Learning and Job Search Dynamics during the Great Recession*

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Abstract
I document two new facts about job search during the Great Recession: (i) search increased after individuals received (and rejected) job offers; and (ii) search decreased with cumulative failed search. To account for these facts I develop a model of sequential search in which Bayesian job seekers learn about the arrival rate of offers through their experiences looking for work. Endogenously-evolving beliefs interact with the intensive margin of search, giving rise to non-monotonic search dynamics over the spell of unemployment. I decompose the effect of failures to find work into competing income and substitution effects corresponding to rigorous notions of motivation and discouragement and demonstrate that the model endogenously generates negative duration dependence in unemployment exit rates. I structurally estimate the model and show that the mechanism simultaneously accounts for the empirical profiles of search time, offer arrival probabilities and offer acceptance probabilities over the first two years of unemployment.

Keywords: unemployment; search theory
JEL Classification: J64, E24, D83

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1 Introduction

Do job seekers learn about their job-finding prospects from their experiences searching for work? If so, how do evolving beliefs affect subsequent search decisions? And to what extent can learning account for observed search dynamics during the Great Recession? This paper seeks to answer these questions. I begin by documenting two new facts about job search during the Great Recession: (i) search increased after individuals received (and rejected) job offers; and (ii) search decreased with cumulative failed search. I account for these facts by developing a model of job search in which job seekers learn about their job-finding prospects through their experiences looking for work. I structurally estimate the model and show that the mechanism simultaneously accounts for the empirical profiles of search time, offer arrival probabilities and offer acceptance probabilities over the first two years of unemployment.

The paper begins by revisiting the results of [Krueger and Mueller (2011)], who use weekly longitudinal data from the Survey of Unemployed Workers in New Jersey (SUWNJ) to show that time devoted to job search fell sharply over the unemployment spell during the Great Recession. I first show that job offers, even when rejected, significantly attenuate the decline in search over the unemployment spell. I then show that cumulative past search—the total amount of time an individual has spent searching for work since job loss—exerts a significant negative influence on subsequent search decisions. Indeed, when an individual’s cumulative past search is included on the right-hand side of [Krueger and Mueller’s] estimating equation, unemployment duration ceases to be a significant determinant of job search. The coefficient on cumulative past search, by contrast, is highly significant and negative across specifications.

These empirical results are important for several reasons. First, the autoregressive nature of search implied by the regression analysis suggests that, at least during the Great Recession, there was an intrinsic tendency for search to decline, independent of exogenous changes in the environment. Second, the fact that cumulative past search is highly significant, and supplants the time trend in the model, suggests that standard narratives of human capital depreciation, employer screening, or ranking—each of which implies that search should vary explicitly with time since job loss—are of limited relevance for understanding individuals’ search decisions. Finally, the results suggest that, contrary to standard search theory, job seekers learn from their experiences searching for work.

Motivated by this evidence, I develop a theory of search in which job seekers learn from experience and search decisions interact dynamically with beliefs about the job-finding process. I implement this through two simple modifications to a standard McCall (1970)-style model of sequential search: (i) at the beginning of each period, job seekers choose how much time to spend looking for work; and (ii) job seekers are Bayesian, and endowed with an endogenous distribution of beliefs over the mean arrival rate of offers per unit of time spent searching. Search dynamics during unemployment are thus driven by the dynamic interaction between search decisions and the endogenous evolution of beliefs: beliefs respond rationally to cumulative past time spent searching and the arrival of job offers, while search decisions are driven by dynamically evolving beliefs.
The model is the first to tractably integrate uncertainty about the offer arrival rate and learning into a fully dynamic framework suitable for studying the intensive margin of job search over the spell of unemployment. Such tractability enables characterization of time devoted to job search and the reservation wage at any duration of unemployment in terms of cumulative past search, the stock of job offers received, and model primitives. I demonstrate that changing beliefs drive search through the competing effects of motivation—which operates as an income effect—and discouragement—which operates as a substitution effect. Because the relative strength of these effects varies endogenously as unemployment progresses, the model is capable of generating non-monotonic search dynamics over the spell of unemployment. I provide conditions under which (i) the effects of discouragement dominate search dynamics and induce monotonically-declining search; and (ii) the model generates endogenous negative duration dependence in unemployment exit rates. I show that the structural model admits a reduced-form representation consistent with the regression framework used to motivate the model, and provide a structural interpretation of the reduced-form parameter estimates.

Finally, I return to the data and structurally estimate the parameters of the model via Indirect Inference. I identify key structural parameters—including those governing beliefs at the time of job loss—using the empirical profiles of search time, job-finding probabilities and job-acceptance probabilities over the first two years of the unemployment spell from the SUWNJ data. The estimated model provides a strong fit for all three data series throughout the first two years of unemployment. Under the estimated model, I find that job seekers overestimate their job-finding prospects by roughly 40% at the time of job loss. I also estimate a flexibly-parameterized alternative model which allows for dynamic selection on heterogeneous search costs, a cubic trend in the offer arrival rate, and a cubic trend in the mean of the wage offer distribution—but no learning. I show that the parsimonious model with learning outperforms the more-flexible alternative.

Interestingly, the estimated model affords new insight into search dynamics prior to the Great Recession as well. To demonstrate this, I fix the standard search-theoretic parameters to their estimated values, and recalibrate the parameters governing beliefs at the time of job loss to match aggregate job-finding data from prior to the Great Recession. Under the pre-Great Recession calibration, the simulated model implies hump-shaped search dynamics over the first two years of unemployment which are qualitatively similar to those documented by Shimer (2004) and Mukoyama et al. (2014) using CPS data.

The remainder of this paper is organized as follows. Section 2 documents two new facts about job search dynamics during the Great Recession. Section 3 develops the theoretical model and characterizes search time and the reservation wage. Section 4 structurally estimates the model. Section 5 concludes.
2 Two Facts about Job Search

During the Great Recession, the amount of time individuals devoted to job search fell sharply over the unemployment spell. Figure 1 depicts this decline. In this section, I document two new facts about job search during the Great Recession: (i) the average decline depicted in Figure 1 is significantly attenuated in periods after a job offer was received; and (ii) the decline disappears after accounting for variation in individuals’ cumulative past search.

Figure 1: Time spent on job search during the Great Recession

2.1 Survey description

The Survey of Unemployed Workers in New Jersey (SUWNJ) is a weekly longitudinal survey of unemployment insurance (UI) benefit recipients in New Jersey. The study was conducted by the Princeton University Survey Research Center starting in the fall of 2009 and lasting for up to 24 weeks. Sampled individuals were asked to participate in a weekly online survey lasting for a minimum of 12 weeks, and up to 24 weeks for the long-term unemployed. The weekly survey consisted of questions pertaining to job search activity, time use, job offers, and consumption. See Appendix A for a more complete description of the survey, and Krueger and Mueller (2011) for a comprehensive description of methodology.

\footnote{This result was first documented by Krueger and Mueller (2011) using data from the SUWNJ. Figure 1 plots average search time over the unemployment spell after removing individual-specific means using the same data.}
2.2 Evidence from job offers

In the standard theory of sequential search, job offers arrive at predictable intervals\(^2\) Such predictability implies that job offers per se should have no bearing on behavior\(^3\).

If, however, job seekers lack information about the availability or existence of work, then an offer itself may have informational value, independent of its nominal value. Furthermore, if this information affects job seekers’ perceptions of the return to searching for work, then behavior may be expected to change after the arrival of an offer. The detailed information on job offers and individuals’ search decisions contained in the SUWNJ allow this simple hypothesis to be tested.

Specifically, I compare the change in search effort the week before and after an offer is received and rejected with the average change in search effort over the unemployment spell, excluding the week of the offer. Table I reports the results for both the unrestricted sample and the prime age sample used in Section 2.3.

<table>
<thead>
<tr>
<th>Table 1: Search Time Before and After Job Offers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prime Age</td>
</tr>
<tr>
<td>Time Diary</td>
</tr>
<tr>
<td>(\Delta_{\text{offer}}^i)</td>
</tr>
<tr>
<td>(\Delta_{\text{avg}}^i)</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Weekly Recall</td>
</tr>
<tr>
<td>(\Delta_{\text{offer}}^i)</td>
</tr>
<tr>
<td>(\Delta_{\text{avg}}^i)</td>
</tr>
<tr>
<td>Observations</td>
</tr>
</tbody>
</table>

Standard errors in parentheses.
Source: Survey of Unemployed Workers in New Jersey
Notes: The samples are restricted to those receiving and rejecting offers. See Appendix A for details.
\[\Delta_{\text{offer}}^i \equiv \left( s_{\text{post}}^i - s_{\text{pre}}^i \right) / 2\]
\[\Delta_{\text{avg}}^i \equiv \frac{1}{T} \sum_t \Delta s_{it}\]

For both measures of search time, the decrease in search after an offer is received, \(\Delta_{\text{offer}}^i\), is significantly attenuated relative to the typical decline, \(\Delta_{\text{avg}}^i\). Indeed, search does not exhibit a significant decline over time when offers are received. This result holds for both the prime age sample as well as the full sample of job seekers in the SUWNJ. In light of the preceding discussion, these results suggest that the simple informational structure of standard search models may be missing an important component.

\(^2\)If arrivals are stochastic, then the arrival time is constant in expectation.
\(^3\)Even when the parameters of the offer distribution are unobserved, the offer itself has no effect on behavior independent of its value. See Burdett and Vishwanath (1988).
2.3 Evidence from search histories

If information about the outcomes of searching for work—job offers—affect subsequent search decisions, then so too should information about the effort put into searching for work. In this section I study how total time spent searching for work since job loss affects subsequent search decisions.

2.3.1 Empirical strategy

Consider expressing time devoted to job search as a function of unemployment duration, time- and individual-fixed effects, observed shocks to search time and—reflecting the preceding intuition—the total time spent looking for work since job loss:

\[
 s_{it} = \iota + \kappa d_{it} + \pi \sum_{k=0}^{t-1} s_{ik} + \tau_t \cdot \begin{bmatrix} e_1^{it} \\ \vdots \\ e_{10}^{it} \end{bmatrix} + (\eta_i + \epsilon_{it}).
\] (1)

For individual \(i\) in interview week \(t\), \(s_{it}\) denotes search time, \(d_{it}\) denotes unemployment duration, \(\tau_t\) is an aggregate time effect, \(e_{1}^{it}, \ldots, e_{10}^{it}\) are indicators for reported shocks to search time, and \(\eta_i\) is the individual effect.\(^4\)

The coefficients of interest are \(\kappa\) and \(\pi\), which determine the roles of duration and cumulative past search, respectively, in driving time spent looking for work.

Equation (1) cannot be estimated directly from the SUWNJ data for two reasons. First, the individual effect \(\eta_i\) is unobserved. Second, no individuals in the sample are observed from the beginning of the unemployment spell, so the stock variable of interest is only partially observed. Accordingly, I take first differences of (1) in order to clean out all unobserved individual-specific terms:

\[
 \Delta s_{it} = \kappa \Delta d_{it} + \pi s_{i,t-1} + \Delta \tau_t \cdot \begin{bmatrix} \Delta e_1^{it} \\ \vdots \\ \Delta e_{10}^{it} \end{bmatrix} + \Delta \epsilon_{it}.
\] (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: \(E[\epsilon_{i,t-1} \Delta \epsilon_{it}] \neq 0\). Following Anderson and Hsiao (1982), I address the endogeneity of \(s_{i,t-1}\) by instrumenting with its first lag, \(s_{i,t-2}\). Under the assumption that \(\epsilon_{it}\) is serially uncorrelated, \(\Delta \epsilon_{it}\) is an MA(1) process, and thus \(s_{i,t-2}\) is a valid instrument for \(s_{i,t-1}\). The Arellano-Bond test for serial correlation confirms that \(s_{i,t-2}\) is indeed a

\(^4\)The indicators for reported shocks to search time are based on responses to the following question from the SUWNJ: “In the last 7 days, did anything happen that made you spend more time or less time looking for work than usual? Please select all that apply.” Respondents were given 10 options from which to select, including, for example “I was sick/ I was caring for a sick person in my family.”
valid instrument. I refrain from including further lags of $s_{t-1}$ because doing so entails considerable loss of data, given that the average individual is observed for fewer than six weeks.

### 2.3.2 Results

Table 2 reports results from the baseline specification described above. I report results for search effort as measured by (i) time diary data documenting time spent looking for work in the day prior to the interview; and (ii) weekly recall data documenting total time spent looking for work in the week prior to the interview. For each measure, I report results from a specification that does not include as a regressor cumulative past search (Static), and results from an identical regression augmented with cumulative past search time (Dynamic).

<table>
<thead>
<tr>
<th></th>
<th>Time Diary</th>
<th>Weekly Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Static</td>
<td>Dynamic</td>
</tr>
<tr>
<td>Duration ($\kappa$)</td>
<td>-0.177***</td>
<td>-0.0370</td>
</tr>
<tr>
<td></td>
<td>(0.0249)</td>
<td>(0.0396)</td>
</tr>
<tr>
<td>Past Search ($\pi$)</td>
<td>-0.105***</td>
<td>-0.0783***</td>
</tr>
<tr>
<td></td>
<td>(0.0269)</td>
<td>(0.0266)</td>
</tr>
<tr>
<td>Observations</td>
<td>10713</td>
<td>10713</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.054</td>
<td>0.148</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses.

Source: Survey of Unemployed Workers in New Jersey

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

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Two principal results emerge from Table 2. First, the coefficient on the stock of past search is highly-significant and negative for both measures of search effort. Moreover, the dynamic 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 unemployment spell documented by [Krueger and Mueller (2011)](#) can be attributed to variation in past search.

5In Appendix A.6, I estimate the model using the GMM estimator developed in [Arellano and Bond (1991)](#) in order to exploit additional available moment conditions while mitigating the data loss associated with differencing. The results are consistent with the results from the more parsimonious instrumenting strategy discussed above. I also estimate the model using the within estimator, though the within transformation is known to induce bias in point estimates for small $T$ panels.

6For brevity, I exclude estimated coefficients associated with time effects and the exogenous search shocks. Full results are reported in Appendix A.4.

7The time diary measure of search time is likely more robust to concerns of reporting bias, as having to account for each hour of the previous day reduces the scope for manipulation.
An interesting implication of the foregoing analysis is that time devoted to job search follows an AR(1) process. To see this, abstracting from exogenous search shocks and time effects, observe that equation (2) may be rearranged as follows:

\[ s_{it} = \kappa + (1 + \pi)s_{i(t-1)} + \Delta \epsilon_{it}. \] (3)

Interpreted in this way, the results imply that progressive withdrawal from the labor force—declining time devoted to job search—is an intrinsic feature of joblessness in the data from the Great Recession. Put differently, negative duration dependence in search occurs absent any exogenous changes in the availability of work over the course of the unemployment spell. To be concrete, the parameter estimates in Table 2 suggest that on average during the Great Recession, the half-life of search effort was just six weeks of unemployment as measured by the time diary data, and just over eight weeks of unemployment as measured by the weekly recall data.

2.3.3 Robustness

I consider several modifications to the baseline model described above to ensure that the results presented in Table 2 are a robust feature of the data. Specifically, I allow for search to depend non-linearly on the duration of unemployment and account for forward-looking search behavior through inclusion of leads of search shock indicators. I also confirm that the results are robust to the use of various sample selection criteria, alternative observation weighting schemes and hold when the sample is restricted to individuals spending a strictly positive amount of time searching. These supplementary results, cataloged in Appendix A.5, provide robust support for the results in Table 2.

2.3.4 Stock-flow matching

One plausible explanation for the results in Table 2 is the presence of stock-flow matching (Coles and Smith, 1998; Ebrahimy and Shimer, 2006; Coles and Petrongolo, 2008). 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 corresponds to the rate at which the initial stock is drawn down, and thus individuals who devote more time to search early in the unemployment spell may more rapidly reduce their search as they are forced to wait for the arrival of new vacancies.

As a simple test of whether stock-flow matching is driving the results in Table 2, I replace the stock of past search time on the right-hand side of equation (1) with the stock of past applications. If search time is constrained by the availability of vacancies, as predicted by a stock-flow model, then

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\(^8\)As noted above, there is considerable evidence that job-finding prospects do change over the unemployment spell. The point here is simply that progressive labor force detachment exists even in the absence of such effects.
the total number of applications submitted since job loss should predict the amount of time devoted to job search. The results, found in Appendix A.7, indicate that the stock of past applications is not a significant determinant of time spent looking for work, as would be expected in a model of stock-flow matching.9

2.3.5 A structural interpretation

An alternative explanation for the results in Table 2 is that job seekers are uncertain about their job-finding prospects and learn from their experiences. If this is the case, and job seekers infer from their past failures to find work that their job-finding prospects are relatively poor, then those who have spent more time unsuccessfully looking for work in the past may substitute away from job search.

To capture this intuition, I reinterpret (1) as the reduced-form of an underlying model in which past failures to find work induce pessimism about job-finding prospects, which in turn causes a substitution away from search effort. Because data on individuals’ perceptions about the job-finding process are not available at a sufficiently high frequency, I use self-reported life satisfaction as a proxy.10 Denoting by \(s_{it}\) the SUWNJ measure of self-reported life satisfaction, consider such a model:

\[
p_{it} = \phi_0 + \phi_1 d_{it} + \phi_2 \sum_{k=0}^{t-1} s_{ik} + \tau_t + \nu_{it} + \omega_{it}
\]

(4)

\[
s_{it} = \theta_0 + \theta_1 d_{it} + \theta_2 p_{it} + \tau_t + \left[ \delta_1 \ldots \delta_{10} \right] \cdot \begin{bmatrix} e_{1t} \\ \vdots \\ e_{10t} \end{bmatrix} + \eta_i + \epsilon_{it}.
\]

(5)

Note that substituting (4) into (5) implies the following structural interpretation of the coefficients in equation (1): \(\kappa = \theta_1 + \theta_2 \phi_1\) and \(\pi = \theta_2 \phi_1\). Duration can affect search decisions directly (\(\theta_1\)) and indirectly through its effect on self-reported life satisfaction (\(\theta_2 \phi_1\)). The effect of past search is the composite of its effect on self-reported life satisfaction, and the effect of life satisfaction on search effort.

The econometric issues discussed in the preceding section largely carry over to the system described by (4) and (5). The methodology is discussed at length in Appendix A.8. The results in Table A.14 suggest that, to a significant extent, cumulative past search is affecting search decisions through life satisfaction: increased time spent looking for work since job loss increases reported dissatisfaction, which in turn reduces time spent looking for work.

9Faberman and Kudlyak (2014) corroborate this result using a new data set on internet job search. They document that applications to newly-posted vacancies account for only 17% of total applications in the sixth month of search, suggesting that stock-flow matching is of limited relevance to search dynamics.

10Insofar as reductions in the perceived probability of exiting unemployment reduce expected permanent income, they should be correlated with reported quality of life.
3 A Theory of Sequential Search with Learning

This section develops a theory of search in which job seekers are uncertain about the rate at which job offers arrive and learn from their experiences. I make two modifications to an otherwise standard McCall (1970)-style model of sequential search: (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 beliefs that evolve endogenously in response to the arrival of new information. Search time and reservation wage dynamics over the unemployment spell are thus driven by the evolution of beliefs, which in turn respond to the idiosyncratic outcomes of search.

3.1 Environment

3.1.1 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 as 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 $\lambda_T^{\text{T}}$. 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

$$Pr(\tilde{\tau}_t \leq s_t) \equiv F(s_t; \lambda_T^{\text{T}}) = 1 - e^{-\lambda_T^{\text{T}} s_t}. \tag{6}$$

If a job offer arrives before search ends ($\tilde{\tau}_t < s_t$), the job seeker updates her estimate of $\lambda_T^{\text{T}}$, and then decides whether or not to accept the offer as in a standard McCall-style search framework. Offers are drawn from a fixed 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 next period.$^{12}$

If no offer arrives before search ends ($\tilde{\tau}_t \geq s_t$), the job seeker receives flow value of unemployment $b$ and updates her estimate of $\lambda_T^{\text{T}}$ to reflect the fact that searching for fraction $s_t$ of the week yielded no offers.

$^{11}$Unemployment duration is discrete, but offers arrive continuously 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.

$^{12}$In Appendix B, I present a generalized version of the model that allows for endogenous separations and an exogenously fixed component of arrivals independent of search time.
Figure 2 depicts the timing of the model.

![Figure 2: Timing of Events](image)

3.1.2 Beliefs

I assume that job seekers do not know the true job offer arrival rate $\lambda^T$. Instead, they form beliefs over the value of $\lambda^T$, which take the form of a Gamma distribution, parameterized by $\alpha_t$ and $\beta_t$. 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 $\alpha_t$ and $\beta_t$, a result which affords the model considerable tractability.

The density of beliefs in week $t$ is thus given by

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

(7)

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

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

(8)

The parameters of the belief distribution $\alpha_t$ and $\beta_t$ evolve endogenously over the unemployment spell according to the following laws of motion:

$$ \alpha_{t+1} = \begin{cases} \alpha_t + 1 & \text{if } \tau_t < s_t \text{ (offer)} \\ \alpha_t & \text{if } \tau_t \geq s_t \text{ (no offer)} \end{cases} $$

(9)

$$ \beta_{t+1} = \begin{cases} \beta_t + \tau_t & \text{if } \tau_t < s_t \text{ (offer)} \\ \beta_t + s_t & \text{if } \tau_t \geq s_t \text{ (no offer)} \end{cases} $$

(10)

See Appendix B.2 for a simple proof of this claim.
Note that $\alpha_t$ counts the number of job offers received since job loss and $\beta_t$ measures accumulated search time since job loss. The endogeneity of beliefs arises from the presence of $s_t$ in (9) and (10).

Figure 3: Beliefs

Figure 3 depicts two belief distributions associated with different values of $\alpha_t$ and $\beta_t$. 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.

In keeping with much of the macroeconomic literature on learning, I assume that job seekers optimize within an anticipated utility framework. 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 4. In Appendix B.7 I numerically solve the model under rational expectations and demonstrate that search decisions are not significantly altered when individuals anticipate the evolution of their own beliefs. I therefore restrict attention to anticipated utility throughout the remainder of the paper.

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14Conditional on not receiving an offer, arrival time $\tau_t$ is not observed. See Appendix B.2 for discussion of this point as it pertains to conjugacy of the Gamma distribution.

3.2 Recursive formulation

The value of entering week \( t \) unemployed with beliefs characterized by \( \alpha_t \) and \( \beta_t \) may be written recursively as

\[
V^U_t(\alpha_t, \beta_t) = \max_{s_t} \left\{ E_t^\lambda \left[ F(s_t; \lambda) E_t^\omega \left[ V^O_t(\omega, \alpha_{t+1}, \beta_{t+1}) \right] \right] + (1 - F(s_t; \lambda)) [b + \delta V^U_{t+1}(\alpha_{t+1}, \beta_{t+1})] \right\} - \eta s_t \tag{11}
\]

where \( V^O_t(\omega, \cdot) \) denotes the value of having offer \( \omega \) in hand and is given by

\[
V^O_t(\omega, \alpha_{t+1}, \beta_{t+1}) = \max \left\{ \frac{\omega}{1 - \delta}, b + \delta V^U_{t+1}(\alpha_{t+1}, \beta_{t+1}) \right\}. \tag{12}
\]

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 \( \lambda^T \) is unobserved, job seekers integrate over possible values of the underlying arrival rate according to the current state of their beliefs.

3.3 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.

3.3.1 Reservation wage

Consider first the problem of an unemployed job seeker with a known offer \( \omega \) in hand. Because the first argument in the max operator in equation (12) is strictly increasing in \( \omega \), while the second is constant, the optimal choice between accepting and rejecting the offer may be characterized by a standard reservation wage policy:

\[
V^O_t(\omega, \alpha_{t+1}, \beta_{t+1}) = \begin{cases} 
\frac{\omega}{1 - \delta} & \text{if } \omega > w_t \\
 b + \delta V^U_{t+1}(\alpha_{t+1}, \beta_{t+1}) & \text{if } \omega \leq w_t
\end{cases} \tag{13}
\]

where the reservation wage is defined as

\[
\frac{w_t}{1 - \delta} = b + \delta V^U_{t+1}(\alpha_{t+1}, \beta_{t+1}). \tag{14}
\]

Job seekers choose a threshold wage rate \( w_t \) such that the present discounted value of accepting an offer \( w_t \) is equated with the flow value of unemployment \( b \) plus the value of remaining unemployed.
### 3.3.2 Search time

Consider next an unemployed job seeker at the beginning of week $t$ who has not yet begun to search for work. Invoking anticipated utility as discussed above, and making explicit the belief distribution, (11) may be written as

$$V_t^U(\alpha_t, \beta_t) = \max_{s_t} \left\{ \int_0^\infty \left[ F(s_t; \lambda) E_t^\omega \left[ V_t^O(\omega, \alpha_t, \beta_t) \right] \right] \right. $$

$$\left. + (1 - F(s_t; \lambda)) \left[ b + \delta V_{t+1}^U(\alpha_t, \beta_t) \right] \right\} \gamma(\lambda; \alpha_t, \beta_t) d\lambda - \eta s_t \right\}.$$  

(15)

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

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

(16)

Job seekers equate the marginal cost of search $\eta$ 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 value of an offer, integrated over the unobserved arrival rate $\lambda$.

### 3.4 Characterizing search dynamics

Using (15) to eliminate the value function from (14) and (16) yields the two key equations describing time devoted to job search and the reservation wage:

$$s_t = \beta_t \left[ \left( \frac{1}{\eta(1 - \delta)} \int_{\omega_t}^B (\omega - \omega_t) \phi(\omega) d\omega \left( \frac{\alpha_t}{\beta_t} \right) \right) \gamma(\lambda; \alpha_t, \beta_t) d\lambda \right]^\frac{1}{\alpha_t + 1} - 1.$$  

(17)

$$w_t = b + \left[ 1 - \left( \frac{\beta_t}{\beta_t + s_t} \right) \right] \left( \frac{\delta}{1 - \delta} \int_{\omega_t}^B (\omega - \omega_t) \phi(\omega) d\omega \right) - \delta \eta s_t.$$  

(18)

Model dynamics are governed by the optimality conditions in (17) and (18), together with the laws of motion for beliefs in (9) and (10).

#### 3.4.1 Learning and job search: a decomposition

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 $\alpha_t$ and $\beta_t$, which in turn govern search decisions.

How exactly do evolving beliefs affect search decisions? Consider a small increase in $\beta_t$, corresponding to a week in which a small amount of time is devoted to search which ultimately 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 reduces the opportunity cost of leisure. This induces a substitution away from time devoted to search. On the other 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. I define the first effect as the **discouragement effect**, and the second as the **motivation effect**. Formally, a reduction in the perceived probability of receiving an offer affects search in the following manner:

\[
\frac{\partial s_t}{\partial \beta_t} = \left[ \frac{\beta_t + s_t}{\alpha_t + 1} \right] \cdot \left[ \frac{\alpha_t}{\beta_t} - \frac{\alpha_t + 1}{\beta_t + s_t} - \frac{(1 - \Phi(w_t))}{B(w_t - \bar{w}_t)\phi(\omega)d\omega} \frac{\partial w_t}{\partial \beta_t} \right].
\]

Because \(\alpha_t\) and \(\beta_t\) in (19) are endogenous, the relative strength of these effects varies over time. The model is therefore capable of generating non-monotonic search dynamics over the unemployment spell. The precise condition under which the effects of discouragement dominate, inducing monotonically declining search in the absence of new job offers, is given in Proposition 1:

**Proposition 1.** For a given number of job offers \(\alpha_t\), the discouragement effect dominates search dynamics iff

\[
\frac{\beta_t}{\alpha_t} > s_t + s_t^2 \left[ \frac{\alpha_t + 1}{\alpha_t} \right] \frac{\delta \eta}{1 - \Phi(w_t)} \int_{w_t}^{B(\omega - \bar{w}_t)} \omega \phi(\omega)d\omega - b.
\]

**Proof.** See Appendix B.

In Section 4, I estimate the structural parameters of the model and demonstrate that, during the Great Recession, the discouragement effect dominated search dynamics at all durations of unemployment. Yet when the initial values of the belief distribution \(\alpha_0\) and \(\beta_0\) are recalibrated to match pre-Great Recession data, the motivation effect dominates for the first 30-40 weeks of unemployment, inducing a hump-shaped profile in time devoted to job search over the unemployment spell.

### 3.4.2 Negative duration dependence

That search declines over the unemployment spell when the discouragement effect dominates suggests that the model may also be capable of generating *endogenous* negative duration dependence in unemployment exit rates. However, because the reservation wage necessarily falls monotonically over the unemployment spell in the absence of job offers, declining search effort is a necessary—but not sufficient—condition for negative duration dependence. Proposition 2 characterizes the precise
condition under which negative duration dependence obtains:

**Proposition 2.** For a given number of job offers \( \alpha_t \), the probability of exiting unemployment is declining iff

\[
\frac{f(s_t; \lambda)}{F(s_t; \lambda)} \left( 1 + \frac{\alpha_t}{\beta_t + s_t} \right) \left[ \frac{\alpha_t + 1}{\beta_t + s_t} - \frac{\delta \eta s_t}{1 - \Phi(w_t)} \int \omega \phi(\omega) d\omega + \delta \eta s_t \right] < \phi(w_t) \left[ \frac{\delta \eta s_t}{1 + (1 - \Phi(w_t)) \delta (1 - \frac{1}{1 - \delta})} \right].
\]

(21)

**Proof.** See Appendix B.

As discussed in Appendix B, the prime notation on the right-hand side of the inequality in Proposition 2 results from the fact that in the model, job seekers update beliefs upon receiving an offer, but before deciding whether or not to accept. This implies that the relevant reservation wage for the accept-reject decision after receiving an offer is different from the reservation wage anticipated at the beginning of the period when the time allocation decision is made.

### 3.4.3 Reduced-form as a linear approximation

The reduced-form relationship between current search and cumulative past search established in Section 2 was not merely descriptive: it derives directly from a linear approximation to the structural model of search described above. In the special case in which (i) the wage offer distribution is degenerate; and (ii) \( \alpha_0 = 1 \), the key reduced-form parameter \( \pi \) from Section 2 can be expressed analytically in terms of structural parameters.

**Proposition 3.** When (i) the wage offer distribution is degenerate; (ii) \( \alpha_0 = 1 \), the reduced-form effect of past search has a closed-form representation in terms of structural parameters:

\[
\pi = \frac{1}{2} \left[ \frac{w - c}{\eta} + \frac{\delta \beta_0^2}{2} \right] - 1.
\]

(22)

Furthermore, \( \pi < 0 \) iff

\[
\beta_0 > \beta_0 \equiv \left( \frac{w - c}{2 \delta \eta} \right) \left[ \left( \frac{1}{1 - \delta} \right) - 1 \right].
\]

(23)

**Proof.** See Appendix B.

Proposition 3 characterizes the conditions under which a linear approximation of the structural model is consistent with the results from Section 2.
4 Structural Estimation

This section structurally estimates the model developed in Section 3. I identify key structural parameters—including those governing beliefs at the time of job loss—using the empirical profiles of search time, job-finding probabilities and job-acceptance probabilities over the first two years of the unemployment spell from the SUWNJ data. The estimated model accounts for unemployment dynamics along all three dimensions. I show that (i) the negative effect of past search under the estimated model is of the same order as that observed in the data in Section 2; (ii) the estimated model outperforms a flexibly-specified alternative nesting three alternative views of job search; and (iii) a simple recalibration of beliefs can provide insight into pre-Great Recession search dynamics.

4.1 Empirical strategy

I use Indirect Inference to estimate the six key structural parameters of the model:

$$\Theta = [\alpha_0, \beta_0, \lambda^T, b, \eta, \nu]' \quad (24)$$

Estimation 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 $\Theta$ so as to minimize the distance between the auxiliary parameters generated by the SUWNJ data and the auxiliary parameters generated by simulating the model.\(^{16}\)

4.1.1 Identification and the auxiliary model

Identifying the parameters governing perceptions about the job-finding process is nontrivial. In a static setting, these parameters are not separately identified from standard structural parameters such as the marginal cost of search $\eta$. However, if individuals are observed for sufficiently long spells of unemployment and at a sufficiently high frequency, as in the SUWNJ, then identification is possible simply because the learning process eventually comes to an end, after which point the model is stationary. Initial beliefs are therefore identified from search dynamics early in the unemployment spell, whereas the remaining structural parameters are identified once beliefs are sufficiently focused and dynamics have died out.\(^{17}\)

I implement the preceding identification strategy by specifying the auxiliary model as three linear

\(^{16}\) This approach is simply a generalization of the Simulated Method of Moments (SMM). Indeed, the auxiliary parameters described in the next section are conditional first moments.

\(^{17}\) Note that, in the model, beliefs need not converge to the true parameter value, though in some cases they will.
For individual $i$ in interview week $t$, $s_{it}$ denotes the fraction of daily time devoted to job search, $j_{it}$ is an indicator for whether or not a job offer was received, and $a_{it}$ is an indicator for whether or not an offer was accepted conditional on having received an offer. The right-hand side variables are indicators for unemployment duration, grouped into five-week bins: $d_{1,it}$ is an indicator for the first five weeks of unemployment; $d_{2,it}$ for the second five weeks, so on and so forth through the first two years of unemployment.

The associated auxiliary parameters, which can be estimated from either actual or simulated data, are then:

**SUWNJ:** $\Omega^e = [\hat{\beta}_{s1}^e, ..., \hat{\beta}_{s20}^e, \hat{\beta}_{j1}^e, ..., \hat{\beta}_{j20}^e, \hat{\beta}_{a1}^e, ..., \hat{\beta}_{a20}^e]'$.  

**Model:** $\Omega^m(\Theta) = [\tilde{\beta}_{s1}(\Theta), ..., \tilde{\beta}_{s20}(\Theta), \tilde{\beta}_{j1}(\Theta), ..., \tilde{\beta}_{j20}(\Theta), \tilde{\beta}_{a1}(\Theta), ..., \tilde{\beta}_{a20}(\Theta)]'$.  

These are just the conditional means of each of the three dependent variables, taken at various durations of unemployment. Together, the auxiliary parameters constitute profiles of search time, the job-finding probability, and the job-acceptance probability over the first two years of unemployment.

### 4.1.2 Data

I use data from the SUWNJ to estimate the model. The sample is identical to the sample used in Section 2 and described in Appendix A.1, with the single exception that I include observations on individuals who have received job offers in order to identify the probability of accepting an offer. I focus on prime age individuals (20-65) who left their previous jobs involuntarily and do not expect to return. In order to control for unmodeled factors that may affect search time, job finding probabilities and job acceptance probabilities, I augment the right-hand sides of (25)-(27) with calendar time effects and an unemployment benefit eligibility indicator as explanatory variables when estimating the auxiliary model on the SUWNJ data. For equation (25), I also include indicators for observed shocks to search time as described in Section 2. Equations (26)-(27) include cohort dummies, where cohorts correspond to unemployment duration at the time of entry into the survey. Standard errors are clustered at the individual level and survey weights are used throughout.

---

18 Search time is measured using the SUWNJ time diary data. Results are not dramatically altered if instead the weekly recall data are used.
4.1.3 Implementation

Prior to estimation, I fix the weekly discount factor $\delta$ to 0.999 and the weekly separation rate $\rho$ to 0.004 following Lentz (2009). I assume that the wage offer distribution $\Phi(\omega)$ is lognormal with mean normalized to one. I estimate the variance of the distribution $\nu$.

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

$$\hat{\Theta} = \arg\min_{\Theta} \left[ \Omega^m(\Theta) - \Omega^e \right]' W \left[ \Omega^m(\Theta) - \Omega^e \right]$$

where $W$ is the weighting matrix, specified as the inverse of a diagonal matrix containing the stacked main diagonal elements of the covariance matrices from the auxiliary model\textsuperscript{19}.

4.2 Results

Table 3 reports estimates of $\Theta$. Standard errors are reported in parentheses. Figures 4-6 plot the profiles of search time, the job-finding probability and the job-acceptance probability, respectively, over the first two years of unemployment as observed in the data and as implied by the estimated model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Concept</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_0$</td>
<td>Initial belief parameter (shape)</td>
<td>2.70 (0.31)</td>
</tr>
<tr>
<td>$\beta_0$</td>
<td>Initial belief parameter (rate)</td>
<td>4.07 (0.29)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Search cost</td>
<td>50.5 (4.41)</td>
</tr>
<tr>
<td>$\lambda_T$</td>
<td>Offer arrival rate</td>
<td>0.48 (0.05)</td>
</tr>
<tr>
<td>$b$</td>
<td>Flow value of unemployment</td>
<td>0.19 (0.04)</td>
</tr>
<tr>
<td>$\nu$</td>
<td>Variance of offer distribution</td>
<td>0.37 (0.04)</td>
</tr>
</tbody>
</table>

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 and who left their previous job involuntarily and do not expect to return.

\textsuperscript{19}Results are not significantly altered if instead the weighting matrix is specified as the inverse of a block diagonal matrix with three blocks corresponding to the covariance matrices of the three auxiliary parameter estimates.
4.2.1 Model fit

Inspection of Figures 4-6 suggests that the parsimonious model developed in Section 3 provides a strong account of unemployment dynamics during the Great Recession. First, observe that the model captures behavior at the time of job loss reasonably well: search time, the probability of receiving an offer and the probability of accepting an offer all correspond roughly to their empirical counterparts. The model is also capable of replicating key non-linearities in observed unemployment dynamics. Specifically, the model captures (i) the monotonic decline in search time, as well as the inflection point at roughly 40 weeks of joblessness; (ii) the modest decline in the probability of receiving an offer; and (iii) the monotonic and concave nature of the probability of accepting an offer.

![Figure 4: Search time](image)

4.2.2 Prior beliefs: irrational optimism or structural break?

An implication of the results in Table 3 is that, at the time of job loss, individuals’ beliefs exhibited substantial upward bias relative to the true arrival rate $\lambda_T$. To see this, observe that the bias in beliefs about $\lambda_T$ is given by

$$
\frac{E_0[\lambda_T] - \hat{\lambda} T}{\hat{\lambda} T} = \frac{\hat{\alpha}_0/\hat{\beta}_0 - \hat{\lambda} T}{\hat{\lambda} T} = 0.39.
$$

Individuals overestimate the rate at which offers arrive by roughly 40% at the time of job loss. This result is qualitatively consistent with the findings of Spinnewijn (2015), who documents evidence that unemployed individuals systematically overestimate how quickly they will find work.

There are, in principal, two ways to interpret this finding. The first is that job seekers are simply irrational in expecting jobs to arrive 40% faster than they actually do under the estimated model. The second is that the Great Recession represented a structural break in the nature of unemploy-
Specifically, suppose that the average arrival rate of job offers per unit of job search during the Great Recession was systematically lower than in previous recessions. If this was the case, then job seekers’ beliefs at the time of job loss may have simply been conditioned by unemployment spells experienced prior to the Great Recession.

4.2.3 Reduced-form analysis revisited

I next revisit the regression analysis of Section 2. Specifically, I investigate whether simulated data from the estimated model can account for the reduced-form relationship between the amount of time individuals devote to job search and cumulative past search documented in Table 2.

In the simulated data, the effect of cumulative past search is very sensitive to the functional form through which duration is assumed to affect search. Specifically, when duration is assumed to have a simple linear relationship with search, the effect of cumulative past search in the simulated data is negative—as expected—but almost an order of magnitude smaller than in the SUWNJ data. However, when duration is modeled more flexibly, the effect of past search comes close to its estimated value from the SUWNJ data.

Table 4 reports parameter estimates obtained by estimating equation (2), augmented with a cubic trend in duration, as well as observed search shocks, using SUWNJ data and data from the simulated model. I only report the coefficients on the linear term in duration (κ) and past search (π).

Conditional on the above-mentioned caveat, Table 4 documents reduced-form parameter estimates from the simulated data that fall within the empirical standard errors from the SUWNJ data. Importantly, the estimation procedure described above makes no direct reference to the reduced-form effect of cumulative past search on individuals’ search decisions. This suggests that the

20 I thank Rosen Valchev for this suggestion.
21 This is not true in the SUWNJ data, wherein the effect of past search is stable regardless of how the effect of duration is modeled. See Appendix A.5.
Table 4: Revisiting Job Search over the Unemployment Spell

<table>
<thead>
<tr>
<th>SUWNJ</th>
<th>Estimated Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time diary Weekly recall</td>
</tr>
<tr>
<td>Duration ($\kappa$)</td>
<td>0.0067 0.0322</td>
</tr>
<tr>
<td></td>
<td>(0.0049) (0.0235)</td>
</tr>
<tr>
<td>Past Search ($\pi$)</td>
<td>-0.0966*** -0.0715***</td>
</tr>
<tr>
<td></td>
<td>(0.0473) (0.0236)</td>
</tr>
<tr>
<td>Observations</td>
<td>7606 7199</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.12 0.08</td>
</tr>
</tbody>
</table>

Source: Survey of Unemployed Workers in New Jersey

Notes: The sample is identical to that used in Section 2. All regressions include cubic trends in unemployment duration. The regression using survey data includes week effects, indicators for observed search shocks and indicators for leads of search shocks, as discussed in Appendix A.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3 Heterogeneity, skill depreciation and screening

As a benchmark against which to evaluate the model in Section 3, I also estimate a flexible alternative model. The alternative model features no learning, but instead introduces seven new estimated parameters allowing for: (i) a cubic trend in the arrival rate of job offers per unit of search time; (ii) a cubic trend in the mean of the wage offer distribution; and (iii) heterogeneity in search costs $\eta$. Heterogeneity is introduced by way of a two-point Gauss-Hermite approximation of a Normal distribution over $\eta$, the parameters of which are estimated directly. Specifically, I estimate the following parameters:

$$\Theta_{alt} = \begin{bmatrix} \lambda^T, b, v, t_1, t_2, t_3, w_1, w_2, w_3, \eta^\mu, \eta^\sigma \end{bmatrix}'.$$

(32)

A trend in the arrival rate of job offers may arise from employers screening employees on the basis of unemployment duration, as documented by Kroft et al. (2013). A trend in the mean of the wage offer distribution is consistent with skill depreciation as studied in Ljungqvist and Sargent (1998). Finally, unobserved heterogeneity (in this case, heterogeneity in the marginal cost of search) has long been conjectured to give rise to declining observed job-finding rates over the unemployment spell due to endogenous selection. In the present model, introducing such heterogeneity adds considerable flexibility by potentially driving a wedge between (25), which includes individual fixed effects, and (26) and (27) which do not.

22 Appendix C.2 describes the alternative model in detail.
Table C.1 reports parameter estimates for the alternative model, and Figure 7 compares the fit of the alternative model with that of the baseline model.

Figure 7: Baseline vs. Alternative model

The alternative model in Figure 7 is less compelling than the baseline model despite its flexibility. Indeed, the minimized value of the criterion suggests that the baseline model (with six estimated parameters) provides a better fit for the data than the alternative model (with eleven estimated parameters). Interestingly, under the estimated parameters of the alternative model, the mean of the wage offer distribution rises for the first 15 weeks of unemployment, and subsequently falls monotonically. By contrast, the (observed) rate at which offers arrive per unit of search, $\lambda^T$, falls for the first 20 weeks and then increases monotonically before asymptoting at roughly three times its initial level.

4.4 Search dynamics prior to the Great Recession

Both Shimer (2004) and Mukoyama et al. (2014) have documented a hump-shaped profile in search effort over the unemployment spell using CPS data from prior to the Great Recession. I propose a simple recalibration of the parameters governing beliefs to match pre-Great Recession job-finding data and, holding other parameters fixed at their estimated values, ask whether the implied search dynamics are qualitatively consistent with these previous studies.

I recalibrate the model by choosing values for $\alpha_0$, $\beta_0$ and $\lambda^T$ in order to match the average pre-Great Recession unemployment exit probability of the short-term unemployed in the United States ($p_0$) for various degrees of bias ($B$) and dispersion ($V$) in the initial belief distribution. This allows me to study the effect of belief dispersion and the aggregate state of the labor market on model dynamics. The key assumption underlying the calibration strategy is that individuals’ beliefs at the time of job loss are conditioned so as to be consistent with the aggregate short-term unemployment

\[^{23}\text{The CPS asks respondents who are searching for work what they are doing to find a job. Shimer (2004) measures search effort as the number of reported methods among searching respondents. Mukoyama et al. (2014) exploit overlap between the CPS and the ATUS to 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.}

\[^{24}\text{I use the short-term unemployment exit probability as an approximation of the unemployment exit probability in the first week of unemployment.}\]
exit probability in the data (allowing for possible bias in those beliefs), after which point beliefs evolve endogenously in response to search outcomes. The remaining structural parameters are fixed at their values from Table 3. See Appendix D for details on the calibration procedure.

The restrictions used to pin down \(\alpha_0, \beta_0, \text{ and } \lambda^T\) are thus:

\[
\text{Bias: } B = \left[ \frac{\alpha_0}{\beta_0} - \lambda^T \right] / \lambda^T
\]

(33)

\[
\text{Dispersion: } V = \frac{\alpha_0}{\beta_0^2}
\]

(34)

\[
\text{Unempl. exit probability: } p_0 = \int_0^s(\alpha_0, \beta_0) \left[ 1 - \Phi(\bar{w}(\alpha_0 + 1, \beta_0 + \tau)) \right] f(\tau; \lambda^T) d\tau.
\]

(35)

Figure 8: Pre-Great Recession search dynamics

Figures 8a and 8b plot the estimated profiles of search time over the first 100 weeks of unemployment generated from simulated data. Evidently, the recalibrated model is capable of generating a hump-shaped profile of search effort that is, at least qualitatively, similar to that documented in Figure 6 of Shimer (2004) and Figure B2 of Mukoyama et al. (2014).

The mechanism at work is precisely the motivation effect described in Section 3. When individuals enter unemployment perceiving a relatively high job-finding rate, failing to find work stimulates search effort by reducing the perceived value of remaining unemployed. Eventually, however, the successful job seekers exit the sample and the search time of the remaining job seekers becomes dominated by discouragement associated with having repeatedly failed to find work.

Figure 8 also suggests that dispersion of beliefs has a strong influence on search behavior. This result is intuitive: when individuals are highly uncertain about the true job-finding rate, the arrival
of any new information should have a relatively strong effect on beliefs, and thus search effort.

5 Conclusion

I document two new facts about job search during the Great Recession: (i) search increased after individuals received (and rejected) job offers; and (ii) search decreased with cumulative failed search. To account for these facts I develop a model of sequential search in which Bayesian job seekers learn about the arrival rate of offers through their experiences looking for work. I characterize search decisions and reservation wages in terms of the number of job offers received and total time devoted to search since job loss. Endogenously-evolving beliefs drive search through competing income and substitution effects, giving rise to potentially non-monotonic search dynamics over the unemployment spell. I structurally estimate the model and show that the mechanism simultaneously accounts for the empirical profiles of search time, offer arrival probabilities and offer acceptance probabilities over the first two years of unemployment.
References


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 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, oversampling the long-term unemployed and those with e-mail addresses on file. To account for the considerable non-response 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, non-response 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).

The empirical results throughout the paper correspond to a subset of the respondents from the SUWNJ. Specifically, the sample includes all prime age individuals (ages 20-65) who, at the time of the interview: (i) had not accepted a job offer; (ii) did not expect to be recalled or return to a previous job; and (iii) were fired from their previous job. The above criteria were selected in order to focus on involuntary and indefinite job loss while excluding outlying age groups, those in school, and those with unreported sources of income. The sample conforms broadly to that used for the empirical analysis of Krueger and Mueller (2011).
### A.2 Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Prime Age</th>
<th></th>
<th>Full Sample</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>Hours/week searching (time diary)</td>
<td>10.69</td>
<td>13.89</td>
<td>9.69</td>
<td>13.47</td>
</tr>
<tr>
<td>Hours/week searching (weekly recall)</td>
<td>13.02</td>
<td>18.81</td>
<td>12.11</td>
<td>18.83</td>
</tr>
<tr>
<td>Number of job applications</td>
<td>6.00</td>
<td>9.40</td>
<td>5.73</td>
<td>9.24</td>
</tr>
</tbody>
</table>

<table>
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<tr>
<th>Time Diary Weekly Recall Applications</th>
<th>Mean</th>
<th>Median</th>
<th>Mean</th>
<th>Median</th>
<th>Mean</th>
<th>Median</th>
</tr>
</thead>
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<tr>
<td>&lt; 20 Duration</td>
<td>10.84</td>
<td>7.00</td>
<td>12.73</td>
<td>7.00</td>
<td>5.38</td>
<td>3.00</td>
</tr>
<tr>
<td>20-39</td>
<td>11.90</td>
<td>7.00</td>
<td>13.92</td>
<td>7.92</td>
<td>5.27</td>
<td>3.00</td>
</tr>
<tr>
<td>40-59</td>
<td>11.78</td>
<td>7.00</td>
<td>13.93</td>
<td>8.00</td>
<td>6.34</td>
<td>3.00</td>
</tr>
<tr>
<td>60-79</td>
<td>11.78</td>
<td>7.00</td>
<td>13.72</td>
<td>7.50</td>
<td>6.56</td>
<td>4.00</td>
</tr>
<tr>
<td>80-99</td>
<td>8.86</td>
<td>0.00</td>
<td>11.93</td>
<td>6.00</td>
<td>6.19</td>
<td>3.00</td>
</tr>
<tr>
<td>≥ 100</td>
<td>6.68</td>
<td>0.00</td>
<td>9.59</td>
<td>4.00</td>
<td>5.39</td>
<td>3.00</td>
</tr>
<tr>
<td>Total</td>
<td>10.69</td>
<td>7.00</td>
<td>13.02</td>
<td>7.00</td>
<td>6.01</td>
<td>3.00</td>
</tr>
</tbody>
</table>

Observations 31584 30515 23325
A.3 Serial correlation

Table A.3 reports the tests for first- and second-order autocorrelation in the first-differenced residuals developed in Arellano and Bond (1991). If the errors $\epsilon_{it}$ of equation (1) in levels are serially uncorrelated, then we should expect to see no evidence of second-order autocorrelation in the differenced residuals. Evidence of second-order autocorrelation suggests that the assumption of no serial correlation in $\epsilon_{it}$ is invalid, which in turn implies that $s_{it-2}$ is not a valid instrument for $s_{it-1}$, thus necessitating the use of further lags.

<table>
<thead>
<tr>
<th>Time Diary</th>
<th>Weekly Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistic p-value</td>
<td>Statistic p-value</td>
</tr>
<tr>
<td>Arellano-Bond test for AR(1)</td>
<td>$z = -6.89$ 0.0000</td>
</tr>
<tr>
<td>Arellano-Bond test for AR(2)</td>
<td>$z = 1.40$ 0.1601</td>
</tr>
</tbody>
</table>

Source: Survey of Unemployed Workers in New Jersey

$H_0$: No serial correlation.

The results in Table A.3 suggest that the disturbances $\epsilon_{it}$ are serially uncorrelated, and therefore that $s_{it-2}$ is a valid instrument for $s_{it-1}$. In Appendix A.6 I consider an expanded set of internal instruments in a GMM framework, the results of which are consistent with the more parsimonious approach developed in the body of the paper.

---

25 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.

26 First-order autocorrelation in the first-differenced residuals results mechanically from the process of taking first differences. In general, differencing an MA(n) process yields an MA(n + 1) process.
### Table A.4: Job Search over the Unemployment Spell

<table>
<thead>
<tr>
<th></th>
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<th>Weekly Recall</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Static</td>
<td>Dynamic</td>
<td>Static</td>
<td>Dynamic</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.177***</td>
<td>-0.0370</td>
<td>-0.325</td>
<td>0.539*</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.04)</td>
<td>(0.24)</td>
<td>(0.29)</td>
</tr>
<tr>
<td>Sick</td>
<td>-0.181**</td>
<td>-0.163*</td>
<td>-0.387</td>
<td>-0.375</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.09)</td>
<td>(0.36)</td>
<td>(0.35)</td>
</tr>
<tr>
<td>Rejected</td>
<td>0.241</td>
<td>0.200</td>
<td>1.824**</td>
<td>1.696**</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(0.24)</td>
<td>(0.74)</td>
<td>(0.71)</td>
</tr>
<tr>
<td>Recalled</td>
<td>-0.727*</td>
<td>-0.678*</td>
<td>-1.908</td>
<td>-1.920</td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
<td>(0.37)</td>
<td>(4.10)</td>
<td>(3.99)</td>
</tr>
<tr>
<td>Not recalled</td>
<td>0.144</td>
<td>0.142</td>
<td>0.305</td>
<td>0.0352</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(0.22)</td>
<td>(1.14)</td>
<td>(1.08)</td>
</tr>
<tr>
<td>Spouse fired</td>
<td>-0.457*</td>
<td>-0.494**</td>
<td>2.378</td>
<td>2.766</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.21)</td>
<td>(3.19)</td>
<td>(3.10)</td>
</tr>
<tr>
<td>Spouse hired</td>
<td>0.309</td>
<td>0.332</td>
<td>0.145</td>
<td>0.383</td>
</tr>
<tr>
<td></td>
<td>(0.47)</td>
<td>(0.45)</td>
<td>(1.05)</td>
<td>(1.05)</td>
</tr>
<tr>
<td>Health cost incr.</td>
<td>-0.0836</td>
<td>-0.0732</td>
<td>0.638</td>
<td>0.745</td>
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<tr>
<td></td>
<td>(0.14)</td>
<td>(0.14)</td>
<td>(0.99)</td>
<td>(0.95)</td>
</tr>
<tr>
<td>Health cost decr.</td>
<td>0.195</td>
<td>0.211</td>
<td>5.304</td>
<td>5.204</td>
</tr>
<tr>
<td></td>
<td>(0.46)</td>
<td>(0.45)</td>
<td>(5.34)</td>
<td>(5.44)</td>
</tr>
<tr>
<td>Family death</td>
<td>0.00356</td>
<td>0.00543</td>
<td>-0.395</td>
<td>-0.297</td>
</tr>
<tr>
<td></td>
<td>(0.33)</td>
<td>(0.31)</td>
<td>(0.80)</td>
<td>(0.74)</td>
</tr>
<tr>
<td>Inheritance</td>
<td>-0.161</td>
<td>-0.137</td>
<td>0.157</td>
<td>0.0146</td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
<td>(0.76)</td>
<td>(0.71)</td>
<td>(0.68)</td>
</tr>
<tr>
<td>10/27/09</td>
<td>-0.480***</td>
<td>-0.382***</td>
<td>-1.187**</td>
<td>-0.972*</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.10)</td>
<td>(0.57)</td>
<td>(0.55)</td>
</tr>
<tr>
<td>11/3/09</td>
<td>-0.690***</td>
<td>-0.518***</td>
<td>-0.460</td>
<td>-0.160</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.16)</td>
<td>(0.91)</td>
<td>(0.85)</td>
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<tr>
<td>11/10/09</td>
<td>-0.691***</td>
<td>-0.486***</td>
<td>-1.202</td>
<td>-0.764</td>
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<td>(0.17)</td>
<td>(0.16)</td>
<td>(1.13)</td>
<td>(1.07)</td>
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<tr>
<td>11/17/09</td>
<td>-0.795***</td>
<td>-0.567***</td>
<td>-1.873</td>
<td>-1.407</td>
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<td>(0.17)</td>
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<td>(1.29)</td>
</tr>
<tr>
<td>11/24/09</td>
<td>-1.256***</td>
<td>-1.019***</td>
<td>-2.608*</td>
<td>-2.145</td>
</tr>
<tr>
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<td>(0.18)</td>
<td>(0.17)</td>
<td>(1.52)</td>
<td>(1.46)</td>
</tr>
<tr>
<td>12/1/09</td>
<td>-0.807***</td>
<td>-0.607***</td>
<td>-2.178</td>
<td>-1.737</td>
</tr>
<tr>
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<td>(0.20)</td>
<td>(1.69)</td>
<td>(1.64)</td>
</tr>
<tr>
<td>12/8/09</td>
<td>-0.778***</td>
<td>-0.567***</td>
<td>-1.406</td>
<td>-0.894</td>
</tr>
<tr>
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<td>(0.22)</td>
<td>(0.21)</td>
<td>(1.82)</td>
<td>(1.78)</td>
</tr>
<tr>
<td>12/15/09</td>
<td>-0.857***</td>
<td>-0.633***</td>
<td>-2.539</td>
<td>-1.875</td>
</tr>
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<td>(0.22)</td>
<td>(2.08)</td>
<td>(2.03)</td>
</tr>
<tr>
<td>12/22/09</td>
<td>-1.093***</td>
<td>-0.879***</td>
<td>-3.533</td>
<td>-2.882</td>
</tr>
<tr>
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<td>(0.24)</td>
<td>(2.29)</td>
<td>(2.25)</td>
</tr>
<tr>
<td>12/29/09</td>
<td>-1.039***</td>
<td>-0.865***</td>
<td>-3.131</td>
<td>-2.792</td>
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<td>(0.26)</td>
<td>(0.25)</td>
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<td>(2.42)</td>
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<td>1/5/10</td>
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<td>-0.319</td>
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<td>-2.145</td>
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<tr>
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<td>(0.27)</td>
<td>(2.70)</td>
<td>(2.64)</td>
</tr>
<tr>
<td>1/12/10</td>
<td>-0.687**</td>
<td>-0.602**</td>
<td>-0.711</td>
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<td>(0.28)</td>
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<td>(3.19)</td>
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<tr>
<td>1/19/10</td>
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<td>-0.304</td>
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<td>(0.28)</td>
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<td>(2.99)</td>
</tr>
<tr>
<td>1/26/10</td>
<td>-0.525*</td>
<td>-0.433</td>
<td>2.913</td>
<td>2.755</td>
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<td>(0.28)</td>
<td>(3.48)</td>
<td>(3.14)</td>
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<tr>
<td>2/2/10</td>
<td>-0.449</td>
<td>-0.377</td>
<td>2.768</td>
<td>2.760</td>
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<td>(0.27)</td>
<td>(3.29)</td>
<td>(2.91)</td>
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<tr>
<td>2/9/10</td>
<td>-0.416</td>
<td>-0.351</td>
<td>2.949</td>
<td>3.016</td>
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<td>(0.28)</td>
<td>(3.50)</td>
<td>(3.08)</td>
</tr>
<tr>
<td>2/16/10</td>
<td>0.0942</td>
<td>0.129</td>
<td>2.203</td>
<td>2.634</td>
</tr>
<tr>
<td></td>
<td>(0.33)</td>
<td>(0.31)</td>
<td>(3.81)</td>
<td>(3.68)</td>
</tr>
<tr>
<td>2/23/10</td>
<td>-0.0281</td>
<td>0.0216</td>
<td>-2.047</td>
<td>-1.277</td>
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<td>(0.25)</td>
<td>(1.92)</td>
<td>(1.78)</td>
</tr>
<tr>
<td>3/2/10</td>
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<td>0.172</td>
<td>-1.772</td>
<td>-1.049</td>
</tr>
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<td>(0.28)</td>
<td>(1.75)</td>
<td>(1.62)</td>
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<tr>
<td>3/9/10</td>
<td>-0.178</td>
<td>-0.122</td>
<td>-2.571</td>
<td>-1.854</td>
</tr>
<tr>
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<td>(0.25)</td>
<td>(0.22)</td>
<td>(1.78)</td>
<td>(1.69)</td>
</tr>
<tr>
<td>3/16/10</td>
<td>-0.141</td>
<td>-0.0911</td>
<td>-1.279</td>
<td>-0.652</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.20)</td>
<td>(1.71)</td>
<td>(1.64)</td>
</tr>
<tr>
<td>Past Search</td>
<td>-0.105***</td>
<td>-0.0783***</td>
<td>-0.146</td>
<td>-0.0783***</td>
</tr>
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<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Observations</td>
<td>10713</td>
<td>10713</td>
<td>10257</td>
<td>10257</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.054</td>
<td>0.148</td>
<td>0.013</td>
<td>0.092</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

Source: Survey of Unemployed Workers in New Jersey

* p < 0.1, ** p < 0.05, *** p < 0.01
A.5 Robustness

I consider several modifications to the baseline model and estimation strategy described in Section 2 in order to ensure that the results presented in Table 2 are a robust feature of the data.

First, I allow for the possibility that search depends non-linearly on duration. To this end, I estimate a specification in which search depends on the log of duration, as well as one in which (1) is augmented with a quartic trend in duration. The results, reported in Table A.5, are unchanged. Second, I allow for the possibility that job seekers make forward-looking time allocation decisions. Specifically, if a job seeker anticipates having limited time to search next week, she may search more in the present week to offset the anticipated future reduction in search time. I account for this by including one-period leads of the search shock indicators discussed above. The results are reported in Table A.6. Again, the coefficient on the stock variable of interest remains significant and negative for both measures of search time.

I also estimate the baseline regression using alternative survey weights (person-specific and unweighted) and restricting the sample to the intensive margin of search. These results are reported in Tables A.7 and A.8 respectively, and do not dramatically alter the results presented in the body of the text. The results are also robust to the use of various age cohorts and sample selection criteria, though those results are not reported here.
Table A.5: Alternative Duration Trends

<table>
<thead>
<tr>
<th></th>
<th>Time Diary</th>
<th></th>
<th>Weekly Recall</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log</td>
<td>Quartic</td>
<td>Log</td>
<td>Quartic</td>
</tr>
<tr>
<td>Past Search</td>
<td>-0.104***</td>
<td>-0.104***</td>
<td>-0.0782***</td>
<td>-0.0787***</td>
</tr>
<tr>
<td></td>
<td>(0.0268)</td>
<td>(0.0270)</td>
<td>(0.0266)</td>
<td>(0.0267)</td>
</tr>
<tr>
<td>ln(Duration)</td>
<td>0.663</td>
<td></td>
<td>0.587</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.492)</td>
<td></td>
<td>(2.703)</td>
<td></td>
</tr>
<tr>
<td>Duration</td>
<td>0.0594</td>
<td>0.820</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0970)</td>
<td>(0.737)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Duration²</td>
<td>-0.00368</td>
<td></td>
<td>-0.0403*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00356)</td>
<td></td>
<td>(0.0244)</td>
<td></td>
</tr>
<tr>
<td>Duration³</td>
<td>0.0000522</td>
<td></td>
<td>0.000641*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0000553)</td>
<td></td>
<td>(0.000383)</td>
<td></td>
</tr>
<tr>
<td>Duration⁴</td>
<td>-0.000000241</td>
<td></td>
<td>-0.00000281</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000000271)</td>
<td></td>
<td>(0.00000192)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>10713</td>
<td>10713</td>
<td>10257</td>
<td>10257</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.148</td>
<td>0.148</td>
<td>0.092</td>
<td>0.093</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
Source: Survey of Unemployed Workers in New Jersey
Notes: Baseline regression augmented with various trends in unemployment duration as described in the body of the text.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Anticipated Search Shocks

<table>
<thead>
<tr>
<th></th>
<th>Time Diary</th>
<th></th>
<th>Weekly Recall</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Static</td>
<td>Dynamic</td>
<td>Static</td>
<td>Dynamic</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.0203</td>
<td>0.110</td>
<td>-0.0758</td>
<td>0.722**</td>
</tr>
<tr>
<td></td>
<td>(0.0437)</td>
<td>(0.0713)</td>
<td>(0.255)</td>
<td>(0.327)</td>
</tr>
<tr>
<td>Past Search</td>
<td>-0.0962**</td>
<td></td>
<td>-0.0720***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0469)</td>
<td></td>
<td>(0.0236)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>7599</td>
<td>7599</td>
<td>7289</td>
<td>7289</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.040</td>
<td>0.126</td>
<td>0.011</td>
<td>0.079</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
Source: Survey of Unemployed Workers in New Jersey
Notes: Baseline regression augmented with one-week leads of reported shocks to time spent looking for work as described in the body of the text.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
### Table A.7: Alternative Weights

<table>
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<tr>
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<th>Time Diary</th>
<th></th>
<th>Weekly Recall</th>
<th></th>
</tr>
</thead>
<tbody>
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<td></td>
<td>Person-Week</td>
<td>Person Unweighted</td>
<td>Person-week</td>
<td>Person Unweighted</td>
</tr>
<tr>
<td>Past Search</td>
<td>-0.105***</td>
<td>-0.132***</td>
<td>-0.0783***</td>
<td>-0.0735***</td>
</tr>
<tr>
<td></td>
<td>(0.0269)</td>
<td>(0.0229)</td>
<td>(0.0266)</td>
<td>(0.0254)</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.0370</td>
<td>0.00696</td>
<td>0.539*</td>
<td>0.577*</td>
</tr>
<tr>
<td></td>
<td>(0.0396)</td>
<td>(0.0377)</td>
<td>(0.288)</td>
<td>(0.309)</td>
</tr>
<tr>
<td>Observations</td>
<td>10713</td>
<td>10713</td>
<td>10257</td>
<td>10257</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.148</td>
<td>0.171</td>
<td>0.092</td>
<td>0.081</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

Source: Survey of Unemployed Workers in New Jersey

Notes: Baseline regression using (i) person-week weights; (ii) person weights; and (iii) no weights.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

### Table A.8: Intensive Margin of Search

<table>
<thead>
<tr>
<th></th>
<th>Time Diary</th>
<th></th>
<th>Weekly Recall</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Static</td>
<td>Dynamic</td>
<td>Static</td>
<td>Dynamic</td>
</tr>
<tr>
<td>Duration</td>
<td>0.349***</td>
<td>0.603***</td>
<td>0.289</td>
<td>1.175***</td>
</tr>
<tr>
<td></td>
<td>(0.0488)</td>
<td>(0.119)</td>
<td>(0.213)</td>
<td>(0.367)</td>
</tr>
<tr>
<td>Past Search</td>
<td>-0.103**</td>
<td></td>
<td>-0.0684***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0472)</td>
<td></td>
<td>(0.0261)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>5342</td>
<td>5342</td>
<td>8802</td>
<td>8667</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.102</td>
<td>0.212</td>
<td>0.009</td>
<td>0.080</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

Source: Survey of Unemployed Workers in New Jersey

Notes: Baseline regression restricted to observations for which reported search time is positive.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
There are two principal drawbacks to the 2SLS procedure implemented 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 significant data loss due to missed interviews. I address both of these concerns using the GMM estimators for dynamic panels developed in Holtz-Eakin et al. (1988) and Arellano and Bond (1991)\(^{27}\).

### A.6.1 Differences

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

<table>
<thead>
<tr>
<th></th>
<th>Time Diary</th>
<th>Weekly Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Static</td>
<td>Dynamic</td>
</tr>
<tr>
<td><strong>Duration</strong></td>
<td>-0.185***</td>
<td>-0.109***</td>
</tr>
<tr>
<td></td>
<td>(0.0211)</td>
<td>(0.0326)</td>
</tr>
<tr>
<td><strong>Past Search</strong></td>
<td>-0.0539***</td>
<td>-0.0490***</td>
</tr>
<tr>
<td></td>
<td>(0.0201)</td>
<td>(0.0149)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>14071</td>
<td>14071</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

Source: Survey of Unemployed Workers in New Jersey

Notes: Two-step Difference GMM with Windmeijer-corrected standard errors.

\(* p<0.1, \quad ** p<0.05, \quad *** p<0.01\)

### A.6.2 Tests of serial correlation and over-identifying restrictions (differences)

<table>
<thead>
<tr>
<th></th>
<th>Time Diary</th>
<th>Weekly Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Statistic</td>
<td>p-value</td>
</tr>
<tr>
<td>Arellano-Bond test for AR(1)</td>
<td>$z = -8.31$</td>
<td>0.000</td>
</tr>
<tr>
<td>Arellano-Bond test for AR(2)</td>
<td>$z = 1.21$</td>
<td>0.225</td>
</tr>
<tr>
<td>Sargan test of over-ID restrictions</td>
<td>$\chi_{23}^2 = 240.11$</td>
<td>0.000</td>
</tr>
<tr>
<td>Hansen test of over-ID restrictions</td>
<td>$\chi_{23}^2 = 33.13$</td>
<td>0.079</td>
</tr>
</tbody>
</table>

Source: Survey of Unemployed Workers in New Jersey

H\(_0\) (AB): No serial correlation; H\(_0\) (Sargan/Hansen): Instruments are jointly exogenous.

\(^{27}\)Specifically, I focus on Difference GMM and Orthogonal Deviations GMM. A System GMM approach is ruled out due to the fact that, for most individuals, the stock variable of interest is itself partially unobserved.
A.6.2 Orthogonal deviations

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

Table A.11: Two-step GMM (Orthogonal Deviations)

<table>
<thead>
<tr>
<th></th>
<th>Time Diary</th>
<th></th>
<th>Weekly Recall</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Static</td>
<td>Dynamic</td>
<td>Static</td>
<td>Dynamic</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.0781***</td>
<td>-0.0230</td>
<td>-0.159***</td>
<td>0.152</td>
</tr>
<tr>
<td></td>
<td>(0.00889)</td>
<td>(0.0142)</td>
<td>(0.0570)</td>
<td>(0.109)</td>
</tr>
<tr>
<td>Past Search</td>
<td>-0.0504***</td>
<td>-0.0357***</td>
<td>0.152</td>
<td>(0.0104)</td>
</tr>
<tr>
<td>Observations</td>
<td>19750</td>
<td>19750</td>
<td>19072</td>
<td>19072</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
Source: Survey of Unemployed Workers in New Jersey
Notes: Two-step Orthogonal-Deviation GMM with Windmeijer-corrected standard errors.

* p < 0.1, ** p < 0.05, *** p < 0.01

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

<table>
<thead>
<tr>
<th></th>
<th>Time Diary</th>
<th></th>
<th>Weekly Recall</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Statistic</td>
<td>p-value</td>
<td>Statistic</td>
<td>p-value</td>
</tr>
<tr>
<td>Arellano-Bond test for AR(1)</td>
<td>z = -8.51</td>
<td>0.000</td>
<td>z = -5.08</td>
<td>0.000</td>
</tr>
<tr>
<td>Arellano-Bond test for AR(2)</td>
<td>z = 1.10</td>
<td>0.273</td>
<td>z = -0.52</td>
<td>0.607</td>
</tr>
<tr>
<td>Sargan test of over-ID restrictions</td>
<td>$\chi^2_{25} = 364.06$</td>
<td>0.000</td>
<td>$\chi^2_{25} = 387.06$</td>
<td>0.000</td>
</tr>
<tr>
<td>Hansen test of over-ID restrictions</td>
<td>$\chi^2_{23} = 42.31$</td>
<td>0.008</td>
<td>$\chi^2_{23} = 16.68$</td>
<td>0.825</td>
</tr>
</tbody>
</table>

Source: Survey of Unemployed Workers in New Jersey
H0 (AB): No serial correlation; H0 (Sargan/Hansen): Instruments are jointly exogenous.

A.6.3 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.

28The forward orthogonal deviation of $y_{it}$ is defined as $y_{it+1}^\perp \equiv c_t \left[ y_{it} \frac{1}{T_{it}} \sum_{s > t} y_{is} \right]$ where $c_t \equiv \sqrt{T_{it} / (T_{it} + 1)}$. 

37
Focusing first on parameter estimates in Tables A.9 and A.11 for both differencing and orthogonal deviations, the estimated coefficients on the proxy for discouragement are highly-significant and negative, but attenuated relative to the 2SLS estimates in the body of the text. In both cases, the coefficient on duration is attenuated dramatically by the presence of the proxy for discouragement; for the weekly recall data, the coefficient becomes insignificant and positive. Reassuringly, when the individual effects are removed by the orthogonal deviation transformation thereby curbing data loss, parameter estimates are largely in line with those from the Difference GMM estimator.

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 test of joint validity of the instruments corroborates these results for the weekly recall data, but not for the time diary data. The Sargan test, by contrast, rejects the null of joint validity for both measures of search time. Two factors may be driving these apparently contradictory results. First, the Sargan test is not robust to heteroskedasticity, which is likely a feature of the data. Second, Arellano and Bond (1991) use simulated panel data from an AR(1) model to demonstrate that their test for serial correlation has greater power to detect invalidity of lagged instruments due to serial correlation than Hansen-Sargan tests. To the extent that their results are applicable here, more weight should be placed on the lack of second-order serial correlation in assessing the validity of the instruments.
A.7 Stock-flow matching

To study whether the results presented in Table 2 are a result of stock-flow matching, I replace the total search time since job loss with total applications submitted since job loss and re-estimate 2. Table (A.13) reports the results. Evidently, the number of applications submitted since job loss does not significantly affect the amount of time individuals devote to job search, as would be predicted by a model of stock-flow matching.

Table A.13: Stock-Flow Matching

<table>
<thead>
<tr>
<th></th>
<th>Time Diary</th>
<th></th>
<th>Weekly Recall</th>
<th></th>
<th>Applications</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Static</td>
<td>Dynamic</td>
<td>Static</td>
<td>Dynamic</td>
<td>Static</td>
<td>Dynamic</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.177***</td>
<td>-0.157***</td>
<td>-0.325</td>
<td>-0.116</td>
<td>-0.108</td>
<td>-0.0368</td>
</tr>
<tr>
<td></td>
<td>(0.0249)</td>
<td>(0.0379)</td>
<td>(0.236)</td>
<td>(0.295)</td>
<td>(0.0917)</td>
<td>(0.219)</td>
</tr>
<tr>
<td>Past Applications</td>
<td>-0.00440</td>
<td>-0.0447</td>
<td>-0.0116</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00677)</td>
<td></td>
<td>(0.0479)</td>
<td></td>
<td>(0.0349)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>10713</td>
<td>10713</td>
<td>10257</td>
<td>10257</td>
<td>9169</td>
<td>9169</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.054</td>
<td>0.055</td>
<td>0.013</td>
<td>0.018</td>
<td>0.022</td>
<td>0.032</td>
</tr>
</tbody>
</table>

Source: Survey of Unemployed Workers in New Jersey

Notes: Baseline regression with the stock of past search time replaced by the stock of past applications submitted. Applications is also included as a left-hand side variable.

* p < 0.1, ** p < 0.05, *** p < 0.01
A.8 A structural interpretation

To estimate the system described by (4) and (5), I begin by taking first differences of both equations to eliminate the individual effects and the unobserved component of total search time since job loss. Estimation then proceeds in three steps: I first construct instruments for the endogenous variables appearing in the equations in differences ($s_{it-1}$ and $\Delta p_{it}$) by projecting these variables on all included exogenous variables and $s_{it-2}$. I then estimate (4) and (5) via 2SLS instrumenting with predicted values from the first step. Finally, I use the residuals from these regressions to construct a consistent estimate of the covariance matrix needed to implement generalized least squares. Table A.14 reports the parameter estimates from the structural model.

Table A.14: Structural Form

<table>
<thead>
<tr>
<th></th>
<th>Time Diary</th>
<th>Weekly Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dissatisfaction</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Past Search</td>
<td>0.00691**</td>
<td>(0.00347)</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.00231</td>
<td>(0.00779)</td>
</tr>
<tr>
<td>Search Time</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dissatisfaction</td>
<td>-17.05*</td>
<td>(9.414)</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.0510</td>
<td>(0.133)</td>
</tr>
<tr>
<td>Observations</td>
<td>14034</td>
<td>13206</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
Source: Survey of Unemployed Workers in New Jersey
Notes: The sample consists of respondents ages 20-65 who have not received a job offer and who left their previous job involuntarily and do not expect to return. The model is estimated via 3SLS as described in the text, with the second lag of search time included as an instrument.

\* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

---

29 This procedure amounts to estimating a seemingly-unrelated regression (SUR) model in which residuals are obtained in the first step using 2SLS.
B  Model Solution and Proofs

Appendix B presents a generalized version of the model described in Section 3. 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 3 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 $\rho$ 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 3.

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:

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

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

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 $\lambda$, arrival times are distributed according to a right-censored exponential distribution with distribution func-
where \( \bar{\tau} \equiv \frac{1}{n^*} \sum_{t \in K} \tau_t \) and \( \bar{s} \equiv \frac{1}{n^*} \sum_{t \in K} s_t. \)

Suppose now that prior beliefs over \( \lambda \) follow a Gamma distribution with hyperparameters \( \alpha_0 \) and \( \beta_0 \), 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 \( \lambda \) is given by

\[
p(\lambda) = \frac{\mathcal{L}(\lambda)g(\lambda|\alpha_0, \beta_0)}{\int \mathcal{L}(\lambda')g(\lambda'|\alpha_0, \beta_0) d\lambda'} = \frac{\lambda^{n^*} e^{-\lambda(n^* \bar{\tau} + n^f(\bar{s} + \xi))} \beta_0^{\alpha_0} \lambda^{\alpha_0 - 1} e^{-\lambda \beta_0}/\Gamma(\alpha_0)}{\int (\lambda')^{n^*} e^{-\lambda'(n^* \bar{\tau} + n^f(\bar{s} + \xi))} \beta_0^{\alpha_0} \lambda^{\alpha_0 - 1} e^{-\lambda' \beta_0}/\Gamma(\alpha_0) d\lambda'}
\]

(\text{B.8})

\[
= \frac{e^{-\lambda(\beta_0 + n^* \bar{\tau} + n^f(\bar{s} + \xi))} \lambda^{\alpha_0 + n^* - 1}}{\int e^{-\lambda'(\beta_0 + n^* \bar{\tau} + n^f(\bar{s} + \xi))} \lambda^{\alpha_0 + n^* - 1} d\lambda'}
\]

(\text{B.9})

\[
= \frac{e^{-\lambda(\beta_0 + n^* \bar{\tau} + n^f(\bar{s} + \xi))} \lambda^{\alpha_0 + n^* - 1}(\beta_0 + n^s \bar{\tau} + n^f(\bar{s} + \xi))^{\alpha_0 + n^*}}{\int e^{-\lambda'(\beta_0 + n^* \bar{\tau} + n^f(\bar{s} + \xi))} \lambda^{\alpha_0 + n^* - 1} d\lambda'}
\]

\[
= \frac{\lambda^{\alpha_0 + n^* - 1} e^{-\lambda \beta_0} \beta_0^{\alpha_0}}{\Gamma(\alpha_0 + n^*)}
\]

(\text{B.10})

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

\[
\int e^{-x'} \left( \frac{x'}{\beta_0 + n^s \bar{\tau} + n^f(\bar{s} + \xi)} \right)^{\alpha_0 + n^* - 1} d\lambda' = \int e^{-x'} \left( \frac{x'}{\beta_0 + n^* \bar{\tau} + n^f(\bar{s} + \xi)} \right)^{\alpha_0 + n^* - 1} \Gamma(\alpha_0 + n^*)
\]

(\text{B.11})

\[
= \Gamma(\alpha_0 + n^*)
\]

(\text{B.12})

\[
\frac{\lambda^{\alpha_0 + n^* - 1} e^{-\lambda \beta_0} \beta_0^{\alpha_0}}{\Gamma(\alpha_0 + n^*)} = g(\lambda|\alpha, \beta)
\]

(\text{B.13})

(\text{B.14})

(\text{B.15})
Thus, as claimed in the text, the Gamma distribution with prior hyperparameters $\alpha_0$ and $\beta_0$ is the conjugate prior for the right-censored exponential distribution. Moreover, the posterior hyperparameters $\alpha$ and $\beta$, which govern the evolution of beliefs in the model, are defined recursively as

$$
\alpha = \alpha_0 + n^s \tag{B.16}
$$

$$
\beta = \beta_0 + \sum_{t \in K} \tau_t + \sum_{t \notin K} (s_t + \xi). \tag{B.17}
$$

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 generalized model and derives equations (17) and (18) in Section 3.

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 $\alpha_t$ and $\beta_t$ may be written recursively as

$$
V_t^U(\alpha_t, \beta_t) = \max_{\tilde{s}_t} \left\{ \mathbb{E}_t^\lambda \left[ F(\tilde{s}_t; \lambda) \mathbb{E}_t^\omega \left[ V_{t+1}^O(\omega, \alpha_{t+1}, \beta_{t+1}) \right] \right] \\
+ (1 - F(\tilde{s}_t; \lambda))(b + \delta V_{t+1}^U(\alpha_{t+1}, \beta_{t+1})) - \eta \tilde{s}_t \right\} \tag{B.18}
$$

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

$$
V_t^O(\omega, \alpha_{t+1}, \beta_{t+1}) = \max \left\{ \omega + \delta V_{t+1}^E(\omega, \alpha_{t+1}, \beta_{t+1}), b + \delta V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}) \right\}. \tag{B.20}
$$

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

$$
V_{t+1}^E(\omega, \alpha_{t+1}, \beta_{t+1}) = (1 - \rho)\left[ \omega + \delta V_{t+2}^E(\omega, \alpha_{t+1}, \beta_{t+1}) \right] + \rho V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}). \tag{B.21}
$$

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.20) and (B.21) reduce to

$$
V_t^O(\omega, \alpha_{t+1}, \beta_{t+1}) = \max \left\{ \omega + \frac{\delta}{1 - \delta(1 - \rho)} \left[ (1 - \rho)\omega + \rho V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}) \right], b + \delta V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}) \right\}. \tag{B.22}
$$

$$
V_{t+1}^E(\omega, \alpha_{t+1}, \beta_{t+1}) = (1 - \rho)\omega + \rho V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}). \tag{B.23}
$$
The optimal choice between accepting and rejecting the offer is characterized by a standard reservation wage policy:

\[ V_t^O(\omega, \alpha_{t+1}, \beta_{t+1}) = \begin{cases} 
\omega + \frac{\delta}{1 - \delta(1 - \rho)} \left[ (1 - \rho)\omega + \rho V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}) \right] & \text{if } \omega > w_t \\
 b + \delta V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}) & \text{if } \omega \leq w_t
\end{cases} \tag{B.24} \]

where

\[ w_t = (1 - \delta(1 - \rho))b + (1 - \delta)(1 - \rho)\delta V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}). \tag{B.25} \]

Imposing the restriction that job seekers are myopic with respect to their own beliefs as discussed above, and making explicit the belief distribution, (B.19) may be written as

\[ V_t^U(\alpha_t, \beta_t) = \max_{\tilde{s}_t} \left\{ \int_0^\infty \left[ F(\tilde{s}_t; \lambda)E_t^\omega [V_t^O(\omega, \alpha_t, \beta_t)] + (1 - F(\tilde{s}_t; \lambda))\left[ b + \delta V_{t+1}^U(\alpha_t, \beta_t) \right] \gamma(\lambda; \alpha_t, \beta_t) d\lambda - \eta\tilde{s}_t \right\}. \tag{B.26} \]

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

\[ \eta = \int_0^\infty f(\tilde{s}_t; \lambda) \left[ \frac{1}{1 - \delta(1 - \rho)} \int_{w_t}^B (\omega - w_t)\phi(\omega)d\omega \right] \gamma(\lambda; \alpha_t, \beta_t) d\lambda. \tag{B.27} \]

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

\[ \int_0^\infty f(\tilde{s}_t; \lambda)\gamma(\lambda; \alpha_t, \beta_t) d\lambda = \frac{\alpha_t\beta_t^{\alpha_t}}{(\beta_t + \tilde{s}_t)^{\alpha_t+1}} \tag{B.29} \]

\[ \int_0^\infty F(\tilde{s}_t; \lambda)\gamma(\lambda; \alpha_t, \beta_t) d\lambda = 1 - \left( \frac{\beta_t}{\beta_t + \tilde{s}_t} \right)^{\alpha_t}. \tag{B.30} \]

These identities will be useful throughout the remainder of the derivation. Making use of (B.29), we see immediately that the first-order condition for \( \tilde{s}_t \) in (16) reduces to

\[ \eta = \frac{\alpha_t\beta_t^{\alpha_t}}{(\beta_t + \tilde{s}_t)^{\alpha_t+1}} \left[ \frac{1}{1 - \delta(1 - \rho)} \int_{w_t}^B (\omega - w_t)\phi(\omega)d\omega \right]. \tag{B.31} \]
Rearranging and solving explicitly for $\tilde{s}_t$, we obtain (17) in the text:

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

(B.32)

Next, using (B.30), the value of beginning the period unemployed in (15) can be written more concisely as

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

(B.33)

Rearranging, we obtain a more convenient form,

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

(B.34)

The term in square brackets represents the expected value of the wage offer in (B.34) conditional on optimal reservation wage behavior net of the option value of unemployment, which reduces to

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

(B.35)

Combining (B.36) and (B.37) we obtain

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

(B.38)

Observe that in (B.39), so long as the period $t + 1$ value function is evaluated at $\alpha_t$ and $\beta_t$ instead of $\alpha_{t+1}$ and $\beta_{t+1}$ (i.e. so long as we impose anticipated utility), and assuming 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 (14). Solving (B.39) for the value function yields

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

(B.40)
Substituting (B.41) into (14) and rearranging yields (18) from the text:

\[ w_t = b + \left[ 1 - \left( \frac{\beta_t}{\beta_t + \tilde{s}_t} \right)^{\alpha_t} \right] \left( \frac{\delta(1 - \rho)}{1 - \delta(1 - \rho)} \right) \int_{y_t}^{B} (w - w_t)\phi(\omega)d\omega - \delta(1 - \rho)\eta \tilde{s}_t. \] (B.42)

Together, (17) and (18) characterize optimal the optimal values of \( \tilde{s}_t \) and \( w_t \), and thus model dynamics.

### B.4 Proof of Proposition 1

**Proof.** Define the derivative of the right-hand side of (15) with respect to \( \tilde{s}_t \) as

\[ h(\tilde{s}_t, \alpha_t, \beta_t) \equiv \int_{0}^{\infty} f(\tilde{s}_t; \lambda) \left[ \frac{1}{1 - \delta(1 - \rho)} \right] \int_{y_t}^{B} (\omega - w_t)\phi(\omega)d\omega \gamma(\lambda; \alpha_t, \beta_t)d\lambda - \eta \] (B.43)

\[ = \left[ \frac{1}{1 - \delta(1 - \rho)} \right] \int_{y_t}^{B} (\omega - w_t)\phi(\omega)d\omega \frac{\alpha_t \beta_t^{\alpha_t}}{(\beta_t + \tilde{s}_t)^{\alpha_t+1}} - \eta. \] (B.44)

Applying the implicit function theorem, the derivative of interest is given by

\[ \frac{\partial \tilde{s}_t}{\partial \beta_t} = -\frac{h_3(\tilde{s}_t, \alpha_t, \beta_t)}{h_1(\tilde{s}_t, \alpha_t, \beta_t)}. \] (B.45)

Differentiating (B.44) with respect to \( \tilde{s}_t \) and \( \beta_t \) respectively yields

\[ h_1 = -\frac{1}{1 - \delta(1 - \rho)} \int_{y_t}^{B} (\omega - w_t)\phi(\omega)d\omega \left[ \left( \frac{\alpha_t + 1}{\beta_t + \tilde{s}_t} \right) \frac{\alpha_t \beta_t^{\alpha_t}}{(\beta_t + \tilde{s}_t)^{\alpha_t+1}} \right] \] (B.46)

\[ h_3 = \frac{\alpha_t \beta_t^{\alpha_t}}{(\beta_t + \tilde{s}_t)^{\alpha_t+1}} \frac{1}{1 - \delta(1 - \rho)} \left[ \int_{y_t}^{B} (\omega - w_t)\phi(\omega)d\omega \left( \frac{\alpha_t}{\beta_t} - \frac{\alpha_t + 1}{\beta_t + \tilde{s}_t} \right) \right. \] (B.47)

\[ \left. - (1 - \Phi(w_t)) \frac{\partial w_t}{\partial \beta_t} \right]. \] (B.48)

Substituting (B.46) and (B.48) into (B.45),

\[ \frac{\partial \tilde{s}_t}{\partial \beta_t} = \left( \frac{\beta_t + \tilde{s}_t}{\alpha_t + 1} \right) \left[ \frac{\alpha_t}{\beta_t} - \frac{\alpha_t + 1}{\beta_t + \tilde{s}_t} - (1 - \Phi(w_t)) \left[ \int_{y_t}^{B} (\omega - w_t)\phi(\omega)d\omega \right]^{-1} \frac{\partial w_t}{\partial \beta_t} \right]. \] (B.49)

Using (B.32) to eliminate references to \( \tilde{s}_t \) from (B.42), and again applying the implicit function theorem,

\[ \frac{\partial w_t}{\partial \beta_t} = \frac{\delta(1 - \rho)\eta - z \alpha_t \left( \beta_t^{-1} \int_{y_t}^{B} (\omega - w_t)\phi(\omega)d\omega \right)^{\frac{1}{\alpha_t+1}}}{1 + (1 - \Phi(w_t)) \left( \frac{\delta(1 - \rho)}{1 - \delta(1 - \rho)} - z \left( \beta_t \left[ \int_{y_t}^{B} (\omega - w_t)\phi(\omega)d\omega \right]^{-1} \right)^{\frac{\alpha_t}{\alpha_t+1}} \right)}. \] (B.50)
where
\[ z \equiv \frac{\delta(1 - \rho)\eta^{-\frac{\alpha_t}{\alpha_t + 1}}}{(\eta(1 - \delta(1 - \rho)))^{\frac{1}{\alpha_t + 1}}}. \] (B.51)

Making use of the optimality conditions for \( \tilde{s}_t \) and \( \bar{w}_t \), (B.50) reduces to
\[ \frac{\partial \bar{w}_t}{\partial \beta_t} = - \left[ \frac{\delta(1 - \rho)\eta \left( \frac{\dot{s}_t}{\beta_t} \right)}{1 + (1 - \Phi(\bar{w}_t)) \left( \frac{\delta(1 - \rho)}{1 - \delta(1 - \rho)} \left[ 1 - \left( \frac{\beta_t}{\beta_t + \dot{s}_t} \right)^{\alpha_t} \right] \right)} \right]. \] (B.52)

Finally, substituting the expression in (B.52) into (B.49) and rearranging, Proposition 1 in the text obtains:
\[ \frac{\partial \dot{s}_t}{\partial \beta_t} < 0 \text{ iff } \frac{\beta_t}{\alpha_t} > \dot{s}_t + \dot{s}_t^2 \left( \frac{\alpha_t + 1}{\alpha_t} \right) \frac{\delta(1 - \rho)\eta}{1 - \Phi(\bar{w}_t)} \int_{w_t}^{B} \omega \phi(\omega) d\omega - b. \] (B.53)

### B.5 Proof of Proposition 2

**Proof.** The true probability of receiving and accepting a job offer \( p_t \) is given by
\[ p_t = (1 - \Phi(w'_t))F(\bar{s}_t; \lambda^T) \] (B.54)
where \( w'_t \) denotes the reservation wage *conditional on receiving an offer*. Because individuals are assumed to updated beliefs immediately upon receiving an offer, the relevant reservation wage is associated with different beliefs than those at the beginning of the period. Differentiating with respect to \( \beta_t \) yields
\[ \frac{\partial p_t}{\partial \beta_t} = (1 - \Phi(w'_t))f(\bar{s}_t; \lambda^T) \frac{\partial \bar{s}_t}{\partial \beta_t} - F(\bar{s}_t; \lambda) \phi(w'_t) \frac{\partial w'_t}{\partial \beta_t}. \] (B.55)

The probability of exiting unemployment is then decreasing in \( \beta_t \) iff
\[ \frac{f(\bar{s}_t; \lambda^T) \partial \bar{s}_t}{F(\bar{s}_t; \lambda^T) \partial \beta_t} < \frac{\phi(w'_t) \partial w'_t}{1 - \Phi(w'_t) \partial \beta_t}. \] (B.56)
Upon receiving an offer, \( \alpha_{t+1} = \alpha_t + 1 \) and \( \beta_{t+1} = \beta_t + \tau_t \). Using this, we can write

\[
\begin{align*}
\frac{\partial w_t}{\partial \beta_t} &= - \left[ \frac{\delta(1-\rho)\eta \left( \frac{\bar{s}_t}{\beta_t} \right)}{1 + (1 - \Phi(w_t)) \left( \frac{\delta(1-\rho)}{1-\delta(1-\rho)} \right) \left[ 1 - \left( \frac{\beta_t}{\beta_t + \bar{s}_t} \right)^{\alpha_t+1} \right]} \right], \\
\frac{\partial w'_t}{\partial \beta_t} &= - \left[ \frac{\delta(1-\rho)\eta \left( \frac{s'_t}{\beta_t + \tau_t} \right)}{1 + (1 - \Phi(w'_t)) \left( \frac{\delta(1-\rho)}{1-\delta(1-\rho)} \right) \left[ 1 - \left( \frac{\beta_t + \tau_t}{\beta_t + \tau_t + \bar{s}_t} \right)^{\alpha_t+1} \right]} \right].
\end{align*}
\]

Substituting (B.59) and (B.60) into (B.58) we obtain the condition in Proposition 2

\[
\begin{align*}
\frac{f(\bar{s}_t; \lambda^T)}{F(\bar{s}_t; \lambda^T)} \left( \frac{\beta_t + \bar{s}_t}{\alpha_t + 1} \right) \left[ \frac{\alpha_t}{\beta_t} - \frac{\alpha_t + 1}{\beta_t + \bar{s}_t} - \frac{\delta(1-\rho)\eta \left( \frac{\bar{s}_t}{\beta_t} \right)}{1 + (1 - \Phi(w_t)) \left( \frac{\delta(1-\rho)}{1-\delta(1-\rho)} \right) \left[ 1 - \left( \frac{\beta_t}{\beta_t + \bar{s}_t} \right)^{\alpha_t+1} \right]} \right] < \frac{\phi(w'_t)}{1 - \Phi(w'_t)} \left[ \frac{\delta(1-\rho)\eta \left( \frac{s'_t}{\beta_t + \tau_t} \right)}{1 + (1 - \Phi(w'_t)) \left( \frac{\delta(1-\rho)}{1-\delta(1-\rho)} \right) \left[ 1 - \left( \frac{\beta_t + \tau_t}{\beta_t + \tau_t + \bar{s}_t} \right)^{\alpha_t+1} \right]} \right].
\end{align*}
\]

\[\Box\]

### 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 \( \beta_t \).

Utilizing (B.29) and (B.30) 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

\[
V^{U}_t(\alpha_t, \beta_t) = \max_{\bar{s}_t} \left\{ \left( 1 - \left( \frac{\beta_t}{\beta_t + \bar{s}_t} \right)^{\alpha_t} \right) \frac{w}{1 - \delta(1-\rho)} + \left( \frac{\beta_t}{\beta_t + \bar{s}_t} \right)^{\alpha_t} \left( b + \delta V^{U}_{t+1}(\alpha_t, \beta_t) \right) - \eta \bar{s}_t \right\}.
\]
The associated first-order condition for search time is then
\[
\eta = \frac{\alpha_t \beta_t^{\alpha_t - 1}}{\tilde{s}_t} \left[ \frac{w}{1 - \delta(1 - \rho)} - b - \delta V^U_{t+1}(\alpha_t, \beta_t) \right].
\] (B.65)

Together, these equations may be rearranged to write the first-order condition as
\[
\tilde{s}_t = \left[ \frac{\alpha_t \beta_t^{\alpha_t - 1}}{\eta} \left( w - b + \delta(1 - \rho)\eta \left( \frac{\beta_t}{\alpha_t} + \left( \frac{\alpha_t - 1}{\alpha_t} \right) \tilde{s}_t \right) \right) \right]^{\frac{1}{\alpha_t + 1}} - \beta_t.
\] (B.66)

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
\[
\tilde{s}_t = \left[ \frac{\beta_t}{\eta} \left( w - b + \delta(1 - \rho)\eta \beta_t \right) \right]^{\frac{1}{2}} - \beta_t.
\] (B.67)

Taking a first-order expansion around \(\beta_t = \beta_0\) yields
\[
\tilde{s}_t \approx \left[ \frac{\beta_0}{\eta} \left( w - b + \delta(1 - \rho)\eta \beta_0 \right) \right]^{\frac{1}{2}} - \beta_0 + (\beta_t - \beta_0) \frac{d\tilde{s}_t}{d\beta_t} |_{\beta_t = \beta_0}
\] (B.68)

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
\[
s_t \approx \iota + \pi \xi t + \pi \sum_{\tau=0}^{t-1} s_\tau + \xi t
\] (B.69)

where
\[
\iota = \left[ \frac{\beta_0}{\eta} \left( w - b + \delta(1 - \rho)\eta \beta_0 \right) \right]^{\frac{1}{2}} - \beta_0 - \xi
\] (B.70)

\[
\pi = \frac{d\tilde{s}_t}{d\beta_t} |_{\beta_t = \beta_0} = \frac{1}{2} \left[ \beta_0 \left( \frac{w - c}{\eta} \right) + \delta(1 - \rho)\beta_0^2 \right]^{-\frac{1}{2}} \left[ \frac{w - c}{\eta} + 2\delta(1 - \rho)\beta_0 \right] - 1
\] (B.71)

Corresponding to the reduced-form parameters in Section 2. Note that \(\pi < 0\) as in Section 2 when
\[
\frac{1}{2} \left[ \beta_0 \left( \frac{w - c}{\eta} \right) + \delta(1 - \rho)\beta_0^2 \right]^{-\frac{1}{2}} \left[ \frac{w - c}{\eta} + 2\delta(1 - \rho)\beta_0 \right] < 1.
\] (B.72)

The left-hand side is quadratic in \(\beta_0\), and so the condition reduces to
\[
\beta_0 > \left( \frac{w - c}{2\delta(1 - \rho)\eta} \right) \left[ \left( \frac{1}{1 - \delta(1 - \rho)} \right)^{\frac{1}{2}} - 1 \right].
\] (B.73)
Setting $\rho = \xi = 0$ yields the expression in Proposition 3.

## B.7 Rational expectations

The model presented in Section 3 is solved under the assumption that job seekers optimize within an anticipated utility framework. While this assumption affords considerable tractability and is commonplace in the literature, it is nonetheless worthwhile to consider the solution when individuals rationally anticipate the evolution of their beliefs.

Figure 9 plots the search policy functions under anticipated utility and rational expectations using the parameters estimated in Section 4. The former is derived analytically in Appendix B, while the latter is solved for via value function iteration. Inspection of the plot suggests that anticipation of the evolution of beliefs only has a limited impact on optimal behavior. This result is qualitatively consistent with the results of Cogley and Sargent (2008), who argue that anticipated utility is a reasonably close approximation of fully rational expectations in a different setting.
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 $\alpha_t$ and $\beta_t$. The initial grid points are chosen as $\alpha_0$ and $\beta_0$ respectively. I compute the policy functions as linear interpolations in $\beta_t$ for each of the ten possible values of $\alpha_t$. The policy functions for search time may then be computed analytically from the reservation wage policies.

In order 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 governing both of these processes ($\lambda^T$ and $\nu$, 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 $\lambda^T$ 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 $\nu$ 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 $\lambda^T$ and $\nu$. 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 so as to permit replication of the cohort structure of the SUWNJ.

Remaining details of the estimation methodology are discussed in Section 4.

C.2 Alternative model

The alternative model estimated in Section 4 is identical to the baseline model with two important modifications: (i) there is no uncertainty, and therefore no learning; and (ii) the model is outfitted with individual heterogeneity in search costs ($\eta_i$), plus exogenous duration-variation in the observed arrival rate of offers per unit of search ($\lambda^T$) and the mean of the wage offer distribution ($m$). The parameters governing heterogeneity and duration-variation in the alternative model are all directly estimated together with other structural parameters of the model.
C.2.1 Exogenous trends

Denoting by $d$ the duration of the unemployment spell, I assume the mean of the wage offer distribution $m$ and the arrival rate of job offers per unit of search time $\lambda^T$ evolve according to:

\begin{align*}
m(d) &= m_0 + m_1 d + m_2 d^2 + m_3 d^3 + m_4 d^4 \quad \text{(C.1)} \\
\lambda^T(d) &= t_0 + t_1 d + t_2 d^2 + t_3 d^3 + t_4 d^4. \quad \text{(C.2)}
\end{align*}

I directly estimate $m_0, m_1, m_2, m_3, t_0, t_1, t_2, t_3, m_4$ and $t_4$ are chosen such that the functions $m(\cdot)$ and $\lambda^T(\cdot)$ are flat in the 100th week of unemployment ($d = 100$), after which point the model is assumed to be stationary. This ensures that there are no discrete shifts in behavior due to the finite time horizon.

C.2.2 Heterogeneity

I assume that there is heterogeneity across job seekers in the linear cost of search $\eta$:

$$\eta_i \sim \mathcal{N}(\mu_\eta, \sigma^2_\eta) \quad \text{(C.3)}$$

I directly estimate $\mu_\eta, \sigma^2_\eta$. To facilitate computation, I model heterogeneity in $\eta_i$ as a 2-point Gauss-Hermite approximation of the Normal distribution above.

C.2.3 Model solution

The alternative model is the limiting case of the baseline model as beliefs become arbitrarily concentrated around the true parameter value $\lambda^T$, augmented with heterogeneity and arbitrary duration dependence as described above. Specifically, job seekers solve the following recursive problem:

\begin{align*}
V_{t+1}^U(d) &= \max_{\hat{s}_t} \left\{ F(\hat{s}_t; \lambda^T(d)) E_t^\omega \left[ V_{t+1}^O(\omega, d + 1) \right] \\
&\quad + (1 - F(\hat{s}_t; \lambda^T(d))) [b + \delta V_{t+1}^U(d + 1)] - \eta_i \hat{s}_t \right\} \quad \text{(C.4)} \\
V_t^O(\omega, d + 1) &= \max \left\{ \omega + \delta V_{t+1}^E(\omega), b + \delta V_{t+1}^U(d + 1) \right\} \quad \text{(C.5)} \\
V_{t+1}^E(\omega) &= (1 - \rho) \left[ \omega + \delta V_{t+2}^E(\omega) \right] + \rho V_{t+1}^U(0). \quad \text{(C.6)}
\end{align*}

Because the value of employment is time-invariant,

$$V^e(\omega) = \frac{1}{1 - \delta(1 - \rho)} \left[ (1 - \rho)\omega + \rho V_{t+1}^U(0) \right]. \quad \text{(C.8)}$$
The value of a known job offer $\omega$ in hand is thus

$$V_t^O(\omega, d+1) = \max \left\{ \omega + \frac{\delta}{1 - \delta(1 - \rho)} [(1 - \rho)\omega + \rho V_{t+1}^U(0)], b + \delta V_{t+1}^U(d+1) \right\}. \quad \text{(C.9)}$$

Conditional on receiving a job offer, optimal behavior is characterized by a reservation wage policy, as in the baseline model. The reservation wage is defined as the value of $\bar{w}_t$ that solves:

$$\bar{w}_t + \frac{\delta}{1 - \delta(1 - \rho)} [(1 - \rho)\bar{w}_t + \rho V_{t+1}^U(0)] = b + \delta V_{t+1}^U(d+1). \quad \text{(C.10)}$$

The first-order condition for time devoted to job search is given by

$$\eta_i = \lambda^T e^{-\lambda^T \hat{z}_t} \left[ E^\omega_t [V_t^O(\omega, d+1)] - [b + \delta V_{t+1}^U(d+1)] \right]. \quad \text{(C.11)}$$

### C.2.4 Numerical solution and simulation

Job seekers are assumed to have complete information in the alternative model. This implies that they anticipate the exogenous changes in $\lambda^T(\cdot)$ and $m(\cdot)$ over the course of the unemployment spell. Accordingly, I solve the model via backward induction, beginning at the end of the second year of unemployment. The value function for the final period is computed under the assumption that the model is stationary after two years. As discussed above, I choose the cubic term in the two exogenous trends such that there is no discrete shift in the environment at the end of two years; the transition from the dynamic model to the stationary model is smooth. Policy functions depend only on the exogenous states, and thus require no interpolation. Simulation and estimation is carried out precisely as in the baseline model described above.

### C.2.5 Parameter estimates

Table C.1 reports parameter estimates for the alternative specification described in the body of the text.
Table C.1: Parameter estimates (alternative model)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Concept</th>
<th>Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Offer arrival rate</td>
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</tr>
<tr>
<td>$b$</td>
<td>Flow value of unemployment</td>
<td>0.30 (0.05)</td>
</tr>
<tr>
<td>$v$</td>
<td>Variance of offer distribution</td>
<td>0.01 (0.03)</td>
</tr>
<tr>
<td>Exog. Trends</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$t_1$</td>
<td>Arrival rate trend 1</td>
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</tr>
<tr>
<td>$t_2$</td>
<td>Arrival rate trend 2</td>
<td>1.38e-04 (3.54e-05)</td>
</tr>
<tr>
<td>$t_3$</td>
<td>Arrival rate trend 3</td>
<td>9.41e-06 (1.35e-07)</td>
</tr>
<tr>
<td>$w_1$</td>
<td>Mean offer trend 1</td>
<td>1.70e-02 (3.63e-04)</td>
</tr>
<tr>
<td>$w_2$</td>
<td>Mean offer trend 2</td>
<td>-8.33e-04 (1.89e-05)</td>
</tr>
<tr>
<td>$w_3$</td>
<td>Mean offer trend 3</td>
<td>9.37e-06 (2.35e-07)</td>
</tr>
<tr>
<td>Heterogeneity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\eta^\mu$</td>
<td>Search cost (mean)</td>
<td>111.3 (4.79)</td>
</tr>
<tr>
<td>$\eta^\sigma$</td>
<td>Search cost (std. dev.)</td>
<td>6.59 (6.53)</td>
</tr>
</tbody>
</table>

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 and who left their previous job involuntarily and do not expect to return.
D Pre-Great Recession Calibration

D.1 Data

In order to implement the calibration described in the text, it is first necessary to obtain an empirical estimate of the probability of transitioning from unemployment to employment during the first week of unemployment. Because the CPS unemployment duration data do not distinguish between individuals who have been unemployed for less than one month, I approximate the transition rate for individuals in their first week of unemployment with that of individuals in their first month of unemployment.

The procedure for measuring the transition probability in the first month of unemployment follows the approach described in Shimer (2004) and Hall (2005). Specifically, begin by expressing the number of medium-term unemployed (1-2 months) as

\[ u_{t+1}^m = (1 - p^s_t) \left[ u^s_t + u_{t-1}^s (1 - p^s_{t-1}) \right] \]  

(D.1)

where \( u_{t}^m \) denotes the number of medium-term unemployed in period \( t \), \( u^s_t \) denotes the number of short-term unemployed in period \( t \), and \( p^s_t \) denotes the job-finding probability of short-term unemployed in period \( t \). It is important to emphasize that the approach neglects transitions from unemployment to out of the labor force. This is a first-order difference equation that can be solved given initial conditions. I therefore assume that, prior to 1950, \( u^s_t \), \( u_{t}^m \) and \( p^s_t \) were constant at their average values for 1948-1950, which are observed in the CPS data. Having pinned down an initial transition probability for short-term unemployed, the dynamic equation can be solved forward for subsequent months, thus yielding a monthly time series for the short-term unemployment exit probability as desired. For use in calibration, I convert the monthly probabilities to their weekly counterparts. Finally, I compute the pre-Great Recession short-term unemployment exit probability as the monthly average of the weekly transition probabilities from 1950M1 to 2007M12.

D.2 Implementation

To calibrate \( \alpha_0, \beta_0 \) and \( \lambda^T \) for given values of \( p_0 \) (described above), \( B \) and \( V \), begin by solving (33) and (34) for \( \alpha_0 \) and \( \beta_0 \):

\[ \alpha_0 = \frac{1}{V} \left[ (1 + B)\lambda^T \right]^2 \]  

(D.2)

\[ \beta_0 = \frac{1}{V} \left[ (1 + B)\lambda^T \right]. \]  

(D.3)

Substituting these expressions into (35) and making use of the optimality conditions in (17) and (18), I obtain a numerical solution for \( \lambda^T \) in terms of \( p_0, B \) and \( V \). This value can then be substituted directly into (D.2) and (D.3) to obtain values for \( \alpha_0 \) and \( \beta_0 \) as desired.