left[\frac{\beta_t}{\eta}\left(w - b + \delta(1-\rho)\eta\beta_t\right)\right]^{\frac{1}{2}} - \beta_t. \tag{B.42}$$

Taking a first-order expansion around $\beta_t = \beta_0$ yields

$$\tilde{s}_t \approx \left[\frac{\beta_0}{\eta}\left(w - b + \delta(1-\rho)\eta\beta_0\right)\right]^{\frac{1}{2}} - \beta_0 + (\beta_t - \beta_0)\frac{d\tilde{s}_t}{d\beta_t}|_{\beta_t=\beta_0}. \tag{B.43}$$

Recalling that $\beta_t - \beta_0 = \sum_{\tau=0}^{t-1} \tilde{s}_\tau = \sum_{\tau=0}^{t-1} s_\tau + \xi t$, we can write

$$s_t \approx \iota + \pi\xi t + \pi \sum_{\tau=0}^{t-1} s_\tau \tag{B.44}$$

where

$$\iota = \left[\frac{\beta_0}{\eta}\left(w - b + \delta(1-\rho)\eta\beta_0\right)\right]^{\frac{1}{2}} - \beta_0 - \xi \tag{B.45}$$

$$\pi = \frac{ds_t}{d\beta_t}|_{\beta_t=\beta_0} = \frac{1}{2}\left[\beta_0\left(\frac{w-c}{\eta}\right) + \delta(1-\rho)\beta_0^2\right]^{-\frac{1}{2}}\left[\frac{w-c}{\eta} + 2\delta(1-\rho)\beta_0\right] - 1 \tag{B.46}$$

corresponding to the reduced-form parameters in Section 3. Note that $\pi < 0$, as in Section 3, when

$$\frac{1}{2}\left[\beta_0\left(\frac{w-c}{\eta}\right) + \delta(1-\rho)\beta_0^2\right]^{-\frac{1}{2}}\left[\frac{w-c}{\eta} + 2\delta(1-\rho)\beta_0\right] < 1. \tag{B.47}$$

The left-hand side is quadratic in β_0, and so the condition reduces to

$$\beta_0 > \underline{\beta}_0 \equiv \left(\frac{w-c}{2\delta(1-\rho)\eta}\right)\left[\left(\frac{1}{1-\delta(1-\rho)}\right)^{\frac{1}{2}} - 1\right]. \tag{B.48}$$

Setting $\rho = \xi = 0$ yields the expression in Proposition 3. □

C Estimation Details

C.1 Numerical solution and simulation

The model described in Appendix B cannot be solved analytically for the reservation wage. I therefore numerically compute the reservation wage on a 10-by-40 grid of values for α_t and β_t. The initial grid points are chosen as α_0 and β_0, respectively. I compute the policy functions as linear interpolations in β_t for each of the 10 possible values of α_t. The policy functions for search time may then be computed analytically from the reservation-wage policies.

To simulate the model, it is necessary to generate two shock matrices. The first is a 500,000-by-100 matrix of exponential offer-arrival times. The second is a 500,000-by-100 matrix of lognormal wage draws. Because I estimate parameters that govern both of these processes (λ^T and ν, respectively) and I need to hold constant the underlying stochastic process in the course of estimation, I cannot directly generate matrices of exponential and lognormal shocks for each iteration of the estimation procedure. Instead, prior to estimation, I generate three 500,000-by-100 matrices of uniformly distributed shocks. These are held fixed throughout the course of estimation. For each value of λ^T considered by the minimization routine, I compute the associated exponential arrival-time shocks by way of an inverse transform sampling procedure using the first matrix of uniform shocks. For each value of ν considered by the minimization routine, I compute the lognormal wage shocks by way of a standard Box-Muller transform of the two remaining matrices of uniform shocks. This ensures that the surface of the objective function is stable across iterations, but dependent on λ^T and ν. I simulate 500,000 individuals each for up to 100 weeks of unemployment. Job seekers who accept offers are dropped from the sample, as in the SUWNJ. The sample is sufficiently large to permit replication of the cohort structure of the SUWNJ.

Remaining details of the estimation methodology are discussed in Section 5.