Job Seekers' Perceptions and Employment Prospects: Heterogeneity, Duration Dependence and Bias*

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Abstract

This paper analyses job seekers' perceptions and their relationship to unemployment outcomes to study heterogeneity and duration-dependence in both perceived and actual job finding. Using longitudinal data from two comprehensive surveys, we document (1) that reported beliefs have strong predictive power of actual job finding, (2) that job seekers are over-optimistic in their beliefs, particularly the long-term unemployed, and (3) that job seekers do not revise their beliefs downward when remaining unemployed. We then develop a reduced-form statistical framework, where we exploit the joint observation of beliefs and ex-post realizations, to disentangle heterogeneity and duration-dependence in true job finding rates while allowing for elicitation errors and systematic biases in beliefs. We find a substantial amount of heterogeneity in true job finding rates, accounting for more than half of the observed decline in job finding rates over the spell of unemployment. Moreover, job seekers' beliefs are systemically biased and under-respond to differences in job finding rates both across job seekers and over the unemployment spell. Finally, we show theoretically and quantify in a calibrated model of job search how these biases in beliefs contribute to the slow exit out of unemployment. The biases jointly explain about 15 percent of the high incidence of long-term unemployment.

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1 Introduction

A critical challenge for unemployment policy is the high incidence of long-term unemployment. While long unemployment durations and a large share of long-term unemployed have been a common phenomenon in European countries (see Ljungqvist and Sargent [1998] and Machin and Manning [1999]), the Great Recession has imported this concern to the US as well (Kroft et al. [2016]).[1] The consequences of job loss can be large, but especially so for people who get stuck in longs spells of unemployment. Moreover, the high incidence of long-term unemployment is indicative of substantial frictions in the search and matching process, and can contribute to the persistence of employment shocks (Pissadires [1992]). Understanding why the employment prospects are worse for the long-term unemployed is crucial for formulating policy responses and has been the topic of a long literature.[2] Empirically, however, separating the role of duration-dependent forces from unobserved heterogeneity across job seekers has proven to be a challenge until today. Since the seminal work by Cox [1972], Lancaster [1979] and Heckman and Singer [1984], several studies have tried to estimate or calibrate the contribution to the negative duration-dependence of job finding rates, coming from dynamic selection effects, true duration-dependence in the search environment (e.g., skill-depreciation or stock-flow sampling of vacancies), or an interaction of the two (e.g., duration-based employer screening).[3]

This paper studies unemployed job seekers' perceptions of their employment prospects together with their actual labor market transitions, and contributes to this literature in three ways. First, we document a number of novel facts about job seekers' perceptions of their re-employment prospects. A crucial feature of our data is its longitudinal nature, which allows to compare reported perceptions to ex-post realizations as well as to analyze the evolution of perceptions over the spell of unemployment. Second, we exploit the empirical relation between perceptions and employment outcomes to disentangle the role of true duration-dependence and unobserved heterogeneity in *true* job finding rates. The elicitation of the perceived employment prospects, both across individuals and over the unemployment spell, allows us to overcome the challenge that we do not observe an individual's job finding rate, but only the time spent unemployed. Finally, we study how heterogeneity and duration-dependence in job seekers' *perceptions* can contribute to the incidence of long-term unemployment. Individuals who overestimate their employment prospects will be overly selective and inefficiently prolong their unemployment spells. Similarly, misperceptions of the heterogeneity and duration-dependence in employment prospects will magnify the observed duration-dependence and incidence of long-term unemployment.

The paper starts with a detailed empirical analysis of job seekers' beliefs collected in two distinct surveys: The first survey is the Survey of Consumer Expectations (SCE), which is run by the Federal Reserve Bank of New York every month and has a rotating panel structure where individuals are interviewed every month for a period of up to 12 months (see Armantier et al. [2017] for details). The

[1] While the share of long-term unemployed workers (unemployed for more than six months) has been consistently above 50% in most European countries in recent decades, in the US this share rose from 20% to just below 50% in the aftermath of the Great Recession (Kroft et al. [2016]).

[2] See Machin and Manning [1999] for a review of the relevant literature. See Shimer and Werning [2006], Pavoni [2009] and Kolsrud et al. [2018] for the consequences for the design of the unemployment benefit profile. See Pavoni and Violante [2007], Spinnewijn [2013] and Wunsch [2013] for the consequences on the design of workfare, job search assistance and training programs.

[3] Recent examples are Kroft et al. [2013], Jarosch and Pilossoph [2017] and Alvarez et al. [2016].

SCE started in December 2012 and surveys a representative sample of 1,300 household heads every month. We focus on the subset of respondents who report being unemployed at least once at the time of the survey. The second survey is the Survey of Unemployed Workers in New Jersey, which surveyed a large sample of unemployment insurance recipients in NJ every week from October 2009 to March 2010 (see the appendix of Krueger and Mueller [2011] for details). The longitudinal nature of both data sets provides a unique opportunity to analyse how perceptions evolve over the unemployment spell. Both surveys contain follow-up information on employment status and thus we can determine how perceptions and actual realizations relate for the same individuals. Moreover, the time frame and geographic variation allows us to study the role of labor market conditions. Finally, we elicit job seekers' perceptions about their re-employment prospects at different horizons and/or in different ways, so we can study robustness to the elicitation method.

The empirical analysis provides three main results. First, comparing the perceived and the actual probability to find employment for the same sample of job seekers, we find an optimistic bias overall. In the NJ sample, which consists mostly of long-term unemployed job seekers, asking beliefs at a 1-month horizon, people report a 26 percent probability to find a job, while the actual job finding probability is around 10 percent. In the SCE, asking beliefs at a 3-month horizon, the overall optimistic bias is smaller, but the optimistic bias is increasing in the duration of the unemployment spell, i.e. the long-term unemployed again substantially over-estimate their job finding probability. Second, when using only within-person variation, we find that job seekers report slightly higher job-finding probabilities the longer they are unemployed. In the NJ sample, this increase is about 2 percent for each additional month of unemployment and is statistically significant. This result is perhaps surprising, given the large empirical literature trying to identify the true duration dependence of actual job finding rates and arguing that it is negative, which would run counter to how it is perceived.[4] Third, despite the observed biases, we find a strong predictive value of the surveyed expectations for ex-post realizations. In both surveys, the perceived job finding probabilities significantly predict actual job finding at the individual level. This holds even when we control for a rich set of observable co-variates. In the SCE, the bi-variate regression coefficient is 0.62 for the ST unemployed and 0.41 for the LT unemployed, suggesting that the LT unemployed are not just more optimistic on average, but less precise in predicting their differences in employability.

We develop a reduced-form statistical framework to take advantage of our ability to observe job seekers' perceived job finding probabilities and actual job finding. The main goal of this exercise is to estimate the heterogeneity and duration-dependence in both the perceived and actual job finding probabilities. Our framework allows for random elicitation errors and biases in reported beliefs, differing systematically both across job seekers as well as along the unemployment spell. Within our framework, we identify the elicitations errors and biases jointly with the extent of ex-ante heterogeneity and duration dependence in true job finding rates. The key idea underlying the identification in our statistical framework is that the covariance between perceptions and actual job finding rates helps uncovering the extent of ex-ante heterogeneity in true job finding probabilities. This relates to the recent work using risk elicitations to estimate heterogeneity in ex-ante risks by Hendren [2013] and Hendren [2017]. Our

[4]An important exception is Alvarez et al. [2016] who estimate true duration dependence to be positive with data on multiple unemployment spells in Austria.

analysis goes further in an important dimension, by allowing for systematic biases in the relation between actual and perceived job finding probabilities. We identify these biases by exploiting how the wedge between perceived and actual job finding probabilities relates to unemployment duration, both across and within job seekers. The main intuition is that biases along the unemployment spell are identified from how perceptions evolve over the unemployment spell for a given individual, i.e. controlling for selection, whereas biases across job seekers determine how perceptions relate to unemployment duration in the cross-section, i.e. not controlling for selection.

The estimates from our statistical model imply substantial ex-ante heterogeneity in true job finding rates, with the ex-ante heterogeneity in job finding rates accounting for 54 percent of the observed decline in job finding rates over the spell of unemployment and true duration dependence explaining the remainder. The model estimates also reveal substantial biases across job seekers: job seekers with a high underlying job finding rate tend to be over-pessimistic, whereas job seekers with a low job finding rate are over-optimistic. As the latter remain unemployed longer, their share grows with duration of unemployment. This type of dynamic selection is one reason why the long-term unemployed tend to be over-optimistic, the other reason being that job seekers under-appreciate the decrease in their own job finding chances when remaining unemployed for longer. Our findings prove to be robust to alternative assumptions about functional form and distributional assumptions. We also show that our statistical framework is parsimoniously specified but fits the key moments in our data very well. Restricted versions of the model, which do not allow for systematic biases in perceptions or abstract from ex-ante heterogeneity in job finding rates perform radically worse in fitting the data moments.

The final question that we try to answer is how biases in beliefs and the corresponding behavior of job seekers contribute to the incidence of LT unemployment. To study the behavioral impact of job seekers' biased beliefs, we set up a job search model a la McCall [1970], but introduce heterogeneity and duration dependence in job offer rates, and biased beliefs. The key mechanism that we highlight in this structural model is that job seekers' behavior mitigates the mechanical effect of changes in job offer rates on job finding rates, conditional on these changes being perceived. Hence, biases in beliefs about job offer rates will amplify (dampen) the impact of the job offer rate on the job finding rate, if job seekers perceptions' under-respond (over-respond) to differences in job offer rates. To put it more simply, if those with a low probability of receiving a job offer are over-optimistic, they raise their reservation wage and thus are even less likely to find a job. Similarly, we show formally that negative duration dependence in job finding rates - either driven by differences in job offer rates across workers or over the unemployment spell - tends to be magnified when these differences are not perceived as such.

We estimate the job search model on a subset of moments that we used for the estimation of the statistical model. While in theory it is possible, to perform the same estimation exercise in the structural model as in the reduced-form statistical model, fitting our cross-sectional data moments requires a large number of types, which is computationally challenging given that we need to solve the decision problem for each type. Instead, in the structural model, we calibrate the true duration dependence in job finding rates and their perceptions as given by the statistical model, and only estimate the parameters relating to ex-ante heterogeneity. We then use the calibrated model to quantify the impact of biases in beliefs on job finding rates over the unemployment spell. Correcting the biases in beliefs reduces the share of unemployment spells lasting longer than 6 months, by 10.1 to 12.5 percent. Defining the incidence of long-term unemployment as the share of these LT vs. ST unemployed, we find that the biases in beliefs jointly explain about 15% of the incidence of long-term unemployment. This result is robust to the relative importance of 'true' heterogeneity vs. 'true' duration-dependence in true job finding, as both sources of observed duration-dependence are under-perceived.

This paper aims to contribute to three different strands in the literature. First, we contribute to the large literature trying to understand the different sources of duration-dependence in job finding by highlighting biases in beliefs as a new source. Moreover, using a novel strategy to separate dynamic selection from *true* duration dependence, we estimate heterogeneity across agents to be more important than *true* duration-dependence. Recent audit studies (e.g., Kroft et al. [2013]) documenting large declines in callback rates over the unemployment the spell have put *true* duration-dependence forward as the natural explanation for the high incidence of long-term unemployment. Jarosch and Pilossoph [2017], however, have questioned the translation of duration-dependence in callback rates into duration-dependence in job finding, and Alvarez et al. [2016], in fact, find evidence for positive duration-dependence using data on multiple unemployment spells.[5] Still, direct evidence on the role of heterogeneity has been limited to the dynamic selection in longer unemployment spells based on observables, which plays a moderate role only (e.g., Kroft et al. [2016]). Second, our analysis of the biases in beliefs relates to a strand in the behavioral labor economics literature trying to understand the role of behavioral frictions in the job search process. Other examples are DellaVigna and Paserman [2005] studying the role of impatience and DellaVigna et al. [2017] studying the role of reference-dependence on job finding rates. The new survey evidence confirms the optimistic bias in beliefs in Spinnewijn [2015], but also identifies the under-response in beliefs to differences, both across workers and over the unemployment spell. Third, our work relates to recent papers using survey elicitations to improve the estimation or calibration of structural models of job search. For example, Hall and Mueller [2018] use elicited reservation wages in the Krueger-Mueller survey to identify different sources of wage dispersion in a search model. Conlon et al. [2018] use elicited expectations on the level of future wage offers and updating in response to received wage offers to estimate a model of on-and-off the job search with learning. Similar to our numerical analysis, they use the estimated structural model to assess the quantitative importance of the information frictions on different outcomes of interest. Elicited expectations have also been used in other applications, for example in educational and occupational choices (e.g., Delavande and Zafar [2014], Arcidiacono et al. [2014], Wiswall and Zafar [2015]) and in household finance applications (e.g., Fuster et al. [2018] and Crump et al. [2018]). Our use of elicited expectations to learn about heterogeneity in ex-ante types builds on the approach in Hendren [2013] and Hendren [2017], who uses elicited risk perceptions to study the potential for adverse selection in settings where private markets do not arise, and we extend his approach by allowing for biases in beliefs.

The paper proceeds as follows. Section 2 discusses the two data sources. Section 3 documents the basic facts in the data. Section 4 sets up the statistical model and estimates heterogeneity and duration-dependence in perceived and actual job finding. Section 5 sets up and characterizes the behavioral model of job search and provides numerical results quantifying the impact of biases in beliefs. Section 6 concludes.

[5]See also Honoré [1993] who proves identification with multiple unemployment spells in the context of the mixed proportional hazard model.

2 Data

Our empirical analysis builds on two distinct surveys:

- The Survey of Consumer Expectations (SCE) is run by the New York Federal Reserve Bank and surveys a representative sample of 1,300 household heads across the US. The sample is a rotating panel where each individual is surveyed every month for up to 12 months (see Armantier et al., 2013, for details). Our sample period stretches from December 2012 to December 2017 during which 777 job seekers have been surveyed while unemployed.

- The Survey of Unemployed Workers in New Jersey was collected by Alan Krueger and Andreas Mueller and surveyed around 6,000 unemployed job seekers (see the appendix of Krueger and Mueller [2011] for details). In what follows, we refer to the survey as the Krueger-Mueller (KM) survey. The surveyed job seekers were unemployment insurance recipients in October 2009 and interviewed every week for 12 weeks until January 2010. The long-term unemployed were surveyed for an additional twelve weeks until March 2012.

Both surveys elicit the beliefs individuals hold when unemployed about their prospects to become employed again. In the SCE, unemployed job seekers report the probability they expect to be employed again within the next 3 months and in the next 12 months. In the KM survey, job seekers report the probability that they expect to be reemployed again within the next 4 weeks, as well as how many weeks they expect it will take before they are employed again.[6] The beliefs are elicited up to 12 times (4 times) in the SCE (KM survey) for job seekers who remain unemployed. The KM survey is a weekly survey, but the belief questions were administered only every four weeks, starting about one month into the survey period.[7] Given that many individuals had already found a job after a month or left the survey for other reasons, and given the lower interview frequency of the belief questions, the sample of interest for our study is substantially smaller than the full weekly panel of the KM survey.

In addition to the elicited beliefs, both surveys contain information on the individuals' employment outcomes, and hence, we can link perceptions and actual outcomes for the same individuals. The SCE survey is superior to the KM survey in this respect because it suffers less from attrition and skipping. As reported by Armantier et al. [2017], out of those who completed one interview, 74 percent completed two interviews. Attrition is much lower after the second interview and, in fact, 58 percent completed all 12 monthly interviews of the SCE panel. In addition, we find that nearly half of surveys where the respondent was unemployed were followed by three consecutive monthly interviews, which is the subsample that we use when comparing elicitations to employment outcomes over the next three months. It should be noted here that even if there was no attrition, this number would be at most 75 percent, since unemployed respondents who are rotating out of the panel survey do not have three monthly follow-up surveys (this affects anyone in interviews 10, 11 and 12).[8] In the KM survey, out of those

[6]Both are online surveys. The KM survey asked participants to slide a bar between 0 and 100, randomizing the initial position. The exact questions and response format is shown in Appendix A.

[7]Individuals who did not complete a weekly survey exactly four weeks after the last time the belief questions were administered, the belief questions were administered at the next interview.

[8]Note also that respondents in the SCE who failed to complete three interviews consecutively are not invited back to the survey.

2,384 individuals who completed the belief questions at least once, 60 percent completed the belief questions twice, but only 21 percent completed them more than twice. This drop-off in participation in the KM survey is to a large extent due to the shorter horizon of the survey, where only the long-term unemployed were invited to participate for more than 12 weeks (see above). We also find that the number of weekly surveys completed following an interview where the belief question was administered was negatively related to the elicited belief about the probability of finding a job within the next four weeks.[9] While the invitations and reminder emails explicitly stated that respondents are invited back to the survey regardless of their employment status, this suggests that the KM survey still exhibited some differential attrition by expected employment outcomes, introducing a potential bias when relating beliefs to employment outcomes later in the survey. For this reason, we focus mostly on the SCE survey when comparing beliefs to employment outcomes.

Table 1 compares some basic survey outcomes and demographics for the unemployed workers in the two surveys. Both samples are restricted to unemployed workers, ages 20-65. The KM survey's sample is further restricted to interviews where the belief questions were administered. Note that while the SCE survey is representative of the population of U.S. household heads[10], the KM survey's sample is representative of unemployment insurance recipients in New Jersey, see Krueger and Mueller [2011] for details. The KM survey over-sampled long-term unemployed workers, but the survey includes survey weights, which adjust for both oversampling and non-response. The differences in the sampling universe explains some of the differences in the characteristics of the unemployed in these surveys, particularly in terms of the composition by age and ethnicity. The monthly job finding rate in the SCE is 17.6 percent compared to 10.5 percent in the KM survey, where the lower rate in the latter is likely due to the lower job finding rate in the immediate aftermath of the Great Recession, but may also be driven by differential attrition.[11]

3 Empirical Evidence

We use the elicited beliefs to analyze the perceptions of job seekers about their employment prospects. Our main object of interest will be the heterogeneity and duration-dependence in both the perceived and actual job finding rates. The job finding rate T_{id} for individual i at unemployment duration d can be modeled as

$$T_{id} = T(T_i, \phi_{id}, \tau_{id}), \tag{1}$$

which depends on the job seeker's type, denoted as T_i, the state she or he is in (e.g., time spent

[9] We find that the elicited probability is 26 percent for those with four weekly surveys within the next four weeks, whereas it was 34 percent for those with less than four weekly survey within the next four weeks. For linking the employment outcomes to the elicited beliefs in the KM survey, we find that only about 17 percent of survey participants completed four consecutive weekly interviews following an interview where the 4-week belief question was elicited.

[10] See Table B1 in the Appendix for a comparison of the SCE to the Current Population Survey (CPS) both for the full sample and the sample of unemployed workers. Note that the CPS is a survey of individuals whereas the SCE is a survey of household heads, which explains why the sample in the SCE is somewhat older.

[11] Note that while Table 1 restricts the sample in both surveys to those unemployed at the time of the survey, in parts of the paper when we compare reported beliefs to outcomes, we also make use of information from other interviews where the respondent was employed.

Table 1: Descriptive Statistics for the Survey of Consumer Expectations (SCE) and the Krueger-Mueller (KM) Survey

	SCE 2012-17	KM Survey 2009-10
Demographic data (in percent)		
High-School Degree or Less	42.8	32.5
Some College Education	21.0	37.4
College Degree or More	35.3	30.1
Female	55.7	48.6
Ages 20-34	24.8	38.1
Ages 35-49	32.7	35.4
Ages 50-65	42.4	26.5
Black	16.5	19.8
Hispanic	11.4	25.6
Survey outcomes		
Avg. monthly job finding rate (in percent)	17.6	10.5
# of respondents	777	2,384
# of respondents w/ at least 2 unemployed surveys	437	1,422
# of unemployed survey responses	2,117	4,803

Notes: Both samples are restricted to unemployed workers, ages 20-65. Data for the KM survey sample is further restricted to interviews where the belief questions were administered. The monthly job finding rate in the SCE is the U-to-E transition rate between two consecutive monthly interviews. See footnote of Table 2 for how job finding is measured in the KM survey. Survey weights are used for all estimates.

unemployed or local labor market conditions), denoted by ϕ_{id}, and an idiosyncratic shock, τ_{id}. The surveys elicit the *perceived* job finding probability Z_{id}, which we model as

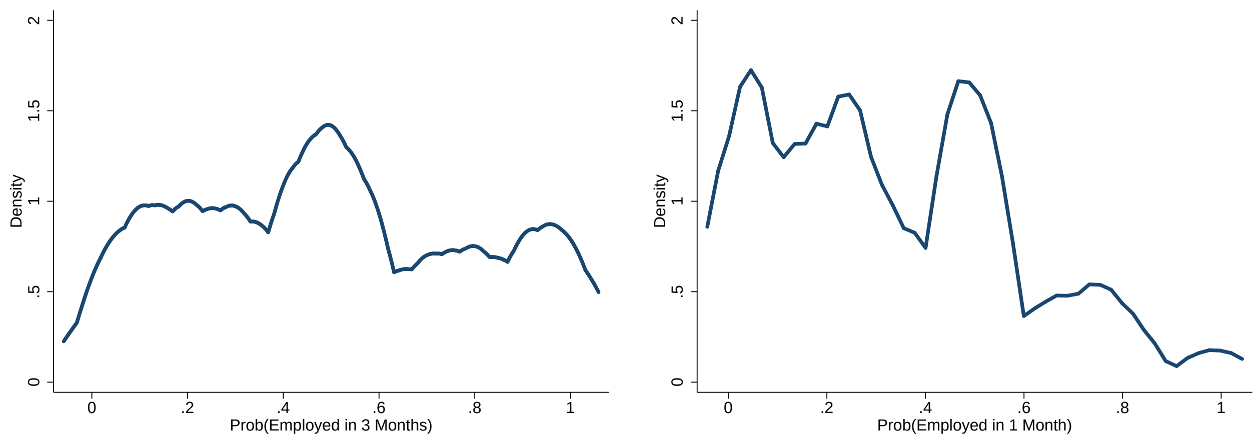
$$Z_{id} = Z(T_i, \phi_{id}, \tau_{id}) + \varepsilon_{id}. \tag{2}$$

where differences between the functions $T(.)$ and $Z(.)$ capture systematic biases in beliefs and ε_{id} is a random error in the perceptions or the elicitation itself.

While an individual's perceived job finding probability Z_{id} *can* be elicited, it is not possible to directly observe an individual's actual job finding probability T_{id} and its state-dependence nor is it possible to directly observe differences in actual job finding T_{id} across individuals. We do, however, observe the outcome E_{it} of the job seeker's job search, that is, whether the job seeker has found a job or not, and we can relate this ex-post outcome to the job seeker's ex-ante perception Z_{id} to potentially learn about heterogeneity and state-dependence in the actual job finding rates.

In what follows in this Section, we describe the elicited beliefs, how they relate to actual job finding and how they change over the spell of unemployment. In the following Section 4, we model the relationship between elicited beliefs and the actual job finding probability and use the facts established in this section to make inferences about the extent of heterogeneity and the nature of state-dependence in true job finding rates.

Figure 1: Kernel Density Estimates of Elicitations of the 3-Month Job Finding Probability in the SCE (left panel) and the 1-Month Probability in the KM survey (right panel)



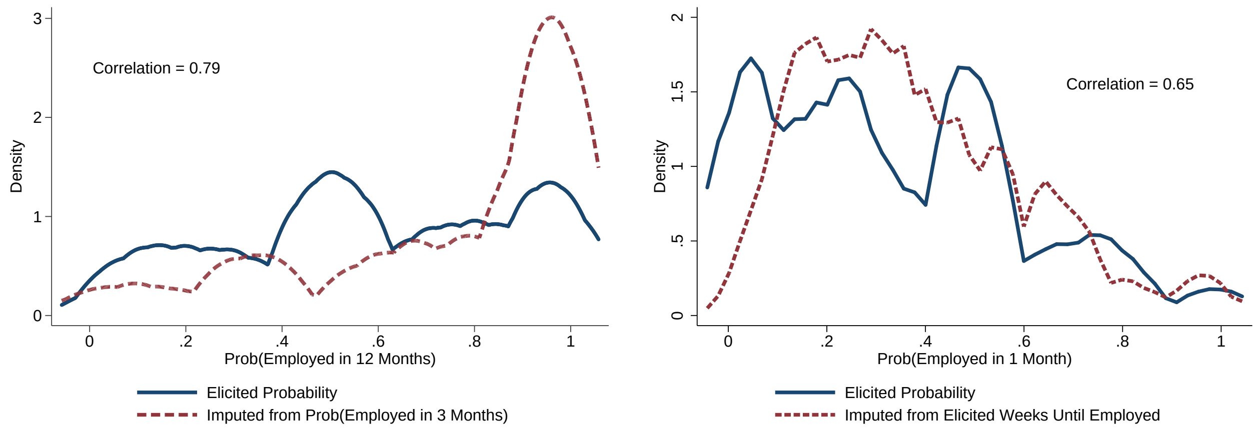
3.1 Elicited Beliefs about Job Finding

The two surveys ask unemployed job seekers to report their perceived job finding probability (see Appendix A for the wording of the main questions asked in both surveys). The left panel of Figure 1 shows the distribution of perceived probabilities at a three-month horizon in the SCE. The right panel of Figure 1 shows the distribution of perceived probabilities at a one-month horizon in the KM survey. Technically, the question in the KM survey was about a 4-week period, but for simplicity we refer to it as 1-month period going forward. For both surveys there is substantial dispersion over the entire range of potential probabilities.[12] The perceived probabilities over the one-month horizon are more skewed to the left than the perceived probabilities over the three-month horizon, but the former seem relatively high compared to the latter. While the elicitation horizon may be relevant, this comparison is difficult because it is across different samples. Another common issue when eliciting probabilities is that subjects bunch at round numbers. We do observe significant bunching for both measures, in particular at 50%, as apparent from Figure 1.

To assess the validity of our elicitations and the robustness to bunching, we compare the elicited beliefs about job finding at different horizons in the same sample of job seekers. In the SCE, job seekers report the perceived job finding probability at a three-month horizon and a twelve-month horizon. The left panel of Figure 2 shows the distribution of the twelve-month job finding probabilities and compares this to the imputed job finding probability over twelve months based on the elicitation over a three-month horizon. The two densities should be comparable if unemployed workers expect the probability of finding a job to remain constant over the spell. The imputation overestimates the ability of finding a job compared to the twelve-month elicitation. Nevertheless, we find a high correlation of 0.76 between the two measures at the individual level. Appendix Figure C1 also shows that the distribution of the ratio of the two statistics has a mode of 1. This suggests that many survey respondents submit responses that would be fully consistent with each other, at least if they believed that they live in a stationary

[12] Manski [2004] discusses other surveys where respondents use the entire range of probabilities from 0 to 100, as well as additional evidence that respondents are willing and able to provide meaningful probabilistic responses.

Figure 2: Comparison of Kernel Density Estimates for Alternative Forms of Elicitations about Re-employment Prospects



world where the unemployment probability does not change over the spell of unemployment.

In the KM survey, job seekers report not only the perceived probability of finding employment, but also how many weeks they expect it will take to be employed again. The inverse of the expected unemployment duration equals the perceived job finding rate averaged over the remaining unemployment spell. Hence, the elicited average job finding rate and the job finding rate for next month should be related, again depending on whether an individual expects the job finding rate to change over the unemployment spell. The right panel of Figure 2 plots the distribution of the inverse of the expected remaining unemployment time.[13] Importantly, the alternative elicitation has the advantage that it avoids the sharp bunching at 0, 50 and 100, but except for the difference in bunching, the distribution looks very similar to the distribution of the perceived job finding rates for the next month. The individual-level correlation between the two measures equals 0.65.[14] The similarity between the different measures is also confirmed by Figure C1 in the Appendix, which plots the distribution of the ratio of the two measures, indicating that for most peoples the two measures indeed coincide. Overall, the similarity between the alternative elicitations is re-assuring. Our empirical analysis will focus on the elicited probability, but we will show robustness of our results for the expected duration measure and for bunching at 0, 50 or 100.

3.2 Job Finding Beliefs and Outcomes

We now study how job seekers' beliefs about job finding probabilities compare to the actual outcomes of their job search.

[13] To be precise, given that the question was phrased in weeks, we impute the implied 1-month re-employment probability as $1-(1-\frac{1}{x})^4$, where x is the elicited remaining weeks unemployed.

[14] Note that throughout the paper we trim extreme outlier observations, by eliminating 51 survey responses where the elicited and imputed probability are more than 75 percentage points apart and thus clearly inconsistent with each other. We report robustness checks in the Appendix for not imposing this restriction. If we do not impose the restriction in Figure 2, the correlation coefficient is somewhat lower but still high at 0.56.

Table 2: Comparison of Perceived and Realized Job-Finding Probabilities

	Perceived Job-Finding Probability	Realized Job-Finding Rate	Sample Size
Panel A. SCE (3-month horizon)			
Full sample	0.474 (0.016)	0.396 (0.024)	983
Duration 0-3 months	0.592 (0.032)	0.622 (0.043)	302
Duration 4-6 months	0.511 (0.034)	0.435 (0.053)	160
Duration 7-12 months	0.540 (0.028)	0.349 (0.050)	164
Duration 13+ months	0.340 (0.016)	0.223 (0.030)	357
Panel B. KM Survey (1-month horizon)			
Full sample	0.256 (0.019)	0.105 (0.022)	734
Duration 0-6 months	0.256 (0.042)	0.135 (0.043)	79
Duration 7-12 months	0.283 (0.031)	0.116 (0.048)	158
Duration 13+ months	0.232 (0.028)	0.076 (0.022)	497

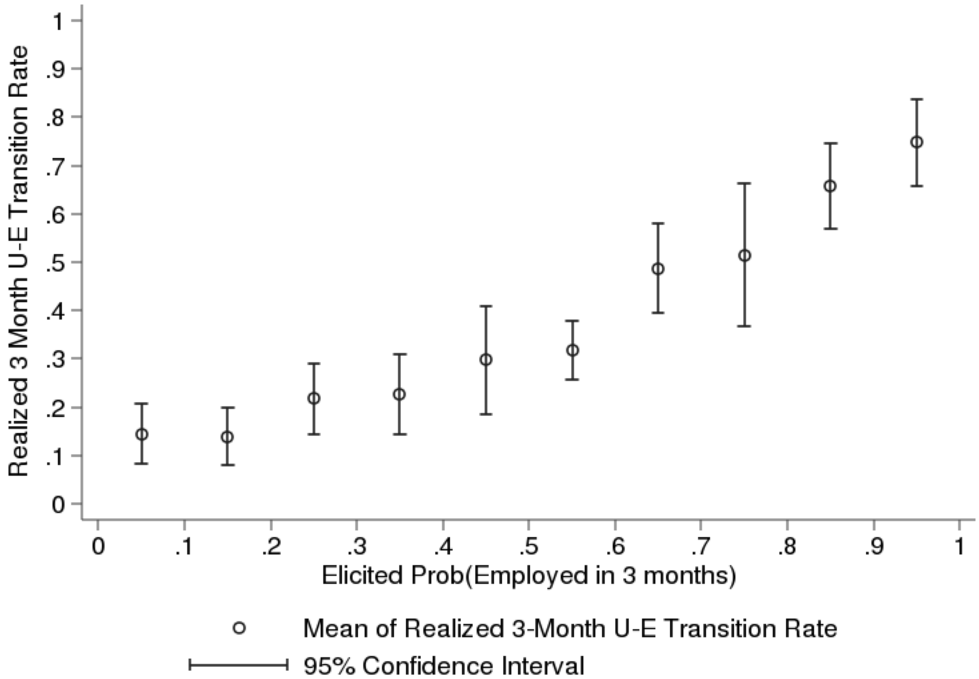
Notes: All samples are restricted to unemployed workers, ages 20-65. The KM sample is further restricted to interviews where the belief questions were administered. Standard errors are in parentheses. Duration refers to self-reported duration in the SCE and duration of weeks of benefit receipt in the KM survey. The SCE sample for this table is restricted to individuals with 4 consecutive interviews. Actual job finding is measured in the SCE as the fraction of individuals who reported being employed in month t+1, t+2 or t+3, where t is the month of the interview where the belief was reported. The KM sample is restricted to those who have not accepted a job in the same or any previous interviews and are not working at the time of the interview. Actual job finding in the KM survey is measured as the fraction accepting a job offer or working in an interview at any point in the 31 days following the interview where the belief was reported.

Average Bias in Beliefs While we cannot compare the actual and perceived job finding probabilites at the individual level, we can compare the average of the actual and perceived job finding probabilities for different groups of job seekers.

Table 2 compares the averages for the actual and perceived job finding probabilities in the SCE and the KM survey, for the respective full samples and by unemployment duration. To address any issues related to attrition, we restrict the sample for this purpose to interviews that were followed by 3 consecutive monthly interviews (SCE) or 4 consecutive weekly interviews (KM survey). At the three-month horizon in the SCE, overall, job seekers slightly overestimate the probability of finding a job. We find an optimistic bias of 8 percentage points. In the KM survey, we find a stronger bias at the one-month horizon of about 15 percentage points. This indicates a severe optimistic bias with the perceived job finding rate being more than twice as high as the actual job finding rate. Interestingly, the overoptimistic bias appears to be more severe for individuals with long unemployment spells. The tendency for the long-term unemployed to be over-optimistic may also explain – in part – why the bias is stronger in the full sample in the KM survey compared to the SCE.[15] In both the SCE and KM we observe negative duration-dependence in the actual job finding rates, as the actual job finding rates are lower for job seekers who are unemployed for longer. The perceived job finding rates are also decreasing,

[15]The KM survey oversampled the long-term unemployed, but the survey weights adjust for that to make the sample representative of the population of unemployment insurance recipients in New Jersey at the time of the survey. Note that the KM survey was also collected at the height of the Great Recession when long-term unemployment was at a unprecedented high level and job seekers may have underestimated the strong decline of the job finding probability during the Great Recession. Moreover, the shorter horizon for the elicitation in the KM survey and the differential attrition discussed above may also contribute to the larger bias.

Figure 3: Averages of Actual Job Finding Probabilities, by Bins of Elicited Probabilities



but at a slower rate. In summary, both surveys show a clear bias towards over-optimism for the long-term unemployed, whereas it is unclear whether such a bias exists for the short-term unemployed. It is not clear at this point whether this is due to selection of over-optimistic job seekers into long-term unemployment or due to changes in beliefs (or a lack thereof) over the spell of unemployment. We will return to this issue in the statistical model in Section 4.

Predictive Power of Beliefs By relating the elicited beliefs about job finding to actual job finding we can also assess how predictive job seekers' beliefs are. We focus on the SCE's 3-month elicitation as it suffers less from attrition and gaps in survey completion. Again, we focus on the subsample of those interviews where we have 3 monthly consecutive follow-up interviews, to make sure that we do not miss any employment spells.[16]

Figure 3 shows the average job finding probability within the next three months by the perceived three-month job finding probability.[17] The positive gradient clearly reveals the strong predictive nature of the elicited beliefs - on average, people who report a higher job finding probability are more likely to find a job. Still, job seekers reporting the lowest probabilities tend to be too pessimistic (on average), while job seekers reporting higher probabilities tend to be too optimistic. The average job finding probability ranges from around 15 percent to over 80 percent for job seekers reporting probabilities in

[16]Note that the SCE has a 12-month panel structure so the maximum follow up period for an individual who is unemployed in survey month 1 is 11 months. The KM survey has a weekly panel structure, but the perception questions were fielded at monthly intervals.

[17]Figure C2 in the Appendix shows a very similar pattern for the 12-month job finding probability.

the first decile to the last decile.

Table 3 reports the corresponding regression estimates, regressing whether a job seeker has found a job within the next three months on the elicited probability. The results confirm the predictive nature of the elicited beliefs. On average, the job finding probability is 0.62 percentage points higher for an individual who reports his or her job finding probability to be 1 percentage point higher. We get a similar coefficient when adding various controls in Column 4 of the Table, demonstrating that individuals' beliefs contain relevant information about future employment prospects above and beyond standard observables. Interestingly, the predictive power as measured by the R^2 for the beliefs ($R^2 = 0.14$) is about the same for all other observables ($R^2 = 0.15$).[18] In similar regressions carried out in the KM survey, we find a coefficient of 0.23 (significant at the 1 percent level) for the 1-month perception question (see Table C3 in the Appendix). While it is plausible that it is more difficult for individuals to predict employment probabilities over a horizon shorter than 3 months, it should be noted that this is a quite selective sample because we restrict the sample to those with four weekly consecutive interviews to avoid under-counting of job finding due to attrition and gaps in the weekly survey (see footnote 9 further above). If relax this restriction, the bi-variate regression coefficients in the KM data become substantially lower, as to be expected.

In the SCE survey the coefficient on the elicited job finding probability is higher, but still significantly smaller than 1. It is important to note that this could both be driven by the imperfect correlation between perceived and actual job finding due to systematic biases in beliefs, or by the variance in the elicitations being larger than the variance in actual job finding probabilities due to random errors in perceptions or noise in elicitations themselves. We separate systematic biases in beliefs from random elicitation errors in the statistical model in Section 4.

The large predictive value is also suggestive of the potential to learn from the elicited beliefs about heterogeneity in true job finding rates. Note that even when the perceived and actual job finding probabilities were to coincide, we would not expect an R^2 of 1 as we are not using the actual job finding *probability* but a dummy for the realization of the probability. The inherent randomness associated with the realization of the job finding probability thus implies an R^2 that is substantially lower than 1 even if beliefs were unbiased and measured without error. To investigate this further, we simulated for each individual a realization of job finding based on the elicited job finding probability, and then ran the same regressions as in Table 3 but used the simulated job finding dummy as the dependent variable. Not surprisingly, the coefficient on the elicited job finding was close to (and statistically indistinguishable from) 1, but the R^2 was still only 0.36. In fact, one can show analytically that, in the case where beliefs about job finding are completely accurate, i.e. without biases and noise, for large N, the R^2 of the regression of actual job finding on beliefs is equal to $\frac{Var(Z)}{E(Z)(1-E(Z))}$. Using these moments from the SCE data, we obtain a value of 0.36, which corresponds to the value in the simulations. Overall, this suggests that the R^2 of 0.14 for the *actual* job finding realizations is substantial and that the elicited job finding probabilities have substantial predictive power. This conclusion is affirmed by the results shown in Column 3 and 4, where the R^2 nearly doubles from 0.15 to 0.25, when adding in Column 4 the elicited beliefs to the regression model in Column 3, which includes demographic controls for gender,

[18] We get a similar estimate (0.54) when including in the same regression the elicited probability of finding a job over the next 12 months, see Appendix Table C1.

Table 3: Linear Regressions of Realized Job Finding Probabilities on Elicitations

Dependent Variable: 3-Month UE Transition Rate	(1)	(2)	(3)	(4)
Prob(Find Job in 3 Months)	0.618***	0.624***		0.565***
	(0.0654)	(0.0886)		(0.0952)
Prob(Find Job in 3 Months) x LT Unemployed		-0.216*		-0.274**
		(0.125)		(0.123)
LT Unemployed		-0.111		-0.0291
		(0.0695)		(0.0738)
Female			-0.143***	-0.0730**
			(0.0424)	(0.0371)
Race: African-American			0.218***	0.129*
			(0.0641)	(0.0664)
Race: Hispanic			-0.0458	-0.0940*
			(0.0577)	(0.0565)
Race: Asian			0.0785	0.167*
			(0.0983)	(0.0886)
Race: Other			-0.0971	-0.0839
			(0.0656)	(0.0602)
Age			0.0158	0.0206*
			(0.0146)	(0.0111)
Age*Age			-0.000280*	-0.000283**
			(0.000157)	(0.000123)
HH income: 30,000-59,999			0.0921*	0.0753*
			(0.0513)	(0.0430)
HH income: 60,000-100,000			0.163**	0.130**
			(0.0633)	(0.0641)
HH income: 100,000+			0.135**	0.122*
			(0.0604)	(0.0689)
High-School Degree			0.333***	0.201***
			(0.0778)	(0.0703)
Some College			0.256***	0.167***
			(0.0661)	(0.0633)
College Degree			0.252***	0.133**
			(0.0640)	(0.0634)
Post-Graduate Education			0.264***	0.143**
			(0.0696)	(0.0690)
Other Education			0.602***	0.416***
			(0.176)	(0.147)
Constant	0.103***	0.207***	0.0600	-0.258
	(0.0328)	(0.0583)	(0.323)	(0.252)
N	983	983	983	983
R2	0.142	0.190	0.152	0.252

Notes: All samples are restricted to unemployed workers, ages 20-65.

Table 4: Linear Regressions of Realized Job Finding Probabilities on Elicitations

Dependent Variable: 3-Period Forward 3-Month UE Transition Rate	(1)	(2)	(3)	(4)
Prob(Find Job in 3 Months)	0.314***	0.486***		0.425***
	(0.0864)	(0.125)		(0.121)
Prob(Find Job in 3 Months) x LT Unemployed		-0.368**		-0.319**
		(0.157)		(0.143)
LT Unemployed		0.0472		0.0344
		(0.0704)		(0.0681)
Controls			X	X
N	392	392	392	392
R2	0.0454	0.0778	0.153	0.207

Notes: All samples are restricted to unemployed workers, ages 20-65.

age, income, educational attainment, race and ethnicity, showing that the elicited beliefs have predictive power above and beyond observable characteristics.

Another interesting finding that comes out of Table 3 is that the beliefs are significantly more predictive for the short-term unemployed than for long-term unemployed (with spells ongoing for more than 6 months). The estimate of the coefficient on the reported job finding probability is about a third lower for the long-term unemployed, as shown in Column 2. This continues to hold when adding controls in Column 4. In addition, we restrict the sample to those who failed to find a job in the next 3 months and remained unemployed, and relate the reported beliefs to the job finding rate in the subsequent 3 months. The results in Table 4 show that the coefficient on the reported belief is smaller, but the reported beliefs retain a strong predictive power beyond the horizon of the 3-month question administered in the SCE survey. This suggests that there are persistent factors in job seekers' job finding prospects, captured by the 3-month horizon question. We revisit this issue below in Section 4 in the context of our statistical framework.

3.3 State-Dependence in Job Finding Beliefs

Exit rates out of unemployment are state-dependent, as they may depend on how long a job seeker has been unemployed, change over the business cycle or vary across labor markets. In what follows, we analyze to what extent *beliefs* about the probability of finding a job are state-dependent, with a focus on unemployment duration as the main state.

3.3.1 Unemployment Duration and Job Finding Beliefs

The panel dimension of the surveys provides a unique opportunity to assess the duration-dependence in perceived job finding. As already shown in Table 2, there is substantial variation in beliefs across job-seekers of different unemployment spell duration. In the SCE, the elicited belief about the probability of finding a job in the next 3 months is 0.62 compared to 0.22 for the very long-term unemployed with spells of unemployment of 13 months or more. The apparent decline in perceived job finding rates is also present, but much less pronounced in the KM survey, which has relatively few short-term unemployed workers. The cross-sectional patterns in both surveys suggest that the long-term unemployed perceive their chances to find a job to be lower. This is confirmed in Table 5, which shows the results of linear regressions of the elicited belief on duration of unemployment, measured in months. The first column shows the results for the sample restricted to the first observation for each unemployment spell, the second and third column shows the results for the pooled cross-section of all observations available during an unemployment spell. The results of all three columns confirm the negative effect of unemployment duration on the elicited beliefs in the cross-section. However, as already noted, it is unclear whether these patterns are due to selection – those with high perceived probabilities find jobs faster and leave the sample – or due to changes in the beliefs at the individual level.

To adjust for selection, we exploit the repeated survey questions answered by the same job seekers over the unemployment spell. Column 4 in the Table 5 includes in the regression spell or person fixed effects. Note that in the SCE, some individuals have multiple unemployment spells and thus we control for each spell separately, whereas in the KM survey we only observe one spell per person. In the SCE, the estimated effect of duration turns from negative to positive when including spell fixed effects with the job finding probability at the 3-month horizon increasing by 0.4 (0.8) percentage points per month, though the coefficient is not statistically significantly different from zero. The Panel B in Table 5 shows that this pattern is much stronger for the KM survey, where an additional month spent unemployed significantly increases the perceived job finding probability by 2.2 (0.8) percentage points per month.[19]

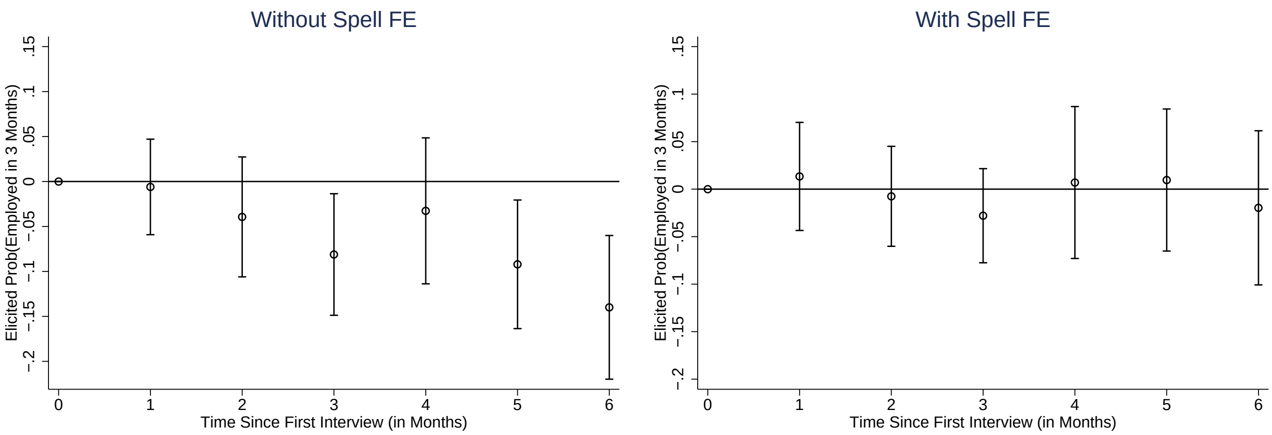
Figure 4 illustrates the difference between the *observed* (cross-sectional) duration-dependence and the *true* (individual-level) duration-dependence in the reported beliefs graphically. To increase power, the left panel shows how the average of the perceived job finding probability is decreasing in time spent unemployed since the first interview observed in a given spell, conditional on still being unemployed. The right panel in Figure 4 controls for individual (or even spell) fixed effects and shows the within-individual increase in the perceived job finding probability, again as a function of time spent unemployed since the first interview. The figures confirm the findings from the regression. In the cross-section, the perceived job finding is decreasing in time spent unemployed, but this decline disappears once we control for selection. In the KM survey, job seekers even report higher job finding rates as they remain unemployed for longer.

We probe the robustness of our main finding in this section and evaluate potential forces that may underly the (weakly) increasing beliefs about job finding probabilities in several ways. First, we check whether the results in Column 4 of Table 5 hold for other measures of perceived job finding. In the KM survey, we find that the expected remaining duration decreases with duration of unemployment when controlling for individual fixed effect. This is obviously consistent with an increasing probability over the spell of unemployment as reported in Table 5. For the purpose of comparison with the probability question, we take the inverse of the expected duration question and convert it into a 4-week probability, assuming that the probability is constant over the spell of unemployment (see footnote 13 for details). Table C5 in the Appendix reports these results. We find that the coefficient is 0.013, which is not too

[19]Note that in an environment where the 1-month horizon probability is increasing, the 3-month horizon probability may increase by less or more, depending on the initial level of the job finding probability.

Figure 4: Perceived Job Finding Probabilities, by Time since First Interview

A. SCE Survey



B. KM Survey

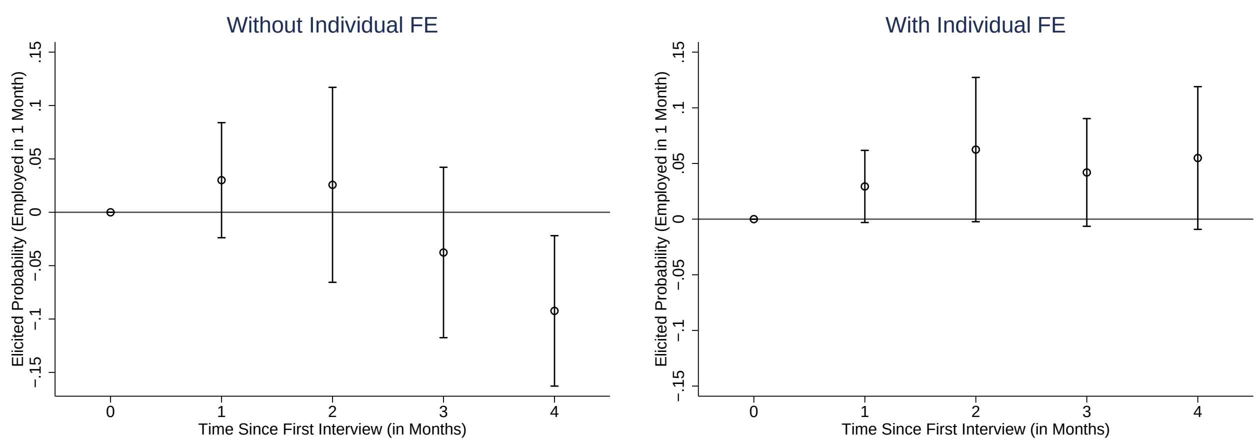


Table 5: Linear Regressions of Elicitations on Duration of Unemployment

Panel A. SCE, Dependent Variable: Elicited 3-Month Probability	(1)	(2)	(3)	(4)
Unemployment Duration, in Months	-0.00544***	-0.00473***	-0.00395***	0.00395
	(0.000767)	(0.000524)	(0.000490)	(0.00761)
Demographics			X	
Spell Fixed Effects				X
Observations	673	1845	1845	1845
R^2	0.107	0.079	0.164	0.822

Panel B. KM Survey, Dependent Variable: Elicited 1-Month Probability	(1)	(2)	(3)	(4)
Unemployment Duration, in Months	-0.0009	-0.0020	-0.0025	0.0216
	(0.0021)	(0.0016)	(0.0014)*	(0.0077)**
Demographics			X	
Individual Fixed Effects				X
Observations	2,088	4,435	4,318	4,435
R-Squared	0.000	0.003	0.119	0.902

Notes: All samples are restricted to unemployed workers, ages 20-65. The demographic controls are the same as the ones included in Table 3. Column (1) shows the results for a sample that is for each individual restricted to the first observation in the survey; Column (2) shows the results for the full sample; Column (3) shows the results for the full sample with demographic controls; and Column (4) shows the results for the full sample with spell or individual fixed effects.

far from the estimate based on the probability question (0.022). Using the 12-month probabilities in the SCE, the coefficient on unemployment duration is negative but insignificant and very close to zero with an estimate of -0.0020 (0.0046). The point estimate implies that the 12-month probability decreases by 2.4 percentage points over a 12-month period, which is almost trivial.

Tables C4 and C5 in the Appendix report results where we exclude answers of 50 percent, results where we exclude answers of 100 percent, and results where we do not trim outlier answers as discussed further above, and results where we use self-reported duration of unemployment as the independent variable. Across all these different specifications, the results are very similar. Tables C4 and C5 show that our results are also robust to controlling for changes in aggregate labor market conditions during our sample period. For the SCE, which uses a rotating panel, controlling for changes in the national or state unemployment rates has little effect on our estimate of the duration-dependence in the perceived job finding rates. Note that, for the KM survey, the sample period coincides for all job seekers, so calendar time and time spent unemployed are collinear and thus it is problematic to include the state or local unemployment rate into the fixed effect regression. As discussed in Krueger and Mueller [2011], however, the unemployment rate in NJ was nearly constant over the period of the survey (October 2009 through April 2010) between 9.5 and 9.8 and did not drop below 9.4 until August 2011, so it seems unlikely that people perceived the job market to improve over the period of the survey.

3.3.2 Further Evidence

In the KM survey, we find that the impact of duration is not affected if we exclude individuals who find and accept a job within the next 4 weeks or exclude individuals who reported a job offer in a previous interview but did not accept it (see Appendix Table C5). The KM survey also allows to dig further into the question of what determines the changes of perceptions over the spell. When we regress the gradient of perceptions over the spell of unemployment, we find few characteristics that correlate significantly with it. For example, measures of impatience, risk aversion or available savings do not correlate with the beliefs gradient.[20] We also find some positive within-person correlation between liquidity constraints and the perceived probability, but controlling for liquidity constraints does not attenuate the positive impact of duration on beliefs. One possibility is that the increase in perceptions in the KM survey is due to the (approaching) exhaustion of unemployment benefits. The canonical model of job search in Mortensen [1977] with limited duration of unemployment insurance predicts increasing search intensity and declining reservation wages over the spell of unemployment and thus increasing job finding rates up to the point of benefit exhaustion. Krueger and Mueller [2011] and Krueger and Mueller [2016], however, test this implication of Mortensen's model with the KM data, and find that search activity is actually decreasing and reservation wages are nearly constant over the spell of unemployment.

In further evidence, we look at how perceptions, search activity and self-reported reservation wages relate to each other in the KM data (see Appendix Table C7). We find that across job seekers, time spent on job search activities is a positive predictor of the elicited 1-month probability (significant at the 1 percent level), whereas the self-reported reservation wage bears a negative association with the 1-month probability though statistically insignificant.[21] Overall, these results are, at least qualitatively, in line with what one would expect from a simple search model with endogenous search effort and a reservation wage choice: search effort increases the probability of finding a job, whereas the reservation wage has a negative effect on the probability of accepting and thus finding a job. Note, however, the causality may well run in the opposite direction, as job seekers who update positively on the probability of receiving a job offer are likely to increase their reservation wage. Indeed, we find some evidence for this in Appendix Table C7 (Column 4): controlling for individual fixed effects, job seekers who decrease their reservation wage, reduce at the same time their expected remaining duration, though for the 1-month probability question the relationship remains small and insignificant.

Finally, Table C8 shows the response in workers' perceptions to aggregate indicators of job finding. We find that for unemployed individuals there is no significant relationship between the national or state-level unemployment rate and the 3-month perception, though standard errors are relatively large. We do find, however, a highly significant positive correlation with the elicited probability that the stock market will rise and a highly significant negative correlation with the elicited probability that the unemployment rate will rise. This suggests that unemployed job seekers take into account their perceptions about aggregate conditions when expressing their perceptions about individual job finding,

[20] Impatience in the KM survey is measured by the choice of a \$20 incentive payment at the beginning of the survey over the option of a \$40 incentive payment after the first 12 weeks of the survey. Risk aversion is elicited as the willingness to take risks on a scale from 0 to 10.

[21] We get similar results for the inverted expected duration, but the reservation wage effect becomes significant in these regressions whereas the coefficient on search activity is of similar magnitude but insignificant.

but it is less clear to what extent their perceptions about aggregate conditions are well informed. Interestingly, when looking at the sample of employed, who were asked the same 3-month perception question for the hypothetical situation where they become unemployed, there is a strongly negative and significant correlation between the 3-month perception and the national or state-level unemployment rate. For the state-level results, where the standard errors are lower, we can reject the hypothesis that the unemployed's perceptions respond as much as the employed's perceptions to the state-level unemployment rate. While we are cautious in interpreting these results, it may suggest that unemployed workers' perceptions are less responsive to the aggregate unemployment rate than one should expect.

3.3.3 Discussion

The empirical evidence indicates that the perceived job finding probability is, if anything, increasing over the unemployment spell. This finding is surprising since several theoretical models predict that a job seeker's actual job finding rate decreases over the spell due to human capital depreciation (see Acemoglu [1995] and Ljungqvist and Sargent [1998]), stock-flow sampling (see Coles and Smith [1998]) or employer-screening based on unemployment duration (see Lockwood [1991]).[22] Similarly, when workers who lose their jobs have imperfect information about their employability, we would expect that they update their beliefs downwards the longer they are unemployed. However, we have not yet answered the empirical question whether job finding rates out of unemployment exhibit *true* duration-dependence and whether job seekers' information about their employability is imperfect. This is exactly what we turn to in the next section, where we use all the facts documented in this Section jointly to inform a simple statistical model with heterogeneity and duration dependence in both actual and perceived job finding rates.

We note that our statistical model explicitly allows for biases in beliefs, both across workers and over the unemployment spell, but we do not attempt to micro-found these biases. A number of behavioral models could, however, explain the observed optimistic biases in beliefs, why biases become more important or why there may be lack of learning over the spell. Regarding the dynamics, job seekers may be subject to the gambler's fallacy (see Rabin and Vayanos [2010]), which is an application of the law of small numbers to infer from the series of bad draws as an unemployment spell lasts that the probability of a good draw increases.[23] Job seekers may also manage their expectations to maintain a positive self-image or to get positive value from optimistic expectation, potentially accounting for the implied distortions in their search behavior (e.g., Brunnermeier and Parker [2005] and Koszegi [2006]).[24] The argument would be that lasting unemployment causes hardship and increases the demand for optimistic expectations. We cannot provide directs test of either theory, but the finding that the perceptions of long-term unemployed are less predictive - either due to bad inference or distorting expectations - seems consistent with these behavioral models. The same is true for the differential response in perceptions to aggregate indicators among the unemployed and the employed.

[22] As discussed before, Alvarez et al. [2016], and Jarosch and Pilossoph [2017] have recently questioned the importance of *true* duration-dependence.

[23] Note that the same application of the law of small numbers may induce job seekers to become overly discouraged as they overinfer from a series of bad draws how employable they are (Rabin and Vayanos [2010]).

[24] Altmann et al. [2015] show that updating in beliefs about job search outcomes is slow in an experimental context.

4 Statistical Framework

The purpose of this section is to describe a reduced-form statistical framework that allows us to use the moments from our empirical analysis to identify (1) the extent of heterogeneity in job finding rates, (2) the dynamics of job finding rates over the spell of unemployment (duration dependence) and (3) the biases in perceived job finding rates as well as their evolution over the spell of unemployment.

We first set up the model and discuss the identification of the different features of the model. As a way of illustrating the identification arguments, we show how the model's fit changes when restricting the key features of the model, in particular regarding the heterogeneity and duration-dependence of both actual and perceived job finding rates. We also show extensively how the model estimates are robust to different functional forms, distributional assumptions and incidental parameters.

In what follows, we focus mostly on the 3-month perception question from the SCE, because, first, compared to the 12-month perception question in the SCE, the 3-month job finding probability is arguably better at capturing the dynamics over the unemployment spell and, second, compared to the KM survey, the SCE suffers less from attrition and thus we have more confidence in the moments in the SCE data that relate to the co-variance of perceptions and actual job finding.

4.1 Assumptions

Let us call T^x_{id} the actual probability of finding a job in the next x months for individual i with unemployment duration d, Z^x_{id} the elicitation of the individual's perceived probability of finding a job in the next x months and F^x_{id} is a dummy for the realization of finding a job in the next x months. Let us denote the monthly job finding probability as $T_{id} = T^1_{id}$, then $T^3_{id} = T_{id} + (1 - T_{id})T_{id+1} + (1 - T_{id})(1 - T_{id+1})T_{id+2}$ is the probability of finding a job in the next 3 months.

We assume that the job finding rate of individual i at duration d satisfies

$$T_{id} = [1 - \theta_d](T_i + \tau_{id}) \in [0, 1], \tag{3}$$

where θ_d is a scalar that depends on duration d only and that determines the depreciation or appreciation in job finding over the spell of unemployment, T_i is the component of the job finding rate that is common across all durations and τ_{id} is a transitory change in job finding rate at duration d. We normalize $\theta_0 = 0$ and assume that the baseline job finding rate, T_i, is distributed according to some distribution $g(T_i)$.

In order to use elicitations Z to infer actual job finding probabilities, we have to impose some minimal structure on how elicitations are reported. We define a variable $\hat{T}_{id}$, which captures the duration dependence in the *perceived* job finding rate, and in analogy to equation 3 above, we assume that it evolves over the unemployment spell according to

$$\hat{T}_{id} \quad = \quad [1 - \hat{\theta}_d](T_i + \tau_{id}) \in [0, 1], \tag{4}$$

where the variable $\hat{\theta}_d$ captures the perceived depreciation or appreciation in job finding rates over the spell of unemployment. We choose to express the perceived duration dependence at the monthly frequency so that it directly corresponds to the parameter that controls the true duration dependence,

θ_d. This allows for a special case of the model where duration dependence is correctly perceived, i.e. where $\hat{\theta}_d = \theta_d$.

We further assume that elicitations of the perceived 3-month job finding rate satisfy[25]

$$Z^3_{id} \quad = \quad b_0 + b_1 \hat{T}^3_{id} + \varepsilon_{id} \in [0,1]. \tag{5}$$

The parameter b_0 captures a bias in perceptions that is common to all individuals. The parameter b_1 captures the fact that different types may have different biases: with $b_1 = 0$ elicitations are completely random, which implies that types with low T_{id} tend to be over-optimistic and types with high T_{id} tend to be over-pessimistic, whereas with $b_1 = 1$ the bias is unrelated to T_i.[26] The variable $\hat{T}^3_{id}$ captures the duration dependence in perceptions, as explained above. The variable ε_{id} captures *both* biases in the perception about the actual job finding probability and random elicitation/measurement errors. Note that the condition that $Z^3_{id} \in [0,1]$ implies that ε_{id} may not be independent of T_{id}.

4.1.1 Functional Form and Distributional Assumptions

We propose to parameterize our model relatively parsimoniously. We would like to stress, however, that in principle the identification of duration dependence does not rely on the functional form assumptions, these are made merely to improve the efficiency of the estimation. For example, it should be possible to estimate the duration dependence in true and perceived job finding rates in our model non-parametrically. This, however, would be very demanding in terms of sample size, especially given that any sample of unemployed has only a small percentage of unemployed workers at longer durations of unemployment.

For this reason, we assume that θ_d is piecewise linear in the following form:

$$\theta_d = \begin{cases} \theta d \text{ if } d \leq 12 \\ \theta 12 \text{ if } d > 12 \end{cases} \qquad \text{and } \hat{\theta}_d = \begin{cases} \hat{\theta} d \text{ if } d \leq 12 \\ \hat{\theta} 12 \text{ if } d > 12 \end{cases} .$$

We introduce the scalar $b_\theta = \hat{\theta}/\theta$ to denote the difference in depreciation (or appreciation) in the actual and perceived job finding rates. In an alternative specification, we assume geometric depreciation of the job finding rate and its perception, $1 - \theta_d = (1-\theta)^d$ and $1 - \hat{\theta}_d = (1 - \hat{\theta})^d$. While our main results do not change when we use this alternative specification, we prefer the piece-wise linear specification, because it more easily accommodates both negative *and* positive duration dependence in job finding rates.

Similarly, for the purpose of estimation, we have to rely on parameterizing the distributions of T_i, τ_{id} and ε_{id}. While our hands are not tied to a particular distribution and we can easily test the robustness of our results to various alternative assumptions about the shape of the distribution, it is important for our exercise here that there is a continuum of job finding probabilities (or at least a large number). Assuming two types for the job finding probabilities and estimating their relative mass is

[25]Note that $\hat{T}^3_{id} = \hat{T}_{id} + (1 - \hat{T}_{id})\hat{T}_{id+1} + (1 - \hat{T}_{id})(1 - \hat{T}_{id+1})\hat{T}_{id+2}$.

[26]Note, however, that the distribution of ε is not independent of T_{id} close to and at the boundaries 0 and 1, since $\varepsilon_{id} \in [-b_0 - b_1\hat{T}^3_{id}, 1 - b_0 - b_1\hat{T}^3_{id}]$.

Table 6: Matched Moments

Moment	Symbol	Value in Data	Value in Model
Mean of 3-Month Job Finding Rates:			
... at 0-3 Months of Unemployment	$m_{F_{03}}$	0.623	0.621
... at 4-6 Months of Unemployment	$m_{F_{46}}$	0.435	0.427
... at 7 Months of Unemployment or More	$m_{F_{7+}}$	0.260	0.259
Mean of 3-Month Elicitations (Deviation from Actual):			
... at 0-3 Months of Unemployment	$m_{Z_{03}} - m_{F_{03}}$	-0.031	-0.027
... at 4-6 Months of Unemployment	$m_{Z_{46}} - m_{F_{46}}$	0.076	0.065
... at 7 Months of Unemployment or More	$m_{Z_{7+}} - m_{F_{7+}}$	0.139	0.141
Mean of Monthly Innovations in Elicitations	m_{dZ}	0.009	0.009
Variance of Elicitations	s_Z^2	0.089	0.089
Covariance of Elicitations and Job Finding	$c_{Z,F}$	0.055	0.055
Covariance of Elicitations and Job Finding in 3 Months	$c_{Z_d,F_{d+3}}$	0.023	0.023

not an attractive option, because our observed elicitations are reported on the interval between 0 and 1. A model with only two underlying job finding rates thus would not perform well in matching the distribution of these elicitations.

Our baseline estimation is based on the following distributional assumptions of variables:

1. Baseline job finding rates, T_i, follow the Beta distribution with shape parameters α and β. The Beta distribution is defined to the interval $[0, 1]$ and quite flexible in terms of its shape. In alternative specifications, we use the Weibull distribution and Gamma distribution.

2. The transitory component of the job finding rate, τ_{id}, follows a uniform distribution subject to the bounds $[-T_i, \frac{1}{\theta_d} - T_i]$, and with masspoint(s) at the bounds of this interval such that $E(\tau|T_i) = 0$ for all T_i.[27] In an alternative specification, we assume that τ_{id} follow a bounded normal distribution, i.e. $\tau_{id} \sim \mathcal{N}(\mu_\tau, \sigma_\tau^2)$ subject to the bounds $[-T_i, \frac{1}{\theta_d} - T_i]$.

3. Random perception errors/noise in elicitations, ε_{id}, follow a uniform distribution on the interval $[-\sigma_\varepsilon, \sigma_\varepsilon]$ subject to the bounds $[-b_0 - b_1\hat{T}_{id}^3, 1 - b_0 - b_1\hat{T}_{id}^3]$, and with masspoint(s) at the bounds of this interval such that $E(\varepsilon|\hat{T}_{id}^3) = 0$ for all $\hat{T}_{id}^3$.[28] In an alternative specification, we assume that ε_{id} follow a bounded normal distribution, i.e. $\varepsilon_{id} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ subject to the same bounds.

4.2 Targeted Moments and Identification

In our data, we observe the means of realized and perceived job finding rates at different durations, as well as their covariance and the variance in perceived job finding rates. As already noted at the

[27] More precisely, $\tau|T_i$ follows a uniform distribution on the interval $[\max(-\sigma_\tau, -T_i), \min(\sigma_\tau, \frac{1}{\theta_d} - T_i)]$, with a masspoint at the bound of this interval with mass $p(T_i) > 0$ if a bound is binding, such that $E(\tau|T_i) = 0$ for all T_i.

[28] More precisely, $\varepsilon|\hat{T}_{id}^3$ follows a uniform distribution on the interval $[\max(-\sigma_\tau, -b_0 - b_1\hat{T}_{id}^3), \min(\sigma_\tau, 1 - b_0 - b_1\hat{T}_{id}^3)]$, with a masspoint at the bound of this interval with mass $p(\hat{T}_{id}^3)$ if a bound is binding, such that $E(\varepsilon|\hat{T}_{id}^3) = 0$ for all $\hat{T}_{id}^3$.

beginning of this section, we focus on the moments from the SCE data, because due to attrition we have less confidence in the moments in the KM data that relate to the co-variance of perceptions and actual job finding. In the SCE data, we observe the following moments that we target in the estimation of our model:

1. The mean of the 3-month job finding rate at duration d: $\{\mathbf{m_{F_d}}\}_{\mathbf{d=1}}^{\mathbf{d=D}}$.
2. The mean of elicitations of the percent chance of finding a job in the next 3 months at duration d: $\{\mathbf{m_{Z_d}}\}_{\mathbf{d=1}}^{\mathbf{d=D}}$.
3. The variance of elicitations of the percent chance of finding a job in the next 3 months at duration $d = 1$: $\mathbf{s_Z} = 0.089$.
4. The covariance of the 3-month job finding rate and elicitations at duration $d = 1$: $\mathbf{c_{F,Z}} = 0.055$.
5. The covariance of the 3-month job finding rate (3-month ahead) and elicitations at duration $d = 1$: $\mathbf{c_{F_{+3},Z}} = 0.023$.
6. The monthly change in 3-month elicitations as measured by the coefficient on duration in the regressions of perceived job finding rates on unemployment duration, controlling for individual fixed effects: $m_{dZ} = 0.009$.[29]

This implies that there are $2D+4$ moments. In our estimation, we match moments for three duration intervals (0-3 months, 4-6 months, 7+ months), as reported earlier in the paper, and thus we have a total of 10 moments that we try to match. With two parameter distributions, there are 8 parameters to estimate (α, β, σ_τ, θ, $\hat{\theta}$, b_0, b_1, σ_ε) and thus the model is over-identified. Identification of the parameters comes from matching the moments listed above as follows:

1. The parameters α, β and θ are mainly identified through the mean of job finding rates at durations 0-3, 4-6 and 7 and higher, and the covariance of elicitations and job finding rates. The key insight is that the covariance of ex-post realizations of actual job finding and ex-ante reports of expected job finding probabilities identifies the extent of heterogeneity in true job finding rates. In other words, the extent to which ex-ante reports of expected job finding rates co-varies (or rather predicts) ex-post realizations, identifies the extent of heterogeneity in job finding rates. It is important to note that b_1 is the other critical determinant of the co-variance between perceived and actual job finding, and thus identification of the heterogeneity in true job finding relies on the identification of the bias parameter b_1.
2. The parameter σ_τ is mainly identified through the differences in the covariances c_{Z_d,F_d} and $c_{Z_d,F_{d+3}}$. The reason is that transitory shocks to job finding rates generate more *contemporary* covariance of elicitations and job finding rates, but not more covariance between elicitations and job finding 3 months ahead.

[29]Note that this is slightly higher than the value reported earlier in the paper, because the sample here is restricted to the sample where we have at least 3 consecutive interviews. In Appendix Table D3, we report a robustness check where we target a value of 0.004 consistent with the regression results reported in Table 5. The estimation results are very similar.

3. The parameters b_0, b_1 and $\hat{\theta}$ are mainly identified through the mean of the deviations of elicitations from actual job finding rates at durations 0-3, 4-6 and 7 and higher, and the mean of monthly innovations in elicitations. The parameter b_0 mainly identifies the average deviation of elicitations. The parameter $\hat{\theta}$ is identified mainly by the monthly innovations in elicitations, which determines the within-person gradient of the bias between elicitation and actual job finding by duration. b_1 is the cross-sectional parameter that matches the observed gradient of the bias between elicitation and job finding rate by duration, having taken out the within-person effect. E.g., with $b_1 < 1$, then the low-T_i types are over-optimistic and thus over-optimism should be more predominant among the long-term unemployed. In other words, the bias in the perception of individual types T_i is revealed by the compression of the distributions of Z's relative to the distribution of T's, i.e. by the LT unemployed being over-optimistic.

4. The parameter σ_ε is identified through the variance of these elicitations.

We would like to emphasize here also the novelty of our approach to the identification of ex-ante heterogeneity in true job finding rates relative to the existing literature. In particular, compared to the approach that uses data on multiple unemployment spells as a source of identification (see, e.g., Honoré [1993] and Alvarez et al. [2016]), our approach is made possible by the availability of elicitations and realizations for the same individual in the *same* unemployment spell and thus does not rely on multiple unemployment spells for the same individual, which may skew the estimation results since a sample of individuals with multiple (frequent) spells may not be entirely representative of the population. In addition, identification through multiple unemployment spells only identifies the extent of heterogeneity that is fixed between unemployment spells, which may be years apart, whereas our approach also identifies the heterogeneity that is fixed within a spell but varies across spells (e.g., consider changes in marital status, savings, access to unemployment insurance, labor market experience etc. that may affect the job finding probability).

4.3 Estimation and Results

We use the method of simulated moments to estimate the model parameters and minimize the sum of squares of the deviation of the model from the data moments. We use the inverse of the bootstrapped variance of each moment as weighting matrix, where the bootstrapped variances were computed with 2,000 repetitions. Standard errors were obtained by estimating the model on 100 bootstrap samples and taking the standard deviation of estimates across the 100 samples. As shown in Table 6, our model matches the 10 moments very well, even though it is over-identified. There is no discernible difference, up to digits shown in the table, for the monthly innovations and the variance and co-variance moments, which all carry a large weight in the estimation. The weighted sum squared of residuals is 0.071 and the unweighted one is 0.0002, which shows how well we fit the moments in the table. Table D1 in the Appendix also shows moments that were not targeted in the estimation, such as the variance of elicitations and the covariance with the contemporary job finding rate by duration interval. While we do not match these moments perfectly, the fit is still fairly good.

Table 7 shows the parameter estimates and the corresponding cross-sectional and longitudinal mo-

Table 7: Estimation Results

A. Parameter Estimates

Parameter	Explanation	Estimate	(S.e.)
α	Parameter of Beta distribution for permanent component, T_i	2.402	(0.621)
β	Parameter of Beta distribution for permanent component, T_i	4.007	(1.468)
σ_τ	Dispersion in transitory component of job finding rate, τ_{id}	0.363	(0.152)
θ	Depreciation in job finding	0.033	(0.018)
$\hat{\theta}$	Depreciation in perceived job finding	0.016	(0.029)
b_0	Intercept bias	0.201	(0.074)
b_1	Cross-sectional bias	0.620	(0.138)
σ_ε	Dispersion in elicitation errors, ε_{id}	0.426	(0.033)

B. Cross-sectional Moments

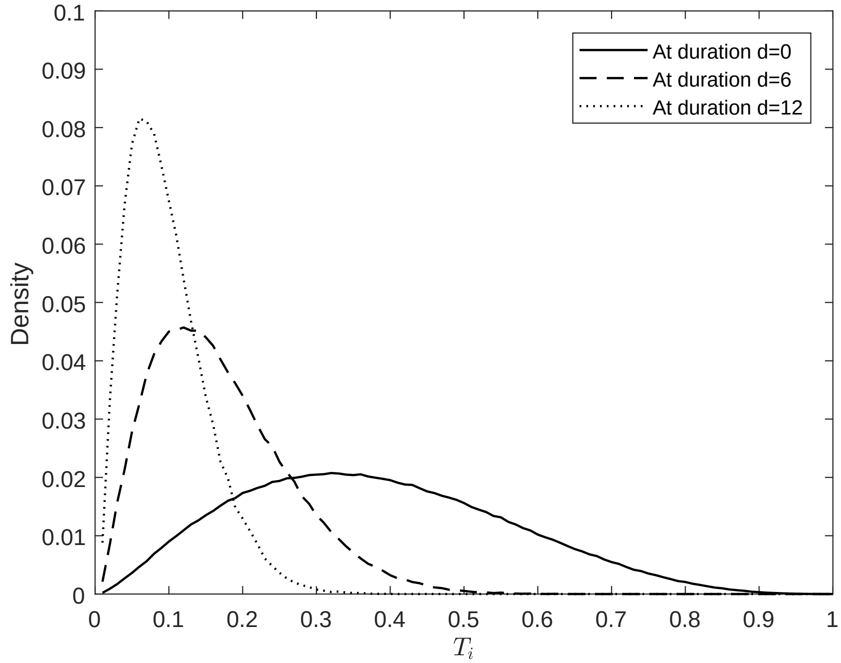
Moment	Explanation	Estimate	(S.e.)
$s^2_{T^3_{i0}}$	Variance in 3-month job finding rates at $d = 0$	0.069	(0.018)
$s^2_{T^3_i}$	Variance in permanent component of T^3_{i0}	0.045	(0.009)
$s^2_{Z^3_{i0}}$	Variance in 3-month elicitations at $d = 0$	0.080	(0.007)
$s^2_{Z^3_{i0}-\varepsilon_{i0}}$	Variance in 3-month elicitations at $d = 0$ (net of elicitation errors)	0.027	(0.008)
$\beta_{Z^3_{i0}-\varepsilon_{i0},T^3_{i0}}$	Cross-sectional bias at duration $d = 0$	0.621	(0.138)

C. Longitudinal Moments

Moment	Explanation	Estimate	(S.e.)
$s^2_{dT^3_{id}}$	Variance in changes in 3-month job finding rates	0.017	(0.009)
$s^2_{dZ^3_{id}}$	Variance in changes in 3-month elicitations	0.118	(0.018)
$s^2_{dZ^3_{id}-d\varepsilon_{id}}$	Variance in changes in 3-month elicitations (net of elicitation errors)	0.008	(0.003)
$\beta_{dZ^3_{id}-d\varepsilon_{id},dT^3_{id}}$	Longitudinal bias	0.668	(0.265)

Note: For two variables y and x, $\beta_{y,x} = \frac{Cov(y,x)}{Var(x)}$ is defined as the coefficient of the bi-variate regression of y on x.

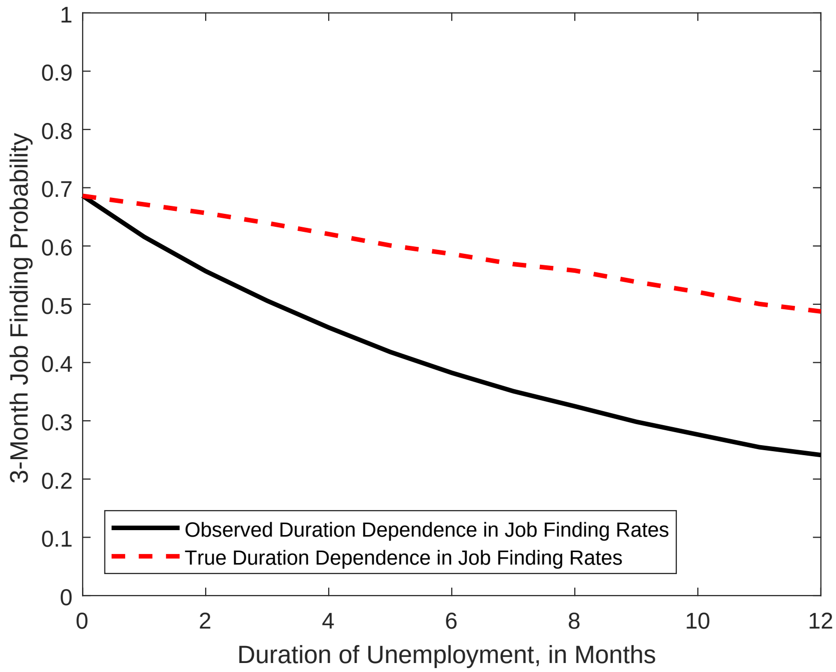
Figure 5: The Distribution of T_i among Survivors



ment. The estimation delivers two important sets of results. First, the estimation reveals substantial heterogeneity in the job finding rates. While this is to a large extent driven by transitory shocks, important heterogeneity in permanent types remains, which drives the duration-dependence in job finding rates through dynamic selection. Figure 5 shows that the model estimates imply a substantial dispersion of types, T_i, at the start of the unemployment spells. The estimated Beta distribution is unimodal and slightly skewed to the left. As the high-T_i types find jobs, the distribution of T_i among survivors becomes more skewed to the left with a lower average overall. The large amount of heterogeneity in job finding rates implies that there is a large divergence between observed and true duration dependence in job finding rates, as is illustrated in Figure 6. The figure compares simulations of the full model (solid black line), with a model where there is no heterogeneity and the only source of duration dependence in job finding rates is $\theta \neq 0$ (dashed red line). As is evident from the figure, our model attributes 54 percent of the total decline in 3-month job finding rates from 0.69 to 0.24 to selection and the remainder– a 20 percentage points decline – to changes in the probability of finding a job over the spell of unemployment. This corresponds to a decline of 13 percentage points in the monthly job finding rate from 0.33 to 0.20, or about 3 percent per month of unemployment as evident by our estimate of θ. The depreciation parameter is, however, somewhat imprecisely estimated, as we cannot reject zero depreciation at the 5 percent level.

We can compare the estimated heterogeneity in job finding rates to what one would predict using observable characteristics. In a regression-control framework, controlling for observable characteristics does attenuate the relationship between realized job finding and unemployment duration, but to a much lesser extent: as shown in Table 2, the difference in the 3-month job finding rate of the short-term

Figure 6: Duration Dependence in Job Finding Rates



unemployed compared to those unemployed for 12 months or longer is 40 percentage points. In the Appendix Table C6, we show that this difference in job finding rates between short- and long-term unemployed does attenuate when controlling for observable characteristics, from 40 percentage points to 29 percentage points, which amounts to a 28 percent difference in the decline of the job finding rate between short- and long-term unemployed workers. This suggests that about half of the 54 percent decline in the job finding rate attributed to selection in our statistical model, can be attributed to selection due to *observed* differences in types. These results are very much in line with the regressions in Table 3, which show that elicited beliefs have substantial predictive power of actual job finding, above and beyond the predictive power of observable characteristics.

Another way to assess the extent of heterogeneity that is predicted by our estimated model is to compare it to a non-parametric lower bound estimate that, as in Hendren [2013], results directly from the predicted values in Figure 3. More precisely, we take the predicted values for each of the 10 bins in the figure, and compute the variance of the predicted values, which amounts to 0.035 and corresponds to 40 percent of the total variance in 3-month job finding probabilities in our model.[30]

Second, the estimation reveals important biases in beliefs. The cross-sectional bias is large and significant. On average, workers who face a 10 percent higher job finding probability on average perceive there chances as only 6.21 percent higher (s.e. of 1.38). The longitudinal bias is very similar in magnitude. On average, if workers face a 10 percent change in their job finding over the unemployment spell, the perceived change is only 6.68 percent (s.e. of 2.65). This may seem relatively large given the

[30]The variance of 3-month job finding probabilities in our model for all durations is 0.089. Note that this value is somewhat larger than the variance of 0.069 that is reported in Table 7, because we did not restrict the sample to newly unemployed workers, in order to be comparable with the sample that was used for the non-parametric lower bound estimate.

absence of downward revisions of the elicited beliefs in the empirical analysis. However, the innovations in job finding dT_{id} are not only due to the depreciation, but also to changes in the transitory shocks $d\tau_{id}$. While the former effect is estimated to be negative, the latter has a positive average effect due to mean reversion. We also find that the random error in the elicitations is important, driving about 70 percent of the variance in elicitations. While part of this may be due to errors in the elicitation procedure, some of it may also be due to errors (or rather random biases) in the perceptions.

Our model allows decomposing observed differences in the bias in perceptions by unemployment duration, as shown in Figure 7. As discussed earlier, our data show a larger bias of perceptions for the long-term unemployed, which the model reproduces nicely (solid black line). Yet, it is a priori unclear whether the increase in the bias is driven by changes in the bias at the individual level (what we call again true duration dependence) or by selection of over-optimistic job seekers into long-term unemployment. The dashed red line provides simulation results of our model for the model without heterogeneity (only one type of job seeker), and thus the only source of changes in the bias are changes in the beliefs relative to the job finding probability at the individual level. The results show that about two thirds of the observed duration dependence in the bias (black solid line) comes from changes at the individual level (red dashed line).[31] The remaining one third is explained by selection of the over-optimistic agents into long-term unemployment, i.e. it is driven by the fact that low-T_i types are estimated to be over-optimistic and conversely high-T_i types are estimated to be over-pessimistic (due to $b_1 < 1$). Our model would attribute less of the observed increase in the bias over the spell to the difference between the true and perceived depreciation, if the true depreciation was smaller, which as noted before is somewhat imprecisely estimated, or at least we cannot reject it to be significantly different from zero.

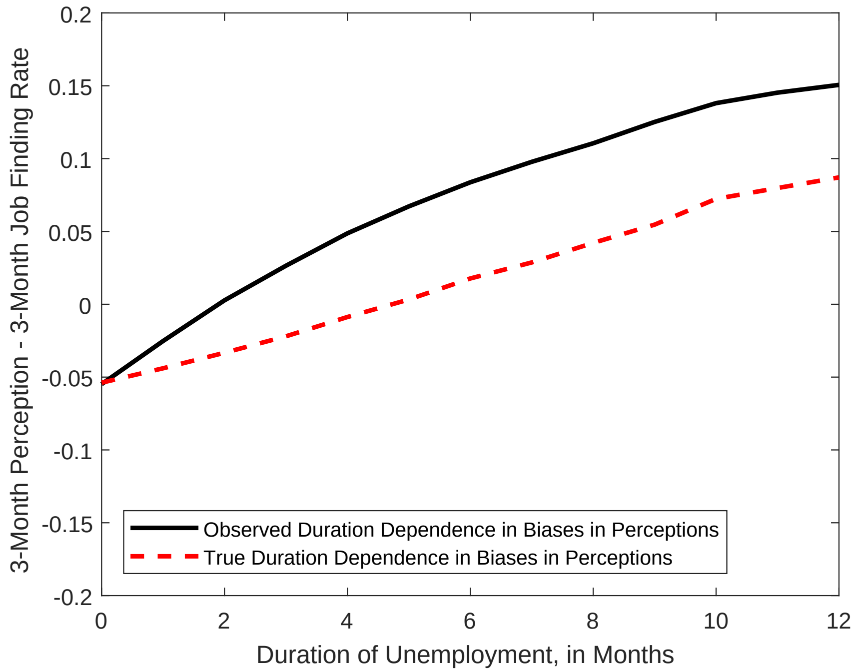
4.4 Robustness

We believe that our model is parametrized as parsimoniously as possible. To illustrate this and provide more insights in the identification of the model, we estimate a number of versions of the model where we restrict parameter choices (see the results in Appendix Table D2).

Regarding the actual job finding rates, we first estimate a version of the model where we do not allow for any depreciation in job finding rates and perceptions, $\theta = \hat{\theta} = 0$ (column 2). This model version still fits the data well, which is not too surprising as we could not reject that, individually, these parameters were 0 in the baseline model. In contrast, when we estimate a version of the model where we do not allow for any heterogeneity in T_{id}, the model fits the data very poorly (column 3). The two versions jointly underline the relative importance of heterogeneity relative to true duration-dependence to explain the empirical moments. We also estimate a version of the model, where we set only $\sigma_\tau = 0$, i.e. we do not allow for any transitory changes in job finding during the unemployment spell. As one can see in the results reported in the Appendix Table D2, this specification has still difficulty in matching both c_{Z_d,F_d} and $c_{Z_d,F_{d+3}}$. Given our estimation procedure leveraging elicitations to learn about heterogeneity in types, it proves important to allow for transitory heterogeneity. Indeed, the version without transitory

[31]This arises in the model not only because estimates show that θ is somewhat more negative than $\hat{\theta}$, but also because $b_1 < 1$ and thus any changes in the actual job finding probability get translated into changes in beliefs by a factor less than one.

Figure 7: Duration Dependence in Biases in Perceptions



shocks implies a much larger extent of heterogeneity in T_i and, as a result, an appreciation of the job finding rates over the unemployment spell.

Regarding the perceived job finding rates, we estimate a version of the model with no differential dynamic bias, i.e. $\theta = \hat{\theta}$. This version of the model fits the data quite well, though not as well as the baseline model. The fit gets worse when we estimate a version with no cross-sectional bias, i.e., $b_1 = 1$, which indicates the importance of allowing for a cross-sectional bias. Importantly, the estimated heterogeneity in permanent types is smaller when it is assumed to be accurately perceived (except for a random error term) and the implied *true* duration-dependence would therefore be substantially larger, with the monthly depreciation rate θ increasing from 0.03 to 0.05. The model fit is still reasonable relative to the baseline model, but gets significantly worse when we allow for no biases in perceptions at all, i.e. with $\theta = \hat{\theta}$, $b_0 = 0$ and $b_1 = 1$. This shows the importance of the biases in beliefs to fit the data well.

We also probe the robustness of our findings to alternative assumptions about the functional form and distributions as well as extensions of the model, as reported in Appendix Tables D3 and D4. Without discussing these estimates in detail, the table shows that the parameter estimates are very stable across all of the results reported in the table. In particular, our results are robust to assuming that T_i follows the Gamma distribution (2), to assuming that T_i follows the Weibull distribution (3), to assuming that ε and τ follow a bounded normal distribution (the bounds are described further above) (4), and to assuming a geometric depreciation in job finding rates rather than piecewise linear duration dependence (5). Our results are also robust to targeting a rate of monthly innovations in elicitations of 0.004 instead of 0.009, mirroring the lower mean of innovations we get for the broader sample (6), to targeting s^2_Z and c_{Z_d,F_d} for the 3 duration intervals 0-3 months, 4-6 months and 7+ months instead of only for the overall sample (14 targeted moments instead of 10) (7), and to excluding individuals with recall expectations when generating the data moments (8). We also extend the model to allow for completely persistent elicitation errors (i.e., $\varepsilon_{id} = \varepsilon_i$) and find that it has no impact on our estimation results (9). This is also true when we extend the model to allow for bunching at 0, 0.5 and 1 of the elicited beliefs, by imposing on the baseline model that *any* belief in the intervals $(0, 0.1]$, $[0.4, 0.6]$ resp. $[0.9, 1)$ are reset to the bunching points 0, 0.5 resp. 1. Despite these relatively strong assumptions about the nature of bunching, the results of the estimation appear not to be affected (10). This suggests that the variations in elicitations across (rather than within) these intervals is the dominant source of variation that is relevant for identification of the key parameters in the model. Our results are very similar when (11) we use the inverse of the full variance-covariance matrix of the 1000 bootstrap samples as the weighting matrix in the estimation (instead of just the diagonal) or (12) if we use the identity matrix as the weighting matrix.

Finally, we also estimate the model (13) on a set of residualized moments, i.e., the moments obtained from the residuals of a set of linear regressions of the 3-month belief question and of the 3-month job finding rate on the same set of demographic controls as in Table 3. The moments are shown in the Appendix Table D5 and the estimation results in Table D4 and Figures D1 and D2 in the Appendix. Overall, the estimation results are quite similar to the baseline, except for the duration dependence, which is now very close to zero.[32] Of course, the extent of ex-ante heterogeneity is estimated to be smaller in this robustness check, as the effects of observables are parsed out from all moments.

5 Structural Model of Job Search with Biased Beliefs

The statistical model in the previous section estimated heterogeneity and duration-dependence in job finding rates as well as biases in job seekers' perceptions, but abstracted from the behavior of job seekers. In this section, we consider a McCall type job search model to study how perceptions affect search and thus unemployment outcomes. We then calibrate this model - using the empirical moments and the estimates from the statistical model - to quantify the impact of biases in beliefs on unemployment duration and the incidence of long-term unemployment. The key mechanism that we highlight is that when a job seeker's employment prospects change, her behavioral response mitigates the change in the job finding rate out of unemployment.[33] This response, however, only comes into play when the change in employment prospects is actually perceived. Hence, any difference across job seekers' or across states that is not perceived leads to larger differences in actual job finding. This mechanism also causes the observed duration dependence in job finding rates to be magnified when the heterogeneity across job

[32]This suggests perhaps that the relationship between observed heterogeneity in job finding and beliefs is not the same as the relationship between unobserved heterogeneity in job finding and beliefs. Indeed, we find some evidence for this, when instrumenting for beliefs in Column 1 of Table 3 with observable demographic characteristics: Instead of a coefficient of 0.618, we obtain a coefficient of 1.12 and cannot reject 1.00, suggesting that there are no biases in beliefs across observable types of job seekers.

[33]Spinnewijn (2015) analyzes biased beliefs in a model with endogenous search efforts. He distinguishes between *baseline beliefs* - regarding the baseline probability of job finding - and *control beliefs* - regarding the increase in the job finding probability when searching more. In a dynamic model, optimistic baseline beliefs induce a job seeker to search less, while optimistic control beliefs induce an individual to search more.

seekers or the true duration-dependence is underestimated.

5.1 Model Setup

We consider a stylized version of McCall's search model and allow for heterogeneity and duration-dependence in the actual and perceived arrival rates. $\lambda_{i,d}$ and $\hat{\lambda}_{i,d}$ denote respectively the actual and perceived probability of receiving a job offer for an unemployed agent i at unemployment duration d. Wages w are drawn from a wage offer distribution $F(w)$. The agent sets a reservation wage $R_{i,d}$.

The perceived value of unemployment for agent i at duration d equals

$$U_{i,d} = u + \frac{1}{1+\delta} \max_R \{U_{i,d+1} + \hat{\lambda}_{i,d} \int_R [V_i(w) - U_{i,d+1})] \, dF(w)\},$$

where δ is the discount rate, u is the per-period utility flow when unemployed and $V_i(w)$ is the value of being employed at wage w. The value of employment satisfies

$$V_i(w) = u(w) + \frac{1}{1+\delta}\{(1-\sigma)V_i(w) + \sigma U_{i,0}\},$$

where $u(w)$ is the per-period utility flow when employed and σ is the exogenous job separation rate.[34]

Agent i sets her reservation wage $R_{i,d}$ to maximize her perceived continuation value at any time of the unemployment spell. At this reservation wage, the agent is indifferent between accepting a job and remaining unemployed, $U_{i,d} = V(R_{i,d})$. The resulting exit rate out of unemployment for agent i at time t equals

$$T_{i,d} = \lambda_{i,d}(1 - F(R_{i,d})). \tag{6}$$

With probability $1 - \lambda_{i,d}$, the unemployed agent receives no wage offer. With probability $\lambda_{i,d} F(R_{i,d})$, the agent receives a wage offer below her reservation wage. The corresponding survival rate equals $S_{i,d} = \Pi_{s=0}^{d-1}(1 - T_{i,s})$ with $S_0 = 1$.

For tractability, all the action in terms of heterogeneity, dynamics and biases is introduced through the arrival rates. We abstract away from other potential biases, for example on the wage offer distribution.[35] For our analytical results in this section, we assume no job separation risk, i.e. $\sigma = 0$, but we relax these assumptions in the numerical analysis further below.

5.2 True vs. Perceived Arrival Rates

We first demonstrate how the (actual) job finding rate is affected by a change $d\lambda$ in the actual arrival rate and a corresponding change $d\hat{\lambda}$ in the perceived arrival rate. The change in the job finding rate consists of a mechanical and a behavioral effect:

$$dT = \underbrace{[1 - F(R)]d\lambda}_{\text{Mechanical Effect}} - \underbrace{[\lambda f(R) \, \partial R / \partial \hat{\lambda}] d\hat{\lambda}}_{\text{Behavioral Effect}}. \tag{7}$$

[34] We ignore intertemporal consumption decisions, assuming agents are hand-to-mouth. Note that beliefs also affect consumption decisions over the unemployment spell [see Spinnewijn (2015) and Ganong and Noel (2017)].

[35] See Conlon et al. [2018] for a model with heterogeneity in the wage offer distribution and learning based on the received wage offers.

The change in the actual arrival rate $d\lambda$ mechanically affects the job finding rate. When the actual arrival rate increases, the mechanical effect is positive and increasing in the share of job offers received above the reservation wage, $1 - F(R)$. The behavioral effect depends on the change in the perceived arrival rate $d\hat{\lambda}$. The job seeker increases her reservation wage and thus decreases her acceptance rate in response to an increase in the perceived arrival rate.

For a single agent in a stationary environment ($\lambda_{i,d} = \lambda, \hat{\lambda}_{i,d} = \hat{\lambda}$) the optimal reservation wage and thus the job finding rate out of unemployment is constant. In this case, the negative behavioral effect is proportional to the difference between the average utility when re-employed and the reservation utility, $E\left(u(w) - u(R)|w \geq R\right)/u'(R)$, which simplifies to the difference between the average accepted wage and reservation wage for linear utility, and the hazard ratio of the wage offer distribution at the reservation wage, $f(R)/(1-F(R))$. In this stationary environment, we can thus establish the following result:

Proposition 1. *In a stationary, single-agent model ($\lambda_{i,d} = \lambda, \hat{\lambda}_{i,d} = \hat{\lambda}$), the pass-through elasticity of the arrival rate to the job finding rate equals*

$$\varepsilon_{T,\lambda} = 1 - \beta\kappa, \tag{8}$$

where $\beta = d\hat{\lambda}/d\lambda$ and $\kappa = T\frac{f(R)}{1-F(R)}E\left(\frac{u(w)-u(R)}{u'(R)}|w \geq R\right) \geq 0$.

See Appendix E.1 for the proof.

The proposition highlights the impact biased beliefs can have on actual unemployment outcomes. Job seekers who overestimate their employment prospects take actions that cause them to leave unemployment more slowly. The resulting dynamic selection leads to a larger optimistic bias among the long-term unemployed relative to the short-term unemployed. Importantly, we attributed this dynamic selection to a cross-sectional bias in perceived job finding rates, where workers with lower job finding rates are more optimistic on average. However, the Proposition suggests that this cross-sectional bias is partly driven by optimistic beliefs causing the lower job finding probability.

5.3 Heterogeneity vs. Duration-Dependence

We now use the McCall search model to illustrate how the wedge between perceived and actual arrival rates, either across agents or over the unemployment spell, changes the observed duration dependence in job finding rates. Job seekers' perceptions crucially affect how the underlying heterogeneity and dynamics of the search environment translate into duration-dependence in job finding probabilities and thus the incidence of long-term unemployment.

Heterogeneity in Arrival Rates We first consider a model with heterogeneous arrival rates $\lambda_i \sim G\left(\lambda, \sigma_\lambda^2\right)$. We assume that agent i's perceived arrival rate equals

$$\hat{\lambda}_i = \beta_0 + \beta_1\lambda_i + \nu_i,$$

where β_0 and β_1 correspond to the intercept bias and cross-sectional bias in the statistical model and ν_i is a mean-zero, random error term. The variance in perceived arrival rates $var(\hat{\lambda}) = \beta_1\sigma_\lambda^2 + \sigma_\nu^2$

depends on the extent to which heterogeneity in true arrival rates is perceived (β_1) and the importance of uncorrelated variation in the perceptions (σ_ν). We consider the impact of heterogeneity in true and perceived arrival rates on the duration-dependence in job finding rates. We evaluate this starting from $\sigma_\lambda \approx 0$ and $\sigma_\nu \approx 0$ so that we can rely on first-order changes in the job finding rates (see equation 7) to characterize the implied duration-dependence. Using notation for the duration-dependent mean, for some duration $d = x$, $E_x(T) = \int \frac{S_{i,x}}{S_x} T_{i,x} di$ and variance $var_x(T) = \int \frac{S_{i,x}}{S_x} [T_{i,x} - E_x(T)]^2 di$, we can state:

Proposition 2. *Starting from $\sigma_\lambda, \sigma_\nu \approx 0$ and $\beta_1 \kappa < 1$, heterogeneity in true arrival rates (σ_λ) increases the negative (observed) duration-dependence in job finding rates, $\frac{E_0(T)}{E_1(T)}$, but the effect is decreasing in β_1. Uncorrelated heterogeneity in the perceived arrival rates (σ_ν), however, further increases the negative duration-dependence.*

See Appendix E.2 for the proof.

Job seekers with lower job finding rates are more likely to remain unemployed. The resulting dynamic selection decreases the average job finding rate over the unemployment spell. The larger the variance in job finding rates at time d of the unemployment spell, for given average job finding rate at duration d, the lower the average job finding rate at duration $d+1$. Indeed, using $S_{i,d+1} = S_{i,d}(1 - T_i)$, we can show that

$$E_{d+1}(T) = E_d(T) - \frac{var_d(T)}{1 - E_d(T)}. \tag{9}$$

This holds for any d. Considering a setting with little heterogeneity, the variance in job finding rates can be approximated by

$$\begin{aligned} var_0(T) &\approx var\left([1 - F(R)]d\lambda - \lambda f(R) \frac{\partial R}{\partial \hat{\lambda}} d\hat{\lambda}\right) && (10) \\ &\propto [1 - \beta_1 \kappa]^2 \sigma_\lambda^2 + \kappa^2 \sigma_\nu. && (11) \end{aligned}$$

where κ captures the relative magnitude of the behavioral response to the mechanical response. The approximation relies on the heterogeneity in the behavioral and mechanical responses being small when the heterogeneity in job finding rates is small to start with. The resulting variance in job finding rates is thus increasing in the heterogeneity in true arrival rates (σ_λ), but less so the more this heterogeneity is perceived (β_1 large). That is, increasing the relation between the actual and perceived arrival rates always decreases the variance in job finding rates. However, any uncorrelated increase in the perceived arrival rates will also increase the variance in job finding rates. This argument regarding the variance holds at any duration d, but the implied duration-dependence for durations $d > 0$ depends on the impact on the average job finding rate $E_d(h)$ as well.

The proposition suggests that the misperceived heterogeneity in job seekers' employment prospects, either due to low β_1 or high σ_ν, may contribute to the duration-dependence in the observed job finding rates. Hence, making job seekers' beliefs more accurate would reduce the duration-dependence and thus the incidence of long-term unemployment. Also, when explaining the observed duration-dependence in exit rates through dynamic selection, we would overestimate the heterogeneity across agents' primitives when not acknowledging that this heterogeneity is not accurately perceived.

Duration-dependence in Arrival Rates We now return to the single-agent model, but allow for geometric duration-dependence in arrival rates:

$$\lambda_{d+1} = (1-\theta)\,\lambda_d \text{ and } \hat{\lambda}_{d+1} = (1-\beta_\theta\theta)\,\hat{\lambda}_d, \tag{12}$$

where θ corresponds to the true duration-dependence in the statistical model and β_θ captures the extent to which these dynamics translate to the perceived arrival rates. Like in the heterogeneous agent-model, we characterize the impact of depreciation on duration-dependence, starting from the stationary, single-agent framework ($\theta \approx 0$). We can state:

Proposition 3. *Starting from $\theta \approx 0$ and $\beta_\theta\kappa/\lambda < 1$, depreciation in the actual arrival rates ($\theta > 0$) increases negative duration-dependence in the job finding rates, $\frac{T_d}{T_{d+1}} > 1$, but this effect is decreasing in β_θ.*

See Appendix E.3 for the proof.

The evolution of the job finding rates over the spell depends on how the arrival rates change over the spell and how the reservation wage responds to this change. That is,

$$\frac{T_d}{T_{d+1}} = \frac{1-F\left(R_d\right)}{1-F\left(R_{d+1}\right)}\frac{\lambda_d}{\lambda_{d+1}}$$

The Proposition states that, in the absence of behavioral responses, duration-dependence in the actual arrival rates ($\lambda_d \neq \lambda_{d+1}$) simply translates into duration-dependence in the job finding rates. However, when job seekers perceive the arrival rates to be duration-dependent ($\beta_\theta > 0$), they will adjust their reservation wages and thus the acceptance rates. Like in the stationary model, the change in the reservation wage at duration d depends on the change in the perceived arrival rate at $d+1$ and the continuation value when remaining unemployed. However, the depreciation lowers the arrival rates more later in the spell and induces workers to lower the reservation wage more later in the spell, which translates into a larger increase in the acceptance rate later on. This behavioral response thus works in the opposite direction of the mechanical effect. We can show that the effect on the relative job finding rate equals

$$\frac{d\left[\frac{T_{d+1}}{T_d}\right]}{d\theta} = \beta_\theta \times \frac{\kappa}{\lambda} - 1,$$

starting from $\theta = 0$, where the behavioral effect is again scaled by the perception of the depreciation β_θ.

Taken together, the Proposition thus indicates that underestimating the duration-dependence in job seekers' employment prospects increases the duration-dependence in the observed job finding rates. However, making job seekers more aware of the duration-dependence in arrival rates would reduce the duration-dependence in job finding rates. Like in the case of heterogeneous arrival rates, we would overstate the importance of this non-stationary force in explaining the observed duration-dependence when not acknowledging the dynamic bias in perceptions.

5.4 Numerical Analysis

We now use the structural model to provide a quantitative assessment of the impact of the biases in job seekers' beliefs on their job finding and the incidence of long-term unemployment in particular. We calibrate our structural model with heterogeneity and duration-dependence in the actual and perceived job finding rates, targeting a subset of moments from our empirical and statistical analysis. While in theory it is possible, to perform the same estimation exercise in the structural model as in the reduced form statistical model, fitting our cross-sectional data moments requires a large number of types, which is computationally challenging, given that we need to solve the decision problem for each type. Instead, we assume two types and calibrate the true duration dependence in job finding rates and their perceptions as given by the estimates in the reduced form statistical framework. We estimate the remaining parameters relating to ex-ante heterogeneity and biases. In line with our theoretical analysis, all biases relate to the job offer arrival rates, while job seekers decide how to set their reservation wages. We consider the impact of the mean bias, the cross-sectional bias and the dynamic bias studied above.

Calibration We consider two types of job seekers: a high type h and a low type l, where the high type is the more employable type receiving job offers at rate $(\lambda^h > \lambda^l)$. For both types of job seekers, the arrival rate depreciates at geometric rate θ and wage offers are drawn from a distribution $w \sim F\left(\mu_w, \sigma_w^2\right)$. The share of high-type job seekers equals φ.

We allow for three types of biases in job seekers beliefs: first, job seekers are subject to a uniform bias B_0 in their beliefs. That is, any type's arrival rate is perceived as $\hat{\lambda}^j = \lambda^j + B_0$. Second, job seekers misperceive their employability type with probability $1 - B_1$. That is, $Prob(\hat{\lambda}_{i,0} = \hat{\lambda}^j | \lambda_{i,0} = \lambda^j) = B_1$. Finally, job seekers perceive a depreciation rate of their arrival rates of $B_\theta \theta$.[36] Like in the statistical and structural model, the respective bias terms B_0, B_1 and B_θ correspond to the mean bias, the cross-sectional bias and the dynamic bias respectively. The model exhibits no biases when $B_0 = 0$ and $B_1 = B_\theta = 1$.[37]

Panel A of Table 8 shows the parameter values that we set based on outside information. We perform the estimation for two versions of the model, which can be seen as a lower bound and upper bound on the modest degree of duration dependence in true job finding rates in our statistical model. The first specification has no duration dependence in job finding rates. In the latter specification a job seeker's job finding rate is on average 35 percent lower when unemployed for more than six months compared to the first six months of unemployment. In both specifications, we assume that the true duration dependence is not perceived (i.e., $B_\theta = 0$). We set the annual discount factor 0.996 and the separation rate at .02 per month, as is standard in the literature. We finally assume CRRA preferences with relative risk aversion equal to 2. We set the consumption flow during unemployment to $b = 0.26$, which is a pure normalization, as we estimate the mean of the wage offer distribution.[38] We also assume that wages are normally distributed, with a standard deviation $\sigma_w = 0.24$ as estimated by Hall and

[36] The arrival rate of worker i of type j after d periods of unemployment equals $\lambda_{i,d} = (1-\theta)^d \lambda^j$, while the perceived arrival rate equals $\hat{\lambda}_{i,d} = (1 - B_\theta \theta)^d \lambda^j + B_0$ with probability B_1 and $\hat{\lambda}_{i,d} = (1 - B_\theta \theta)^d \lambda^{-j} + B_0$ otherwise.

[37] Note that the correlation coefficient B_1 in our stylized calibration captures a mixture of the cross-sectional bias β_1 and the uncorrelated heterogeneity in perceptions σ_ν.

[38] Alternatively, we could set the mean of the wage offer distribution to one, and estimate the consumption value during unemployment.

Mueller [2018] with the KM survey data.

We estimate the remaining 6 parameter of our model $\{\lambda_h, \lambda_l, \varphi, \mu_w, B_0, B_1\}$, as shown in Panel B of Table 8, by targeting a vector of 7 moments shown in Table E1. The targeted moments include the actual and perceived job finding rates for the shorter- and longer-term unemployed as well as the job acceptance rate in the KM survey (see Hall and Mueller [2018] fore details). We choose the parameters by minimizing the sum of squared differences between data moments and simulated moments from the model. As shown in the table, we closely match our targeted moments, in both versions of the model. Note that the uniform bias parameter B_0 is negative, while the average bias is still positive. The imperfect correlation between true and perceived types (i.e., $B_1 < 1$) contributes to this average wedge too by making some agents of the low type perceive themselves as a high type (and vice versa). As shown in Panel B of Table 8, the relative difference in estimated arrival rates across types is smaller, but it is perceived more accurately in the model with duration-dependence.[39]

Table 8: Calibrated Parameters

Parameters	Symbol	Value in Model: W/o Duration Dependence	Value in Model: W/ Duration Dependence
A. Set Parameters			
Depreciation Rate in Arrival Rate	θ	0.00	0.06
Longitudinal Bias	B_θ	0.00	0.00
Standard Deviation of Wage Offer Distribution	σ_w	0.24	0.24
Exogeneous Job Loss Probability	σ	0.02	0.02
Discount Rate	δ	0.004	0.004
Coefficient of Relative Risk Aversion	γ	2.00	2.00
Unemployed Consumption	b	0.26	0.26
B. Estimated Parameters			
Uniform bias	B_0	-0.02	-0.10
Cross-sectional bias	B_1	0.78	0.90
Low-type arrival rate	λ_l	0.10	0.20
High-type arrival rate	λ_h	0.63	0.71
Share of high-types	φ	0.83	0.76
Mean of wage offer distribution	μ_w	0.70	0.70

Numerical Results Figure E1 illustrates the opposing impacts of the mechanical and behavioral effects on job finding depending on whether changes in arrival rates are perceived or not. Panel A of Figure E1 plots average unemployment duration as a function of changes in the actual and perceived arrival rates for all types relative to the baseline model. Decreasing the arrival rate of workers by 10 percent increases the unemployment duration by 9.5 percent, but only by 6.3 percent when the worse employment prospects are perceived. Panel B shows that a larger (mean-preserving) spread of the actual

[39] We have also extended our model with a type-specific bias in the perceived arrival rates. This relaxes the restriction from our stylized model that on average the low-type job seekers are more optimistic than the high-type job seekers. Interestingly, the estimated type-specific biases are very close, suggesting that this restriction is not binding.

Table 9: Comparative Statics in Structural Model

	Baseline	$B_0 = 0$	$B_1 = 1$	$B_\theta = 1$	$B_0 = 0$, $B_1 = 1$, $B_\theta = 1$
A. Model W/o Duration Dependence					
Unemployment duration	3.599	3.658	3.642	-	3.707
Share of LT unemployed	0.263	0.264	0.236	-	0.236
B. Model W/ Duration dependence					
Unemployment duration	3.785	4.092	3.824	3.406	3.614
Share of LT unemployed	0.266	0.285	0.258	0.235	0.233

arrival rates increases the incidence of long-term unemployment. However, by increasing the extent to which these differences are perceived reduces the incidence of long-term unemployment. A 10 percent increase in the spread of arrival rates increases the share of LT unemployed by 9.9 percent. A 10 percent increase in the correlation between the actual and perceived arrival rates, however, reduces the share by 2.5 percent. In a similar spirit, Panel C illustrates that stronger depreciation of the actual arrival rates increases the incidence of long-term unemployment, while the effect is mitigated if the stronger depreciation is also perceived. Increasing the depreciation rate from its lower bound of 0 to its upper bound of 0.061 almost doubles the share of LT unemployed (increase of 86 percent), but the impact would be mitigated to an increase of 64 percent if the higher depreciation is perceived as such.

Table 9 shows the impact of eliminating the biases in beliefs on the different unemployment outcomes. The intermediate columns consider the elimination of one bias at a time, the last column of all biases simultaneously. The top panel shows the results for the model with no duration dependence. The bottom panel shows the results for the model with negative duration dependence in arrival rates. In both models, the impact on the average duration is relatively small, but the impact on the share of LT unemployed is substantial. The share of LT unemployed decreases by 10.1 percent (2.7 percentage points) when eliminating both the uniform and cross-sectional bias in the model with no duration dependence. In the model with true duration-dependence, the elimination of the biases also involves correcting the perception of the duration-dependence. The corresponding decrease in the share of LT unemployed equals 12.5 percent (3.3 percentage points). Defining the incidence of LT unemployment as the share of LT vs. ST unemployed the model thus predicts that about 15 percent of the relatively high incidence is due job seekers' under-estimating their differences in job finding, both cross-sectionally and over the spell. This finding is robust to the relative importance of heterogeneity vs. depreciation in the actual arrival rates, and we view this as a lower bound of the importance of biases for the incidence of long-term unemployment, because our quantitative exercise focused only on systematic biases in perceptions but ignored random errors in perceptions as a source of additional biases in beliefs.

6 Conclusion

In this paper we analyse job seekers' perceptions about their employment prospects and their relationship to employment outcomes. Using longitudinal data from two comprehensive surveys, we analyse how reported beliefs about job finding probabilities predict actual job finding and how they evolve over the spell of unemployment. We start with an empirical analysis of the data and document (1) that reported beliefs have a strong predictive power of actual job finding, (2) that job seekers are over-optimistic in their beliefs, particularly the long-term unemployed, and (3) that job seekers do not revise their beliefs downward when remaining unemployed.

In the second part of the paper, we develop a novel framework, where we exploit the joint observation of beliefs and ex-post realizations, to disentangle heterogeneity and duration-dependence in true job finding rates. Our framework allows for random elicitations errors as well as systematic biases in beliefs both across job seekers and over the unemployment spell. Within our framework, we identify the elicitation errors and biases jointly with the ex-ante heterogeneity and the duration dependence in true job finding rates. We find that the reported beliefs reveal a substantial amount of heterogeneity in true job finding rates, accounting for more than half of the observed decline in job finding rates over the spell of unemployment. Moreover, we find that job seekers' beliefs are systemically biased and under-respond to differences in job finding rates across job seekers, that is over-optimistic job seekers are less likely to find jobs and thus select into long-term unemployment.

In the third and final part of the paper, we show theoretically in a model of job search how biases in beliefs contribute to the slow exit out of unemployment and the incidence of long-term unemployment. Unemployed workers who are over-optimistic about the job offer arrival rate set their reservation wage too high and do not adjust it as the unemployment spell progresses. We calibrate the model and find that this mechanism significantly increases the share of long-term unemployment. The finding also raises the question whether behavioral biases may amplify the rise of long-term unemployment in recessions. If unemployed workers fail to adjust their beliefs about their employment prospects in response to developments in the aggregate labor market, the lack of a behavioral response is likely to lead to greater unemployment levels than would otherwise be the case in the absence of behavioral biases.

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Appendix

A Survey Questions

A.1 Survey of Consumer Expectations

Question about 12-Month Job Finding Prospect

What do you think is the percent chance that within the coming 12 months, you will find a job that you will accept, considering the pay and type of work?

[Ruler & box]

Question about 3-Month Job Finding Prospect

And looking at the more immediate future, what do you think is the percent chance that within the coming 3 months, you will find a job that you will accept, considering the pay and type of work?

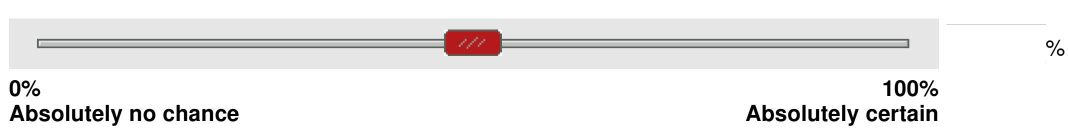
[Ruler & box]

A.2 KM Survey

Question about 1-Month Job Finding Prospect

What do you think is the percent chance that you will be employed again within the next 4 weeks?

Please move the red button on the bar below to select the percent chance, where 0% means 'absolutely no chance' and 100% means 'absolutely certain'.



[NB: Initial position on bar is randomized.]

Question about Expected Duration

How many weeks do you estimate it will actually take before you will be employed again?

________ *Weeks*

B Comparison of the SCE to the CPS

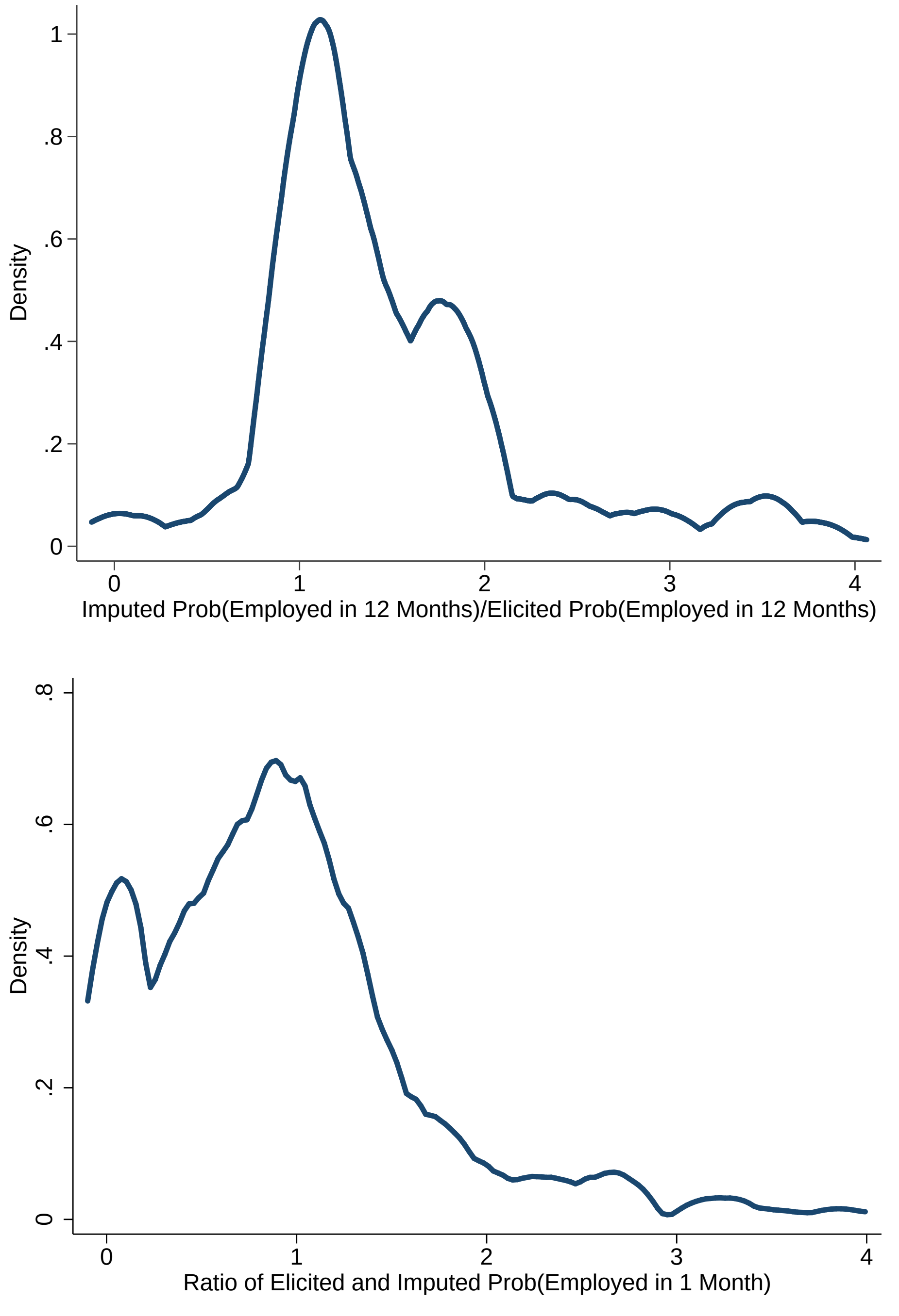
Table B1: Descriptive Statistics for the Survey of Consumer Expectations (SCE) and Comparison to the Current Population Survey (CPS)

	SCE 2012-17 All	CPS 2012-17 All	SCE 2012-17 Unemployed	CPS 2012-17 Unemployed
Demographic data (in percent)				
High-School Degree or Less	31.9	35.3	42.8	45.0
Some College Education	18.7	18.9	21.0	21.3
College Degree or More	49.0	45.8	35.3	33.6
Female	49.5	48.2	55.7	49.2
Ages 20-34	26.4	26.6	24.8	35.2
Ages 35-49	37.4	34.0	32.7	33.3
Ages 50-65	36.2	39.4	42.4	31.6
Black	11.4	14.3	16.5	23.6
Hispanic	9.8	15.2	11.4	18.1
Survey outcomes				
Avg. monthly job finding rate (in percent)	n.a.	n.a.	17.6	22.7
# of respondents	8,396	n.a.	777	n.a.
# of survey responses	53,089	2,427,795	2,117	86,761

Notes: All samples, including the CPS, are restricted to individuals of ages 20-65. The monthly job finding rate in the SCE and CPS is the U-to-E transition rate between two consecutive monthly interviews. Survery weights are used for all estimates. Note that we did not match survey responses in the CPS across all eight rotation groups and thus cannot distinguish number of survey respondents from number of survey responses.

C Additional Empirical Results

Figure C1: Ratio of Elicited Probabilities and Imputed Probabilities based on Alternative Forms of Elicitations



Note: See Figure 2 in the main text for details.

Figure C2: Averages of Actual Job Finding Probabilities, by Bins of Elicited Probabilities

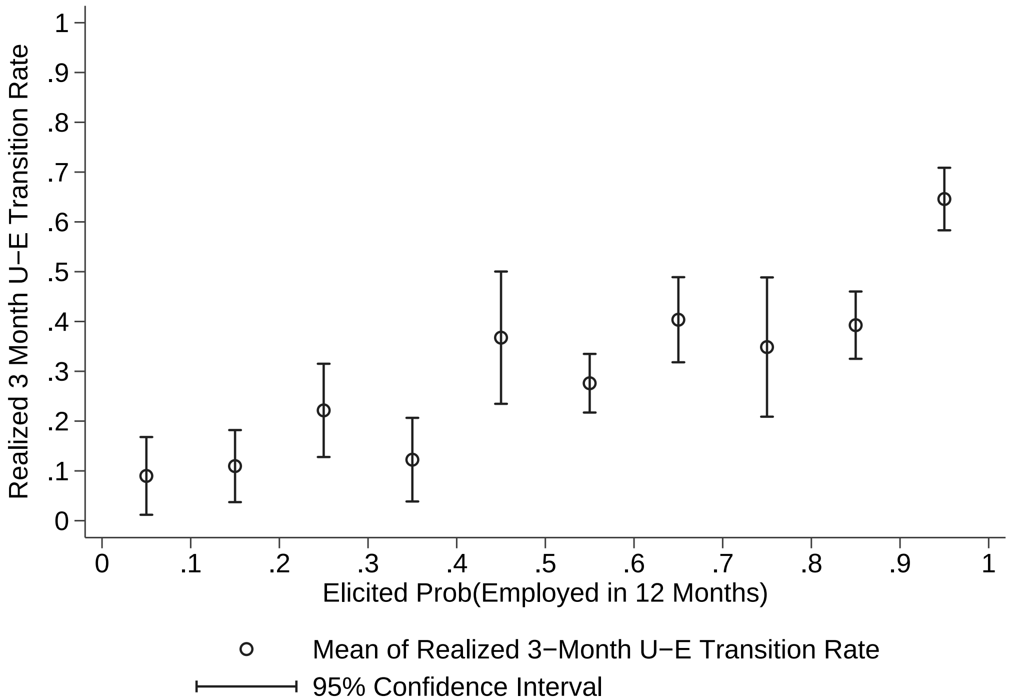


Figure C3: Perceived 12-month Job Finding Probabilities, by Time since First Interview

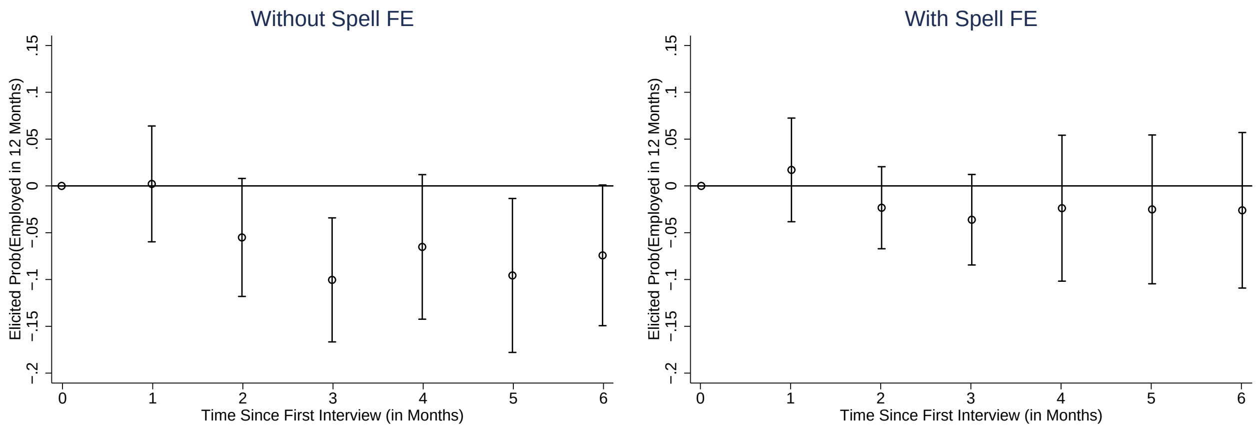


Figure C4: Perceived Expected Duration (Inverted), by Time since First Interview

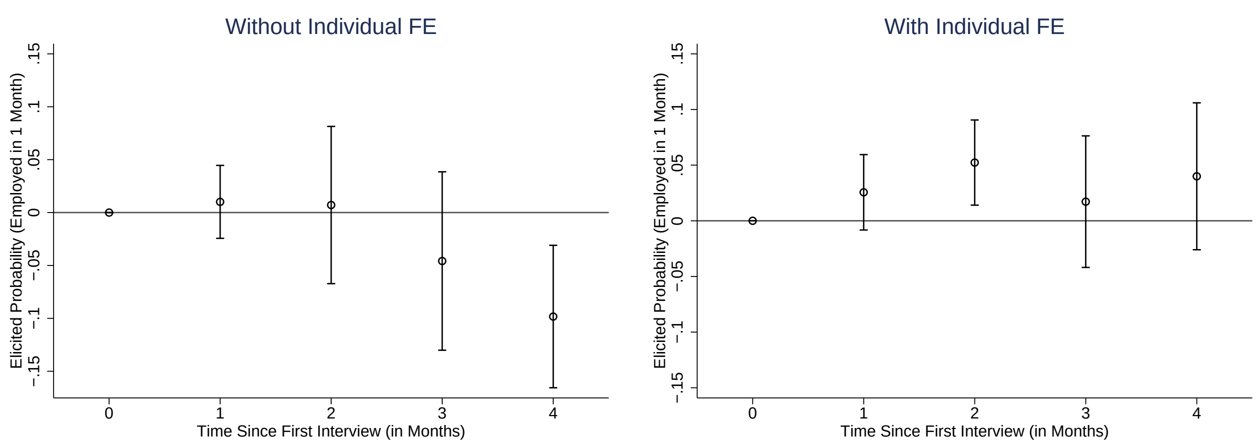


Table C1: Linear Regressions of Realized Job Finding Probabilities on Elicitations (12-Month Horizon)

Dependent Variable: 3-Month UE Transition Rate	(1)	(2)	(3)	(4)
Prob(Find Job in 12 Months)	0.539***	0.498***		0.425***
	(0.0672)	(0.111)		(0.109)
Prob(Find Job in 12 Months) x LT Unemployed		-0.124		-0.210
		(0.136)		(0.129)
LT Unemployed		-0.146		-0.0424
		(0.0950)		(0.0967)
Female			-0.143***	-0.0821**
			(0.0424)	(0.0383)
Race: African-American			0.216***	0.161**
			(0.0641)	(0.0668)
Race: Hispanic			-0.0374	-0.0778
			(0.0578)	(0.0590)
Race: Asian			0.0783	0.142
			(0.0982)	(0.0902)
Race: Other			-0.103	-0.0944
			(0.0659)	(0.0630)
Age			0.0161	0.0162
			(0.0146)	(0.0119)
Age*Age			-0.000283*	-0.000245*
			(0.000157)	(0.000132)
HH income: 30,000-59,999			0.0945*	0.0677
			(0.0514)	(0.0457)
HH income: 60,000-100,000			0.162**	0.119*
			(0.0633)	(0.0630)
HH income: 100,000+			0.134**	0.105
			(0.0605)	(0.0717)
High-School Degree			0.333***	0.213***
			(0.0779)	(0.0698)
Some College			0.255***	0.159**
			(0.0662)	(0.0621)
College Degree			0.251***	0.124**
			(0.0642)	(0.0623)
Post-Graduate Education			0.263***	0.124*
			(0.0697)	(0.0679)
Other Education			0.602***	0.438***
			(0.176)	(0.154)
Constant	0.0636	0.205**	0.0533	-0.123
	(0.0421)	(0.0841)	(0.323)	(0.275)
N	982	982	982	982
R2	0.106	0.156	0.152	0.223

Notes: All samples are restricted to unemployed workers, ages 20-65.

Table C2: Linear Regressions of Realized Job Finding Probabilities on Elicitations (12-Month Horizon)

Dependent Variable: 3-Period Forward 3-Month UE Transition Rate	(1)	(2)	(3)	(4)
Prob(Find Job in 12 Months)	0.275***	0.415***		0.371***
	(0.0719)	(0.126)		(0.120)
Prob(Find Job in 12 Months) x LT Unemployed		-0.280*		-0.279*
		(0.149)		(0.145)
LT Unemployed		0.0650		0.0691
		(0.0910)		(0.0880)
Controls			X	X
N	392	392	392	392
R2	0.0389	0.0630	0.153	0.196

Notes: All samples are restricted to unemployed workers, ages 20-65.

Table C3: Linear Regressions of Realized Job Finding on Elicitations (KM Survey)

Dependent Variable: Finding a Job (1-Month Horizon)	(1)	(2)	(3)	(4)
Panel A.				
Prob(Find Job in 1 Month)	0.230	0.355		0.353
	(0.094)**	(0.138)**		(0.121)***
Prob(Find Job in 1 Month) x LT Unemployed		-0.311		-0.237
		(0.171)*		(0.169)
LT Unemployed		0.053		0.054
		(0.043)		(0.044)
Controls			X	X
N	734	734	709	709
R2	0.032	0.048	0.190	0.231
Panel B.				
Expected Duration (Inverted)	0.398	0.690		0.513
	(0.176)**	(0.206)***		(0.139)***
Expected Duration (Inverted) x LT Unemployed		-0.686		-0.493
		(0.215)***		(0.155)***
LT Unemployed		0.181		0.145
		(0.060)***		(0.053)***
Controls			X	X
N	668	668	650	650
R2	0.079	0.139	0.189	0.249

Notes: All samples are restricted to unemployed workers, ages 20-65. Expected duration (inverted) is calculated as $1-(1-\frac{1}{x})^4$, where x is the elicited expected remaining duration of unemployment (in weeks). Controls are dummies for gender, race, ethnicity, household income brackets (4), educational attainment (6), and age and age squared.

Table C4: Linear Regressions of Elicitations on Unemployment Duration, Robustness Checks (SCE)

Dependent Variable (Unless Otherwise Stated in Footnote): Prob(Employed in 3 Months)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemployment Duration, in Months	0.00395	-0.00202	0.00379	0.00228	-0.000209	0.00147	0.00104	0.00535	0.00272
	(0.00460)	(0.00458)	(0.00420)	(0.00637)	(0.00399)	(0.00483)	(0.00128)	(0.00473)	(0.00174)
FE Type	S	S	S	S	S	S	S		I
Observations	1,845	1,844	2,116	1,535	1,715	1,536	1,842	1,845	1,845
R^2	0.822	0.836	0.796	0.864	0.790	0.817	0.821	0.822	0.806

Notes: All samples are restricted to unemployed workers, ages 20-65. Column (1) reports the baseline results from Column 4 in Table 5; Column (2) reports results where use the 12-month probability as dependent variable; Column (3) reports the results where we did not trim the sample for inconsistent answers between the two survey questions (i.e., where the 3-month probability was larger than the 12-month probability); Column (4) reports results where we excluded answers with a probability of 50 percent; Column (5) reports results where we excluded answers with a probability of 100 percent; Column (6) reports the results where we excluded answers where the person was employed at the next interview; Column (7) reports results with self-reported duration as the independent variable; Column (8) reports results where we control for the monthly national unemployment rate as reported by the BLS; Column (9) reports results where we control for individual fixed effects (I) instead of spell fixed effects (S).

Table C5: Linear Regressions of Elicitations on Unemployment Duration, Robustness Checks (KM survey)

Dependent Variable (Unless Otherwise Stated in Footnote): Prob(Employed in 4 Weeks)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemployment Duration,	0.022	0.013	0.020	0.021	0.022	0.020	0.017	0.021	0.030
in Months	(0.008)**	(0.008)	(0.008)**	(0.009)**	(0.008)**	(0.008)**	(0.008)**	(0.008)**	(0.014)**
Person Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	4,435	4,269	4,486	3,862	4,292	4,105	4,044	4,272	4,435
R-Squared	0.902	0.887	0.913	0.920	0.890	0.900	0.900	0.900	0.902

Notes: All samples are restricted to unemployed workers, ages 20-65. The results in Panel B use the the inverse of the expected remaining duration as dependent variable (see footnote 13 in the maintext for details). Column (1) reports the baseline results from Table 5; Column (2) uses the inverse of the expected duration question (converted into a 4-week probability) as dependent variable; Column (3) reports the results where we did not trim the sample for inconsistent answers between the two survey questions (i.e., where the difference between the probability question and the inverse of the remaining duration was more than 75 percentage points apart); Column (4) reports results where we excluded answers with a probability of 50 percent in Panel A or a remaining duration of 26 or 52 weeks in Panel B; Column (5) reports results where we excluded probabilities of 80 percent or more; Column (6) reports the results where we excluded answers where the person reported in the following 4 weeks that she or he accepted a job or was working; Column (7) reports the results where we excluded answers where the respondent had previously received but not accepted a job offer; Column (8) reports results with self-reported duration as the independent variable; Column (9) reports results where we control for the monthly unemployment rate in New Jersey as reported by the BLS.

Table C6: Linear Regressions of Realized Job Finding Rate on Unemployment Duration

Dependent Variable: 3-Month UE Transition Rate	(1)	(2)	(3)	(4)
Unemployment Duration, in Months	-0.0090***	-0.0071***		
	(0.0009)	(0.0009)		
Unemployment Duration: 4-6 Monthts			-0.187***	-0.152**
			(0.069)	(0.064)
Unemployment Duration: 7-12 Monthts			-0.274***	-0.239***
			(0.066)	(0.060)
Unemployment Duration: 13+ Monthts			-0.400***	-0.287***
			(0.053)	(0.052)
Female		-0.084**		-0.090**
		(0.039)		(0.038)
Black/African-American		0.192***		0.189***
		(0.066)		(0.066)
Hispanic		-0.072		-0.043
		(0.058)		(0.060)
Asian American Indian Hawaiian		0.044		0.097
		(0.093)		(0.096)
Other		-0.155**		-0.103
		(0.063)		(0.065)
Age		0.013		0.012
		(0.013)		(0.012)
Age Squared		-0.000*		-0.000
		(0.000)		(0.000)
HH income: 30,000-59,999		0.057		0.068
		(0.047)		(0.045)
HH income: 60,000-100,000		0.111*		0.108
		(0.066)		(0.072)
HH income: 100,000+		0.062		0.082
		(0.065)		(0.071)
High School		0.210***		0.230***
		(0.063)		(0.075)
Some College		0.164***		0.184***
		(0.055)		(0.067)
College		0.128**		0.155**
		(0.054)		(0.066)
Post Graduate		0.112*		0.169**
		(0.064)		(0.075)
Other Education		0.400**		0.499***
		(0.161)		(0.162)
Constant	0.543***	0.304	0.623***	0.345
	(0.031)	(0.287)	(0.043)	(0.272)
Observations	983	983	983	983
R^2	0.119	0.213	0.116	0.205

Notes: All samples are restricted to unemployed workers, ages 20-65.

Table C7: Linear Regressions of Elicited Perceptions on Time Spent on Job Search and the Reservation Wage

Dependent variable:	Prob(Find Job in 1 Month)		Expected Duration (Inverted)	
	(1)	(2)	(3)	(4)
Time Spent on Job Search (Hours per Week)	0.0013	-0.0013	0.0009	0.0007
	(0.0006)**	(0.0010)	(0.0005)	(0.0013)
Log(Hourly Reservation Wage)	-0.0387	-0.0099	-0.0586	0.1374
	(0.0360)	(0.0758)	(0.0316)*	(0.0828)*
Reservation Commuting Distance (in min)	-0.0000	-0.0010	-0.0006	-0.0003
	(0.0006)	(0.0013)	(0.0005)	(0.0013)
Controls	X		X	
Individual F.E.		X		X
N	3,992	4,087	3,911	3,990
R2	0.129	0.915	0.097	0.891

Notes: All samples are restricted to unemployed workers, ages 20-65. Expected duration (inverted) is calculated as $1-(1-\frac{1}{x})^4$, where x is the elicited expected remaining duration of unemployment (in weeks).

Table C8: Linear Regressions of Macroeconomic Measures on Elicitations

Panel A. Unemployed Individuals: Elicited 3-Month Probability	(1)	(2)	(3)	(4)
National Unemployment Rate	2.059			
	(1.946)			
National Job Openings Rate	3.535			
	(4.792)			
State Unemployment Rate		0.534	-0.150	
		(0.729)	(0.727)	
Elicited Prob(rise in US stock prices)				0.170***
				(0.0399)
Elicited Prob(rise in US unemployment)				-0.0905**
				(0.0373)
Demographics	X	X	X	X
State FE			X	X
Observations	1,826	1,832	1,832	1,821
R^2	0.116	0.115	0.183	0.195
Panel B. Employed Individuals: Elicited (Conditional) Job 3-Month Probability	(1)	(2)	(3)	(4)
National Unemployment Rate	-1.407***			
	(0.426)			
National Job Openings	4.984***			
	(1.094)			
State Unemployment Rate		-2.812***	-3.120***	
		(0.147)	(0.177)	
Elicited Prob(rise in US stock prices)				0.223***
				(0.00920)
Elicited Prob(rise in US unemployment)				-0.109***
				(0.00924)
Demographics	X	X	X	X
State FE			X	X
Observations	44,309	44,380	44,380	44,494
R^2	0.056	0.058	0.073	0.086

Notes: All samples are restricted to unemployed workers, ages 20-65.

D Statistical Framework

Table D1: Additional Moments

Moment	Symbol	Value in Data	Value in Model
Variance of Elicitations:			
... at 0-3 Months of Unemployment	$s^2_{Z_{03}}$	0.091	0.084
... at 4-6 Months of Unemployment	$s^2_{Z_{46}}$	0.092	0.084
... at 7 Months of Unemployment or More	$s^2_{Z_{7+}}$	0.074	0.077
Covariance of Elicitations and Job Finding:			
... at 0-3 Months of Unemployment	$c_{Z_{03},F_{03}}$	0.055	0.047
... at 4-6 Months of Unemployment	$c_{Z_{46},F_{46}}$	0.054	0.042
... at 7 Months of Unemployment or More	$c_{Z_{7+},F_{7+}}$	0.030	0.030

Table D2: Parameter Estimates and Model Fit for Restricted Versions of the Model

A. Parameter Estimates and Selected Moments:	(1) Baseline	(2) $\theta = 0$ $\hat{\theta} = 0$	(3) No heterog. in T_{id}	(4) $\sigma_\tau = 0$	(5) $\theta = \hat{\theta}$	(6) $b_1 = 1$	(7) $\theta = \hat{\theta}$ $b_0 = 0$ $b_1 = 1$
Parameter 1 of distribution	2.402	1.620	0.151	1.066	2.034	4.726	6.725
Parameter 2 of distribution	4.007	2.485	0	1.592	3.205	8.870	15.332
σ_τ	0.363	0.319	0	0	0.379	0.296	0.384
θ	0.033	0	0.070	-0.133	0.023	0.052	0.050
$\hat{\theta}$	0.016	0	0.083	-0.071	0.023	0.013	0.050
b_0	0.201	0.265	0.310	0.300	0.252	-0.058	0
σ_ε	0.426	0.443	0.488	0.452	0.437	0.351	0.308
b_1	0.620	0.528	0.492	0.495	0.557	1	1
$s^2_{T^3_{i0}}$	0.069	0.080	0	0.084	0.077	0.044	0.053
$s^2_{T^3_i}$	0.045	0.062	0	0.085	0.051	0.025	0.019
$s^2_{Z^3_{i0}}$	0.080	0.079	0.074	0.079	0.080	0.079	0.080
$s^2_{Z^3_{i0}-\varepsilon_{i0}}$	0.027	0.022	0	0.020	0.024	0.045	0.053
$\beta_{Z^3_{i0}-\varepsilon_{i0},T^3_{i0}}$	0.621	0.528	-0.679	0.494	0.557	1.004	1
$\beta_{dZ^3_{i0}-d\varepsilon_{i0},dT^3_{i0}}$	0.668	0.528	0.626	0.449	0.557	1.159	1

B. Model Fit:	Data	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Targeted Moments:								
$m_{F_{03}}$	0.623	0.621	0.624	0.627	0.630	0.625	0.618	0.582
$m_{F_{46}}$	0.435	0.427	0.420	0.476	0.424	0.425	0.447	0.444
$m_{F_{7+}}$	0.260	0.259	0.262	0.206	0.252	0.260	0.257	0.277
$m_{Z_{03}} - m_{F_{03}}$	-0.031	-0.027	-0.030	-0.017	-0.033	-0.025	-0.023	-0.001
$m_{Z_{46}} - m_{F_{46}}$	0.076	0.065	0.068	0.042	0.057	0.066	0.050	0.001
$m_{Z_{7+}} - m_{F_{7+}}$	0.139	0.141	0.142	0.141	0.144	0.137	0.143	0.001
s^2_Z	0.089	0.089	0.089	0.089	0.088	0.089	0.089	0.089
$c_{Z,F}$	0.055	0.055	0.055	0.022	0.052	0.055	0.054	0.062
$c_{Z_d,F_{d+3}}$	0.023	0.023	0.024	0.021	0.029	0.022	0.024	0.021
m_{dZ}	0.009	0.009	0.009	-0.021	0.006	0.009	0.010	0.003
Weighted SSR		0.071	0.098	25.985	1.001	0.096	0.333	17.154

Table D3: Robustness Checks

A. Parameter Estimates and Selected Moments:		(1) Baseline	(2) Gamma (T_i)	(3) Weibull (T_i)	(4) Normal (ε, τ)	(5) Geometric Depreciation	(6) m_{dZ} $= 0.004$	(7) 14 Moments	(8) W/o recall Expectation	(9) ε_i	(10) Bunching
Parameter 1 of distribution		2.402	0.452	2.517	2.084	2.170	2.650	2.276	2.421	2.380	2.340
Parameter 2 of distribution		4.007	1.944	0.191	3.410	3.407	4.246	3.467	3.971	3.896	3.755
σ_τ		0.363	0.365	0.153	0.159	0.382	0.357	0.481	0.381	0.389	0.377
θ		0.033	0.024	0.030	0.041	0.028	0.04	0.034	0.033	0.033	0.033
$\hat{\theta}$		0.016	0.015	0.009	0.003	0.023	0.031	0.037	0.022	0.020	0.021
b_0		0.201	0.238	0.202	0.018	0.243	0.212	0.231	0.217	0.219	0.227
σ_ε		0.426	0.434	0.426	0.241	0.437	0.431	0.440	0.429	0.444	0.417
b_1		0.620	0.570	0.618	0.901	0.569	0.622	0.611	0.602	0.599	0.584
$s^2_{T^3_{i0}}$		0.069	0.075	0.07	0.056	0.073	0.064	0.083	0.071	0.072	0.071
$s^2_{T^3_i}$		0.045	0.052	0.060	0.051	0.048	0.041	0.046	0.044	0.045	0.046
$s^2_{Z^3_{i0}}$		0.080	0.080	0.080	0.079	0.079	0.078	0.084	0.079	0.083	0.080
$s^2_{Z^3_{i0}-\varepsilon_{i0}}$		0.027	0.024	0.027	0.046	0.024	0.025	0.031	0.026	0.026	0.024
$\beta_{Z^3_{i0}-\varepsilon_{i0},T^3_{i0}}$		0.621	0.570	0.617	0.901	0.569	0.622	0.611	0.603	0.600	0.585
$\beta_{dZ^3_{i0}-d\varepsilon_{i0},dT^3_{i0}}$		0.668	0.593	0.635	1.055	0.580	0.649	0.603	0.636	0.636	0.619
B. Model Fit:	Data	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Targeted Moments:											
$m_{F_{03}}$	0.623	0.621	0.627	0.627	0.624	0.631	0.632	0.634	0.625	0.625	0.627
$m_{F_{46}}$	0.435	0.427	0.423	0.424	0.428	0.432	0.432	0.424	0.429	0.429	0.429
$m_{F_{7+}}$	0.26	0.259	0.262	0.262	0.262	0.257	0.256	0.254	0.26	0.261	0.260
$m_{Z_{03}} - m_{F_{03}}$	-0.031	-0.027	-0.028	-0.029	-0.027	-0.028	-0.022	-0.017	-0.027	-0.026	-0.027
$m_{Z_{46}} - m_{F_{46}}$	0.076	0.065	0.066	0.066	0.061	0.064	0.064	0.063	0.063	0.063	0.064
$m_{Z_{7+}} - m_{F_{7+}}$	0.139	0.141	0.141	0.142	0.144	0.141	0.138	0.127	0.140	0.141	0.141
s^2_Z	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.097	0.089	0.089	0.089
$c_{Z,F}$	0.055	0.055	0.055	0.056	0.054	0.055	0.053	0.065	0.055	0.055	0.055
$c_{Z_d,F_{d+3}}$	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.022	0.022	0.022	0.023
m_{dZ}	0.009	0.009	0.009	0.007	0.008	0.008	0.005	0.011	0.009	0.009	0.009
Weighted SSR		0.0708	0.0839	0.1065	0.1219	0.091	0.2037	0.8147	0.1176	0.0884	0.0793

Table D4: Robustness Checks (Continued)

A. Parameter Estimates and Selected Moments:		(1) Baseline	(11) $W = Cov^{-1}$	(12) $W = I$	(13) Residualized Moments
Parameter 1 of distribution		2.402	2.297	2.435	3.510
Parameter 2 of distribution		4.007	3.560	4.052	7.056
σ_τ		0.363	0.372	0.351	0.304
θ		0.033	0.033	0.033	0.007
$\hat{\theta}$		0.016	0.016	0.016	0.012
b_0		0.201	0.208	0.203	0.269
σ_ε		0.426	0.427	0.438	0.404
b_1		0.620	0.611	0.620	0.535
$s^2_{T^3_{i0}}$		0.069	0.070	0.067	0.054
$s^2_{T^3_i}$		0.045	0.046	0.044	0.034
$s^2_{Z^3_{i0}}$		0.080	0.078	0.081	0.066
$s^2_{Z^3_{i0}-\varepsilon_{i0}}$		0.027	0.026	0.026	0.016
$\beta_{Z^3_{i0}-\varepsilon_{i0},T^3_{i0}}$		0.621	0.611	0.621	0.535
$\beta_{dZ^3_{i0}-d\varepsilon_{i0},dT^3_{i0}}$		0.668	0.659	0.671	0.527
B. Model Fit:	Data	(1)	(2)	(3)	(4)
Targeted Moments:					
$m_{F_{03}}$	0.623	0.621	0.635	0.623	0.623
$m_{F_{46}}$	0.435	0.427	0.430	0.431	0.502
$m_{F_{7+}}$	0.260	0.259	0.256	0.262	0.383
$m_{Z_{03}} - m_{F_{03}}$	-0.031	-0.027	-0.032	-0.025	-0.023
$m_{Z_{46}} - m_{F_{46}}$	0.076	0.065	0.067	0.067	0.032
$m_{Z_{7+}} - m_{F_{7+}}$	0.139	0.141	0.146	0.143	0.083
s^2_Z	0.089	0.089	0.089	0.091	0.071
$c_{Z,F}$	0.055	0.055	0.056	0.054	0.036
$c_{Z_d,F_{d+3}}$	0.023	0.023	0.023	0.023	0.017
m_{dZ}	0.009	0.009	0.010	0.009	0.008
Weighted SSR		0.0708	0.2953	0.0001	0.5787

Notes: See Table D5 for the residualized moments targeted in the estimation of the results reported in Column 4.

Table D5: Matched Moments (Residualized)

Moment	Symbol	Value in Data	Value in Model
Mean of 3-Month Job Finding Rates:			
... at 0-3 Months of Unemployment	$m_{F_{03}}$	0.623	0.623
... at 4-6 Months of Unemployment	$m_{F_{46}}$	0.482	0.502
... at 7 Months of Unemployment or More	$m_{F_{7+}}$	0.387	0.383
Mean of 3-Month Elicitations (Deviation from Actual):			
... at 0-3 Months of Unemployment	$m_{Z_{03}} - m_{F_{03}}$	−0.031	−0.023
... at 4-6 Months of Unemployment	$m_{Z_{46}} - m_{F_{46}}$	0.063	0.032
... at 7 Months of Unemployment or More	$m_{Z_{7+}} - m_{F_{7+}}$	0.076	0.083
Mean of Monthly Innovations in Elicitations	m_{dZ}	0.009	0.008
Variance of Elicitations	s_Z^2	0.071	0.071
Covariance of Elicitations and Job Finding	$c_{Z,F}$	0.035	0.036
Covariance of Elicitations and Job Finding in 3 Months	$c_{Z_d,F_{d+3}}$	0.019	0.017

Figure D1: Duration Dependence in Job Finding Rates
(Targeting Residualized Moments)

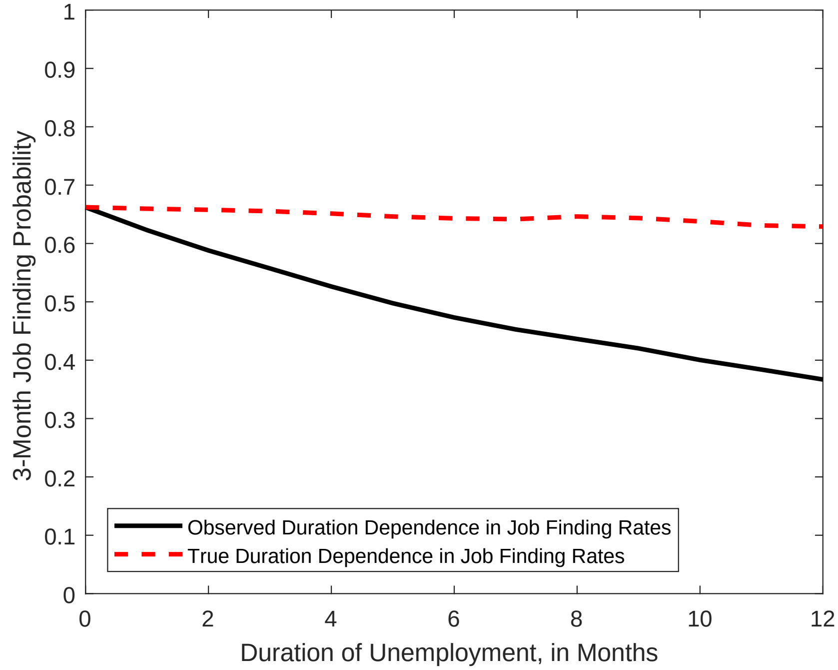
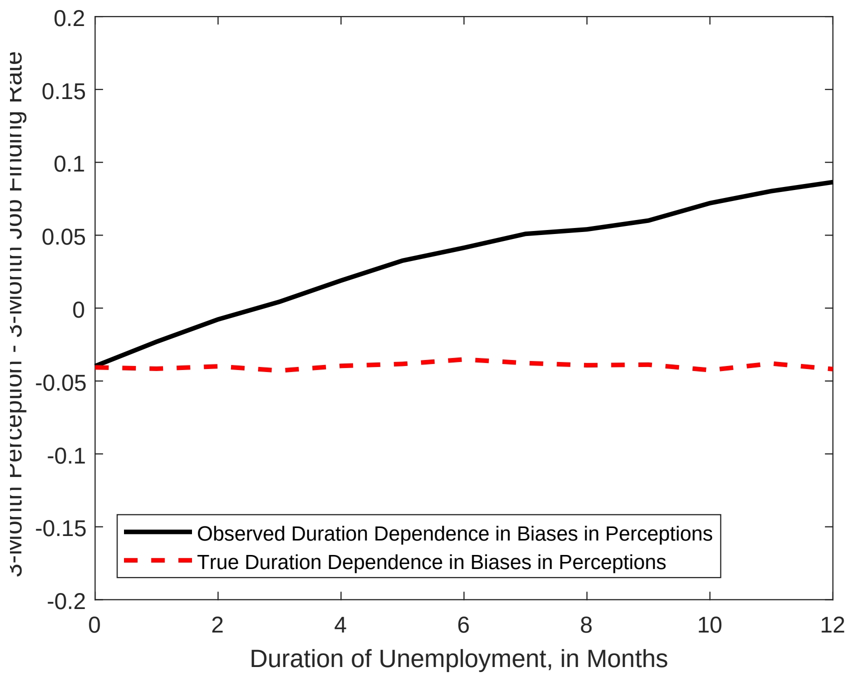


Figure D2: Duration Dependence in Biases in Perceptions
(Targeting Residualized Moments)



E Structural Model

E.1 Proof of Proposition 1

In the stationary single-agent model we have,

$$T = \lambda[1 - F(R)].$$

We consider the impact on the job finding rate T of infinitesimal changes in λ and $\hat{\lambda}$,

$$dT = [1 - F(R)]d\lambda - \lambda f(R)\frac{dR}{d\hat{\lambda}}d\hat{\lambda},$$

A change in λ does not trigger a change in the reservation wage R since it is only the perceived arrival rate that informs the agent's reservation wage. Rearranging this equation we get,

$$\frac{dT}{d\lambda}\frac{\lambda}{T} = 1 - \lambda\frac{f(R)}{1 - F(R)}\frac{dR}{d\hat{\lambda}}\frac{d\hat{\lambda}}{d\lambda}.$$

To unpack the $\frac{dR}{d\hat{\lambda}}$ term we consider the determination of the reservation wage. The reservation wage is defined by $U = V(R)$, where

$$\begin{aligned} U =& u + \frac{1}{1+\delta}\max_R\left\{U + \hat{\lambda}\int_R [V(w) - U]dF(w)]\right\}, \\ V(w) =& u(w) + \frac{1}{1+\delta}\left\{(1-\sigma)V(w) + \sigma U\right\}. \end{aligned}$$

Therefore, we can write,

$$V(R) = \frac{1+\delta}{\delta}u(R)$$

and thus

$$\frac{1+\delta}{\delta}u(R) = u + \frac{1}{1+\delta}\max_R\left\{\frac{1+\delta}{\delta}u(R) + \hat{\lambda}\int_R\left[V(w) - \frac{1+\delta}{\delta}u(R)\right]dF(w)\right\}.$$

We can totally differentiate this condition with respect to R and $\hat{\lambda}$, applying the envelope theorem to the right hand side (i.e., $dU/dR = 0$) and assuming no job separation risk such that $V(w) = (1+\delta)u(w)/\delta$,

$$\frac{u'(R)}{1 - \frac{1}{1+\delta}}dR = \frac{1}{1+\delta}\left\{\int_R\left[\frac{u(w)}{1 - \frac{1}{1+\delta}} - \frac{u(R)}{1 - \frac{1}{1+\delta}}\right]dF(w)\right\}d\hat{\lambda}.$$

So, we can conclude

$$\frac{dR}{d\hat{\lambda}} = \frac{1}{1+\delta}\left\{\int_R\left[\frac{u(w) - u(R)}{u'(R)}\right]dF(w)\right\}.$$

Combining this with our earlier result, we find

$$\begin{aligned}
\frac{dT}{d\lambda}\frac{\lambda}{T} &= 1 - \frac{1}{1+\delta}\lambda f(R)\frac{\int_R \left[\frac{u(w)-u(R)}{u'(R)}\right] dF(w)}{1-F(R)}\frac{d\hat{\lambda}}{d\lambda}, \\
&= 1 - \frac{1}{1+\delta} T \frac{f(R)}{1-F(R)} E\left[\frac{u(w)-u(R)}{u'(R)}\middle| w \geq R\right]\frac{d\hat{\lambda}}{d\lambda}.
\end{aligned}$$

E.2 Proof of Proposition 2

We consider heterogeneity in true arrival rates $\lambda_i \overset{d}{\sim} G(\lambda, \sigma_\lambda^2)$ and parametrize the perceived arrival rate as

$$\hat{\lambda}_i = \beta_0 + \beta_1 \lambda_i + \nu_i,$$

where $\nu_i \overset{d}{\sim} H(0, \sigma_\nu^2)$. Therefore,

$$\begin{aligned}
E(\hat{\lambda}_i) &= \beta_0 + \beta_1 \lambda, \\
V(\hat{\lambda}_i) &= \beta_1^2 \sigma_\lambda^2 + \sigma_\nu^2,
\end{aligned}$$

and we assume the degenerate type $(\lambda, \beta_0 + \beta_1 \lambda)$ for $\sigma_\lambda, \sigma_\nu \to 0$ sets reservation wage R and has job finding rate $T = \lambda \left[1 - F(R)\right]$.

We define the duration-dependent mean and variance for the job finding rate out of unemployment, respectively,

$$\begin{aligned}
E_d(T_i) &= \int \frac{S_{i,d}}{S_d} T_{i,d} di, \\
V_d(T_i) &= \int \frac{S_{i,d}}{S_d} [T_{i,d} - E_d(T_i)]^2 di,
\end{aligned}$$

where $S_{i,d} = \prod_{j=0}^{d-1}(1 - T_{i,j})$ with $S_{i,0} = 1$. We proceed in two steps.

First, we show that

$$E_1(T_i) = E_0(T_i) - \frac{V_0(T_i)}{1 - E_0(T_i)}.$$

Using $S_{i,1} = S_{i,0}(1 - T_i)$ and $V_0(T_i) = E_0(T_i^2) - E_0(T_i)^2$ the definitions above, we can state

$$\begin{aligned}
E_1(T_i) &= \int \frac{S_{i,1}}{S_1} T_i di = \int \frac{S_{i,0}(1-T_i)}{S_1} T_{i,1} di, \\
&= \frac{S_0}{S_1}\left[\int \frac{S_{i,0}}{S_0} T_i di - \int \frac{S_{i,0}}{S_0} T_i^2 di\right], \\
&= \frac{S_0}{S_1}[E_0(T_i) - E_0(T_i^2)] = \frac{S_0}{S_1}[E_0(T_i)\{1 - E_0(T_i)\} - V_0(T_i)].
\end{aligned}$$

Also note that

$$
\begin{aligned}
E_0(T_i) &= \int \frac{S_{i,0}}{S_0} T_i di = \int \frac{S_{i,0}}{S_0} \left(\frac{S_{i,0} - S_{i,1}}{S_{i,0}} \right) di, \\
&= \int \frac{S_{i,0} - S_{i,1}}{S_0} di = 1 - \frac{S_1}{S_0},
\end{aligned}
$$

where we use $S_d = \int S_{i,d} di$. Combined, we have

$$
E_1(T_i) = \frac{1}{1 - E_0(T_i)} [E_0(T_i)\{1 - E_0(T_i)\} - V_0(T_i)]
$$

and thus obtain the expression above.

Second, using $\lambda_i \approx \lambda + d\lambda_i$ and $\hat{\lambda}_i \approx \lambda + d\hat{\lambda}_i$ for small differences in actual and perceived arrival rates, we can approximate

$$
\begin{aligned}
T_i &\approx T + \frac{dT}{d\lambda_i} d\lambda_i + \frac{dT}{d\hat{\lambda}_i} d\hat{\lambda}_i, \\
&= \lambda[1 - F(R)] + [1 - F(R)] d\lambda_i - \lambda f(R) \frac{dR}{d\hat{\lambda}_i} d\hat{\lambda}_i, \\
&= \lambda[1 - F(R)] + [1 - F(R)] \Big\{ (1 - \kappa\beta_1) d\lambda_i - \kappa d\nu_i \Big\}.
\end{aligned}
$$

Hence, with $E(d\lambda_i) = 0$ and $E(d\nu_i) = 0$, we have

$$
E_0(T_i) \approx \lambda[1 - F(R)],
$$

while

$$
\begin{aligned}
V_0(T_i) &\approx V\Big([1 - F(R)] \Big\{ [(1 - \kappa\beta_1) d\lambda_i - \kappa d\nu \Big\} \Big), \\
&= [1 - F(R)]^2 V\Big([(1 - \kappa\beta_1) d\lambda_i - \kappa d\nu_i \Big), \\
&= [1 - F(R)]^2 \Big((1 - \kappa\beta_1)^2 \sigma_\lambda^2 + \kappa^2 \sigma_\nu^2 \Big).
\end{aligned}
$$

Therefore, small changes in the dispersion σ_λ and σ_ν leave the expected job finding rate unaffected to a first-order, but do increase the variance in job finding rates. However, the increase in σ_λ is scaled by $(1 - \kappa\beta_1)$ and thus has a smaller impact on the variance in job finding rates, the higher β_1 (assuming that the degenerate type $(\lambda, \beta_0 + \beta_1\lambda)$ remains the same). Given the negative relationship between the variance and the average job finding in the next period, the Proposition follows.

E.3 Proof of Proposition 3

We consider a single-agent model with geometric duration-dependence in true and perceived arrival rates,

$$\begin{aligned}\lambda_{d+1} =& (1-\theta)\lambda_d,\\ \hat{\lambda}_{d+1} =& (1-\beta_\theta\theta)\lambda_d.\end{aligned}$$

We can write,

$$\begin{aligned}\frac{T_{d+1}}{T_d} =& (1-\theta)\frac{1-F(R_{d+1})}{1-F(R_d)},\\ \Rightarrow \frac{d\left[\frac{T_{d+1}}{T_d}\right]}{d\theta} =& -\frac{1-F(R_{d+1})}{1-F(R_d)} + (1-\theta)\frac{d\left[\frac{1-F(R_{d+1})}{1-F(R_d)}\right]}{d\theta}.\end{aligned}$$

Unpacking the last term, we find

$$\begin{aligned}\frac{d\left[\frac{1-F(R_{d+1})}{1-F(R_d)}\right]}{d\theta} =& \frac{f(R_d)[1-F(R_{d+1})]\frac{dR_d}{d\theta} - f(R_{d+1})[1-F(R_d)]\frac{dR_{d+1}}{d\theta}}{[1-F(R_d)]^2},\\ =& \frac{f(R_d)\frac{1-F(R_{d+1})}{1-F(R_d)}\frac{dR_d}{d\theta} - f(R_{d+1})\frac{dR_{d+1}}{d\theta}}{1-F(R_d)},\\ =& \frac{f(R_{d+1})\frac{dR_{d+1}}{d\theta}}{1-F(R_d)}\left[\frac{f(R_d)}{f(R_{d+1})}\frac{1-F(R_{d+1})}{1-F(R_d)}\frac{\frac{dR_d}{d\theta}}{\frac{dR_{d+1}}{d\theta}} - 1\right].\end{aligned}$$

We now look at the reaction of the respective reservations wage to the depreciation parameter. The reservation wage is characterized by $V(R_d) = U_d$ where,

$$\begin{aligned}V(R_d) =& \frac{1+\delta}{\delta}u(R_d)\\ U_d =& u + \frac{1}{1+\delta}\max_{R_d}\left\{U_{d+1} + (1-\beta_\theta\theta)^d\lambda_0\int_{R_d}\left[V(w) - U_{d+1}\right]dF(w)\right\},\end{aligned}$$

so substituting the former into the latter for U_d, U_{d+1},and $V(w)$ gives,

$$\frac{1+\delta}{\delta}u(R_d) = u + \frac{1}{\delta}\max_{R_d}\left\{u(R_{d+1}) + (1-\beta_\theta\theta)^d\lambda_0\int_{R_d}\Big[u(w) - u(R_{d+1})\Big]dF(w)\right\}.$$

Total differentiation yields,

$$\begin{aligned}\frac{1+\delta}{\delta}u'(R_d)dR_d =& -\frac{1}{\delta}d\beta_\theta(1-\beta_\theta\theta)^{d-1}\lambda_0\int_{R_d}\Big[u(w) - u(R_{d+1})\Big]dF(w)d\theta\ldots\\ & \ldots + \frac{1}{\delta}u'(R_{d+1})\frac{dR_{d+1}}{d\theta}d\theta - \frac{1}{\delta}(1-\beta_\theta\theta)^t\lambda_0 u'(R_{d+1})\frac{dR_{d+1}}{d\theta}d\theta,\end{aligned}$$

Hence, we find

$$\frac{dR_d}{d\theta} = \frac{1}{1+\delta}\bigg\{ - d\frac{\beta_\theta}{1-\beta_\theta\theta}\left(\frac{1-\beta_\theta\theta}{1-\theta}\right)^d T_d E\left[\frac{u(w)-u(R_{d+1})}{u'(R_d)}\bigg| w > R_d\right] + \frac{u'(R_{d+1})}{u'(R_d)}(1-\hat{\lambda}_d)\frac{dR_{d+1}}{d\theta}\bigg\},$$

and, then by iterating, we get

$$\frac{dR_d}{d\theta} = -\frac{1}{1+\delta}\frac{\beta_\theta}{1-\beta_\theta\theta}\sum_{s=d}^{\infty}\bigg\{\left(\frac{\prod_{k=d}^{s}[1-\hat{\lambda}_k]}{1-\hat{\lambda}_s}\right)\frac{u'(R_{s+1})}{u'(R_d)}s\left(\frac{1-\beta_\theta\theta}{1-\theta}\right)^s T_s E\left[\frac{u(w)-u(R_{s+1})}{u'(R_s)}\bigg| w > R_s\right]\bigg\}.$$

Starting from $\theta \approx 0$, the reservation wage, arrival rate, and job finding rate are approximate constant and the perceived arrival rate equals the actual arrival rate. Denoting by R and $T = \lambda\,[1 - F\,(R)]$ the reservation wage and the job finding for the stationary type, we can write

$$\left.\frac{dR_{d+1}}{d\theta}\right|_{\theta=0} = -\frac{1}{1+\delta}\beta_\theta T E\left[\frac{u(w)-u(R)}{u'(R)}\bigg| w > R\right]\sum_{s=d+1}^{\infty}\bigg\{(1-\lambda)^{s-d-1}s\bigg\},$$

and thus

$$\left.\frac{\frac{dR_d}{d\theta}}{\frac{dR_{d+1}}{d\theta}}\right|_{\theta=0} = \frac{\sum_{s=d-}^{\infty}(1-\lambda)^{s-d}s}{\sum_{s=d+1}^{\infty}(1-\lambda)^{s-d-1}s} = \frac{d + (1-\lambda)\sum_{s=d+1}^{\infty}(1-\lambda)^{s-d-1}s}{\sum_{s=d+1}^{\infty}(1-\lambda)^{s-d-1}s},$$
$$= \frac{d + (1-\lambda)\left[\frac{d+1}{\lambda} + \frac{1-\lambda}{\lambda^2}\right]}{\frac{d+1}{\lambda} + \frac{1-\lambda}{\lambda^2}} < 1,$$

which proves that the reservation wage responds more at longer durations. The last equality above follows from expanding the power series as follows:

$$\begin{aligned}
\sum_{s=d+1}^{\infty}(1-\lambda)^{s-d-1}s =& d+1+(1-\lambda)(d+2)+(1-\lambda)^2(d+3)+(1-\lambda)^3(d+4)+\ldots,\\
=&(d+1)(1+(1-\lambda)+(1-\lambda)^2+(1-\lambda)^3+\ldots)+(1-\lambda)+2(1-\lambda)^2+\ldots,\\
=&\frac{d+1}{\lambda}+(1-\lambda)(1+(1-\lambda)+(1-\lambda)^2+(1-\lambda)^3+\ldots)+(1-\lambda)^2+2(1-\lambda)^3+\ldots,\\
=&\frac{d+1}{\lambda}+\frac{1-\lambda}{\lambda}+(1-\lambda)^2(1+(1-\lambda)+(1-\lambda)^3+\ldots)+(1-\lambda)^3+2(1-\lambda)^4+\ldots,\\
=&\frac{d+1}{\lambda}+\frac{1-\lambda}{\lambda}+\frac{(1-\lambda)^2}{\lambda}+\frac{(1-\lambda)^3}{\lambda}+\frac{(1-\lambda)^4}{\lambda}+\ldots,\\
=&\frac{d+1}{\lambda}+\frac{1-\lambda}{\lambda}(1+(1-\lambda)+(1-\lambda)^2+(1-\lambda)^3+\ldots),\\
=&\frac{d+1}{\lambda}+\frac{1-\lambda}{\lambda^2}.
\end{aligned}$$

So now putting things together and starting from $\theta \approx 0$, we have

$$
\begin{aligned}
\left.\frac{d\left[\frac{T_{d+1}}{T_d}\right]}{d\theta}\right|_{\theta=0} =& -1+\frac{f(R)\left.\frac{dR_{d+1}}{d\theta}\right|_{\theta=0}}{1-F(R)}\left[\left.\frac{\frac{dR_d}{d\theta}}{\frac{dR_{d+1}}{d\theta}}\right|_{\theta=0}-1\right], \\
=& -1+\frac{f(R)}{1-F(R)}\frac{1}{1+\delta}\beta_\theta TE\left[\frac{u(w)-u(R)}{u'(R)}\middle| w>R\right]\left\{\frac{d+1}{\lambda}+\frac{1-\lambda}{\lambda^2}\right\}\dots \\
&\dots\left[1-\frac{d+(1-\lambda)\left[\frac{d+1}{\lambda}+\frac{1-\lambda}{\lambda^2}\right]}{\frac{d+1}{\lambda}+\frac{1-\lambda}{\lambda^2}}\right], \\
=& -1+\frac{f(R)}{1-F(R)}\left[1+\frac{1-\lambda}{\lambda}\right]\frac{1}{1+\delta}\beta_\theta TE\left[\frac{u(w)-u(R)}{u'(R)}\middle| w>R\right], \\
=& \frac{1}{1+\delta}\beta_\theta E\left[\frac{u(w)-u(R)}{u'(R)}\middle| w>R\right]f(R)-1, \\
=& \beta_\theta\times\frac{\kappa}{\lambda}-1.
\end{aligned}
$$

Moreover, since $\frac{dR}{d\beta_\theta}=0$ for $\theta=0$, we also have

$$
\left.\frac{d^2\left[\frac{T_{d+1}}{T_d}\right]}{d\theta d\beta_\theta}\right|_{\theta=0}=\frac{\kappa}{\lambda}>0.
$$

E.4 Comparative Statics

Figure E1: Comparative Statics: True vs. Perceived Changes in Arrival Rates

A. Impact of Arrival Rates on Duration

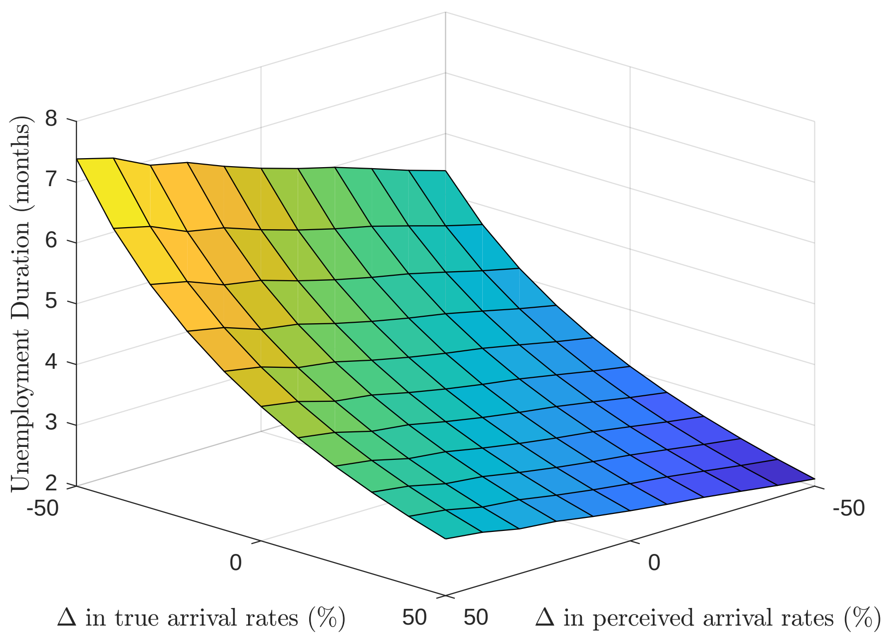
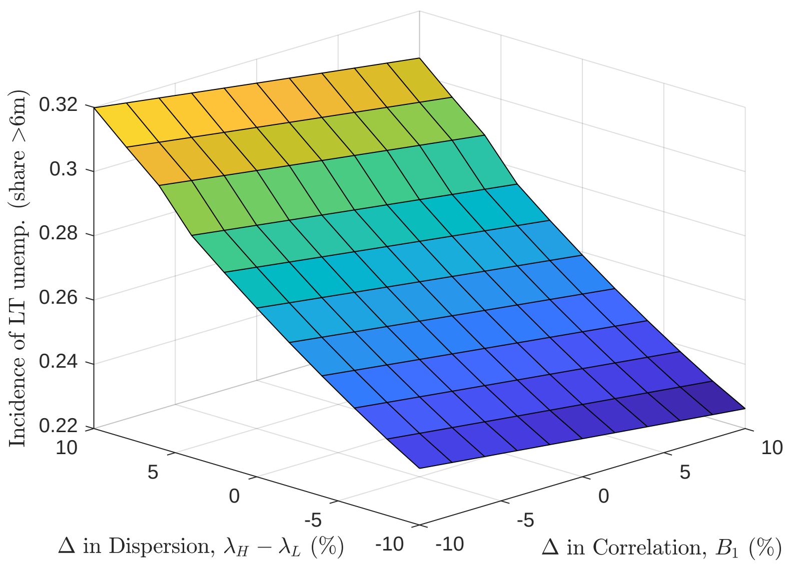
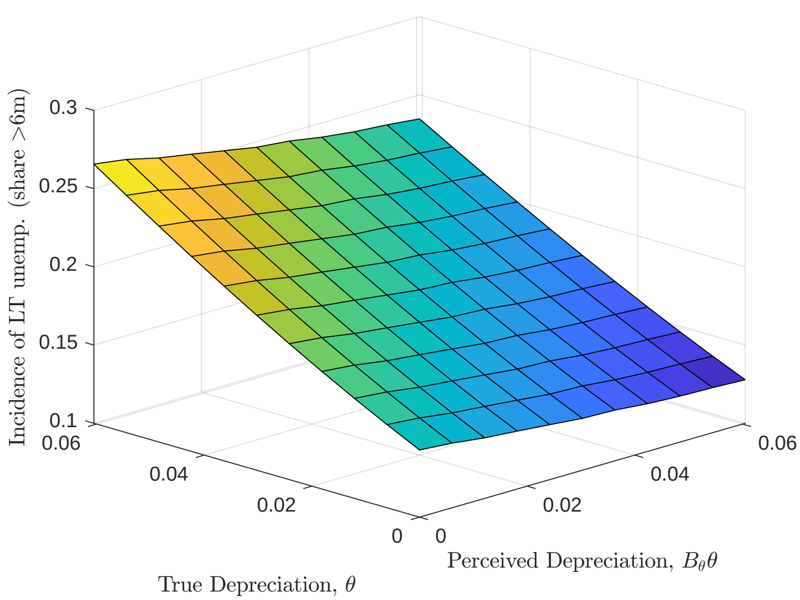


Figure E1: Comparative Statics: True vs. Perceived Changes in Arrival Rates (*continued)*

B. Impact of Heterogeneity on LT Incidence



C. Impact of Depreciation on LT Incidence



E.5 Targeted Moments

Table E1: Targeted Data Moments and Corresponding Moments in Structural Model

Moments	Data	Model: W/o Duration Dependence	Model: W/ Duration Dependence
Mean of 3-Month Job Finding Rates:			
... at 0-3 Months of Unemployment	0.623	0.621	0.604
... at 4-6 Months of Unemployment	0.435	0.438	0.464
... at 7 Month of Unemployment or More	0.260	0.257	0.242
Mean of 3-Month Elicitations:			
... at 0-3 Months of Unemployment	0.592	0.594	0.594
... at 4-6 Months of Unemployment	0.511	0.508	0.532
... at 7 Months of Unemployment or More	0.399	0.400	0.399
Acceptance Rate	0.710	0.716	0.716