Updating about Yourself by Learning about the Market:

The Dynamics of Beliefs and Expectations in Job Search[*]

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Abstract

This study demonstrates that job seekers update their perceived job-finding prospects by unemployment duration and by learning about aggregate unemployment. Using data from the Survey of Consumer Expectation, we find that job seekers perceive a decrease of approximately 20% in their subjective job-finding probability for each additional month of unemployment. However, job seekers perceive a higher job-finding probability when the aggregate unemployment rate is lower than they expected, and their expectation tends to be too low during an economic expansion. Finally, we develop a job search model that incorporates subjective beliefs with learning and updating to quantify the impact of perceived aggregate unemployment on subjective job search probability, which reveals an overreaction to news about aggregate conditions.

Keywords: expectation, job search, unemployment, dynamics

JEL: D83, E24, J64

1 Introduction

A key empirical finding in the job search literature is the strong negative correlation between observed job-finding probability and duration of unemployment (Kaitz, 1970). While the literature has debated the exact extent to which this is truly due to a decline in the job finding probability for a given individual or simply a result of selection, there is clear evidence that the environment for a given individual is changing over time: for example, randomized experiments that change only the length of unemployment on a job application show that longer unemployment leads to less employer callbacks.[1] (Kroft et al., 2013; Farber et al., 2016). Models have long incorporated the idea that job seekers as well as the employers or the social planner learn such negative news over time, and have incorporated this in the design of optimal unemployment benefits.[2] In these papers the beliefs of job seekers about their own future prospects are important, but despite being a long-standing topic of interest, relatively little is known about how unemployed job seekers themselves think their *job-finding probability* will evolve if they remain unemployed for longer.

Only very recently, a literature has emerged that focuses specifically on the role of beliefs in job search, utilizing the availability of survey evidence on beliefs. In their seminal work, Mueller et al. (2021) document a number of novel and important stylized facts using the Survey of Consumer Expectation (hereafter: SCE) collected by the Federal Reserve Bank of New York and the Survey of Unemployed Workers in New Jersey (known as the Krueger-Mueller Survey, hereafter: KM survey). A particularly striking finding is that unemployed job seekers perceive no change in their job-finding probability on average over their unemployment spell: controlling for individual fixed effects, the job-finding probability is constant over the unemployment duration. Furthermore, Mueller et al. (2021) find that there is no significant relationship between the national unemployment rate and unemployed job seekers' perceived job-finding probability. This evidence suggests that job seekers "do not respond to either new individual information (the length of an unemployment spell) or to new aggregate information (the state of the business cycle)" (Menzio, 2022, p. 2).[3]

In this paper, we revisit these insights. Using the exact same data selection as Mueller et al.

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[1]For example, Van den Berg and Van Ours (1996), Kroft et al. (2016) and Mueller et al. (2021) discuss the difference between selection effects and "true" duration dependence.

[2]Please refer to Vishwanath (1989), Acemoglu (1995), Shimer (2008) and Gonzalez and Shi (2010) for relevant models. Pavoni and Violante (2007), Pavoni (2009) and Wunsch (2013) are examples for the discussion of policy design.

[3]While we believe that this quote represents a more widely held interpretation of the recent evidence, we are aware that it is possible for job seekers to understand that their environment is changing with unemployment duration but to react by searching harder or by accepting worse jobs such as to leave their probability of becoming employed constant.

[(2021)](), we exploit the fact that participants in the SCE are simultaneously asked about their chance of accepting a new job over two different time horizons: within 3 months and withing 12 months. Using a simple model of beliefs based around geometric increases or decreases in the subjective job-finding probability over time, one can assign at any point in time a belief about the current job-finding probability and its expected future decline. Mapped to monthly frequency, the answers reveal on average a roughly 20% expected decline in job-finding probability, which is closely in line with the observed duration dependence, though there is substantial dispersion in these expectations.[4]

If job seekers truly expect their job-finding probability to decline substantially in the future when asked at a given point in time, this seems to contradict the earlier finding that job seekers do not report such a decline when asked the same question at a future point in time. One plausible explanation is that job seekers expect a decline at a given point in time but experience a positive shock that lifts expectations by the next time they are interviewed. If this is an aggregate shock that affects most job seekers, this could explain the observed pattern.

We explore this possibility by examining job seekers' beliefs about aggregate economic conditions, specifically the aggregate US unemployment rate (and, for robustness, the US stock market). Participants in the SCE are asked about the expected evolution of this rate over the next year as part of a different model of the survey that precedes questions about their current individual situation. We use an AR1 model for the perceived US unemployment rate. Since the question in the SCE only asks about expected increases or decreases in unemployment relative to today's unemployment rate, we interpret the data under the assumption that the contemporaneous unemployment rate is known, though we also consider alternatives for robustness.[5] The estimated perceived US unemployment projection for the future centers around 1, implying that job seekers, on average, expect a similar US unemployment rate in the future. However, due to the prolonged economic recovery during the entire sample period, the actual unemployment rate is continuously improving. Comparing the actual development with individuals' expectations indicates that job seekers are positively "surprised" by the improving aggregate.[6]

We study how job seekers update their beliefs by combining their perceived US unemployment

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[4]The duration dependence that we refer to here is the average job-finding probability of a group of job seekers with a same unemployment duration, without taking the individual heterogeneity into account.

[5]SCE elicits the perceived probability of the US unemployment rate being higher 12 months later.

[6]As a comparison, we show that professional forecasters more accurately anticipate the decreasing trend of US unemployment during the same sample period using data from the Survey of Professional Forecasters from the Federal Reserve Bank of Philadelphia.

dynamics with their perceived job-finding probability. To do so, we calculate the update about the unemployment rate for each participant at each period after their first interview. This update reflects the difference between the realized unemployment rate and the job seekers' pre-period expectation of this rate. We then examine the relationship between this update about the unemployment rate and the change in the individual's subjective job-finding probability, while controlling for individual, time, and duration fixed effects. The controls isolate our analysis from aggregate effects and rely only on variation at the individual level over time that deviates from some average duration effect. We find that job seekers' update of the US unemployment rate leads to a significant change in their perceived individual job-finding probability.[7] In other words, unexpectedly improving aggregate unemployment rates increase job seekers' assessment of their employment prospects. As a reassuring side-remark, we do not observe such effects for aggregate variables that have no direct connections to the job market, such as the US stock market.

We can use the magnitude calculated in the previous analysis to estimate how much the aggregate "surprise" each period would lift up the reported job-finding probability. It's important to note that the aggregate effect was removed from the previous analysis through the use of controls. Despite job seekers expecting roughly a 20% decline in their job-finding probabilty by next month, the aggregate shock generates nearly a 17% increase in their job-finding expectations a month later, thereby keeping the overall report roughly constant. This is demonstrated in Table 5.1 and illustrated in Figure 3 in the main body. These findings suggest a remarkable consistency between the two previous findings regarding job seekers' individual job-finding probability assessments: that they expect a decline but report relatively similar numbers over time. This inconsistency arises because job seekers are more pessimistic about the unemployment rate during this time horizon than is warranted by the aggregate trend (or by the assessment of professional forecasters, who are in line with the aggregate trend). As a result, they repeatedly experience positive surprises on average about their economic environment, which they use to update about their own job finding chances.

We conducted two robustness exercises to further validate our insights. First, our finding that job seekers anticipate a decline in their individual job-finding probability over time is based on the SCE and two questions that inquire about the probability of finding a job at different horizons.The KM survey has two rather different questions: the probability of finding a job and the expected

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[7]Using a similar procedure, we show that beliefs about the US stock market dynamics have no effect on the residual changes of perceived job-finding probability.

duration of finding a job. Using the same geometric model for beliefs, the responses to these two questions reveal an expected decline in job-finding probability over time that is remarkably similar to that obtained from the SCE. Unfortunately, the KM survey does not ask about beliefs regarding aggregate conditions. Second, during times when job seekers are not positively surprised about their job prospects, we should observe a decline in their subjective job-finding probability over time.[8] We take advantage of the fact that the SCE now has more data, including one episode in which aggregate market conditions declined: the Covid-Recession. Although observations during this period are limited, they do suggest that job seekers reduced their beliefs over time, in a pattern that was exceedingly rare during the period studied by Mueller et al. (2021).

Finally, we adopt a more structural approach and develop a belief model of job search to investigate potential mechanisms that could explain the aforementioned empirical pattern. We begin with a model that combines subjective duration dependence with a standard matching function frequently used in macroeconomics. We show that in this straightforward setting, the model can produce a job-finding probability trajectory that aligns with subjective duration dependence but contradicts the empirical findings on a flat job-finding probability within the unemployment spell. This is because, in a standard model, job seekers must respond to unemployment news far more than is appropriate: while there may be fluctuations in the unemployment rate, during the SCE sample period, these fluctuations are relatively minor on a monthly basis and hence cannot elicit substantial shifts in beliefs about individual job-finding probability.

Then, we extend the model to enable job seekers to overweight their recent update. In particular, we distinguish between the general economy and the job seekers own "island". A job seeker has to form an expectation of her "individual island's unemployment rate", which is the what matters for her job-finding probability. Moreover, job seekers perceived "individual island unemployment rate" is affected by how much they are "surprised" by the national unemployment rate realization compared to their previous forecasts.[9] We estimate the model using data from the SCE and show that the model can fit empirical patterns well. Notably, estimates show that job seekers perceive a lower "individual unemployment rate" if they are positively "surprised" by the national unemployment rate realization compared to their previous forecasts. We show these features in a naive

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[8]In subsection 5.5.2, we demonstrate that job seekers who are not surprised by the US unemployment rate do experience a decrease in perceived job-finding probability within-spell using our main SCE sample.

[9]The gist of this setup is similar to models of diagnostic expectations that have recently been proposed in the finance literature to capture over-weighing of recent information, but such models tend to harder to integrate into the search structure, which is the reason why we build a similar logic into the well-known "island" metaphor often used in this area.(Bordalo et al., 2018, 2019, 2020)

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calibration that borrows the geometric decline for the analysis of beliefs while strictly speaking the model generates period-specific declines, and then follow up with a more serious calibration that carefully accounts for the correct micro-founded patterns within the model.

We simulate the model and show that the model generated job-finding probability is very responsive to the changes of aggregate unemployment rate, primarily driven by the fact that job seekers over-react to the recent "surprise" of the unemployment rate in our model. However, we show that it is not easy to detect such dependence in the limited sample of job seekers with statistically significant precision when we augment the model with calibrated individual heterogeneity. The result echoes the findings discussed in Mueller and Spinnewijn (2021), Mueller et al. (2021) and Menzio (2022).

Finally, we illustrate how the detected belief pattern can affect the amount of effort exerted in job search by augmenting the job search belief model with an additional parameter representing search effort. We discover that job seekers, when perceiving lower job-finding prospects for the future, are motivated to exert more effort in the present. A quantitative evaluation reveals that the amplification of search effort induced by perceiving lower job-finding prospects is equivalent to a 20% decrease in future unemployment benefits, thereby demonstrating that the effect size of beliefs on search effort is substantial.

Overall, our findings suggest that job seekers expect a decline in their job-finding probability over time, and they are responsive to the aggregate information around them. This reconciles job seekers' pessimistic answers to multiple questions about job-finding in the future with time-series observations where such a decline is not present. Our results also show that job seekers appear to be surprised by aggregate conditions precisely because their beliefs about aggregates are not aligned with the trend or with the beliefs of professional forecasters, and they seem to update too strongly on recent surprises. After reviewing the related literature (Section 2) and data sources (Section 3), we present the main empirical methodology and resulting evidence in Sections 4 and 5. We then introduce a structural model and its calibration/estimation in Sections 6. We illustrate the implications for job search in Section 7 before our conclusion in Section 8.

2   Related Literature

The paper makes a significant contribution to multiple strands of literature. First, it adds to the growing body of research that investigates biased beliefs and learning in the job search process

(Spinnewijn (2015); Arni (2015); Conlon et al. (2018); Mueller et al. (2021); Mueller and Spinnewijn (2021); Balleer et al. (2021b); Braun and Figueiredo (2022)). For instance, Conlon et al. (2018) uses survey data from SCE to examine workers' wage expectations and how they react to wage offers. They find that higher-than-expected salary offers cause workers' to update their beliefs about future wages upward (and vice versa) which is inconsistent with Bayesian updating. They further consider the implications of the imperfect information through the lens of a job search model. In addition, some studies also consider the aggregate implications of biased beliefs and learning (Potter, 2021; Balleer et al., 2021a; Menzio, 2022). We build on these findings by presenting new evidence about the dynamic adjustment of beliefs in job search and highlighting the critical role of aggregate market beliefs in determining individual perceived job-finding probability.

Mueller et al. (2021) documents that elicited job-finding probabilities are flat over the unemployment spell at the individual level using survey data from both KM survey and SCE. They further use the predictability of beliefs to study the true duration dependence in job-finding, which they assess as small after controlling for heterogeneity of beliefs. Our paper builds on the important findings from their paper and replicates several of their findings, such as the flat within-spell perceived job-finding probability. Different from their paper, we focus explicitly on the dynamics of perceived job-finding probability and show that it is significantly affected by job seekers' perceptions about the dynamics of aggregate unemployment rate. Results indicate that an explanation for the flat perceived job-finding probability is job seekers' over-reaction to the aggregate unemployment conditions rather than an absence of perceived duration dependence. We find that job seekers seem to think that there is duration dependence, and closely in line with the duration dependence that is observable when not controlling for heterogeneity of hard-to-observe objects such as beliefs. So job seekers may also overreact to unemployment duration.

The paper adds to the literature on behavioral frictions that distort the job search process. Previous research has examined various behavioral biases, such as present bias (DellaVigna and Paserman, 2005), reference dependence (DellaVigna et al., 2017), and locus-of-control (Caliendo et al., 2015; Spinnewijn, 2015). We identify belief about the aggregate unemployment condition as a potentially new behavioral friction that distorts the dynamics of beliefs on individual job-finding probability.

The model we built deviates from the rational expectation framework, which adds to the potential mechanisms that explains the over-reaction in beliefs. Our paper is related to the literature in

behavioral finance that studies expectation formations.(e.g., Coibion and Gorodnichenko (2015))
While our model has a similar flavor to the Diagnostic Expectation (DE) model, the model structure is different because of the information provided by the survey questions and job search as a research context (Bordalo et al., 2018, 2019, 2020).[10]

3   Data

The main dataset for the empirical analysis comes from the Survey of Consumer Expectations (SCE) run by the Federal Reserve Bank of New York. SCE surveys a national representative sample of about 1,300 household heads in the United States.[11] The survey elicits expectations about a variety of economic variables, including inflation and labor market conditions. The sample is a rotating panel where each individual is surveyed every month for up to 12 months (see Armantier et al. (2017), Conlon et al. (2018) and Mueller et al. (2021) for additional details). We complement the SCE Labor Market Survey (SCE LMS) in some of our analysis, which is a rotating module of the Survey of Consumer Expectations (SCE), conducted every four months. SCE LMS surveys a subset of respondents from the main SCE survey to obtain their perceived probability of finding a job within four months.

The SCE sample we use is taken from Mueller et al. (2021), which spans from December 2012 to June 2019. This allows for clear replicability and comparability with their study. During the sample period, 948 job seekers were surveyed while unemployed. Additionally, we download the public version of the SCE monthly data stretching from Jun 2013 to December 2019 directly from the Federal Reserve Bank of New York's website and find that the empirical patterns are similar using both versions of the SCE.[12] For robustness analysis, we further include SCE sample during the Covid-19 pandemic downloaded directly from the New Yord Fed.

SCE elicits unemployed job seekers' perceived job-finding probability by asking about the prob-

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[10]Other strands of literature that deviate from the rational expectation literature includes beauty contest style model with behavioral biases (Angeletos et al., 2021; Valente et al., 2022), biases to over-extrapolate the past (Gennaioli et al., 2016; Fuster et al., 2010), cognitive discounting and level-K thinking (Gabaix, 2020; García-Schmidt and Woodford, 2019; Farhi and Werning, 2019), are other expectation models that have been used extensively.

[11]Please refer to Mueller et al. (2021) for comparisons of some basic survey outcomes and demographics for the unemployed workers between the SCE and the Current Population Survey (CPS).

[12]The main SCE sample used is taken from Mueller et al. (2021), which spans from December 2012 to June 2019. This allows for clear replicability and comparability with their study. During the sample period, 948 job seekers were surveyed while unemployed. Additionally, we download the public version of the SCE monthly data directly from the Federal Reserve Bank of New York's website, which stretches from Jun 2013 to December 2019. The empirical patterns are similar using both versions of the SCE. We use the public version of the SCE whenever the analysis needs information from the SCE LMS.

ability that they will be offered a job that they would like to accept. This is asked over two time horizons: 3 months and 12 months. This feature allows us to separate their expectations over different time horizons. Additionally, SCE asks each respondent to report their perceived probability of the US unemployment rate being higher in twelve months, allowing us to study job seekers' beliefs about the aggregate market.[13]

Additionally, we use the Survey of Unemployed Workers in New Jersey collected by Alan Krueger and Andreas Mueller (KM survey). They surveyed around 6,000 unemployed job seekers (see the Appendix of Krueger et al. (2011) for details). In the KM survey, job seekers who received unemployment insurance in October 2009 were interviewed every week for 12 weeks until January 2010. The long-term unemployed were surveyed for an additional 12 weeks until April 2010. The KM survey elicits each job seeker's perceived job-finding probability and their expected unemployment duration, but has no information about how job seekers perceive aggregate unemployment conditions. Using the KM survey, we show that job seekers perceive a decreasing job-finding probability on average in the future.

To compare job seekers' perceived dynamics of the US unemployment condition, we download individual forecasts for the US unemployment rate from the Survey of Professional Forecasters (SPF hereafter) from the Federal Reserve Bank Philadelphia website. Professional forecasters give estimates for the quarterly average of the underlying monthly levels (seasonally adjusted, percentage points). We restrict the sample to 2012-2019 to align with our primary SCE sample.

4 Empirical Framework

The empirical framework we propose assumes that the individual's perceived job-finding probability and the US unemployment rate each follows a geometric increase or decline, possibly with an noise term that induces the well-known AR1 structure. This functional form is a commonly used to to model belief dynamics. It allows us to study data patterns empirically and visually.[14] For now, we assume that the perceived job-finding probability and the perceived dynamics of aggregate economic variables are independently formed. However, in later sections, we will structurally link them in a model.[15]

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[13]In fact, SCE also asks respondents' perceived probability of a higher US inflation rate (US stock market) in twelve months.

[14]Later in the paper, we build a richer model to explore the dynamics of beliefs in a more complex model structure.

[15]In the empirical sections, we provide evidence that the perceived dynamics of the US unemployment rate significantly affect perceived dynamics of job-finding probability. Guided by this empirical evidence, we build a quantitative model to further investigate how they interact.

4.1 Individual Job-finding Probability

Conditional on still being unemployed at the beginning of period t, we denote an individual i's true job-finding probability in month t as X_t^i, which is not observed by either individual i or researchers. At the beginning of month t, individual i forecasts $X_{t+\tau}^i$ as $F_t^i X_{t+\tau}^i$, where $\tau = 0$ captures the belief about the upcoming month. Individual i's belief about the probability of finding a job in k months is denoted as $FindJobk_t^i$, which is a cumulative object.

The SCE elicits the beliefs of unemployed job seekers about their job-finding probability for both three and twelve months. We can calculate the three and twelve-month job-finding probabilities ($FindJob3_t^i$ and $FindJob12_t^i$, respectively):

$$FindJob3_t^i = 1 - \prod_{\tau=0}^{2} \left(1 - F_t^i X_{t+\tau}^i\right), \quad FindJob12_t^i = 1 - \prod_{\tau=0}^{11} \left(1 - F_t^i X_{t+\tau}^i\right). \tag{4.1}$$

The answers to the questions then provide an insight whether the individual is more optimistic about the early periods of unemployment or the later periods of unemployment. As an easy diagnostic tool to understand this, we assume that the individual's perceived dynamics of job-finding ($\hat{X}_t^i$) follows a geometric increase or decline:

$$F_t^i \hat{X}_{t+1}^i = \hat{\beta}_{i,t}^x F_t^i \hat{X}_t^i, \quad F_t^i \hat{X}_{t+k}^i = \left(\hat{\beta}_{i,t}^x\right)^k F_t^i \hat{X}_t^i. \tag{4.2}$$

$\hat{\beta}_{i,t}^x$ represents the individual's perceived dynamics of job-finding probability for an additional month of unemployment. We assume that the perceived job-finding probability changes at a constant rate for a job seeker i in period t ($\hat{\beta}_{i,t}^x$). As we do not make any assumptions about the level and dynamics of true job-finding probability X_t^i, job seekers may misunderstand both the level and dynamics of the job-finding probability.

By substituting the belief dynamics described in equation 4.2 into both equalities in equation 4.1, we are left with a problem with two equations and two unknowns: $F_t^i \hat{X}_t^i$ and $\hat{\beta}_{i,t}^x$. As both $FindJob3_t^i$ and $FindJob12_t^i$ are observed, we can back out $F_t^i \hat{X}_t^i$ and $\hat{\beta}_{i,t}^x$. The intuition here is that the difference between $FindJob12_t^i$ and $FindJob3_t^i$ provides information about how a job seeker evaluates their future job-finding probability earlier and later in their unemployment spell. The filter in equation 4.2 provides a convenient way to quantify the information provided by $FindJob12_t^i$ and $FindJob3_t^i$.

4.2 Aggregate Economic Variable

The SCE asks individuals for the probability that the unemployment rate in twelve months will be higher than today. It does do not ask questions about the level of the unemployment rate. To interpret this, we assume that job seeker i holds a belief about the unemployment rate U_t when surveyed at time t that equals the true unemployment rate of month t, which might not be unreasonable because respondents are typically surveyed in the second half of the month. Nevertheless, news sources often report how much unemployment has declined, rather than about actual levels. For robustness, Appendix C.1 explores what happens if individuals enter the sample with a wrong belief about the level of unemployment: if individuals obtain correct information about improvements or declines in unemployment from one period to the next, results stay approximately valid even if individuals perceive the level of unemployment as 10% too high or too low.

We again assume that the evolution of the unemployment rate follows a geometric increase or decrease, but allow for noise in the form of the commonly-used AR(1) process:

$$U_{t+1} = \hat{\beta}_{i,t}^u U_t + \hat{\epsilon}_{i,t+1}^u, \quad \hat{\epsilon}_{i,t+1}^u \sim N(0, \hat{\sigma}_{u,\epsilon}^2). \tag{4.3}$$

We also explored a specification with the logged unemployment rate or with deviations of the unemployment rate from some long-run level, neither of which changes the nature of the empirical patterns.[16] We therefore present this version for simplicity.

$\hat{\beta}_{i,t}^u$ represents a job seeker i's perceived unemployment rate dynamics at time t. $\hat{\epsilon}_{i,t+1}^u$ is a noise to individual i's believe, which is assumed to follow a normal distribution $N(0, \hat{\sigma}_{u,\epsilon}^2)$ with $\hat{\sigma}_{u,\epsilon}$ being the subjective variance of U_{t+1}. While we impose these assumptions on agent's beliefs, this need not be the form by which the unemployment rate truly evolves.

Using the perceived unemployment rate dynamics specified in Equation 4.3, we can compute the perceived probability that the unemployment rate in month $t + k$ (i.e., U_{t+k}) exceeds the unemployment rate in month t (i.e., U_t) for any integer value of k:

Proposition 1 *Based on the belief dynamics specified in equation 4.3, the probability that the unemployment*

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[16]Appendix C.2 reports the version with deviations from a long-run trend, and shows that empirical patterns remain unchanged. We omit the version in $log(U_t)$ for brevity.

rate in month $t + k$ (U_{t+k}) is higher than the unemployment rate in month t (U_t) is

$$F_t^i \Pr\left(U_{t+k} > U_t\right) = 1 - \Phi\left(\sqrt{\frac{\left(1 - \left(\hat{\beta}_{i,t}^u\right)^2\right)\left(1 - \left(\hat{\beta}_{i,t}^u\right)^k\right)^2}{\left(1 - \left(\hat{\beta}_{i,t}^u\right)^{2k-2}\right)}} \times \frac{U_t}{\hat{\sigma}_{u,\epsilon}}\right) \quad (4.4)$$

Please refer to appendix B.1 for the derivation. In our empirical exercise, we select $k = 11$, since the SCE survey only inquires about the probability of the unemployment rate being higher twelve months later than its current level. Nonetheless, despite equation 4.4, we still need to specify $\hat{\sigma}_{u,\epsilon}$ to estimate $\hat{\beta}_{i,t}^u$. To accomplish this task in our empirical analysis, we calibrate $\hat{\sigma}_{u,\epsilon}$ based on the actual sequence of unemployment data by calculating the standard deviation of the cyclical component of U_t.[17] Once we have estimated $\hat{\sigma}_{u,\epsilon}$, we can use Equation 4.4 to obtain $\hat{\beta}_{i,t}^u$ for each individual i and month t.

5 Empirical Analysis

In this section, we present the empirical findings pertaining to the dynamics of job seekers' beliefs while they are unemployed. First, we estimate the crucial variables of interest using the proposed empirical framework. Our analysis reveals that unemployed job seekers anticipate a decline in their job-finding probability for every additional month of unemployment in the future, but their job-finding beliefs remain constant within-spell. Subsequently, we demonstrate that the perceived dynamics of the US unemployment rate have an significant impact on the updating of individual job-finding probability. Finally, we conduct empirical analyses to show that results found are robust using alternative survey samples and specifications.

5.1 The Sample and Summary Statistics

The sample used for the empirical analysis is directly taken from Mueller et al. (2021). Note that some answers in the SCE report a probability of finding a job in the next 12 months that is weakly lower than the probability of finding a job in the next 3 months, suggesting a lack of serious consideration. Mueller et al. (2021) exclude such answers to arrive at a consistent sample,

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[17]The cyclical component of U_t is computed via the Hodrick-Prescott (HP) Filter.

and we follow their approach.[18] Among the 2597 observations (derived from 933 unemployed job seekers) that contain both $FindJob3_t^i$ and $FindJob12_t^i$, this excludes 1005 (38.7%) who have $FindJob3_t^i \geq FindJob12_t^i$ (of which 26.5% are $FindJob3_t^i = FindJob12_t^i$).[19]

Table 1: Descriptive Statistics For the Survey of Consumer Expectations (SCE) and Comparisons to the Current Population Survey (CPS)

| | SCE (consistent) | SCE | CPS |
	2012-2019	2012-2019	2012-2019
High school degree or less	38.1%	44.5%	44.7%
Some college education:	33.7%	32.4%	31.5%
College Degree of More:	28.2%	23.%	23.8%
Ages 20–34	22.8%	25.4%	35.3%
Ages 35–49	35.6%	33.5%	33.0%
Ages 50–65	41.6%	41.1%	31.7%
Female	58.4%	59.3%	49.3%
Black	16.6%	19.1%	23.6%
Hispanic	12.5%	12.5%	18.4%
Monthly job-finding probability	15.8%	18.7%	23.5%
Number of respondents	681	948	—
Number of survey responses	1592	2,597	103,309

Notes: We use the same SCE and CPS sample as in Mueller et al. (2021). In column 1, we show the summary statistics of the consistent sample. All samples restricted to unemployed workers, ages 20–65. The SCE sample is restricted to interviews where all relevant belief questions were administered. To be comparable to the SCE, the CPS sample in column 3 is restricted to household heads. The monthly job-finding probability in the SCE and CPS is the U-to-E transition rate between two consecutive monthly interviews.

Table 1 shows that the consistent sample closely resembles the full SCE sample used in Mueller et al. (2021), with similar distributions of gender, race, education, and age. Overall, these comparisons suggest that the consistent sample constructed in this analysis is representative of the SCE sample and can provide reliable estimates of beliefs and job-finding probabilities for unemployed job seekers. Mueller et al. (2021) documents that SCE replicates the key feature or CPS. We also report the corresponding summary statistics in table 1 along with the two SCE samples.

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[18]In many part of the paper, Mueller et al. (2021) show that their main results are robust using the unrestricted sample. In our case, the model presented in equation 4.1 cannot justify $FindJob3_t^i \geq FindJob12_t^i$ because the 12-month cumulative job-finding probability cannot be lower than the 3-month cumulative job-finding probability.

[19]The 2597 observations come from 933 unemployed job seekers, 382 of whom (59%) have answered at least once $FindJob3_t^i \geq FindJob12_t^i$. An alternative procedure from the one adopted in Mueller et al. (2021) would be to drop all the unemployed job seekers who have answered at least once $FindJob3_t^i \geq FindJob12_t^i$, which would leave 806 observations from 387 job seekers. We did not pursue this path for lack of comparability.

5.2 Belief Dynamics: Job-finding Probability

This subsection presents a set of new empirical patterns on belief dynamics from unemployed job seekers, based on the data from Mueller et al. (2021). All results shown in this subsection can be replicated using the public version of SCE.

Using equation 4.2 and 4.1, we estimate the perceived 1-month job-finding probability $F_t^i \hat{X}_t^i$ and the perceived job-finding probability projection $\hat{\beta}_{i,t}^x$. Figure 1 displays the histogram of $\hat{\beta}_{i,t}^x$. We observe that unemployed job seekers anticipate their job-finding probability to decline by approximately 18% on average for an additional month of unemployment, though there is large heterogeneity as indicated by a standard deviation of 0.19. The average decline is in line with a naive observation of duration dependence in our data: in our SCE sample the unemployment-to-employment transition probability declines by 22% per month. One can also use our method to predict the 4-month job finding rate and compare it to the independently but infrequently elicited empirical counterpart: they predict the same average decline, which indicates that our filtering equation (4.2) and our assumption that individuals can compound such probabilities is not at obvious odds with the data.[20]

That individuals expect a decline in their job finding chances is backed out from their answers to multiple questions at a given point in time. These questions cover different future horizons. One can ask the same questions again at later periods (if the individual stayed unemployed). This reveals that individuals consistently expect on average a roughly 20% decline in their job finding probability from one period to the next, independent of how long they have already been unemployed (see Appendix Figure A.3 that plots $\hat{\beta}_{i,t}^x$ within an individual unemployment spells against the time spent unemployed since the first interview).[21]

Given the consistent expectation of lower future job finding probabilities, one might conjecture that individuals would report lower and lower job finding probabilities when they remain unemployed for longer. That is, one might expect $F_t^i \hat{X}_t^i$ to decline with t for a given individual i. But already Mueller et al. (2021) noted that the perceived job-finding probability of unemployed job

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[20]Once every quarter, the SCE Labor Market Survey (SCE LMS) surveys a subset of respondents from the main SCE survey to obtain their perceived probability of finding a job in four months. In Appendix D.1, we demonstrate that the estimated 4-month job-finding probability is not significantly different from the reported probability for the same job seeker in the SCE LMS at the same interview time on average. Our main analysis does not rely on the SCE LMS because it is too infrequent to allow for fixed effects per job seeker.

[21]Time spent unemployed since the first interview is defined exactly as in Mueller et al. (2021) to facilitate comparison. It calculates the time since the first interview by counting the days, so it is possible that a job seeker is labeled as unemployed for one month since the first interview for two consecutive interviews, since the time between two interviews can be less than a month. Consistent with Mueller et al. (2021), we aggregate job seekers by time unemployed in the survey, rather than the duration of unemployment, to increase power and control for potential cohort effects.
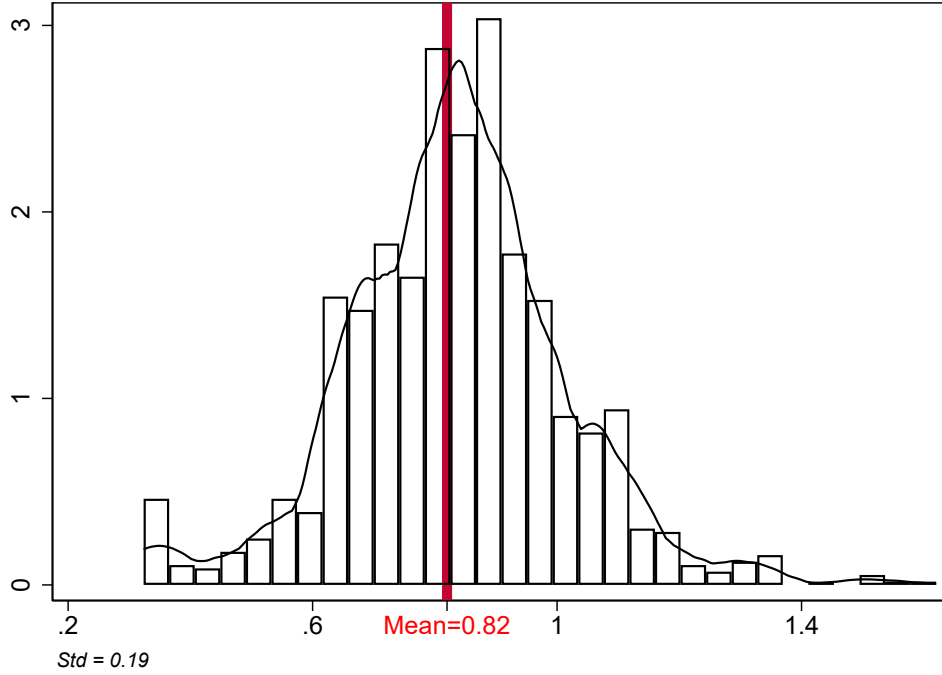
Figure 1: Histogram of job-finding Probability Projection $\hat{\beta}_{i,t}^{x}$

Notes: we plot the histogram of job-finding probability projection $\hat{\beta}_{i,t}^{x}$ estimates for each individual at each interview using the empirical framework proposed in equation 4.1. The line connects the fitted kernel density estimates using the Epanechnikov kernel. The samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample).

seekers remains constant within-spell. In Figure A.1, we replicate this empirical pattern using our estimated 1-month perceived job-finding probability $(F_t^i \hat{X}_t^i)$. Specifically, we plot the change in the perceived job-finding probability $(F_t^i \hat{X}_t^i)$ within individual unemployment spells against the time spent unemployed since the first interview, which is the same variable for duration that Mueller et al. (2021) used.[22]

Maybe researchers have not investigated the changes that job seekers expect at a given point in time going forward, because when asked repeatedly their answers do not change much over time. The conjecture might have been that this should indicate flat beliefs about the future from the outstart. But on average, the implied difference between the perceived job-finding probability in period t and period $t-1$ $(F_t^i \hat{X}_t^i - F_{t-1}^i \hat{X}_t^i)$ is negative, indicating systematic errors. In the

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[22]On average, the perceived 1-month job-finding probability is 0.22 with a standard error of 0.18. Its dispersion is depicted in the left panel of Appendix Figure A.2, which presents the histogram of $F_t^i \hat{X}_t^i$. For comparison, the histogram of the 1-month job-finding probability directly imputed from the 3-month job-finding probability via formular $1 - (1 - FindJob3_t^i)^{\frac{1}{3}}$, as in Mueller et al. (2021), is represented in the right panel of Figure A.2. The two histograms are qualitatively similar.

future subsection, we provide a potential explanation for this pattern, which is the result of belief surprises in the aggregate job market that act as an aggregate shock to job seekers' job-finding probability in every period.

5.3   Belief Dynamics: Aggregate Unemployment Conditions

Figure 2 shows the histogram of perceived US unemployment rate projection ($\hat{\beta}_{i,t}^u$) for unemployed job seekers using the consistent sample. It displays a mean of 1, which indicates that unemployed job seekers believe that the US unemployment rate in the next month will be the same as the current month, albeit with some disagreement. There is a significant mass in Figure 2 at $\hat{\beta}_{i,t}^u = 1$, which corresponds to the fact that many surveyed individuals report that the probability of the US unemployment rate being higher is 50% ($\hat{\Pr}\left(E_t^i U_{t+k} > U_t\right) = 0.5$). But even when one excludes individuals that select the focal answer that increases and decreases in unemployment are exactly equally likely, the overall average remains unchanged and the remaining individuals on average continue to expect the unemployment rate to stay constant.

With longer unemployment duration, individuals become slightly more optimistic about the future evolution of the unemployment rate. The perceived US unemployment rate projection ($\hat{\beta}_{i,t}^u$) declines with months in the survey (see Figure A.4), but the economic magnitude is negligible: if we regress $\hat{\beta}_{i,t}^u$ on the month since the first interview, unemployment rate projection ($\hat{\beta}_{i,t}^u$) decreases significantly by 0.0007 on average for one additional month of unemployment. So on average individuals in our sample expect economic conditions to stay constant, with minimally more optimistic outlook for those who are more periods in our sample.

During our sample period (2013-2019), the US economy experienced a recovery, with a 3% monthly decrease of unemployment rate ($\frac{U_t}{U_{t-1}} \approx 0.97$) on average. This average decline is in line with the positive expectations of professional forecasters (Appendix D.2 shows that professional forecasters' reports imply an expected 3% - 6% decline). But the 3% average monthly decline in the unemployment rate during our sample period contrasts with the average belief of job seekers who expect a 0% decline. The persistent perception among job seekers of a relatively stable US unemployment rate in face of an ever improving labor market suggests a certain level of resilience in their response to fluctuations in the overall economy, which is related to the notion of "stubbornness" as discussed in Menzio (2022).

It also suggests a repeated degree of surprise. Whenever the US unemployment rate realizes, a job seeker should be, on average, "surprised" by the larger decline of the US unemployment rate
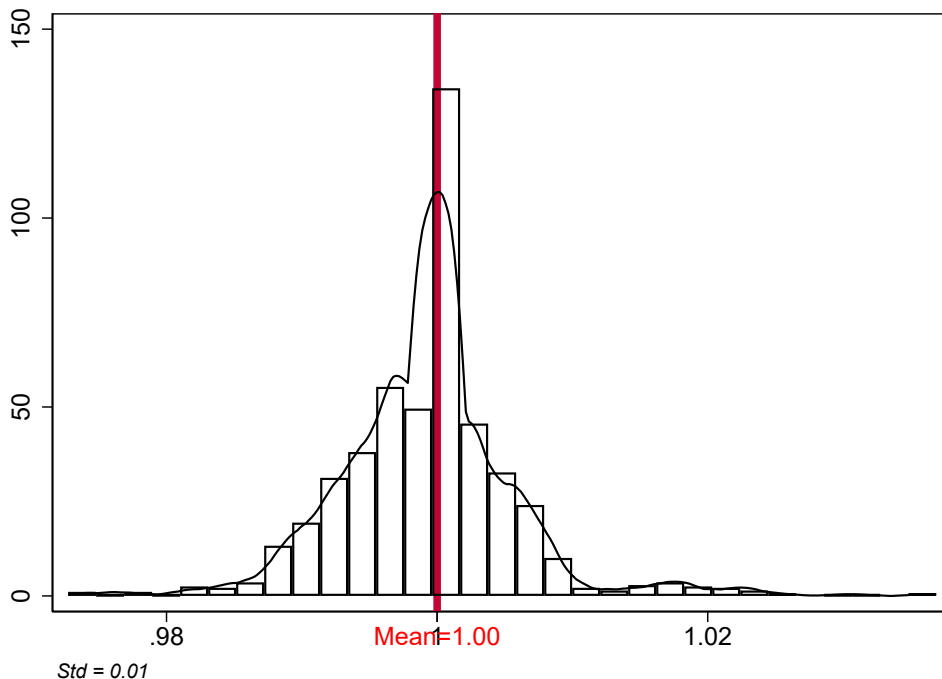
Figure 2: Histogram of US Unemployment Rate Projection $\hat{\beta}^u_{i,t}$

Notes: we plot the histogram of US unemployment rate projection $\hat{\beta}^u_{i,t}$ for each individual at each interview using the empirical framework proposed in equation 4.4. The line connects the fitted kernel density estimates using the Epanechnikov kernel. The samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (consistent sample).

than they expected. While this section and the previous section have studied job finding prospects and unemployment rate expectations in isolation, the next section combines them both: we examine how the "surprise" $(U_t - F^i_{t-1}U_t)$ affects the individual perceived job-finding probability.[23]

5.4 Beliefs about the Aggregate and Perceived Individual Job-Finding

In this section, we analyze how belief dynamics regarding the aggregate market condition can shed light on the empirical puzzle we have identified. Specifically, we aim to explain the co-existence of a flat perceived job-finding probability within an unemployment spell and a job-finding probability projection ($\hat{\beta}^x_{i,t}$) of around 0.82 indicating that job seekers expect a steep decline in job finding in the future.

Before moving on to the analysis, we clarify the timing assumption that we stick to hereafter. Since the SCE survey is conducted on a monthly basis, respondents are interviewed at slightly

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[23]In Appendix D.8, we show that both job seekers' perceived job-finding probability and US employment rate dynamics significantly affect their job-finding realizations.

different times during the month, which means that the time between two interviews may be more or less than a month. In this analysis, we refer to $t+1$ as the next month after month t.[24] We assume that the sequence of play within a month t follows these three steps:

1. At the time of the month t interview, each agent i forms a correct expectation about the national unemployment rate for the month t.[25]

2. Based on the information available at the time of the interview, agent i forms a belief on how the national unemployment rate will evolve $(\hat{\beta}_{i,t}^u)$.

3. Using her beliefs about the national unemployment rate (both the level and the dynamics), agent i forms a belief about her own job-finding probability in three months $(FindJob3_t^i)$ and her expected probability of finding a job over the next 12 months, conditional on being unemployed at month t.

We use the following fixed effects regression model to investigate how the individual "surprise" on US unemployment can explain the update of individual perceived job-finding probability[26]:

$$\left(F_t^i \hat{X}_t^i - F_{t-1}^i \hat{X}_t^i\right) = \vartheta \left(U_t - F_{t-1}^i U_t\right) + \delta_i + \delta_t + \varepsilon_{i,t} \tag{5.1}$$

The dependent variable $F_t^i \hat{X}_t^i - F_{t-1}^i \hat{X}_t^i$ can be calculated as $F_t^i \hat{X}_t^i - \hat{\beta}_{i,t}^x F_{t-1}^i \hat{X}_{t-1}^i$. The parameter of interest is ϑ, which indicates how changes in perceived individual national unemployment "surprise" affect perceived individual job-finding probability. To eliminate the selection effect, we control for individual fixed effect δ_i. We also use a time fixed effect at the month level δ_t to remove the systematic impact of the monthly aggregate environment. So we exploit whether an individual job seeker is more surprised about aggregate unemployment in a given month, both relative to other job seekers in the same month and himself across time. We cluster standard error at the individual level. Furthermore, the inclusion of individual unemployment duration as a control variable does not significantly alter the main empirical pattern.

Table 2 presents the results. In column (1), we find that ϑ is estimated to be around -68, which is statistically significant at the 0.1 level. Incorporating the unemployment duration fixed effect

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[24]We do not distinguish between a month and the time gap between two interviews in the reduced form empirical analysis to maximize data utilization.

[25]The interview is typically at the end of the month, providing some rationale for this assumption. See also Appendix C.1 for some robustness if individuals perceive the level of unemployment incorrectly but obtain current information on relative changes in unemployment.

[26]We show empirical evidence in appendix D.6 indicating that it is unlikely for job seekers to learn about the aggregate market (U_t) based on their own job search experiences.

Table 2: Belief Surprise of US Unemployment on job-finding Probability Update

	(1)	(2)
	Job-Finding Prob Update	Job-Finding Prob Update
Belief Surprise: US Unemployment	-67.70*	-75.71*
	(39.13)	(42.09)
Person FE	Yes	Yes
Month FE	Yes	Yes
Duration FE	No	Yes
Cluster STD	Person	Person
Obs	456	456

Notes: job-finding probability update is calculated by $F_t^i \hat{X}_t^i - \hat{\beta}_{i,t}^x F_{t-1}^i \hat{X}_{t-1}^i$. Belief surprise of US unemployment rate is calculated by $U_t - F_{t-1}^i U_t$. We remove the individual fixed effects, time fixed effects at the month level, and cluster standard errors at the individual level. Column (2) further controls for the unemployment duration fixed effects. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

increases the magnitude of ϑ to around -76, which remains statistically significant. The results suggest that at the individual level, the subjective belief "surprise" on national unemployment among unemployed job seekers is negatively correlated with their perceived job-finding probability update. Additionally, the large estimate magnitude suggests a n economically important impact.

In table 3, we explore the implications of ϑ. In the first row, we verify that the average contemporaneous perceived job-finding probability $(F_t^i \hat{X}_t^i)$ is similar for both periods $t-1$ and t, consistent with the empirical findings in figure A.1. In the third row, we compute the average $F_{t-1}^i \hat{X}_t^i$, which represents the perceived job-finding probability in period t evaluated in period $t-1$. $F_{t-1}^i \hat{X}_t^i = \hat{\beta}_{i,t}^x F_{t-1}^i \hat{X}_{t-1}^i$ is approximately 80% of the contemporaneous perceived job-finding probability, indicating that job seekers believe their job-finding probability will decline by around 20% in the next period. The difference between $F_{t-1}^i \hat{X}_t^i$ and $F_t^i \hat{X}_t^i$ is statistically significant.

The adjusted job-finding probability forecasts predicted by the equation

$$\widehat{F_t^i \hat{X}_t^i} = F_{t-1}^i \hat{X}_t^i + \hat{\vartheta} \left(U_t - F_{t-1}^i U_t \right)$$

can be used to examine the extent to which the second term $\hat{\vartheta} \left(U_t - F_{t-1}^i U_t \right)$ can help mitigate the empirical puzzle, i.e., the difference between the average contemporaneous perceived job-finding probability $(F_t^i \hat{X}_t^i)$ and its period $t-1$ forecast $F_{t-1}^i \hat{X}_t^i$. Table 3, second row, presents the results. After accounting for the impact of perceived unemployment rate "surprise" $U_t - F_{t-1}^i U_t$, the adjusted job-finding probability forecast $\widehat{F_t^i \hat{X}_t^i}$ is approximately 0.196. In comparison to the period

$t-1$ perceived period t job-finding probability $(F^i_{t-1}\hat{X}^i_t)$, the adjusted perceived job-finding probability $\widehat{F^i_t\hat{X}^i_t}$ is statistically significantly larger and cannot be statistically distinguished from the contemporaneous perceived job-finding probability $(F^i_t\hat{X}^i_t)$. In other words, including the impact of perceived unemployment rate "surprise" $(U_t - F^i_{t-1}U_t)$ mitigates around 85% percent of the difference between the average contemporaneous perceived job-finding probability $(F^i_t\hat{X}^i_t)$ and its period $t-1$ forecast $F^i_{t-1}\hat{X}^i_t$. This exercise shows a substantial impact of beliefs about the aggregate market on the level of contemporaneous perceived job-finding probability.

Table 3: JFR Updates Induced by Belief Surprise of Unemployment Rate

	$t-1$	t
contemporaneous job-finding prob forecast $F^i_\tau X^i_\tau$ $(\tau = t-1, t)$	0.201	0.204
	(0.147)	(0.164)
job-finding prob forecasts predicted by model $\widehat{F^i_t\hat{X}^i_t}$		0.196
		(0.283)
job-finding prob forecasts predicted at $t-1$, $F^i_{t-1}\hat{X}^i_t$		0.154
		(0.104)

Notes: the contemporaneous JFR forecast $(F^i_t\hat{X}^i_t)$ at period t is statistically significantly different from the JFR forecasts predicted by JFR projections $(F^i_{t-1}\hat{X}^i_t)$ at 0.01 level, while not statistically significantly different from JFR forecasts predicted by beliefs on U $(\widehat{F^i_t\hat{X}^i_t})$. Survey weights are used when calculating the averages, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample).

Figure 3 visually represents the effect of incorporating the impact of perceived unemployment rate "surprise" on job seekers' perceived job-finding probabilities. The downward arrow connects the average contemporaneous perceived job-finding probability $F^i_t\hat{X}^i_t$ (the solid blue dot on the left) and the period $t-1$ forecast of period t job-finding probability $F^i_{t-1}\hat{X}^i_t$ (the solid red dot), showing that job seekers believe their one period ahead job-finding probability is around 20% lower than the contemporaneous one. The green circle represents the model-adjusted job-finding probability forecast $\widehat{F^i_t\hat{X}^i_t}$, which incorporates the impact of perceived unemployment rate "surprise" $U_t - F^i_{t-1}U_t$. From the red dot to the green circle, the figure shows the substantial impact of beliefs about the aggregate market on the level of contemporaneous perceived job-finding probability. In particular, the green circle is closer to the blue dot than the red dot, indicating that the adjusted job-finding probability forecast is closer to the contemporaneous perceived job-finding probability than the period $t-1$ forecast of period t job-finding probability. This demonstrates the importance of incorporating the impact of perceived unemployment rate "surprise" in understanding job

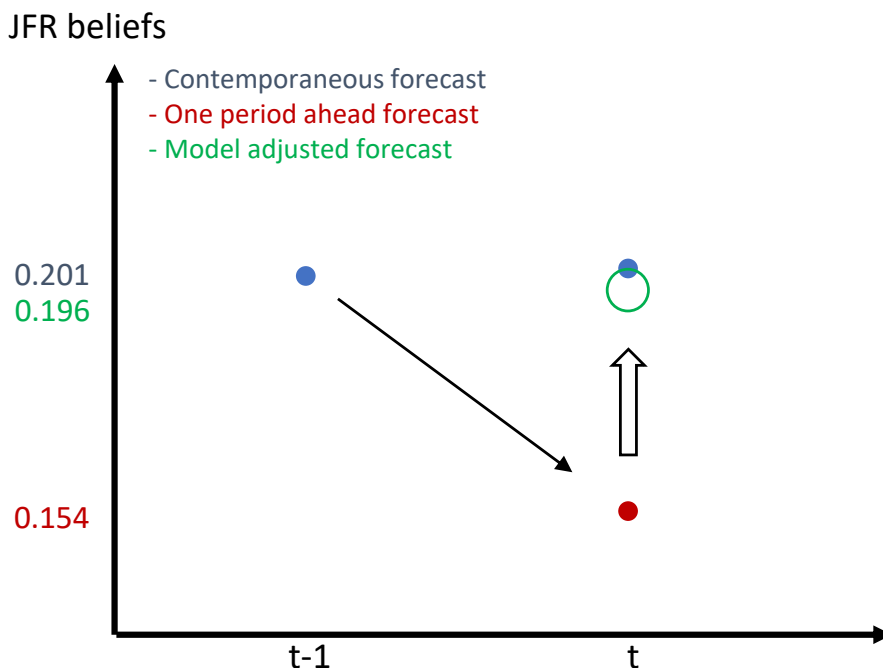seekers' beliefs about their job-finding probabilities.

JFR beliefs

Figure 3: JFR Updates Induced by Belief "Surprise" of Unemployment Rate

Notes: this figure is a visualization of the table 3. Contemporaneous forecast is $F_\tau^i X_\tau^i$ ($\tau = t-1, t$). One period ahead forecast is $F_{t-1}^i \hat{X}_t^i$. Model adjusted forecast is the JFR forecasts predicted by beliefs on U_t, i.e., $\widehat{F_t^i \hat{X}_t^i}$. The figure is for illustration.

5.5 Robustness Analysis

The preceding sections provide evidence in support of two points: job seekers (1) anticipate their job prospects to decline in the future, and (2) do not report lower job prospects in the future *because* of unanticipated positive news about the overall labor market which form an aggregate shock that lifts job finding prospects. This section considers alternative datasets or time periods to investigate these premises. First, it shows that (1) is also present in the KM survey, with comparable magnitude. Second, the combination of (1) and (2) indicates that individuals without positive surprises about the unemployment rate should report declining job finding probabilities over time. This is indeed the case within the SCE sample for those without positive surprises, and there is also suggestive evidence from a different time period (the Covid recession). Finally, we investigate reverse causality: whether positive news about the own job finding probability might be used to positively

update about the aggregate labor market. This does not seem to be the case.

5.5.1 KM Survey

Our first robustness test aims to show that job seekers believe their job-finding probability will decrease in the future using KM survey.

The KM survey asks unemployed job seekers to report their perceived 4-week job-finding probability together with their expected duration of unemployment in weeks. We exclude job seekers who report missing data on either their 4-week job-finding probability or expected duration. We also drop job seekers who report a 4-week perceived job-finding probability equal to 1 while their duration of unemployment is longer than 4 weeks. Conversely, we exclude job seekers who report a 4-week perceived job-finding probability of less than 1 while their duration of unemployment is shorter than 4 weeks. The remaining sample, which we refer to as the consistent sample.

We calculate the one-week elicited job-finding probability by transforming the 4-week elicited job-finding probability. Since this transformation assumes a constant elicited one-week job-finding probability, it should be interpreted as the average job-finding probability for the immediate 4 weeks in the future. We then combine the converted weekly job-finding probability with the expected duration in weeks to estimate the monthly job-finding probability projection using a simulation exercise.

We denote the initial weekly job-finding probability as $\hat{X}_t^i$ and the expected duration as $\hat{\tau}_i$ weeks, which we empirically measure using the converted weekly job-finding probability. We assume that the weekly job-finding probability follows a geometric process as shown in Equation 4.2 and that the weekly job-finding probability depreciation rate at time t is $\hat{\beta}_{i,t}$. Then the expected duration of unemployment, $\hat{\tau}_i$, equals

$$\hat{\tau}_i = \hat{X}_t^i + \sum_{\tau=2}^{T} \tau (\hat{\beta}_{i,t})^{\tau-1} \hat{X}_t^i \prod_{k=2}^{\tau} \left(1 - (\hat{\beta}_{i,t})^{k-2} \hat{X}_t^i\right), \quad T \to \infty \tag{5.2}$$

Since both $\hat{X}_t^i$ and $\hat{\tau}_i$ are elicited by the KM survey for each job seeker in each interview, we can estimate $\hat{\beta}_{i,t}$ by setting a large enough value of T. We choose $T = 300$ because after 300 weeks, the probability that a job seeker is still unemployed will be very low.[27] After obtaining the weekly job-finding probability projection $\hat{\beta}_{i,t}$, we convert it into a monthly rate using the fact that one month is approximately 4.33 weeks.

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[27]The empirical pattern is robust to other choices of the number of weeks of simulations.

We estimate the monthly $\hat{\beta}_{i,t}$ for each job seeker in the KM survey and plot the histogram in Figure 4.[28] We find that job seekers believe their job-finding probability will depreciate by an average of 18%, which remarkably similar to what we find using the main SCE sample. This evidence further supports the finding that job seekers perceive declining job-finding probabilities for themselves. [29]
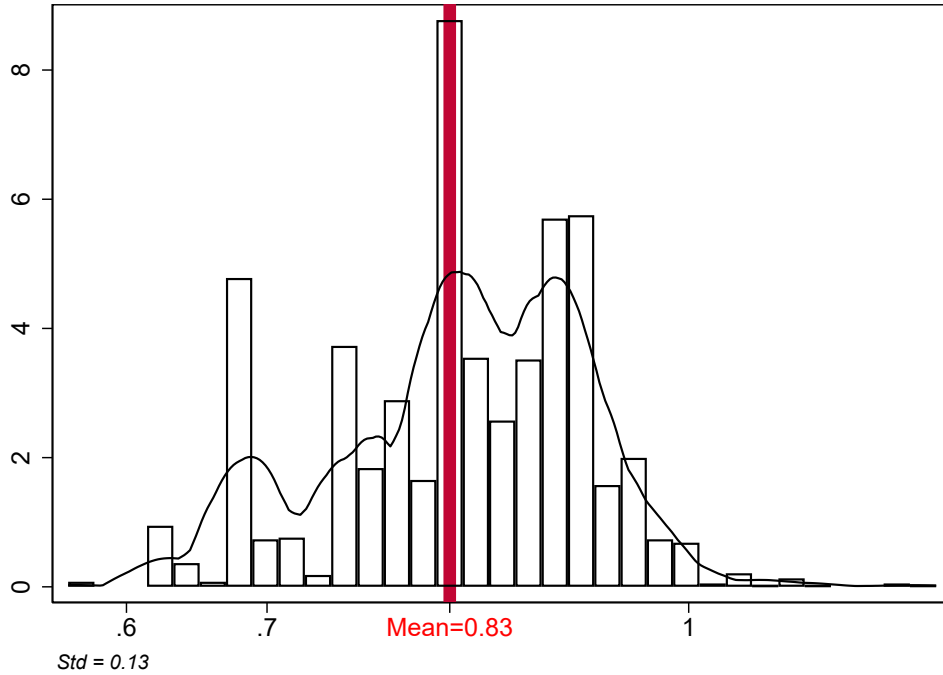

Figure 4: Histogram of job-finding Probability Projection $\hat{\beta}^u_{i,t}$ (KM survey)

Notes: we present the histogram of job-finding probability projection $\hat{\beta}^u_{i,t}$ for each individual at each interview using the empirical framework proposed in equation 5.2. The line connects the fitted kernel density estimates using the Epanechnikov kernel. The samples are restricted to unemployed workers ages 20–65 who report consistent answers for weekly job-finding probability and expected unemployment duration.

Unfortunately, as the KM survey did not elicit job seekers' perceived US unemployment rate projection, we cannot study how job seekers update their job-finding probability by learning about the aggregate US unemployment condition using this sample.

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[28]The consistent sample has 3039 observations. After the simulation exercise, we are left with 1995 estimated $\hat{\beta}_{i,t}$. The numerical solver cannot find a reasonable solution for the rest of the observations.

[29]In Appendix D.7, we provide evidence supporting job seekers perceive their job-finding probabilities to decline in the future using another method.

5.5.2 Job Seekers without "Surprise"

In our empirical analysis, we discover that, on average, job seekers hold pessimistic views towards the aggregate unemployment rate. Consequently, they are often "surprised" by the low realizations of the US unemployment rate. This observation prompts an intriguing query: How does an individual's perception of the aggregate market influence their personal job-finding probability when they ascertain that the US unemployment rate exceeds their expectations? We offer two examinations addressing this question. The initial examination utilizes the sample from the Covid-19 pandemic, whereas the subsequent examination concentrates on optimistic job seekers within our principal sample period.

The dynamics of the pandemic recession are unique because they largely depend on disease propagation and related mitigation policies. During the COVID-19 pandemic, the US unemployment rate spiked quickly from March 2020 to May 2020. We use the SCE 2020 sample and restrict our attention to all job seekers who were unemployed between March 2020 and April 2020.[30]

To account for selection, we only include job seekers who have been consecutively unemployed for three months. We calculate the average elicited 3-month job-finding probabilities $FindJob3_t^i = 0.480$, $FindJob3_{t+1}^i = 0.357$, and $FindJob3_{t+2}^i = 0.174$ for all six job seekers in the sample, who all under-estimate how quickly the US unemployment rate evolves during the pandemic period. Figure 5 plots the decreasing trend, which shows a sharp decline in perceived job-finding probability compared to the evidence generated from our main pre-pandemic sample (dashed line in Figure 5).

The above results are based on a very small sample, and it is possible that six job seekers may have declining perceived job-finding probabilities within-spell even in the pre-pandemic sample. To test this hypothesis, we randomly draw six job seekers 1000 times using the pre-pandemic sample with replacement and calculate their average elicited 3-month job-finding probability $FindJob3_t^i$, as we did for the pandemic sample. We find that the probability of drawing six job seekers whose beliefs decline for each of two consecutive periods at least as much as the Covid sample is always less than 1%.[31] This exercise shows that when job seekers believe their unemployment opportunities are deteriorating, they perceive their job-finding probabilities to decrease sharply.

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[30]Though the Covid-19 pandemic lasted for a long time, the US unemployment rate spiked quickly only in the first several months then started a steady decline.

[31]Specifically, we calculate the probability that the average $\frac{FindJob3_t^i}{FindJob3_{t-1}^i}$ and $\frac{FindJob3_{t+1}^i}{FindJob3_t^i}$ calculated by 6 job seekers randomly drawn our main sample is smaller than average $\frac{FindJob3_t^i}{FindJob3_{t-1}^i}$ and $\frac{FindJob3_{t+1}^i}{FindJob3_t^i}$ from the 6 job seekers from our Covid sample respectively.
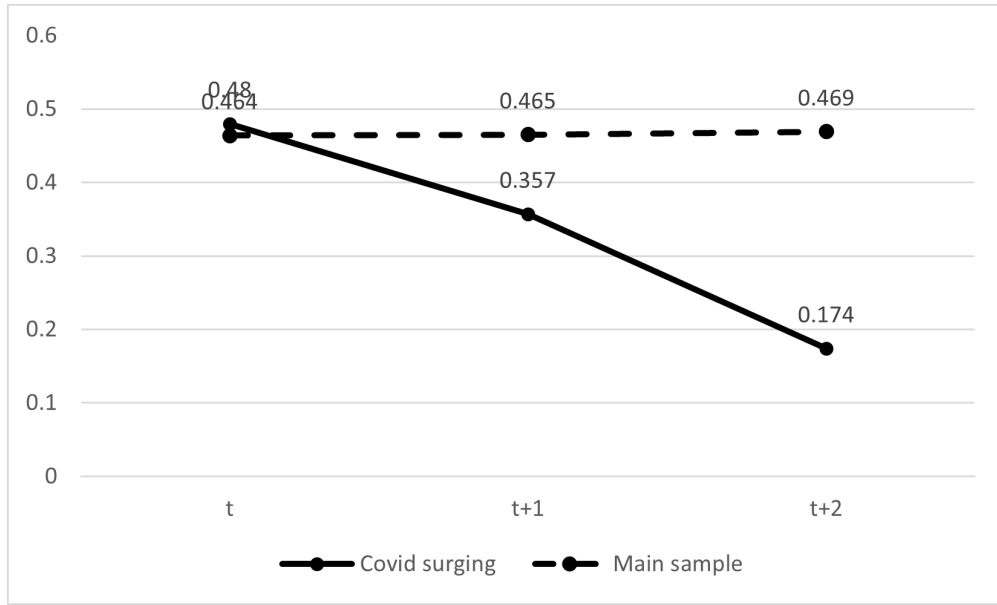
Figure 5: Perceived 3-month job-finding Probability During COVID Pandemic

Notes: we present the average perceived 3-month job-finding probability ($FindJob3_t^i$) of the same individual for period t, $t+1$ and $t+2$ using the main sample and the sample when Covid pandemic was surging (Feb 2020 to May 2020). The samples are restricted to unemployed workers ages 20–65 who report consistent answers for weekly job-finding probability and expected unemployment duration.

The second empirical exercise aims to analyze the job-finding probability of job seekers who do not experience any "surprises" using our main SCE sample. Specifically, we examine the case where job seekers perceive $U_t > \hat{\beta}_{i,t}^x U_{t-1}$ (no "surprise"). In this scenario, we expect their perceived job-finding probability to be at least non-increasing within unemployment spell, or $F_t^i \hat{X}_t^i < F_{t-1}^i \hat{X}_{t-1}^i$. Our findings indicate that job seekers with $U_t > \hat{\beta}_{i,t}^x U_{t-1}$ experience a decline of approximately 11% in their perceived job-finding probability from period t to period $t+1$, denoted as $\beta_{i,t-1}^x = 0.888$. Moreover, upon reaching period $t+1$, their perceived job-finding probability declines by an average of around 12%, which aligns with our initial expectations.

Figure 6 graphically illustrates this pattern. Compared to figure 3, we observe a decrease in the perceived job-finding probability within an unemployment spell for job seekers without any "surprise" concerning the US unemployment rate.

5.5.3 Alternative Explanation?

In the empirical analysis, we argue that unexpected variations in the US unemployment rate prompt job seekers to adjust their perceived job-finding probability. However, one could argue that those job seekers who happen to get favorable private signals about their job finding chances also alter
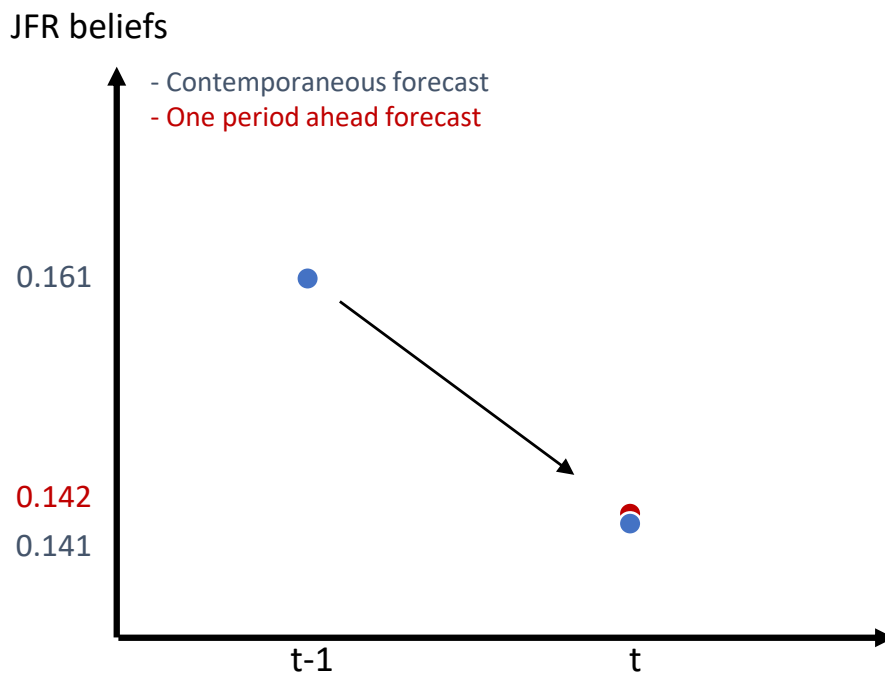
JFR beliefs

- Contemporaneous forecast
- One period ahead forecast

0.161 ●

0.142 ●
0.141 ●

t-1   t

Figure 6: JFR Updates of Unemployment Rate Without Belief "Surprise"

Notes: contemporaneous forecast is $F_\tau^i X_\tau^i$ ($\tau = t-1, t$). One period ahead forecast is $F_{t-1}^i \hat{X}_t^i$. The figure is for illustration. We include the sample that job seekers who have no "surprise" about the unemployment rate realization, i.e., $U_t - \hat{\beta}_{i,t-1}^u U_{t-1} > 0$

their beliefs about the US unemployment rate, i.e., an instance of reverse causality.

Luckily, it is possible to investigate this because the SCE Labor Market Survey (LMS) provides an observable counterpart to individual experiences in job search: it indicates whether the individual had a job interview or not. In the appendix D.6, we utilize this and find that the hypothesis of job seekers adjusting their beliefs about the US unemployment rate based on their own job-finding experience is inconsistent with the empirical evidence. Specifically, our findings indicate that while job search experience (i.e., being interviewed in the past four weeks) leads job seekers to revise their individual perceived job-finding probability upwards, it does not affect how they perceive the aggregate labor market.

6   A Belief Model of Job Search

In our previous empirical analysis, we demonstrated the critical influence of beliefs regarding the aggregate unemployment condition on the perceived job-finding probability. While the previ-

ous section examined individual beliefs about job-finding and aggregate unemployment dynamics separately and then correlated them, in this section, we establish a structural connection between the two. Specifically, we present a model that incorporates duration dependence, individual unemployment environment, and behavioral responses to the aggregate unemployment rate. Our model successfully accounts for the main empirical findings.

6.1 The Model Setup

In this subsection, we setup the model. We assume that a job seeker i's period t perceived job-finding probability is a function of her unemployment duration $D_{i,t}$, individual perceived unemployment environment and individual perceived vacancy environment $V_{i,t}$. Specifically, it takes the following functional form:

$$\hat{X}_t^i = \exp(A_i) \exp\left(\gamma_d D_{i,t}\right) \times \frac{M\left(U_{i,t}, V_{i,t}\right)}{U_{i,t}} \tag{6.1}$$

The individual efficient unit (A_i) and effect of duration ($D_{i,t}$) enters through an exponential term. We assume that the matching function $M = UV/\left(U^l + V^l\right)^{-1/l}$ in the calibration exercise, which is a commonly used matching function found in Den Haan et al. (2000) and Hagedorn and Manovskii (2008).[32] We deviate from the canonical formulation of job-finding probability by assuming that job seekers perceive their job-finding probability using their individual unemployment and vacancy environment. We illustrate in details the learning and updating of them in the immediate subsection.

6.2 Learning and Updating

We assume that each job seeker i believes that there exists an individual unemployment environment that directly impacts their job-finding probability. Specifically, we denote the unemployment rate that matters for individual i as $U_{i,t}$, which is the aggregate unemployment rate (i.e., the fundamental) plus a shock $\eta_{i,t}$, i.e., $U_{i,t} = U_t + \eta_{i,t}$. The intuition behind $U_{i,t}$ can be viewed from different perspectives in labor economics. First, we can consider an island model where each job seeker resides on an island. The impact of the aggregate fundamentals (U_t) transmits to each island with noise. Second, job seekers work in different industries, each of which has a unique local economic environment. The shock $\eta_{i,t}$ may also reflect how different individual characteristics, such as age

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[32]Note that the main idea is robust to other choices of matching functions, such as a C-D matching function.

and education level, affect job-finding.

Consistent with the maintained assumption in the previous empirical exercise, we assume that a job seeker i knows the unemployment rate U_t at period t. However, neither the job seeker i nor the researchers know the individual unemployment environment $U_{i,t}$. Job seekers must forecast $U_{i,t}$, so each job seeker i perceives the shock on the individual unemployment environment as $\hat{\eta}_{i,t}$.

We assume that the perceived individual unemployment "shock" $\hat{\eta}_{i,t}$ is correlated with the common shock on unemployment rate in period t, denoted by $\hat{\epsilon}_{i,t}^u$.[33] Specifically,

$$\hat{\eta}_{i,t} = \underbrace{\theta \hat{\epsilon}_{i,t}^u}_{\text{how aggregate shock matters}} + \underbrace{\hat{\epsilon}_{i,t}^\eta}_{\text{idiosyncratic shock}} = \theta \left(U_t - \hat{\beta}_{i,t-1}^u U_{t-1} \right) + \hat{\epsilon}_{i,t}^\eta, \quad E_t \left[\hat{\epsilon}_{i,t}^\eta \right] = 0$$

where $\hat{\epsilon}_{i,t}^\eta$ is a mean zero idiosyncratic shock. Based on the construction outlined above, we can express the perceived individual unemployment environment of job seeker i in period t as $F_t^i U_{i,t} = U_t + \theta \left(U_t - \hat{\beta}_{i,t-1}^u U_{t-1} \right)$.

The parameter θ represents the extent to which a job seeker i's evaluation of their individual unemployment environment is influenced by the perceived aggregate unemployment "surprise" $\hat{\epsilon}_{i,t}^u$.[34] Job seekers over-reacting to the most recent information shares a similar insight to the "Diagnostic Expectation" that widely used to model over-reactions in macroeconomics. (Bordalo et al., 2019, 2020, 2022) We setup the model in a slightly different way to fit the job search context.

Though vacancy rate is an important input in meeting rates for a canonical job search model, none of the available survey elicits an individual's belief on aggregate vacancies. To progress, we assume that job seekers form subjective beliefs on the Beveridge curve and take it as given, i.e., a subjective relationship between $U_{i,t}$ and $V_{i,t}$. We parameterized the subjective Beveridge curve to be log-linear, i.e., $F_t^i V_{i,t} = b(F_t^i U_{i,t})^k$ for each t.[35] During the sample period, the US economy experienced a long recovery, leading to a downward sloping Beveridge curve. Figure A.5 displays a log-normal Beveridge curve can well approximate trend in the data.

With a specified Beveridge curve, we can express the individual vacancy environment as a function of the individual unemployment environment, i.e., $F_t^i V_{i,t}(F_t^i U_{i,t})$. As a result, we can

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[33]Recall that $\hat{\epsilon}_{i,t} = U_t - \hat{\beta}_{i,t-1}^u U_{t-1}$ is known at period t because job seeker i knows unemployment rate U_t, U_{t-1}, and her period $t-1$ unemployment projection $\hat{\beta}_{i,t-1}^u$.

[34]It is worth noting that, in practice, the average value of $\hat{\eta}_{i,t}$ is typically non-zero, which means that $\int_i U_{i,t} di \neq U_t$. To see this, observe that $\int_i U_{i,t} di = U_t + \int_i \theta \hat{\epsilon}_{i,t}^u + \epsilon_{i,t}^\eta di = U_t$ holds only if $\theta = 0$, assuming that $\int_i \epsilon_{i,t}^\eta di = 0$ and $\int_i \hat{\epsilon}_{i,t}^u di \neq 0$. This implies that there is no aggregate consistency if $\theta \neq 0$. Furthermore, we will demonstrate later on that the value of θ estimated from the data rejects the notion of perceived aggregate consistency.

[35]In the appendix D.8, we conduct two exercises to show that alternative specifications of obtaining parameter k and b does not change the estimation result significantly.

derive future job-finding probability beliefs using only perceived dynamics of US unemployment rate.

6.3 Initial Calibration

In this subsection, we perform a simple calibration of the model. For simplicity, we normalize the individual efficiency $A_i = 1$ in both parts of the calibration to focus on the mean response rather than the individual heterogeneity, which we will get back to later in a simulation. The calibration consists of two parts: first, the simplest model with a matching function based on aggregate unemployment and a duration dependence in job-finding; second, the full model that allows beliefs to overreact to the most recent unemployment rate "surprise." Only the latter model fits the empirical pattern well. We utilize individual perceived job-finding probability and the US unemployment rate perception estimated using the proposed empirical framework in section 4, even though the framework proposed in section 4 no longer consistent with the model because the model predicted perceived job-finding probability no longer preserves a geometric structure. Nevertheless, the calibration is informative of the model mechanism. We estimate the full model in the next immediate subsection.

We begin by setting $\gamma_d = 0$ and $\theta = 0$, making our job search model a standard meeting rate $\hat{X}_t^i = \frac{M(U_t, V_t)}{U_t}$. Using estimated b, k, and average $\beta_{i,t}^u$, we require $l = 0.493$ to match the average one-month job-finding probability of 20%, given the average unemployment rate.

By applying the matching function, we can derive the forecast for the job-finding probability in the next period $(F_t^i \hat{X}_{i,t+1})$ by a first order approximation around U_t.[36]:

$$F_t^i \hat{X}_{t+1}^i = \left[b^{-1} \left(U_t \right)^{l(1-k)} + 1 \right]^{-\frac{1}{l}} + \left[b^{-1} \left(U_t \right)^{l(1-k)} + 1 \right]^{-\frac{1}{l}-1} (k-1) b^l U_t^{l(1-k)} \left(\hat{\beta}_{i,t}^u - 1 \right) \quad (6.2)$$

By substituting in b, k, $\beta_{i,t}^u$, $l = 0.493$, and the average U_t, we obtain $F_t^i \hat{X}_{t+1}^i \approx 0.2$. However, this value is inconsistent with the empirical result shown in Figure 1, which concerns the perceived individual job-finding probability dynamics. As demonstrated in Figure 1, a job seeker perceives her job-finding probability to decrease by around 18% on average each month. In other words, the empirical average of $F_t^i \hat{X}_{t+1}^i$ is approximately 0.16.

Since a standard meeting rate generates a forecast on the next period job-finding probability that is too high compared to the empirical results, we now introduce $\gamma_d \neq 0$ and examine whether

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[36]Please refer to appendix B.2 for derivations.

duration dependence induces more consistent patterns. With the duration $D_{i,t}$, our job search model becomes

$$F_t^i \hat{X}_t^i = \exp(\gamma_d D_{i,t}) \left[b^{-1} \left(U_t \right)^{l(1-k)} + 1 \right]^{-\frac{1}{l}} \tag{6.3}$$

Similarly, we can derive the corresponding one month ahead job-finding probability forecast $F_t^i \hat{X}_{t+1}^i$.[37] The equation presented above includes negative duration dependence, which distinguishes it from Equation 6.2 and may assist in fitting the empirical pattern.

Panel (A) of table 4 presents our calibration of the model by targeting the average current period job-finding probability $(F_t^i \hat{X}_t^i)$ and its dynamics $\hat{\beta}_{i,t}^x$. We calibrate b, k, and $\hat{\beta}_{i,t}^u$ outside of the model by performing a linear regression with the model $log(V_t) = log(b) + klog(U_t)$. We estimate the duration effect (γ_d) and elasticity in the matching function (l) by targeting two moments: the contemporaneous job-finding probability $(F_t^i \hat{X}_t^i)$ and the percentage of its monthly decline rate $(\hat{\beta}_{i,t}^x)$.

Our results demonstrate that incorporating negative duration dependence improves the fit of the targeted moments compared to the model with $\gamma_d = 0$. This indicates that a negative duration is necessary to explain the 18% decline in perceived one month ahead job-finding probability $(F_t^i \hat{X}_{t+1}^i)$ compared to current month belief $(F_t^i \hat{X}_t^i)$. Despite the improvement in the model's fit, an important empirical finding in this literature is that perceived job-finding probability remains flat within a spell during the sample period. However, panel (A) of our results show that the model with only a negative duration generates $F_t^i \hat{X}_{t+1}^i \approx F_{t+1}^i \hat{X}_{t+1}^i < F_t^i \hat{X}_t^i$, which is inconsistent with the empirical pattern.[38]

We now turn our attention to the full model, which incorporates both the duration dependence and the individual unemployment environment. Specifically, we have:

$$F_t^i \hat{X}_t^i \approx \exp\left(\gamma_d D_{i,t}\right) \left[b^{-1} \left(F_t^i U_{i,t} \right)^{l(1-k)} + 1 \right]^{-\frac{1}{l}} \tag{6.4}$$

Recall that $F_t^i U_{i,t} = U_t + \theta \left(U_t - \hat{\beta}_{i,t-1}^u U_{t-1} \right)$, where θ is an additional parameter. The corresponding perceived job-finding probability for one month ahead is given by:

$$F_t^i \hat{X}_{t+1}^i \approx \exp\left(\gamma_d D_i, t+1\right) \left[b^{-1} \left(F_t^i U_t \right)^{l(1-k)} + 1 \right]^{-\frac{1}{l}} +$$
$$\exp(\gamma_d D_{i,t+1}) \left[b^{-1} \left(U_t \right)^{l(1-k)} + 1 \right]^{-\frac{1}{l}-1} (k-1) b^l U_t^{l(1-k)-1} \left(F_t^i U_{i,t+1} - U_t \right) \tag{6.5}$$

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[37]Please refer to appendix B.2 for derivations.

[38]Even if we targeted $F_{t+1}^i \hat{X}_{t+1}^i$ in the calibration, the model with $\theta = 0$ cannot fit it well.

To calibrate the full model, we follow the same procedure as in panel (A) and estimate the duration effect (γ_d), the elasticity in the matching function (l), and the correlation between aggregate and individual unemployment environment (θ).[39] In this case, we target the monthly job-finding probability in period $t+1$ as our new moment. The results of the calibration are reported in panel (B) of Table 4. We find that the job search model with a negative duration dependence ($\gamma_d > 0$) and a positive correlation between aggregate and individual unemployment environment ($\theta > 0$) can fit all three moments well.

Table 4: Initial Calibration

Panel A: model with $\theta = 0$			
Parameters:	γ_d	l	
Estimates:	-0.193	0.980	
Moments:	$F_t^i \hat{X}_t^i$	$\hat{\beta}_{i,t}^x$	$F_{t+1}^i \hat{X}_{t+1}^i$
Fit:	0.000	0.000	-0.035
Panel B: full model			
Parameters:	γ_d	l	θ
Estimates:	-0.103	0.909	1.476
Moments:	$F_t^i \hat{X}_t^i$	$\hat{\beta}_{i,t}^x$	$F_{t+1}^i \hat{X}_{t+1}^i$
Fit:	0.000	0.000	0.000

Notes: in panel A, moment $F_{t+1}^i \hat{X}_{t+1}^i$ is non-targeted, though the model with $\theta = 0$ cannot fit it well even if it was targeted. k and b are estimated by a linear regression ($log(V_t) = log(b) + k log(U_t)$) using true US unemployment rate and Us vacancy rate. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample). We keep unemployed workers who reported at least 3 times about their perceived job-finding probabilities.

To understand why introducing the parameter θ enables the job search model to generate a flat within-spell job-finding probability forecast, despite the negative duration dependence, we can linearize the period $t+1$ job search model shown in Equation 6.4 around $F_{t+1}^i U_{i,t+1}$. This gives us:

$$F_{t+1}^i \hat{X}_{t+1}^i \approx \exp(\gamma_d) \left[1 + \left[b^{-1} \left(F_t^i U_{i,t} \right)^{l(1-k)} + 1 \right]^{-1} (k-1) b^{-l} \left(F_t^i U_{i,t} \right)^{l(1-k)-1} \left(F_{t+1}^i U_{i,t+1} - F_t^i U_{i,t} \right) \right) F_t^i \hat{X}_t^i$$

(6.6)

We can observe the difference between equation 6.5 and 6.6. Equation 6.5 refers to the period t forecast of period $t+1$ job-finding probability, while equation 6.6 pertains to the period $t+1$ forecast of period $t+1$ job-finding probability forecast. As the period $t+1$ perceived surprise on

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[39] Estimates of b, k and $\hat{\beta}_{i,t}^u$ are calibrated outside the model as before.

individual unemployment environment $\hat{\eta}_{i,t+1}$ is not realized in period t, the forecast of the next period individual unemployment environment becomes $F_t^i U_{i,t+1} = F_t^i U_{t+1} = \hat{\beta}_{i,t}^u U_t$.[40]

However, in period $t+1$, when the period $t+1$ perceived surprise on individual unemployment $\hat{\eta}_{i,t+1}$ realizes, we have $F_{t+1}^i U_{i,t+1} = U_{t+1} + \theta \left(U_{t+1} - \hat{\beta}_{i,t}^u U_t \right)$. During our sample period, the term $\left(U_{t+1} - \hat{\beta}_{i,t}^u U_t \right)$ is on average negative, implying a smaller perceived individual unemployment environment in period $t+1$ than in period t (when the shock $\hat{\eta}_{i,t+1}$ is not realized). Together with a positive θ which reinforces the impact of the shock, the period $t+1$ belief of period $t+1$ job-finding probability is higher than the period t belief of period $t+1$ job-finding probability. In other words, the way that job seekers perceive the aggregate unemployment environment affects their individual job-finding probability, which is the underlying reason why our full model can fit all the key empirical patterns.[41]

6.4 Calibration with Micro-data

In the previous subsection, we conducted a simple calibration exercise to demonstrate how our job search model can fit the documented key empirical pattern. In this subsection, we calibrate the model using the simulated method of moments with individual-level survey responses directly taken from the SCE survey.

One goal of calibrating the model with individual-level data is to examine the precision of the estimates. Moreover, in the first calibration, we estimated the perceived job-finding probability using equation 4.1, which relies on the underlying process of the perceived job-finding probability model of equation 4.2. This implies that the perceived job-finding probability decreases at the same rate $\hat{\beta}_{i,t}^x$ for all future periods, which differs from the job search model that implies a different rate of decline for each period looking forward:[42]

Lemma 1 *The job search model (equation 6.4) implies* $\dfrac{F_t^i \hat{X}_{t+2}^i}{F_t^i \hat{X}_t^i} \neq \left(\dfrac{F_t^i \hat{X}_{t+1}^i}{F_t^i \hat{X}_t^i} \right)^2$.

To address the above points, we construct a set of new moments. We use three moments: the period t 3-month job-finding probability, period $t+1$ 3-month job-finding probability, and 12-month job-finding probability reported in the SCE survey. The objective is to investigate whether

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[40] A job seeker i cannot predict the future individual unemployment surprise, i.e., $F_{t-1}^i (\hat{\eta}_{i,t}) = 0$.

[41] One may also notice that the estimated γ_d in panel (A) is greater than in panel (B). This difference is due to the full model's information structure. Specifically, the non-presence of the individual unemployment environment in the one-month ahead job-finding probability can help generate a negative duration dependence, which can result in a smaller γ_d estimate in panel (B) compared to panel (A).

[42] Please refer to the appendix B.3 for the proof.

we can replicate the findings using original data questions from the SCE.

$$\frac{1}{N}\left(FindJob3_t^i - 1 - \left(1 - F_t^i \hat{X}_t^i\right)\left(1 - F_t^i \hat{X}_{t+1}^i\right)\left(1 - F_t^i \hat{X}_{t+2}^i\right)\right) = 0$$

$$\frac{1}{N}\left(FindJob3_{t+1}^i - 1 - \left(1 - F_{t+1}^i \hat{X}_{t+1}^i\right)\left(1 - F_{t+1}^i \hat{X}_{t+2}^i\right)\left(1 - F_{t+1}^i \hat{X}_{t+3}^i\right)\right) = 0 \tag{6.7}$$

$$\frac{1}{N}\left(FindJob12_t^i - 1 - \prod_{\tau=0}^{11}\left(1 - F_t^i \hat{X}_{t+\tau}^i\right)\right) = 0$$

The idea is that the model-predicted 3-month and 12-month job-finding probabilities should match with their empirical counterparts.[43] All other moments are constructed based on these two moments. Specifically, we interact the aggregate unemployment rate U_t with the period t 3-month job-finding probability and the period $t+1$ 3-month job-finding probability. The idea is that the aggregate unemployment rate U_t should not be mean-dependent on the residuals of the first two moments.

Using the five moments, we can estimate the duration effect (γ_d), the elasticity in the matching function (l), and the correlation between aggregate to individual unemployment environment (θ). To estimate these parameters, we use simulated generalized method of moments (GMM) and consider the parameter vector $\Theta = \gamma_d, \theta, l$. The minimization problem can be expressed as follows:

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

We use identity matrix as the weight matrix. Results are robust to using other weighting matrices.

Table 5: Calibration with Micro-data

Parameters:	γ_d	θ	l
Value	-0.141	1.393	0.606
(Std)	(0.000)	(0.033)	(0.000)
Model-fit:	$log(1 - FindJob3)$	$log(1 - FindJob3)$	$log(1 - FindJob12)$
Data	-0.532	-1.199	-0.539
Model	-0.532	-1.199	-0.539

Notes: k and b are estimated by a linear regression ($log(V_t) = log(b) + k log(U_t)$) using true US unemployment rate and Us vacancy rate. Survey weights are used, and the samples are restricted to unemployed workers age 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample). We keep unemployed workers who reported at least 3 times about their perceived job-finding probabilities.

[43]Please refer to Appendix B.3 for details on how to construct $F_t^i \hat{X}_{t+\tau}^i$ for $\tau > 0$ in general.

The estimation result is presented in Table 5. In the upper panel, we report all the estimates, including the subjective duration effect ($\gamma_d = -0.141$), the correlation between the aggregate and individual unemployment environment ($\theta = 1.383$), and the job-finding probability elasticity ($l = 0.606$). The negative value of γ_d indicates that job seekers believe their job-finding probability will decrease as unemployment duration becomes longer. Moreover, the estimated value of θ suggests that job seekers' beliefs are significantly affected by aggregate unemployment. Finally, the estimated value of l is relatively high, indicating that job seekers believe their job-finding probability is more responsive to their individual unemployment environment than to the aggregate statistics. Previous literature mostly reports l values of around 0.4 (e.g., Hagedorn and Manovskii (2008)), which implies that perceived job-finding probability is more responsive to aggregate labor market conditions than a standard matching function. In the lower panel of Table 5, we demonstrate that the model-generated counterparts closely match the three key moments.

Thus far, we have employed a linear regression ($\log(V_t) = \log(b) + k \log(U_t)$) to estimate parameters k and b, utilizing observed aggregate unemployment and vacancy rates independent of the estimation procedure. However, the correlation between unemployment and vacancy rates in actuality may differ from the belief held by job seekers. Furthermore, job seekers perceiving an large response of vacancy rate on unemployment rate may also contribute to explaining the empirical pattern, weakening the elastic response to the unemployment rate "surprise".

To explore the sensitivity of our estimation results relative to different values of k and b, we consider a range of combinations of these parameters that could be shaped by job seekers' subjective beliefs. As detailed in Appendix D.8, our findings indicate that the estimation outcomes remain robust. Notably, we ascertain that θ not only maintains its positive value, but also is statistically significantly greater than zero, notwithstanding any modifications in k and b. Figure D.4 in the appendix provides a graphical representation.

After obtaining estimates from the calibration, we use a simulation exercise to demonstrate that although perceived job-finding probability model results in an significant response to the aggregate unemployment rate, the large response can be statistically insignificant upon incorporating individual heterogeneity. Please refer to appendix D.9 for the details of the analysis. This is in line with the empirical evidence that perceived job-finding probability is not sensitive to changes in the aggregate unemployment rate.(Mueller et al., 2021; Mueller and Spinnewijn, 2021; Menzio, 2022).

We now assume that each job seeker has an individual heterogeneity term A_i that can be different than 1. This term accounts for differences in job seekers' effectiveness in search and their

varying human capital accumulation. We calibrate the variance of the heterogeneity term, A_i, to match the model-generated variance of perceived monthly job-finding probabilities with observed data. We conduct 500 simulations of individual job-finding probabilities, each using unique draws from a normal distribution, $N(0, VAR(A_i))$. The results, depicted in Figure D.5, show the correlation between simulated probabilities and the aggregate unemployment rate, U_t, as well as their confidence intervals. Interestingly, 60% of these intervals include 0, indicating that despite a strong response of the model to the aggregate unemployment rate, the statistical significance is lacking in most scenarios.

7 Illustration of Possible Implications for Job Search

In this section, we explore the implications of the pattern of perceived job-finding prospects on search efforts. To do this, we expand the model detailed in equation 6.1, incorporating a search effort term, and analyze how job seekers might alter their search strategy in accordance with their belief dynamics.

Our focus is on a risk-neutral unemployed job seeker i who lives for T periods ($t = 1, 2, ..., T$) and search in the first $T - 1$ periods ($t = 1, 2, ..., T - 1$) when unemployed. For simplicity, we normalize job seeker's search efficiency by setting $A_i = 1$. Consistent with the literature, discount factor is set to be $\delta = (0.99)^{1/12}$. Nonetheless, we introduce a search effort term $e_{i,t} \geq 0$ to the perceived job-finding probability and denote the remaining terms as $f(D_{i,t}, U_{i,t})$, representative of a perceived job search prospect.

$$F_t^i \hat{X}_t^i(e_{i,t}) = e_{i,t} \underbrace{\exp\left(\gamma_d D_{i,t}\right) \times \frac{M\left(U_{i,t}, V_{i,t}\right)}{U_{i,t}}}_{f(D_{i,t}, U_{i,t})} \tag{7.1}$$

In the contemporaneous period, equation (7.1) indicates that the perceived job-finding probability increases with the search effort, depends on unemployment duration and the unemployment condition of the island that job seeker i lives.

Implementing the search effort $e_{i,t}$ comes with a strictly concave cost function $c(e_{i,t})$. During unemployment, the job seeker receives an unemployment benefit equal to B. If job seeker i's search effort in period t leads to a job, she receives wage W instead of unemployment benefits B in the subsequent periods. This implies that the last period of search is $T-1$, which leads to consumption W in the last period if successful and B otherwise.

We aim to understand the choice of search effort by job seeker i in period 1, given various beliefs about the job search environment $\{f(D_{i,\tau}, U_{i,\tau})\}$ of the subsequent periods. Because search efforts today and tomorrow are substitutes, a job seeker has the incentive to lower her search effort today she expects a brighter future job-finding prospects. The empirical evidence shown in section 5 suggests that job seekers seem to expect low chances in the future, but when the future arrives they are again more optimistic. This means that the job seekers exert more efforts initially then they would have had they anticipated the better times ahead. Note that in our empirical setting we showed that professional forecasters seem to anticipate the better times, and one could envision an information campaign that aims to educate workers, which here would have the consequence of lowering search effort.

Appendix D.10 provides some supporting evidence for this intuition: using the infrequent supplementary Labor Market Survey to the SCE we show that job seekers who expect larger declines in future job finding rates tend to apply more for jobs, controlling for individual characteristics and the state of the aggregate economy. Unfortunately we cannot apply fixed effects here, as the supplement is administered too infrequently.

How large could these effects be? We conduct a calibration to demonstrate that this channel might be nontrivial. Following the works of Christensen et al. (2005), Lise (2013), and Gomme and Lkhagvasuren (2015), we presume a quadratic search cost function. Using the UI data from the United States Department of Labor, we assume a monthly UI benefit of $B = \$1820$ and a wage of $W = \$3640$. We assume that job seekers can search for 12 total periods when unemployed to align with the horizon in SCE. We calibrate the remaining parameters to target the average monthly perceived job-finding probability of 0.2 and the 18% perceived job-finding probability decrease looking forward. Please refer to appendix D.11 for details of the calibration.

We find that, if job seeker i perceives that her future job-finding probability will decrease deterministically by around 20% because of expected duration effects (e.g., a lower $\{F_1^i f(D_{i,\tau}, U_{i,\tau})\}$) and its consequences on job search. Then her first period search effort increases by 11.6% compared to the scenario where she perceives that her job-finding probability stays constant in the future (e.g., because improving aggregates offset the negative duration dependence as we have argued in the empirical section). If expectations about $\{F_2^i f(D_{i,\tau}, U_{i,\tau})\}$ jump back upwards in the second period but are expected to fall again in the future, as appears to be the case in the data, then a similar overreaction repeats itself in the second period. And so forth. We find that search effort in this environment is robustly too high when job seekers are too negative about the future,

relative to the true developments and those anticipated by professional forecasters.

A social planner might like such effects. This effect of belief on search effort is equivalent to a 20% unemployment benefit cut, holding everything else constant. This makes it evident that the perceived threat of a worse future mitigates the usual moral hazard in job search. This can also be seen by considering the associated problem of a social planner who maximizes a similar problem as that of the individual job seeker, but expects that $\{F_1^i f(D_{i,\tau}, U_{i,\tau})\}$ is truly constant and who does not value unemployment benefits as it has to be financed from other people's taxes. The first period search effort of the individual is around 72.2% of the optimal effort level that the planner would like. Her first period search effort falls to only 63.9% of the optimal effort level when she perceives that her job-finding probability stays constant in the future. So the fear of a worse labor market closes the efficiency gap by 22%.

This section illustrates that the perceived threat of declining labor market prospects can have large implications for job search. If it is incorrect, and job seekers continue to perceive a constant sequence over time, then their search effort in the first period is too high relative to the effort they would have chosen under anticipation of a constant future. If beliefs unanticipatedly jump back upward after that period, as seems to be the case in the data, then search effort jumps back up in the next period, again above the effort that would be chosen under anticipation of a constant future. A government that is worried about free-riding might not want to counter such behavior, as it mitigates free-riding by a non-trivial degree.

These are just tentative insights, and more work on this domain is needed. But is is clear that the perceptions of future threats in a given period and their resolution over time can be a powerful force, and a clear understanding is important for the correct design of unemployment benefits. This seem in particular relevant because the magnitude of the anticipated labor market decline is substantial, offering the possibility of large real effects on job search decisions.

8   Conclusions

Understanding how job seekers form beliefs about their job-finding probability is recent but burgeoning topic in the literature on the job search. This paper investigates the dynamics of such beliefs, and decouples the anticipation of future trends at a given point in time, from the dynamics of anticipation at different points in time. It finds evidence indicating that job seekers believe at a given point in time that their job-finding probability decreases as unemployment duration

increases. This perceived "duration dependence" detected in job seekers' survey responses highlights the critical need to study how job seekers form their beliefs, as it can offer valuable insights into labor market dynamics and policy interventions.

Our findings also emphasize the importance and benefit of investigating belief interactions. We demonstrate that job seekers' perceived dynamics of the aggregate unemployment environment strongly impact how they perceive their job-finding probability. While job seekers seem stubbornly non-optimistic about their own future job finding prospects and about how the unemployment rate will develop, they seem to very positively update about their own prospects when the aggregate labor market does improve. The sheer size of these effects make them a promising target for future work.

Overall, our research underscores the importance of studying the learning and updating process of job seekers' beliefs. We anticipate that more research will follow, utilizing available belief data from job seekers to answer important questions about how job seekers form beliefs, the role of beliefs in job search behavior, and the impact of policy interventions on job search outcomes. Our analysis highlights the value of studying the dynamics of beliefs and the interactions between market-level expectations and individual job finding expectations.

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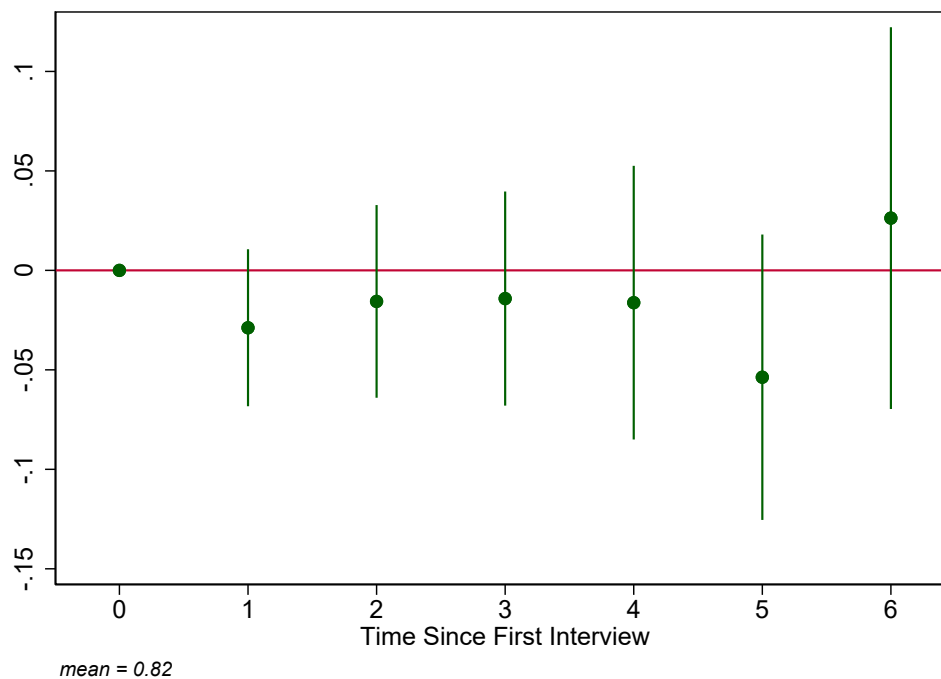# Appendices

A   Additional Figures

Figure A.1: Estimated job-finding Probability Projection $\hat{\beta}_{i,t}^x$, by Time since First Interview

Notes: we plot the estimated job-finding probability projection $\hat{\beta}_{i,t}^x$ by month since first interview. The job-finding probability projection is calculated using the empirical framework proposed in equation 4.1. We remove the individual fixed effects, time fixed effects at the month level and cluster standard errors at the individual level. The bars indicate the 95 percent confidence interval. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample).
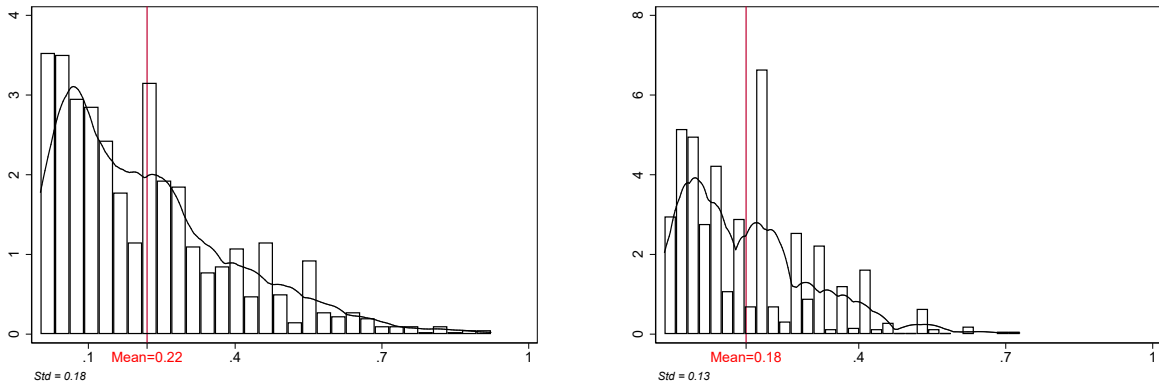
Figure A.2: Histogram of job-finding Probability $F_t^i \hat{X}_t^i$

Notes: in the left panel, we present the histogram of job-finding probability $F_t^i \hat{X}_t^i$ estimates for each individual at each interview using the empirical framework proposed in equation 4.1. In the right panel, we demonstrate the the histogram of job-finding probability $F_t^i \hat{X}_t^i$ estimates directed imputed from the self-reported 3-month job-finding probability. Black lines connect the fitted kernel density estimates using the Epanechnikov kernel. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample).
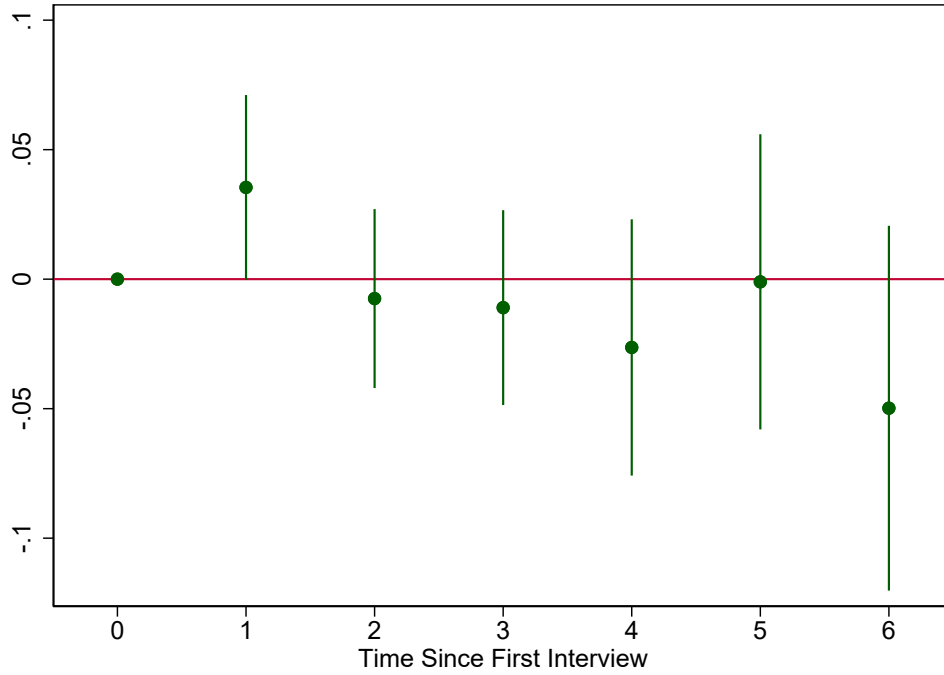
Figure A.3: Estimated job-finding Probability $F_t^i \hat{X}_t^i$, by Time since First Interview

Notes: we plot the estimated job-finding probability $F_t^i \hat{X}_t^i$ by month since first interview. The job-finding probability projection is calculated using the empirical framework proposed in equation 4.1. We remove the individual fixed effects, time fixed effects at the month level, and cluster standard errors at the individual level. The bars indicate the 95 percent confidence interval. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample).
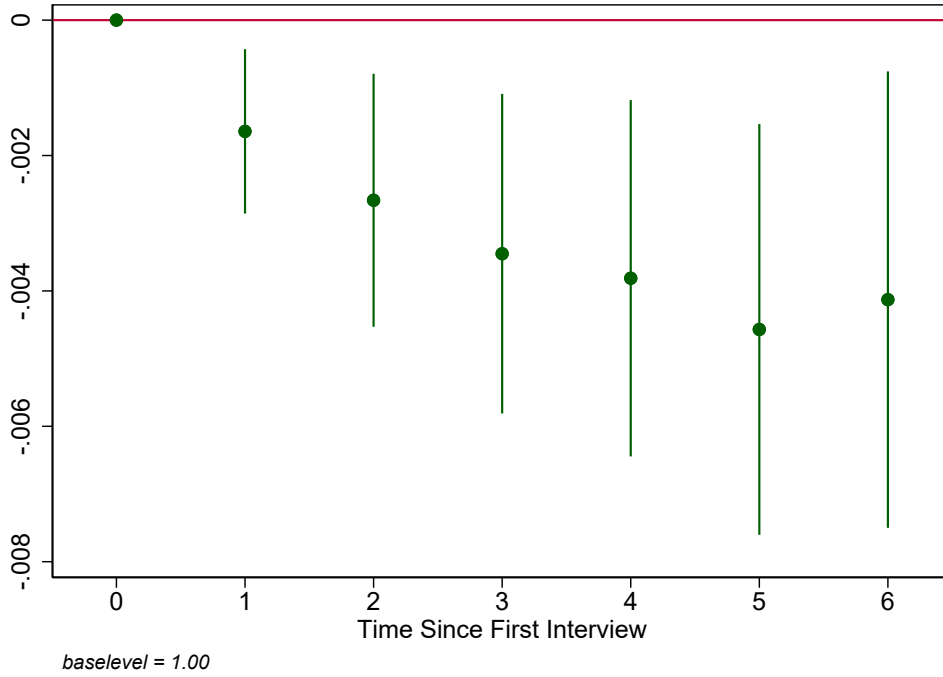
Figure A.4: Estimated $F_t^i \hat{X}_t^i \hat{\beta}_{i,t}^u$, by Time since First Interview

Notes: we plot the estimated US unemployment rate projection $\hat{\beta}_{i,t}^u$ by month since first interview. The US unemployment rate projection is calculated using the empirical framework proposed in equation 4.4. We remove the individual fixed effects, time fixed effects at the month level, and cluster standard errors at the individual level. The bars indicate the 95 percent confidence interval. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample).
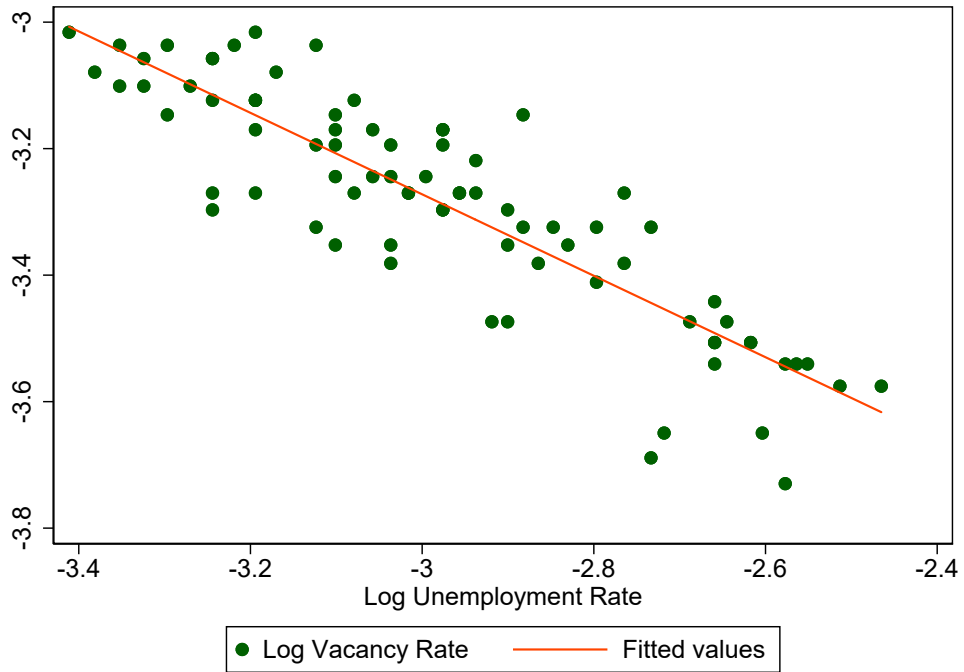
Figure A.5: Beveridge Curve with a Log-linear Fit

Notes: we use the model $Log(V_t) = log(b) + klog(U_t)$ to fit the Beveridge curve. We precisely estimate $k = -0.644$ and $b = 0.005$ with a $Adj - R^2 = 0.77$. The figure shows the plot of $Log(V_t)$ and $log(U_t)$ together with the linear fit.

B Omitted Proofs

B.1 Proof for Proposition 1

We can first write

$$F_t^i \Pr\left(U_{t+k} > U_t\right) = \Pr\left(\left(\hat{\beta}_{i,t}^u\right)^k U_t + \sum_{\tau=1}^{k} \left(\hat{\beta}_{i,t}^u\right)^{k-\tau} \epsilon_{t+\tau}^u \geq U_t\right)$$

$$= \Pr\left(\frac{\sum_{\tau=1}^{k} \left(\hat{\beta}_{i,t}^u\right)^{k-\tau} \epsilon_{t+\tau}^u}{1 - \left(\hat{\beta}_{i,t}^u\right)^k} \geq U_t\right)$$

Because of the distributional assumption on $\epsilon_{t+\tau}^u$, we know that

$$\frac{\sum_{\tau=1}^{k} \left(\hat{\beta}_{i,t}^u\right)^{k-\tau} \epsilon_{t+\tau}^u}{1 - \left(\hat{\beta}_{i,t}^u\right)^k} \sim N\left(0, \frac{\left(1 - \left(\hat{\beta}_{i,t}^u\right)^{2k-2}\right)}{\left(1 - \left(\hat{\beta}_{i,t}^u\right)^2\right)\left(1 - \left(\hat{\beta}_{i,t}^u\right)^k\right)^2} \hat{\sigma}_{u,\epsilon}^2\right)$$

.

Taken together, we have

$$F_t^i \Pr\left(E_t^i U_{t+k} > U_t\right) = 1 - \Phi\left(\sqrt{\frac{\left(1 - \left(\hat{\beta}_{i,t}^u\right)^2\right)\left(1 - \left(\hat{\beta}_{i,t}^u\right)^k\right)^2}{\left(1 - \left(\hat{\beta}_{i,t}^u\right)^{2k-2}\right)}} * \frac{U_t}{\hat{\sigma}_{u,\epsilon}}\right)$$

B.2 Derivations for equation 6.2

We only show derivations for the case where the duration effect is present. The case without a duration effect is analogous.

In general, we set up a model of belief as the following:

$$F_t^i \hat{X}_t^i = F_t^i f(D_{i,t}, U_t)$$

We linearize $F_{t-1}^i \hat{X}_t^i$ around U_{t-1} and then take expectation to find:

$$F_{t-1}^i \hat{X}_t^i \approx f(D_{i,t}, U_{t-1}) + f'(D_{i,t}, U_{t-1})\left(F_{t-1}^i U_t - U_{t-1}\right)$$

Some rearrangements to align with our statistical model:

$$F_{t-1}^i \hat{X}_t^i \approx f(D_{i,t}, U_{t-1}) \underbrace{\left[1 + \frac{f'(D_{i,t}, U_{t-1})}{f(D_{i,t}, U_{t-1})} \left(F_{t-1}^i U_t - U_{t-1}\right)\right]}_{\text{This is } \beta_{i,t}^x}$$

We can use any functional form to conduct empirical analysis by substituting it into the general equation. It is important to note that the procedure for the case of individual unemployment environment $(U_{i,t})$ is similar, except for the difference in taking expectations.

B.3   Derivations for lemma 1 and equation 6.7

We first derive the τ period ahead job-finding probability $F_t^i \hat{X}_{t+\tau}^i$ by first order approximation around $F_t^i U_{i,t}$

$$F_t^i \hat{X}_{t+\tau}^i \approx \exp(\tau\gamma_d) \left[1 + \left[b^{-1}\left(F_t^i U_{i,t}\right)^{l(1-k)} + 1\right]^{-1} (k-1)b^{-l}\left(F_t^i U_{i,t}\right)^{l(1-k)-1}\left(E_t U_{t+\tau} - U_t - \theta\left(U_t - E_{t-1}U_t\right)\right)\right] F_t^i \hat{X}_t^i$$

This is the general formula we use to construct the moments in our calibration with micro data.

Then we can see that

$$\frac{F_t^i \hat{X}_{t+\tau}^i}{F_t^i \hat{X}_t^i} \approx \exp(\tau\gamma_d) \left[1 + \left[b^{-1}\left(F_t^i U_{i,t}\right)^{l(1-k)} + 1\right]^{-1} (k-1)b^{-l}\left(F_t^i U_{i,t}\right)^{l(1-k)-1}\left(E_t U_{t+\tau} - U_t - \theta\left(U_t - E_{t-1}U_t\right)\right)\right]$$

It is intuitive that $\dfrac{F_t^i \hat{X}_{t+\tau}^i}{F_t^i \hat{X}_t^i} \neq \left(\dfrac{F_t^i \hat{X}_{t+1}^i}{F_t^i \hat{X}_t^i}\right)^\tau$.

C   Perceived US Unemployment Rate Projection: Robustness Analysis

C.1   The Level of Unemployment Rate

In Section 4, we posit that job seekers form rational expectations about the US unemployment rate for the given month, partly because the SCE did not capture perceived unemployment rate levels. Based on this assumption, we develop an empirical method to back out perceived US unemployment Rate dynamics. Here, we relax our maintained information assumption and demonstrate that the estimated US Unemployment rate projection, denoted as $\hat{\beta}_{i,t}^u$, does not change significantly even when job seekers have misconceptions about the level of the US unemployment rate.

In Proposition 1, we elucidate how we can calculate individual perceived US unemployment rate projection by utilizing $F_t^i \Pr(U_{t+k} > U_t)$, the US unemployment rate U_t, and $\hat{\sigma}_{u,\epsilon}$. In this scenario, we alternatively hypothesize that a job seeker i might enter our sample with an incorrect

belief about the unemployment rate U_t. Specifically, we suggest that the perceived US unemployment rate for job seeker i when entering our sample could be either 10% higher or lower than the actual US unemployment rate U_t; this implies that the perceived rate, $\hat{U}_t$, would fall within the range $\hat{U}_t \in [0.9 \times U_t, 1.1 \times U_t]$. We further assume that the job seeker learns accurately about changes in the unemployment, but gets no additional information about the level. So we utilize $\hat{U}_t$ to determine $\hat{\beta}_{i,t}^u$ by employing Equation 4.4.

Given that $\hat{\beta}_{i,t}^u$ exhibits a monotonically decreasing behavior with increasing $\hat{U}_t$ (as observed in Equation 4.4), it is sufficient to only scrutinize the upper and lower bounds ($0.9 \times U_t$ and $1.1 \times U_t$ respectively). We denote the perceived US unemployment rate projection computed using $0.9 \times U_t$ (or $1.1 \times U_t$) as $\hat{\beta}_{i,t}^{uh}$ (or $\hat{\beta}_{i,t}^{ul}$). We observe that the mean difference between $\hat{\beta}_{i,t}^{uh}$ and $\hat{\beta}_{i,t}^u$ is approximately 6.6×10^{-5}, while the mean difference between $\hat{\beta}_{i,t}^{ul}$ and $\hat{\beta}_{i,t}^u$ is roughly -8.1×10^{-5}. Both differences are small compared with the value and variation of $\hat{\beta}_{i,t}^u$, thus validating our claim that the estimated US Unemployment rate projection ($\hat{\beta}_{i,t}^u$) remains fairly constant, irrespective of whether job seekers harbor misconceptions about the level of the US unemployment rate.

C.2 An Alternative Specification

This subsection presents an alternative method for modeling job seekers' perceptions of the dynamics of aggregate unemployment rates. Furthermore, we demonstrate that the primary empirical pattern highlighted in section 5 remains robust when employing this alternative belief model.

C.2.1 Statistical Model

Here we present an alternative specification of the perceived unemployment rate dynamics. Again, we assume that job seeker i forms a belief about the unemployment rate U_t when surveyed at time t that equals the true unemployment rate of month t. Additionally, we assume that job seekers know the natural unemployment rate (U^n) of the economy.

Job seeker i's subjective beliefs about the evolution of the difference between unemployment rate and natural unemployment rate $U_t - U^n$ at each t are assumed to follow an AR(1) process:

$$U_{t+1} - U^n = \hat{\beta}_{i,t}^u(U_t - U^n) + \hat{\epsilon}_{i,t+1}^u, \quad \hat{\epsilon}_{i,t+1}^u \sim N(0, \hat{\sigma}_{u,\epsilon}^2). \tag{C.1}$$

$\hat{\beta}_{i,t}^u$ represents a job seeker i's perceived dynamics at time t. $\hat{\epsilon}_{i,t+1}^u$ is a noise to individual i's believe, which is assumed to follow a normal distribution $N(0, \hat{\sigma}_{u,\epsilon}^2)$ with $\hat{\sigma}_{u,\epsilon}$ being the subjective variance

of U_t.

Similarly, we can use the result from proposition 1 to compute the probability that the unemployment rate in month $t + k$ (i.e., U_{t+k}) exceeds the unemployment rate in month t (i.e., U_t) for any integer value of k given the perceived process.

We calibrate the natural unemployment rate of the US economy by natural unemployment rate period found in Federal Reserve Economic Data (FRED). During our sample period, $U^n \approx 4.64\%$. We calibrate $\hat{\sigma}u, \epsilon$ based on the actual sequence of unemployment data by calculating the standard deviation of the cyclical component of $U_t - U^n$.[44] Once we have estimated $\hat{\sigma}u, \epsilon$, we can use Equation 4.4 to obtain $\hat{\beta}^u_{i,t}$ for each individual i and month t.

We can the alternatively specified perceived unemployment rate process to calculate the job seeker's perceived "surprise" about the aggregate market ($F^i_t U_t - F^i_{t-1} U_t$).

C.2.2 Empirical Results

In this subsection, we use the alternatively estimated perceived "surprise" to replicate table 2. We use the following fixed effects regression model to investigate how the individual "surprise" on US unemployment can explain the update of individual perceived job-finding probability:

$$\left(F^i_t \hat{X}^i_t - F^i_{t-1} \hat{X}^i_t \right) = \vartheta \left(U_t - F^i_{t-1} U_t \right) + \delta_i + \delta_u + \varepsilon_{i,t} \tag{C.2}$$

The dependent variable is the update of job-finding probability $F^i_t \hat{X}^i_t - F^i_{t-1} \hat{X}^i_t$. The parameter of interest is ϑ, which indicates how changes in perceived individual national unemployment "surprise" affect perceived individual job-finding probability. To eliminate the selection effect, we control for individual fixed effect δ_i. We also use a unemployment rate fixed effect to remove the systematic impact of monthly aggregate environment.[45] We cluster standard error at the individual level. Furthermore, the inclusion of individual unemployment duration as a control variable does not significantly alter the main empirical pattern.

Table C.1 presents the results. In column (1), we find that ϑ is estimated to be around -3, which is statistically significant at the 0.2 level. Incorporating the unemployment duration fixed effect increases the magnitude of ϑ to around -4, which is statistically significant at the 0.1 level. The results suggest that at the individual level, the subjective belief "surprise" on national unem-

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[44]The cyclical component of U_t is computed via the Hodrick-Prescott (HP) Filter.

[45]We do not use the time fixed effect at the month level as in the main specification because the variation from $\left(U_t - F^i_{t-1} U_t \right)$ is significantly smaller given the alternative specification as compared to the specification we used in the main part of the paper.

Table C.1: Belief Surprise of US Unemployment on job-finding Probability Update

| | (1) | (2) |
	Job-Finding Prob Update	Job-Finding Prob Update
Belief Surprise: US Unemployment	-2.830	-4.323*
	(2.185)	(2.370)
Person FE	Yes	Yes
U Rate FE	Yes	Yes
Duration FE	No	Yes
Cluster STD	Person	Person
Obs	456	456

Notes: job-finding probability update is calculated by $F_t^i \hat{X}_t^i - \hat{\beta}_{i,t}^x F_{t-1}^i \hat{X}_{t-1}^i$. Belief surprise of US unemployment rate is calculated by $U_t - F_{t-1}^i U_t$ using alternative specification C.1. We use specification C.2 and cluster standard errors at the individual level. Column (2) further controls for the unemployment duration fixed effects. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ployment among unemployed job seekers is negatively correlated with their perceived job-finding probability change. Additionally, the large estimate magnitude suggests a significant impact.

We further evaluate the magnitude of the estimated ϑ by producing a table similar to 3. We define the adjusted job-finding prob forecasts predicted by the following equation:

$$\widehat{F_t^i \hat{X}_t^i} = F_{t-1}^i \hat{X}_t^i + \hat{\vartheta} \left(U_t - F_{t-1}^i U_t \right)$$

The second row of table C.2 shows that incorporating the impact of perceived unemployment rate "surprise" helps mitigate the empirical puzzle. The adjusted job-finding probability forecast $(\widehat{F_t^i \hat{X}_t^i})$ is around 0.188, which is statistically significantly larger than the period $t-1$ perceived job-finding probability forecast $(F_{t-1}^i \hat{X}_t^i)$. The impact of perceived unemployment rate "surprise" on job seekers' beliefs about their own job-finding probability change accounts for around 68% of the difference between the contemporaneous and period $t-1$ perceived job-finding probability forecasts.

The empirical results shows that the empirical pattern highlighted in section 5 is robust to an alternative specification of how the job seekers perceive the dynamics of US unemployment rate.

Table C.2: JFR Updates Induced by Belief Surprise of Unemployment Rate

	$t-1$	t
contemporaneous job-finding prob forecast $(F_t^i \hat{X}_t^i)$	0.201	0.204
	(0.147)	(0.164)
job-finding prob forecasts predicted by model $(\widehat{F_t^i \hat{X}_t^i})$		0.188
		(0.122)
job-finding prob forecasts predicted at $t-1$ $(F_{t-1}^i \hat{X}_t^i)$		0.154
		(0.104)

Notes: the contemporaneous JFR forecast $(F_t^i \hat{X}_t^i)$ at period t is statistically significantly different from the JFR forecasts predicted by JFR projections $(F_{t-1}^i \hat{X}_t^i)$ at 0.01 level, while not statistically significantly different from JFR forecasts predicted by beliefs on U $(\widehat{F_t^i \hat{X}_t^i})$. Survey weights are used when calculating the averages, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample).

D Additional Empirical Results

D.1 Perceived Job-finding Probability: Compounding

The SCE Labor Market Survey (SCE LMS) is a rotating module of the Survey of Consumer Expectations (SCE), conducted every four months. SCE LMS surveys a subset of respondents from the main SCE survey to obtain their perceived probability of finding a job within four months.

Using the estimates $\hat{\beta}_{i,t}^x$ and $F_t^i \hat{X}_t^i$, we can calculate the perceived probability of finding a job within four months for each job seeker at each time of interview, denoted as $\widehat{FindJob4}_t^i$. We also have the reported probability of finding a job within four months for the same job seeker in the SCE LMS at the same interview time, denoted as $FindJob4_t^i$.

Table D.1: Estimated and Reported 4-month Job-finding Probability

	$\widehat{FindJob4}_t^i$	$FindJob4_t^i$
Average	0.499	0.490
Std	(0.291)	(0.264)
Observations	245	245
T-test of the two variables:		
H0: $\widehat{FindJob4}_t^i \neq FindJob4_t^i$	P-value 0.512	

Notes: We only use the job seekers who are surveyed in both SCE and SCE LMS. All SCE samples restricted to unemployed workers, ages 20–65 with consistent answers. The sample is restricted to interviews where the belief questions were administered.

Table D.1 shows that on average, the estimated probability of finding a job within four months is not significantly different from the reported probability for the same job seeker in the SCE LMS at the same interview time.

Figure D.1 compares the 3, 4 and 12 month perceived job-finding probability calculated using both SCE and SCE LMS.
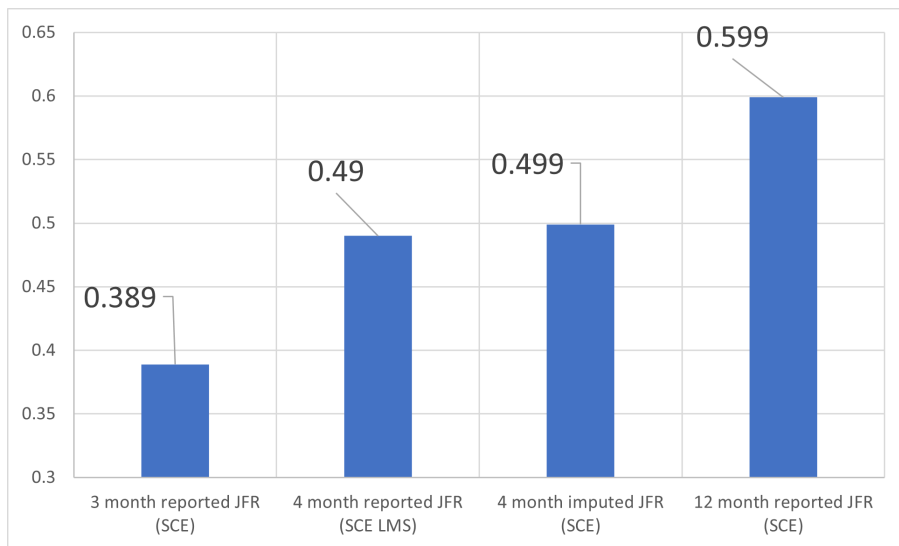
Figure D.1: Comparison: 3, 4 and 12 Month Perceived Job-finding Probability

Notes: 3 and 12 month reported perceived job-finding probability are the average values directly taken from the main SCE sample. The 4 month reported perceived job-finding probability is the average values taken from the SCE LMS sample. The 4 month imputed JFR are imputed 4 month perceived job-finding probability using estimated $\hat{X}_t^i$ and $\hat{beta}_{i,t}^x$ for those job seekers who reported 4 month perceived job-finding probability in SCE LMS. All SCE samples restricted to unemployed workers, ages 20–65 with consistent answers. The sample is restricted to interviews where the belief questions were administered. The average perceived 3-month perceived job-finding probability $FindJob3_t^i$ is around 0.435.

D.2 Perceived Unemployment Rate Dynamics from SPF

We demonstrate that job seekers hold pessimistic views about the future of the US unemployment rate, which contrasts with what actually occurred. To provide a comparison for the unemployed job seekers' perceived unemployment rate dynamics, we estimate a similar $\hat{\beta}_{i,t}^u$ for professional forecasters.

We obtain individual forecasts for the unemployment rate from the Survey of Professional Forecasters (SPF), which we download directly from the Federal Reserve Bank of Philadelphia's website. Professional forecasters provide estimates for the quarterly average of the underlying monthly levels (seasonally adjusted, percentage points). To align with our primary SCE sample, we limit the sample to the years 2012-2019.

We denote the average monthly unemployment rate forecast for the quarter that just passed as $U-1$, while we denote the current quarter as $U0$. For the q quarter ahead forecast, we denote it as Uq ($q = 1, 4$). To compare with the unemployment rate dynamics measure we constructed for unemployed job seekers $\hat{\beta}_{i,t}^u$, we calculate the ratios of unemployment rate level forecast to obtain its dynamics.

In Figure D.2, we plot the ratios $\frac{U0}{U-1}$, $\frac{U1}{U-1}$ and $\frac{U4}{U-1}$, respectively. The SPF averages for $\frac{U0}{U-1}$, $\frac{U1}{U-1}$ and $\frac{U4}{U-1}$ are approximately 0.980, 0.966, and 0.945, respectively, which align much more closely with the average true unemployment decline ($\frac{U_{t+1}}{U_t}$) over the same period.

Furthermore, the entire distribution of perceived unemployment rate dynamics from professional forecasters is significantly left-shifted compared to the forecasts from unemployed job seekers in the SCE sample (see Figure 2).
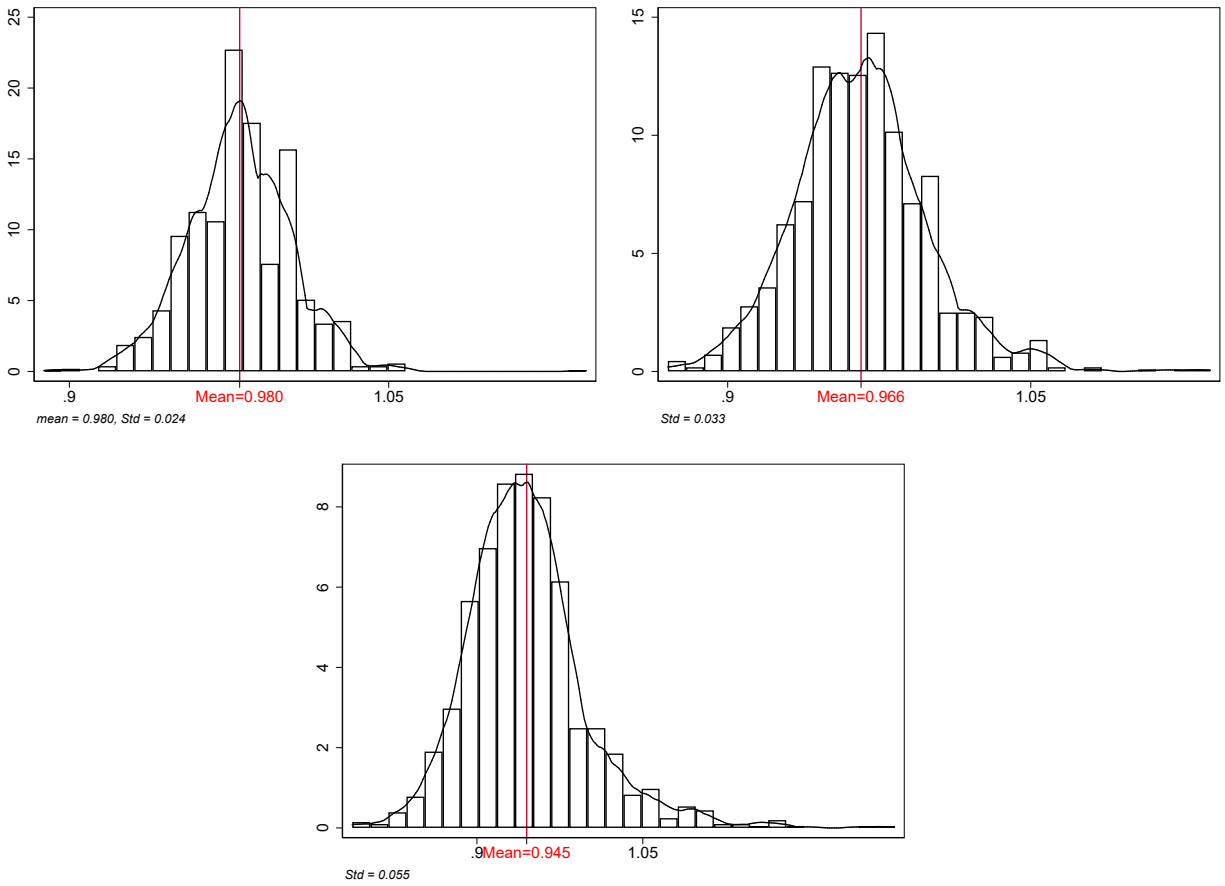
Figure D.2: Histogram of Perceived US Unemployment Rate Dynamics (SPF)

D.3 Beliefs on US Stock Market on Individual job-finding Beliefs

One key empirical finding of the paper is that job seekers update their perceived job-finding probability based on their perceived dynamics of the US unemployment rate. One may question whether job seekers also respond to other macroeconomic indicators that are not directly relevant to their job-finding probability. In this subsection, we demonstrate that the dynamics of belief in the US stock market have no effect on individual job-finding beliefs. The result indicates that job seekers appear to update their job-finding probability based on the most pertinent measure of the aggregate economy.

Similar to the US unemployment rate, respondents in the SCE survey are asked about their perceived probability that the US stock market will be higher than its current level. We use the S&P 500 index to measure the US stock market. Therefore, we can directly apply the statistical model we developed for the perceived dynamics of the US unemployment rate. Specifically, we assume that job seeker i's subjective beliefs regarding the evolution of the US stock market S_t at each time t follow an AR(1) process:

$$S_{t+1} = \hat{\beta}_{i,t}^s S_t + \hat{\epsilon}_{i,t+1}^s, \quad \hat{\epsilon}_{i,t+1}^s \sim N(0, \hat{\sigma}_{s,\epsilon}^2). \tag{D.1}$$

We then derive an analogous expression for $F_t^i \Pr(S_{t+k} > S_t)$ $(k = 11)$ as in proposition 1. We calibrate $\hat{\sigma}_{s,\epsilon}$ using the true sequence of the S&P 500 index by calculating the standard deviation of its cyclical component. Finally, we estimate $\hat{\beta}_{i,t}^u$ for each individual i and month t.

We use the same specification to investigate the relationship between individual surprise on the US stock market and the individual surprise on job-finding probability. The model is given by:

$$\left(F_t^i \hat{X}_t^i - F_{t-1}^i \hat{X}_t^i \right) = \vartheta \left(S_t - F_{t-1}^i S_t \right) + \delta_i + \delta_t + \varepsilon_{i,t}$$

The equation is similar to equation 5.1, but the main independent variable of interest is now $\left(S_t^i - F_{t-1}^i S_t \right)$.

Table D.2 presents the results of the analysis examining the relationship between update on individual job-finding probability and surprise on the US stock market. The estimated coefficient for the surprise in the US stock market, represented by $\left(S_t^i - F_{t-1}^i S_t \right)$, is close to zero and statistically insignificant in both specifications, indicating that job seekers do not update their job-finding probability based on the US stock market.

Table D.2: Belief Surprise of US Stock on job-finding Probability Update

	(1)	(2)
	Job Finding Prob Update	Job Finding Prob Update
Belief Shock: SP500	0.0000481	-0.000307
	(0.000595)	(0.000532)
Person FE	Yes	Yes
Month FE	Yes	Yes
Nedur FE	No	Yes
Cluster STD	Person	Person
Obs	449	449

Notes: job-finding probability update is calculated by $F_t^i \hat{X}_t^i - \hat{\beta}_{i,t}^x F_{t-1}^i \hat{X}_{t-1}^i$. Belief Surprise of US stock market is calculated by $S_t - F_{t-1}^i S_t$ where S_t is the S&P 500 index. We remove the individual fixed effects, time fixed effects at the month level, and cluster standard errors at the individual level. Column (2) further controls for the unemployment duration fixed effects. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.4 Impact of Beliefs on Job-Finding Realizations

According to Mueller et al. (2021), job seekers' perception of their 3-month job-finding probability has an impact on their job-finding outcomes. In this subsection, we demonstrate that both the estimated probability of finding a job within one month ($F_t^i \hat{X}_t^i$) and the projected US unemployment rate ($\hat{\beta}_{i,t}^u$) are also significant factors that affect job seekers' job-finding outcomes.

To examine whether job seekers' beliefs have an impact on their actual job-finding outcomes, we regress a binary indicator for whether a job seeker finds a job within the next month on their estimated beliefs ($F_t^i \hat{X}_t^i$ and $\hat{\beta}_{i,t}^u$). To account for individual heterogeneity, we use the consistent sample and control for individual fixed effects in all regression results. The findings are presented in Table D.3. In column (1), we report that on average, a 0.1 increase in perceived 1-month job-finding probability results in a 0.0433 increase in the actual job-finding probability, which is similar to the magnitude reported in Mueller et al. (2021). Column (2) shows that job seekers' negative perception of US employment prospects, as indicated by an increase in the perceived US unemployment rate change ($\hat{\beta}_{i,t}^u$), is associated with a decrease in actual job-finding probability. Specifically, a 0.01 increase in $\hat{\beta}_{i,t}^u$ is associated with a 0.09 decrease in actual job-finding probability on average.

In summary, we replicate the empirical findings of Mueller et al. (2021) that job seekers' perceived job-finding probability matters for actual job-finding outcomes. Additionally, we provide evidence that job seekers' projection of the US unemployment rate also plays a crucial role in their actual job-finding outcomes.

Table D.3: Estimated Beliefs on Job-Finding Outcomes

	(1)	(2)
	Realized Job Finding	Realized Job Finding
Estimated Job-Finding Probability	0.433***	
	(0.143)	
Estimated US Unemployment Rate Projection		-9.036**
		(4.290)
Person FE	Yes	Yes
Month FE	Yes	Yes
Cluster STD	Person	Person
Obs	799	799

Notes: realized job-finding is a dummy variable that equals 1 if the a unemployed job seeker surveyed at time t is employed at time $t+1$. The job-finding probability projection is calculated using the empirical framework proposed in equation 4.1. The US unemployment rate projection is calculated using the empirical framework proposed in equation 4.4. We remove the individual fixed effects, time fixed effects at the month level, and cluster standard errors at the individual level. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample). Standard errors reported in brackets are clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.5 Job-finding Outcomes

In this subsection, we explore the observed duration dependence of job search, which refers to the decrease in job-finding realizations as the duration of unemployment increases. We calculate the observed decline rate of a one-month unemployment-to-employment (U-E) transition using data from the Survey of Consumer Expectations (SCE) and compare it to the perceived decline rate of job-finding probability. Our findings indicate that the two decline rates are similar in magnitude.

Figure D.3 displays the one-month U-E transition rate plotted against the number of months since the first interview. The dashed line represents the average U-E transition rates calculated using the consistent sample, while the solid line represents the inconsistent sample. Despite using different samples, the calculated U-E transition rates follow similar trends. However, for the inconsistent sample, the U-E transition rates are higher for the first three months. By assuming that the U-E transition rate follows a process similar to the one described in Equation 4.2, we can estimate the decline rate of U-E transition, which is comparable to the perceived decline in job-finding probability ($\hat{\beta}_{i,t}^x$) we have calculated. For the sample used, we estimate the monthly decline rate of U-E transition to be 0.78. Comparing this to the monthly 18% decline in job-finding probability, we find that job seekers have fairly accurate estimates of their job-finding probability decline.
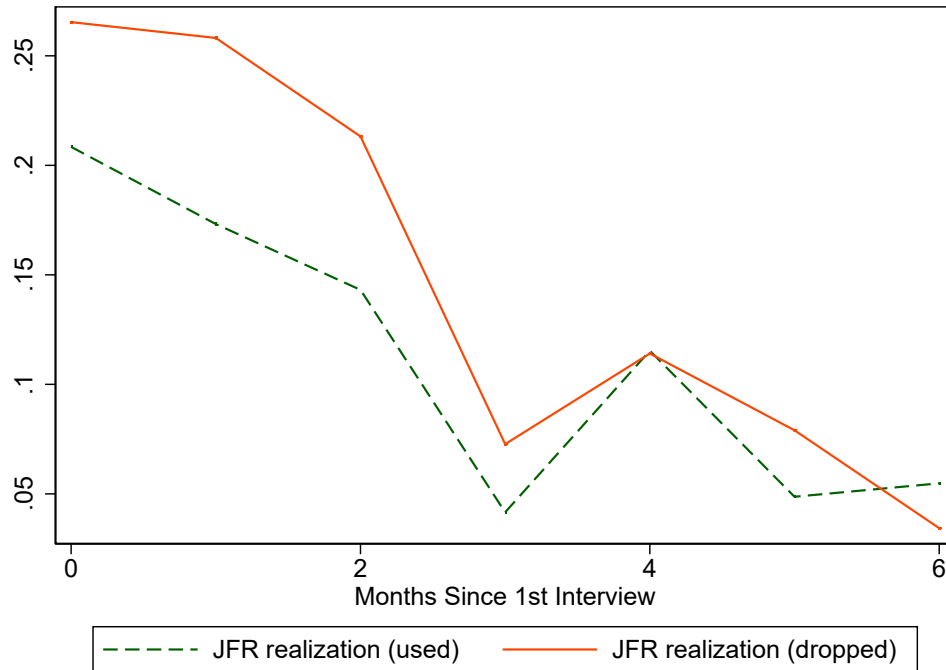
Notes: we calculate the average one month U-E transition rate by months since 1st interview. The dashed line connects average U-E transitions rates that are calculated using the consistent sample, while the solid line connects averages calculated using the inconsistent sample. Survey weights are used, and the samples are restricted to unemployed workers age 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample).

Figure D.3: U-E Transition Rate by Months Since 1st Interview

D.6 Perceptions and Job Search Experience

In order to examine the relationship between perceptions on job search and job search experience, we employ two sets of empirical results derived from combining the primary SCE survey downloaded from the NY Fed website and the supplementary Labor Market Survey (SCE LMS). Because the Labor Market Survey is conducted every four months, it poses a challenge to study the within-spell changes given the limited sample size. Instead, we account for a wide array of individual characteristics encompassing age, gender, education, household income, and race. Additionally, we control for the US unemployment rate and job seeker unemployment duration.

Table D.4: Belief on Job Search and Job Search Activities

	(1) $F_t^i \hat{X}_{i,t}$	(2) $\hat{\beta}_{i,t}^u$
Interview (last 4 weeks)	0.0686***	-0.00104
	(0.0245)	(0.00104)
Nedur	Yes	Yes
U rate	Yes	Yes
Demographics	Yes	Yes
Obs	241	241

Notes: individual characteristics include age, gender, education, household income and race. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The first set of results explore how past job search experience influences perceived job-finding probability and perceived US unemployment rate. The results are illustrated in Table D.4. We discern that the contemporaneous perceived job-finding probability $(F_t^i \hat{X}_t^i)$ exhibits a statistically significant positive correlation with the event of a job seeker having an interview in the past 4 weeks. This is an intuitively outcome as receiving an interview serves as an positive feedback for the job seeker in terms of her individual job search perspective. Conversely, we observe that the perceived unemployment rate projection shows no correlation with whether a job seeker was interviewed in the past 4 weeks. This suggests that job seekers do not seem to update their view of the aggregate market based on their own job search experience, indicating that the narrative of job seekers updating their perceptions of US unemployment dynamics predicated on their assessment of their own job search prospects is less compelling.

The second set of results show how past job search experiences influence the update of per-

ceived job-finding probability ($F_t^i \hat{X}i, t - F_t^i \hat{X}i, t-1$) and the "surprise" in the US unemployment rate ($F_t^i \hat{U}t - F_t^i \hat{U}t - 1$). Table D.5 exhibits regression results. We find that the update of current period perceived job-finding probability is only statistically significantly positively associated with the indicator of a job seeker being interviewed in the past 4 weeks. As procuring an interview in the past 4 weeks is a strong signal of job-finding, it is intuitive that job seekers adjust their perceived job-finding probability upwards. Once again, we discover that the "surprise" in unemployment rate shows no correlation with job search activities, implying that job seekers do not modify their beliefs on the aggregate market based on individual job search activities.

Table D.5: Belief Update on Job Search and Job Search Activities

	(1) Job-Finding Prob Update	(2) "Surprise" of U_t
Interview (last 4 weeks)	0.0673**	0.0000584
	(0.0319)	(0.000348)
Nedur	Yes	Yes
U rate	Yes	Yes
Demographics	Yes	Yes
Obs	131	131

Notes: Individual characteristics include age, gender, education, household income and race. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.7 KM Survey: An Alternative Specification

In subsection 5.5.1, we have proposed an empirical method to estimate job seekers' perceived job-finding probability projection $\hat{\beta}_{i,t}^x$, leveraging KM survey data. In this subsection, we incorporate an alternative empirical approach to juxtapose job seekers' perceived job-finding probabilities over diverse time frames. Specifically, we convert the reported expected duration into a weekly job-finding probability (hereafter referred to as the inverted one-week job-finding probability), founded on the expectation of a negative binomial distribution. It should be noted that this inversion assumes a constant job-finding probability throughout the entire expected duration. Consequently, the inverted one-week job-finding probability ought to be perceived as the average expected job-finding probability spanning the entire forecasted duration. Subsequently, we compute the one-week elicited job-finding probability by transposing the 4-week elicited job-finding probability. Given the transformation assumes a constant elicited job-finding probability, it should be interpreted as the average job-finding probability for the forthcoming 4 weeks.

In Table D.6, it is demonstrated that the elicited job-finding probability is statistically significantly larger than the inverted one-week job-finding probability. This infers that job seekers are of the belief that their probability of securing employment will diminish in the future. This finding is consistent with what is depicted in Figure 4.

Table D.6: Job-Finding Probability Comparisons Using the KM Survey

	mean	Std	Obs	T-statistic
Inverted one-week job-finding probability	0.087	0.117	3039	3.5975
Elicited one-week job-finding probability	0.093	0.066	3039	

Notes: We use the same KM survey sample as in Mueller et al. (2021). All samples restricted to unemployed workers, ages 20–65 with consistent answers/ The sample is restricted to interviews where the belief questions were administered. The p-value of T-test that inverted one-week job-finding probability is less than elicited one-week job-finding probability is 0.000.

D.8 Subjective Beveridge Curve

In the calibration with micro data, we assume that job seekers perceive a Beveridge Curve that is estimated by a linear regression $(\log(V_t) = \log(b) + k\log(U_t))$ using the true US unemployment rate and US vacancy rate. One may question whether the empirical pattern will significantly vary when we assume that job seekers perceive a different Beveridge Curve. In this subsection, we conduct two analyses to demonstrate that the calibration is robust when including job seekers' perceived Beveridge Curve.

In the first exercise, we estimate the model as in the main micro calibration by using the same set of moments defined in Equation 6.7. However, we independently vary the value of the elasticity of individual unemployment rate on individual vacancy rate (k) and the constant of individual unemployment rate on individual vacancy rate (b). Figure D.4 presents the estimated θ with different values of ks and bs.

In the left panel of Figure D.4, we fix k to be the value estimated from the linear regression $(\log(V_t) = \log(b) + k\log(U_t))$ and vary b from 0.0045 to 0.0065 (the estimated value of b from $\log(V_t) = \log(b) + k\log(U_t)$ is around 0.0055). We find that the estimated θ values given different values of b range from 1 to 1.7. The estimated θ values are statistically significantly larger than 0. Similarly, in the right panel of Figure D.4, we fix b to be the value estimated from the linear regression $(\log(V_t) = \log(b) + k\log(U_t))$ and vary k from -0.75 to -0.55 (the estimated value of k from $\log(V_t) = \log(b) + k\log(U_t)$ is around -0.64). We find that the estimated θ values given different values of k range from 1.2 to 1.55. The estimated θ values are statistically significantly larger than 0. The first exercise demonstrates that our main empirical pattern is robust to different values of ks and bs.

In the second exercise, we estimate k together with other model parameters γ_d, θ, and l, allowing job seekers to have subjective beliefs on the elasticity of individual unemployment rate on individual vacancy rate. We choose not to estimate the level effect b since the elasticity k can better reflect subjective beliefs on how individual unemployment rate affects individual vacancy rate. Additionally, the estimated b using aggregate unemployment rate U_t and vacancy rate V_t is very small (0.005). We use the same set of moments as in the main calibration exercise with micro data. Results are shown in Table D.7. We estimate that $\theta = 1.794$, indicating that the main finding is robust. Unemployed job seekers project their individual aggregate unemployment rate surprises into their own job-finding probability.
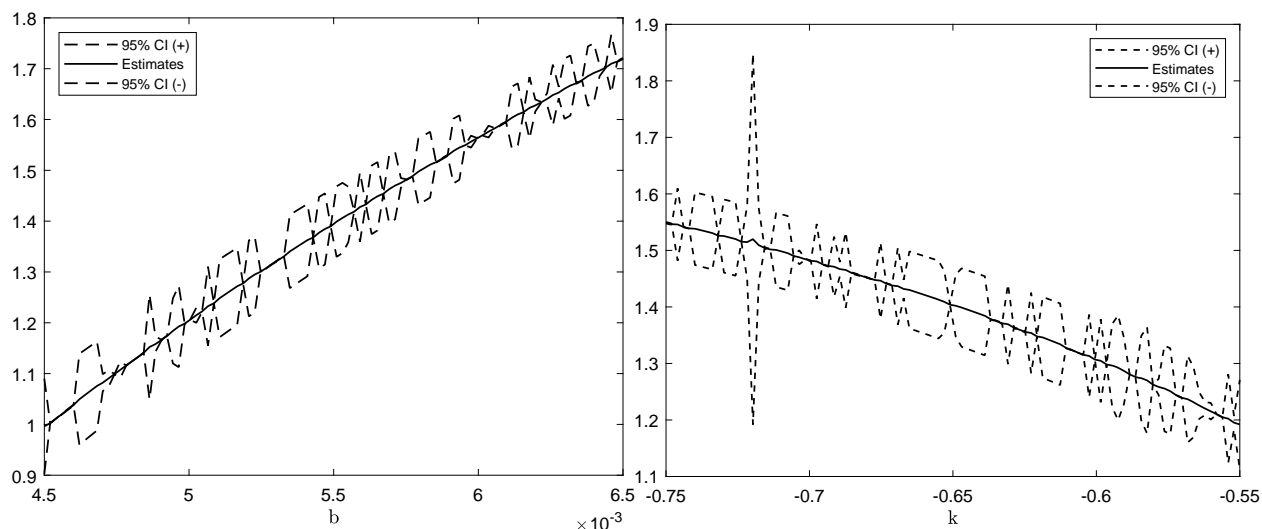
Notes: θ plotted are estimated the same way as in the main calibration with micro data. k and b are varied. Survey weights are used, and the samples are restricted to unemployed workers age 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample). We keep unemployed workers who report at least 3 times about their perceived job-finding probabilities.

Figure D.4: θ with Different Values of k and b

Table D.7: Calibration with Micro-data

Parameter:	γ_d	θ	l	k
Estimate	-0.141	1.794	0.329	-1.387
Model-fit:	$log(1 - FindJob3)$	$log(1 - FindJob3)$	$log(1 - FindJob12)$	
Data	-0.532	-1.199	-0.539	
Model	-0.532	-1.199	-0.539	

Notes: b is estimated by a linear regression ($log(V_t) = log(b) + klog(U_t)$) using true US unemployment rate and Us vacancy rate. Survey weights are used, and the samples are restricted to unemployed workers age 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample). We keep unemployed workers who reported at least 3 times about their perceived job-finding probabilities.

D.9 Response to Unemployment Rate U_t

We use a simulation exercise to demonstrate that although perceived job-finding probability model results in an significant response to the aggregate unemployment rate, the large response can be statistically insignificant upon incorporating individual heterogeneity.

To begin, we enhance the model by incorporating an individual heterogeneity term, which is rooted in various perspectives from the job search literature. For instance, it can account for differences in individuals' efficiency in securing employment, as well as variations in their human capital accumulation. By including this term, our model is improved as follows:

$$\tilde{X}_t^i = \exp(A_i) \underbrace{\exp\left(\gamma_d D_{i,t}\right) \times F_t^i \frac{M(U_{i,t}, b(U_{i,t})^k)}{U_{i,t}}}_{\hat{X}_t^i} \tag{D.2}$$

Subsequently, we parameterize the distribution of A_i using a normal distribution with a mean of zero. In order to match the variance of the model-generated perceived monthly job-finding probability with the corresponding data counterpart, $VAR(\tilde{X}_t^i)$, we calibrate the variance of the individual heterogeneity term, $VAR(A_i)$.[46]

We proceed by simulating individual monthly job-finding probabilities using the model given in equation D.2, performing 500 simulations, with each using a different set of draws of A_i from the distribution $N(0, VAR(A_i))$.

Finally, we regress the simulated monthly perceived job-finding probability on U_t and a constant, yielding the correlation δ^b and its confidence interval. Figure D.5 presents the correlation coefficients δ^b and their corresponding 95% confidence intervals across all 500 simulations. Majority (60%) of confidence intervals include 0, which suggests that while the simulated monthly perceived job-finding probability exhibits a large correlation coefficient, it is not statistically significant in most simulations.

The result shows that even though the model is very responsive to the aggregate unemployment rate, rich individual heterogeneity in the data can prevent us from detecting the response with statistically significant precision. This echoes the findings discussed in Mueller and Spinnewijn (2021), Mueller et al. (2021) and Menzio (2022), where they find that job seekers perceived job-finding probability is not statistically significantly responsive to the aggregate unemployment rate.

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[46]The calibration of $VAR(A_i)$ uses the equality: $VAR(log(\tilde{X}_t^i)) = VAR(A_i) + VAR(log(\hat{X}_t^i))$
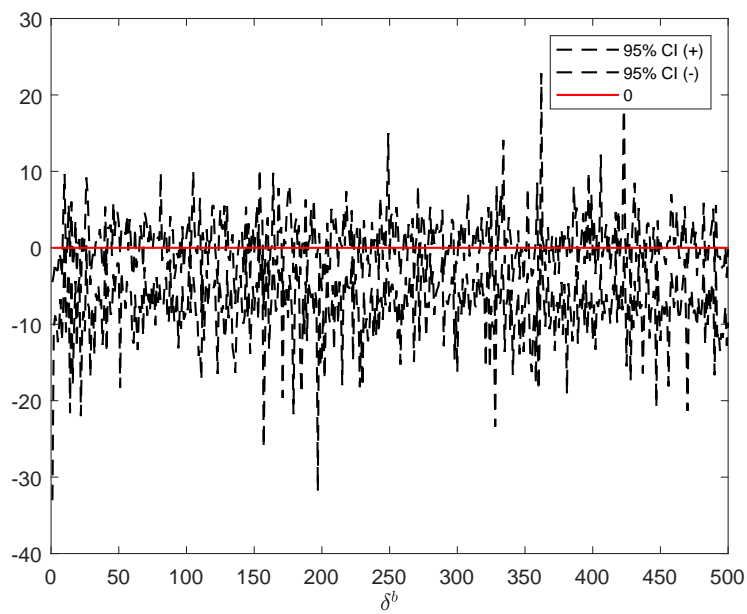
Figure D.5: Simulated Correlation Between $\tilde{X}_t^i$ and U_t

Notes: we plot the correlation coefficients δ^b between simulated monthly perceived job-finding probability and U_t. The simulation uses the same sample that is used in the calibration exercies.

D.10 Perceptions and Job Search Effort

In this subsection, we furnish empirical evidence in alignment with the arguments in section 7. Specifically, we demonstrate a negative correlation between the perceived job search projection, denoted as $\hat{\beta}^x_{i,t}$, and the effort exerted in job search.

The datasets we use combines the primary SCE survey downloaded from the NY Fed website and the supplementary Labor Market Survey (SCE LMS). Because the Labor Market Survey is conducted every four months, it poses a challenge to study the within-spell changes given the limited sample size. Instead, we account for a wide array of individual characteristics encompassing age, gender, education, household income, and race. Additionally, we control for the US unemployment rate and job seeker unemployment duration.

We employ three distinct measures of search effort. The first is a binary indicator denoting whether the job seeker has applied for a job within the preceding 4-week period. The second gauges the count of job search activities that a job seeker has engaged in during the last 4 weeks. The third measure estimates the number of hours that a job seeker has allocated towards job search activities in the past 7 days.

Table D.8: Belief on Job Search and Job Search Activities

	(1) Applied Jobs (last 4 weeks)	(2) JS activities (last 4 weeks)	(3) JS Hours (last 7 days)
Lagged $\hat{\beta}^x$	-0.639***	-1.369	-9.160
	(0.196)	(1.269)	(6.931)
Nedur	Yes	Yes	Yes
U rate	Yes	Yes	Yes
Demographics	Yes	Yes	Yes
Obs	146	131	131

Notes: individual characteristics include age, gender, education, household income and race. Survey weights are used, and the samples are restricted to unemployed workers ages 20–65 who report a 3-month job-finding probability less or equal to the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The findings are encapsulated in Table D.8. We discern that job seekers, who anticipate a higher job finding probability in the subsequent period, tend to exert less effort in their current period job search.

D.11 Calibration: Job Search Effort

In this subsection, we explain in details about how we conduct the calibration in section 7. With equation 7.1, job seeker i's expected payoff V_t at period $t < T$ during unemployment can be recursively formulated as follows:

$$V_t = B + F_t^i \hat{X}_t^i(e_{i,t}) \left(W(T - t + 2)\right) + (1 - F_t^i \hat{X}_t^i(e_{i,t}))V_{t+1} - \frac{c}{2}(e_{i,t})^2$$

Given that a job seeker can no longer search in period T, the terminal value V_{T-1} is provided by

$$V_{T-1} = B + F_{T-1}^i \hat{X}_{T-1}^i(e_{i,T-1}) \left(W\right) + (1 - F_{T-1}^i \hat{X}_{T-1}^i(e_{i,T-1}))B - \frac{c}{2}(e_{i,T-1})^2$$

Our calibration exercise aims to comprehend the first period effort choice $(e_{i,1})$ of a job seeker. We assume that job seeker i anticipates her future job-finding prospects $F_1^i f(D_{i,k}, U_k)$ $(k > 1)$ to decline at a rate β_f. More precisely, $F_1^i f(D_{i,k}, U_k) = (\beta_f)^{k-1} f(D_{i,1}, U_1)$. The parameter β_f controls the rate of decline. The search effort cost function is presumed to be $c(e_{i,1}) = \frac{c}{2}(e_{i,t})^2$. The quadratic search cost function follows results shown in Christensen et al. (2005), Lise (2013), and Gomme and Lkhagvasuren (2015). With these specifications in place, the job seeker's problem can be resolved analytically via backward induction.

The SCE measures each job seeker's perceived job-finding probability over both 3-month and 12-month spans. Consequently, we fix $T = 13$ to permit job seekers to search throughout the 12 periods. The discount factor δ is set at $(0.99)^{1/12}$, aligning with Hagedorn and Manovskii (2008). As per the UI data released by the United States Department of Labor, we establish the monthly UI benefit at $B = 1,820\$$ and the wage at $W = 3,640\$$. The UI benefit approximately represents 50% of the compensation that a job seeker could earn upon employment.

Table D.9: Calibration: Search Effort

Parameters:	c	$f(D_{i,1}, U_1)$	β_f
Estimates	0.084	0.917	0.589

There three remaining parameters that are undetermined: scalar of the search effort function c, the period 1 job-finding prospect $f(D_{i,1}, U_1)$ and its changing rate β_f. We calibrate the above 3 parameters by targeting 3 moments. The first moment we target is that job seeker i's perceived first period job-finding probability $F_1^i \hat{X}_1^i(e_{i,1})$ is 0.2. The second moment we target is that job seeker i's

perceived second period job-finding probability $F_2^i \hat{X}_2^i(e_{i,2})$ when she arrives at period two being unemployed is 0.2. The third moment we target is that job seeker i's perceived second period job-finding probability $F_1^i \hat{X}_2^i(e_{i,2})$ at period one is 0.164, i.e., 18% lower than $F_1^i \hat{X}_1^i(e_{i,1})$. The calibrated parameters are shown in Table D.9.

Three parameters remain undetermined: the scalar of the search effort function c, the period 1 job-finding prospect $f(D_{i,1}, U_1)$, and its rate of change β_f. These three parameters are calibrated by targeting three distinct moments. The first moment we target is job seeker i's perceived first-period job-finding probability $F_1^i \hat{X}_1^i(e_{i,1})$, which we set at 0.2 according to the empirical evidence shown in section 5. The second moment is job seeker i's perceived second-period job-finding probability $F_2^i \hat{X}_2^i(e_{i,2})$, when she enters the second period unemployed, also fixed at 0.2. The final moment we aim for is job seeker i's anticipated second-period job-finding probability $F_2^i \hat{X}_2^i(e_{i,2})$ at the first period, defined as 0.164, i.e., 18% lower than $F_1^i \hat{X}_1^i(e_{i,1})$. The resulting calibrated parameters are presented in Table D.9.

Using the calibrated parameters, we compute the job seeker's first period effort choice $e_{i,1}^*$. For comparison, we determine the job seeker's first period effort choice $e_{i,1}'$ when $\beta_f = 1$, i.e., when the job seeker anticipates her future job-finding prospects will remain constant. We discover that $e_{i,1}^*$ is approximately 11.6% greater than $e_{i,1}'$. This result is in line with the intuition that job seekers intensify their search efforts when they perceive their job-finding prospects to be deteriorating.

What does an 11.6% increase in effort represent? By way of a simulation exercise, we ascertain that an 11.6% surge in effort can be equivalently achieved by a 20% reduction in UI benefits (B) when job seekers anticipate a constant future job-finding prospect.

Our final simulation exercise compares a job seeker's optimal first period effort choice $e_{i,1}^*$ with the first period search effort determined by the social planner ($e_{i,1}^p$). In this exercise, we assume that the planner anticipates a constant future job-finding prospect and does not utilize the unemployment benefit ($B = 0$). We establish that $\frac{e_{i,1}^*}{e_{i,1}^p}$ approximates 63.9% while $\frac{e_{i,1}'}{e_{i,1}^p}$ is roughly 72.2%, suggesting that the belief pattern we uncover drives the first period job search effort closer to the optimal search effort level.