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 permanently increased after individuals received (and rejected) job offers; and (ii) search decreased with cumulative failed search. Motivated by these facts I develop a model of search in which job seekers learn about the availability of jobs through their experiences looking for work. Endogenously-evolving beliefs influence search decisions through income and substitution effects, giving rise to non-monotonic search dynamics over the unemployment spell. The model accounts for the observed effects of job offers and past search, generates declining reservation wages and negative duration dependence in unemployment exit rates, and yields a theoretical measure of the impact of discouragement on job search. I structurally estimate the model and show that the mechanism simultaneously accounts for the 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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Contents

1 Introduction 1

2 Related Literature 2

3 Empirics of Job Search during the Great Recession 3
   3.1 Survey description ........................................ 3
   3.2 Evidence from job offers ................................. 4
   3.3 Evidence from search histories .......................... 5
      3.3.1 Empirical strategy .................................. 5
      3.3.2 Results .............................................. 6
      3.3.3 Robustness ......................................... 7
      3.3.4 Stock-flow matching ................................. 7

4 A Theory of Sequential Search with Learning 8
   4.1 Environment .............................................. 8
      4.1.1 Timing ............................................... 8
      4.1.2 Beliefs ............................................. 9
   4.2 Recursive formulation .................................. 11
   4.3 Solution ............................................... 11
      4.3.1 Reservation wage .................................. 11
      4.3.2 Search time ....................................... 12
      4.3.3 Model dynamics .................................. 13
   4.4 Implications ............................................ 13
      4.4.1 Motivation and discouragement: a decomposition .. 13
      4.4.2 Job offers and past search ....................... 14
      4.4.3 Reservation wages and hazard rates ............... 16

5 Structural Estimation 17
   5.1 Empirical strategy ..................................... 17
      5.1.1 Identification and the auxiliary model ............. 17
      5.1.2 Data .................................................. 18
      5.1.3 Implementation ................................... 19
   5.2 Results ............................................... 19
      5.2.1 Model fit .......................................... 19
      5.2.2 Prior beliefs: irrational optimism or structural break? . 20
   5.3 Heterogeneity, skill depreciation and screening .......... 21
   5.4 Reduced-form analysis revisited ....................... 22

6 Conclusion 23

References 28
1 Introduction

Do the unemployed learn about their job-finding prospects from their experiences searching for work? If so, how do evolving perceptions of the labor market affect subsequent search decisions? And to what extent can learning account for observed search dynamics during the Great Recession? I begin by presenting evidence that individuals' job search decisions during the Great Recession were profoundly influenced by their personal experiences trying to find work. The canonical theory of sequential search cannot account for this result. To reconcile theory with the data, I develop a model of search in which job seekers learn from their search experiences. I use the model to study the mechanisms through which beliefs dynamically affect search decisions, and demonstrate that these mechanisms alone provide a forceful account of unemployment dynamics during the Great Recession.

The paper begins with an empirical study of job search dynamics during the Great Recession using the Survey of Unemployed Workers in New Jersey (SUWNJ). I first show that time devoted to job search increased permanently after individuals received and rejected job offers. I then show that cumulative past search—the total amount of time an individual had spent searching for work since job loss—exerted a significant negative influence on subsequent search decisions. Moreover, in the presence of cumulative past search, unemployment duration ceases to be a significant determinant of search time. These results are important because they suggest that randomness inherent to the job-finding process may induce systematic changes in behavior that impinge on subsequent re-employment prospects. Insofar as re-employment prospects are related to expected future income, the results here suggest that the welfare costs of long-term unemployment may be substantially greater than previously believed.

Motivated by this evidence, I articulate a theory of search in which job seekers learn about their job-finding prospects from the past outcomes of their search—both successes and failures. I implement this through two modifications to a standard McCall (1970)-style model of sequential search: (i) at the beginning of each week of unemployment, job seekers choose how much time to spend looking for work; and (ii) job seekers do not know how long they should expect to have to search before an offer arrives. Search dynamics during unemployment are thus driven by the dynamic interaction between search decisions and beliefs: beliefs respond rationally to the outcomes of past search, while search decisions are driven by endogenously-evolving beliefs.

The model is the first to integrate learning about the arrival of job offers into a 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 and the stock of job offers received. Indeed, I demonstrate that a first-order approximation of the structural model implies the reduced-form regression equation discussed above, and provide a structural interpretation of the reduced-form parameters. I use the model to show 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 as
unemployment progresses, the model is capable of generating non-monotonic search dynamics, declining reservation wages and endogenous negative duration dependence in unemployment exit rates.

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.

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

2 Related Literature

This paper lies at the intersection of an empirical literature seeking to understand the determinants of individuals’ job search decisions during unemployment, and a theoretical literature seeking to integrate learning into models of job search.

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

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

The paper is also closely-related to a literature that studies job search in the context of learning. Burdett and Vishwanath (1988) argue that the observed decline in reservation wages can be explained by a model in which job seekers do not have precise knowledge about the distribution of wages. This paper studies uncertainty about the distribution of offer arrival times, which turns out to generate not only declining reservation wages, but also a variety of other empirically-salient features of search. Falk et al. (2006a) present evidence from a laboratory experiment that job seekers exhibit substantial uncertainty about their job-finding prospects, and update beliefs based on search outcomes. In a companion paper, Falk et al. (2006b) develop an equilibrium model in which job seekers who learn about their linear job-finding probability. The results from their laboratory experiment broadly conform to the message in this paper; their theoretical model only accommodates an extensive margin of search and thus is constrained only to focus on the implications of learning for aggregate labor market dynamics. This paper, by contrast, is concerned with the contours of the intensive margin of search throughout the course of unemployment, and quantifying the underlying theoretical mechanism governing search decisions.

3 Empirics of Job Search during the Great Recession

In this section I document two new facts about job search during the Great Recession using the Survey of Unemployed Workers in New Jersey (SUWNJ). First, I show that job offers (even when rejected) induce a permanent increase in time devoted to job search. Second, I show that cumulative search since job loss exerts a strong negative influence on subsequent search effort. Indeed, the negative effect of past search accounts for the observed decline in search over the unemployment spell documented by Krueger and Mueller (2011): when cumulative past search is included on the right-hand side of Krueger and Mueller’s estimating equation, unemployment duration drops out of the model, while cumulative past search remains highly-significant and negative.

3.1 Survey description

The 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 and the data have been made publicly available. The survey began in the fall of 2009 and covers 6,025 unemployed job seekers for up to 24 weeks for a total of 39,201 weekly interviews. Sampled individuals were asked to participate in a weekly online survey 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.

3.2 Evidence from job offers

Do job offers affect individuals’ search decisions? The standard theory of sequential search—according to which job offers arrive at predictable intervals—suggests they should not. In reality, however, it stands to reason that job offers may convey meaningful information to job seekers. If this is the case, and such information serves to inform job seekers’ perceptions of the availability of work, then job offers may affect subsequent search decisions. The high-frequency and longitudinal nature of the SUWNJ data allows this conjecture to be tested.

To study the effect of job offers on time devoted to job search, I compare the change in hours of search 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 in which the offer is received. I only consider offers that have already been rejected because these offers cannot be credibly used to leverage other offers, which may affect search effort.

Table 1: Search Time Before and After Job Offers

<table>
<thead>
<tr>
<th></th>
<th>Prime Age</th>
<th>Full Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time Diary</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta_{offer}$</td>
<td>0.12 (0.21)</td>
<td>0.13 (0.16)</td>
</tr>
<tr>
<td>$\Delta_{avg}$</td>
<td>-0.48 (0.09)</td>
<td>-0.41 (0.07)</td>
</tr>
<tr>
<td>Observations</td>
<td>90</td>
<td>134</td>
</tr>
<tr>
<td><strong>Weekly Recall</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta_{offer}$</td>
<td>-0.57 (0.77)</td>
<td>-0.78 (0.55)</td>
</tr>
<tr>
<td>$\Delta_{avg}$</td>
<td>-2.10 (0.86)</td>
<td>-1.53 (0.56)</td>
</tr>
<tr>
<td>Observations</td>
<td>99</td>
<td>160</td>
</tr>
</tbody>
</table>

Table 1 reports 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. I report results for a prime age

1 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 The 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.
sample as well as the full sample, both of which are described in Appendix A.1. Figure 1 depicts the average change in search in the weeks surrounding the receipt of a job offer.

Figure 1: The effect of offers on job search

For both measures of search time, there is a permanent increase in search effort following the rejection of a job offer. While search typically declines over the course of the unemployment spell, the decline is absent in the period after an offer is received and rejected.

3.3 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.

3.3.1 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:

\[
s_{it} = \tau + \kappa d_{it} + \pi \sum_{k=0}^{t-1} s_{ik} + \tau_t + \begin{bmatrix} \delta_1 & \cdots & \delta_{10} \end{bmatrix} \cdot \begin{bmatrix} e_{1it} \\ \vdots \\ e_{10it} \end{bmatrix} + (\eta_i + \epsilon_{it}). \tag{1}
\]

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

$$\Delta s_{it} = \kappa \Delta d_{it} + \pi s_{it-1} + \Delta \tau_t + \left[ \delta_1 \ldots \delta_{10} \right] \cdot \left[ \begin{array} {c} \Delta e_{it}^1 \\ \vdots \\ \Delta e_{it}^{10} \end{array} \right] + \Delta \epsilon_{it}.$$ (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: $E[s_{it-1} \Delta \epsilon_{it}] \neq 0$. Following Anderson and Hsiao (1982), I address the endogeneity of $s_{it-1}$ by instrumenting with its first lag, $s_{it-2}$. Under the assumption that $\epsilon_{it}$ is serially uncorrelated, $\Delta \epsilon_{it}$ is an MA(1) process, and thus $s_{it-2}$ is a valid instrument for $s_{it-1}$. The Arellano-Bond test for serial correlation confirms that $s_{it-2}$ is indeed a valid instrument. I refrain from including further lags of $s_{it-1}$ because doing so entails considerable loss of data, given that the average individual is observed for fewer than six weeks.

### 3.3.2 Results

Table 2 reports results from the baseline specification described above for both measures of search time. 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).

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

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3The 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.”

4In 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.

5For brevity, I exclude estimated coefficients associated with time effects and the exogenous search shocks. Full results are reported in Appendix A.4.
Table 2: Job Search over the Unemployment Spell

<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></td>
</tr>
</tbody>
</table>

Observations 10713 10713 10257 10257

Adjusted $R^2$ 0.054 0.148 0.013 0.092

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.

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

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.

3.3.3 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.

3.3.4 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. Thus, individuals who devote more time to search early in the unemployment spell may more rapidly reduce their search.
As a simple test of whether stock-flow matching is driving the results in Table 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 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.

4 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.

4.1 Environment

4.1.1 Timing

Unemployment duration is discrete and measured in weeks. Unemployed job seekers maximize the present discounted value of income net of search costs: \( E_0 \sum_{t=0}^{\infty} \delta^t (y_t - \eta s_t) \). Search costs may be thought of as monetary costs or 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 \( \lambda^T \). Letting \( \tilde{\tau}_t \) denote the stochastic arrival time of the first offer, the true probability of a job offer arriving before search ends is given by

\[
Pr(\tilde{\tau}_t \leq s_t) \equiv F(s_t; \lambda^T) = 1 - e^{-\lambda^T s_t}. \tag{3}
\]

Faberman 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.

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.
If a job offer arrives before search ends ($\tilde{\tau}_t < s_t$), the job seeker updates her estimate of $\lambda_T$, 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.\footnote{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.}

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 $\lambda_T$ to reflect the fact that searching for fraction $s_t$ of the week yielded no offers.

Figure 2 depicts the timing of the model.

Figure 2: Timing of Events

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Figure2.png}
\caption{Timing of Events}
\end{figure}

4.1.2 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.\footnote{See Appendix [B.2] for a simple proof of this claim.}

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

$$Pr(\tilde{\lambda} = \lambda) \equiv \gamma(\lambda; \alpha_t, \beta_t) = \frac{\beta_t^{\alpha_t} \lambda^{\alpha_t - 1} e^{-\beta_t \lambda}}{\Gamma(\alpha_t)}. \quad (4)$$

The mean and variance of the distribution of beliefs in week $t$ are
The parameters of the belief distribution $\alpha_t$ and $\beta_t$ evolve endogenously over the unemployment spell according to the following laws of motion:

$$\alpha_{t+1} = \begin{cases} 
\alpha_t + 1 & \text{if } \tau_t < s_t \text{ (offer)} \\
\alpha_t & \text{if } \tau_t \geq s_t \text{ (no offer)}
\end{cases} \quad (6)$$

$$\beta_{t+1} = \begin{cases} 
\beta_t + \tau_t & \text{if } \tau_t < s_t \text{ (offer)} \\
\beta_t + s_t & \text{if } \tau_t \geq s_t \text{ (no offer)}
\end{cases} \quad (7)$$

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 (6) and (7).

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.\textsuperscript{10}

In keeping with much of the macroeconomic literature on learning, I assume that job seekers optimize within an anticipated utility framework.\textsuperscript{11} This assumption serves to simplify the exposition.

\textsuperscript{10} Conditional 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.

\textsuperscript{11} Kreps (1998).
of the model, and provides a significant reduction in the computational burden associated with estimating the model in Section 5. In Appendix B.9 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.

4.2 Recursive formulation

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

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

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

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

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.

4.3 Solution

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

4.3.1 Reservation wage

Consider first the problem of an unemployed job seeker with a known offer $\omega$ in hand. Because the first argument in the max operator in equation (9) 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:

$$V_t^O(\omega, \alpha_{t+1}, \beta_{t+1}) = \begin{cases} \frac{\omega}{1 - \delta} & \text{if } \omega > w_t \\ b + \delta V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}) & \text{if } \omega \leq w_t \end{cases}$$
where the reservation wage is defined as
\[ \frac{w_t}{1 - \delta} = b + \delta V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}). \] (11)
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.

### 4.3.2 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, (8) may be written as

\[
V_U^U(t, \alpha_t, \beta_t) = \max_{s_t} \left\{ \int_0^{\infty} \left[ F(s_t; \lambda) E_\omega \left[ V_O^O(\omega, \alpha_t, \beta_t) \right] \right. \right. \\
+ (1 - F(s_t; \lambda))[b + \delta V_{t+1}^U(\alpha_t, \beta_t)] \gamma(\lambda; \alpha_t, \beta_t) d\lambda - \eta s_t \left. \right] \right\}. \tag{12}
\]

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

\[
\eta = \int_0^{\infty} f(s_t; \lambda) \left[ E_\omega \left[ V_O^O(\omega, \alpha_t, \beta_t) \right] - b - \delta V_{t+1}^U(\alpha_t, \beta_t) \right] \gamma(\lambda; \alpha_t, \beta_t) d\lambda. \tag{13}
\]

The expression in brackets is the expected net benefit from receiving an (unknown) offer. Making use of (10) and (11), this term may be written as

\[
E_\omega \left[ V_O^O(\omega, \alpha_t, \beta_t) \right] - b - \delta V_{t+1}^U(\alpha_t, \beta_t) = \frac{1}{1 - \delta} \int_{w_t}^{\infty} (\omega - w_t) \phi(\omega) d\omega. \tag{14}
\]

The first-order condition thus reduces to

\[
\eta = \int_0^{\infty} f(s_t; \lambda) \left[ \frac{1}{1 - \delta} \int_{w_t}^{B} (\omega - w_t) \phi(\omega) d\omega \right] \gamma(\lambda; \alpha_t, \beta_t) d\lambda. \tag{15}
\]
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 net value of an offer, integrated over the unobserved arrival rate \( \lambda \).
4.3.3 Model dynamics

Using (12) to eliminate the value function from (11) and explicitly integrating over beliefs yields the two key equations describing time devoted to job search and the reservation wage:

\[
\begin{align*}
  s_t &= \beta_t \left[ \left( \frac{1}{\eta(1-\delta)} \int_{\omega_t}^B (\omega - w_t) \phi(\omega) d\omega \left( \frac{\alpha_t}{\beta_t} \right)^{1/\alpha_t + 1} - 1 \right) \right] \quad (16) \\
  w_t - b + \delta \eta s_t &= \left[ 1 - \left( \frac{\beta_t}{\beta_t + s_t} \right)^{1/\alpha_t} \right] \left( \frac{\delta}{1-\delta} \int_{\omega_t}^B (\omega - w_t) \phi(\omega) d\omega \right). \quad (17)
\end{align*}
\]

Model dynamics are governed by the optimality conditions in (16) and (17), together with the laws of motion for beliefs in (6) and (7).

4.4 Implications

With the model solution in hand, I turn to studying some implications of the theory. First, I show that failures to find work influence search decisions through two channels—motivation and discouragement—and quantify the contribution of each effect. Next, I provide conditions under which the model is consistent with the results of Section 3. Finally, I show that the model is capable of generating negative duration dependence in unemployment exit rates and declining reservation wages.

4.4.1 Motivation and discouragement: 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 does learning 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 means that remaining unemployed is a less attractive option. Just as lower unemployment benefits reduce the option value of remaining unemployed in the standard McCall (1970) model of sequential search, a perceived reduction in the probability of finding work likewise reduces the option value of remaining unemployed in the model described above. On the other hand, a lower perceived probability of finding work reduces the opportunity cost of leisure. This induces a substitution away from time devoted to search. Indeed, these effects are properly understood as income and substitution effects associated with changing beliefs. I define the first effect as the motivation effect, and the second as the discouragement effect. Formally, the effect of failing to find work on subsequent search time is decomposed as follows:
Because $\alpha_t$ and $\beta_t$ in (18) 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 even in the absence of job offers.\footnote{The stochastic arrival of job offers introduces yet another source of non-monotonicity, as discussed in Section 4.4.3.}

The decomposition above is important both theoretically and empirically. Theoretically, it rigorously quantifies the oft-invoked but ill-defined notions of motivation and discouragement in the context of individuals’ job search decisions. Empirically, non-monotonic search dynamics are a robust feature of pre-Great Recession data: both Shimer (2004) and Mukoyama et al. (2014) have independently documented that search effort appears to exhibit a hump-shaped profile over the first year of unemployment using CPS data.\footnote{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.} A credible theory of search should therefore be able to account for this feature of the data; through the competing effects of motivation and discouragement, the model developed in this paper can.\footnote{In Appendix D I demonstrate that a version of the model calibrated to match pre-Great Recession data generates a hump-shaped profile of job search over the first two years of unemployment.}

### 4.4.2 Job offers and past search

Section 3 documented two new facts about job search during the Great Recession: (i) time devoted to job search does not significantly decline in periods when a job offer is received; and (ii) cumulative past search exerts a negative influence on current search. Propositions 1 and 2 provide conditions under which the model is consistent with these observations. Proposition 3 provides conditions under which a linear approximation to the first-order condition for job search implies the reduced-form regression in Section 3, and provides a structural interpretation of the reduced-form parameter estimates.

**Proposition 1.** Time devoted to job search is unchanged after receiving an offer iff

\[
\frac{\partial s_t}{\partial \beta_t} = \left[ \frac{\beta_t + s_t}{\alpha_t + 1} \right] \cdot \left[ \frac{\alpha_t}{\beta_t} - \frac{\alpha_t + 1}{\beta_t + s_t} \right] - \frac{1}{\beta_t} \left( \frac{1 - \Phi(w_t)}{\beta_t} \right) \frac{\partial w_t}{\partial \beta_t} \cdot \int_{w_t}^{B} (\omega - w_t) \phi(\omega) d\omega \frac{\partial \beta_t}{\partial \beta_t}. \tag{18}\]

\[
(19)
\]

\[
(20)
\]
Proof. See Appendix B.

Proposition 1 follows directly from the first-order condition for search time and the laws of motion for beliefs. The condition requires that the effect of receiving an offer is exactly offset by the effect of the observed arrival time of that offer.

**Proposition 2.** For a given number of job offers $\alpha_t$, time devoted to job search is declining in the stock of past search iff

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

(21)

Proof. See Appendix B.

Proposition 2 is directly related to the decomposition of search time in (18). Specifically, the condition is equivalent to the conditions under which the discouragement effect dominates the motivation effect, implying declining search in the absence of job offers.

Propositions 1 and 2 demonstrate that the model is, in principle, capable of accounting for the empirical results in Section 3. However, they afford only limited intuition about how the reduced-form results relate to the structural parameters of the model. Proposition 3 considers the special case in which a linear approximation to the first-order condition for search time in (16) yields a precise structural interpretation of the reduced-form parameter estimates from Section 3.

**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:

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

(22)

Furthermore, $\pi < 0$ iff

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

(23)

Proof. See Appendix B.

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

4.4.3 Reservation wages and hazard rates

A vast literature in empirical labor economics has sought to understand how reservation wages and unemployment exit rates vary with unemployment duration. As an empirical matter, reservation wages are widely-believed to decline over the course of unemployment (cf. Devine and Kiefer [1991]; Barnes 1975; Feldstein and Poterba 1984; Krueger and Mueller 2011). Hazard rates are likewise typically observed to decline over the course of unemployment, but it is unclear whether such negative duration dependence is an artifact of unobserved heterogeneity or a structural feature of behavior (cf. Devine and Kiefer 1991).

Proposition 4 establishes that the model predicts monotonically-declining reservation wages, as frequently observed in the data:

**Proposition 4.** For a given number of job offers $\alpha_t$, the reservation wage is monotonically declining.

*Proof.* See Appendix B.

The intuition for this result is straightforward: reductions in the perceived likelihood of finding work reduce the option value of remaining unemployed—thus making job seekers more willing to accept offers and reducing the reservation wage. In this sense, failing to find work in the model developed above is analogous to a progressive reduction in the level of unemployment benefits in terms of its implications for reservation wages. Monotonically-declining reservation wages can coexist with non-monotonic search dynamics because reductions in the perceived likelihood of finding work also affect search decisions by inducing a substitution towards leisure that has no analog for the reservation wage.

Proposition 5 establishes the conditions under which the model generates structural negative duration dependence in unemployment exit rates:

**Proposition 5.** For a given number of job offers $\alpha_t$, the probability of exiting unemployment is declining iff

$$
\frac{f(s_t; \lambda T)}{F(s_t; \lambda T)} \left( \frac{\beta_t + s_t}{\alpha_t + 1} \right) \left[ \frac{\alpha_t}{\beta_t} - \frac{\alpha_t + 1}{\beta_t + s_t} - \frac{\delta \eta s_t}{\beta_t + \bar{s}_t + \alpha_t + 1} \right] < \frac{\delta \eta s_t}{\beta_t + \bar{s}_t + \alpha_t + 1},
$$

(24)
Proof. See Appendix B

The model is capable of generating structural negative duration dependence in unemployment exit rates because, under the conditions specified in Proposition 2, search falls monotonically over the unemployment spell. However, because the reservation wage also falls monotonically in the absence of offers, declining search is necessary, but not sufficient, for negative duration dependence.

5 Structural Estimation

This section structurally estimates the model developed in Section 4. 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 3; (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.

5.1 Empirical strategy

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

\[ \Theta = [ \alpha_0, \beta_0, \lambda^T, b, \eta, \nu ]' \] (25)

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.

5.1.1 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

\[ \text{This approach is simply a generalization of the Simulated Method of Moments (SMM). Indeed, the auxiliary parameters described in the next section are conditional first moments.} \]
unemployment spell, whereas the remaining structural parameters are identified once beliefs are sufficiently focused and dynamics have died out.\textsuperscript{16}

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

\[
\begin{align*}
    s_{it} &= \beta_1^s d_{1, it} + \beta_2^s d_{2, it} + \cdots + \beta_{20}^s d_{20, it} + (\eta_i + \epsilon_{it}^s) \\
    j_{it} &= \beta_1^j d_{1, it} + \beta_2^j d_{2, it} + \cdots + \beta_{20}^j d_{20, it} + \epsilon_{it}^j \\
    a_{it} &= \beta_1^a d_{1, it} + \beta_2^a d_{2, it} + \cdots + \beta_{20}^a d_{20, it} + \epsilon_{it}^a.
\end{align*}
\]

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.\textsuperscript{17} 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:

\[
\text{SUWNJ:} \quad \Omega^e = [\hat{\beta}_1^s, \ldots, \hat{\beta}_{20}^s, \hat{\beta}_1^j, \ldots, \hat{\beta}_{20}^j, \hat{\beta}_1^a, \ldots, \hat{\beta}_{20}^a]^\prime. \tag{29}
\]

\[
\text{Model:} \quad \Omega^m(\Theta) = [\tilde{\beta}_1^s(\Theta), \ldots, \tilde{\beta}_{20}^s(\Theta), \tilde{\beta}_1^j(\Theta), \ldots, \tilde{\beta}_{20}^j(\Theta), \tilde{\beta}_1^a(\Theta), \ldots, \tilde{\beta}_{20}^a(\Theta)]^\prime. \tag{30}
\]

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.

\subsection*{5.1.2 Data}

I use data from the SUWNJ to estimate the model. The sample is identical to the sample used in Section 3 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 (26)-(28) with calendar time effects and an unemployment benefit eligibility indicator as explanatory variables when estimating the auxiliary model on the SUWNJ data. For equation (26), I also include indicators for observed shocks to search time as described in Section 3. Equations (27)-(28) include cohort dummies, where cohorts correspond to unemployment duration at the time of entry.

\textsuperscript{16}Note that, in the model, beliefs need not converge to the true parameter value, though in some cases they will.

\textsuperscript{17}Search time is measured using the SUWNJ time diary data. Results are not dramatically altered if instead the weekly recall data are used.
into the survey. Standard errors are clustered at the individual level and survey weights are used throughout.

### 5.1.3 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.

### 5.2 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.

#### 5.2.1 Model fit

Inspection of Figures 4-6 suggests that the parsimonious model developed in Section 4 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.

\[18\] 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.
Table 3: Parameter estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Concept</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beliefs</td>
<td></td>
<td></td>
</tr>
<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>Physical</td>
<td></td>
<td></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>( v )</td>
<td>Variance of offer distribution</td>
<td>0.37 (0.04)</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.

5.2.2 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 unemployment. 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.

5.3 Heterogeneity, skill depreciation and screening

As a benchmark against which to evaluate the model in Section 4, 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:

$$\Theta^{alt} = [\lambda^T, b, v, t_1, t_2, t_3, w_1, w_2, w_3, \mu_\eta, \sigma_\eta]^T.$$  \hspace{1cm} (33)

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

---

19 I thank Rosen Valchev for this suggestion.
20 Appendix C.2 describes the alternative model in detail.
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 unemployment exit 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 (26), which includes individual fixed effects, and (27) and (28) which do not.

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. 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.

5.4 Reduced-form analysis revisited

Finally, I return to the regression analysis of Section 3 as a means of discriminating between the baseline and alternative models described above. Because the parameter estimates of Section 3 were not included in the auxiliary model used for estimation in Section 5, the structural models are not directly constrained to account for the reduced-form results.

In order to implement the exercise, I randomly draw samples from the simulated data generated by the models in order to replicate the entry cohort structure, and thus the duration structure, of the SUWNJ data. I describe this in Appendix C. Table 4 reports parameter estimates obtained by estimating the exact same regression as in equation (2).

21 Despite the fact that the baseline model appears to fit the empirical point estimates of the auxiliary model better than the alternative model, the width of the confidence bands is such that it is difficult to assert that the alternative model fails to account for the data.

22 Regressions on simulated data exclude controls that have no counterpart in the model.
### Table 4: Revisiting Job Search over the Unemployment Spell

<table>
<thead>
<tr>
<th></th>
<th>SUWNJ Time diary</th>
<th>SUWNJ Weekly recall</th>
<th>Baseline Model</th>
<th>Alternative Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration (κ)</td>
<td>0.0067 (0.0049)</td>
<td>0.0322 (0.0235)</td>
<td>-0.0152 (0.0007)</td>
<td>-0.0182 (0.0011)</td>
</tr>
<tr>
<td>Past Search (π)</td>
<td>-0.0966*** (0.0473)</td>
<td>-0.0715*** (0.0236)</td>
<td>-0.0121 (0.0005)</td>
<td>0.0002 (0.0006)</td>
</tr>
<tr>
<td>Observations</td>
<td>7606</td>
<td>7199</td>
<td>39125</td>
<td>17293</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.12</td>
<td>0.08</td>
<td>0.03</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Source: Survey of Unemployed Workers in New Jersey

Notes: The sample is identical to that used in Section 3. All regressions include linear terms 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.

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

Two principal results emerge from Table 4. First, the simulated baseline model accounts for a statistically significant negative influence of past search, as observed in the SUWNJ data, whereas the alternative model does not. Indeed, in the alternative model, the effect is positive and insignificant. Second, the estimated effect of past search in the baseline model is attenuated relative to its effect in the SUWNJ data. However, when a cubic trend in duration is included in the model, the negative effect of past search increases substantially, and falls within the empirical standard errors of the estimates from the SUWNJ.

### 6 Conclusion

This paper argues that individuals’ job search decisions during the Great Recession were profoundly influenced by their personal experiences trying to find work. I show that search increased permanently in response to job offers, and decreased in response to the cumulative negative effects of failing to find a job. To account for these facts I develop a tractable model of sequential search that is consistent with the observed state-dependence in search decisions. I show that the model delivers declining reservation wages and negative duration dependence in unemployment exit rates, and admits a rigorous theoretical measure of the impact of discouragement on job search. Structural estimation provides further evidence of the model’s broad empirical relevance: the mechanism alone can account for the non-linear profiles of search time, the probability of receiving an offer and the probability of accepting an offer throughout the first two years of unemployment.

The analysis in this paper is part of a research program aimed at improving our understanding of

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23 Despite replicating the cohort structure of the SUWNJ, standard errors on simulated regressions should be interpreted with caution.
the nature of unemployment. There are a number of promising directions for future research. From a macroeconomic perspective, future work should focus on how search decisions at the individual level map into aggregate labor market dynamics and affect the measurement of labor market slack. Indeed, the absence of a reliable measure of excess capacity in labor markets to guide monetary policy is at least in part due to an incomplete understanding of the behavioral underpinnings of unemployment. From a microeconomic perspective, future work should seek to understand how the behavioral mechanisms described in this paper interact with various policy interventions such as time-varying unemployment insurance benefits and job search assistance programs.
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 A.1: Search Effort (weekly)

<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 A.2: Search Effort by Duration (weekly)

<table>
<thead>
<tr>
<th>Time Diary</th>
<th>Weekly Recall</th>
<th>Applications</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 20 Duration</td>
<td>10.84</td>
<td>12.73</td>
</tr>
<tr>
<td>20-39</td>
<td>11.90</td>
<td>13.92</td>
</tr>
<tr>
<td>40-59</td>
<td>11.78</td>
<td>13.93</td>
</tr>
<tr>
<td>60-79</td>
<td>11.78</td>
<td>13.72</td>
</tr>
<tr>
<td>80-99</td>
<td>8.86</td>
<td>11.93</td>
</tr>
<tr>
<td>≥ 100</td>
<td>6.68</td>
<td>9.59</td>
</tr>
<tr>
<td>Total</td>
<td>10.69</td>
<td>13.02</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 A.3: Tests for Serial Correlation

<table>
<thead>
<tr>
<th></th>
<th>Time Diary</th>
<th></th>
<th></th>
<th>Weekly Recall</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Statistic</td>
<td>p-value</td>
<td></td>
<td>Statistic</td>
<td>p-value</td>
<td></td>
</tr>
<tr>
<td>Arellano-Bond test</td>
<td>$z = -6.89$</td>
<td>0.0000</td>
<td></td>
<td>$z = -4.47$</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>for AR(1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Arellano-Bond test</td>
<td>$z = 1.40$</td>
<td>0.1601</td>
<td></td>
<td>$z = -0.30$</td>
<td>0.7679</td>
<td></td>
</tr>
<tr>
<td>for AR(2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></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.

---

24 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.

25 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.
### A.4 Additional parameter estimates

Table A.4: Job Search over the Unemployment Spell

<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>-0.177***</td>
<td>(0.02) -0.0370</td>
<td>(0.04)</td>
<td>-0.325 (0.24)</td>
</tr>
<tr>
<td>Sick</td>
<td>-0.181**</td>
<td>(0.09) -0.163*</td>
<td>(0.09)</td>
<td>-0.387 (0.36)</td>
</tr>
<tr>
<td>Rejected</td>
<td>0.241 (0.25)</td>
<td>0.200 (0.24)</td>
<td>1.824** (0.74)</td>
<td>1.696** (0.71)</td>
</tr>
<tr>
<td>Recalled</td>
<td>-0.727*</td>
<td>(0.39) -0.678*</td>
<td>(0.37)</td>
<td>-1.908 (4.10)</td>
</tr>
<tr>
<td>Not recalled</td>
<td>0.144 (0.24)</td>
<td>0.142 (0.22)</td>
<td>0.305 (1.14)</td>
<td>0.0352 (1.08)</td>
</tr>
<tr>
<td>Spouse fired</td>
<td>-0.457*</td>
<td>(0.25) -0.494**</td>
<td>(0.21)</td>
<td>2.378 (3.19)</td>
</tr>
<tr>
<td>Spouse hired</td>
<td>0.309 (0.47)</td>
<td>0.332 (0.45)</td>
<td>0.145 (1.05)</td>
<td>0.383 (1.05)</td>
</tr>
<tr>
<td>Health cost incr.</td>
<td>-0.0836</td>
<td>(0.14) -0.0732</td>
<td>(0.14)</td>
<td>0.638 (0.99)</td>
</tr>
<tr>
<td>Health cost decr.</td>
<td>0.195 (0.46)</td>
<td>0.211 (0.45)</td>
<td>5.304 (5.34)</td>
<td>5.204 (5.44)</td>
</tr>
<tr>
<td>Family death</td>
<td>0.00356 (0.33)</td>
<td>0.00543 (0.31)</td>
<td>-0.395 (0.80)</td>
<td>-0.297 (0.74)</td>
</tr>
<tr>
<td>Inheritance</td>
<td>-0.161 (0.78)</td>
<td>-0.137 (0.76)</td>
<td>0.157 (0.71)</td>
<td>0.0146 (0.68)</td>
</tr>
<tr>
<td>10/27/09</td>
<td>-0.480***</td>
<td>(0.10) -0.382***</td>
<td>(0.10)</td>
<td>-1.187** (0.57)</td>
</tr>
<tr>
<td>11/3/09</td>
<td>-0.690***</td>
<td>(0.18) -0.518***</td>
<td>(0.16)</td>
<td>-0.460 (0.91)</td>
</tr>
<tr>
<td>11/10/09</td>
<td>-0.691***</td>
<td>(0.17) -0.486***</td>
<td>(0.16)</td>
<td>-1.202 (1.13)</td>
</tr>
<tr>
<td>11/17/09</td>
<td>-0.795***</td>
<td>(0.17) -0.567***</td>
<td>(0.17)</td>
<td>-1.873 (1.34)</td>
</tr>
<tr>
<td>11/24/09</td>
<td>-1.256***</td>
<td>(0.18) -1.019***</td>
<td>(0.17)</td>
<td>-2.608* (1.52)</td>
</tr>
<tr>
<td>12/1/09</td>
<td>-0.807***</td>
<td>(0.20) -0.607***</td>
<td>(0.20)</td>
<td>-2.178 (1.69)</td>
</tr>
<tr>
<td>12/8/09</td>
<td>-0.778***</td>
<td>(0.22) -0.567***</td>
<td>(0.21)</td>
<td>-1.406 (1.82)</td>
</tr>
<tr>
<td>12/15/09</td>
<td>-0.857***</td>
<td>(0.23) -0.633***</td>
<td>(0.22)</td>
<td>-2.539 (2.08)</td>
</tr>
<tr>
<td>12/22/09</td>
<td>-1.093***</td>
<td>(0.25) -0.879***</td>
<td>(0.24)</td>
<td>-3.533 (2.29)</td>
</tr>
<tr>
<td>12/29/09</td>
<td>-1.039***</td>
<td>(0.26) -0.865***</td>
<td>(0.25)</td>
<td>-3.131 (2.47)</td>
</tr>
<tr>
<td>1/5/10</td>
<td>-0.423 (0.28)</td>
<td>-0.319 (0.27)</td>
<td>-2.256 (2.70)</td>
<td>-2.145 (2.64)</td>
</tr>
<tr>
<td>1/12/10</td>
<td>-0.687**</td>
<td>(0.29) -0.602**</td>
<td>(0.28)</td>
<td>-0.711 (3.35)</td>
</tr>
<tr>
<td>1/19/10</td>
<td>-0.384 (0.29)</td>
<td>-0.304 (0.28)</td>
<td>2.643 (3.35)</td>
<td>2.388 (2.99)</td>
</tr>
<tr>
<td>1/26/10</td>
<td>-0.525*</td>
<td>(0.28) -0.433 (0.28)</td>
<td>2.913 (3.48)</td>
<td>2.755 (3.14)</td>
</tr>
<tr>
<td>2/2/10</td>
<td>-0.449 (0.28)</td>
<td>-0.377 (0.27)</td>
<td>2.768 (3.29)</td>
<td>2.760 (2.91)</td>
</tr>
<tr>
<td>2/9/10</td>
<td>-0.416 (0.28)</td>
<td>-0.351 (0.28)</td>
<td>2.949 (3.50)</td>
<td>3.016 (3.08)</td>
</tr>
<tr>
<td>2/16/10</td>
<td>0.0942 (0.33)</td>
<td>0.129 (0.31)</td>
<td>2.203 (3.81)</td>
<td>2.634 (3.68)</td>
</tr>
<tr>
<td>2/23/10</td>
<td>-0.0281 (0.27)</td>
<td>0.0216 (0.25)</td>
<td>-2.047 (1.92)</td>
<td>-1.277 (1.78)</td>
</tr>
<tr>
<td>3/2/10</td>
<td>0.130 (0.30)</td>
<td>0.172 (0.28)</td>
<td>-1.772 (1.75)</td>
<td>-1.049 (1.62)</td>
</tr>
<tr>
<td>3/9/10</td>
<td>-0.178 (0.25)</td>
<td>-0.122 (0.22)</td>
<td>-2.571 (1.78)</td>
<td>-1.854 (1.69)</td>
</tr>
<tr>
<td>3/16/10</td>
<td>-0.141 (0.23)</td>
<td>-0.0911 (0.20)</td>
<td>-1.279 (1.71)</td>
<td>-0.652 (1.64)</td>
</tr>
<tr>
<td>Past Search</td>
<td>-0.105***</td>
<td>(0.03)</td>
<td>-0.0783***</td>
<td>(0.03)</td>
</tr>
</tbody>
</table>

Observations: 10713 10713 10257 10257

Adjusted $R^2$: 0.054 0.148 0.013 0.092

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 3 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 Log Quartic</th>
<th>Weekly Recall Log Quartic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past Search</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.104***</td>
<td>-0.104***</td>
</tr>
<tr>
<td></td>
<td>(0.0268)</td>
<td>(0.0270)</td>
</tr>
<tr>
<td>ln(Duration)</td>
<td>0.663</td>
<td>0.587</td>
</tr>
<tr>
<td></td>
<td>(0.492)</td>
<td>(2.703)</td>
</tr>
<tr>
<td>Duration</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0594</td>
<td>0.820</td>
</tr>
<tr>
<td></td>
<td>(0.0970)</td>
<td>(0.737)</td>
</tr>
<tr>
<td>Duration²</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.00368</td>
<td>-0.0403*</td>
</tr>
<tr>
<td></td>
<td>(0.00356)</td>
<td>(0.0244)</td>
</tr>
<tr>
<td>Duration³</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0000522</td>
<td>0.000641*</td>
</tr>
<tr>
<td></td>
<td>(0.0000553)</td>
<td>(0.000383)</td>
</tr>
<tr>
<td>Duration⁴</td>
<td>-0.000000241</td>
<td>-0.00000281</td>
</tr>
<tr>
<td></td>
<td>(0.000000271)</td>
<td>(0.00000192)</td>
</tr>
<tr>
<td>Observations</td>
<td>10713</td>
<td>10713</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.148</td>
<td>0.148</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 Static Dynamic</th>
<th>Weekly Recall Static Dynamic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration</td>
<td>-0.0203</td>
<td>-0.0758</td>
</tr>
<tr>
<td></td>
<td>(0.0437)</td>
<td>(0.255)</td>
</tr>
<tr>
<td>Past Search</td>
<td>-0.0962**</td>
<td>-0.0720***</td>
</tr>
<tr>
<td></td>
<td>(0.0469)</td>
<td>(0.0236)</td>
</tr>
<tr>
<td>Observations</td>
<td>7599</td>
<td>7289</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.040</td>
<td>0.011</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>
<thead>
<tr>
<th></th>
<th>Person-Week</th>
<th>Person</th>
<th>Unweighted</th>
<th>Person-week</th>
<th>Person</th>
<th>Unweighted</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Past Search</strong></td>
<td>-0.105***</td>
<td>-0.132***</td>
<td>-0.119***</td>
<td>-0.0783***</td>
<td>-0.0735***</td>
<td>-0.0520***</td>
</tr>
<tr>
<td></td>
<td>(0.0269)</td>
<td>(0.0229)</td>
<td>(0.0163)</td>
<td>(0.0266)</td>
<td>(0.0254)</td>
<td>(0.0116)</td>
</tr>
<tr>
<td><strong>Duration</strong></td>
<td>-0.0370</td>
<td>0.00696</td>
<td>0.0135</td>
<td>0.539*</td>
<td>0.577*</td>
<td>0.423***</td>
</tr>
<tr>
<td></td>
<td>(0.0396)</td>
<td>(0.0377)</td>
<td>(0.0250)</td>
<td>(0.288)</td>
<td>(0.309)</td>
<td>(0.148)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>10713</td>
<td>10713</td>
<td>10713</td>
<td>10257</td>
<td>10257</td>
<td>10257</td>
</tr>
<tr>
<td><strong>Adjusted $R^2$</strong></td>
<td>0.148</td>
<td>0.171</td>
<td>0.153</td>
<td>0.092</td>
<td>0.081</td>
<td>0.051</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>
<thead>
<tr>
<th></th>
<th>Static</th>
<th>Dynamic</th>
<th>Static</th>
<th>Dynamic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Duration</strong></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><strong>Past Search</strong></td>
<td>-0.103***</td>
<td>-0.0684***</td>
<td>-0.0684***</td>
<td>-0.0684***</td>
</tr>
<tr>
<td></td>
<td>(0.0472)</td>
<td></td>
<td>(0.0261)</td>
<td></td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>5342</td>
<td>5342</td>
<td>8802</td>
<td>8667</td>
</tr>
<tr>
<td><strong>Adjusted $R^2$</strong></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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
A.6 GMM

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).

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 A.9: Two-step GMM (Differences)

<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</td>
<td>-0.185***</td>
<td>-0.109***</td>
</tr>
<tr>
<td></td>
<td>(0.0211)</td>
<td>(0.0326)</td>
</tr>
<tr>
<td>Past Search</td>
<td>-0.0539***</td>
<td>-0.0490***</td>
</tr>
<tr>
<td></td>
<td>(0.0201)</td>
<td>(0.0149)</td>
</tr>
<tr>
<td>Observations</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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: 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>$\chi^2_{23} = 240.11$</td>
<td>0.000</td>
</tr>
<tr>
<td>Hansen test of over-ID restrictions</td>
<td>$\chi^2_{23} = 33.13$</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.

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) |
|----------------------------------|----------------------------------|
| Time Diary                       | Weekly Recall                   |
|                                  | Static  | Dynamic | Static  | Dynamic |
| Duration                         | -0.0781*** | -0.0230 | -0.159*** | 0.152 |
|                                  | (0.00889) | (0.0142) | (0.0570) | (0.109) |
| Past Search                      | -0.0504*** | -0.0357*** |
|                                  | (0.0104) | (0.0104) |
| Observations                     | 19750   | 19750   | 19072   | 19072   |

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

Source: Survey of Unemployed Workers in New Jersey
$H_0$ (AB): No serial correlation; $H_0$ (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.

$y_{it}$ is defined as $y_{it}^\perp = c_{it} \left[ y_{it} - \frac{1}{T_{it}} \sum_{s > t} y_{is} \right]$ where $c_{it} \equiv \sqrt{T_{it}}/(T_{it} + 1)$.

27 The forward orthogonal deviation of $y_{it}$ is defined as $y_{it}^\perp = c_{it} \left[ y_{it} - \frac{1}{T_{it}} \sum_{s > t} y_{is} \right]$ where $c_{it} \equiv \sqrt{T_{it}}/(T_{it} + 1)$.
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>(0.0479)</td>
<td></td>
<td></td>
<td></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>

Standard errors in parentheses

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

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. Denoting by $p_{it}$ the SUWNJ measure of self-reported life satisfaction, consider such a model:

\[ p_{it} = \phi_0 + \phi_1 d_{it} + \phi_2 \sum _{k=0}^{t-1} s_{it} + \tau_t + \nu_i + \omega_{it} \]  
(A.1)

\[ s_{it} = \theta_0 + \theta_1 d_{it} + \theta_2 p_{it} + \tau_t + \left[ \delta_1 \ldots \delta_{10} \right] \cdot \begin{bmatrix} e_{1it} \\ \vdots \\ e_{10it} \end{bmatrix} + \eta_i + \epsilon_{it}. \]  
(A.2)

Note that substituting (A.1) into (A.2) 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 (A.1) and (A.2). 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. To estimate the system described by (A.1) and (A.2), 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 (A.1) and (A.2) 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.

\[ 28 \] Insofar as reductions in the perceived probability of exiting unemployment reduce expected permanent income, they should be correlated with reported quality of life.

\[ 29 \] This procedure amounts to estimating a seemingly-unrelated regression (SUR) model in which residuals are obtained in the first step using 2SLS.
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** (0.00347)</td>
<td>0.000944*** (0.000308)</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.00231 (0.00779)</td>
<td>-0.00527 (0.00701)</td>
</tr>
<tr>
<td>Search Time</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dissatisfaction</td>
<td>-17.05* (9.414)</td>
<td>-45.53** (18.07)</td>
</tr>
<tr>
<td>Duration</td>
<td>-0.0510 (0.133)</td>
<td>0.0235 (0.336)</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.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
B Model Solution and Proofs

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

B.1 Separations and the arrival of offers

I introduce separations by assuming that employed agents separate from their jobs at rate \( \rho \) 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 4.

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

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

(\ref{7})

\( \xi \) 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 \( t = 1, \ldots, n \) 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 \( t \not\in K \), 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-
tion $F$ and density $f$. The corresponding likelihood function for $\lambda$ is thus given by

$$
\mathcal{L}(\lambda) = \mathcal{L}(\lambda | \{\tau_t\}_{t \in K}; \{s_t\}_{t \notin K})
$$

$$(B.2)$$

$$
= \prod_{t \in K} f(\tau_t | \lambda) \prod_{t \notin K} (1 - F(s_t + \xi | \lambda))
$$

$$(B.3)$$

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

$$(B.4)$$

$$
= \lambda^{n_s} e^{-\lambda (\sum_{t \in K} \tau_t + \sum_{t \notin K} (s_t + \xi))}
$$

$$(B.5)$$

$$
= \lambda^{n_s} e^{-\lambda (n^s \bar{\tau} + n^f (\bar{s} + \xi))}
$$

$$(B.6)$$

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

Suppose now that prior beliefs over $\lambda$ 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

$$
p(\lambda) = \frac{\mathcal{L}(\lambda) g(\lambda | \alpha_0, \beta_0)}{\int \mathcal{L}(\lambda') g(\lambda' | \alpha_0, \beta_0) d\lambda'}
$$

$$(B.7)$$

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

$$(B.8)$$

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

$$(B.9)$$

$$
= e^{-\lambda (\beta_0+n^s \bar{\tau}+n^f (\bar{s} + \xi))} \lambda^{\alpha_0+n^s-1} (\beta_0+n^s \bar{\tau}+n^f (\bar{s} + \xi))^{\alpha_0+n^s}
$$

$$(B.10)$$

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

$$
\int e^{-x'} \left( \frac{x'}{\beta_0+n^s \bar{\tau}+n^f (\bar{s} + \xi)} \right)^{\alpha_0+n^s-1} dx' (\beta_0+n^s \bar{\tau}+n^f (\bar{s} + \xi))^{\alpha_0+n^s-1}
$$

$$(B.11)$$

$$
= \int e^{-x'} \left( x' \right)^{\alpha_0+n^s-1} dx'
$$

$$(B.12)$$

$$
= \Gamma(\alpha_0 + n^s).
$$

$$(B.13)$$

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

$$
p(\lambda) = \frac{\lambda^{\alpha-1} e^{-\lambda \beta} \beta^\alpha}{\Gamma(\alpha)}
$$

$$(B.14)$$

$$
= g(\lambda | \alpha, \beta).
$$

$$(B.15)$$
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

\[
\alpha = \alpha_0 + n^s \\
\beta = \beta_0 + \sum_{t \in K} \tau_t + \sum_{t \notin K} (s_t + \xi).
\]

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 (16) and (17) in Section 4.

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

\[
V_U^t(\alpha_t, \beta_t) = \max_{\tilde{s}_t} \left\{ E^\lambda_{\tilde{s}_t} \left[ F(\tilde{s}_t; \lambda) E^\omega_{\tilde{s}_t} \left[ V_O^t(\omega, \alpha_{t+1}, \beta_{t+1}) \right] \right] + (1 - F(\tilde{s}_t; \lambda))[b + \delta V_U^{t+1}(\alpha_{t+1}, \beta_{t+1})] - \eta \tilde{s}_t \right\} \tag{B.18}
\]

where \( V_O^t(\omega, \cdot) \) denotes the value of having offer \( \omega \) in hand and may be written as

\[
V_O^t(\omega, \alpha_{t+1}, \beta_{t+1}) = \max \left\{ \omega + \delta V_{t+1}^E(\omega, \alpha_{t+1}, \beta_{t+1}), b + \delta V_U^{t+1}(\alpha_{t+1}, \beta_{t+1}) \right\}. \tag{B.20}
\]

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

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

Assuming that the wage rate during employment is expected to be constant and that no offers arrive during employment, \( V_E^E(\cdot) \) is time-invariant which implies that (B.20) and (B.21) reduce to

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

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

\[ V_t^O(\omega, \alpha_{t+1}, \beta_{t+1}) = \begin{cases} 
\omega + \frac{\delta}{1 - \delta(1 - \rho)} [(1 - \rho)\omega + \rho V_{t+1}^U(\alpha_{t+1}, \beta_{t+1})] & \text{if } \omega > \bar{w}_t \\
\bar{w}_t + \delta V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}) & \text{if } \omega \leq \bar{w}_t
\end{cases} \]  

(B.24)

where

\[ \bar{w}_t = (1 - \delta(1 - \rho))b + (1 - \delta)(1 - \rho)\delta V_{t+1}^U(\alpha_{t+1}, \beta_{t+1}). \]  

(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

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

(B.26)

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

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

(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

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

(B.29)

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

(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 (15) reduces to

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

(B.31)
Rearranging and solving explicitly for $\bar{s}_t$, we obtain (16) in the text:

$$\bar{s}_t = \beta_t \left[ \frac{1}{\eta(1-\delta(1-\rho))} \int_{w_t}^{B} (\omega - w_t) \phi(\omega) d\omega \left( \frac{\alpha_t}{\beta_t} \right)^{\frac{1}{1+\delta}} - 1 \right]. \quad (B.32)$$

Next, using (B.30), the value of beginning the period unemployed in (12) can be written more concisely as

$$V_U(t, \alpha_t, \beta_t) = \max_{\bar{s}_t} \left\{ (1 - \left( \frac{\beta_t}{\beta_t + \bar{s}_t} \right)^{\alpha_t}) E_t^\omega \left[ V^O_t(\omega, \alpha_t, \beta_t) \right] + \left( \frac{\beta_t}{\beta_t + \bar{s}_t} \right)^{\alpha_t} \left[ b + \delta V_{t+1}^U(\alpha_t, \beta_t) \right] - \eta \bar{s}_t \right\}. \quad (B.33)$$

Rearranging, we obtain a more convenient form,

$$V_U(t, \alpha_t, \beta_t) = \max_{\bar{s}_t} \left\{ (1 - \left( \frac{\beta_t}{\beta_t + \bar{s}_t} \right)^{\alpha_t}) \left[ E_t^\omega \left[ V^O_t(\omega, \alpha_t, \beta_t) \right] - b - \delta V_{t+1}^U(\alpha_t, \beta_t) \right] + b + \delta V_{t+1}^U(\alpha_t, \beta_t) - \eta \bar{s}_t \right\}. \quad (B.34)$$

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

$$E_t^\omega \left[ V^O_t(\omega, \alpha_t, \beta_t) \right] - b - \delta V_{t+1}^U(\alpha_t, \beta_t) = \frac{1}{1-\delta(1-\rho)} \int_{w_t}^{\infty} (\omega - w_t) \phi(\omega) d\omega. \quad (B.35)$$

Combining (B.34) and (B.37) we obtain

$$V_U(t, \alpha_t, \beta_t) = \max_{\bar{s}_t} \left\{ (1 - \left( \frac{\beta_t}{\beta_t + \bar{s}_t} \right)^{\alpha_t}) \left[ \frac{1}{1-\delta(1-\rho)} \int_{w_t}^{\infty} (\omega - w_t) \phi(\omega) d\omega \right] + b + \delta V_{t+1}^U(\alpha_t, \beta_t) - \eta \bar{s}_t \right\}. \quad (B.36)$$

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 (11). Solving (B.39) for the value function yields

$$V_U(t, \alpha_t, \beta_t) = \max_{\bar{s}_t} \left\{ \frac{1}{1-\delta} \left[ (1 - \left( \frac{\beta_t}{\beta_t + \bar{s}_t} \right)^{\alpha_t}) \right] \left[ \frac{1}{1-\delta(1-\rho)} \int_{w_t}^{\infty} (\omega - w_t) \phi(\omega) d\omega \right] + b - \eta \bar{s}_t \right\}. \quad (B.40)$$
Substituting (B.41) into (11) and rearranging yields (17) from the text:

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

Together, (16) and (17) characterize optimal the optimal values of \( \tilde{s}_t \) and \( \bar{w}_t \), and thus model dynamics.

### B.4 Proof of Proposition 1

**Proof.** The result follows immediately from (B.16), (B.17) and (B.31).

### B.5 Proof of Proposition 2

**Proof.** Define the derivative of the right-hand side of (12) with respect to \( \tilde{s}_t \) as

\[ h(\tilde{s}_t, \alpha_t, \beta_t) \equiv \int_0^\infty f(\tilde{s}_t; \lambda) \left[ \frac{1}{1 - \delta(1 - \rho)} \int_{w_t}^B (\omega - w_t) \phi(\omega) d\omega \right] \gamma(\lambda; \alpha_t, \beta_t) d\lambda - \eta \] (B.43)

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

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

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

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

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

\[ \frac{\partial \tilde{s}_t}{\partial \beta_t} = \left( \frac{\beta_t + \tilde{s}_t}{\alpha_t + 1} \right) \left[ \frac{\alpha_t}{\beta_t} - \frac{\alpha_t + 1}{\beta_t + \tilde{s}_t} - (1 - \Phi(w_t)) \left[ \int_{w_t}^B (\omega - w_t) \phi(\omega) d\omega \right]^{-1} \frac{\partial w_t}{\partial \beta_t} \right]. \] (B.49)
Using (B.32) to eliminate references to \( \tilde{s}_t \) from (B.42), and again applying the implicit function theorem,

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

(B.50)

where

\[
z \equiv \frac{\delta(1 - \rho)\eta}{(\eta(1 - \delta(1 - \rho)))^{\frac{1}{\alpha_t + 1}}}.
\]

(B.51)

Making use of the optimality conditions for \( \tilde{s}_t \) and \( \bar{w}_t \), (B.50) reduces to

\[
\frac{\partial \bar{w}_t}{\partial \beta_t} = -\left[ \frac{\delta(1 - \rho)\eta (\tilde{s}_t)}{\beta_t} \right] \left[ \frac{1 + (1 - \Phi(\bar{w}_t)) \left( \frac{\delta(1 - \rho)}{1 - \delta(1 - \rho)} \right) \left[ 1 - \left( \frac{\beta_t}{\beta_t + \tilde{s}_t} \right)^{\alpha_t} \right]}{1 + (1 - \phi(\bar{w}_t)) \left( \frac{\delta(1 - \rho)}{1 - \delta(1 - \rho)} \right) - z \left( \beta_t \left[ \int_{\bar{w}_t}^{B} (\omega - \bar{w}_t) \phi(\omega) d\omega \right]^{-1} \right)^{\frac{1}{\alpha_t + 1}}} \right].
\]

(B.52)

Finally, substituting the expression in (B.52) into (B.49) and rearranging, Proposition 2 in the text obtains:

\[
\frac{\partial \tilde{s}_t}{\partial \beta_t} < 0 \text{ iff } \frac{\beta_t}{\alpha_t} > \tilde{s}_t + \tilde{s}_t^2 \left[ \left( \frac{\alpha_t + 1}{\alpha_t} \right) \frac{\delta(1 - \rho)\eta}{1 - \phi(\bar{w}_t)} \int_{\bar{w}_t}^{B} \omega \phi(\omega) d\omega - b \right].
\]

(B.53)

**B.6 Proof of Proposition 3**

*Proof.* Assume that (i) the wage offer distribution is degenerate at \( \bar{w} \); 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

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

(B.54)
The associated first-order condition for search time is then
\[
\eta = \frac{\alpha_t \beta_t}{(\beta_t + \tilde{s}_t)^{\alpha_t + 1}} \left[ \frac{w}{1 - \delta(1 - \rho)} - b - \delta V_{t+1}^U(\alpha_t, \beta_t) \right]. \tag{B.56}
\]
Together, these equations may be rearranged to write the first-order condition as
\[
\tilde{s}_t = \left[ \frac{\alpha_t \beta_t}{\eta} \left( w - b + \delta(1 - \rho)\eta \left( \frac{\beta_t}{\alpha_t} + \left( \frac{\alpha_t - 1}{\alpha_t} \right) \tilde{s}_t \right) \right) \right]^{\frac{1}{\alpha_t + 1}} - \beta_t. \tag{B.57}
\]
A few observations are warranted. First, when the offer distribution is degenerate, it must be that \(\alpha_t = \alpha_0 = 1\) \(\forall t\), simply because all offers are accepted. Second, \(\beta_t \equiv \beta_0 + \sum_{\tau=0}^{t-1} \tilde{s}_\tau\) for \(t \geq 1\). As before, this follows from the fact that the first offer that arrives before search expires is accepted; search is never terminated prematurely by an offer that is subsequently rejected.

Imposing \(\alpha_t = \alpha_0 = 1\), the first-order condition reduces to
\[
\tilde{s}_t = \left[ \frac{\beta_t}{\eta} \left( w - b + \delta(1 - \rho)\eta \beta_t \right) \right]^{\frac{1}{2}} - \beta_t. \tag{B.58}
\]
Taking a first-order expansion around \(\beta_t = \beta_0\) yields
\[
\tilde{s}_t \approx \left[ \frac{\beta_0}{\eta} \left( w - b + \delta(1 - \rho)\eta \beta_0 \right) \right]^{\frac{1}{2}} - \beta_0 + (\beta_t - \beta_0) \left. \frac{d\tilde{s}_t}{d\beta_t} \right|_{\beta_t = \beta_0} \tag{B.59}
\]
Recalling that \(\beta_t - \beta_0 = \sum_{\tau=0}^{t-1} \tilde{s}_\tau = \sum_{\tau=0}^{t-1} s_\tau + \xi t\), we can write
\[
s_t \approx \iota + \pi \xi t + \pi \sum_{\tau=0}^{t-1} s_\tau \tag{B.60}
\]
where
\[
\iota = \left[ \frac{\beta_0}{\eta} \left( w - b + \delta(1 - \rho)\eta \beta_0 \right) \right]^{\frac{1}{2}} - \beta_0 - \xi \tag{B.61}
\]
\[
\pi = \left. \frac{d\tilde{s}_t}{d\beta_t} \right|_{\beta_t = \beta_0} = \frac{1}{2} \left[ \beta_0 \left( \frac{w - c}{\eta} \right) + \delta(1 - \rho)\beta_0^2 \right]^{-\frac{1}{2}} \left[ \frac{w - c}{\eta} + 2\delta(1 - \rho)\beta_0 \right] - 1 \tag{B.62}
\]
corresponding to the reduced-form parameters in Section 3. Note that \(\pi < 0\) as in Section 3 when
\[
\frac{1}{2} \left[ \beta_0 \left( \frac{w - c}{\eta} \right) + \delta(1 - \rho)\beta_0^2 \right]^{-\frac{1}{2}} \left[ \frac{w - c}{\eta} + 2\delta(1 - \rho)\beta_0 \right] < 1. \tag{B.63}
\]
The left-hand side is quadratic in \(\beta_0\), and so the condition reduces to
\[
\beta_0 > \left( \frac{w - c}{2\delta(1 - \rho)\eta} \right) \left[ \left( \frac{1}{1 - \delta(1 - \rho)} \right)^{\frac{1}{2}} - 1 \right]. \tag{B.64}
\]
Setting $\rho = \xi = 0$ yields the expression in Proposition 3.

B.7 Proof of Proposition 4

Proof. The result follows immediately from (B.52).

B.8 Proof of Proposition 5

Proof. The true probability of receiving and accepting a job offer $p_t$ is given by

$$p_t = (1 - \Phi(w_t'))F(s_t; \lambda^T)$$  \hspace{1cm} (B.65)

where $w_t'$ denotes the reservation wage \textit{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

$$\frac{\partial p_t}{\partial \beta_t} = (1 - \Phi(w_t'))f(s_t; \lambda^T) \frac{\partial s_t}{\partial \beta_t} - F(s_t; \lambda)\phi(w_t') \frac{\partial w_t'}{\partial \beta_t}$$  \hspace{1cm} (B.66)

The probability of exiting unemployment is then decreasing in $\beta_t$ iff

$$\frac{f(s_t; \lambda^T)}{F(s_t; \lambda^T)} \frac{\partial s_t}{\partial \beta_t} < \frac{\phi(w_t')}{{\Phi(w_t')}} \frac{\partial w_t'}{\partial \beta_t}$$  \hspace{1cm} (B.67)

Substituting (B.49) into (B.67), we obtain

$$\frac{f(s_t; \lambda^T)}{F(s_t; \lambda^T)} \left( \frac{\beta_t + s_t}{\alpha_t + 1} \right) \left[ \frac{\alpha_t}{\beta_t} - \frac{\alpha_t + 1}{\beta_t + s_t} - (1 - \Phi(w_t)) \left[ \int_{w_t}^B (\omega - w_t)\phi(\omega)d\omega \right]^{-1} \frac{\partial w_t}{\partial \beta_t} \right]$$  \hspace{1cm} (B.68)

$$< \frac{\phi(w_t')}{1 - \Phi(w_t')} \frac{\partial w_t'}{\partial \beta_t}$$  \hspace{1cm} (B.69)

Upon receiving an offer, $\alpha_{t+1} = \alpha_t + 1$ and $\beta_{t+1} = \beta_t + \tau_t$. Using this, we can write

$$\frac{\partial w_t}{\partial \beta_t} = -\left[ \frac{\delta(1 - \rho)\eta}{1 + (1 - \Phi(w_t))} \left( \frac{s_t}{\beta_t} \right) \right] \left[ 1 - \left( \frac{\beta_t}{\beta_t + s_t} \right)^{\alpha_t} \right]$$  \hspace{1cm} (B.70)

$$\frac{\partial w_t'}{\partial \beta_t} = -\left[ \frac{\delta(1 - \rho)\eta}{1 + (1 - \Phi(w_t'))} \left( \frac{s_t'}{\beta_t + \tau_t} \right) \right] \left[ 1 - \left( \frac{\beta_t + \tau_t}{\beta_t + \tau_t + s_t'} \right)^{\alpha_t+1} \right]$$  \hspace{1cm} (B.71)
Substituting (B.70) and (B.71) into (B.69) we obtain the condition in Proposition 5:

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

(B.72)

(B.73)

B.9 Rational expectations

The model presented in Section 4 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 8 plots the search policy functions under anticipated utility and rational expectations using the parameters estimated in Section 5. 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.

Figure 8: Search policy functions
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 5.

C.2 Alternative model

The alternative model estimated in Section 5 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:

$$m(d) = m_0 + m_1d + m_2d^2 + m_3d^3 + m_4d^4 \quad (C.1)$$

$$\lambda^T(d) = t_0 + t_1d + t_2d^2 + t_3d^3 + t_4d^4. \quad (C.2)$$

I directly estimate $m_0, m_1, m_2, m_3, t_0, t_1$ and $t_2, t_3$. $m_4$ 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 $\eta$:

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

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 $\lambda^T_t$, augmented with heterogeneity and arbitrary duration dependence as described above. Specifically, job seekers solve the following recursive problem:

$$V^U_t(d) = \max\limits_{\tilde{s}_t} \left\{ F(\tilde{s}_t; \lambda^T_t(d))E_t^\omega[V^O_t(\omega, d + 1)] \ight.$$  

$$+ (1 - F(\tilde{s}_t; \lambda^T_t(d)))[b + \delta V^U_{t+1}(d + 1)] - \eta_i \tilde{s}_t \right\} \quad (C.4)$$

$$V^O_t(\omega, d + 1) = \max \left\{ \omega + \delta V^E_{t+1}(\omega), b + \delta V^U_{t+1}(d + 1) \right\} \quad (C.5)$$

$$V^E_{t+1}(\omega) = (1 - \rho)[\omega + \delta V^E_{t+2}(\omega)] + \rho V^U_{t+1}(0). \quad (C.6)$$

Because the value of employment is time-invariant,

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

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

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:

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

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

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

### 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><strong>Physical</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Offer arrival rate</td>
<td>1.01 (0.04)</td>
</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><strong>Exog. Trends</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$t_1$</td>
<td>Arrival rate trend 1</td>
<td>-1.27e-02 (7.10e-04)</td>
</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>
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<td>Mean offer trend 1</td>
<td>1.70e-02 (3.63e-04)</td>
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<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><strong>Heterogeneity</strong></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

I calibrate 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 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.

The restrictions used to pin down $\alpha_0$, $\beta_0$ and $\lambda^T$ are thus:

\begin{align}
\text{Bias:} & \quad B = \left(\frac{\alpha_0}{\beta_0} - \lambda^T\right) / \lambda^T \quad (D.1) \\
\text{Dispersion:} & \quad V = \frac{\alpha_0}{\beta_0^2} \quad (D.2) \\
\text{Unempl. exit probability:} & \quad p_0 = \int_0^\infty \left[1 - \Phi(w(\alpha_0 + 1, \beta_0 + \tau))\right] f(\tau; \lambda^T) d\tau. \quad (D.3)
\end{align}

D.1 Data

In order to implement the calibration, 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

\begin{equation}
\begin{aligned}
u_{m}^{t+1} &= (1 - p_s^t) \left[u_s^t + u_s^{t-1} (1 - p_s^{t-1})\right] \quad (D.4)
\end{aligned}
\end{equation}

where $u_m^t$ 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

---

\footnote{I use the short-term unemployment exit probability as an approximation of the unemployment exit probability in the first week of unemployment.}
given initial conditions. I therefore assume that, prior to 1950, $u_t^s$, $u_t^{m0}$ and $p_t^s$ 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 (D.1) and (D.2) for $\alpha_0$ and $\beta_0$:

\[
\alpha_0 = \frac{1}{V} \left( (1 + B) \lambda^T \right)^2 \quad (D.5)
\]
\[
\beta_0 = \frac{1}{V} \left( (1 + B) \lambda^T \right) . \quad (D.6)
\]

Substituting these expressions into (D.3) and making use of the optimality conditions in (16) and (17), 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.5) and (D.6) to obtain values for $\alpha_0$ and $\beta_0$ as desired.

Figures 9a and 9b 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).

**Figure 9: Pre-Great Recession search dynamics**

![Figure 9](image-url)