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UPDATING ABOUT YOURSELF BY LEARNING ABOUT THE MARKET: THE DYNAMICS OF BELIEFS AND EXPECTATIONS IN JOB SEARCH

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ABSTRACT

This study documents how job seekers update perceived job-finding prospects by unemployment duration and by learning about aggregate unemployment. We find that job seekers perceive an 18% decline in their job-finding probability for each additional month of unemployment, but perceive a higher job-finding probability when the aggregate unemployment rate is unexpectedly low. We develop a job search model with learning and updating to quantify the impact of perceived aggregate unemployment on subjective job-finding probabilities, revealing an overreaction to news about aggregate conditions. These beliefs can potentially offset a non-trivial part of the negative consequences of moral hazard in job search.

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1 Introduction

A key empirical finding in the job search literature is the strong negative correlation between observed job-finding rates and duration of unemployment (Kaitz, 1970). While the literature has debated to which extent this is truly due to decreasing prospect to a given individual rather than selection across individuals, 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 (Kroft et al., 2013; Farber et al., 2016).[1] 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 novel survey evidence. 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). Exploiting the fact that job seekers repeatedly answer the same question about the job-finding probability, they document the particularly striking finding that unemployed job seekers perceive no change in their job-finding probability on average over their unemployment spell: controlling for individual fixed effects, the perceived 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]

[1]For a broader discuss of the difference between selection effects and "true" duration dependence, see for example Van den Berg and Van Ours (1996), Kroft et al. (2016), Mueller et al. (2021) and Zuchuat et al. (2023).

[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]We believe that this particular quote nicely sums up the broader consensus in the profession about the interpretation of the existing evidence, though we are aware of the possibility that job seekers could be reporting a constant job-finding rate even if their environment deteriorates in terms of call-back rates and other features if they offset this

In this paper, we revisit these insights by analyzing job seekers' beliefs about their current job-finding probability and its expected future change. Using the exact same data selection as Mueller et al. (2021), we exploit the fact that participants in the SCE are simultaneously asked about their chance of finding and accepting a new job over two different time horizons: within 3 months and withing 12 months. Using a simple model of beliefs based on 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 survey responses reveal on average a roughly 20% expected decline in job-finding probability, which is closely in line with monthly decrease in the average job-finding-hazard for a given survey cohort, 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 they are asked repeatedly over 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. Participants in the SCE are asked about the expected evolution of this rate over the next 12 months as part of a different module 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 the perceived probability that the US unemployment rate will be higher or lower 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. 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 (2012-2019), the actual unemployment rate was continuously improving. Comparing the actual development with individuals' expectations indicates that

through accepting worse jobs or searching harder.

[4]The sharp decline in the job-finding-hazard has been the driving empirical observation that spawned the literature on duration dependence, whose goal has been to disentangle two channels: true duration dependence where a given individual's chances decline and selection effects that arise when those who find jobs easily leave the unemployment pool faster. While there is ample evidence a non-trivial role of the second channel, including in Mueller et al. (2021), it seems that job seekers attribute duration dependence to the first channel.

job seekers are positively "surprised" by the improving aggregate.[5]

We study how job seekers update their beliefs by combining their perceived US unemployment dynamics with their perceived job-finding probability. To do so, we calculate the “surprise" about the unemployment rate for each participant at each period after their first interview. This “surprise" 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 “surprise" 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. In other words, individual perceived 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.[6]

We can use the estimate calculated in the previous analysis to evaluate 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 probability by next month, the aggregate “surprise" 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 3 and illustrated in Figure 5 in the main body. These findings suggest a remarkable consistency between the two previous findings regarding job seekers' individual job-finding probability assessments: They expect their individual chances to decline but revise their assessment upward when the labor market does better than expected. The driver for the repeated upward correction is a persistent pessimistic outlook of job seekers about the evolution of the labor market: on average they expect the unemployment rate to remain constant while during this episode of economic expansion the labor market consistently improves (in line with predictions of professional forecasters). As a result, they repeatedly experience positive surprises on average about their economic environment.

[5] 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.

[6] 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. Please refer to Online Appendix O.3 for more details.

We conduct several 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, which simultaneously asks two questions that inquire about the probability of finding a job at different horizons. We alternatively consider the Survey of Unemployed Workers in New Jersey collected by Alan Krueger and Andreas Mueller (see Krueger et al. (2011)), which simultaneously asks two rather different questions: the probability of finding a job in four weeks and the expected duration before finding a job. Using the same geometric model of 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, but since it is also elicited during a time of declining unemployment one might conjecture that job seekers are similarly positively surprised about the improving aggregate conditions. Second, according to our logic individuals who are not positively surprised by aggregate conditions should report a declining subjective job-finding probability over time. We take advantage of the fact that the SCE now has more data, including one episode in which aggregate labor 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). Alternatively, we can restrict our pre-Covid SCE sample to focus those situations where job seekers were more realistic and not positively surprised by the unemployment rate: again we see a clear decline in their reported job-finding probability over time.

On a more structural level, we then 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. Such a model is consistent with subjective duration dependence and produces positive updates on individual perceived job-finding probabilities when the aggregate unemployment rate improves. However, the magnitude of this positive update is small due to the small improvement in the unemployment rate. We extend the model to allow for overreactions where workers expect surprises in aggregate conditions to be particularly relevant for their own labor market prospects, which allows us to align all empirical facts we discussed.[7] We estimate the model

[7] To model overreaction we use an "island"-methaphore that is common in labor economics, and allow job seekers to believe that news about national unemployment is overly relevant for their own island. 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 (Bordalo et al., 2018, 2019, 2020), but it is hard to integrate such model into the job search structure, which is the reason why we build a similar logic into the well-known "island" metaphor.

using data from the SCE and show that the model can fit empirical patterns well when overreaction to aggregate conditions is significant. This model also ensures that beliefs about the individual's job-finding probability are formed in a way that properly takes into account the beliefs about the aggregate conditions.

To round off, we highlight the importance of these insights in a a final exercise that extends the focus to include search effort. There is a long tradition of modelling unemployment insurance as a moral hazard problem, where more generous insurance leads to lower search effort. Cutting unemployment benefits reduces the moral hazard problem. In our setting, job seekers expect their job market prospects to decline substantially, only to be surprised next period that they assess their chances again as positively as before. In comparison to an otherwise identical individual who expects constant future job search prospects, the fear of declining prospects induces substantially more effort: the fear effect of a bad future provides current incentives. The effects are large because the magnitude of the expected decline is large: an expected decline in prospects of roughly 20% lead to 12% more job search. We present evidence from a supplement of the SCE that indicates that these magnitudes might indeed be reasonable.[8] In the model, the additional job search is similar to the effect induced by a permanent unemployment benefit reduction of roughly 20%, and allow the planner to mitigate a non-trivial fraction of the moral hazard problem. This highlights that the effect of beliefs on job search effort can be substantial and a clear understanding is important for the correct design of unemployment benefits.

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.

[8]Unemployed job seekers search harder when they perceive a lower job-finding prospects echoes the empirical finding in the literature, e.g., Mukoyama et al. (2018) and Faberman and Kudlyak (2019).

2 Related Literature

Our work relates to multiple strands of literature. First, it adds to the growing body of research that investigates beliefs and learning in the job search process, including a focus on biases in this 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 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 the 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 reported job-finding probability within-spell. Different from their paper, we focus explicitly on how job seekers perceive the future dynamics of their job-finding probability, and show that it is declining and significantly affected by job seekers' surprises about the dynamics of the aggregate unemployment rate. Results indicate that an explanation for the flat perceived job-finding probability is job seekers' overreaction 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, with a magnitude that matches the observed change in job-finding-hazard without correcting for selection.[9] Since previous work has shown that selection matters and true duration dependence is smaller, one might interpret this evidence as overreaction in the worry about the downsides of remaining unemployed.

The paper adds to the literature on behavioral frictions that distort the job search process. Previ-

[9] Although our finding of duration dependence is about perceived job-finding probability, it is consistent with some recent studies that demonstrate actual duration dependence in job searches as a significant factor in observed duration dependence such as Kroft et al. (2016) and Zuchuat et al. (2023). However, other work, such as Mueller et al. (2021) and Jarosch and Pilossoph (2019), suggests that the scope for true duration dependence may be limited.

ous 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 surprises about the development of aggregate unemployment as a source that strongly affects the dynamics of beliefs on the individual job-finding probability. Our results indicate an overreaction in this effect, at least relative to the effects that one would expect if job seekers would form beliefs according to a standard aggregate matching function borrowed from the macro-labor literature.

The model we build deviates from the rational expectation framework where expectations align on average with actual realizations. We allow job seekers to overreact in the sense that they expect improvements in aggregate conditions to matter more for people on their own "island".[10] 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).[11]

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. 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 it with the SCE Labor Market Survey (SCE LMS) in some of our analyses, which is a rotating module of the SCE, conducted every four months. Due to the infrequent nature of this supplement, the analysis that rely on it cannot include individual fixed effects.

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

[10] Obviously, if all job seekers expect their "island" to be more affected than the average island, this violates rational expectations.

[11] Other strands of literature that deviate from the rational expectations literature include 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), and cognitive discounting and level-K thinking (Gabaix, 2020; García-Schmidt and Woodford, 2019; Farhi and Werning, 2019), among others.

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 York Fed.

SCE elicits unemployed job seekers' perceived job-finding probability by asking about the probability that they will be offered a job that they would like to accept. This is asked over two time horizons: 12 months and 3 months, with the exact question formulated as below

> *What do you think is the percent chance that within the coming 12 months, you will find a job that you will accept, considering the pay and type of work?*
>
> *And looking at the more immediate future, what do you think is the percent chance that within the coming 3 months, you will find a job that you will accept, considering the pay and type of work?*

This gives us two answers per individual at a given point in time, which we call $FindJob12_t^i$ and $FindJob3_t^i$. This feature allows us to separate their expectations over different time horizons. Clearly, the time horizon in the second question is more restrictive than that in the first question. Careful reflection requires a lower reply to the second than to the first. Due to rush or lack of concentration, this is not always the case. Mueller et al. (2021) exclude such answers to arrive at a consistent sample, and we follow their approach.[13] Among the 2597 observations (derived from 933 unemployed job seekers) that contain answers to both questions, this excludes 12.3% that strictly violate consistency and 26.5% where the answer to both questions coincides.[14]

Table 1 shows that the consistent sample closely resembles the full SCE sample, 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 features of CPS. We also report the corresponding summary statistics in Table 1 along with the two SCE samples.

[12] We use the public version of the SCE whenever the analysis needs information from the SCE LMS.

[13] In many parts of the paper, Mueller et al. (2021) show that their main results are robust using the unrestricted sample. In our case, consistency is embedded in the equations we use and we cannot extend our analysis to inconsistent observations.

[14] 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.

Additional to the SCE's questions about the individual's job-finding probabilities, we also exploit its question about the US unemployment rate:

> *What do you think is the percent chance that 12 months from now the unemployment rate in the U.S. will be higher than it is now?*

This allows us to study job seekers' beliefs about the aggregate labor market. [15]

To compare job seekers' forecast of US unemployment with that of professionals, 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.

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 rate in the SCE and CPS is the U-to-E transition rate between two consecutive monthly interviews.

For some of our robstness analysis, we use the Survey of Unemployed Workers in New Jersey

[15] SCE also asks respondents' perceived probability of a higher US stock market valuation and inflation in twelve months.

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 probability of finding a job in the next four weeks and their expected unemployment duration, but has no information about how job seekers perceive aggregate unemployment conditions.

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 a noise term that induces the well-known AR1 structure. This functional form is commonly used to model belief dynamics. It allows us to study data patterns empirically and visually. For now, we assume that the perceived job-finding probability and the perceived dynamics of aggregate economic variables are independently formed. 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 stated 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 product on the right side of these equalities gives the probability of being unsuccessful in job search in all of the k periods. Its complement gives the probability of being successful in at least one of them. The left side is data. It is the self-reported probability of obtaining and accepting a job offer in k month. The answer to the first question compared to the second question then indicates whether an individual is more optimistic about changes of success in the early months of job search compared to the later months of job search (conditional on remaining unemployed). As an easy diagnostic tool to understand whether an individual sees his chances as increasing or decreasing, we assume that the individual's perceived dynamics of job-finding ($\hat{X}_t^i$) follows a geometric increase or decline:

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

This reduces the beliefs about the future to two variables: $F_t^i \hat{X}_t^i$ denotes the perceived job-finding probability immediately in the month that follows, while $\hat{\beta}_{i,t}^x$ sums up by how much this probability will change for each subsequent month. The first captures the initial level and the second captures the dynamics. 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 an example, $\hat{\beta}_{i,t}^x = 0.8$ indicates a belief that each additional month of unemployment reduces the chances of finding a job that month by roughly 20%. 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 future job-finding probability forecast 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 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, and the filter in 4.2 provides a convenient way to quantify this information.

This begs the question whether this functional form is too restrictive, and whether job seekers can even form complicated compounded probability assessments as assumed in (4.1) and (4.2). We cannot test this directly with just a short 3-month and a long 12-month horizon. Nevertheless, we can use the answers to these two questions in combination with our model to impute the job-finding probability over a 4-month horizon.[16] Infrequently, labor market supplement SCE LMS

[16] For individual i and time t our method extracts the belief about the next-month job-finding probability $F_t^i \hat{X}_t^i$ and the future evolution $\hat{\beta}_{i,t}^x$ from the two answers $FindJob12_t^i$ and $FindJob3_t^i$. Our equation then imply a prediction for

asks each respondent about their 4-month job-finding probability, on top of the usual 3 and 12-month question. Figure 1 shows the average reported job-finding probability over the 4-month horizon (second entry). It also shows the analogue constructed by our model equations (third entry).[17] They are remarkable similar. And they are very different from either the 3-month answer (first entry) or 12-month answer (forth entry). This provides at least some indications that our filtering equation (4.2) and our assumption that individuals can compound such probabilities is not at obvious odds with the data.

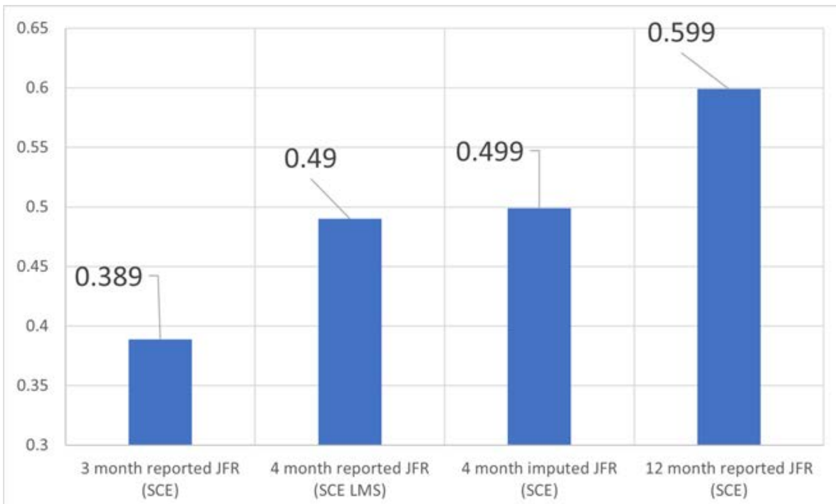

Figure 1: Comparison: 3, 4 and 12 Month Perceived Job-finding Probability
Notes: 3 and 12 month reported perceived job-finding probability are the average values directly taken from the main SCE sample. The 4 month reported perceived job-finding probability is the average values taken from the SCE LMS sample. The 4 month imputed job-finding probability are imputed 4 month perceived job-finding probability using estimated $F_t^i \hat{X}_t^i$ and $\hat{\beta}_{i,t}^x$ for those job seekers who reported 4 month perceived job-finding probability in the SCE LMS. All the SCE samples restricted to unemployed workers, ages 20–65 with consistent answers. The sample is restricted to interviews where the belief questions were administered.

4.2 Aggregate Economic Variable

The SCE asks respondents for the probability that the unemployment rate in twelve months will be higher than today. We again assume that the evolution of the unemployment rate follows a geometric increase or decrease, but allow for a noise term to capture the probabilistic nature of the answer. This yields the commonly-used AR(1) process:

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

the 4-month job-finding probability of $1 - \prod_{\tau=0}^{3} \left(1 - \left(\hat{\beta}_{i,t}^x\right)^\tau F_t^i \hat{X}_t^i\right)$.

[17] In Appendix A.3.1, we provide more detailed statistics for the reference.

where $\hat{\beta}^u_{i,t}$ represents a job seeker i's perceived unemployment rate dynamics at time t, and $\hat{\epsilon}^u_{i,t+1}$ is a noise to individual i's belief process, which is assumed to follow a normal distribution $N(0, \hat{\sigma}^2_{u,\epsilon})$ with $\hat{\sigma}_{u,\epsilon}$ being the subjective variance of U_{t+1}. 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.[18] We therefore present this version for simplicity. While we impose these assumptions on agent's beliefs, this need not be the form by which the unemployment rate truly evolves.

If the job seeker thinks that the unemployment rate is equally likely to go up and as down, this is captured by $\hat{\beta}^u_{i,t} = 1$. If the job seeker believes that it is more likely that unemployment declines, the value of this parameter is less than one. Conversely, if the belief is that it is more likely that unemployment increases, this parameter exceeds one. To determine the level of this parameter more precisely, we make some additional assumptions. We assume that job seekers are aware of the current unemployment rate U_t. While this is convenient, in reality news organizations are more likely to inform about the changes in unemployment, rather than its levels.[19] We highlight in Online Appendix O.4.1 that even sizable misperceptions of $\pm 10\%$ regarding this level have only minimal consequences for the determination of $\hat{\beta}^u_{i,t} = 1$. Intuitively, a job seeker who expects the unemployment rate in expectation to stay constant induces $\hat{\beta}^u_{i,t} = 1$ no matter what exact level of the unemployment rate he currently assumes, and for probabilities close to a half this continues to hold approximately. We also assume that job seekers share a common perception of the variance the noise in line with historical data, as discussed below.

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 $k \geq 1$:

Proposition 1 *Based on the belief dynamics specified in equation (4.3), the probability that the unemploy-*

[18]Online Appendix O.4.2 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.

[19]In principle it is possible for job seekers to obtain relatively precise information about the current unemployment rate, since the interview typically takes place in the second half of the month. As discussed, the nature of news reporting might nevertheless not necessarily convey the current level clearly.

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

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

Please refer to Appendix A.2.1 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. For $k = 11$ the SCE answers provide data for the left side of equation (4.4). In the 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.[20] 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 objects 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 a significant impact on the updating of the individual job-finding probability. Finally, we conduct empirical analysis to show that the results are robust, using alternative survey samples and specifications.

5.1 Belief Dynamics: Job-finding Probability

This subsection presents a set of new empirical patterns on belief dynamics from unemployed job seekers, based on the consistent SCE sample of Mueller et al. (2021).[21]

Using equation (4.1) and (4.2), we estimate the perceived current month job-finding probability $F_t^i \hat{X}_t^i$ and the perceived future increase or decline $\hat{\beta}_{i,t}^x$. Figure 2 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

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

[21] All results shown in this subsection can be replicated using the public version of SCE.

heterogeneity as indicated by a standard deviation of 0.19. While the expected monthly decline is large, it does not only rationalize the 3-month and 12-months horizon but also accounts well for how individuals perceive the increase in job finding when going from a 3-month to a 4-month horizon, as discussed in connection with Figure 1. The average decline is in line with a naive observation of duration dependence in our data: in our SCE sample the monthly unemployment-to-employment transition probability declines by 22% per month for a given cohort.[22]

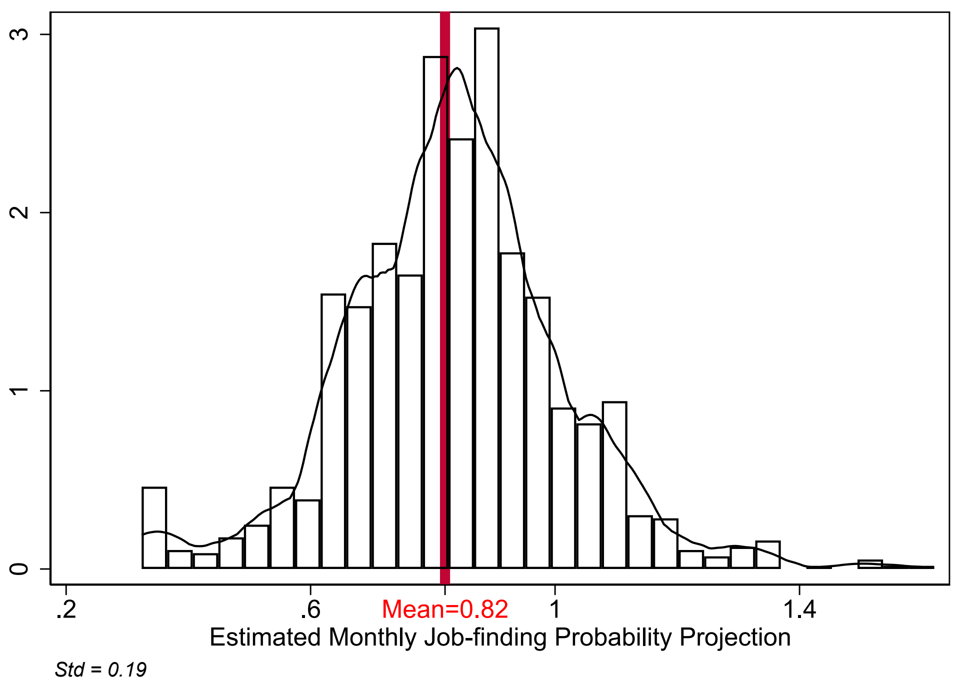

Figure 2: Histogram of Job-finding Probability Projection $\hat{\beta}^{x}_{i,t}$

Notes: We plot the histogram of job-finding probability projection $\hat{\beta}^{x}_{i,t}$ 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 than or equal to the 12-month job-finding probability (the consistent sample).

The expected decline in future job-finding chances is backed out at a given point in time, by exploiting answers covering different future horizons. For an individual that remains unemployed for multiple periods, one can do this exercise multiple times. 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

[22]Online Appendix O.6.2 documents this decline in the job-finding hazard in our sample. We note that this observed duration dependence is a "naive" measure as it does not correct for selection: the observed pattern could be driven by an unemployment pool where those with low job-finding chances accumulate over time while those with high chances exit.

A.1.1 that plots $\hat{\beta}^x_{i,t}$ within an individual unemployment spells against the time spent unemployed since the first interview).[23]

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 $F^i_t \hat{X}^i_t$ 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 seekers remains constant within-spell. In Figure 3, we replicate this empirical pattern using our estimated 1-month perceived job-finding probability ($F^i_t \hat{X}^i_t$). Specifically, we plot the change in the perceived job-finding probability ($F^i_t \hat{X}^i_t$) 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.[24]

Figure 3 indicates that job seekers do not change their belief about their job-finding chances much over the course of unemployment, which might be the reason why researchers up to now have not further investigated belief dynamics. Our analysis of belief dynamics based on multiple contemporaneous answers over different future horizons highlighted a substantial pessimism about the future. Another way to express this tension is to consider the implied difference between the job-finding probability in period t as assessed in the previous period ($t-1$) compared to the contemporaneous assessment (in t): on average the term $F^i_t \hat{X}^i_t - F^i_{t-1} \hat{X}^i_t$ is strongly positive, indicating systematic forecast errors. In subsection 5.3, we investigate a potential explanation for this pattern based on "surprises" in the aggregate job market that act as an aggregate shock to job seekers' perceived job-finding probability in every period.

5.2 Belief Dynamics: Aggregate Unemployment Conditions

Figure 4 shows the histogram of perceived US unemployment rate projection ($\hat{\beta}^u_{i,t}$) for unemployed job seekers using the consistent sample. It displays a mean around 1, which indicates that unemployed job seekers believe that the US unemployment rate in the next month will be roughly the

[23] 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.

[24] On average, the perceived 1-month job-finding probability is 0.22 with a standard deviation of 0.18. Its dispersion is depicted in the left panel of Appendix Figure A.1.2, which presents the histogram of $F^i_t \hat{X}^i_t$. For comparison, the histogram of the 1-month job-finding probability directly imputed from the 3-month job-finding probability via $1-(1-FindJob3^i_t)^{\frac{1}{3}}$, as in Mueller et al. (2021), is represented in the right panel of Appendix Figure A.1.2. The two histograms are qualitatively similar.

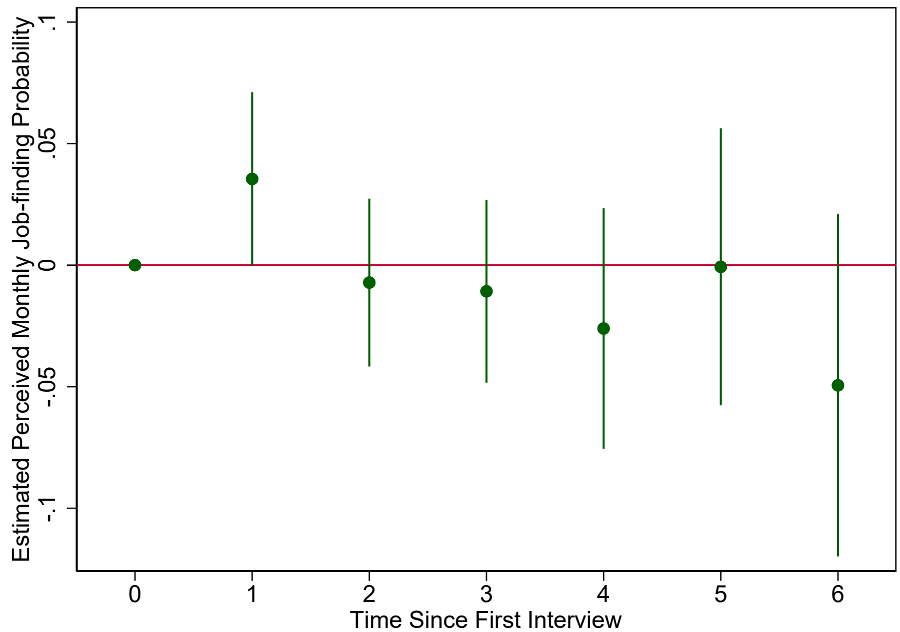

Figure 3: Estimated Job-finding Probability $F_t^i \hat{X}_t^i$, by Time since First Interview

Notes: We plot the estimated perceived job-finding probability $F_t^i \hat{X}_t^i$ by months 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 than or equal to the 12-month job-finding probability (the consistent sample).

same as the current month, albeit with some disagreement. There is a significant mass in Figure 4 at $\hat{\beta}^u_{i,t} = 1$, which corresponds to the fact that many surveyed individuals report that the probability of the US unemployment rate being higher is around 50% ($\hat{\Pr}\left(E_t^i U_{t+k} > U_t\right) \approx 0.5$). 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 (see Figure O.1.1).[25] 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 (2012-2019), the US economy experienced a recovery, with a 0.6%

[25]The perceived US unemployment rate projection ($\hat{\beta}^u_{i,t}$) declines with months in the survey , but the economic magnitude is negligible. If we regress $\hat{\beta}^u_{i,t}$ on the month since the first interview, unemployment rate projection ($\hat{\beta}^u_{i,t}$) decreases significantly by 0.0007 on average for one additional month of unemployment.

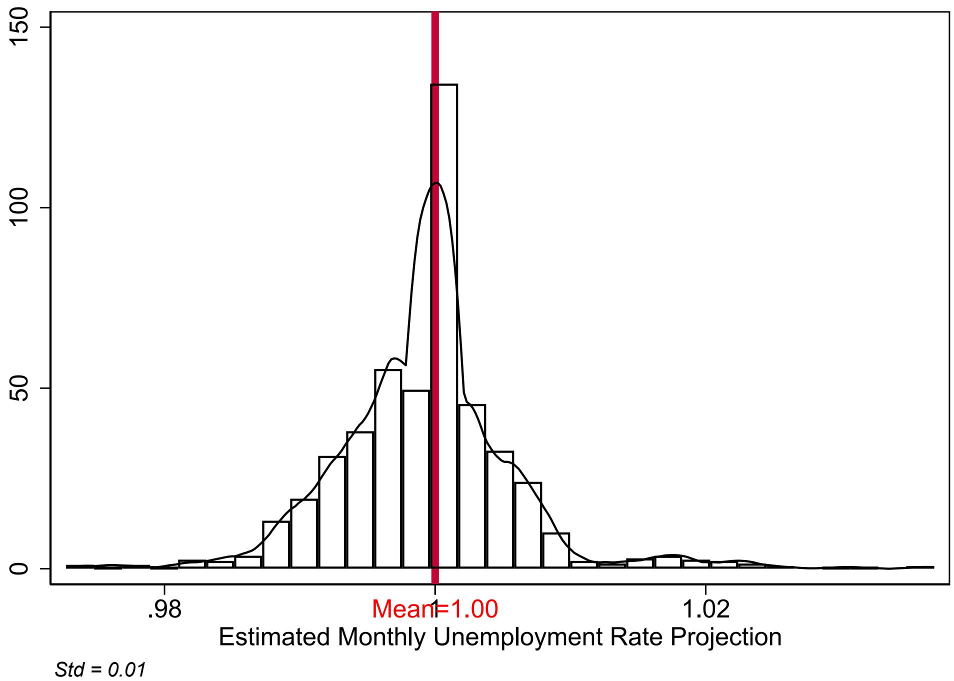

Figure 4: Histogram of US Unemployment Rate Projection $\hat{\beta}^u_{i,t}$

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 than or equal to the 12-month job-finding probability (consistent sample).

monthly decrease of unemployment rate (or $\frac{U_t}{U_{t-1}} \approx 0.994$) on average. This average decline is in line with the positive expectations of professional forecasters (Appendix A.3.2 shows that professional forecasters' reports imply an expected 0.5% - 0.7% decline). But the 0.6% average monthly decline in the unemployment rate during our sample period contrasts with the average belief of job seekers who expect a 0% decline on average. 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 unresponsiveness to fluctuations in the overall economy, which might be related to the notion of "stubbornness" as discussed in Menzio (2022).[26]

It also suggests a repeated degree of "surprise" during this long economic expansion. Whenever the US unemployment rate realizes, a job seeker should be, on average, "surprised" by the larger decline of the US unemployment rate than they expected. While this subsection and the

[26]If we focus on the long run and regresses U_t on U_{t-1} using the monthly US unemployment rate from 1948 to 2019, the auto-regression coefficient is around 1 (0.99). This is related to a discussion of Hysteresis that can be dated back to Blanchard and Summers (1986).

previous subsection have studied job-finding prospects and unemployment rate expectations in isolation, the next subsection combines them both: we examine how the "surprise" $(U_t - F^i_{t-1}U_t)$ affects the individual perceived job-finding probability.[27]

5.3 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 (see Figure 3) and a job-finding probability projection centered around $\hat{\beta}^x_{i,t} = 0.82$ indicating that job seekers expect a steep decline in job finding in the future (see Figure 2).[28]

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[29]:

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

The dependent variable $F^i_t \hat{X}^i_t - F^i_{t-1}\hat{X}^i_t$ is equivalent to $F^i_t \hat{X}^i_t - \hat{\beta}^x_{i,t} F^i_{t-1}\hat{X}^i_{t-1}$. The parameter of interest is ϑ, which indicates how changes in perceived "surprise" about the national labor market affects the 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 errors at the individual level.

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. Furthermore, the inclusion of individual unemployment duration as a control variable in column (2) does not alter the main empirical pattern: Incorporating the unemployment duration fixed effect yields an estimated ϑ of around -76, which remains statistically significant. The results suggest that at the individual level, the subjective belief "sur-

[27]In Online Appendix O.6.1, we show that both job seekers' perceived job-finding probability and US employment rate dynamics significantly affect their job-finding realizations.

[28]We do not distinguish between a month and the time gap between two interviews in the reduced form empirical analysis to maximize data utilization. In this analysis, we refer to $t+1$ as the next month after month t.

[29]We show empirical evidence in Appendix A.3.3 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 SE	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 (months since first interview) 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 than or equal to the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

prise" on national unemployment among unemployed job seekers is negatively correlated with their perceived job-finding probability update. In this sense job seekers seem no longer "stubborn" with regards to aggregate conditions.

The large estimated magnitude suggests an economically important impact. In Table 3, we explore the implications. Consider unemployed job seekers who report beliefs in two consecutive period, t-1 and t. The first row of the table indicates the average belief about the job-finding probability in each of these periods, showing a monthly job-finding expectation of 20%. The two numbers are very similar, reflecting the flat response observed earlier in Figure 3. The third row represents the average forecast in the early period (t-1) about the job-finding probability in the latter period (t). At 15.4% it is substantially lower then either of the contemporaneous beliefs in the first row. It 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. This is consistent with the finding in Figure 2 that individuals are rather pessimistic about their chances of finding jobs in the future.

We now define the "surprise" adjusted job-finding probability forecasts using the equation

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

which 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. That is, we investigate whether the surprise about the aggregate labor market can explain the difference between the average contemporaneous perceived job-finding probability ($F_t^i \hat{X}_t^i$) and its period $t-1$ forecast ($F_{t-1}^i \hat{X}_t^i$). The second row in Table 3 presents the result. After accounting for the impact of the labor market "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 19.6%. This is significantly larger than the unadjusted forecast of 15.4%, and cannot be statistically distinguished from the contemporaneous job-finding probability of 20.4%. In other words, including the impact of perceived unemployment rate "surprise" $\left(U_t - F_{t-1}^i U_t\right)$ mitigates around 85% percent of the difference between the average contemporaneous perceived job-finding probability ($F_t^i \hat{X}_t^i$) and its period $t-1$ forecast $F_{t-1}^i \hat{X}_t^i$. This exercise indicates a substantial impact of beliefs about the aggregate market on the individual perceived job-finding probability.

Table 3: Job-Finding Probability Updates Induced by Belief Surprise of Unemployment Rate

	$t-1$	t
Contemporaneous job-finding probability forecast $F_\tau^i \hat{X}_\tau^i$ ($\tau = t-1, t$)	0.201	0.204
	(0.147)	(0.164)
Job-finding probability forecasts predicted by model $\widehat{F_t^i \hat{X}_t^i}$		0.196
		(0.283)
Job-finding probability forecasts predicted at $t-1$, $F_{t-1}^i \hat{X}_t^i$		0.154
		(0.104)

Notes: The contemporaneous job-finding probability forecast ($F_t^i \hat{X}_t^i$) at period t is statistically significantly different from the job-finding probability forecasts at period $t-1$ ($F_{t-1}^i \hat{X}_t^i$) at 0.01 level, while not statistically significantly different from "surprise" adjusted job-finding probability forecasts ($\widehat{F_t^i \hat{X}_t^i}$). Survey weights are used when calculating the averages, and the samples are restricted to unemployed workers ages 20–65.

Figure 5 illustrates this visually. The solid dot on the left represents the contemporaneous belief in the early period, with associated confidence interval. It shows that job seekers on average report a 20.1% job-finding probability in the first period. The downward arrow connects this with their prediction for the second period, indicated by the square with value of 15.4%. That means that in the early period they are rather pessimistic about their future job-finding prospects in the second period. The upward arrow indicates the labor market "surprise" adjustment, which leads to the circle that represents $\widehat{F_t^i \hat{X}_t^i}$. When one takes into account how much job seekers are surprised about the improving aggregate conditions and how much they react to it, the resulting beliefs indicated by the circle represent a 19.6% job-finding probability. This is significantly higher than the unadjusted probability indicated by the square, and statistically indistinguishable from the answer that job seekers give when they are asked again about the chances in the second period. That contemporaneous forecast is represented by the solid dot on the right.

So the reaction to unexpected positive news about the labor market is surprisingly potent in reconciling a negative outlook about future job market prospects with rather positive assessments when the future actually comes around.

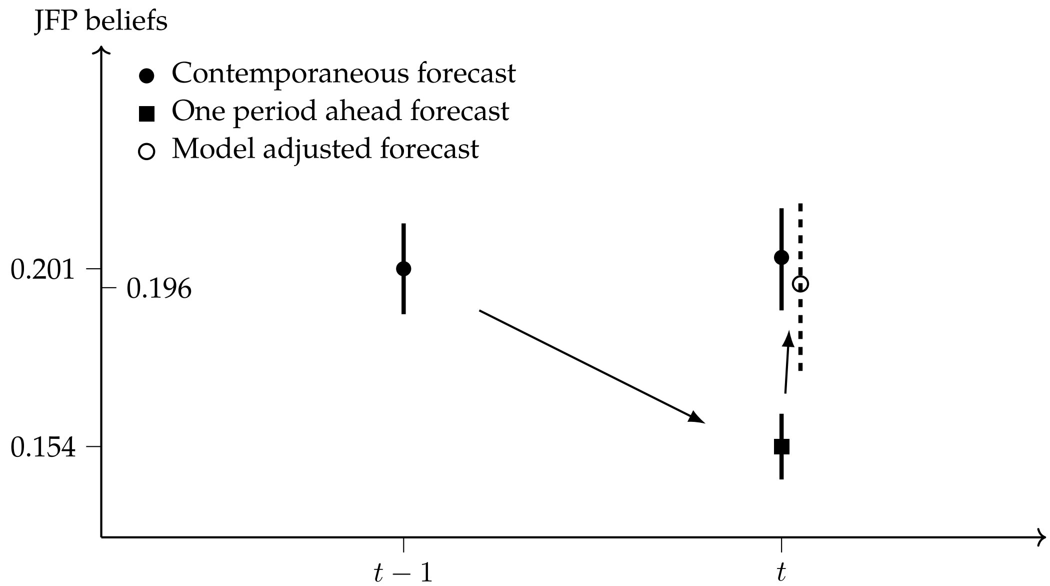

Figure 5: Job-finding Probability Updates Induced by Belief "Surprise" of Unemployment Rate

Notes: This figure is a visualization of the table 3. Contemporaneous forecast is $F^i_\tau \hat{X}^i_\tau$ $(\tau = t-1, t)$. One period ahead forecast is $F^i_{t-1}\hat{X}^i_t$. Model adjusted forecast is the job-finding probability forecasts predicted by beliefs on U_t, i.e., $\widehat{F^i_t \hat{X}^i_t}$. We include 95% confidence interval as vertical lines (or a dashed line) around point estimates.

5.4 Robustness Analysis

The preceding subsections 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.

5.4.1 KM Survey

Our first robustness test investigates whether job seekers appear pessimistic about their future job market chances also in the 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 drop the missing data on either their 4-week job-finding probability or expected duration and exclude job seekers who report obviously contradictory answers.[30] We refer to the remaining observations as the consistent sample. We calculate the one-week elicited job-finding probability by transforming the 4-week elicited job-finding probability. This transformation assumes a constant elicited one-week job-finding probability and should be interpreted as the average job-finding probability for the immediate 4 weeks in the future. We then combine this weekly job-finding probability with the expected unemployment 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, where we empirically measure the first 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 $T = 300$ for computational purposes.[31] 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.

We estimate the monthly $\hat{\beta}_{i,t}$ for each job seeker in the KM survey and plot the histogram in

[30] We 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.

[31] The empirical pattern is robust to other choices of T.

Figure 6.[32] We find that job seekers believe their job-finding probability will depreciate by an average of 18%, which is 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. [33]

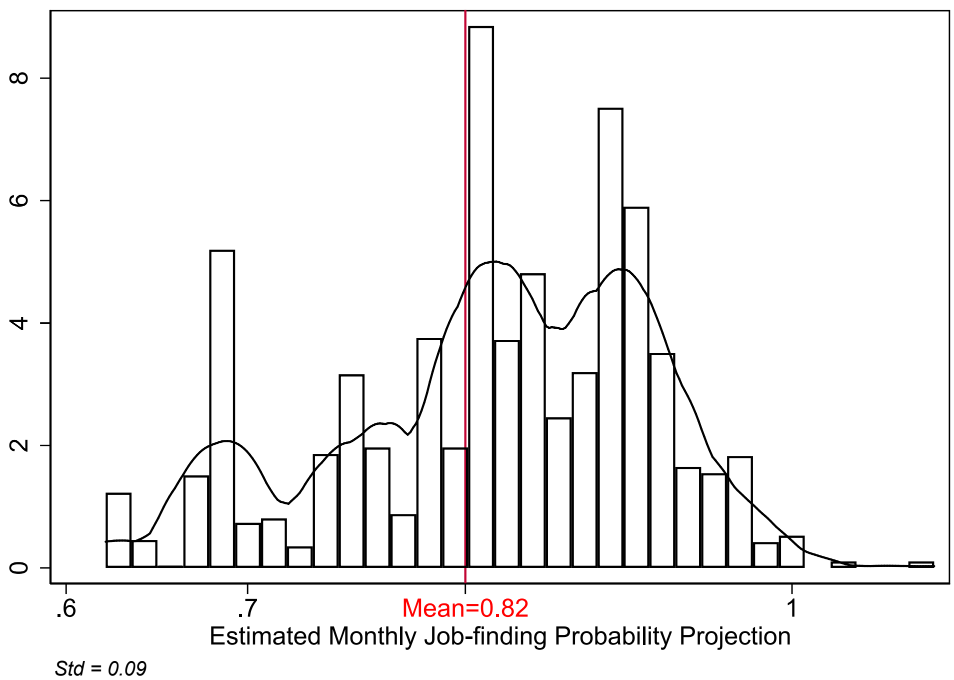

Figure 6: Histogram of Job-finding Probability Projection $\hat{\beta}_{i,t}$ (KM survey)
Notes: We present the histogram of job-finding probability projection $\hat{\beta}_{i,t}$ for each individual at each interview using the empirical framework proposed in equation (5.2). The line connects the fitted 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 in weeks.

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. Effects might be similar though, as this sample was also taken during a period of declining unemployment.

[32] 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.

[33] In Online Appendix O.6.3, we provide evidence that job seekers perceive their job-finding probabilities to decline in the future using another method.

5.4.2 Job Seekers without “Surprise"

In our empirical analysis, we discover that, on average, job seekers hold pessimistic views towards the aggregate unemployment rate relative to its actual development. Consequently, they are often "surprised" by the low realizations of the US unemployment rate. This observation prompts an intriguing query: How does an individual assess his/her labor market prospects over time if he/she is not positively surprised by the aggregate unemployment rate? Do they still stubbornly report the same job-finding probability over time, as in Figure 3? Or do they report a declining sequence over time, in line with the roughly 20% per-period decline expected about the future as indicated by the average in Figure 2? Without positive shocks, our theory would predict the latter. We offer two examinations addressing this question. The initial examination utilizes the sample from the Covid-19 pandemic, whereas the subsequent examination concentrates on job seekers within our principal sample period that do not experience positive labor market surprises.

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 February 2020 to April 2020 then started a steady decline. We use the SCE 2020 sample and restrict our attention to all job seekers who were unemployed between February 2020 and April 2020.

To account for the selection, we only include job seekers who have been consecutively unemployed and surveyed 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 7 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 7).

The above results are based on a very small sample, and one might wonder if this steep decline is just coincidence. Maybe six randomly drawn job seekers in our main pre-Covid sample would also display such patterns just by chance. To test this hypothesis, we randomly draw six job seekers with replacement 1000 times using the pre-pandemic sample 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

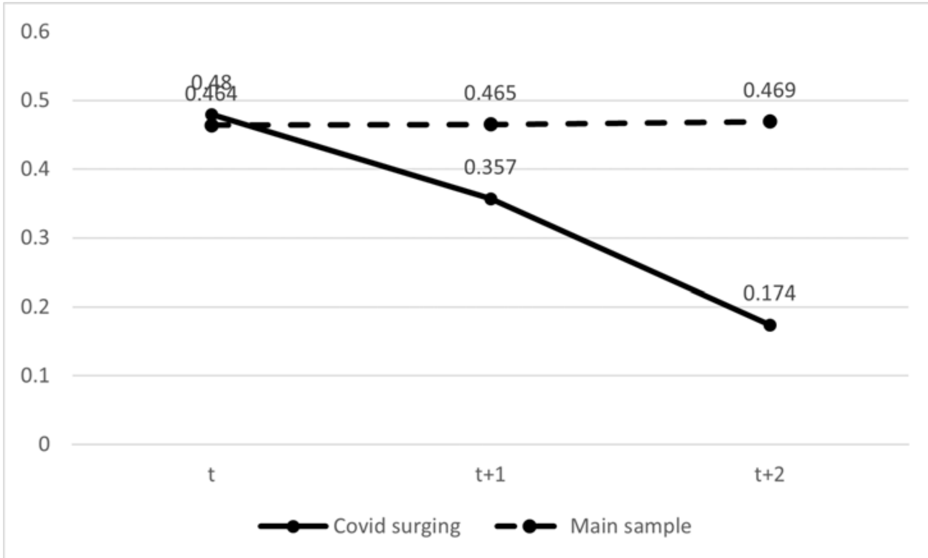

Figure 7: Perceived 3-month Job-finding Probability During COVID Pandemic
Notes: We present the average perceived 3-month job-finding probability ($FindJob3_t^i$) of the same individual for period t, $t+1$ and $t+2$ using the main sample and the sample when Covid pandemic was surging (February 2020 to April 2020). The samples are restricted to unemployed workers ages 20–65 who report consistent answers for weekly job-finding probability and expected unemployment duration.

at least as much as the Covid sample is less than 1%.[34] This exercise shows that when job seekers believe their unemployment opportunities are deteriorating, they perceive their job-finding probabilities to decrease sharply.

The second empirical exercise concentrates on our main (pre-Covid) SCE sample and aims to analyze the job-finding probability of job seekers who do not experience positive labor market "surprises". Specifically, we examine the case where job seekers perceive $U_t \geq \hat{\beta}^u_{i,t} U_{t-1}$ (no positive "surprise"). In this scenario, we expect their perceived job-finding probability not to exceed its forecast ($F^i_t \hat{X}^i_t \leq F^i_{t-1} \hat{X}^i_t$), and if the forecast for the next period was lower than the current period, we would expect to see reports about the contemporaneous job-finding rate to be decreasing over the unemployment spell. Job seekers with $U_t \geq \hat{\beta}^u_{i,t} U_{t-1}$ expect a decline of approximately 11% in their job-finding probability from period $t-1$ to period t, denoted as $\hat{\beta}^x_{i,t-1} = 0.888$. Moreover, upon reaching period t, their perceived job-finding probability declines by an average of around $1 - \frac{F^i_t \hat{X}^i_t}{F^i_{t-1} \hat{X}^i_{t-1}} \approx 12\%$, which aligns with our hypothesis.

Figure 8 graphically illustrates this pattern. Compared to Figure 5, we observe a decrease in

[34] Specifically, we calculate the probability that the average $\frac{FindJob3^i_t}{FindJob3^i_{t-1}}$ and $\frac{FindJob3^i_{t+1}}{FindJob3^i_t}$ calculated by 6 job seekers randomly drawn from our main sample is smaller than average $\frac{FindJob3^i_t}{FindJob3^i_{t-1}}$ and $\frac{FindJob3^i_{t+1}}{FindJob3^i_t}$ from the 6 job seekers from our Covid sample respectively.

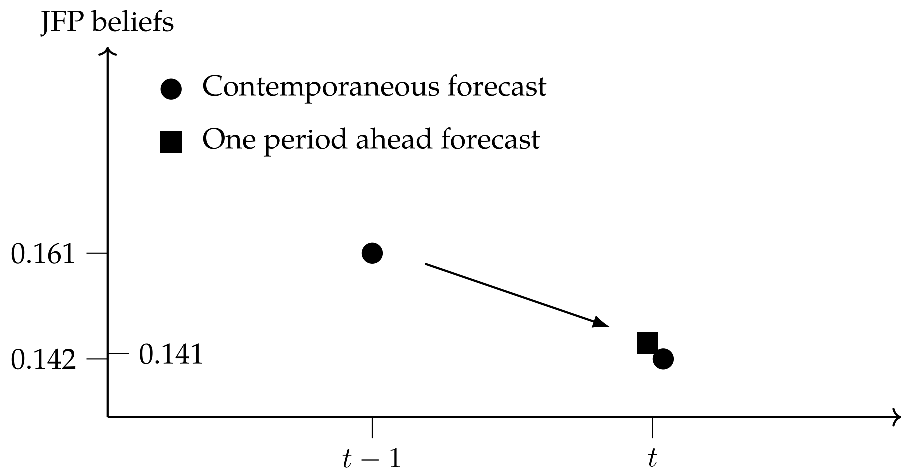

Figure 8: Job-finding Probability Updates of Unemployment Rate Without Belief "Surprise"

Notes: Contemporaneous forecast is $F^i_\tau \hat{X}^i_\tau$ $(\tau = t-1, t)$. One period ahead forecast is $F^i_{t-1}\hat{X}^i_t$. We include the sample that job seekers who have no "surprise" about the unemployment rate realization, i.e., $U_t - \hat{\beta}^u_{i,t-1}U_{t-1} \geq 0$. We residualize the perceived job-finding probability by a month fixed effect to remove the potential influence from business cycle when calculating the changes.

the perceived job-finding probability within an unemployment spell for job seekers without any "surprise" concerning the US unemployment rate.

5.4.3 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 worry that job seekers who happen to get favorable private signals about their job-finding chances update 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) elicits individual past experiences in job search: it indicates whether the individual had a job interview or not. In the Appendix A.3.3, 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 significantly revise their individual perceived job-finding probability in the coming month 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 previous 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. This is important as our previous analysis establishes precisely that these two processes are not independent, and therefore a consistent view requires a model that links these. Specifically, we present a model that incorporates duration dependence and behavioral responses to the aggregate unemployment rate. Our model successfully accounts for the main empirical findings and sheds light on driving forces.

6.1 The Model Setup

We assume that a job seeker i's period t perceived job-finding probability is a function of her unemployment duration $D_{i,t}$ and an aggregate matching function M commonly used in job search environments. The matching function depends on the individual perceived unemployment environment $U_{i,t}$ and individual perceived vacancy environment $V_{i,t}$. Specifically, the job-finding probability 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 the effect of duration $(D_{i,t})$ enters through an exponential term. A_i is centered around 0 so that $\exp(A_i)$ has a mean 1. We assume a commonly used matching function $M = UV/\left(U^l + V^l\right)^{-1/l}$ in the calibration exercise, see Den Haan et al. (2000) and Hagedorn and Manovskii (2008) for examples.[35]

We allow for the possibility that job seeker i might face an individual unemployment environment with unemployment rate $U_{i,t}$ that is relevant for his/her job-finding probability. It is presumed to depend on 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

[35] Note that the main idea is robust to other choices of matching functions, such as a Cobb-Douglas matching function.

$\eta_{i,t}$ may also reflect how different individual characteristics, such as age and education level, affect job finding. We use this setup to model the possibility that job seekers think of their own labor market to be more or less sensitive to the most recent changes in the economy.

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 we denote the job seeker i perceived shock on the individual unemployment environment as $\hat{\eta}_{i,t}$, which is assumed to be correlated with the individual "surprise" on unemployment rate in period t, denoted by $\hat{\epsilon}^u_{i,t}$. Specifically,

$$\hat{\eta}_{i,t} = \underbrace{\theta\hat{\epsilon}^u_{i,t}}_{\text{how aggregate shock matters}} + \underbrace{\hat{\epsilon}^\eta_{i,t}}_{\text{idiosyncratic shock}} = \theta\left(U_t - \hat{\beta}^u_{i,t-1}U_{t-1}\right) + \hat{\epsilon}^\eta_{i,t}, \quad E_t\left[\hat{\epsilon}^\eta_{i,t}\right] = 0 \quad (6.2)$$

where $\hat{\epsilon}^\eta_{i,t}$ 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 $F^i_t U_{i,t} = U_t + \theta\left(U_t - \hat{\beta}^u_{i,t-1}U_{t-1}\right)$. 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" $\hat{\epsilon}^u_{i,t}$.[36] A large θ implies that job seekers overreact to the most recent information in the sense that they expect changes in the national unemployment rate to be particular relevant for their own "island", which shares a similar insight to the "Diagnostic Expectation" widely used to model overreactions in macroeconomics (Bordalo et al., 2019, 2020, 2022). We set up the model in a slightly different way to fit the job search context.

Though the vacancy rate is an important input in meeting rates for a canonical job search model, none of the available survey elicits beliefs about 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., $F^i_t V_{i,t} = b(F^i_t U_{i,t})^k$ for each t.[37] With a specified Beveridge curve, we can express the individual vacancy environment as a function of the individual unemployment environment, i.e., $F^i_t V_{i,t}(F^i_t U_{i,t})$. Consequently, we can derive future job-finding probability beliefs using solely per-

[36] It is worth noting that, in practice, the average value of $\hat{\eta}_{i,t}$ is typically non-zero, which means that $\int_i U_{i,t} d_i \neq U_t$. To see this, observe that $\int_i U_{i,t} d_i = U_t + \int_i \theta\hat{\epsilon}^u_{i,t} + \epsilon^\eta_{i,t} d_i = U_t$ holds only if $\theta = 0$, assuming that $\int_i \epsilon^\eta_{i,t} d_i = 0$ and $\int_i \hat{\epsilon}^u_{i,t} d_i \neq 0$. 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.

[37] During the sample period, the US economy experienced a long recovery, leading to a downward sloping Beveridge curve. Figure A.1.3 displays a log-normal Beveridge curve can well approximate trend in the data.

ceived dynamics of the unemployment rate. We obtain estimates of b and k by a linear regression ($log(V_t) = log(b) + klog(U_t)$) using true US unemployment rate and US vacancy rate.[38]

6.2 Building Intuition

In this subsection, we explore potential mechanisms within the proposed model presented in equation (6.1). We begin by discussing γ_d, which governs the perceived duration dependence. The 18% estimated monthly perceived job-finding probability decline suggests that $\gamma_d < 0$ is required for the model to align with the empirical pattern. An important empirical finding in the literature, as demonstrated by Mueller et al. (2021), is that the perceived job-finding probability remains consistent within-spell during the sample period. Following this observation, we aim to understand which mechanism within the model can explain this phenomenon. The model has three ingredients for explaining this: (1) the standard matching function when individuals correctly perceive the empirical Beveridge curve and do not overreact, (2) a misperception of the Beveridge curve that links the level of unemployment to the associated vacancies, and (3) an overreaction where individuals think that surprises in the aggregate unemployment rate matter particularly to the situation on their own "island". We show that job seekers' overreacting to the most recent unemployment information is important in explaining the empirical pattern.

A fundamental parameter in the analysis of unemployment is the elasticity of the unemployment rate l of matching functions. An natural question then arises: can the matching function elasticity l alone ($\theta = 0$) account for a flat perceived job-finding probability within-spell, especially given the 18 % perceived monthly job-finding probability decline? Utilizing $F^i_{t-1}\hat{X}^i_t \approx 0.154$ and $F^i_t\hat{X}^i_t \approx 0.204$ from Table 3, we observe that the perceived job-finding probability experiences an increase of $\frac{F^i_t\hat{X}^i_t - F^i_{t-1}\hat{X}^i_t}{F^i_{t-1}\hat{X}^i_t} \approx 0.325$ empirically. According to the model depicted in equation (6.1), we obtain $\frac{F^i_t\hat{X}^i_t - F^i_{t-1}\hat{X}^i_t}{F^i_{t-1}\hat{X}^i_t} = -1 + \frac{\left[b^{-1}(U_t)^{l(1-k)}+1\right]^{-\frac{1}{l}}}{\left[b^{-1}(U_{t-1})^{l(1-k)}+1\right]^{-\frac{1}{l}}}$ when $\theta = 0$. Considering an average value for the unemployment rate and its forecast ($U_t \approx 0.051$, $F^i_{t-1}U_t \approx 0.054$) and estimates for k and b in line with the empirical Beveridge curve, even an exceedingly high value for l (where $l > 20$) cannot make the model-derived $\frac{F^i_t\hat{X}^i_t - F^i_{t-1}\hat{X}^i_t}{F^i_{t-1}\hat{X}^i_t}$ approach 0.325. It's worth noting that l is typically estimated to be around 0.4 in the existing literature (e.g., Hagedorn and Manovskii (2008)).

Since the elasticity parameter l alone is inadequate to fully account for the observed empirical patterns, our attention turns to the other two mechanisms inherent in the job search model:

[38] In the Online Appendix O.5, we conduct two exercises to show that alternative specifications of obtaining parameter k and b does not materially change the estimation results.

specifically, the subjective Beveridge Curve and overreactions to recent news. While the implications of the subjective Beveridge Curve will be further explored in the calibration exercise, we delve in-depth here into how overreaction manifests in a job-search context.

To understand why introducing overreactions ($\theta > 0$) may enable the job search model to generate a flat within-spell job-finding probability forecast, despite the negative duration dependence, we linearize the period t and $t+1$ perceived period $t+1$ job-finding probability around $F^i_{t+1}U_{i,t+1}$ to find

$$F^i_t \hat{X}^i_{t+1} \approx \exp\left(\gamma_d D_{i,t+1}\right)\left[b^{-1}\left(U_t\right)^{l(1-k)}+1\right]^{-\frac{1}{l}} + \exp(\gamma_d D_{i,t+1})\left[b^{-1}\left(U_t\right)^{l(1-k)}+1\right]^{-\frac{1}{l}-1}(k-1)b^l(U_t)^{l(1-k)-1}\left(F^i_t U_{i,t+1}-U_t\right) \tag{6.3}$$

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

Equation (6.3) refers to the period t forecast of period $t+1$ job-finding probability. Because a job seeker i cannot predict the future individual unemployment surprise, i.e., $F^i_t\left(\hat{\eta}_{i,t+1}\right)=0$, the forecast of the next period individual unemployment environment is $F^i_t U_{i,t+1} = F^i_t U_{t+1} = \hat{\beta}^u_{i,t} U_t$. However, when the period $t+1$ perceived "surprise" on individual unemployment $\hat{\eta}_{i,t+1}$ realizes, i.e., $F^i_{t+1}U_{i,t+1} = U_{t+1} + \theta\left(U_{t+1} - \hat{\beta}^u_{i,t}U_t\right)$, job seekers update their perceived job-finding probability as in equation (6.4). Since they believe that the latest changes particularly matter to them, this amplifies their reaction.

6.3 Calibration with Micro-data

In this subsection, we calibrate the model using the simulated method of moments with individual-level survey responses directly taken from the SCE. We calibrate the model using the empirically estimated Beveridge curve and demonstrate that incorporating the overreaction mechanism can explain the empirical pattern well. Furthermore, even when employing a more flexible subjective Beveridge curve setup - where the parameters k and b span a spectrum of combinations — the overreaction consistently emerges as the principal factor in explaining the empirical patterns.

We normalize the individual efficiency $A_i = 1$ because only the average individual efficiency matters in the calibration (see Online Appendix O.2 for details). We examine the impact of individual efficiencies later in a simulation. Moreover, the framework proposed in section 4 is no longer consistent with the model because the model predicted perceived job-finding probability no longer preserves a geometric structure, i.e., the perceived job-finding probability does not decrease at the same rate $\hat{\beta}^x_{i,t}$ for all future periods because of the feedback coming from beliefs about the aggregate labor market.[39]

Lemma 1 *The job search model (equation 6.1) implies* $\frac{F^i_t \hat{X}^i_{t+2}}{F^i_t \hat{X}^i_t} \neq \left(\frac{F^i_t \hat{X}^i_{t+1}}{F^i_t \hat{X}^i_t} \right)^2$.

The calibration in this subsection does not rely on the perceived job-finding probability filter as in equation (4.1) and (4.2). Instead, we aim to match the model implied period t average perceived 3-month job-finding probability $\frac{1}{N}\sum_i \left(1 - \prod_{\tau=0}^{2} \left(1 - F^i_t \hat{X}^i_{t+\tau}\right)\right)$, period $t+1$ average perceived 3-month job-finding probability $\frac{1}{N}\sum_i \left(1 - \prod_{\tau=1}^{3} \left(1 - F^i_{t+1} \hat{X}^i_{t+\tau}\right)\right)$ and period t average perceived 12-month job-finding probability $\frac{1}{N}\sum_i \left(1 - \prod_{\tau=0}^{11} \left(1 - F^i_t \hat{X}^i_{t+\tau}\right)\right)$ with their empirical counterparts $\frac{1}{N}\sum_i \left(FindJob3^i_t\right)$, $\frac{1}{N}\sum_i \left(FindJob3^i_{t+1}\right)$ and $\frac{1}{N}\sum_i \left(FindJob12^i_t\right)$ reported in the survey. i.e., original data questions from the SCE.

$$
\begin{aligned}
\frac{1}{N}\sum_i \left(FindJob3^i_t - 1 + \prod_{\tau=0}^{2} \left(1 - F^i_t \hat{X}^i_{t+\tau}\right)\right) &= 0 \\
\frac{1}{N}\sum_i \left(FindJob3^i_{t+1} - 1 + \prod_{\tau=1}^{3} \left(1 - F^i_{t+1} \hat{X}^i_{t+\tau}\right)\right) &= 0 \\
\frac{1}{N}\sum_i \left(FindJob12^i_t - 1 + \prod_{\tau=0}^{11} \left(1 - F^i_t \hat{X}^i_{t+\tau}\right)\right) &= 0
\end{aligned}
\tag{6.5}
$$

Appendix A.2.2 presents details on how to construct model implied $F^i_t \hat{X}^i_{t+\tau}$ for $\tau > 0$. For additional moments, we interact the aggregate unemployment rate U_t with the residuals of the first two moment conditions in equation (6.5).[40] The idea is that the aggregate unemployment rate U_t should be mean-independent on the residuals of the first two moments. With the five moments, 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.

[39]Please refer to the Appendix A.2.2 for the proof.

[40]Interacting the aggregate unemployment rate U_t with additional moment conditions does not change the empirical result.

The estimation result is presented in Table 4.

In the upper panel of Table 4, we report all estimates, including the subjective duration effect ($\gamma_d = -0.141$), the correlation between the aggregate and individual unemployment environment ($\theta = 1.383$), and the perceived 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 higher than what's reported (around 0.4) in the previous literature (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 4, we demonstrate that the model-generated counterparts closely match the three key moments.

Table 4: Calibration with Micro-data

Parameters:	γ_d	θ	l
Value	-0.141	1.393	0.606
(SE)	(0.000)	(0.033)	(0.000)
Model-fit:	$\frac{1}{N}\sum_i log(1 - FindJob3^i_t)$	$log(1 - FindJob3^i_{t+1})$	$\frac{1}{N}\sum_i log(1 - FindJob12^i_t)$
Data	-0.532	-1.199	-0.539
Model	-0.532	-1.199	-0.539

Notes: k and b are estimated by a linear regression ($log(V_t) = log(b) + klog(U_t)$) 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 than 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. Appendix A.4.1 provides additional details regarding the sample.

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 rates and vacancy rates independent of the estimation procedure. However, the correlation between unemployment and vacancy rates may differ from the belief held by job seekers in reality. Furthermore, job seekers perceiving an large response of vacancy rate on unemployment rate may also contribute to the explanation of 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.[41] As detailed in Online Appendix O.5, our findings indicate that the estimation outcomes

[41]When setting $\theta = 0$ and allowing the Beveridge curve parameter k to vary freely, the model is inadequate to fit the data even with a elasticity parameter (l) exceeding 10.

remain robust. Notably, we ascertain that θ maintains its statistically significantly positive value, notwithstanding any modifications in k and b considered. Figure O.5.1 in the Online Appendix provides a graphical representation.

After obtaining estimates from the calibration, we employ a simulation exercise to examine the role of individual efficiency heterogeneity, specifically, the dispersion of A_i. We demonstrate that, while the perceived job-finding probability model indicates a significant response to the aggregate unemployment rate, such a response is unlikely to be detected with statistical precision using the existing dataset when incorporating the heterogeneous individual efficiency as calibrated from the data. Please refer to Appendix A.4.3 for further details. This finding aligns with the empirical evidence suggesting that the perceived job-finding probability in the SCE sample does not exhibit significant sensitivity to fluctuations in the aggregate unemployment rate (Mueller et al., 2021; Mueller and Spinnewijn, 2021; Menzio, 2022).

6.4 Robustness: Long-term Effects of Surprises

Up to this point, we assumed that surprises that matter for the individual's "island" in (6.2) are deviations relative to a short-run prediction. This allowed for a relatively simple representation. On the other hand it might be restrictive, and required surprises to be short-lived. In this section we outline an alternative process in which "island"-relevant surprises are those relative to some longer-term outlook. We presume job seekers are aware of an unemployment rate (the baseline) for a particular month. They assume that there is a stable parameter for the evolution of the unemployment rate. They can update their belief about this parameter, and it is reflected in their answer to the probability that the unemployment rate will deteriorate. They use this to form an expectation where the economy would have evolved from their baseline, and assess deviations from this as relevant information for their own "island"-specific unemployment rate. Given that these deviations can accumulate over multiple periods, we can accommodate long-term effects of perceived aggregate unemployment rate “surprise" and show robustness in the sense that over-reaction remains relevant and accounting for the empirical patterns remains possible. We also allow for a slightly different process for aggregate unemployment, which again serves to highlight that the fine details of the model process do not matter.

As alluded to in the previous sentence, for this exercise it turns out to be easier to formulate beliefs about the perceived aggregate unemployment rate to evolve as follows:

$$U_{t+1} = \tilde{\beta}^u_{i,t} U_t \times \varepsilon_{t+1} \tag{6.6}$$

where $\varepsilon_{t+1} = \exp(\epsilon_{t+1})$ and $\epsilon_t \sim N(0, \sigma^2_\epsilon)$. Here $\tilde{\beta}^u_{i,t}$ is how job seeker i at period t perceives the US unemployment rate changes between any two consecutive periods. While this is not the standard AR1 specification used in the literature, it has the advantage that one can formulate the belief about the probability that the unemployment rate will be higher in k months without a reference to the current level of unemployment. In particular, we obtain

$$\hat{\Pr}(U_{t+k-1} > U_t) = \Phi\left(\frac{(k-1) \times \log(\tilde{\beta}^u_{i,t})}{\sigma_\epsilon \sqrt{k-1}}\right) \tag{6.7}$$

for each job seeker i at any time t. With σ_ϵ calibrated by the standard deviation of the cyclical component of $log(U_t)$, we can estimate $\tilde{\beta}^u_{i,t}$ for each i and t, and do not need to extract a belief about U_t. Beliefs about the level of unemployment can therefore evolve in arbitrary ways. We do not need to impose that the individual has correct beliefs about U_t in every period to interpret the answer to the SCE question about unemployment.

We assume that each job seeker has a baseline belief U_τ in an initial period τ. For convenience, we set τ to the initial period when job seeker i enters the survey. While we could set the baseline belief at some arbitrary level, it is again convenient to anchor it at the actual U.S. unemployment rate. In each period $\tau + k$, the job seeker indicates his/her belief about the long-run evolution of the unemployment rate by reporting $\tilde{\beta}^u_{i,\tau+k}$ as extracted from his/her SCE answer according to (6.7). The main novelty is the formulation about the "surprise" for the job seeker. Given a revised long-run expectation of how unemployment evolves and his baseline, a job seeker in period $\tau + k$ would have expected that unemployment in period $\tau + h$ be $(h > k)$

$$F^i_{\tau+k} U_{\tau+h} = \left(\tilde{\beta}^u_{i,\tau+k}\right)^h U_\tau \exp(\sigma^2_\epsilon/2)$$

where the constant $\exp(\sigma^2_\epsilon/2)$ is a known constant needed for the correct expectation due to the Log-Normal distribution of the noise term ε_{t+1} in equation (6.6). If unemployment truly changed according to $\beta^u_{\tau+h,\tau} = U_{\tau+h}/U_\tau$, it is misaligned relative to expectations by

$$F^i_{\tau+h} U_{\tau+h} - F^i_{\tau+k} U_{\tau+h} = \left(\beta^u_{\tau+h,\tau} - \left(\tilde{\beta}^u_{i,\tau+k}\right)^h \exp(\sigma^2_\epsilon/2)\right) U_\tau.$$

We use this as the notion of "surprise" that is relevant for the conditions on the job seeker's own "island". By setting $h = k+1$, the above equation provides the one-period-ahead "surprise", where surprised is measured relative to long-run expectations starting from baseline but using the most recent assessment about how unemployment tends to evolve over time.[42] If the labor market overall does better than this longer-run prediction the job seeker might think that the difference particularly materializes on the his/her own "island", so this one-period-ahead surprise replaces the round bracket in equation (6.2). Long-term impacts are now possible: A job seeker who believes that structurally the unemployment rate remains constant but faces $h = k + 1$ periods where unemployment actually declines, attributes the cumulative difference as relevant for the own island.

Table 5: Calibration with Micro-data: Long-term Effects of Surprises

Parameters:	γ_d	θ	l
Value	-0.144	0.261	0.613
(SE)	(0.000)	(0.000)	(0.000)
Model-fit:	$\frac{1}{N}\sum_i log(1 - FindJob3_t^i)$	$log(1 - FindJob3_{t+1}^i)$	$\frac{1}{N}\sum_i log(1 - FindJob12_t^i)$
Data	-0.532	-1.199	-0.539
Model	-0.532	-1.199	-0.539

Notes: k and b are estimated by a linear regression ($log(V_t) = log(b) + klog(U_t)$) 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 than 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. Appendix A.4.2 provides additional details regarding the sample and the estimation.

Building upon the specification of belief processes described in this subsection, and utilizing the individual unemployment environment formulated in equation (6.2), we proceed to calibrate the model employing the same set of moments that were used in equation (6.5).[43] Estimates are presented in Table 5. The estimated γ_d and l closely align with those found in Table 4. The estimated θ is smaller in this setting. This difference arises because, in the current scenario, the "surprise" manifests as a long-term effect, as opposed to a monthly update.

[42]Here the mechanism of updating about the long-run evolution of unemployment $\tilde{\beta}_{i,t}^u$ is not specifically modeled. Using the same perceived unemployment rate process 6.6, we demonstrate how to incorporate the long-term impact of updating into the job seekers' updating problem in a slightly different setup. Though requiring more structures and assumptions, this framework provides a micro-structure of how long-term updating can be integrated. Please refer to Appendix O.7 for more details.

[43]Appendix A.4.2 provides additional details regarding how we construct the sample for the estimation and how we pick the base period U_τ in the estimation.

7 Implications for Job Search, Unemployment Insurance, and Moral Hazard

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. This allows us to capture the usual moral hazard problem in job search, where unemployment benefits induce suboptimal job search decisions.

Our focus is on an unemployed job seeker i who lives for T periods ($t = 1, 2, ..., T$) and searches in the first $T - 1$ periods ($t = 1, 2, ..., T - 1$) when unemployed. For simplicity, we normalize job seeker's search efficiency by setting $A_i = 0$. Consistent with the literature, the monthly 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.

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

In the contemporaneous period, equation (7.1) indicates that the perceived job-finding probability increases with the search effort, depending on unemployment duration and the unemployment condition job seeker i faces. Implementing the search effort $e_{i,t}$ comes with a strictly convex utility cost $c(e_{i,t})$. 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 all remaining periods. For simplicity we assume risk neutrality since we focus on the cost of moral hazard in job search, rather than the optimal benefit level. Benefit levels are calibrated to the observed average in the US.

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 if she expects brighter future job-finding prospects.[44] 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

[44] Job seekers searching more intensively when they expect a lower future employment prospect is related to the findings of counter-cyclical search efforts over the business cycle.(Mukoyama et al., 2018; Faberman and Kudlyak, 2019)

are again more optimistic. This means that job seekers exert more efforts initially than they would have had they anticipated the better times ahead.

Appendix A.3.4 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 probabilities tend to apply to more 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 rough assessment 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 the SCE. We calibrate the remaining parameters to target the average monthly perceived job-finding probability of 0.2 and the roughly 20% perceived job-finding probability decrease looking forward. Please refer to Appendix A.5 for details of the calibration.

Table 6 reports the effect of belief dynamics on search effort based on the calibration. We find that, if job seeker i perceives that her future job-finding probability will decrease by roughly 20% per month because of expected duration effects (e.g., a lower $\{F_1^i f(D_{i,\tau}, U_{i,\tau})\}$, $\tau > 1$), her first period search effort ($e_{i,1}$) 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.

The model-implied effect of declining beliefs on search effort is large, but not out of line with the magnitude of the effects that we find in the SCE labor market supplement.[45] A social planner might like such effects. The impact of declining beliefs on job search effort is equivalent to the

[45] The 11.6% search effort increase is consistent with the supporting empirical evidence shown in Appendix A.3.4, where the point estimate suggests that perceiving a 18% higher job-finding probability in the next month is associated with a 16.6% decline in job applications. It is also inline with the 12.8% decline in the hours spent on job search, though this is not significant at conventional levels.

Table 6: Belief Dynamics and Search Effort

Perceived $F_1^i f(D_{i,\tau}, U_\tau)$ dynamics :	Constant	Declining
% change of $e_{i,1}$ relative to a constant $F_1^i f(D_{i,\tau}, U_\tau)$	0%	11.6%
% of $e_{i,1}$ relative to $e_{i,1}^{sp}$ with a constant $F_1^i f(D_{i,\tau}, U_\tau)$	63.9%	72.2%

Notes: $e_{i,1}$ is the first period search effort we are interested in for the calibration in this section. We calibrate $e_{i,1}$ under different perceived future dynamics of $F_1^i f(D_{i,\tau}, U_\tau)$. $e_{i,1}^{sp}$ is the social planner's search effort choice under a constant perceived future dynamics of $F_1^i f(D_{i,\tau}, U_\tau)$.

effect of a 20% unemployment benefit cut for a person with constant beliefs, 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 $(e_{i,1})$ of the individual is around 72.2% of the optimal effort level $(e_{i,1}^{sp})$ that the planner would like. Her first period search effort $(e_{i,1})$ falls to only 63.9% of the optimal effort level $(e_{i,1}^{sp})$ 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 there is a forecast error, 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.

While more work on this domain is needed, this rough calculation highlights 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 Conclusion

Understanding how job seekers form beliefs about their job-finding probability is a 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 determinants of labor market choices and policy interventions, as illustrated in the previous section. Since the size of the expected decline in future prospects is large in magnitude, it is likely that the effects of these are important.

Our findings 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. 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.

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Appendices

A.1 Figures

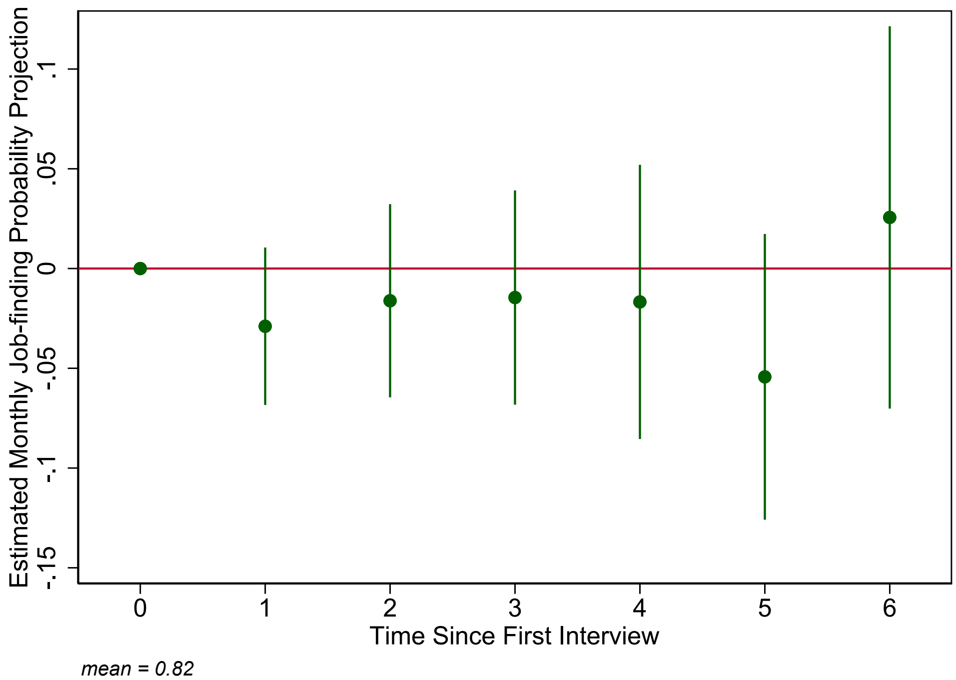


Figure A.1.1: Estimated Job-finding Probability Projection $\hat{\beta}^x_{i,t}$, by Time since First Interview

Notes: We plot the estimated job-finding probability projection $\hat{\beta}^x_{i,t}$ by months 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 than or equal to the 12-month job-finding probability (the consistent sample).

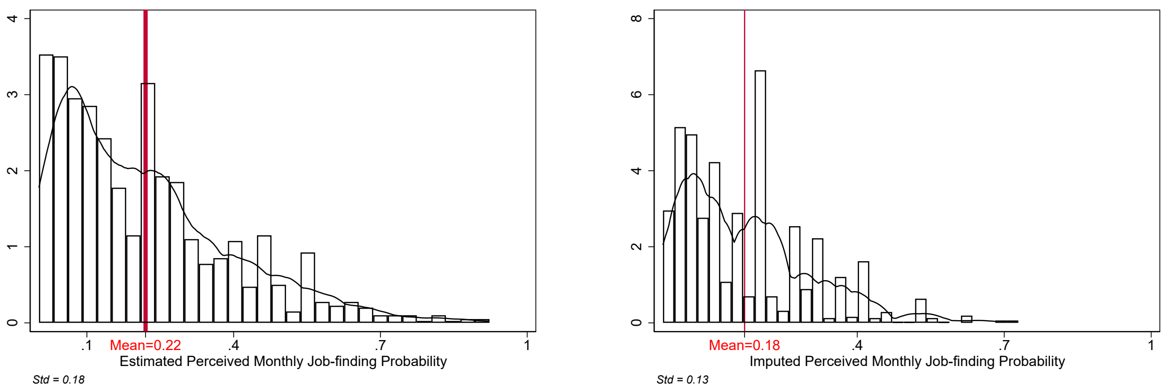


Figure A.1.2: Histogram of Job-finding Probability $F_t^i \hat{X}_t^i$

Notes: In the left panel, we present the histogram of job-finding probability $\hat{X}_t^i$ estimates using the empirical framework proposed in equation (4.1). In the right panel, we demonstrate that 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 than or equal to the 12-month job-finding probability (the consistent sample).

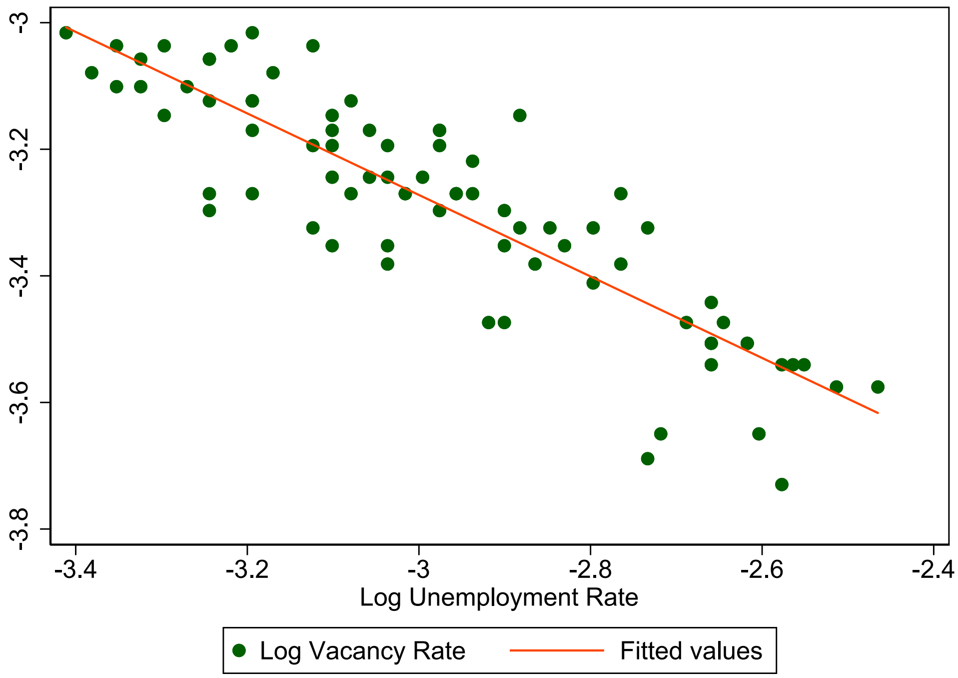


Figure A.1.3: Beveridge Curve with a Log-linear Fit

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.

A.2 Omitted Proofs and Derivations

A.2.1 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

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

A.2.2 Derivations for lemma 1 and equation (6.5)

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 $\frac{F_t^i \hat{X}_{t+\tau}^i}{F_t^i \hat{X}_t^i} \neq \left(\frac{F_t^i \hat{X}_{t+1}^i}{F_t^i \hat{X}_t^i}\right)^\tau$.

A.3 Additional Empirical Results

A.3.1 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. The 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 $\hat{\beta}^{x}_{i,t}$ and $F^i_t \hat{X}^i_t$, we can calculate the perceived probability of finding a job within four months for each job seeker at each time t, denoted as $\widehat{FindJob4}^i_t$. 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 t, denoted as $FindJob4^i_t$.

Table A.3.1 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.

Table A.3.1: Estimated and Reported 4-month Job-finding Probability

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

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

A.3.2 Perceived Unemployment Rate Dynamics from Professional Forecasters

We demonstrate that job seekers hold pessimistic views about the future of the US unemployment rate, which contrasts with what actually occurred in the main body of the paper. To provide a comparison for the unemployed job seekers' perceived unemployment rate dynamics, we estimate a similar $\hat{\beta}^u_{i,t}$ 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 $\hat{\beta}^u_{i,t}$, we calculate the ratios of unemployment rate level forecast to obtain its dynamics.

In Figure A.3.1, we plot the ratios $\left(\frac{U0}{U-1}\right)^{1/3}$, $\left(\frac{U1}{U-1}\right)^{1/6}$ and $\left(\frac{U4}{U-1}\right)^{1/12}$, respectively. The SPF averages for $\left(\frac{U0}{U-1}\right)^{1/3}$, $\left(\frac{U1}{U-1}\right)^{1/6}$ and $\left(\frac{U4}{U-1}\right)^{1/12}$ are approximately 0.993, 0.994, and 0.995, respectively, which align much more closely with the average true unemployment decline ($\frac{U_t}{U_{t-1}}$) over the same period (0.6%).

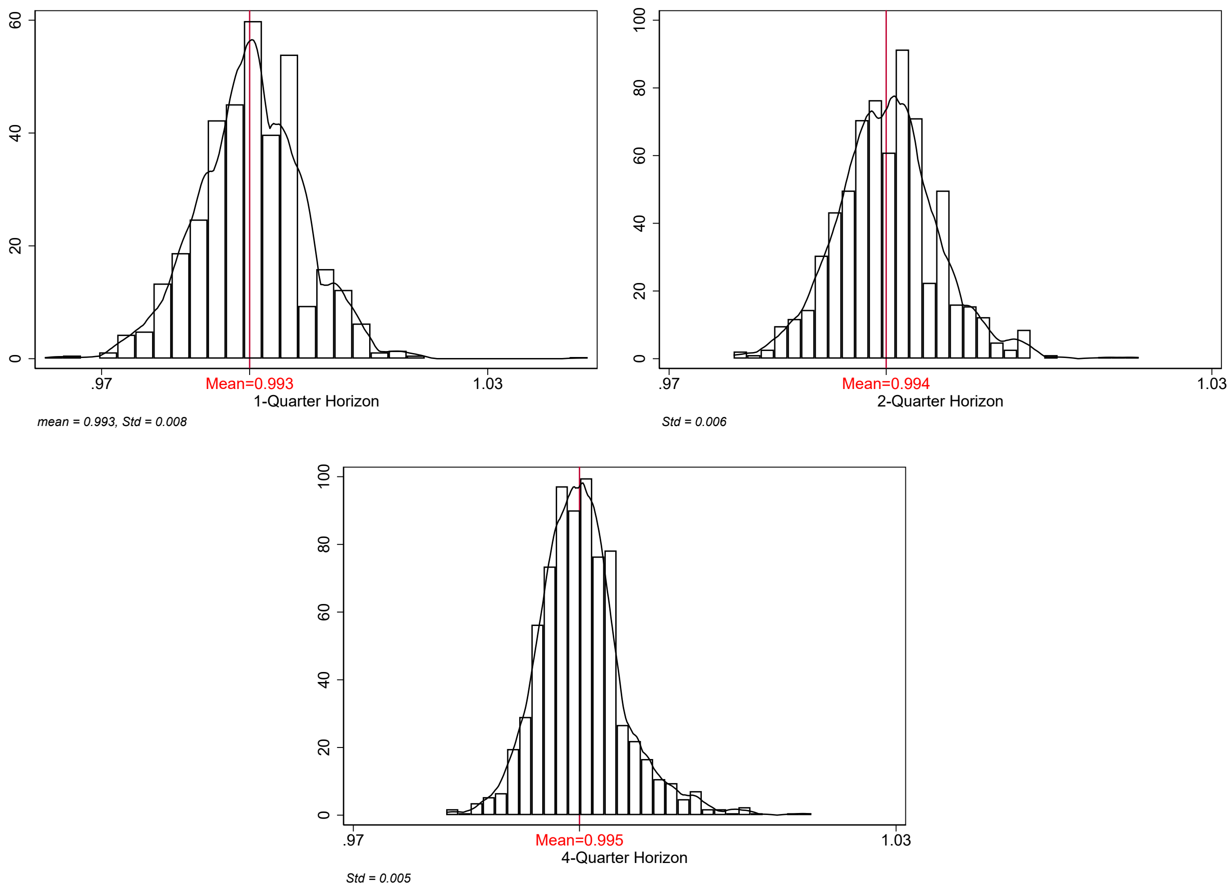


Figure A.3.1: Histogram of Perceived US Unemployment Rate Dynamics (SPF)

Notes: We plot the histogram of the average monthly unemployment rate projection forecast calculated using the Survey of Professional Forecasters. 1-Quarter, 2-Quarter and 4-Quarter horizon forecasts correspond to $\left(\frac{U0}{U-1}\right)^{1/3}$, $\left(\frac{U1}{U-1}\right)^{1/6}$ and $\left(\frac{U4}{U-1}\right)^{1/12}$. The average monthly unemployment rate forecast for the quarter that just passed is denoted as $U-1$. We denote the current quarter as $U0$. For the q quarter ahead average monthly unemployment rate forecast, we denote it as Uq $(q = 1, 4)$. When piloting the histogram, We use the SPF sample from 2012 to 2019 to match with the year span of our main SCE sample.

A.3.3 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 SCE survey downloaded from the NY Fed website and the SCE LMS. Because the SCE LMS 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's unemployment duration.

Table A.3.2: Job Search Beliefs and Job Search Activities

	(1) $F_t^i \hat{X}_{i,t}$	(2) $\hat{\beta}^u_{i,t}$
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 than 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 A.3.2. We find 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 being offered an interview serves as a positive feedback for the job seeker in terms of her individual job search perspective. Nevertheless, 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.

We can also look at whether job search experience affects the update of perceived job-finding probability ($F_t^i \hat{X}_{i,t} - F_t^i \hat{X}_{i,t-1}$) and the "surprise" about the US unemployment rate ($F_t^i \hat{U}_t - F_t^i \hat{U}_{t-1}$). Table A.3.3 shows regression results. We find that only the update of current period perceived job-finding probability update is statistically significantly positively associated with whether the job seeker was interviewed in the past 4 weeks. Since securing 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" about the unemployment rate shows no correlation with positive job search activities, implying that job seekers do not modify their beliefs on the aggregate market based on individual job search activities.

Table A.3.3: Belief Update on Job Search and Job Search Activities

	(1)	(2)
	Job-Finding Prob Update	"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 than or equal to the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.3.4 Perceptions and Job Search Effort

In this subsection, we demonstrate 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 dataset we use in this exercise combines the SCE survey downloaded from the NY Fed website and the SCE LMS. Because the SCE LMS 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.

The findings are presented in Table A.3.4. We find 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. Moreover, we find that perceived job-finding probability projection has a large effect on search effort. Column 1 suggests that if a job seeker forecasts a 18% lower future perceived job-finding probability (or $\hat{\beta}^x_{i,t-1} = 0.82$), the contemporaneous probability of applying for a job increases by around 16.6%. Consistently, column 2 suggests that a 18% lower future perceived job-finding probability (or $\hat{\beta}^x_{i,t-1} = 0.82$) increases the number of job search activities that a job seeker will engage by around 4.3%. Column 3 focuses on a different time horizon because the dependent variable is the job search hours in the last 7 days. We again find a large response that a 18% lower future perceived job-finding probability (or $\hat{\beta}^x_{i,t-1} = 0.82$) increases job search hours by 12.8%.

Table A.3.4: 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)
$\hat{\beta}^x_{i,t-1}$	-0.639***	-1.369	-9.160
	(0.196)	(1.269)	(6.931)
Unemployment Duration	Yes	Yes	Yes
Unemployment rate	Yes	Yes	Yes
Demographics	Yes	Yes	Yes
Dep. Var. Mean	0.692	5.717	12.868
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 than or equal to the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.4 Main Calibration: Additional Details and Results

A.4.1 Calibration: Sample Construction

In this subsection, we introduce in detail how we construct the sample for the calibration exercise in subsection 6.3 and 6.4.

Specifically, we keep unemployed workers who reported at least 3 times about their perceived job-finding probabilities consecutively. This is because calculating model predicted $F_t^i \hat{X}_t^i$ and $F_{t+1}^i \hat{X}_{t+1}^i$ rely on survey responses of the current period (t) and the immediate future period $(t+1)$ from the same job seeker.

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

Additionally, model predicted $F_t^i \hat{X}_{t+\tau}^i$ requires calculating $E_{t-1}U_t$, which elicited $\hat{\beta}_{i,t-1}^u$ from period $t-1$ is a necessary input as is shown in the above equation.

Given the limited number of job seekers who have 3 consecutive interviews, we maximize the utilization of the sample by putting survey responses from those job seekers into tuples. Each tuple is an observation of the calibration exercise that consists a job seeker's survey response from period $t-1$, t and $t+1$ for all t.

A.4.2 Calibration: Long-term Effect of Updating

The calibration exercise shown in subsection 6.4 uses the same empirical sample as the previous subsection 6.3 for consistency and comparison, i,e, each observation consists a job seeker's survey response from period $t-1$, t and $t+1$ for all t.

For exposition purpose, we denote the first response as r_1, the second response as r_2 and the third response as r_3. Because the calibration exercise in subsection 6.4 is based on the learning process in equation (6.6), we assume that each job seeker i knows the US unemployment rate when they provided their first response as unemployed. In other words, we anchor each job seeker's belief about the unemployment rate at its level of the first response as a unemployed job seeker in the survey, which need not be the unemployment rate when they provided the response r_1. Then we can follow the updating process described in subsection 6.4 to calculate the "surprise" about the aggregate labor market.

A.4.3 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 augment 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:

$$\tilde{X}_t^i = \exp(A_i) \underbrace{\exp\left(\gamma_d D_{i,t}\right) \times F_t^i \frac{M(U_{i,t}, b(U_{i,t})^k)}{U_{i,t}}}_{\hat{X}_t^i} \tag{A.4.1}$$

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 (A.4.1), 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 A.4.1 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.

[46] The calibration of $VAR(A_i)$ uses the equality: $VAR(log(\tilde{X}_t^i)) = VAR(A_i) + VAR(log(\hat{X}_t^i))$

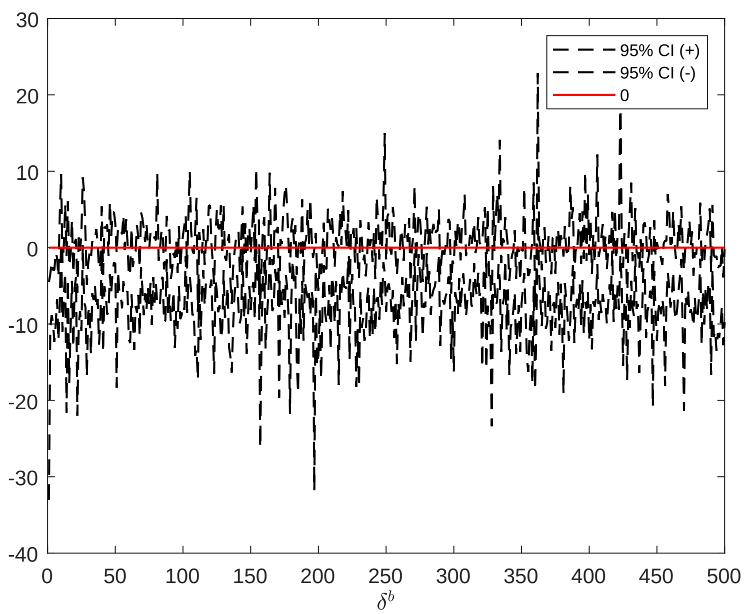


Figure A.4.1: Simulated Correlation Between $\tilde{X}_t^i$ and U_t

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.

A.5 Job Search Effort Calibration: Details

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:

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

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 understand 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 solved 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 A.5.1: Calibration: Search Effort

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

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 A.5.1.

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 roughly 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.

Online Appendix: Not for Publication

O.1 Additional Figures

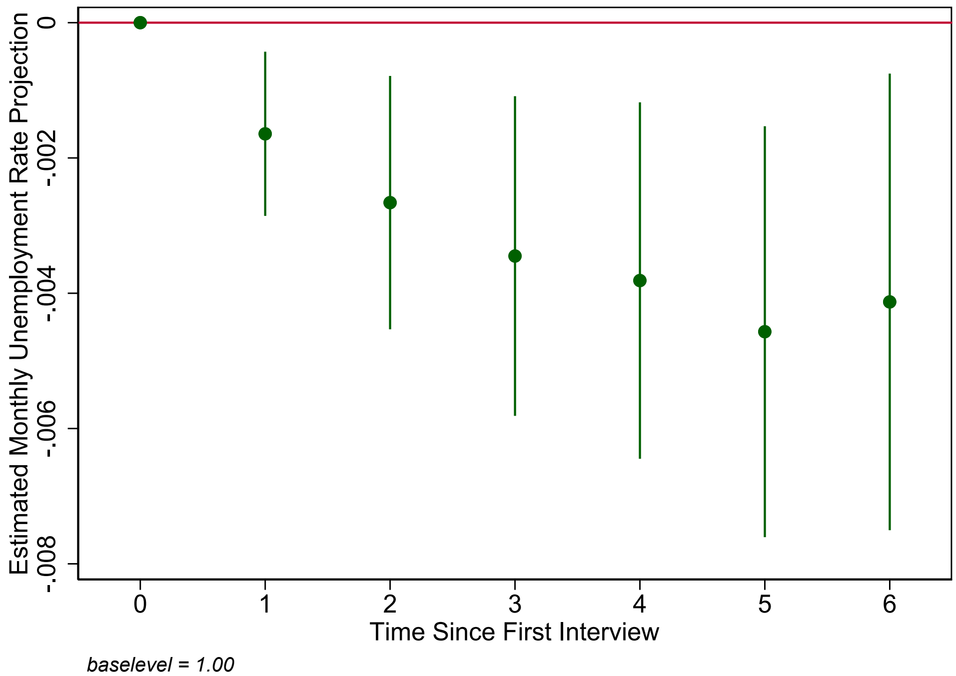


Figure O.1.1: Estimated $\hat{\beta}^{u}_{i,t}$, by Time since First Interview

Notes: We plot the estimated US unemployment rate projection $\hat{\beta}^{u}_{i,t}$ by months 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 than or equal to the 12-month job-finding probability (the consistent sample).

O.2 Discussions of the Individual Efficiency Parameter A_i

In this subsection, we show that the individual efficiency parameter A_i does not have first-order effect on the job search model that is presented in equation (6.1) when A_i is centered around 0. Therefore, normalizing $A_i = 0$ in the calibration exercise is not a major concern. The basic idea here is that since the calibration exercise in section 6 only targets the average perceived job-finding probability, the individual heterogeneity does not matter much.

We reformulate equation (6.1) as $\hat{X}_t^i = \exp(A_i) f(D_{i,t}, U_{i,t})$ to focus on the individual efficiency A_i. By taking log on both sides we find

$$log(\hat{X}_t^i) = A_i + log(f(D_{i,t}, U_{i,t}))$$

The first calibration exercise we do targets the mean of perceived job-finding probability from the data. By averaging over all job seekers, we find

$$\frac{1}{N}\sum_i log(\hat{X}_t^i) = \frac{1}{N}\sum_i A_i + \frac{1}{N}\sum_i log(f(D_{i,t}, U_{i,t})) = 0$$

with $\frac{1}{N}\sum_i A_i = 0$.

Now we move on to the empirical moments shown in 6.5. We focus on the first moment that we targeting while all other moments are analogous.

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

We can equivalently reformulate it as

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

The LHS is data while the RHS is model. Let's now focus on the term

$$\frac{1}{N}\sum_i log\left(1 - F_t^i \hat{X}_t^i\right)$$

while all other terms follow the same logic. Let us denote it as $\frac{1}{N}\sum_i H(A_i, D_{i,t}, U_{i,t})$, where we collect individual specific variables as arguments. Therefore, we are left to show that A_i does not have first-order effect on it. We first order expand $H(A_i, D_{i,t}, U_{i,t})$ around $A_i = 0$, $D_{i,t} = D$, and

$U_{i,t} = U_t$ to find

$$\frac{1}{N}\sum_i H(A_i, D_{i,t}, U_t) = H(0, D, U_t) + H_1(0, D, U_t)\left(\frac{1}{N}\sum_i A_i - 0\right) + H_2(0, D, U_t)\left(\frac{1}{N}\sum_i D_{i,t} - D\right) + H_3(0, D, U_t)\left(\frac{1}{N}\sum_i F_t^i U_{i,t} - U_t\right)$$

According to the assumption that A_i is mean 0 and the law of large number ($\frac{1}{N}\sum_i A_i \to 0$), we show that A_i does not have first-order effect on the job search model that is presented in equation (6.1). Therefore, normalizing $A_i = 0$ in both calibration exercises is not a major concern.

O.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:

$$S_{t+1} = \hat{\beta}^s_{i,t} S_t + \hat{\epsilon}^s_{i,t+1}, \quad \hat{\epsilon}^s_{i,t+1} \sim N(0, \hat{\sigma}^2_{s,\epsilon}). \tag{O.3.1}$$

We then derive an analogous expression for $F^i_t \Pr(S_{t+k} > S_t)$ $(k = 11)$ 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 $\hat{\beta}^u_{i,t}$ 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:

$$\left(F^i_t \hat{X}^i_t - F^i_{t-1} \hat{X}^i_t\right) = \vartheta \left(S_t - F^i_{t-1} S_t\right) + \delta_i + \delta_t + \varepsilon_{i,t}$$

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

Table O.3.1 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 $\left(S^i_t - F^i_{t-1} S_t\right)$, 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 O.3.1: Belief Surprise of US Stock on Job-finding Probability Update

	(1) Job Finding Prob Update	(2) 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 SE	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 than or equal to the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

O.4 Perceived US Unemployment Rate Projection: Robustness Analyses

O.4.1 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 $\hat{\beta}^u_{i,t}$, 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 $F^i_t \Pr(U_{t+k} > U_t)$, 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 $\hat{\beta}^u_{i,t}$ by employing equation (4.4).

Given that $\hat{\beta}^u_{i,t}$ 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 $\hat{\beta}^{uh}_{i,t}$ (or $\hat{\beta}^{ul}_{i,t}$). We observe that the mean difference between $\hat{\beta}^{uh}_{i,t}$ and $\hat{\beta}^u_{i,t}$ is approximately 6.6×10^{-5}, while the mean difference between $\hat{\beta}^{ul}_{i,t}$ and $\hat{\beta}^u_{i,t}$ is roughly -8.1×10^{-5}. Both differences are small compared with the value and variation of $\hat{\beta}^u_{i,t}$, thus validating our claim that the estimated US Unemployment rate projection ($\hat{\beta}^u_{i,t}$) remains fairly constant, irrespective of whether job seekers harbor misconceptions about the level of the US unemployment rate.

O.4.2 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.

O.4.2.1 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:

$$U_{t+1} - U^n = \hat{\beta}^u_{i,t}(U_t - U^n) + \hat{\epsilon}^u_{i,t+1}, \quad \hat{\epsilon}^u_{i,t+1} \sim N(0, \hat{\sigma}^2_{u,\epsilon}). \tag{O.4.1}$$

$\hat{\beta}^u_{i,t}$ represents a job seeker i's perceived dynamics at time t. $\hat{\epsilon}^u_{i,t+1}$ is a noise to individual i's believe, which is assumed to follow a normal distribution $N(0, \hat{\sigma}^2_{u,\epsilon})$ 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 $U_t - U^n$.[47] 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 ($F^i_t U_t - F^i_{t-1} U_t$).

O.4.2.2 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

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

unemployment can explain the update of individual perceived job-finding probability:

$$\left(F_t^i \hat{X}_t^i - F_{t-1}^i \hat{X}_t^i\right) = \vartheta \left(U_t - F_{t-1}^i U_t\right) + \delta_i + \delta_u + \varepsilon_{i,t} \tag{O.4.2}$$

The dependent variable is the update of job-finding probability $F_t^i \hat{X}_t^i - F_{t-1}^i \hat{X}_t^i$. 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 unemployment rate fixed effect to remove the systematic impact of monthly aggregate environment.[48] We cluster standard errors at the individual level. Furthermore, the inclusion of individual unemployment duration as a control variable does not significantly alter the main empirical pattern.

Table O.4.1: 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 SE	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 O.4.1. We use specification O.4.2 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 than or equal to the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table O.4.1 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 unemployment 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

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

define the adjusted job-finding probability 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 O.4.2 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.

Table O.4.2: Job-finding Probability Updates Induced by Belief Surprise of Unemployment Rate

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

Notes: The contemporaneous job-finding probability forecast ($F_t^i \hat{X}_t^i$) at period t is statistically significantly different from the job-finding probability forecasts predicted at period $t-1$ ($F_{t-1}^i \hat{X}_t^i$) at 0.01 level, while not statistically significantly different from job-finding probability 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 than or equal to the 12-month job-finding probability (the consistent sample).

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.

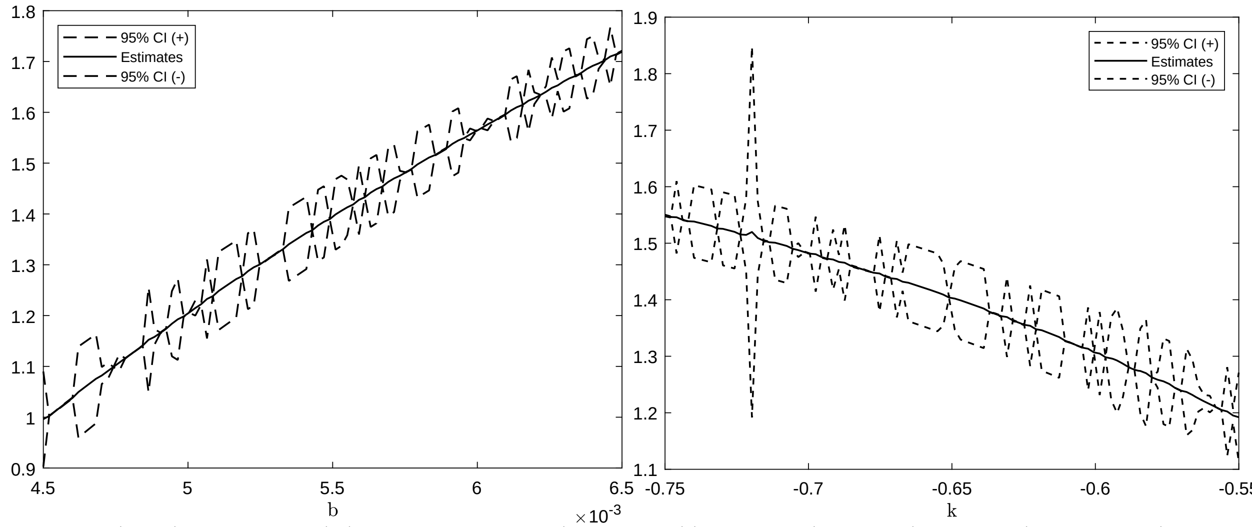
O.5 Subjective Beveridge Curve

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 (6.5). 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 O.5.1 presents the estimated θ with different values of ks and bs.

In the left panel of Figure O.5.1, 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 O.5.1, 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 O.5.1. 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 than 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 O.5.1: θ with Different Values of k and b

Table O.5.1: Calibration with Micro-data (with k)

Parameter:	γ_d	θ	l	k
Estimate	-0.141	1.794	0.329	-1.387
Model-fit:	$\frac{1}{N}\sum_i log(1-FindJob3_t^i)$	$log(1-FindJob3_{t+1}^i)$	$\frac{1}{N}\sum_i log(1-FindJob12_t^i)$	
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 than 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.

O.6 Additional Empirical Results

O.6.1 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 O.6.1. 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 O.6.1: The Effect of Beliefs on Job-Finding Outcomes

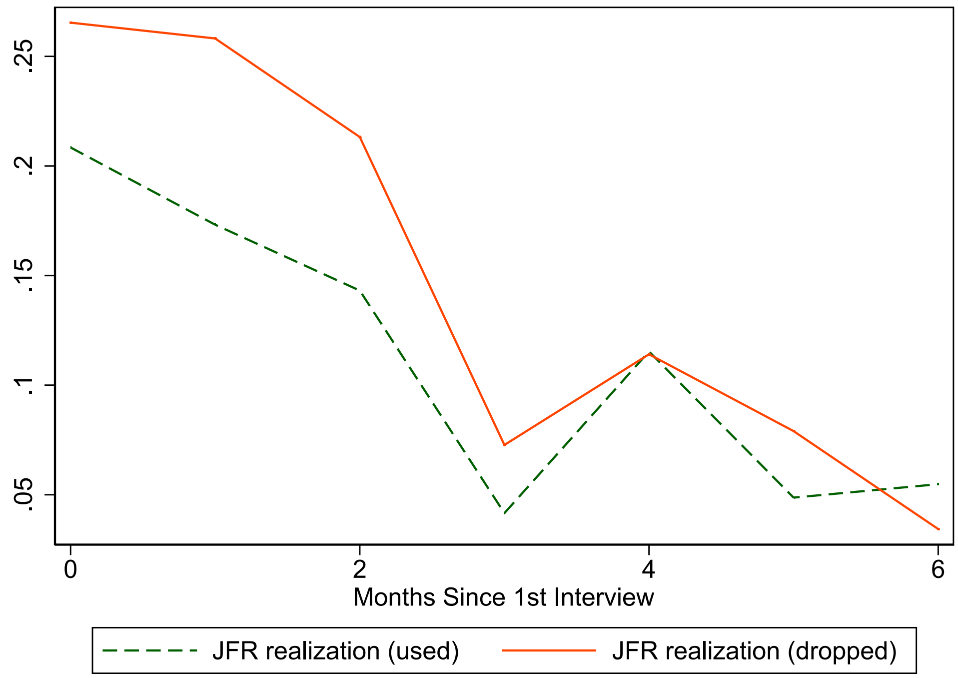
	(1) Realized Job Finding	(2) Realized Job Finding
Estimated Job-Finding Probability	0.433***	
	(0.143)	
Estimated US Unemployment Rate Projection		-9.036**
		(4.290)
Person FE	Yes	Yes
Month FE	Yes	Yes
Cluster SE	Person	Person
Obs	799	799

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 than or equal to the 12-month job-finding probability (the consistent sample). Standard errors reported in brackets are clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

O.6.2 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 O.6.1 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 $(\hat{\beta}^{x}_{i,t})$ 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 than or equal to the 12-month job-finding probability (the consistent sample).

Figure O.6.1: U-E Transition Rate by Months Since 1st Interview

O.6.3 KM Survey: An Alternative Specification

In subsection 5.4.1, we have proposed an empirical method to estimate job seekers' perceived job-finding probability projection $\hat{\beta}^x_{i,t}$, 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 O.6.2, 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 6.

Table O.6.2: 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.

O.7 Long-term Impact of Updating with the Perceived U_t Process in Equation (6.6): An Alternative Learning Process

In section, we examine the long-term effect of updating based on the US unemployment rate based on the learning process in equation (6.6) in a specific updating setup. In this environment, the job seekers form beliefs about their "island" unemployment rates which is used to forecast future "island" unemployment rates.

Following the setup shown in subsection 6.4, we assume that the perceived unemployment rate evolves according to equation (6.6). We also assume that each job seeker i who knows the US unemployment rate at period t (U_t) as a baseline level. We first explain how job seeker i forecast the period t forecast of period $t+1$ US unemployment rate and the "surprise" that the job seeker perceives when period $t+1$ arrives. According to the perceived U_t process in equation (6.6), i's perceived period $t+1$ US unemployment rate is

$$F_t^i U_{t+1} = \tilde{\beta}^u_{i,t} U_t \exp(\sigma_\epsilon^2/2)$$

where the constant $\exp(\sigma_\epsilon^2/2)$ is a known constant needed for the correct expectation due to the Log-Normal distribution of the noise term ε_{t+1} in equation (6.6). Again denote the true US unemployment rate between period $t+1$ and t is denoted as $\beta^u_{t+1,t}$, then we obtain "surprise" about the aggregate as

$$F_{t+1}^i U_{t+1} - F_{t+1}^i U_t = \left(\beta^u_{t+1,t} - \tilde{\beta}^u_{i,t} \exp(\sigma_\epsilon^2/2)\right) U_t.$$

According to the updating process in the job search model (equation 6.2), the "island" unemployment rate ($U_{i,t}$) can be represented as

$$U_{i,t} = U_t + \theta \left(\beta^u_{t+1,t} - \tilde{\beta}^u_{i,t} \exp(\sigma_\epsilon^2/2)\right) U_t$$

Different from the job search model shown in section 6, we assume that job seekers believe $U_{i,t}$ as the true island unemployment rate and us it to update future "island" unemployment rates.

Similarly, job seeker i forecast the period $t+k$ ($k>0$) forecast of period $t+k+1$ US unemployment rate according to

$$F_{t+k}^i U_{t+k+1} = \left(\tilde{\beta}^u_{i,t}\right)^{k+1} U_t \exp(\sigma_\epsilon^2/2)$$

Since each job seeker now has a perceived “island" unemployment rate or every period t, she updates it according to a perceived “island" unemployment rate process different than equation (6.2). Specifically, the perceived “island" unemployment rate is updated dynamically according to the following

$$U_{i,t+k+1} = U_{i,t+k} + \theta \left(\beta^u_{t+k_1,t} - F^i_{t+k} U_{t+k+1} \right) U_t + \hat{\epsilon}^{\eta}_{i,t}, \quad E_t \left[\hat{\epsilon}^{\eta}_{i,t} \right] = 0$$

Through this dynamic process, all past “surprises" are integrated in the current period perceived “island" unemployment rate, which facilitates the long-term impact of updating.

In this section, we demonstrate that the long-term impact of updating can be integrated into the job search model through a different updating setup for the island unemployment rate. We emphasize that the crucial assumption facilitating this is that job seekers perceived “island" unemployment rate is only affected by job seekers' “surprises" but not influenced by the realizations of aggregate unemployment rate.

In this section, we illustrate how the long-term impact of updating can be incorporated into the job search model via an alternate updating setup for the “island" unemployment rate. We highlight that a key assumption of this approach is that the perceived "island" unemployment rate for job seekers is influenced solely by their own past "surprises" and remains unaffected by the realizations of the aggregate unemployment rate.