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 almost all of the observed decline in job finding rates over the spell of unemployment. Moreover, job seekers' beliefs are systematically biased and under-respond to these differences in job finding rates. Finally, we show theoretically and quantify in a calibrated model of job search how biased beliefs contribute to the slow exit out of unemployment. The biases can explain more than 10 percent of the 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 (e.g., Jacobson et al. [1993], Kolsrud et al. [2018]). Moreover, the high incidence of long-term unemployment seems indicative of substantial frictions in the search and matching process (e.g., Clark and Summers [1979]), and can contribute to the persistence of employment shocks (e.g., Pissarides [1992]).

An ubiquitous empirical finding in the literature is the negative duration-dependence of exit rates out of unemployment. As it is crucial for formulating policy responses, understanding why employment prospects are worse for the long-term unemployed has been the topic of a long literature.[2] In theory, long-term unemployment may reduce a worker's chances to find a job (e.g., due to skill-depreciation or duration-based employer screening), but less employable workers also select into long-term unemployment. Empirically, separating the role of duration-dependent forces from heterogeneity across job seekers has been a challenge until today. Since the seminal work by Lancaster [1979] and Heckman and Singer [1984] among others, several studies have tried to estimate or calibrate the contribution of different forces to the negative duration-dependence in exit rates out of unemployment. Direct evidence on the potential role of heterogeneity has been particularly limited.[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 identify heterogeneity in *true* job finding rates and separate dynamic selection from true duration-dependence. Finally, we study how heterogeneity and duration-dependence in job seekers' *perceptions* contribute to the incidence of long-term unemployment. Individuals who overestimate their employment prospects will be overly selective and inefficiently prolong their unemployment spell, and vice versa. As a consequence, the under-reaction of beliefs to heterogeneity or 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 unemployed job seekers' beliefs about their

[1] While the share of long-term unemployed workers (longer 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. At the start of 2019, the share of LT unemployed was 50.4% and 20.3% in the EU and the US respectively (Eurostat; CPS).

[2] 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] For a review of the relevant literature, see Machin and Manning [1999] who write: '*To conclude, it does not really seem possible in practice to identify separately the effect of heterogeneity from that of duration dependence without making some very strong assumptions about functional form which have no foundation in any economic theory.*' See Kroft et al. [2013], Alvarez et al. [2016], Jarosch and Pilossoph [2018] and Farber et al. [2018] for recent examples in this literature.

chances of re-employment - which we will refer to as the job finding probability. We elicited the beliefs in two distinct surveys. The first survey is the Survey of Consumer Expectations (SCE), which started in December 2012 and is run by the Federal Reserve Bank of New York. The survey has a rotating panel structure where a representative sample of about 1,300 household heads is interviewed every month for a period of up to 12 months (see Armantier et al. [2017] for details). 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 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. Finally, we elicit job seekers' beliefs about job finding 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 actual job finding 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 strongly 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, if anything, 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. We use this framework to estimate the heterogeneity and depreciation in both perceived and true job finding probabilities. The key idea underlying the identification in our statistical framework is that the covariance between perceptions and actual job finding helps uncovering the extent of ex-ante heterogeneity in true job finding probabilities. This builds on the recent work using risk elicitations to estimate heterogeneity in ex-ante risks in Hendren [2013] and Hendren [2017]. Our analysis goes further in two dimensions, which are key to uncover the heterogeneity in job finding that contributes to the observed duration-dependence, but also relevant by themselves. First, we allow for a systematic bias in the relationship between true and perceived job

[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.

finding probabilities, in addition to idiosyncratic error in the beliefs or elicitations. We identify this systematic bias by leveraging variation in job finding rates at different unemployment durations. Our model can allow for a differential response in beliefs to cross-sectional and longitudinal variation in job finding, using both changes in the means of perceived and true job finding and their covariances over the spell. Second, we allow for transitory shocks to job seekers' job finding during the unemployment spell (e.g., temporary spells of reduced search or increased job finding). We separately identify permanent and transitory differences in job finding using the covariances between elicited beliefs and contemporaneous vs. future job finding. We prove the semi-parametric identification of a stylized two-period version of the model and then verify that the identification arguments hold up in the estimation of the fully-specified dynamic model, showing how parameter estimates change with the empirical moments.

The estimates from our statistical model imply substantial ex-ante heterogeneity in true job finding rates, accounting for almost all of the observed decline in job finding rates over the spell of unemployment (97.8 percent; s.e. 38.3). True duration dependence explains the remainder and thus plays a very limited role, also in comparison to the importance it has been attributed in prior work. The pre-dominant role played by dynamic selection proves to be robust to alternative distributional and functional-form assumptions. While the structural estimates on the residual role of true duration dependence are quite imprecise, the finding is corroborated by non-parametric evidence, which simply leverages the explanatory power of beliefs relative to other observables (including income, education and standard demographics). The estimates also lead to the exact same conclusions when we first residualize the empirical moments using these other observables.

The second main finding from this estimation concerns the biases in job seekers' beliefs. On average, only 54.0 (s.e. 11.8) of the variation in job finding is perceived. 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. The latter remain unemployed longer, but they do not revise their beliefs downward. In the absence of significant duration-dependence in true job finding, this explains why the long-term unemployed are over-optimistic. Our statistical framework is parsimoniously specified but fits the key moments in our data very well. Importantly, restricted versions of the model, which abstract from ex-ante heterogeneity in job finding rates or do not allow for the under-reaction in beliefs, 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 allow for 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 than in the absence of biased beliefs. 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 by targeting the realized and perceived job finding rates by duration of unemployment in the cross-section of unemployed job seekers. In addition, we also target the true (individual-level) duration dependence in realized and perceived job finding rates, as given by the statistical model. 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 workers who are unemployed for longer than 6 months, by $2-3$ percentage points. Defining the incidence of long-term unemployment as the ratio of the LT vs. ST unemployment rate, we find that the biases in beliefs jointly explain $12-14\%$ of the incidence of long-term unemployment. This result is robust to the relative importance of heterogeneity vs. true duration-dependence in true job finding, as beliefs under-react to either source of observed duration-dependence.

Our paper aims to contribute to three different strands in the literature. As discussed before, we try to contribute to the large literature studying the different sources of duration-dependence in job finding. We use a novel strategy to separate dynamic selection from *true* duration dependence, finding a predominant role played by dynamic selection, and we also highlight the importance of biases in beliefs as an amplifier of this source. Recent resume audit studies (e.g., Kroft et al. [2013]) have documented large declines in callback rates over the unemployment the spell, suggesting the importance of *true* duration-dependence instead. The evidence from audit studies themselves, however, is mixed (see Farber et al. [2018]) and the duration-dependence in callback rates may not translate into duration-dependence in job finding (e.g., Jarosch and Pilossoph [2018]). Alvarez et al. [2016] use data on multiple unemployment spells instead and find evidence for positive duration-dependence.[5] In general, direct evidence on the role of heterogeneity has been limited to the dynamic selection in longer unemployment spells based on observables, which (just like in our empirical setting) tends to play 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 information frictions and behavioral biases in the job search process. The new survey evidence confirms the optimistic bias in job seekers' beliefs in Spinnewijn [2015] and is consistent with the lack of updating of reservation wages over the unemployment spell in Krueger and Mueller [2016]. Relatedly, Conlon et al. [2018] find an optimistic bias regarding the expected arrival of job offers and document frictions in the expectations and learning about wage offers. Using field experiments with information treatments, Belot et al. [2018] show how tailored information can change job seekers' scope of search, while Altmann et al. [2018] show how information treatments can improve the re-employment outcomes of job seekers at risk of long-term unemployment in particular. Our paper studies the under-reaction in beliefs to differences in job finding, both across workers and over the unemployment spell, and confirms the importance of informational frictions among long-term unemployed in particular.[6] Other papers on behavioral frictions in job search are DellaVigna and Paserman [2005], studying the role of impatience, and DellaVigna et al. [2017], studying the role of

[5]See also Honoré [1993] who proves identification with multiple unemployment spells in the context of the mixed proportional hazard model. The comparative advantage of our approach is that it also captures heterogeneity that is specific to a given unemployment spell (e.g., savings, family structure, etc.).

[6]In a related job search experiment, Falk et al. [2006] find that subjects are uncertain about their ability and update their beliefs only slowly.

reference-dependence.

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 and offered 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 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 are increasingly used in other applications, too, for example to study 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]).

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.

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 about 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.[7] 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

[7]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.

survey, but the belief questions were administered only every four weeks, starting about one month into the survey period.[8]

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 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 in the SCE, 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 sub-sample 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).[9] In the KM survey, out of those 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. To a large extent, this drop-off in participation in the KM survey is simply due to the shorter horizon of the survey. However, we also find that the elicited belief about the probability of finding a job was negatively related to the number of follow-up surveys completed.[10] 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 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 is representative of the population of U.S. household heads[11], 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

[8] 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. Note also that for 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.

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

[10] 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.

[11] 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.

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.

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.[12]

3 Empirical Evidence

We use elicited beliefs and how they relate to actual job finding to analyze 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 modelled 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 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

[12]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.

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

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 impossible to directly observe an individual's actual job finding probability T_{id} and its state-dependence. Neither is it possible to directly observe differences in actual job finding T_{id} across individuals. We do, however, observe the outcome F_{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 then model the relationship between elicited beliefs and actual job finding and use the facts established in this section to make inferences about heterogeneity and state-dependence in true and perceived job finding rates.

3.1 Elicited Beliefs about Job Finding

The two surveys ask unemployed job seekers to report their chances of finding a job that they will accept, which we will refer to as the 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 these perceived job finding 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.[13] 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

[13] 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 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)

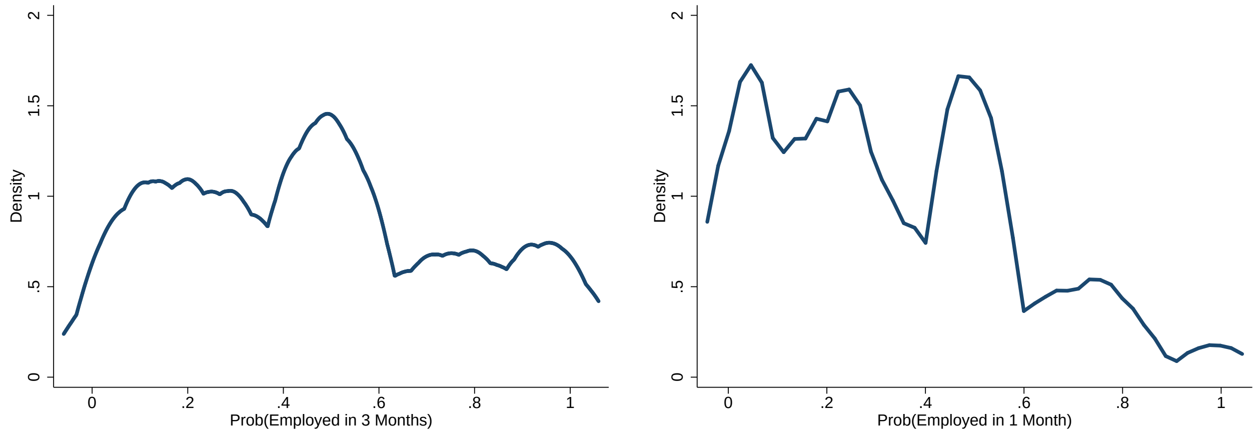
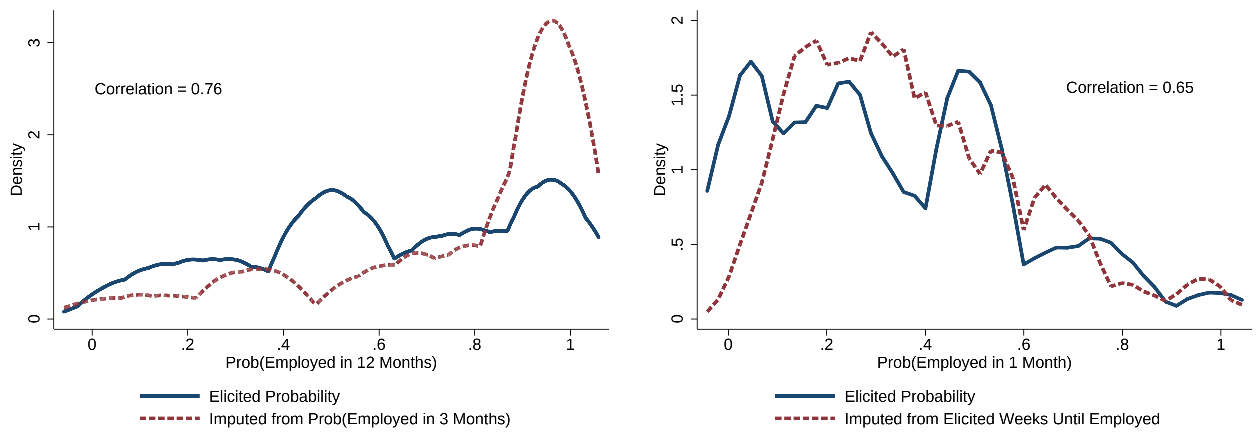


Figure 2: Comparison of Kernel Density Estimates for Alternative Forms of Elicitations about Re-employment Prospects



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 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.[14] Importantly, the alternative elicitation has the advantage that it

[14] 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.

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.

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.[15] 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 using the KM survey will focus on the elicited probability, but we will show that our results are similar for the expected duration measure and robust to the observed 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 actual job finding outcomes.

Average Bias in Beliefs While we cannot compare the actual and perceived job finding probabilities at the individual level, we can compare averages at the group level. Table 2 compares the averages for the actual and perceived job finding probabilities in the SCE and the KM survey, for the respective

[15]Note that throughout the paper we trim extreme outlier observations: In the KM survey, we eliminate 51 survey responses where the elicited and imputed probability are more than 75 percentage points apart and thus clearly inconsistent with each other. Similarly, in the SCE, we eliminate 271 observations, where the 3-month probability was larger than the 12-month probability. We report robustness checks in the Appendix for not imposing these restrictions. If we do not impose the restriction in Figure 2, the correlation coefficient is somewhat lower but still high at 0.56 in the KM survey and 0.72 in the SCE.

full samples and by unemployment duration. Overall, the results indicate an average optimistic bias that is largely driven by the long-term unemployed.[16] At the three-month horizon in the SCE, we find an optimistic bias (8 pp) indicating that job seekers perceive their chances to be 20 percent higher than they are. At the one-month horizon in the KM survey, the optimistic bias (15 pp) is even more severe, corresponding to an average perceived job finding rate that is more than double of the actual job finding rate. In both the SCE and KM survey, the overoptimistic bias is more severe for individuals with long unemployment spells.[17] We confirm that the observed duration-dependence in true job finding rates is negative in both surveys: the true job finding rates are lower for job seekers who are unemployed for longer.[18] The perceived job finding rates are also decreasing, but at a slower rate. As a result, the bias seems to be increasing with unemployment duration, resulting in a clear bias towards over-optimism for the long-term unemployed in both surveys. 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 perceived and true job finding 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.[19] Figure 3 shows the average job finding probability within the next three months by the perceived three-month job finding probability in the SCE.[20] 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 80 percent for job seekers reporting probabilities in 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

[16] Note that we restrict the sample for this comparison to interviews that were followed by 3 consecutive monthly interviews (SCE) or 4 consecutive weekly interviews (KM survey).

[17] 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. 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.

[18] Appendix Table B1 shows that the job finding rate in the SCE, especially in the first three months, is somewhat higher than in the CPS, making the observed duration-dependence more pronounced in the SCE than in the CPS.

[19] 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. 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.

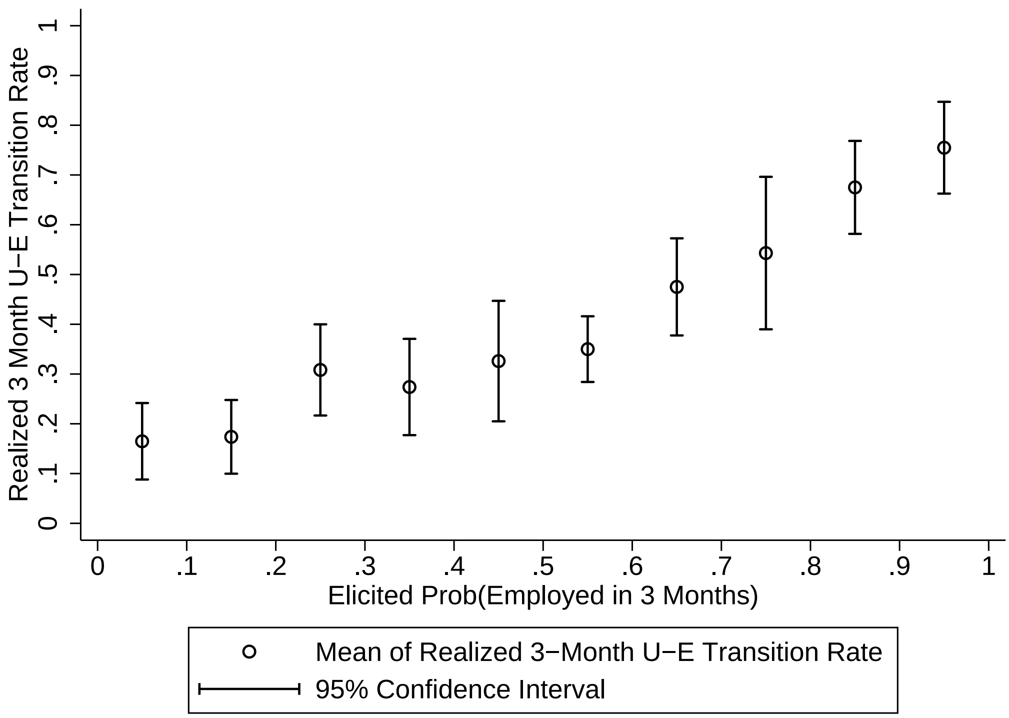
[20] Figure C2 in the Appendix shows a similar pattern for the 12-month job finding probability.

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)
Age			0.0158	0.0206*
			(0.0146)	(0.0111)
Age*Age			-0.000280*	-0.000283**
			(0.000157)	(0.000123)
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)
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)
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)
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, in the SCE.

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



observables.[21] The coefficient on the elicited job finding probability is high, but still significantly smaller than 1. This could be driven both by random errors in perceptions or elicitations, which increase the variance in elicited beliefs, or by biases in the beliefs formation that systematically distort how differences in job finding are perceived and lower the correlation between perceived and actual job finding. We separate systematic biases in beliefs from random errors in the statistical model in Section 4.

Another interesting finding that comes out of Table 3 is that the beliefs are more predictive for 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 similar regressions carried out for the 1-month perception question in the KM survey, where most of the job seekers are long-term unemployed, we find a coefficient of 0.23, which is significant at the 1 percent level (see Table C2 in the Appendix).[22]

The explanatory power of the beliefs in the SCE is large ($R^2 = 0.14$) and almost the same as for all other observables together ($R^2 = 0.15$). Note that even if the perceived and actual job finding

[21] We get a similar estimate (0.54) when running the same regression with the elicited probability of finding a job over the next 12 months instead (see Appendix Table C1).

[22] The smaller coefficient in the KM survey can also be driven by the different horizon used for the elicitation. Note that 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 10 further above). If we relax this restriction, the bi-variate regression coefficients in the KM data are even lower, as to be expected.

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, in the SCE. The demographic controls are the same as the ones included in Table 3.

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 variable 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. In the case where job seekers have perfect information about their types (and rational expectations), the R^2 of the regression of actual job finding on beliefs is equal to $\frac{Var(Z)}{E(Z)(1-E(Z))}$ for large N. Using these moments from the SCE data, we obtain a value of 0.36. 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, age, income, educational attainment, race and ethnicity, showing that the elicited beliefs have predictive power above and beyond observable characteristics.

The large predictive value is suggestive of the potential to learn from the elicited beliefs about heterogeneity in true job finding rates, which we will leverage in the context of our statistical model in Section 4. Interestingly, we can also use the beliefs to infer the persistence in individual job finding rates, which is key to understand the role of dynamic selection. To do so, 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. This suggests that there are persistent factors in job seekers' job finding prospects, captured by the 3-month horizon question.

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 for those who just became unemployed is 0.59 compared to 0.34 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 thus 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, it is again 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. 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.[23]

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 shows the change in the perceived job finding probability within individual unemployment spells, 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 probability is decreasing in time spent unemployed, but this decline disappears once we control for selection and look at the within-spell changes only.[24] In the KM survey, job seekers even report higher job finding rates

[23]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.

[24]In principle, the pattern of the within-spell changes by time spent unemployed could be driven by dynamic selection, since the observations later in the spell require the job seeker to be unemployed for longer. Note, however, the relationship

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)
Demographic Controls			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)**
Demographic Controls			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.

as they remain unemployed for longer.

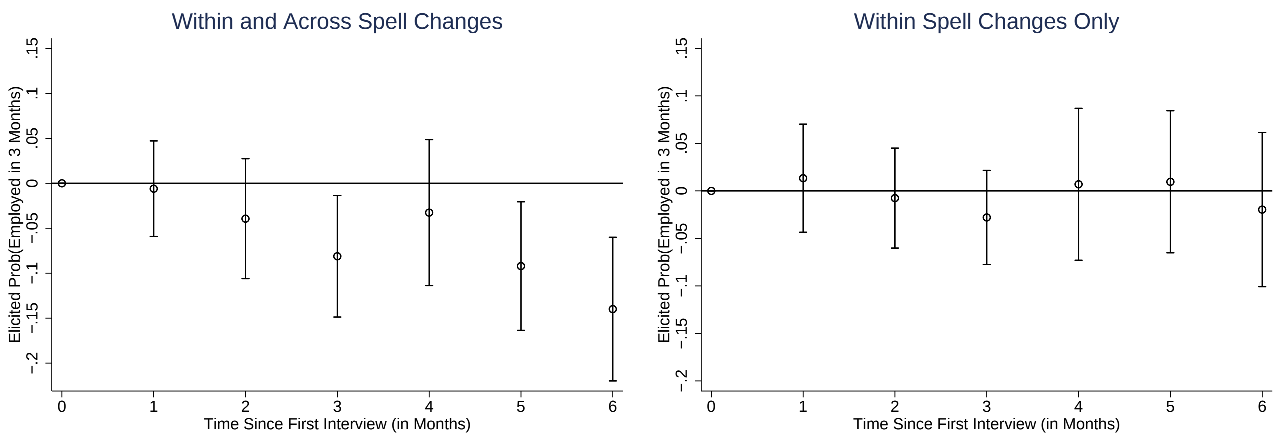
We probe the robustness of the finding that beliefs are not revised downward in several ways and also evaluate potential forces that may underlie the (weakly) increasing beliefs about job finding probabilities. First, we check whether the results in Column 4 of Table 5 hold for other measures of perceived 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 14 for details). Table C4 in the Appendix reports these results. We find that the coefficient is 0.013, which is rather close to 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.

The first columns in Tables C3 and C4 in the Appendix report results where we exclude answers of 50 percent, results where we exclude answers of 100 percent, results where we do not trim outlier

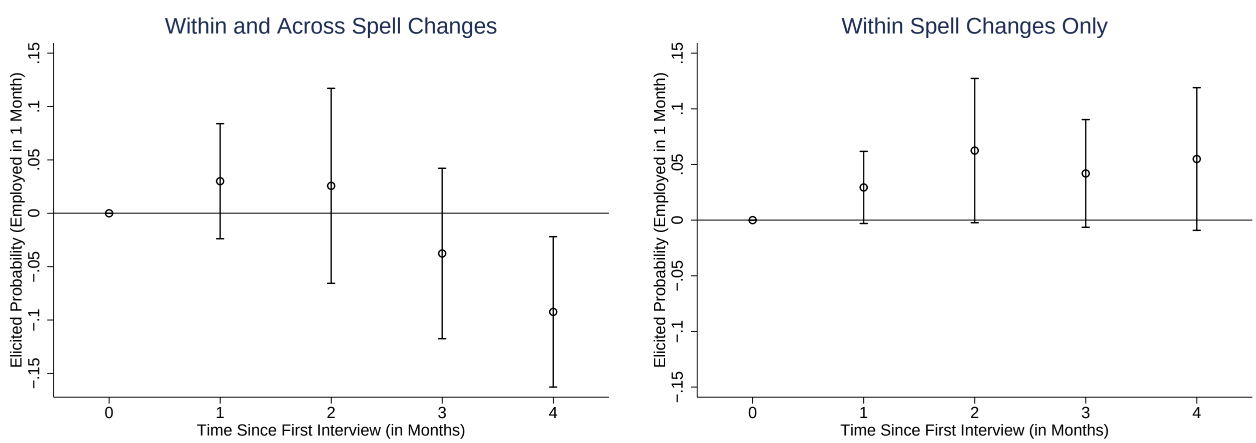
in Column 4 of Table 5 remains positive in both surveys even when we restrict the sample to those with relatively shorts spells of 6 months or less.

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

A. SCE Survey



B. KM Survey



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. We also find that our results are 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 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 sample period.

3.3.2 Further Evidence on Belief Updating and Behavior

The surveys allow us to shed some additional light on the determinants of changes in perceptions and how they relate to search behavior.

The lack of updating over the spell seems pervasive across different groups of job seekers. While individuals increase their perceived job finding probability as they approach re-employment, the result remains if we exclude individuals who find and accept a job within the next 4 weeks in the KM survey. Neither is the estimate affected when we exclude individuals who reported a job offer in a previous interview but did not accept it (see Appendix Table C4). 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.[25] We find a positive within-person correlation between liquidity constraints and the perceived probability - a job seeker reports a higher job finding probability when liquidity constraints become binding - but controlling for liquidity constraints does not attenuate the positive impact of duration on beliefs.

The lack of updating over the spell is consistent with the fact that reservation wages are nearly constant over the spell, as documented by Krueger and Mueller [2016] using the KM survey. Krueger and Mueller [2011] also find that search activity is decreasing over the spell of unemployment. Both findings contradict the predictions of the canonical model of job search in Mortensen [1977] with limited duration of unemployment insurance, suggesting that the increase in perceptions over the spell is not driven by (approaching) exhaustion of unemployment benefits either. The empirical question whether the beliefs actually drive job seekers' behavior remains open. Appendix Table C5 reports how perceptions relate to reported search behavior in the KM data. We find that across job seekers, the self-reported reservation wage bears a negative association with the 1-month probability though statistically insignificant, whereas time spent on job search activities is a positive predictor of the elicited 1-month probability (significant at the 1 percent level).[26] Overall, these results are, at least qualitatively, in line with what one could

[25] 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.

[26] We get similar results for the inverted expected duration, but the reservation wage effect becomes significant in these

expect from a simple search model with a reservation wage choice and endogenous search effort: the reservation wage has a negative effect on the probability of accepting and thus finding a job, whereas search effort increases the probability of finding a job. The causality, however, may well run in the opposite direction. 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 C5 (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. Reverse causality may confound the relationship between job finding beliefs and search effort as well. Controlling for individual fixed effects, the correlation between perceived job finding and search disappears. However, when deciding how hard to search, the perceived returns to search are key as well (Spinnewijn [2015]). The survey gauges job seekers' perceived control by asking whether they could increase their job finding chances by spending more time searching for a job. Interestingly, the vast majority of job seekers state that they cannot. The Appendix Table C5 shows, controlling for search effort, that workers who report a positive return to search at the margin also report higher job finding probabilities. We revisit the question on the role of beliefs for job search in our structural analysis in Section 5, where we specify a search model allowing for heterogeneous beliefs about the primitives of the job search environment and calibrate this model targeting the true and perceived job finding in our data. Note that our analysis in the statistical model in Section 4 abstracts from job search decisions and does not rely on any assumption about how beliefs affect job search either.

We also study how workers' perceptions respond to aggregate indicators of job finding in the SCE (see Appendix Table C6). 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 (or vice versa), but their perceptions about aggregate conditions seem ill-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. At the same time, the correlation between the perceived individual job finding and the perceived aggregate conditions is very similar for the employed and unemployed. Overall, the results seem to suggest that unemployed workers' perceptions also under-react to aggregate indicators of their employment prospects.

regressions whereas the coefficient on search activity is of similar magnitude but insignificant.

3.3.3 Discussion

The empirical finding that job seekers, if anything, update their perceived job finding probability upward over the unemployment spell is surprising since several theoretical models predict that a job seeker's actual job finding rate decreases over the spell. Potential reasons are 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]). Similarly, when workers who lose their jobs have imperfect information about their employability, we would expect they learn from the lack of success and 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, nor 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 true 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, 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 (Rabin and Vayanos [2010]).[27] Job seekers may also have motivated beliefs, managing 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]). 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 findings that the perceptions of long-term unemployed are more biased and less predictive can be consistent with these behavioral models.[28] The same is true for the differential response in perceptions to aggregate indicators among the unemployed and the employed.

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 formally show how the different parameters and moments are identified in a stylized version of the model. We also check the identification arguments in the full model by showing how the estimated parameters change with the values of the targeted moments and how the model's fit changes

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

[28] This finding is also supported by the recent experimental evidence in Altmann et al. [2018] showing the differential impact of information on workers by predicted time spent unemployed.

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.

4.1 Model Setup

Let us call T_{id}^x the probability of finding a job in the next x months for individual i with unemployment duration d and Z_{id}^x the elicitation of the individual's perceived probability of finding a job in the next x months. We denote by F_{id}^x the actual job finding in the next x months for individual i. This is a binary variable that takes value 1 with probability T_{id}^x and 0 otherwise. The monthly job finding probability equals $T_{id} = T_{id}^1$ and $T_{id}^3 = T_{id} + (1 - T_{id})T_{id+1} + (1 - T_{id})(1 - T_{id+1})T_{id+2}$ is the probability of finding a job in the next 3 months.

We assume that the monthly 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 persistent component of the job finding rate that is common across durations and τ_{id} is a transitory change in job finding rate at duration d with $E(\tau_{id}|T_{id}) = 0$. 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 elicited beliefs Z to infer actual job finding probabilities, we have to impose some structure on the relationship between job finding rates and elicited beliefs. We assume the following linear model for the elicitations of the perceived 3-month job finding rate:[29]

$$Z_{id}^3 \quad = \quad b_0 + b_1 \hat{T}_{id}^3 + \varepsilon_{id} \in [0, 1], \tag{4}$$

where we define the variable $\hat{T}_{id}$, in analogy to equation 3 above,[30]

$$\hat{T}_{id} \quad = \quad [1 - \hat{\theta}_d](T_i + \tau_{id}) \in [0, 1]. \tag{5}$$

The intercept b_0 captures a bias in perceptions that is common to all individuals. The slope parameter b_1 captures the extent to which the variation in job finding rates is perceived: 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. We allow the variation in job finding rates to be perceived differently across and within job seekers. In particular, the variable $\hat{T}_{id}^3$ captures the duration dependence in perceptions through the parameter $\hat{\theta}_d$. This dynamic parameter depends on the perceived depreciation, but also any learning from unsuccessful job search and is expressed at the monthly frequency so that it directly corresponds to the parameter that controls

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

[30]We also set up an alternative version of the model where the coefficient b_1 was equal to one for temporary shocks to job finding, but b_1 was allowed to differ from one for permanent differences in job finding across job seekers. The main results are very robust to this change and are available on request.

the true duration dependence, θ_d. In particular, $\hat{\theta}_d < \theta_d$ implies that perceptions change less with variation in job finding over the spell than with variation in job finding across individuals. Finally, the variable ε_{id} captures random error in the reported perceptions. This error can be driven by either noise in the beliefs themselves or by noise in the elicitation of the beliefs. Note that the bounded support for $Z^3_{id} \in [0,1]$ implies that the distribution of ε_{id} cannot be specified independently of T_{id} in the vicinity of the bounds. In our baseline model, we assume that the conditional mean of the error term is independent of T_{id}, $E(\varepsilon_{id}|\hat{T}^3_{id}) = 0$, but we relax this mean-independence assumption in the robustness checks.

4.2 Identification

We face two main identification challenges in our statistical model that are interdependent. The first is to disentangle the heterogeneity and true duration dependence in job finding rates that underlies the observed duration-dependence. The second is to identify how beliefs change with the respective sources of variation in job finding rates.

Heterogeneity vs. Duration Dependence We overcome the first main challenge by leveraging the relationship between ex-post realizations of actual job finding and ex-ante reports of expected job finding probabilities. The extent to which ex-ante reports of expected job finding rates co-vary with (or rather predict) ex-post realizations, identifies the extent of heterogeneity in job finding rates, as shown before in Hendren [2013]. Indeed, if elicited beliefs were a noisy, but unbiased measure of job finding, $Z^3_{id} = \hat{T}^3_{id} + \varepsilon_{id}$ with $E(\varepsilon_{id}|\hat{T}^3_{id}) = 0$, the covariance between perceived and actual job finding would exactly pin down the variance in true job finding,

$$cov(Z^3_{id}, F^3_{id}) = var(T^3_{id}). \tag{6}$$

Two key practical issues arise when implementing this strategy:

First, job seekers' reported perceptions do contain information about both the persistent and transitory components underlying their job finding. However, only heterogeneity in the persistent component contributes to the observed duration-dependence. Indeed, we can show that the evolution of the observed job finding depends on the depreciation in job finding and the variance in the persistent component only:[31]

$$\frac{E_{d+1}(T_{i,d+1})}{E_d(T_{i,d})} = \frac{1-\theta_{d+1}}{1-\theta_d}\left[1 - \frac{var_d(T_i)}{E_d(T_{i,d})(1-E_d(T_{i,d}))}\right], \tag{7}$$

where the subindex denotes the duration at which the job seekers are sampled to evaluate the corresponding moment. The transitory shocks to job finding rates generate more *contemporaneous* covariance of elicitations and job finding rates, but not more covariance between elicitations and the job finding one period ahead. Hence, we can separately identify the variance in transitory shocks through the difference in covariances, since the contemporaneous covariance depends on both persistent and temporary

[31] This derivation extends the arguments used in the proofs of the Propositions characterizing the impact of heterogeneity and duration-dependence in our structural model (see Appendix Sections E.2 and E.3).

components of T_{id}, whereas the one period ahead covariance only depends on the persistent component. We develop this identification argument formally in Appendix Section D.1.

Second, job seekers' perceptions are not just noisy, but subject to systematic biases in general. In our context, the slope parameter b_1 will directly affect the co-variance between perceived and actual job finding. Indeed, for $Z^3_{id} = b_0 + b_1 \hat{T}^3_{id} + \varepsilon_{id}$ with $E(\varepsilon_{id}|\hat{T}^3_{id}) = 0$, we instead have

$$cov(Z^3_{id}, F^3_{id}) = b_1 var(T^3_{id}). \tag{8}$$

Hence, the identification of the heterogeneity in true job finding relies on the identification of the bias parameter b_1. If job seekers under-react to variation in job finding ($b_1 < 1$), the covariance between perceived and actual job finding underestimates the variance in true job finding.

Biases in Beliefs The second main challenge is then to identify the biases in beliefs, which we overcome by leveraging the variation in job finding rates across durations. Intuitively, since job seekers who are unemployed for longer have lower job finding rates, we can simply use the corresponding difference in beliefs to identify the slope parameter b_1. In other words, the bias is revealed by the compression of the differences in Z's relative to the distribution of T's across durations. E.g., with $b_1 < 1$, the low-T_i types tend to be more optimistic and thus over-optimism should be more predominant among the long-term unemployed. In principle, we could use other observable variation in job finding rates to estimate how perceived and true job finding relate, for example between more and less educated job seekers. However, in that case we would need to assume that the average bias remains constant across workers with different education (or any other observable used). Using time spent unemployed to obtain variation in job finding rates gives the advantage that we can actually observe how job seekers' beliefs change over the spell, allowing us to relax the assumption that perceptions respond in the same way to variation in job finding across and within job seekers. In particular, we can identify any additional duration-dependence in beliefs (i.e., $\hat{\theta} \neq \theta$) using not just the difference in the means of perceived and true job finding over the spell, but also the difference in the covariance between the perceived and true job finding over the spell. Intuitively, the difference in covariances depends on the depreciation in both perceived and true job finding, while the difference in means depends on selection terms and either the depreciation in perceived or in true job finding. We again develop this identification argument formally in Appendix Section D.1.[32]

For the interpretation of the belief parameters, it is important to stress that we are not identifying the causal impact of a change in true job finding on perceived job finding, neither are we aiming to identify the beliefs formation and updating that is underlying the reported perceptions. Further, the identification does not rely either on how beliefs affect a job seeker's search strategy, which underlies the observed difference between perceived and true job finding. (We study the impact of beliefs on search in Section 5).) For the identification of ex-ante heterogeneity in job finding, it is useful to emphasize

[32]In particular, Appendix Section D.1 starts with a formal proof of identification, showing that in a two-period version of the statistical model, where $\sigma_\tau = 0$ and $\hat{\theta} = \theta$, all other parameters are an explicit function of moments with an empirical counterpart in the data. We then develop the identification arguments in a two-period model with $\sigma_\tau > 0$ and $\hat{\theta} \neq \theta$ respectively. While we cannot solve explicitly for these parameters, we complement the argument by showing that a monotone relationship exists between σ_τ and $\hat{\theta}$ and the respective covariances in the data.

that we go beyond earlier work identifying the role of heterogeneity through the dynamic selection on observables only. To do this, we are jointly exploiting the elicited beliefs - which could simply be seen as another observable (with high predictive value) - and the structure we impose on the relationship between elicited beliefs and job finding in equation (4).[33] We compare our results below with what we can conclude when using other variables or without the imposed structure. Most prior work has tried to use direct evidence on the true duration dependence instead. For example, 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.[34]

4.3 Distributional and Functional Form Assumptions

We propose to parametrize our model relatively parsimoniously. Our baseline estimation is based on the following distributional and functional form assumptions:

1. Baseline job finding rates, T_i, follow the Beta distribution with shape parameters α and β. The Beta distribution is defined over the interval $[0, 1]$ and is quite flexible in terms of its shape. In alternative specifications, we use the Weibull distribution and Gamma distribution.[35]

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 $E(\tau_{id}|T_i) = 0$ for all T_i.[36]

3. Random error in perceptions or elicitations, ε_{id}, follows a uniform distribution on the interval $[-\sigma_\varepsilon, \sigma_\varepsilon]$ subject to the bounds $[-b_0 - b_1\hat{T}^3_{id}, 1 - b_0 - b_1\hat{T}^3_{id}]$, and with masspoint(s) at the bounds of this interval such that $E(\varepsilon_{id}|\hat{T^3_{id}}) = 0$ for all T^3_{id}.[37] In alternative specifications, we consider a bounded normal distribution, we relax the mean-independence of the error term, and we allow for bunching in the elicited beliefs respectively.

4. Both true and perceived job finding rates depreciate at a geometric rate over the unemployment spell, with $1 - \theta_d = (1 - \theta)^d$ and $1 - \hat{\theta}_d = (1 - \hat{\theta})^d$. In an alternative specification, we a assume

[33] Note also that, without further assumptions on the distribution of the error term, we cannot separately identify b_1 and how the 'non-classical' error in elicitations relates to T_{id}. While this separation is not needed to identify the heterogeneity in job finding, we do gauge the robustness of our estimates to different distributional assumptions on the error term.

[34] Relying on multiple unemployment spells 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).

[35] Note that for our exercise here it is important 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 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.

[36] 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 $E(\tau_{id}|T_i) = 0$ for all T_i.

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

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	0.626
... at 4-6 Months of Unemployment	$m_{F_{46}}$	0.435	0.441
... at 7 Months of Unemployment or More	$m_{F_{7+}}$	0.260	0.261
Mean of 3-Month Elicitations (Deviation from Actual):			
... at 0-3 Months of Unemployment	$m_{Z_{03}} - m_{F_{03}}$	−0.031	−0.029
... at 4-6 Months of Unemployment	$m_{Z_{46}} - m_{F_{46}}$	0.076	0.057
... 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	0.008
Variance of Elicitations	s_Z^2	0.089	0.089
Covariance of Elicitations and Job Finding	$c_{Z,F}$	0.055	0.057
Covariance of Elicitations and Job Finding in 3 Months	$c_{Z_d,F_{d+3}}$	0.023	0.023

piece-wise linear specification for the depreciation, which in principle accommodates both negative *and* positive duration dependence in job finding rates more easily.[38]

As discussed before, the identification of heterogeneity and duration dependence does not rely on particular distributions or functional forms, which 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. So our hands are not tied to these particular distributions or functional forms and we can easily test the robustness of our results to various alternative assumptions.

4.4 Targeted Moments and Estimated Parameters

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 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: $\{\mathbf{m_{F_d}}\}_{\mathbf{d=1}}^{\mathbf{d=D}}$.

[38]The piecewise linear duration-dependence takes the following form:

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

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: $\mathbf{s_Z} = 0.089$.

4. The covariance of the 3-month job finding rate and elicitations: $\mathbf{c_{F,Z}} = 0.055$.

5. The covariance of the 3-month job finding rate (3-month ahead) and elicitations: $\mathbf{c_{F_{+3},Z}} = 0.023$.

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: $m_{dZ} = 0.009$.[39]

This implies that there are $2D + 4$ moments. In our baseline 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. Note that we assume that the maximum duration for each job seeker is two years, but we relax this assumptions in a set of robustness checks, where we allow for a maximum duration of up to five years. With two parameter distributions, there are 7 parameters to estimate (α, β, σ_τ, θ, b_0, b_1, σ_ε) and thus the model is over-identified. Following our earlier discussion, identification of the parameters comes from matching the moments listed above as follows:

1. The parameters α and 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.

2. The parameter σ_τ is mainly identified through the differences in the covariances c_{Z_d,F_d} and $c_{Z_d,F_{d+3}}$.

3. The parameters b_0 and b_1 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. While b_0 is mainly identified by the average bias between elicitations and job finding, b_1 is identified by the gradient of this bias by duration.[40]

4. The parameter $\hat{\theta}$ is set equal to θ in our baseline specification. When we relax this constraint, it is mainly identified by the difference in the covariance of elicitations and job finding rates c_{Z_d,F_d} at different durations d.

5. The parameter σ_ε is identified through the variance of elicitations.

4.5 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 empirical moments from the moments simulated from the model. We use

[39] 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 results available on request, we find that targeting a value of 0.004 consistent with the regression results reported in Table 5 does not change our main parameter estimates.

[40] Note that the gradient of the perceived job finding depends on the covariance of elicitations and job finding rates, determining the dynamic selection, and on the mean of monthly innovations in elicitations, determining the true-duration dependence in beliefs. As shown in Appendix Section D.1, the mean of monthly innovations provides no additional identifying variation in a stylized two-period model.

Table 7: Estimation Results

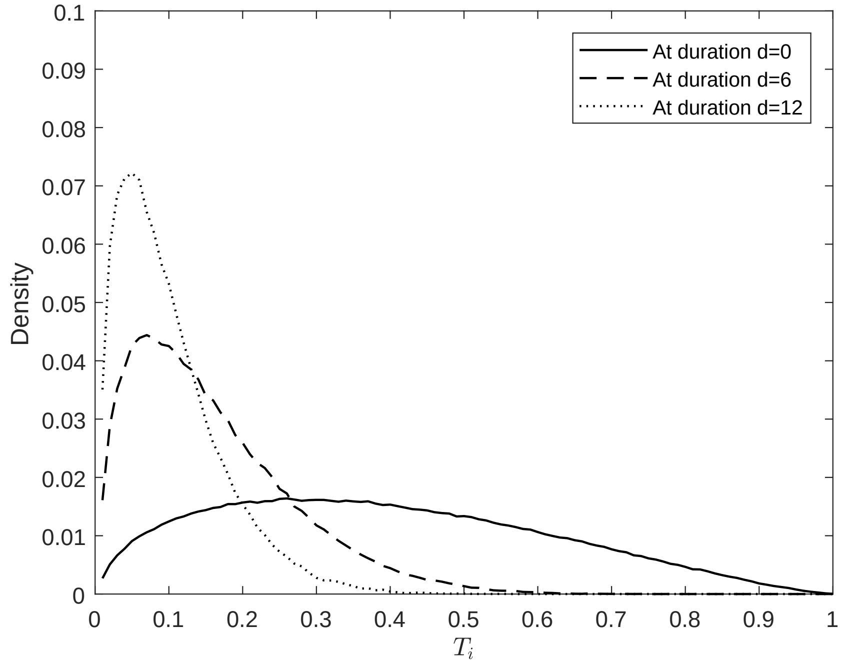
A. Parameter Estimates

Parameter/Moment	Explanation	Estimate	(S.e.)
$E(T_i)$	Mean of distribution of permanent component, T_i	0.389	(0.068)
$Var(T_i)$	Variance of distribution of permanent component, T_i	0.048	(0.025)
σ_τ	Dispersion in transitory component of job finding rate, τ_{id}	0.325	(0.246)
θ	Depreciation in job finding	0.003	(0.054)
b_0	Intercept bias	0.262	(0.056)
b_1	Slope bias	0.537	(0.118)
σ_ε	Dispersion in elicitation errors, ε_{id}	0.438	(0.025)

B. Additional Moments

Moment	Explanation	Estimate	(S.e.)
$Var(T^3_{i0})$	Variance in 3-month job finding rates at $d = 0$	0.084	(0.016)
$Var(T^3_i)$	Variance in permanent component of T^3_{i0} at $d = 0$	0.065	(0.025)
$Var(dT^3_{id})$	Variance in changes in 3-month job finding rates	0.017	(0.010)
$E(T^3_{i0} - T^3_{i12})$	12-month decline in job finding rates (longitudinal)	0.010	(0.172)
$E(T^3_{i0}) - E(T^3_{i12})$	12-month decline in job finding rates (cross-sectional)	0.442	(0.078)
$\frac{E(T^3_{i0}-T^3_{i12})}{E(T^3_{i0})-E(T^3_{i12})}$	Ratio of longitudinal to cross-sectional decline in job finding	0.022	(0.383)
$Var(Z^3_{i0})$	Variance in 3-month elicitations at $d = 0$	0.080	(0.005)
$Var(Z^3_{i0} - \varepsilon_{i0})$	Variance in 3-month elicitations at $d = 0$ (net of elicit. errors)	0.024	(0.008)
$Var(dZ^3_{id})$	Variance in changes in 3-month elicitations	0.124	(0.013)
$Var(dZ^3_{id} - d\varepsilon_{id})$	Variance in changes in 3-month elicitations (net of elicit. err.)	0.005	(0.003)
$E(Z^3_{i0} - Z^3_{i12})$	12-month decline in elicitations (longitudinal)	0.006	(0.090)
$E(Z^3_{i0}) - E(Z^3_{i12})$	12-month decline in elicitations (cross-sectional)	0.238	(0.047)
$\frac{E(Z^3_{i0}-Z^3_{i12})}{E(Z^3_{i0})-E(Z^3_{i12})}$	Ratio of longitudinal to cross-sectional decline in elicitations	0.026	(0.381)

Figure 5: The Distribution of T_i among Survivors

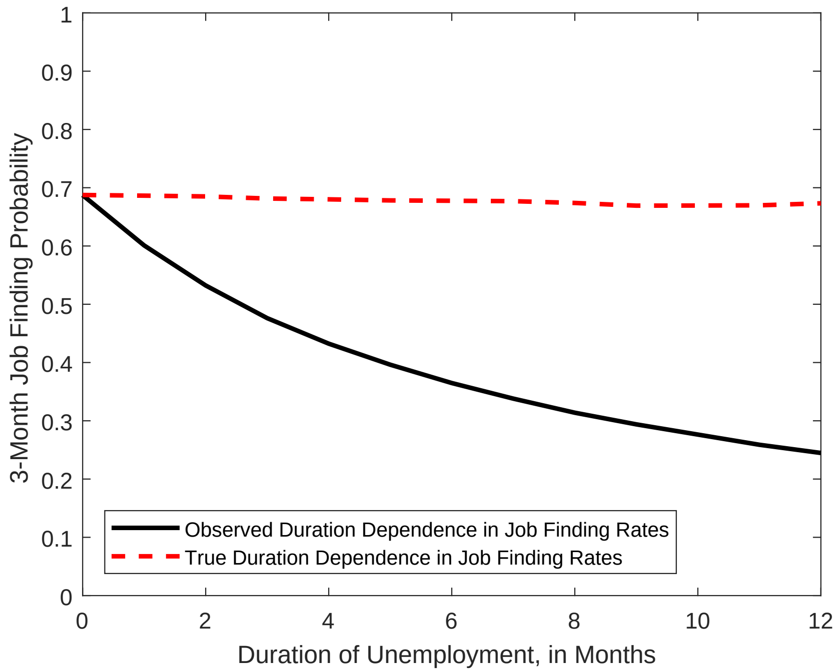


the inverse of the bootstrapped covariance matrix of the empirical moments as weighting matrix, where the bootstrapped variances were computed with 2,000 repetitions. Standard errors were obtained by estimating the model on 200 bootstrap samples and taking the standard deviation of estimates across the 200 samples. As shown in Table 6, our model matches the 10 moments very well, even though it is over-identified. There isn't nearly any discernible difference 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 0.34. Table D1 in the Appendix also shows moments that were not targeted in the baseline estimation, such as the variance of elicitations and the covariance with the contemporaneous 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 moments of interest. The estimation delivers two important sets of results.

Heterogeneity vs. Depreciation The estimation reveals substantial heterogeneity in the job finding rates. A significant share of the heterogeneity is driven by transitory shocks, but there is important persistent heterogeneity as well, 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 substantially lower average overall. These changes are more extreme one year into the unemployment spell. The large amount of heterogeneity in job finding rates

Figure 6: Duration Dependence in Job Finding Rates



accounts for virtually all of the observed duration dependence in job finding rates, as shown in Figure 6. The figure compares simulations of the baseline model (solid black line), with a model where all heterogeneity is eliminated and the only source of duration dependence in job finding rates is $\theta \neq 0$ (dashed red line). Our model attributes 97.8% (s.e. of 38.3) of the decline in 3-month job finding rates, which is from 0.69 to 0.24 over the first year of unemployment, to selection.[41] The remainder – a decline of only 1 percentage point – is due to the depreciation of the job finding probability over the spell of unemployment. This correspond to a negligible monthly depreciation rate of .2 percent.

Biases in Beliefs The estimation also reveals important biases in beliefs. Perceptions substantially under-react to the variation in job finding across workers. On average, workers who face a 10 percent higher job finding probability on average perceive their chances as only 5.40 percent higher (s.e. of 1.18). The slope bias is thus large and significant. Since the average wedge between true and perceived job finding is small, the low-T_i types are estimated to be over-optimistic and conversely high-T_i types are estimated to be over-pessimistic. The conclusions are very similar in an extended model, where we allow for a differential cross-sectional and longitudinal bias (i.e., $\hat{\theta} \neq \theta$) and add the covariances between perceived and true job finding at different duration intervals as additional moments to identify these differential biases (column 8 of Appendix Table D2). The slope coefficient is almost identical ($b_1 = 0.528$) and there is no discernible difference between $\hat{\theta}$ and θ. The finding that job seekers have imperfect information about their job finding type ($b_1 < 1$), indicates that there is scope for

[41] We note that this relative role is relatively imprecisely estimated, but this is not too surprising, given its residual nature and thus dependence on all other parameters in the estimation. Moreover, note that we strongly reject the case that attributes all of the observed duration dependence to depreciation at the individual level.

learning from remaining unemployed. However, since job seekers do not revise their beliefs downward, actual learning from remaining unemployed seems limited. The assumption that the cross-sectional and longitudinal response in beliefs are the same is not restrictive in the extended model (column 10 of Appendix Table D2), which is why use the more parsimonious specification as our baseline model. We note though that the estimated variance in permanent types is somewhat smaller in the extended model, leading to a larger depreciation rate, accounting for 18 percent of the observed duration dependence, but the perceived job finding decreases at a slower rate (see Appendix Figures D1). Finally, we also find that the random error in the elicitations is important, driving about 70 percent of the variance in elicitations. This can be due to errors in the elicitation procedure, but also due to idiosyncratic errors in perceptions.

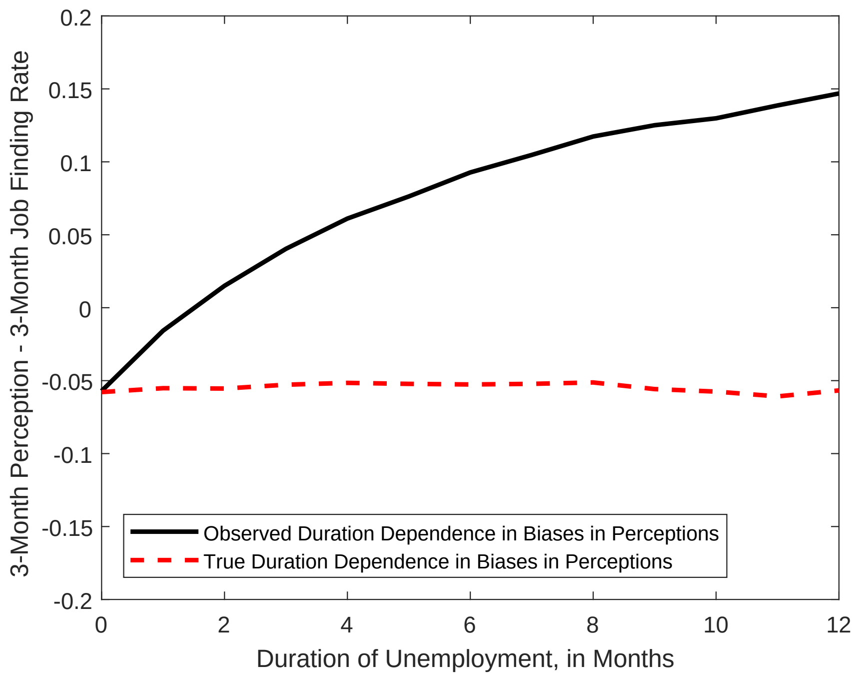
Our model allows decomposing observed differences in the bias in perceptions by unemployment duration, as shown in Figure 7. As discussed earlier, our data show a larger bias of perceptions for the long-term unemployed, which the model reproduces nicely (solid black line). Yet, it is a priori unclear whether the increase in the bias is driven by differential changes in perceived and true job finding at the individual level or by selection of over-optimistic job seekers into long-term unemployment. Since there is basically no depreciation in either true or perceived job finding rate, the gradient of the optimistic bias by time spent unemployed is almost entirely driven by the dynamic selection. The job seekers with low job finding probability are too optimistic, select into long-term unemployment and do not revise their beliefs downward while they remain unemployed. The dashed red line provides simulation results for our model without heterogeneity (only one type of job seeker), and is basically flat. Of course, we would attribute more of the observed increase in the bias over the spell to the difference between the true and perceived depreciation, if the true depreciation was in fact larger (see Appendix Figure D2).

Observables vs. Beliefs To assess the estimated heterogeneity in our statistical model, we can compare the estimated heterogeneity in job finding rates to what one would predict when using observable characteristics and/or when not relying on the structure imposed by the model.

First, 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 unemployed compared to those unemployed for 12 months or longer is 40 percentage points. In Appendix Table C7, we show that this difference in job finding rates is attenuated 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 over the first year of unemployment. When controlling for both observable characteristics and beliefs, the difference in job finding is reduced further to only 20 percentage points. These results are 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. Loosely interpreted, this suggests that only about a quarter of the decline in the job finding rate attributed to selection in our statistical model, can be attributed to dynamic selection on *observed* differences in types. This share increases to 50 percent when also including beliefs as an observed characteristic.[42]

[42]Note that this loose interpretation requires that job seekers do not revise their beliefs over the spell.

Figure 7: Duration Dependence in Biases in Perceptions



A related way to assess the amount of heterogeneity predicted by our model is to compare it to the variance in the conditional mean of job finding $var(E(T_{id}|Z_{id}))$. This variance provides a non-parametric lower bound on the variance in job finding $var(T_{id})$ by the variance decomposition (see Morrison and Taubinsky [2019]). We obtain a lower bound by taking the variance of the predicted values for each of the 10 bins in Figure 3, which corresponds to 32 percent of the estimated variance in 3-month job finding probabilities in our model.[43] We can tighten this bound further by also including the observables used before to obtain a variance of predicted values of 0.056, which now corresponds to 53 percent of the estimated variance. Hence, we come to the same conclusion as in the statistical model that heterogeneity in job finding is important, but now without relying on any model assumptions on beliefs.

A final check we perform is to estimate the model 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 estimation results are shown in Table D4 and the moments in Table D5 in the Appendix. Overall, the estimation results are very similar to the baseline, with the role played by true duration dependence being again close to zero. 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. We also obtain a comparable estimate for the slope coefficient b_1 of 0.566, which suggests that the relationship between observed heterogeneity in job finding and beliefs is similar as the relationship between unobserved heterogeneity in job finding

[43]The variance of 3-month job finding probabilities in our model for all durations is 0.106. Note that this value is somewhat larger than the variance of 0.084 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.

and beliefs.

4.6 Robustness

We study the robustness of our results when using alternative specifications and using different functional forms and distributions.

We have aimed to parametrize our model as parsimoniously as possible. To illustrate this, we estimate a number of versions of the model where we restrict parameter choices as reported 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, $\theta = 0$ (column 2). Unsurprisingly, this model version fits the data very well. 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 $\sigma_\mathcal{T} = 0$, i.e., we do not allow for any transitory changes in job finding during the unemployment spell. As shown in column (4) of Appendix Table D2, this specification has difficulty in matching both c_{Z_d,F_d} and $c_{Z_d,F_{d+3}}$. The version without transitory 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 ($\theta < 0$). Given our estimation procedure leveraging elicitations to learn about heterogeneity in types, it proves important to allow for transitory heterogeneity.

Regarding the perceived job finding rates, we estimate a version of the model where we do not allow for any under-response to differences in job finding (column 5 with $b_1 = 1$). The fit gets substantially worse, indicating the importance of allowing for the slope bias. Very similar results are obtained when adding also the restriction that the intercept bias equals zero (column 6 with $b_0 = 0$). The model fit gets also worse, but is still reasonable relative to the baseline model, when we allow only for a longitudinal bias, but no cross-sectional bias (columns 7 with $b_1 = 1, \hat{\theta} \neq \theta$). The estimated heterogeneity in persistent types is smaller when this variation 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 true (but not the perceived) monthly depreciation rate θ equal to 0.067. However, as discussed before, when adding additional moments to separately identify the cross-sectional and longitudinal bias (column 8), we find no difference between the two and the role of true duration-dependence is again small. Moreover, the model fit gets substantially worse in the extended model when only allowing for a longitudinal bias (column 9), but not when restricting the cross-sectional and longitudinal bias to be the same (column 10).

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), and to assuming that ε follows a bounded normal distribution, which no longer satisfies mean-independence of the error term (4). Our results are also robust to assuming piecewise linear duration dependence instead of geometric depreciation (5), extending the horizon of the model to 5 years (6), and doing both (7). 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 (8). 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 (9). 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 also very similar when using the residualized data moments as discussed before (10), or when excluding individuals with recall expectations when generating the data moments (11). Finally, the results do not change either when restricting the set of moments by using only 0-6 and 7+ months for the time intervals and dropping the mean of monthly innnovations, so that the model is exactly identified (12), or when using the inverse of the bootstrapped variances on the diagonal of the weighting matrix (and zero otherwise) instead of the full variance-covariance matrix as the weighting matrix (13).

5 Structural Model of Job Search with Biased Beliefs

In the statistical model we have estimated heterogeneity and duration-dependence in perceived and true job finding, but we have abstracted from the underlying behavior of job seekers. In this section, we consider a McCall type job search model to study how search behavior and employment outcomes can be affected by the perceptions about employment prospects. We calibrate our model with job search by matching the average wedges between perceived and true job finding by duration of unemployment as well as by leveraging the estimates from the statistical model in the previous section. We then use this 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 in our theoretical analysis is that when a job seeker's employment prospects change, she changes her job search strategy to mitigate the impact on her employment chances. 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 is consistent with the observed negative correlation between job finding and optimistic bias, but also causes the observed duration dependence in job finding rates to be magnified when the heterogeneity across job 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

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

where δ is the discount rate, $u(b_u)$ 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.[44]

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

$$T_{i,d} = \lambda_{i,d}(1 - F(R_{i,d})). \tag{9}$$

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 $S_0 = 1$.

In order to provide tractable characterizations of the impact on job finding and on duration-dependence, 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.[45]

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:

$$dT = \underbrace{[1 - F(R)]d\lambda}_{\text{Mechanical Effect}} - \underbrace{[\lambda f(R)\,\partial R/\partial\hat{\lambda}]d\hat{\lambda}}_{\text{Behavioral Effect}}. \tag{10}$$

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

[44] We ignore intertemporal consumption decisions, assuming agents are hand-to-mouth, but we acknowledge that beliefs about job finding would affect consumption decisions over the unemployment spell [see Spinnewijn (2015) and Ganong and Noel (2017)]. For our analytical derivations, we assume no job separation risk, i.e. $\sigma = 0$, but we relax this in the numerical analysis, where we also allow for job-to-job transitions as well. This is through positive job arrivals when employed λ^e.

[45] See Conlon et al. [2018] for a model with heterogeneity in the mean wage offer expectations and learning based on the received wage offers. See Spinnewijn [2015] for a model of search efforts with biased beliefs, distinguishing between *baseline beliefs* - regarding the baseline probability of job finding - and *control beliefs* - regarding the increase in the job finding probability when searching more.

response to an increase in the perceived arrival rate. The mechanical and behavioral effect thus work in opposite directions.

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 hazard ratio of the wage offer distribution, $f(R)/(1 - F(R))$, and 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. 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*

$$\varepsilon_{T,\lambda} = 1 - \beta\kappa, \tag{11}$$

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 are more optimistic about their employment prospects take actions that cause them to leave unemployment more slowly. Importantly, this also implies that the behavioral response to differences in beliefs gives rise to a negative correlation between the optimistic bias and the job finding rate. As a result, our empirical finding that workers with low job finding rates are more optimistic, may not be driven only by the fact that their beliefs under-react to their differences, but also by the fact that workers with more optimistic beliefs reduce their job finding rates more.

While we introduce variation in job finding rate through the arrival rates, it is important to note that the mechanical and behavioral effect would continue to have opposite signs when changing the mean of the wage offer distribution instead, like in Conlon et al. [2018]. A more favorable wage offer distribution increases job finding for a given reservation wage, but workers would increase their reservation wage if this is perceived. The mechanical and behavioral effect have also opposite signs in a model with endogenous search, like in Spinnewijn [2015], when varying the baseline probability of finding employment, keeping the returns to search fixed. The two effects would have the same sign, however, when varying the returns to search instead; job seekers with higher returns to search find jobs at a higher rate and search more if they perceive the higher returns. In contrast with the other three sources of heterogeneity, this final source of heterogeneity would give rise to a positive correlation between job finding and the optimistic bias, which is opposite to what we find in the data.

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 and slope bias in the statistical model and ν_i is a mean-zero, random error term. The variance in perceived arrival rates $var(\hat{\lambda}) = \beta_1^2 \sigma_\lambda^2 + \sigma_\nu^2$ 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 (10)) 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 $var_x(T) = \int \frac{S_{i,x}}{S_x} \left[T_{i,x} - E_x(T)\right]^2 di$, 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 $d+1$. Using $S_{i,d+1} = S_{i,d}(1 - T_i)$, we have

$$E_{d+1}(T) = E_d(T) - \frac{var_d(T)}{1 - E_d(T)}, \tag{12}$$

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

$$\begin{aligned} var_0(T) &\approx var\left([1 - F(R)]d\lambda - \lambda f(R) \frac{\partial R}{\partial \hat{\lambda}} d\hat{\lambda}\right) & (13) \\ &\propto [1 - \beta_1 \kappa]^2 \sigma_\lambda^2 + \kappa^2 \sigma_\nu^2, & (14) \end{aligned}$$

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.[46]

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

[46] 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 $E_d(T)$ as well.

rates. Intuitively, a high β_1 implies that agents with lower offer rates set lower reservation wages because they perceive their offer rates accurately, mitigating the negative observed duration dependence; if β_1 is low, however, this mitigating mechanism is less active. 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 (i.e., the true offer rates) 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:

$$\lambda_{d+1} = (1-\theta)\,\lambda_d \text{ and } \hat{\lambda}_{d+1} = \left(1-\hat{\theta}\right)\hat{\lambda}_d, \tag{15}$$

where θ corresponds to the true duration-dependence in the statistical model and $\beta_\theta = \hat{\theta}/\theta$ 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, $Prob(\hat{\lambda}_{i,0} = \hat{\lambda}^j | \lambda_{i,0} = \lambda^j) = B_1$. This is a parsimonious way to capture that job seekers' beliefs under-react to their differences in risk. Finally, job seekers perceive a depreciation rate of their arrival rates of $B_\theta \theta$.[47] Like in the statistical and structural model, the 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 $B_1 = B_\theta = 1$.[48]

Table E1 in the Appendix shows the 8 moments that we target in the calibration of our structural model. Like in the statistical model, the targeted moments include the actual and perceived job finding rates for the short, medium and long-term unemployed. We additionally target an average job acceptance rate underlying the job finding rates of 0.71, as estimated by Hall and Mueller [2018] using the KM survey. As we already estimated the true duration-dependence in our statistical model using elicited beliefs moments, instead of targeting these again, we directly target a moment capturing the depreciation in job finding, i.e., the average of the ratio of true job finding when long-term vs. short-term

[47] 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.

[48] Note that our model ignores additional random errors in the beliefs, as we cannot credibly separate these from noise in the elicitations. This implies that our results provide a lower bound on how much biased beliefs contribute to the incidence of LT unemployment.

unemployed within a spell (i.e., $E_{7+}(T_{id})/E_{06}(T_{id})$ for a given spell). We simulate this moment using the baseline estimation of our statistical model, obtaining a value of .99. We also gauge the robustness of our results to the rate of depreciation and recalibrate the model targeting the larger depreciation in job finding in the specification with no cross-sectional bias (see Appendix Table D3, column 7), for which we obtain a value of .65 instead. We set the perceived duration dependence B_θ equal to 0 in both specifications.

Panel A of Table E2 in the Appendix shows the parameter values that we set based on outside information. We set the separation rate at 0.02 per month and the arrival rate of job offers for employed workers at 0.15, in line with recent evidence in Faberman et al. [2017]. We assume that wages are log-normally distributed, with a standard deviation of the logged distribution of $\sigma_w = 0.24$ as estimated by Hall and Mueller [2018] with the KM survey data. We normalize the median of the wage offer distribution to 1. We also assume an annual discount factor 0.996 and CRRA preferences with relative risk aversion equal to 2. Panel B of Table E2 shows the remaining 7 parameters of our model $\{B_0, B_1, \lambda_l, \lambda_h, \varphi, \theta, b_u\}$ that are estimated by targeting the vector of 8 moments. We find that the uniform bias parameter B_0 is negative, but the average bias is still positive. This is due to the share of low types perceiving themselves as high, who remain unemployed for the longest. The probability that high (low) types perceive themselves as high (low) types equals $B_1 = 0.81$ in the baseline specification. As we assume that no duration-dependence is perceived ($B_\theta = 0$), the corresponding cross-sectional bias becomes smaller in the model where we target high true duration-dependence ($B_1 = 0.93$).[49] The estimated parameters minimize the sum of squared differences between data moments and simulated moments from the model. Appendix Table E1 shows that we closely match our targeted moments. We also obtain plausible values for standard labor market statistics; the elasticity of the unemployment duration with respect to unemployment benefits is 0.51, which is within the range of estimates in the literature (see Schmieder and von Wachter [2016]). The monthly rate of job-to-job transitions equals 0.024, which is within the range considered by Hornstein et al. [2011].[50]

Counterfactual Analysis We can now use the calibrated model to quantify the impact of biases in beliefs. Starting from our baseline model, decreasing the arrival rate of job offers by 10 percent increases the unemployment duration by 9.1 percent, but only by 5.1 percent when the worse employment prospects are perceived. These opposite mechanical and behavioral effects on job finding correspond to the findings in Proposition 1. In line with Propositions 2 and 3, we also find that a 10 percent increase in the spread of arrival rates increases the share of LT unemployed (i.e., the share of unemployed workers who are unemployed for longer than 6 months) by 31 percent. A 10 percent increase in the correlation between the actual and perceived arrival rates, however, reduces that share by 3.8 percent. Furthermore, increasing the depreciation rate from nearly zero to a high depreciation rate of

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

[50] We also performed sensitivity checks when changing incidental parameters, including the arrival rate of job offers for the employed, the dispersion of the wage distribution and the level of risk aversion, which all change the relative value of unemployment to employment. For the baseline model, it is mainly the parameter b_u affecting the flow value of unemployment that adjusts, while the other parameter estimates remain very similar. The other parameter estimates become more sensitive in the model with high depreciation.

Table 8: Comparative Statics in Structural Model

	Calibrated Model	Eliminating Biases $B_0 = 0$	$B_1 = 1$	$B_\theta = 1$	$B_0 = 0$, $B_1 = 1$, $B_\theta = 1$
A. Baseline Model					
Unemployment duration	4.24	4.24	4.21	4.24	4.21
Share of LT unemployed	0.319	0.319	0.292	0.319	0.292
B. High Depreciation Model					
Average unemployment duration	4.30	4.56	4.27	3.99	4.08
Share of LT unemployed	0.317	0.327	0.305	0.301	0.293

0.06, corresponding to our baseline and alternative calibration respectively, the share of LT unemployed increases by 33 percent, but the impact would be mitigated to an increase of 28 percent if the higher depreciation is perceived as such. We illustrate these comparative statics for a range of parameter values in Appendix Figure E1.

Table 8 shows the impact of eliminating the biases in beliefs on the average unemployment durations and the share of long-term unemployed. The intermediate columns consider the elimination of one bias at a time, the last column the elimination of all biases simultaneously. From Panel A, which shows the results for the baseline model, we see that eliminating all biases lowers the average unemployment duration, but this effect is numerically very small. Despite the small impact on the overall duration, the impact on the share of LT unemployed is substantial, which decreases by 9 percent (2.8 percentage points) when all biases are eliminated. Panel B shows the results for the model calibrated with high depreciation rate. The effect on the average unemployment duration is somewhat larger, at around 0.2 months. However, eliminating the biases reduces the share of LT unemployed by 2.3 percentage points, which is slightly lower than in the baseline model. Overall, the model's prediction that biased beliefs contribute substantially to the high incidence of LT unemployment is robust to the relative importance of heterogeneity vs. depreciation in the arrival rates.[51] This is not too surprising as job seekers perceptions under-react to both sources of variation. Expressed as the ratio of the LT vs. ST unemployment rate, about 12 - 14 percent of the high incidence of LT unemployment is explained by the biased beliefs. We view this as a lower bound as we focused only on systematic biases in perceptions but ignored random errors in perceptions as a source of additional biases in beliefs.

6 Conclusion

This paper analyzes job seekers' perceptions about their employment prospects and how these perceptions relate to employment outcomes. We have offered three sets of results:

We have documented empirically (1) that reported beliefs have a strong predictive power of actual job

[51] We note that these counterfactual results remain very similar when changing incidental parameters (i.e., wage offer distribution, arrival rates, risk aversion) in the baseline calibration, but are somewhat sensitive in the calibration with high depreciation.

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 have then developed a novel framework, where we show how the relation between beliefs and ex-post realizations can be used to disentangle heterogeneity and duration-dependence in true job finding rates. Using this framework, we find that the reported beliefs reveal a substantial amount of heterogeneity in true job finding rates, accounting for most 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. Job seekers with low job finding are over-optimistic and select into long-term unemployment without adjusting their beliefs downward.

We have also shown 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. Calibrating this model, we find that this mechanism significantly increases the incidence of long-term unemployment.

Our analysis demonstrates the broader value of having data on both expectations and realizations for the same individuals over time. In our context, the data allow us to learn about job seeker's *true* employment prospects, providing us with a novel identification strategy to separate dynamic selection and true duration dependence, with well-known implications with regard to a broad range of labor market policies. Further, the data allow us to learn about biases in the *perceived* employment prospects and to study their interplay with behavior in determining unemployment outcomes. We believe this opens up an important area of research with again wide-ranging policy implications. Our findings for example raise the question whether biases in beliefs 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.

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Online 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?

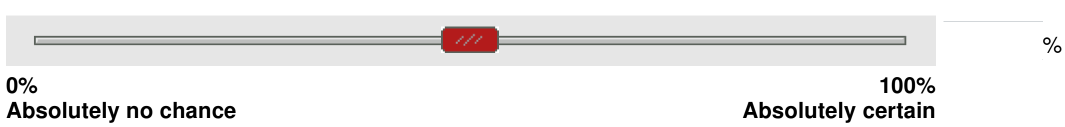
[Ruler & box]

A.2 Krueger-Mueller 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

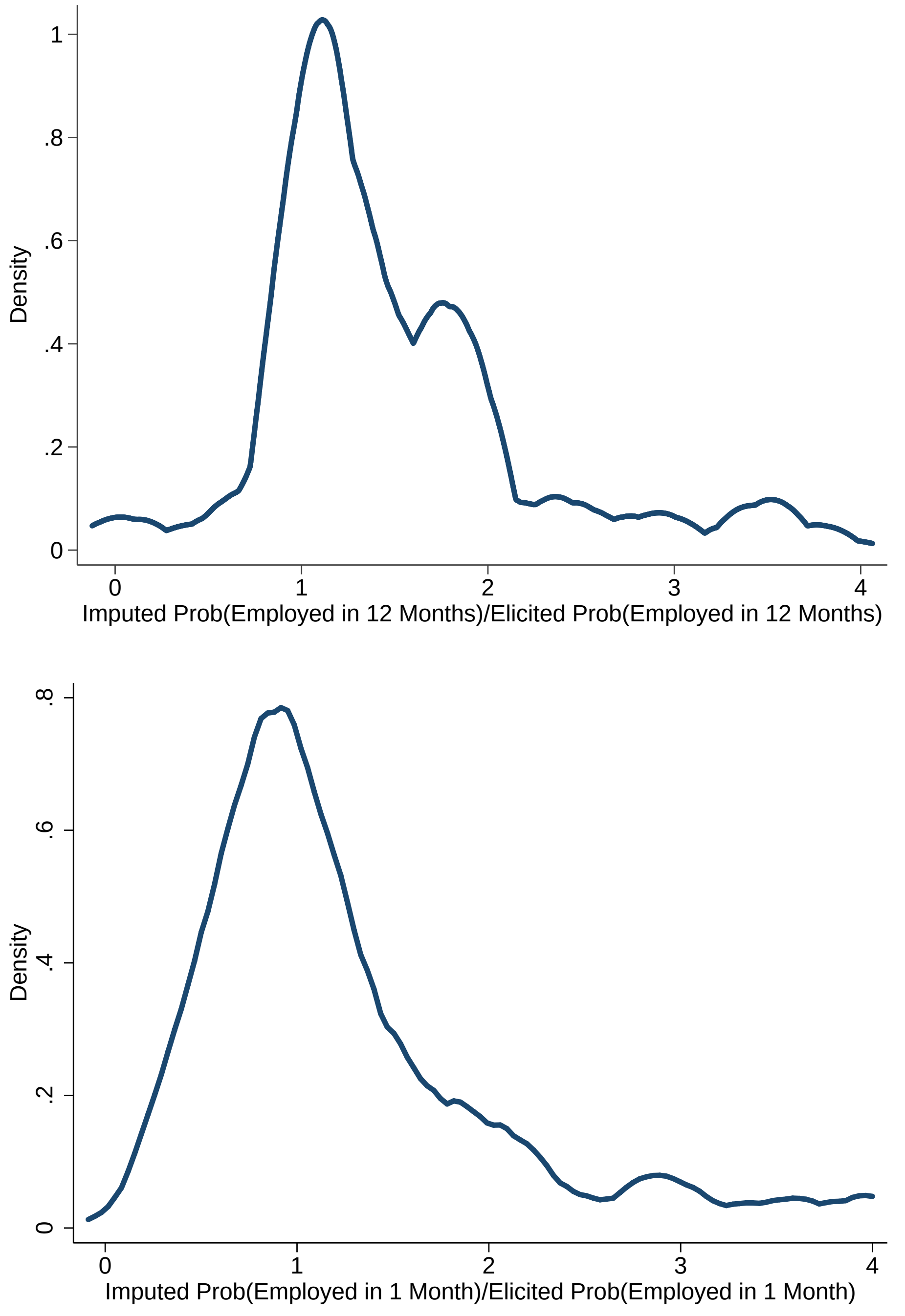
Table B1: Descriptive Statistics for the Survey of Consumer Expectations (SCE) and Comparison to the Current Population Survey (CPS)

	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
Surveyed job finding rates (in percent)				
Monthly job finding rate	n.a.	n.a.	17.6	22.7
3-Month job finding rate	n.a.	n.a.	39.6	43.2
... at 0-3 Months of Unemployment	n.a.	n.a.	62.2	54.0
... at 4-6 Months of Unemployment	n.a.	n.a.	43.5	39.8
... at 7-12 Months of Unemployment	n.a.	n.a.	34.9	30.9
... at 13+ Months of Unemployment	n.a.	n.a.	22.3	23.5
# 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. The 3-month job finding rate in the SCE is computed in the same sample as in Table 2. The 3-month job finding rate in the CPS is measured as the fraction of unemployed workers in rotation groups 1 and 5 who reported being employed 1, 2 or 3 months later. Survey 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 Imputed Probabilities and Elicited Probabilities based on Alternative Forms of Elicitations in the SCE (top panel) and KM Survey (bottom panel)



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

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

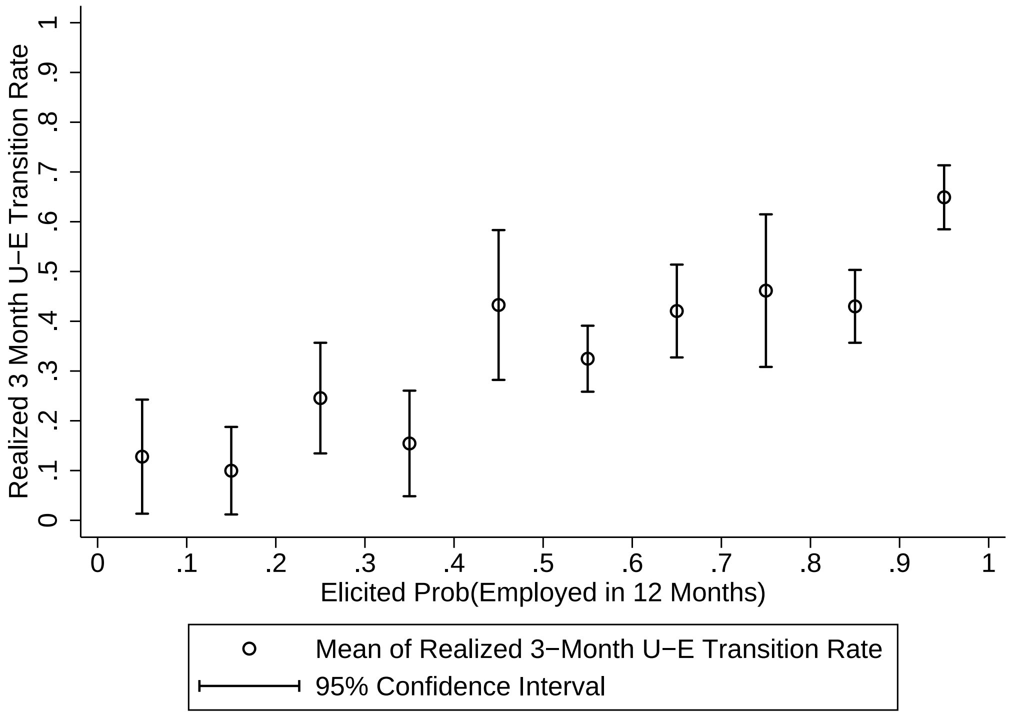


Figure C3: Perceived 12-month Job Finding Probabilities, by Time since First Interview (SCE)

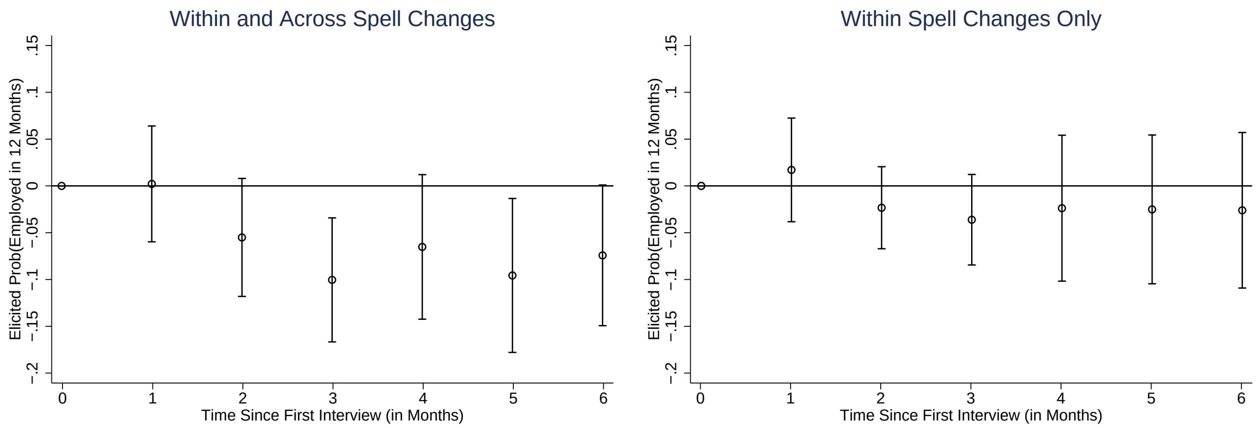


Figure C4: Perceived Expected Duration (Inverted), by Time since First Interview (KM Survey)

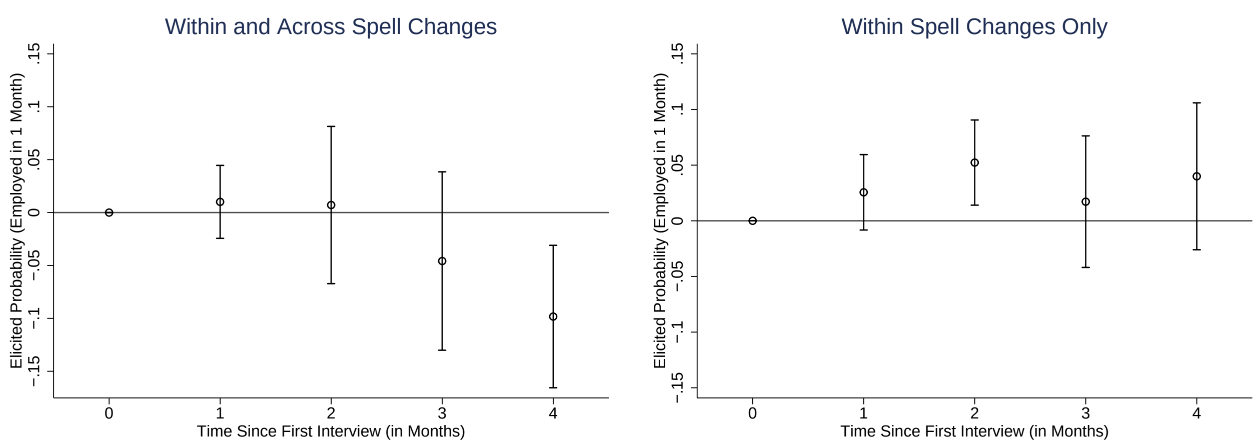


Table C1: Linear Regressions of Realized Job Finding Probabilities on Elicitations (SCE; 12-Month Horizon)

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)
Controls			X	X
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, in the SCE. Controls include dummies for gender, race, ethnicity, household income, educational attainment, and age and age squared.

Table C2: 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, in the KM survey. 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 C3: 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, in the SCE. 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 C4: 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, in the KM survey. Column (1) reports the baseline results from Table 5; Column (2) uses the inverse of the expected duration question as dependent variable (see footnote 14 in the maintext for details); 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; 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 C5: Linear Regressions of Elicited Perceptions on Time Spent on Job Search and the Reservation Wage (KM Survey)

Dependent variable:	Prob(Find Job in 1 Month)		Expected Duration (Inverted)	
	(1)	(2)	(3)	(4)
Dummy for Control Belief	0.0884	-0.0109	0.1053	0.0533
	(0.0253)***	(0.0230)	(0.0197)***	(0.0307)*
Time Spent on Job Search (Hours per Week)	0.0013	-0.0014	0.0011	0.0008
	(0.0006)**	(0.0011)	(0.0006)*	(0.0014)
Log(Hourly Reservation Wage)	-0.0304	-0.0109	-0.0477	0.1346
	(0.0346)	(0.0758)	(0.0298)	(0.0812)*
Reservation Commuting Distance (in min)	-0.0002	-0.0009	-0.0008	-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, in the KM survey. Expected duration (inverted) is calculated as $1-(1-\frac{1}{x})^4$, where x is the elicited expected remaining duration of unemployment (in weeks). The dummy for control belief is set to one for respondents who believe that chances of finding a job increase if they spent more time searching.

Table C6: Linear Regressions of Macroeconomic Measures on Elicitations (SCE)

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, in the SCE.

Table C7: Linear Regressions of Realized Job Finding Rate on Unemployment Duration, Controlling for Observables (SCE)

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 Months			-0.187***	-0.152**
			(0.069)	(0.064)
Unemployment Duration: 7-12 Months			-0.274***	-0.239***
			(0.066)	(0.060)
Unemployment Duration: 13+ Months			-0.400***	-0.287***
			(0.053)	(0.052)
Controls		X		X
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, in the SCE. Controls include dummies for gender, race, ethnicity, household income, educational attainment, and age and age squared.

Table C8: Linear Regressions of Realized Job Finding Rate on Unemployment Duration, Controlling for Elicited Beliefs (SCE)

Dependent Variable: 3-Month UE Transition Rate	(1)	(2)	(3)	(4)
Unemployment Duration, in Months	-0.0064***	-0.0053***		
	(0.0009)	(0.0010)		
Unemployment Duration: 4-6 Months			-0.145**	-0.127**
			(0.060)	(0.059)
Unemployment Duration: 7-12 Months			-0.240***	-0.214***
			(0.061)	(0.058)
Unemployment Duration: 13+ Months			-0.274***	-0.200***
			(0.050)	(0.052)
Belief Controls (10 Bins)	X	X	X	X
Demographic Controls		X		X
Observations	983	983	983	983
R^2	0.200	0.262	0.199	0.261

Notes: All samples are restricted to unemployed workers, ages 20-65, in the SCE. Demographic controls include dummies for gender, race, ethnicity, household income, educational attainment, and age and age squared.

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	0.085
... 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	0.048
... at 4-6 Months of Unemployment	$c_{Z_{46},F_{46}}$	0.054	0.045
... at 7 Months of Unemployment or More	$c_{Z_{7+},F_{7+}}$	0.030	0.032

Notes: The sample is restricted to unemployed workers, ages 20-65, in the SCE.

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

A. Parameter Estimates and Selected Moments:	(1) Baseline	(2) $\theta = 0$	(3) No heterog. in T_{id}	(4) $\sigma_\tau = 0$	(5) $b_1 = 1$	(6) $b_0 = 0$ $b_1 = 1$	(7) $b_1 = 1$ $\theta \neq \hat{\theta}$	Extended Model (8) $b_1 \neq 1$ $\theta \neq \hat{\theta}$	(9) $b_1 = 1$ $\theta \neq \hat{\theta}$	(10) $b_1 \neq 1$ $\theta = \hat{\theta}$
$E(T_i)$	0.388	0.386	0.286	0.412	0.269	0.298	0.345	0.397	0.342	0.395
$Var(T_i)$	0.048	0.048	0	0.076	0.017	0.017	0.016	0.044	0.014	0.044
σ_τ	0.325	0.316	0	0	0.201	0.21	0.306	0.448	0.519	0.448
θ	0.003	0	0.097	-0.069	0.001	0.001	0.067	0.021	0.077	0.022
$\hat{\theta}$	—	—	—	—	—	—	0.012	0.021	0.049	0.022
b_0	0.262	0.26	0.34	0.264	0.057	0	-0.062	0.271	0.07	0.27
b_1	0.537	0.541	0.295	0.525	1	1	1	0.528	1	0.529
σ_ε	0.438	0.438	0.423	0.44	0.35	0.358	0.343	0.431	-0.07	0.432
$s^2_{T^3_{i0}}$	0.084	0.084	0	0.095	0.053	0.048	0.045	0.09	0.073	0.09
$s^2_{T^3_i}$	0.065	0.066	0	0.095	0.041	0.036	0.026	0.058	0.024	0.058
$E(T^3_{i0} - T^3_{i12})$	0.010	-0.001	0.382	0.272	0.005	0.006	0.302	0.087	0.337	0.09
$E(T^3_{i0}) - E(T^3_{i12})$	0.442	0.438	0.382	0.438	0.258	0.266	0.42	0.461	0.431	0.459
$s^2_{Z^3_{i0}}$	0.080	0.081	0.060	0.083	0.087	0.085	0.078	0.079	0.117	0.08
$s^2_{Z^3_{i0}-\varepsilon_{i0}}$	0.024	0.025	0	0.026	0.053	0.048	0.046	0.025	0.074	0.025
$E(Z^3_{i0} - Z^3_{i12})$	0.006	0	0.113	0.142	0.006	0.007	0.057	0.048	0.07	0.048
$E(Z^3_{i0}) - E(Z^3_{i12})$	0.238	0.236	0.113	0.231	0.258	0.268	0.233	0.244	0.193	0.243

B. Model Fit:	Data	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Targeted Moments:											
$m_{Z_{03}} - m_{F_{03}}$	-0.031	-0.029	-0.027	-0.055	-0.025	0.056	0	-0.023	-0.030	-0.025	-0.030
$m_{Z_{46}} - m_{F_{46}}$	0.076	0.057	0.057	0.03	0.073	0.057	0	0.042	0.060	0.105	0.059
$m_{Z_{7+}} - m_{F_{7+}}$	0.139	0.141	0.14	0.184	0.141	0.057	0.001	0.141	0.153	0.154	0.153
$m_{F_{03}}$	0.623	0.626	0.624	0.560	0.612	0.543	0.589	0.618	0.636	0.61	0.635
$m_{F_{46}}$	0.435	0.441	0.440	0.440	0.401	0.453	0.498	0.470	0.444	0.457	0.445
$m_{F_{7+}}$	0.260	0.261	0.263	0.222	0.261	0.33	0.375	0.257	0.249	0.236	0.250
s^2_Z	0.089	0.089	0.09	0.062	0.088	0.093	0.093	0.089	0.089	0.087	0.089
$c_{Z,F}$	0.055	0.057	0.057	0.008	0.054	0.058	0.056	0.055	0.060	0.055	0.060
$c_{Z_d,F_{d+3}}$	0.023	0.023	0.024	0.007	0.029	0.033	0.033	0.024	0.021	0.022	0.021
m_{dZ}	0.009	0.008	0.009	-0.010	0.008	0.008	0.009	0.009	0.010	0.009	0.010
Weighted SSR		0.3347	0.3374	45.663	1.9952	10.141	14.983	0.4761	0.7739*	4.8157*	0.7739*

Notes: *The targeted moments for the extended model include the covariance of F and Z for duration intervals 0-6 and 7+ (not shown here; see Table D6 for empirical and model moments for the extended model) instead of the covariance in the full sample (shown). For this reason, the SSR for the extended model cannot be directly compared to the SSR of the results shown in the other columns.

Table D3: Robustness Checks

A. Parameter Estimates and Selected Moments:		(1) Baseline	(2) Gamma T_i	(3) Weibull T_i	(4) Normal ε	(5) Linear Depreciation	(6) Horizon=5y	(7) Horizon=5y Lin. Depr.	(8) Persistent errors	(9) Bunching
$E(T_i)$		0.389	0.387	0.37	0.388	0.388	0.366	0.361	0.385	0.387
$Var(T_i)$		0.048	0.047	0.038	0.048	0.049	0.043	0.038	0.046	0.047
σ_τ		0.325	0.326	0.343	0.337	0.316	0.282	0.324	0.346	0.323
θ		0.003	0.003	0.006	0.003	0.000	-0.012	-0.001	0.006	0.003
b_0		0.262	0.261	0.262	0.235	0.262	0.262	0.260	0.257	0.268
b_1		0.537	0.539	0.538	0.597	0.537	0.534	0.540	0.543	0.523
σ_ε		0.438	0.438	0.438	0.276	0.438	0.440	0.439	0.449	0.425
$s^2_{T_i^3}$		0.084	0.084	0.082	0.085	0.084	0.080	0.078	0.085	0.084
$s^2_{T_{i0}^3}$		0.065	0.064	0.06	0.065	0.066	0.064	0.057	0.063	0.065
$E(T_{i0}^3 - T_{i12}^3)$		0.010	0.012	0.024	0.010	-0.001	-0.043	-0.001	0.024	0.011
$E(T_{i0}^3) - E(T_{i12}^3)$		0.442	0.441	0.435	0.442	0.441	0.398	0.396	0.439	0.441
$s^2_{Z_{i0}^3}$		0.080	0.080	0.080	0.079	0.081	0.081	0.080	0.083	0.081
$s^2_{Z_{i0}^3-\varepsilon_{i0}}$		0.024	0.024	0.024	0.030	0.024	0.023	0.023	0.025	0.023
$E(Z_{i0}^3 - Z_{i12}^3)$		0.006	0.008	0.013	0.009	0.000	-0.020	0.002	0.014	0.007
$E(Z_{i0}^3) - E(Z_{i12}^3)$		0.238	0.238	0.235	0.232	0.236	0.216	0.215	0.236	0.239
B. Model Fit:	Data	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Targeted Moments:										
$m_{Z_{03}} - m_{F_{03}}$	-0.031	-0.029	-0.028	-0.027	-0.028	-0.028	-0.026	-0.026	-0.028	-0.028
$m_{Z_{46}} - m_{F_{46}}$	0.076	0.057	0.057	0.054	0.057	0.058	0.051	0.046	0.057	0.058
$m_{Z_{7+}} - m_{F_{7+}}$	0.139	0.141	0.141	0.143	0.141	0.142	0.144	0.144	0.141	0.141
$m_{F_{03}}$	0.623	0.626	0.626	0.623	0.627	0.625	0.619	0.622	0.625	0.625
$m_{F_{46}}$	0.435	0.441	0.441	0.448	0.441	0.439	0.454	0.464	0.442	0.441
$m_{F_{7+}}$	0.260	0.261	0.261	0.259	0.261	0.261	0.257	0.256	0.260	0.261
s^2_Z	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089	0.089
$c_{Z,F}$	0.055	0.057	0.057	0.056	0.057	0.057	0.056	0.055	0.057	0.057
$c_{Z_d,F_{d+3}}$	0.023	0.023	0.023	0.024	0.023	0.024	0.024	0.024	0.024	0.024
m_{dZ}	0.009	0.008	0.008	0.009	0.008	0.009	0.010	0.009	0.008	0.008
Weighted SSR		0.3347	0.3325	0.3031	0.3353	0.3372	0.3306	0.3848	0.281	0.2932

Table D4: Robustness Checks (Different Targeted Moments)

Parameter Estimates and Selected Moments:	(1) Baseline	(10) Residualized Moments	(11) Excluding Recall	(12) Exact Identification	(13) Diagonal W
$E(T_i)$	0.389	0.322	0.388	0.365	0.387
$Var(T_i)$	0.048	0.02	0.047	0.042	0.051
σ_τ	0.325	0.244	0.325	0.323	0.301
θ	0.003	-0.001	0.004	0.008	-0.008
b_0	0.262	0.238	0.26	0.255	0.272
b_1	0.537	0.581	0.541	0.555	0.514
σ_ε	0.438	0.392	0.438	0.436	0.443
$s^2_{T^3_{i0}}$	0.084	0.052	0.083	0.082	0.087
$s^2_{T^3_i}$	0.065	0.038	0.064	0.062	0.07
$E(T^3_{i0} - T^3_{i12})$	0.010	-0.007	0.016	0.032	-0.03
$E(T^3_{i0}) - E(T^3_{i12})$	0.442	0.287	0.443	0.420	0.437
$s^2_{Z^3_{i0}}$	0.080	0.066	0.080	0.081	0.081
$s^2_{Z^3_{i0}-\varepsilon_{i0}}$	0.024	0.018	0.024	0.025	0.023
$E(Z^3_{i0} - Z^3_{i12})$	0.006	-0.003	0.009	0.018	-0.015
$E(Z^3_{i0}) - E(Z^3_{i12})$	0.238	0.167	0.239	0.234	0.224
Weighted SSR	0.3347	0.9067	0.3284	0.0000	0.1059

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	0.620
... at 4-6 Months of Unemployment	$m_{F_{46}}$	0.482	0.518
... at 7 Months of Unemployment or More	$m_{F_{7+}}$	0.387	0.386
Mean of 3-Month Elicitations (Deviation from Actual):			
... at 0-3 Months of Unemployment	$m_{Z_{03}} - m_{F_{03}}$	-0.031	-0.020
... at 4-6 Months of Unemployment	$m_{Z_{46}} - m_{F_{46}}$	0.063	0.021
... at 7 Months of Unemployment or More	$m_{Z_{7+}} - m_{F_{7+}}$	0.076	0.076
Mean of Monthly Innovations in Elicitations	m_{dZ}	0.009	0.007
Variance of Elicitations	s_Z^2	0.071	0.071
Covariance of Elicitations and Job Finding	$c_{Z,F}$	0.035	0.037
Covariance of Elicitations and Job Finding in 3 Months	$c_{Z_d,F_{d+3}}$	0.019	0.021

Notes: The sample is restricted to unemployed workers, ages 20-65, in the SCE. Moments are computed based on residuals from a regression on dummies for gender, race, ethnicity, household income, educational attainment, and age and age squared. Note that the raw mean of the variables in the full sample is added to the residual.

Table D6: Matched Moments (Extended Model)

Moment	Symbol	Data	Extended Model $\theta \neq \hat{\theta}$ $b_1 \neq 1$	$\theta \neq \hat{\theta}$ $b_1 = 1$	$\theta = \hat{\theta}$ $b_1 \neq 1$
Mean of 3-Month Job Finding Rates:					
... at 0-3 Months of Unemployment	$m_{F_{03}}$	0.623	0.636	0.610	0.635
... at 4-6 Months of Unemployment	$m_{F_{46}}$	0.435	0.444	0.457	0.445
... at 7 Months of Unemployment or More	$m_{F_{7+}}$	0.260	0.249	0.236	0.250
Mean of 3-Month Elicitations (Deviation from Actual):					
... at 0-3 Months of Unemployment	$m_{Z_{03}} - m_{F_{03}}$	-0.031	-0.030	-0.025	-0.030
... at 4-6 Months of Unemployment	$m_{Z_{46}} - m_{F_{46}}$	0.435	0.444	0.457	0.445
... at 7 Months of Unemployment or More	$m_{Z_{7+}} - m_{F_{7+}}$	0.139	0.153	0.154	0.153
Mean of Monthly Innovations in Elicitations	m_{dZ}	0.009	0.010	0.009	0.010
Variance of Elicitations	s_Z^2	0.089	0.089	0.087	0.089
Covariance of Elicit. and Job Finding at 0-6 Months	$c_{Z_{06},F_{06}}$	0.058	0.055	0.041	0.055
Covariance of Elicit. and Job Finding at 7 Months or More	$c_{Z_{7+},F_{7+}}$	0.030	0.032	0.040	0.032
Covariance of Elicit. and Job Finding in 3 Months	$c_{Z_d,F_{d+3}}$	0.023	0.021	0.022	0.021

Notes: The sample is restricted to unemployed workers, ages 20-65, in the SCE. The versions of the extended model correspond to the ones shown in Columns 8, 9 and 10 in Table D2.

Figure D1: Duration Dependence in Job Finding Rates (Extended Model)

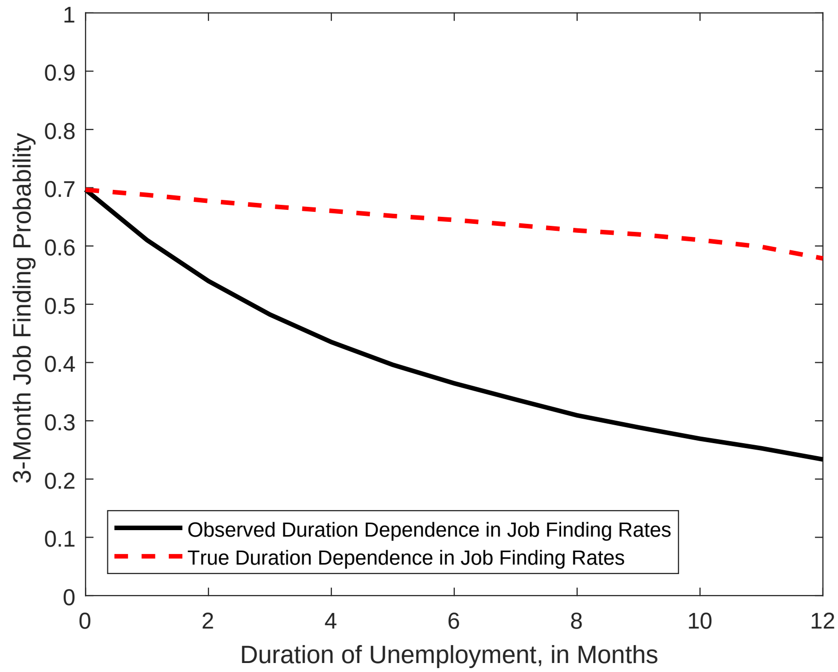
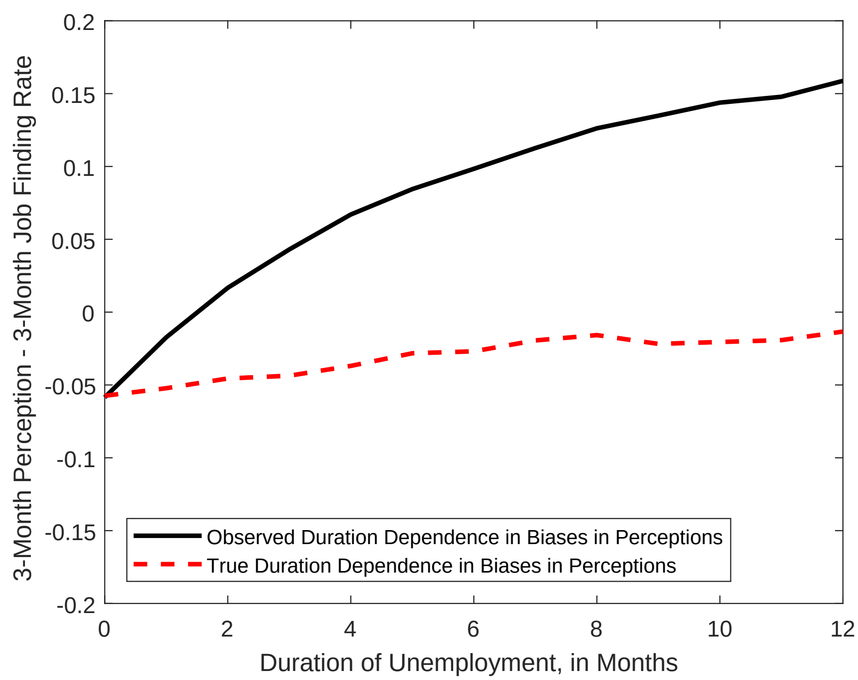


Figure D2: Duration Dependence in Biases in Perceptions (Extended Model)



D.1 Identification

In this section, we provide further details on the identification of the parameters in the statistical model. We proceed in two steps:

First, we prove that in a two-period version of the statistical model, where $\sigma_\tau = 0$ and $\hat{\theta} = \theta$, all other parameters are a function of moments with an empirical counterpart in the data and thus are identified.

Second, we provide a formal identification argument in a model where $\sigma_\tau > 0$ or $\hat{\theta} \neq \theta$ and then show that a monotone relationship exists between σ_τ and $\hat{\theta}$ and additional moments in the data that were not used for the proof of identification in the first step.

D.1.1 Identification in model with $\sigma_\tau = 0$ and $\hat{\theta} = \theta$

Proposition 4. *In a two-period version of the statistical model with classical measurement error and $\sigma_\tau = 0$ and $\hat{\theta} = \theta$, the parameters b_0, b_1, and θ as well as the mean and the variance of the persistent component of job finding rates, $E(T_i)$ and $var(T_i)$, and the variance of the elicitation error, $var(\varepsilon)$, are identified by the moment conditions for: (1) the means of the elicitations in period 1 and 2, m_{Z_1} and m_{Z_2}, (2) the means of the job finding rates in period 1 and 2, m_{F_1} and m_{F_2}, (3) the covariance of job finding and elicitations in period 1, c_{F_1,Z_1}, and (4) the variance of elicitations in period 1, $s^2_{Z_1}$.*

Proof. We start by assuming that there are only two periods, and that $\sigma_\tau = 0$ and $\hat{\theta} = \theta$. In this case, we can write down the moment conditions for the moments mentioned in the proposition above as:

$$\begin{aligned}
m_{Z_1} &= b_0 + b_1 E(T_i) && (16)\\
m_{Z_2} &= b_0 + b_1(1-\theta)E(T_i|S) && (17)\\
m_{F_1} &= E(T_i) && (18)\\
m_{F_2} &= (1-\theta)E(T_i|S) && (19)\\
c_{F_1,Z_1} &= cov(F_1, b_1 T_i) && (20)\\
s^2_{Z_1} &= b_1^2 var(T_i) + var(\varepsilon) && (21)
\end{aligned}$$

where S stands for survival to period 2. The first two moments directly pin down b_0 and b_1:

$$\begin{aligned}
b_1 &= \frac{m_{Z_2} - m_{Z_1}}{m_{F_2} - m_{F_1}} && (22)\\
b_0 &= m_{Z_1} - \frac{m_{Z_2} - m_{Z_1}}{m_{F_2} - m_{F_1}} m_{F_1} && (23)
\end{aligned}$$

Then, we can write:

$$\begin{aligned} c_{F_1,Z_1} &= cov(F_1, b_1 T_i) \\ &= b_1[E(F_1T_i) - E(F_1)E(T_i)] \\ &= b_1[E(E(F_1T_i|T_i)) - E(T_i)^2] \\ &= b_1[E(T_i^2) - E(T_i)^2] \\ &= b_1 var(T_i) \end{aligned} \tag{24}$$

Hence, we can pin down the mean and the variance of T_i from moment conditions (18) and (24):

$$E(T_i) = m_{F_1} \tag{25}$$

$$var(T_i) = \frac{m_{F_2} - m_{F_1}}{m_{Z_2} - m_{Z_1}} c_{F_1,Z_1} \tag{26}$$

We next note that we can re-write the expected value of T_i, conditional on survival as:

$$\begin{aligned} E(T_i|S) &= \frac{E\big[T_i(1-T_i)\big]}{1-E(T_i)} \\ &= \frac{E(T_i) - E(T_i^2)}{1-E(T_i)} \\ &= \frac{E(T_i)(1-E(T_i)) - var(T_i)}{1-E(T_i)} \end{aligned} \tag{27}$$

Substituting this into the moment condition for m_{F_2}, we get:

$$m_{F_2} = (1-\theta)\frac{E(T_i)(1-E(T_i)) - var(T_i)}{1-E(T_i)} \tag{28}$$

Rearranging and using equation (25), we get:

$$\begin{aligned} \theta &= 1 - \frac{m_{F_2}(1-m_{F_1})}{m_{F_1}(1-m_{F_1}) - var(T_i)} \\ &= 1 - \frac{m_{F_2}(1-m_{F_1})}{m_{F_1}(1-m_{F_1}) - \frac{m_{F_2}-m_{F_1}}{m_{Z_2}-m_{Z_1}} c_{F_1,Z_1}} \\ &= 1 - \frac{(m_{Z_2}-m_{Z_1})(m_{F_2}(1-m_{F_1}))}{m_{F_1}(1-m_{F_1}) - (m_{F_2}-m_{F_1})c_{F_1,Z_1}} \end{aligned} \tag{29}$$

Finally, given b_1, we can solve for $var(\varepsilon)$ by using the moment condition for $s^2_{Z_1}$:

$$var(\varepsilon) = s^2_{Z_1} - \frac{m_{Z_2} - m_{Z_1}}{m_{F_2} - m_{F_1}} c_{F_1,Z_1} \tag{30}$$

Since $var(\varepsilon)$ is increasing in σ_ε, the equation implies a value for σ_ε.

In conclusion, equations 22, 23, 25, 26, 29 and 30 solve parameters b_0, b_1, θ and moments $E(T_i)$, $Var(T_i)$ and $var(\varepsilon)$ for *any* distribution of these variables as function of moments that we observe in the data (m_{Z_1}, m_{Z_2}, m_{F_1}, m_{F_2}, c_{F_1,Z_1} and $s^2_{Z_1}$). The model with $\sigma_\tau = 0$ and $\hat{\theta} = \theta$ is thus identified.

$\square$

D.1.2 Identification of σ_τ

Our conjecture is that in a two-period version of the statistical model with classical measurement error, where $\hat{\theta} = \theta$ and $G(T_i)$ follows a two-parameter distribution, the parameters b_0, b_1, θ, and σ_τ as well as the mean and the variance of the persistent component of job finding rates, $E(T_i)$ and $var(T_i)$, and the variance of the elicitation error, $var(\varepsilon)$, are identified by the moment conditions for: (1) the means of the elicitations in period 1 and 2, m_{Z_1} and m_{Z_2}, (2) the means of the job finding rates in period 1 and 2, m_{F_1} and m_{F_2}, (3) the covariance of job finding and elicitations in period 1, c_{F_1,Z_1}, (4) the covariance of job finding in period 2 and elicitations in period 1, c_{F_2,Z_1}, and (5) the variance of elicitations in period 1, $s^2_{Z_1}$.

We again consider a model with only two periods, period 1 and 2. In this case, we can write down the moment conditions for the moments mentioned in the proposition above as:

$$
\begin{aligned}
m_{Z_1} &= b_0 + b_1 E(T_i + \tau_{i1}) && (31)\\
m_{Z_2} &= b_0 + b_1(1-\theta)E(T_i + \tau_{i2}|S) && (32)\\
m_{F_1} &= E(T_i + \tau_{i1}) && (33)\\
m_{F_2} &= (1-\theta)E(T_i + \tau_{i2}|S) && (34)\\
c_{F_1,Z_1} &= cov(F_1, b_1(T_i + \tau_{i1})) && (35)\\
c_{F_2,Z_1} &= cov(F_2, b_1(T_i + \tau_{i1})) && (36)\\
s^2_{Z_1} &= b_1^2 var(T_i + \tau_{i1}) + \sigma^2_\varepsilon && (37)
\end{aligned}
$$

The first two moments again directly pin down b_0 and b_1:

$$
\begin{aligned}
b_1 &= \frac{m_{Z_2} - m_{Z_1}}{m_{F_2} - m_{F_1}} && (38)\\
b_0 &= m_{Z_1} - \frac{m_{Z_2} - m_{Z_1}}{m_{F_2} - m_{F_1}} m_{F_1} && (39)
\end{aligned}
$$

We can again re-write the conditional expectation, now of $T_i + \tau_{i1}$, as:

$$
\begin{aligned}
E(T_i + \tau_{i1}|S) &= \frac{E\big[(T_i + \tau_{i1})(1 - T_i - \tau_{i1})\big]}{1 - E(T_i + \tau_{i1})}\\
&= \frac{E(T_i) - E(T_i^2) - E(\tau_{i1}^2)}{1 - E(T_i)}\\
&= \frac{E(T_i)(1 - E(T_i)) - var(T_i) - var(\tau_{i1})}{1 - E(T_i)} && (40)
\end{aligned}
$$

because $E(\tau_{i1}) = E(T_i\tau_{i1}) = 0$. Similarly, we obtain

$$
E(T_i + \tau_{i2}|S) = \frac{E(T_i)(1 - E(T_i)) - var(T_i)}{1 - E(T_i)} \quad (41)
$$

because $E(\tau_{i1}) = E(T_i\tau_{i2}) = E(T_i\tau_{i1}) = E(\tau_{i1}\tau_{i2}) = 0$. Hence, we can re-write:

$$\begin{aligned}
c_{F_1,Z_1} &= cov(F_1, b_1(T_i + \tau_{i1})) \\
&= b_1[E(F_1(T_i + \tau_{i1})) - E(F_1)E(T_i + \tau_{i1})] \\
&= b_1[E(E(F_1(T_i + \tau_{i1})|T_i, \tau_{i1})) - E(T_i + \tau_{i1})E(T_i + \tau_{i1})] \\
&= b_1[E(E((T_i + \tau_{i1})(T_i + \tau_{i1})|T_i, \tau_{i1})) - E(T_i + \tau_{i1})E(T_i + \tau_{i1})] \\
&= b_1[E((T_i + \tau_{i1})^2) - E(T_i + \tau_{i1})E(T_i + \tau_{i1})] \\
&= b_1[E((T_i^2 + 2T_i\tau_{i1} + \tau_{i1}^2) - E(T_i)E(T_i)] \\
&= b_1[E((T_i^2) + E(\tau_{i1}^2) - E(T_i)E(T_i)] \\
&= b_1[var(T_i) + var(\tau_{i1})] \qquad (42)
\end{aligned}$$

because $E(T_i\tau_{i1}) = 0$. Similarly, we obtain:

$$\begin{aligned}
c_{F_2,Z_1} &= cov(F_2, b_1(T_i + \tau_{i1})|S) \\
&= b_1[E(F_2(T_i + \tau_{i1})|S) - E(F_2|S)E(T_i + \tau_{i1}|S)] \\
&= b_1[E(E(F_2(T_i + \tau_{i1})|T_i, \tau_{i1})|S) - (1-\theta)E(T_i + \tau_{i2}|S)E(T_i + \tau_{i1}|S)] \\
&= b_1[E((1-\theta)(T_i + \tau_{i2})(T_i + \tau_{i1})|S) - (1-\theta)E(T_i + \tau_{i2}|S)E(T_i + \tau_{i1}|S)] \\
&= b_1(1-\theta)[E((T_i + \tau_{i2})(T_i + \tau_{i1})|S) - E(T_i + \tau_{i2}|S)E(T_i + \tau_{i1}|S)] \\
&= b_1(1-\theta)\left[\frac{E(T_i^2) - E(T_i^3) - E(T_i\tau_{i1}^2)}{1 - E(T_i)} - \left(E(T_i) - \frac{var(T_i)}{1 - E(T_i)}\right)\left(E(T_i) - \frac{var(T_i) + var(\tau_{i1})}{1 - E(T_i)}\right)\right]
\end{aligned}$$

where the last equality uses the same steps as before to re-write the conditional expectation. Re-arranging terms and using $m_{F_1} = E(T_i)$, $m_{F_2} = (1-\theta)\left[m_{F_1} - \frac{var(T_i)}{1-m_{F_1}}\right]$ and $b_1 = \frac{m_{Z_2} - m_{Z_1}}{m_{F_2} - m_{F_1}}$, we get:

$$\begin{aligned}
c_{F_2,Z_1} &= b_1(1-\theta)\left[\frac{var(T_i) + m_{F_1}^2 - E(T_i^3) - E(T_i\tau_{i1}^2)}{1 - m_{F_1}}\right] - b_1 m_{F_2}\left(m_{F_1} - \frac{1}{b_1}\frac{c_{F_1,Z_1}}{1 - m_{F_1}}\right) \\
&= \frac{m_{Z_2} - m_{Z_1}}{m_{F_2} - m_{F_1}}\frac{m_{F_2}(1 - m_{F_1})}{m_{F_1}(1 - m_{F_1}) - var(T_i)}\left[\frac{var(T_i) + m_{F_1}^2 - E(T_i^3) - E(T_i\tau_{i1}^2)}{1 - m_{F_1}}\right] \\
&\quad - \frac{m_{Z_2} - m_{Z_1}}{m_{F_2} - m_{F_1}} m_{F_2} m_{F_1} + m_{F_2}\frac{c_{F_1,Z_1}}{1 - m_{F_1}} \\
&= \frac{m_{Z_2} - m_{Z_1}}{m_{F_2} - m_{F_1}}\frac{m_{F_2}(1 - m_{F_1})}{m_{F_1}(1 - m_{F_1}) - var(T_i)}\left[\frac{var(T_i) + m_{F_1}^2 - E(T_i^3) - E(T_i var(\tau_{i1}|T_i))}{1 - m_{F_1}}\right] \\
&\quad - \frac{m_{Z_2} - m_{Z_1}}{m_{F_2} - m_{F_1}} m_{F_2} m_{F_1} + m_{F_2}\frac{c_{F_1,Z_1}}{1 - m_{F_1}}
\end{aligned}$$

Using equation (42) to get $var(T_i) = \frac{c_{F_1,Z_1}}{b_1} - var(\tau_{i1})$, we can rearrange the equation above, to get:

$$\begin{aligned} c_{F_2,Z_1} &= \frac{m_{Z_2}-m_{Z_1}}{m_{F_2}-m_{F_1}} \frac{m_{F_2}(1-m_{F_1})}{m_{F_1}(1-m_{F_1}) - \frac{m_{F_2}-m_{F_1}}{m_{Z_2}-m_{Z_1}} c_{F_1,Z_1} + var(\tau_{i1})} \\ &\left[\frac{\frac{m_{F_2}-m_{F_1}}{m_{Z_2}-m_{Z_1}} c_{F_1,Z_1} - var(\tau_{i1}) + m_{F_1}^2 - E(T_i^3) - E(T_i var(\tau_{i1}|T_i))}{1-m_{F_1}} \right] \\ &- \frac{m_{Z_2}-m_{Z_1}}{m_{F_2}-m_{F_1}} m_{F_2} m_{F_1} + m_{F_2} \frac{c_{F_1,Z_1}}{1-m_{F_1}} \end{aligned}$$

For two-parameter distributions of T_i where $E(T_i^3)$ is either implicitly or explicitly defined by the first two moments of the distribution, we can define a function $h(.,.)$, such that $E(T_i^3) = h(E(T_i), var(T_i))$, and thus:

$$\begin{aligned} c_{F_2,Z_1} &= \frac{m_{Z_2}-m_{Z_1}}{m_{F_2}-m_{F_1}} \frac{m_{F_2}(1-m_{F_1})}{m_{F_1}(1-m_{F_1}) - \frac{m_{F_2}-m_{F_1}}{m_{Z_2}-m_{Z_1}} c_{F_1,Z_1} + var(\tau_{i1})} \\ &\left[\frac{\frac{m_{F_2}-m_{F_1}}{m_{Z_2}-m_{Z_1}} c_{F_1,Z_1} - var(\tau_{i1}) + m_{F_1}^2 - h(m_{F_1}, \frac{m_{F_2}-m_{F_1}}{m_{Z_2}-m_{Z_1}} c_{F_1,Z_1} - var(\tau_{i1})) - E(T_i var(\tau_{i1}|T_i))}{1-m_{F_1}} \right] \\ &- \frac{m_{Z_2}-m_{Z_1}}{m_{F_2}-m_{F_1}} m_{F_2} m_{F_1} + m_{F_2} \frac{c_{F_1,Z_1}}{1-m_{F_1}} \end{aligned} \quad (43)$$

While it is not possible to solve explicitly for σ_τ, we note that for $h_2 \leq 0$ and assuming that the term $E(T_i var(\tau_{i1}|T_i))$ is negligible, the right-hand side of the equation (43) above depends negatively on σ_τ, and thus a solution for σ_τ exists.[52] A solution also exists for $h_2 \leq \tilde{h}$, where $\tilde{h}$ is some positive number, as long as $\tilde{h}$ is smaller than some upper bound $\bar{h}$.

Having solved for $var(\tau_{i1})$, when a solution to equation (43) exists, we can then find a solution for the mean and variance of T_i:

$$E(T_i) = m_{F_1} \quad (44)$$
$$var(T_i) = \frac{m_{F_2}-m_{F_1}}{m_{Z_2}-m_{Z_1}} c_{F_1,Z_1} - var(\tau_{i1}) \quad (45)$$

Rearranging and using equation (34), we also get:

$$\theta = 1 - \frac{m_{F_2}(1-m_{F_1})}{m_{F_1}(1-m_{F_1}) - \frac{m_{F_2}-m_{F_1}}{m_{Z_2}-m_{Z_1}} c_{F_1,Z_1} + var(\tau_{i1})} \quad (46)$$

As before, given b_1, we can also solve for $var(\varepsilon)$ by using the moment condition for $s_{Z_1}^2$:

$$var(\varepsilon) = s_{Z_1}^2 - \frac{m_{Z_2}-m_{Z_1}}{m_{F_2}-m_{F_1}} c_{F_1,Z_1} \quad (47)$$

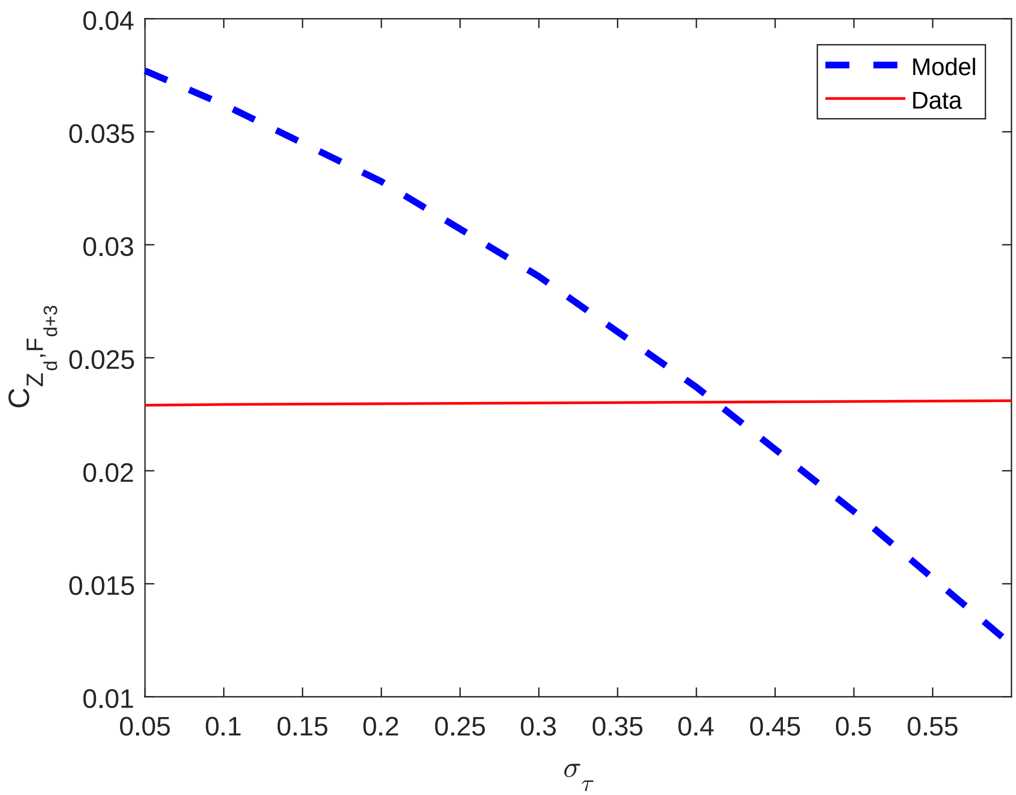
In conclusion, if a solution exists to equation (43), implicitly defining σ_τ, we can solve for parameters b_0, b_1, σ_ε, and θ as well as the mean and variance of the persistent component of job finding rates, $E(T_i)$

[52]Note σ_τ is monotonically increasing in but not equal to $var(\tau_{i1})$, because of the boundary conditions.

and $var(T_i)$, as a function of the moments m_{Z_1}, m_{Z_2}, m_{F_1}, m_{F_2}, c_{F_1,Z_1}, c_{F_2,Z_1}, $s^2_{Z_1}$, as shown in equations 38, 39, 44, 45, 46 and 47.

To provide further evidence on identification of the parameter σ_τ, we now proceed by showing that in the context of our estimated model (i.e., with more than two periods), there is a monotone mapping between the parameter σ_τ and the moment $C_{Z_d,F_{d+3}}$. More precisely, we estimate a sub-model of the baseline version of our statistical model for different levels of σ_τ, by targeting all of the same moments *except* $C_{Z_d,F_{d+3}}$. Figure D3 shows that there is a monotone relationship between the level of σ_τ and the covariance of elicitations and the 3-month forward job finding rates in this estimated sub-model, which shows that our parameter σ_τ is identified by the moment $C_{Z_d,F_{d+3}}$ in the full (baseline) model.

Figure D3: The relationship between σ_τ and the moment $C_{Z_d,F_{d+3}}$ in the estimated sub-model



D.1.3 Identification of $\hat{\theta}$

Our conjecture is that in a two-period version of the statistical model with classical measurement error, where $\sigma_\tau = 0$ and $G(T_i)$ follows a two-parameter distribution, the parameters b_0, b_1, θ, $\hat{\theta}$ as well as the mean and the variance of the persistent component of job finding rates, $E(T_i)$ and $var(T_i)$, and the variance of the elicitation error, $var(\varepsilon)$, are identified by the moment conditions for: (1) the means of the elicitations in period 1 and 2, m_{Z_1} and m_{Z_2}, (2) the means of the job finding rates in period 1 and 2, m_{F_1} and m_{F_2}, (3) the covariance of job finding and elicitations in periods 1 and 2, c_{F_1,Z_1} and c_{F_2,Z_2},and (4) the variance of elicitations in period 1, $s^2_{Z_1}$.

We assume that there are only two periods, and that $\sigma_\tau = 0$. In this case, we can write down the moment conditions for the moments mentioned in the proposition above as:

$$m_{Z_1} = b_0 + b_1 E(T_i) \tag{48}$$
$$m_{Z_2} = b_0 + b_1(1-\hat{\theta})E(T_i|S) \tag{49}$$
$$m_{F_1} = E(T_i) \tag{50}$$
$$m_{F_2} = (1-\theta)E(T_i|S) \tag{51}$$
$$c_{F_1,Z_1} = cov(F_1, b_1 T_i) \tag{52}$$
$$c_{F_2,Z_2} = cov(F_2, b_1 T_i|S) \tag{53}$$
$$s^2_{Z_1} = b_1^2 var(T_i) + var(\varepsilon) \tag{54}$$

We first note that one can express the additional moment condition (53) as follows:

$$\begin{aligned}
c_{F_2,Z_2} &= cov(F_2, b_1(1-\hat{\theta})T_i|S) \\
&= b_1(1-\hat{\theta})[E(F_2 T_i|S) - E(F_2|S)E(T_i|S)] \\
&= b_1(1-\hat{\theta})[E(E(F_2 T_i|T_i)|S) - (1-\theta)E(T_i|S)^2] \\
&= b_1(1-\hat{\theta})(1-\theta)[E(T_i^2|S) - E(T_i|S)^2] \\
&= b_1(1-\hat{\theta})(1-\theta)var(T_i|S)
\end{aligned}$$

Re-arranging the moment conditions 48-54 and using equations (24) and (27), we thus get:

$$m_{Z_1} = b_0 + b_1 m_{F_1} \tag{55}$$
$$m_{Z_2} = b_0 + b_1 \frac{1-\hat{\theta}}{1-\theta} m_{F_2} \tag{56}$$
$$m_{F_1} = E(T_i) \tag{57}$$
$$m_{F_2} = (1-\theta)\left[m_{F_1} - \frac{var(T_i)}{1-m_{F_1}}\right] \tag{58}$$
$$c_{F_1,Z_1} = b_1 var(T_i) \tag{59}$$
$$c_{F_2,Z_2} = b_1(1-\hat{\theta})(1-\theta)var(T_i|S) \tag{60}$$
$$s^2_{Z_1} = b_1^2 var(T_i) + var(\varepsilon) \tag{61}$$

The mean of the job finding rate, $E(T_i)$, is directly identified by moment condition in equation (57). We then take the difference of the first two moment conditions:

$$m_{Z_1} - m_{Z_2} = b_1\big(m_{F_1} - \frac{1-\hat{\theta}}{1-\theta} m_{F_2}\big)$$

which gives b_1 as a function of moments and $\hat{\theta}$ and $var(T_i)$:

$$\begin{aligned}
b_1 &= \frac{m_{Z_1} - m_{Z_2}}{m_{F_1} - \frac{1-\hat{\theta}}{1-\theta} m_{F_2}} \\
&= \frac{m_{Z_1} - m_{Z_2}}{m_{F_1} - (1-\hat{\theta})\left[m_{F_1} - \frac{var(T_i)}{1-m_{F_1}}\right]} \\
&= \frac{(1-m_{F_1})(m_{Z_1} - m_{Z_2})}{\hat{\theta} m_{F_1}(1-m_{F_1}) + (1-\hat{\theta}) var(T_i)}
\end{aligned} \tag{62}$$

We next rearrange the moment condition for the covariance in period 1 by plugging in the expression for b_1:

$$c_{F_1,Z_1} = \frac{(1-m_{F_1})(m_{Z_1} - m_{Z_2})}{\hat{\theta} m_{F_1}(1-m_{F_1}) + (1-\hat{\theta}) var(T_i)} var(T_i) \tag{63}$$

$$\tag{64}$$

Rearranging this further gives:

$$\hat{\theta} = \frac{(1-m_{F_1})(m_{Z_1} - m_{Z_2}) - c_{F_1,Z_1}}{(1-m_{F_1})m_{F_1} - var(T_i)} \frac{var(T_i)}{c_{F_1,Z_1}} \tag{65}$$

which shows that $\hat{\theta}$ can be solved as a function of $var(T_i)$ and targeted moments in the data. Note also that using the fact that $m_{dZ} = m_{Z_2} - m_{Z_1} + \frac{c_{F_1,Z_1}}{1-m_{F_2}}$, we can express the equation above as:

$$\hat{\theta} = -m_{dZ} \frac{(1-m_{F_1})}{(1-m_{F_1})m_{F_1} - var(T_i)} \frac{var(T_i)}{c_{F_1,Z_1}} \tag{66}$$

which shows that the sign of $\hat{\theta}$ is strictly related to the longitudinal change in elicitations (the denominator can be shown to be always positive). Note this is no longer necessarily true with transitory shocks to job finding, because of mean reversion (more precisely, the sample of survivors is on average experiencing a positive change in transitory shocks in period 2, because those with a high transitory shock in period 1 are less likely to remain unemployed).

Let us now turn to the covariance in period 2, or rather the ratio of the covariance in period 2 and period 1, and plug in expressions for b_1, θ and $\hat{\theta}$:

$$\begin{aligned}
\frac{c_{F_2,Z_2}}{c_{F_1,Z_1}} &= (1-\theta)(1-\hat{\theta}) \frac{var(T_i|S)}{var(T_i)} \\
&= \frac{m_{F_2}(1-m_{F_1})}{m_{F_1}(1-m_{F_1}) - var(T_i))} \left(1 - \frac{(1-m_{F_1})(m_{Z_1} - m_{Z_2}) - c_{F_1,Z_1}}{(1-m_{F_1})m_{F_1} - var(T_i)} \frac{var(T_i)}{c_{F_1,Z_1}}\right) \frac{var(T_i|S)}{var(T_i)} \\
&= \frac{m_{F_2}(1-m_{F_1})^2 (m_{F_1} c_{F_1,Z_1} - (m_{Z_1} - m_{Z_2}) var(T_i))}{c_{F_1,Z_1}(m_{F_1}(1-m_{F_1}) - var(T_i))^2} \frac{var(T_i|S)}{var(T_i)}
\end{aligned} \tag{67}$$

One can show that $var(T_i|S)$ is a function of the first, second and third moment of the distribution of T_i. Therefore, for any two parameter distribution of T_i, equation (67) implicitly defines the second parameter of the distribution (assuming a solution exists), and thus gives the variance of the distribution. The first parameter of the distribution is obviously implied by the moment condition for m_{F_1}.

Given $var(T_i)$, one can then use equation (65) to solve for $\hat{\theta}$. Given $var(T_i)$ and $\hat{\theta}$, one can then use equation (62) to solve for b_1. And using the moment condition for m_{Z_1}, one can then solve for b_0:

$$b_0 = m_{Z_1} - b_1 m_{F_1} \tag{68}$$

Re-arranging the moment condition for m_{F_2}, we get:

$$\theta = 1 - \frac{m_{F_2}(1 - m_{F_1})}{m_{F_1}(1 - m_{F_1}) - var(T_i)} \tag{69}$$

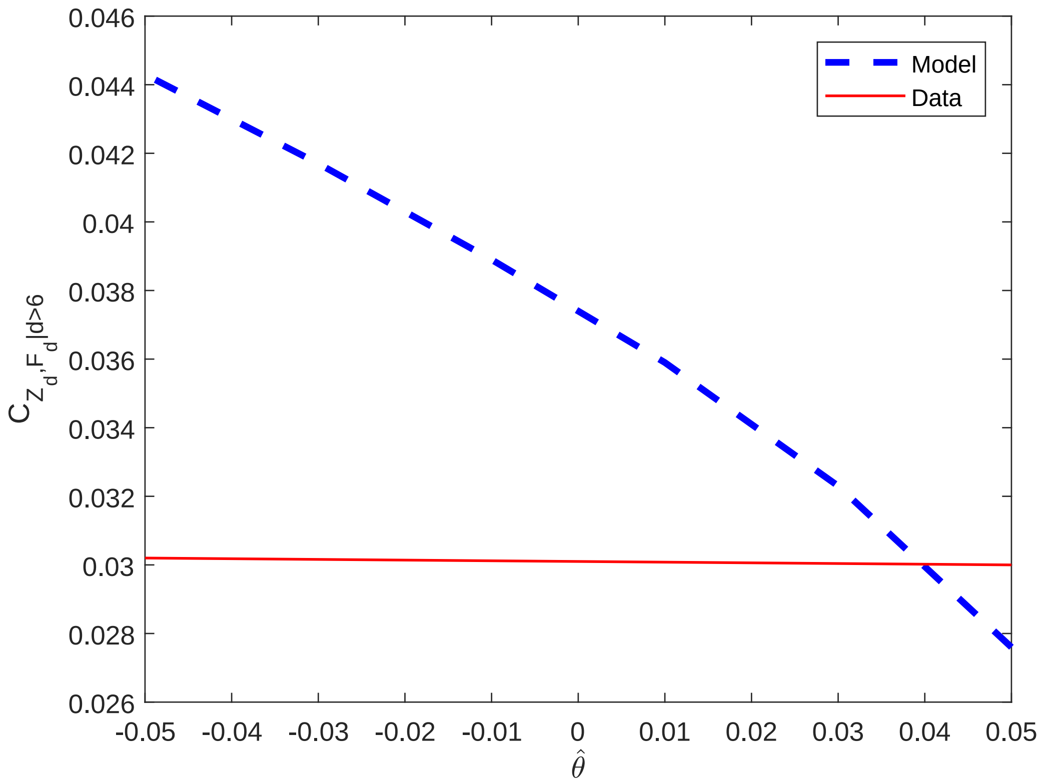
which gives the value of θ if we use the estimate of $var(T_i)$ from above. Given b_1, we can solve for σ_ε by using the moment condition for $s^2_{Z_1}$:

$$var(\varepsilon) = s^2_{Z_1} - b_1 c_{F_1,Z_1} \tag{70}$$

In conclusion, if a solution exists to equation (67) with a two parameter distribution for T_i, we have solved for parameters b_0, b_1, σ_ε, θ, and $\hat{\theta}$ as well as the mean and variance of the persistent component of job finding rates, $E(T_i)$ and $var(T_i)$, as a function of the moments m_{Z_1}, m_{Z_2}, m_{F_1}, m_{F_2}, c_{F_1,Z_1}, c_{F_2,Z_2}, $s^2_{Z_1}$, as shown in equations 57, 62, 65, 67, 68, 69 and 70. The parameters of the model are therefore identified, *assuming* a solution exists to equation (67). While it seems intuitive that such a solution exists for simple two-parameter distributions, it is difficult to prove analytically given the non-linearities.

To provide evidence on the identification of the parameter $\hat{\theta}$, we proceed by showing that in the context of our estimated model (i.e., with more than two periods), there is a monotone mapping between $\hat{\theta}$ and the covariance in duration interval 7+, $C_{Z_d,F_d|d\geq 7}$. More precisely, we estimate a sub-model of the extended version of our statistical model in Column 8 in Table D2 for different levels of $\hat{\theta}$, targeting all the same moments *except* $C_{Z_d,F_d|d\geq 7}$. Figure D4 shows that there is a monotone relationship between the level of $\hat{\theta}$ and the covariance of elicitations and job finding rates at duration interval 7+ in this estimated sub-model, which shows that our parameter $\hat{\theta}$ is identified in the full (extended) model.

Figure D4: The relationship between $\hat{\theta}$ and the moment $C_{Z_d,F_d|d>6}$ in the estimated sub-model



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

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

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

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

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,

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

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

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

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

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

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

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

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,

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

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

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

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

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

and, then by iterating, we get

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

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

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

and thus

$$\begin{aligned}\frac{\frac{dR_d}{d\theta}}{\frac{dR_{d+1}}{d\theta}}\Bigg|_{\theta=0} &= \frac{\sum_{s=d-}^{\infty}(1-\lambda)^{s-d}s}{\sum_{s=d+1}^{\infty}(1-\lambda)^{s-d-1}s} = \frac{d + (1-\lambda)\sum_{s=d+1}^{\infty}(1-\lambda)^{s-d-1}s}{\sum_{s=d+1}^{\infty}(1-\lambda)^{s-d-1}s},\\ &= \frac{d + (1-\lambda)\big[\frac{d+1}{\lambda} + \frac{1-\lambda}{\lambda^2}\big]}{\frac{d+1}{\lambda} + \frac{1-\lambda}{\lambda^2}} < 1,\end{aligned}$$

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

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

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

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

E.4 Numerical Analysis

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

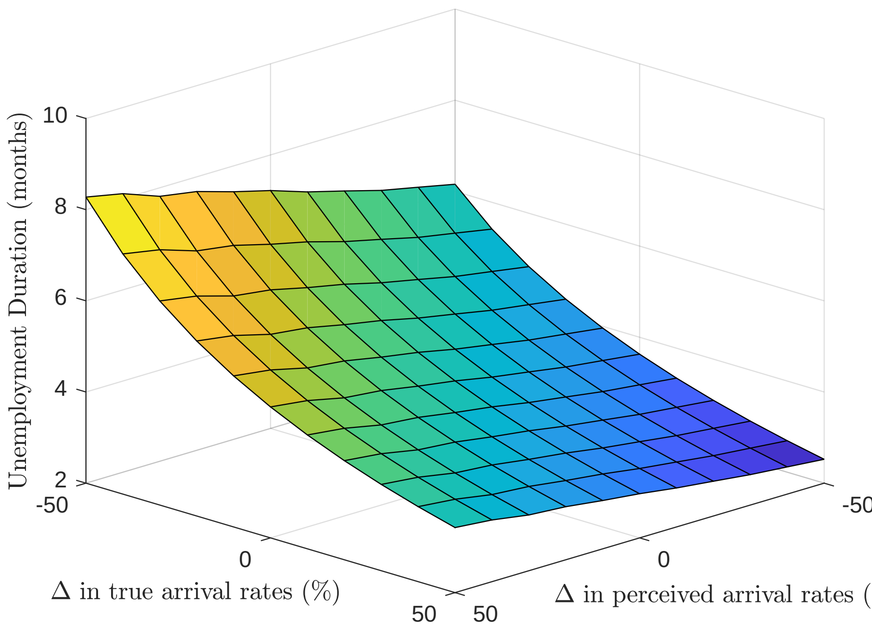
Moments	Data	Baseline Model	High Depreciation Model
Mean of 3-Month Job Finding Rates:			
... at 0-3 Months of Unemployment	0.623	0.622	0.613
... at 4-6 Months of Unemployment	0.435	0.436	0.455
... at 7 Months of Unemployment or more	0.260	0.259	0.244
Mean of 3-Month Elicitations:			
... at 0-3 Months of Unemployment	0.592	0.592	0.594
... at 4-6 Months of Unemployment	0.511	0.510	0.511
... at 7 Months of Unemployment or more	0.399	0.400	0.399
Acceptance Rate:	0.710	0.710	0.716
True Duration Dependence:			
... Baseline	0.991	0.982	-
... High Depreciation	0.650	-	0.654

Table E2: Calibrated Parameters

Parameters	Symbol	Baseline Model	High Depreciation Model
A. Set Parameters			
Median of wage offer distribution	μ_w	1	1
Std. dev. of logged wage offer distribution	σ_w	0.24	0.24
Exogeneous job loss probability	σ	0.02	0.02
Arrival rate when employed	λ^e	0.15	0.15
Discount rate	δ	0.004	0.004
Coefficient of relative risk aversion	γ	2	2
Longitudinal bias	B_θ	0	0
B. Estimated Parameters			
Uniform bias	B_0	-0.001	-0.068
Cross-sectional bias	B_1	0.81	0.93
Low-type arrival rate	λ_l	0.10	0.19
High-type arrival rate	λ_h	0.64	0.72
Share of high-types	φ	0.74	0.65
Depreciation in arrival rate	θ	1.1E-05	0.060
Unemployed consumption	b_u	0.51	0.52

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

A. Impact of Arrival Rates on Duration



B. Impact of Heterogeneity on LT Incidence

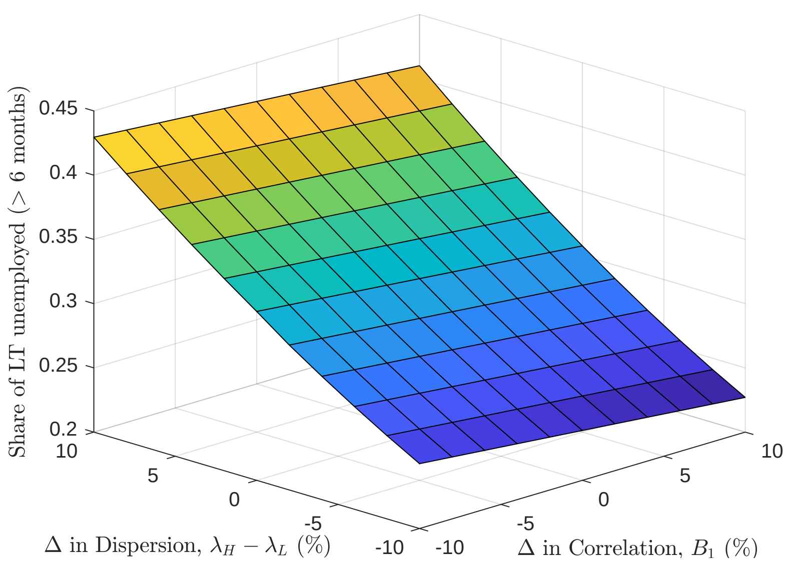
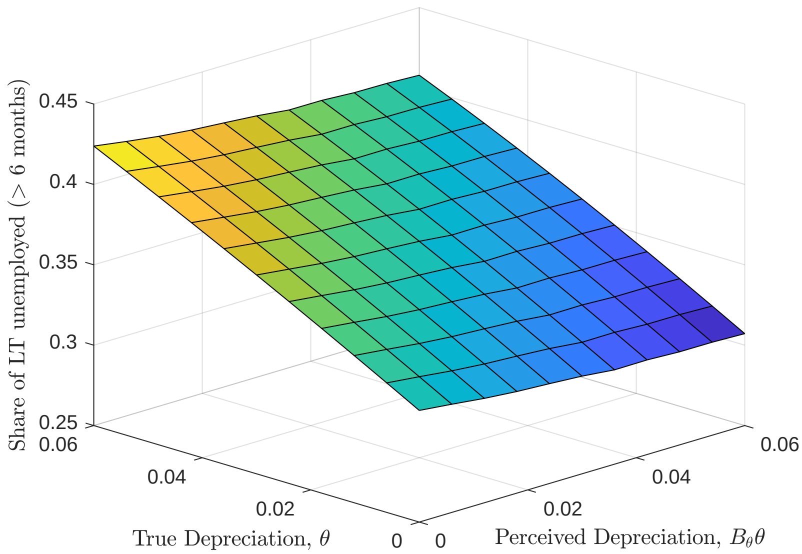


Figure E1: Comparative Statics: True vs. Perceived Changes in Arrival Rates (*continued)*

C. Impact of Depreciation on LT Incidence



Notes: Panel A plots the average unemployment duration as a function of actual and perceived arrival rates, changing them in the same way for all types relative to the baseline model. Panel B plots the share of long-term unemployment (i.e., the share of unemployed workers who are unemployed for longer than 6 months) as a function of the spread of true arrival rates (while preserving the mean arrival rate) and the correlation between the perceived and true arrival rates. Panel C plots the share of long-term unemployment as a function of the true and perceived depreciation rate. The output in the panels corresponds to the results in Propositions 1, 2 and 3 respectively.