Understanding Expectations in Job Search:

Subjective Duration Dependence, Aggregate Labor Market Shocks and Overreaction*

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Abstract

Unemployed job seekers might worry about their chances of finding a job, especially if they remain unemployed for longer or labor market conditions turn out different than expected. We find, based on multiple survey samples, that job seekers anticipate a significant decline in their job-finding probability with an additional month of unemployment. However, they adjust their job-finding probabilities upward (downward) when the aggregate unemployment rate is unexpectedly low (high). Evaluated with a quantitative job search model, subjective job-finding probabilities substantially overreact to aggregate conditions - consistent with Diagnostic Expectations. These beliefs have the potential to offset a substantial part of the negative consequences of moral hazard in job search.

Keywords: belief, dynamics, job search, unemployment, overreaction, diagnostic expectation

JEL: D83, E24, J64

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1 Introduction

For a cohort of unemployed job seekers, the observed hazard of transitioning into employment decreases by approximately 20% monthly during the initial six months of unemployment (Kroft et al. (2013) for the US). A similar decline in job finding hazard can be observed in the Survey of Consumer Expectations (henceforth: SCE). Such observed "duration dependence" has long attracted the attention of policymakers, and an extensive body of economic literature has engaged with this issue. While increasingly sophisticated statistical models seem to indicate that selection of less employable individuals into longer unemployment durations is a major driver of this observation (e.g., Ahn and Hamilton, 2020; Mueller et al., 2021; Mueller and Spinnewijn, 2023; Alvarez et al., 2023), there remains respectable empirical evidence (e.g., Zuchuat et al., 2023), field experiment evidence (e.g., Kroft et al., 2013; Farber et al., 2016), theoretical arguments (e.g., Pavoni, 2009; Fawcett and Shi, 2018) and public policy concern (e.g., Powell, 2020) that duration dependence could be due to a real deterioration of employment opportunities at the individual level.

Instead of identifying the source of duration dependence, this paper studies how the unemployed themselves view their future employment prospects in case they remain unemployed for longer. It is unlikely that job seekers have read the many contributions in the economics literature, but they might have noticed that their unemployed peers who stay unemployed longer seem to have a harder time finding a job. If they believe that this arises because finding a job gets harder when a person is unemployed for longer, this would translate into beliefs that their own job-finding prospects decline with unemployment duration. Whether job seekers hold such beliefs is important for our general understanding of how job seekers view the labor market. It also affects how we model duration dependence in job search models (e.g., Vishwanath, 1989; Acemoglu, 1995; Shimer, 2008; Gonzalez and Shi, 2010; Fawcett and Shi, 2018) and how we design unemployment insurance (e.g., Pavoni and Violante, 2007; Pavoni, 2009; Wunsch, 2013). In this paper, we make progress on this issue in four distinct steps.

1) We document new patterns of beliefs about individual's job-finding prospects in the future. We exploit answers about re-employment prospects over different horizons in the Survey of Consumer Expectations (SCE). The short horizon answer relative to the long horizon answer then identifies whether the job seeker is more optimistic about the earlier or the later periods. Using a simple model of beliefs with geometric decreases or increases to filter the data, we show that job seekers anticipate an 18% monthly decline in job-finding probability during unemployment. Job seekers, therefore seem to attribute much of the empirical duration dependence to individual deterioration of future chances. In a similar exercise, we use answers to different questions from the Survey of Unemployed Workers in New Jersey (known as the Krueger-Mueller Survey, hereafter: KM survey) and find the same 18% expected monthly decline in future job-finding prospects.

Our ideal data would simply ask about the chances of accepting at least one job over the next 3 month and - in the absence of a job acceptance - in the subsequent 3 months. Neither of the surveys asks the question in such a straight way, and we therefore need a simple model of beliefs to filter the answers. Moreover, we need to assume that individuals are able to preform involved calculation including compounding. We provide some support that this assumption is potentially palatable.[1] Furthermore, we fielded an online survey that elicits perceived job-finding probability for the next three months and the three subsequent months. Therefore, we can interpret the report beliefs directly without relying on a model. Indeed, we also observe that job seekers assign significantly higher probabilities to finding a job in the earlier period as compared to the later one.

These novel results are arguably surprising in light of the existing evidence. In their seminal contribution, Mueller et al. (2021) document a wealth of novel and important stylized facts using the SCE and the KM survey. Exploiting the fact that job seekers repeatedly answer the same question about the job-finding probability, they document a striking finding that unemployed job seekers perceive no change in their job-finding probability on average over their unemployment spell. Among other things, they also document a non-significant relationship between the national unemployment rate and unemployed job seekers' perceived job-finding probability. This paints a rather passive picture of the unemployed, which is succinctly summed up in the following quote: This evidence suggests a "stubborn" view of job seekers who "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).[2]

Evidently our approach reveals a very different picture about perceived duration dependence, in which job seekers anticipate a substantial decline in job-finding prospects in the future. Unlike

[1] We show that majority of the job seekers in the SCE is capable of numerical calculations by looking at their answers to a set of numerical questions in the SCE, including a compounding interest rate question. We also use our geometric model of beliefs based on answers to the 3- and 12- month cumulative job-finding probability to project the 4-month cumulative job-finding probability, which is infrequently asked in the SCE Labor Market Survey. Even though 4 month is much closer to 3 than to 12 months, we predict the average answer to lie at the mid-point between the 3- and 12- month job-finding probability. This is indeed the case in the data.

[2] We note that job seekers could have constant job-finding rates even if they have declining contact rates, if they offset such a decline in contact rates by accepting less desirable jobs. We do not think that this is the most common interpretation of the existing evidence, but in any case the point of this paper is that job seekers do seem to anticipate falling job-finding rates.

Mueller et al. (2021), we do not rely on repeated questions over time. Instead, we extract beliefs at a given point in time about a job seeker's current job-finding chances and about his/her future chances should s/he remain unemployed. This captures job seekers' anticipation about their own future and is the closest analogue to expectations about future duration dependence.

2) *We investigate the role of expectations regrading the aggregate shocks to individual beliefs in job search.* Consistent with Mueller et al. (2021), we do replicate that, overtime, the average reported contemporaneous job-finding probability does not decline. How does this align with our finding that individuals expect a decline in future job-finding probabilities? One plausible path to reconcile these observations is that job seekers are pessimistic about the future, but they receive positive news that makes them more positive when asked the next time. Labor economics suggests that the unemployment rate might serve as such a shock, which does not average out across job seekers. It turns out that both the SCE and the KM survey were conducted during periods of steady improvement in the unemployment rate. We exploit the question in the SCE that asks about the evolution of the unemployment rate (there is no such question in the KM survey), and find that job seekers do not expect such an improvement. On average, they appear to believe that the unemployment rate is equally likely to increase or decrease. Filtered through the lense of an AR(1) belief model with common variance, we find that job seekers expect no change, unlike professional forecasters, whose responses indicate a better understanding of the favorable trend in the unemployment rate. As a result, job seekers are repeatedly positively surprised.

We therefore 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. Individuals for whom the actual unemployment rate deviates from expectations see large revisions in their reported job-finding probability. [3] Using the micro-estimate and scaling it by the aggregate unemployment "surprise" generates a 17% update in the perceived job-finding probability from one period to the next, which essentially offsets that 18% decline that job seekers had anticipated one month earlier (see Figure 5 for an illustration). This indicates a consistency between the two previous findings: Job seekers expect their individual chances to decline but revise their assessments upward when the labor market does better than expected. The repeated upward correction is driven by large revisions to the pessimistic outlook of job seekers about the evolution of the labor market.

[3] As a reassuring side-remark, such effects are not observed for aggregate variables with no direct connections to the job market, such as the US stock market.

An analysis from our online survey show a similar pattern that job seekers perceive substantially lower job-finding probabilities in reaction to a hypothetical US unemployment rate increase. Furthermore, we verify with the SCE sample that, consistent with our logic, individuals who are not positively surprised by aggregate conditions report a declining job-finding probability over time.

3) *We estimate a job-search-based model of such belief patterns to uncover the drivers of beliefs, and find strong overreaction to aggregate labor market conditions.* Is the empirical evidence that job seekers strongly update their beliefs in response to unexpected changes in aggregate conditions quantitatively consistent with predictions from a standard job search model? To address this question, we first model job seekers' perceived job-finding probability by combining subjective duration dependence with a standard job search matching function. A standard matching function ensures that job seekers take into account beliefs about the aggregate conditions when forming beliefs about the individual's job-finding probability. While the aggregate unemployment rate is still assumed to follow an AR(1) process, the model no longer restricts perceived job-finding probabilities to change geometrically and takes the impact of the aggregate unemployment rate into account. A calibration using the SCE data indicates that a negative subjective duration dependence accounts for most of the anticipated decline in perceived job-finding probability. The matching function produces positive updates on individual perceived job-finding probabilities when the aggregate unemployment rate improves. However, the magnitude of this positive update is small, which is not aligned with the large update we see in the data. This result indicates that job seekers overreact to the change of aggregate unemployment rate relative to standard matching functions.

We demonstrate that modeling job seekers' belief dynamics through diagnostic expectation, as a novel mechanism of belief formation in job search, successfully accounts for the large updates in job-finding probability induced by unexpected changes in the aggregate conditions. Diagnostic expectations have been applied to capture over-reaction in other domains (e.g., Bordalo et al., 2018, 2019, 2020). In our job search context, we need to link multiple domains of beliefs: job seekers information about aggregate unemployment maps into beliefs about their own chances of finding a job. To capture this, we model belief overreactions using an "island" metaphor common in labor economics. Specifically, job seekers overweight the good employment conditions in their own "island", whose likelihood increases the most in light of recent news about the US unemployment rate relative to what they expected before. In other words, job seekers believe that good news about national unemployment is overly relevant (i.e., they overreact) for their own labor market prospects.

Quantitative analysis reveals that overreactions is an important mechanism that allows us to align all the empirical facts we documented.

In the model, job seekers overreact to the most recent information, which affects the short term much more than the long term. Specifically, the average surprise about the unemployment rate has an order of magnitude greater effect on short-run job-finding probabilities, driven by diagnostic expectations, than on future probabilities through adjustments in the expected unemployment rate within the matching function. The short-lived nature of belief updating is supported by the data: surprises about the unemployment rate significantly affect forecasts of job-finding probabilities in the immediate period, whereas their effects on subsequent forecasts are an order of magnitude smaller and statistically insignificant.

4) *We highlight the importance of these insights by examining the potential effects of beliefs on search efforts and the moral hazard costs of unemployment insurance.* In our setting, job seekers expect their job market prospects to decline substantially, only to be surprised next period so that they revise their chances upward again. In this final part of the paper, we extend the model such that the initial decline is partially because lower expected returns per unit of search effort in the future, and partially due to endogenous search effort response since individuals expect to search less in the future when the returns are lower. Compared to an individual who rationally expect future aggregate labor market condition, the fear of declining prospects induces substantially more initial effort (approximately 4.34%). Evidence from a supplement of the SCE indicates that the magnitude may indeed be reasonable.[4] In the model, the additional job search effort due to correctly anticipating future aggregate labor market evolution is similar to the effect induced by a permanent unemployment benefit reduction of 9%. Misalgined expectations thus allowed the planner to mitigate a non-trivial fraction of the moral hazard problem. This highlights the importance of beliefs for job search effort, and clearly understanding their impact seems essential for the correct design of unemployment benefits.

After reviewing some additional literature (Section 2) and describing our data sources (Section 3), we present the empirical framework and resulting evidence in Sections 4. We discuss robustness in Section 5, and 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.

[4] The finding that 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). Also, in our own online survey individuals also indicate that they would search more immediately if they are told that prospects in the future are lower than expected.

2 Additional Related Literature

Our work contributes 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). Conlon et al. (2018) uses survey data from the SCE to examine workers' wage expectations and how they react to wage offers.[5] Our paper builds on the important findings from Mueller et al. (2021). They provide a wealth of insights, and we focus on the anticipated evolution of job-finding probabilities and its reaction to updates about the labor market. This reveals the new insight that job seekers anticipate duration dependence with an average expected decline in the job-finding probability of 18% per month; and are pessimistic about the labor market but highly sensitive to its actual evolution. The 18% anticipated duration dependence nearly matches the observed change in job-finding-hazard without correcting for selection.[6] Since previous work including that of Mueller et al. (2021) has shown that selection matters and true duration dependence is smaller than observed duration dependence, one might interpret this evidence as a form of overreaction.

Our paper contributes to the understanding of non-rational beliefs formation in the context of job search. The strong effects of beliefs about the aggregate unemployment rate on individual job-finding probability cannot be rationalized by aggregate matching functions standard in the macro-labor literature. We find that that job seekers overreacting to the recent updates of aggregate unemployment rates consistent with diagnostic expectation can quantitatively account for the empirical pattern (Bordalo et al., 2018, 2019, 2020, 2022). In this sense, our paper expands the domain of applicability of diagnostic expectation (Bordalo et al., 2022).

The paper is also related to the modeling of duration dependence (e.g., Vishwanath, 1989; Acemoglu, 1995; Shimer, 2008; Gonzalez and Shi, 2010) and the literature on optimal unemployment insurance (e.g., Pavoni and Violante, 2007; Pavoni, 2009; Wunsch, 2013). For these papers it matters whether individuals anticipate that future prospects to decline or not, which is precisely the topic of empirical investigation that we undertake. These papers usually feature rational expectations, while our results indicate that individuals tend to overreact. This links to the literature

[5] Some studies also consider the aggregate implications of biased beliefs and learning (Potter, 2021; Balleer et al., 2021a; Menzio, 2022).

[6] 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.

on behavioral frictions that distort the job search process. Previous research has examined various behavioral biases, such as present bias (DellaVigna and Paserman, 2005), reference dependence (DellaVigna et al., 2017), non-Bayesian updating (Conlon et al., 2018), and locus-of-control (Caliendo et al., 2015; Spinnewijn, 2015).

3 Data

The main dataset for the empirical analysis comes from the Survey of Consumer Expectations (SCE). SCE surveys a national representative sample of about 1,300 household heads in the United States. 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 (hereafter: SCE LMS) in some of our analyses, which is a rotating module of the SCE, conducted every four months.

The SCE sample we use is taken from Mueller et al. (2021), which spans from December 2012 to June 2019. This allows for clear replicability and comparability with their study. During the sample period, 948 job seekers were surveyed while unemployed.[7] For robustness analysis, we additionally study the SCE responses during the Covid-19 pandemic. 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: *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 responders' expectations over different time horizons. Careful reflection requires a lower reply to the second question 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.[8] Among the 2597 observations (derived from 933 unemployed job seekers) that contain answers to both questions, this excludes

[7] All empirical results in the paper can be replicated using a SCE sample that we downloaded directly from the New York Fed website. The public version spans from Jun 2013 to December 2019. We use the public version of the SCE whenever the analysis needs information from the SCE LMS.

[8] 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.

12.3% that strictly violate consistency and 26.5% where the answer to both questions coincides.[9]

Table 1 shows that the consistent sample closely resembles the full SCE sample, with similar distributions of gender, race, education, and age. This indicates that the consistency requirement does not alter the demographics of the participant pool substantially. Following Mueller et al. (2021) we also report the summary statistics from the CPS in Table 1 along with the two SCE samples.

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). Both samples restricted to unemployed workers, ages 20–65. . In column 1, we show the summary statistics of the consistent sample. 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.

We also exploit SCE's 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. To compare job seekers' forecast of US unemployment with that of professionals, we downloaded individual forecasts for the US unemployment rate from the Survey of Professional Forecasters (SPF hereafter) from the

[9]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.

Federal Reserve Bank of Philadelphia website.

For some of our analysis, we use the KM survey (see Krueger et al. (2011) for details). 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 does not ask questions about the aggregate unemployment rate.

We designed and fielded a survey in the fall of 2024 through `Prolific.com` which asks more direct questions about job finding in different future horizons, as well as the impact of a hypothetically change in unemployment rate. In early October, we recruited 300 unemployed job seekers aged 20-65. We obtained 272 responses after excluding incomplete and non-human responses, which serves as our main sample. We also surveyed 200 respondents aged 20-65 and find that insights from our main sample remain valid among employed individuals in the hypothetical scenario that they would be unemployed. Therefore, we focus mostly on our main sample. In late September, we fielded an earlier round with limited checks against non-human responses and without aligning our questions closely to the SCE, which led to extremely noisy data. Online Appendix O.3 provides more details.[10] Table O.3.1 reports basic demographics of the main online survey sample, which is not as representative as the SCE.

4 Statistical Framework and New Empirical Evidence

This section proposes statistical frameworks to filter the belief data. We document two new empirical findings on the dynamics of unemployed job seekers' beliefs: (1) unemployed job seekers anticipate a substantial decline in their job-finding probability for every additional month of unemployment in the future; (2) the belief dynamics of the US unemployment rate have a significant impact on the updating of the individual job-finding probability.

4.1 Belief Dynamics: Job-finding Probability

Conditional on being unemployed at the beginning of period t, an individual i's true job-finding probability in month t is denoted as X_t^i, which is neither observed by individual i nor by researchers. At the beginning of month t, individual i forecasts his/her future job-finding probabilities conditional on remaining unemployed ($X_{t+\tau}^i$) as $F_t^i X_{t+\tau}^i$, where $\tau = 0$ captures the belief about the upcoming month.[11] 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. We can calculate the three and

[10]Please refer to our registry (`https://osf.io/6de43`) for more details on the hypothesis, survey implementation, questionnaire, power analyses, and analysis plan.

[11]We make no assumption on the level and dynamics of true job-finding probability X_t^i, so job seekers may misunderstand both the level and dynamics of the job-finding probability.

twelve-month job-finding probabilities ($FindJob3^i_t$ and $FindJob12^i_t$, respectively):

$$FindJob3^i_t = 1 - \prod_{\tau=0}^{2} \left(1 - F^i_t X^i_{t+\tau}\right), \quad FindJob12^i_t = 1 - \prod_{\tau=0}^{11} \left(1 - F^i_t X^i_{t+\tau}\right). \tag{4.1}$$

The right side gives the probability of being successful in job search for at least one of the next k future months. The left side is data: every period (t) unemployed individual (i) in the SCE is asked about the probability of obtaining and accepting a job offer over the next 12 months ($FindJob12^i_t$), and is then asked to narrow it down to probability over the next three month ($FindJob3^i_t$). The answer to the long-horizon question compared to the short-horizon question then indicates whether an individual is more pessimistic about chances of success in the later months of job search compared to the earlier months of job search (conditional on remaining unemployed).

To get a first idea whether individuals seem more pessimistic about their chances later in an unemployment spell, undertake the following thought experiment: take their 12-month perceived job-finding probability and assume that individuals expect their job-finding probabilities to be the same across time (i.e., $F^i_t X^i_{t+\tau}$ being constant in τ). If this were the case, we can impute a three-month perceived job-finding probability for each individual using $1 - \sqrt[4]{1 - FindJob12^i_t}$.[12] The third bar in Figure 1 shows that participants on average report roughly 60% chance of finding a job in the next 12 months. The second bar is the average imputed 3-month job-finding probability assuming a constant job-finding probability over time. If this assumption were correct, individuals should on average report a 1/4 chance of finding a job in the next 3 month. Nevertheless, this is significantly smaller than the roughly 40% average perceived 3-month job-finding probability that participants actually report in the first bar. This simple calculation suggests that individuals are more pessimistic about later months then about early months, since the imputed short-run answers (derived from the long horizon) are on average much more pessimistic than the actual short-horizon answers. This analysis obviously relies on the idea that individuals can do numerical calculations, which we discuss extensively in Sections 5.1 - 5.3.

To quantify the information of belief dynamics indicated by $FindJob3^i_t$ and $FindJob12^i_t$ more precisely, we draw on insights from the literature of expectation formation (e.g., Afrouzi et al. (2020)) and assume that the individual's perceived dynamics of job-finding ($F^i_t \hat{X}^i_{t+k}$) follows a geometric increase or decline. This is an easy diagnostic tool to understand whether an individual sees his/her chances as increasing or decreasing. The specific functional form assumption attached

[12] If $F^i_t X^i_{t+\tau} = F^i_t X^i$ for some level of $F^i_t X^i$, then (4.1) implies $1 - FindJob3^i_t = (1 - F^i_t X^i)^3$ and $1 - FindJob12^i_t = (1 - F^i_t X^i)^{12}$, so that $1 - FindJob3^i_t = \sqrt[4]{1 - FindJob12^i_t}$. This formula enables us to impute a three month job-finding probability for each 12-month job-finding probability.

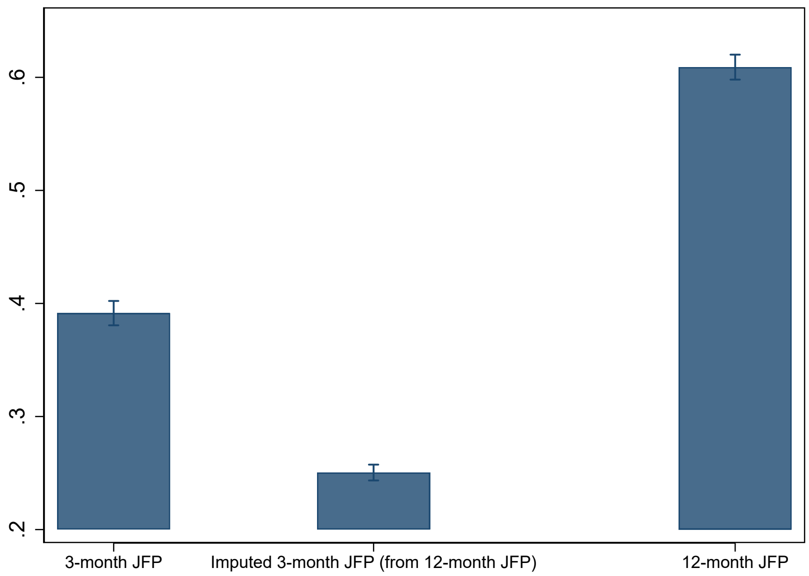

Figure 1: Comparison: 3 and 12 Month Perceived Job-finding Probability

Notes: 3 and 12 month reported perceived job-finding probability are the average values directly taken from the consistent SCE sample. The imputed 3-month perceived job-finding probability is derived from the 12-month job-finding probability under the assumption that chances are constant over time, and is calculated using $1-\left(1-FindJob12_t^i\right)^{1/4}$. We also plot their corresponding 90% confidence interval.

to it does not seem critical: We offer a more structural approach in Section 6 that echoes well the results coming out of this simple model.

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

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 $\hat{\beta}_{i,t}^x$ captures by how much this probability will change for each subsequent month. This specification assumes that job seeker i perceives a constant change ($\hat{\beta}_i^x$) in job-finding probability for each additional months of unemployment going forward. If job seekers would only be asked once, this parameter would not have a time subscript as it applies to all future periods. Since individuals are asked in different months about their future job-finding probabilities, and their assessment of the future might be different when asked in period t and period τ, this parameter is therefore sub-scripted by the period in which the individual is asked.[13] By substituting the future job-finding probability forecast described in

[13]This also applies to the second parameter that characterizes beliefs: the probability $F_t^i \hat{X}_t^i$ of finding a job in the upcoming month. Note that the time subscript indicates the time at which the individual is asked the questions, and so an individual who is asked twice could in principle change his view about the upcoming month as well as about the speed at which the job-finding probability changes over future periods.

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 $\hat{\beta}_{i,t}^x$ uniquely for every individual(i) and every time (t) s/he is interviewed.

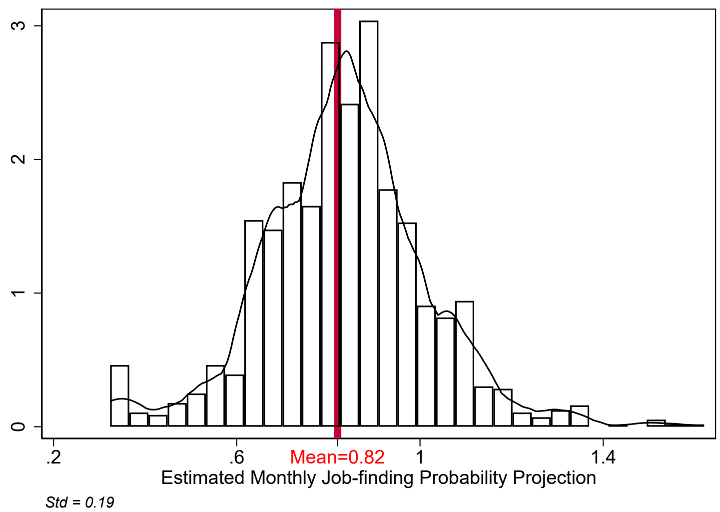

Figure 2: Histogram of Job-finding Probability Projection $\hat{\beta}_{i,t}^x$

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

Figure 2 displays the histogram of estimated $\hat{\beta}_{i,t}^x$. We observe that unemployed job seekers anticipate their job-finding probability to decline by approximately 18% on average for an additional month of unemployment, though there is large heterogeneity (standard deviation of 0.19). While the expected monthly decline is large, 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.[14] In Table A.1.1, we find that job seekers who are white, with higher education and higher household income anticipate a smaller decline in their job-finding probabilities over time (i.e., higher $\hat{\beta}_t^i$).[15] Higher US unemployment rate and state unemployment rate is associated with a stronger anticipated decline in future job-finding rates (i.e., lower $\hat{\beta}_t^i$) but this is statistically insignificant. In Appendix Figure A.1.1, we show that job seekers consistently expect on average a 18% decline in their job-finding probability,

[14]Online Appendix O.7.3 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.

[15]These correlations are broadly consistent with the heterogeneous duration dependence patterns in Zuchuat et al. (2023).

independent of how long they have already been unemployed.[16]

Given the consistent expectation of lower future job-finding probabilities, one might conjecture that individuals would perceive lower and lower job-finding probabilities when they remain unemployed for longer. This is not the case. In Figure 3, we replicate this empirical pattern that the perceived job-finding probability of unemployed job seekers remains constant within-spell first documented by Mueller et al. (2021), using our estimated 1-month perceived job-finding probability ($F_t^i \hat{X}_t^i$).[17]

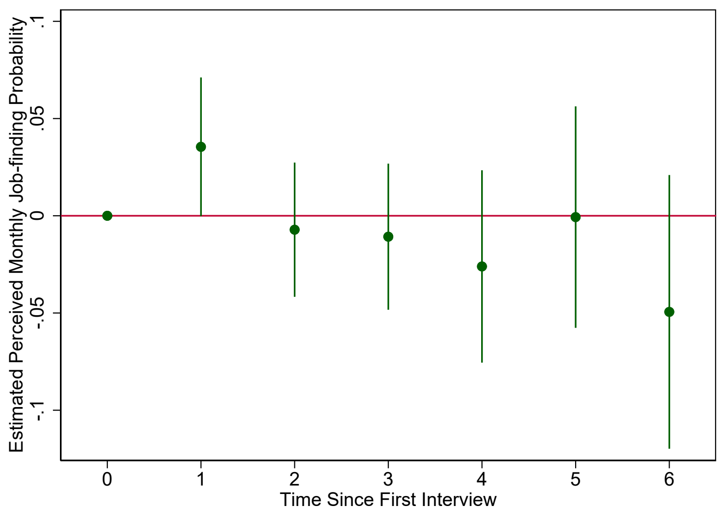

Figure 3: Estimated Job-finding Probability $F_t^i \hat{X}_t^i$, by Time since First Interview

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 the 12-month job-finding probability (the consistent sample).

Our analysis reveals an large 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 $F_t^i \hat{X}_t^i - F_{t-1}^i \hat{X}_t^i$ is strongly positive, indicating systematic forecast errors. Job

[16]We use time spent unemployed since the first interview which is defined exactly as in Mueller et al. (2021) in order 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.

[17]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 O.1.1, which presents the histogram of $F_t^i \hat{X}_t^i$. For comparison, the histogram of the 1-month job-finding probability directly imputed from the 3-month job-finding probability via $1-(1-FindJob3_t^i)^{\frac{1}{3}}$, as in Mueller et al. (2021), is represented in the right panel of Appendix Figure O.1.1. The two histograms are qualitatively similar.

seekers seem to indicate at a given point in time that their future looks pessimistic, but when asked again in the future they do not express this pessimism but are back at original levels. To understand the source of this, we entertain two possibilities: 1) Our analysis of the anticipation could be misguided. 2) Even when initial expectations of job seekers are negative, there could be positive aggregate shocks that lift these expectations before the next period arrives.

For the first point, we devote the bulk of the robustness section (Section 5) to show evidence that our statistical model passes various checks for its reasonableness. We recover very similar anticipation effects in the KM survey that features very different questions, and that we find similar anticipation effects in our online survey that relies neither on restrictions on consistent answers, nor statistical models to filter the beliefs. Therefore, we turn to the second possibility and examine the most intuitive candidate for an aggregate shock that could raise job-finding expectations—the aggregate unemployment rate evolving more favorably than anticipated.

4.2 Belief Dynamics: Aggregate Unemployment Conditions

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) specification:

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

where $\hat{\beta}^u_{i,t}$ represents job seeker i's perceived unemployment rate dynamics at time t. $\hat{\epsilon}^u_{i,t+1}$ 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}.[18] Notice that no assumptions are imposed on the process of the true unemployment rate.

If the job seeker thinks that the unemployment rate is equally likely to go up or down, this is captured by $\hat{\beta}^u_{i,t} = 1$. If the job seeker believes that it is more (less) likely that unemployment declines, the value of this parameter is less (more) than one. 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] If individuals

[18] We also explored specifications 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. Online Appendix O.6.2 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

are informed about changes but are initially off on the level of the unemployment rate, We show in Online Appendix O.6.1 that sizable misperceptions of $\pm 10\%$ of the level have only minimal consequences for our measurement of $\hat{\beta}^u_{i,t}$. Intuitively, a job seeker who expects the unemployment rate to remain constant induces $\hat{\beta}^u_{i,t} = 1$, regardless of the level of the unemployment rate they perceive. This holds approximately true for probabilities close to one-half.

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 process in equation (4.3), the probability that the unemployment rate in month $t+k$ (U_{t+k}) is higher than the unemployment rate in month t (U_t) is*

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

Please refer to Appendix A.2.1 for the derivation. We select $k = 11$ since the SCE inquires about the probability of the unemployment rate being higher twelve months later than its current level. 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 via the Hodrick-Prescott (HP) Filter. 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.

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 same as in the current month, albeit with some disagreement. This is not driven by focal answers such as equal likelihood that unemployment increases or decreases.[20]

During our sample period (2012-2019), the US economy experienced a recovery, with a 0.6% 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.4.2 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

might nevertheless not necessarily convey the current level clearly.

[20] There is a significant mass in Figure 4 at $\hat{\beta}^u_{i,t} = 1$ since many respondents report that the probability of the US unemployment rate being higher is around 50% ($\hat{\Pr}\left(E^i_t U_{t+k} > U_t\right) \approx 0.5$). But even when one excludes those observations, the overall average remains unchanged. With longer unemployment duration, individuals become slightly more optimistic about the future evolution of the unemployment rate (see Figure O.1.3). The unemployment rate projection ($\hat{\beta}^u_{i,t}$) decreases by 0.0007 on average for one additional month of unemployment.

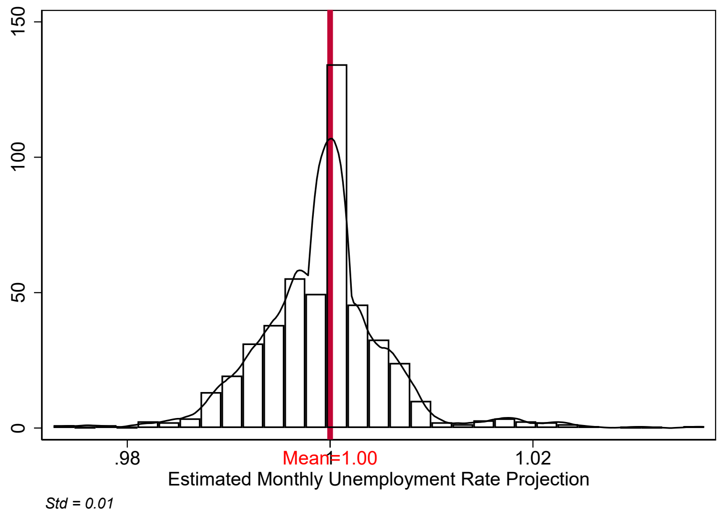

Figure 4: Histogram of US Unemployment Rate Projection $\hat{\beta}^{u}_{i,t}$

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 the 12-month job-finding probability (consistent sample).

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).

It also suggests a repeated degree of "surprise" at the individual level 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. The next subsection examines how the "surprise" $(U_t - F^i_{t-1}U_t)$ affects the individual perceived job-finding probability.[21]

4.3 Beliefs about the Aggregate and Perceived Individual Job-Finding

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[22]:

$$\left(F^i_t \hat{X}^i_t - F^i_{t-1}\hat{X}^i_t\right) = \vartheta\left(U_t - F^i_{t-1}U_t\right) + \delta_i + \delta_t + \varepsilon_{i,t} \tag{4.5}$$

The dependent variable is the update of perceived job-finding probability, which is equivalent

[21] In Online Appendix O.7.2, we show that both job seekers' perceived job-finding probability and US employment rate dynamics significantly affect their job-finding realizations.

[22] 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.

to $F_t^i \hat{X}_t^i - \hat{\beta}_{i,t}^x F_{t-1}^i \hat{X}_{t-1}^i$. The parameter of interest is ϑ, which indicates how changes in perceived "surprise" about the national labor market affects the perceived individual job-finding probability. To eliminate the selection effect, we control for an 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. The fixed effects also absorb any average effects (such as the average forecast error in job-finding probabilities) and exploits 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: Belief Surprise of US Unemployment on Job-finding Probability Update

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

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. The results suggest that at the individual level, the subjective belief "surprise" about national unemployment among unemployed job seekers is negatively correlated with their update about their own job-finding probability. In this sense job seekers seem no longer "stubborn" with regards to aggregate conditions.[23] Reassuringly, this link between updates about the aggregate economy and updates about the reported personal job-finding probability exists only for unemployment, but not for other

[23]The strong correlation between perceived dynamics of the US unemployment rate is not affected by how we filter the belief data. In Online Appendix Table O.2.1, we show that the strong correlation between individual job-finding probability and perceived dynamics of the US unemployment rate remains when the original survey question $F_t^i \Pr(U_{t+12} > U_t) - F_{t-1}^i \Pr(U_{t+11} > U_{t-1})$ is used in the regression.

aggregate variables that are not directly linked to the labor market such as the US stock market.[24]

The large estimated magnitude suggests an economically important impact. In Figure 5 (with relevant statistics in Table A.1.2), we illustrate the implications visually. Job seekers report an average job-finding probability of 20.1% in period $t-1$, which they anticipate will decrease to 15.4% in period t. This represents an expected decline of about 18%, as depicted by the downward arrow in the figure. The discrepancy between initial beliefs and future expectations ($F^i_{t-1}\hat{X}^i_t$ and $F^i_t\hat{X}^i_t$) is statistically significant, aligning with the prevalent pessimism about future job-finding prospects observed in Figure 2.

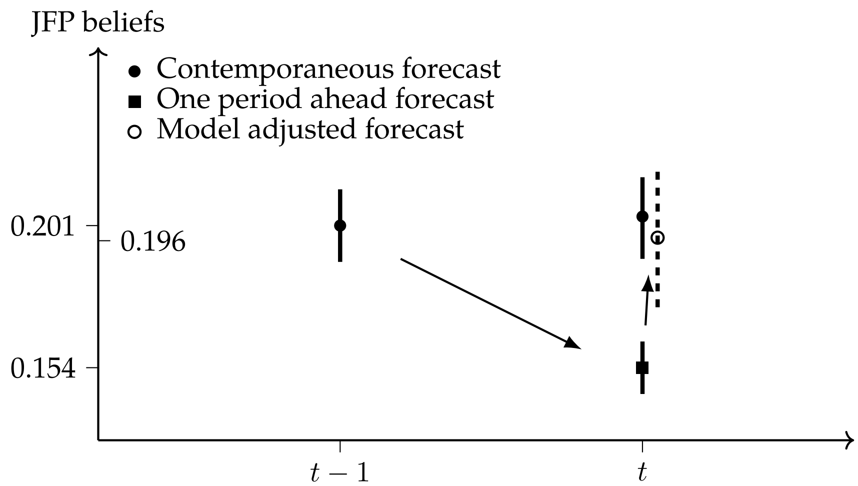

Figure 5: Job-finding Probability Updates Induced by "Surprise" of Unemployment Rate

Notes: This figure is a visualization of the table A.1.2. 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.

We define the "surprise" adjusted job-finding probability forecasts as $\widehat{F^i_t\hat{X}^i_t} = F^i_{t-1}\hat{X}^i_t + \hat{\vartheta}\left(U_t - F^i_{t-1}U_t\right)$ to explore if "surprises" about the aggregate can explain these differences. The "surprise" adjusted job-finding probability forecasts is 19.6%, closer to the initial 20.1% and substantially higher than the unadjusted 15.4%. This adjustment accounts for about 85% of the update, underscoring the significant role of "surprises" about the aggregate. 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.

[24]Using a similar approach, we show that beliefs about the US stock market dynamics have no effect on residual changes in perceived job-finding probability. Online Appendix O.5 provides more details.

5 Robustness Analysis

The section provides several analyses in support of two main points: job seekers (1) anticipate their job prospects to decline in the future, and (2) are “surprised" by unanticipated positive news about the overall labor market which lifts job-finding prospects. For the first, we show evidence of participant’s ability to perform numerical calculation and that our geometric model of beliefs is suitable to capture participant’s answers to additional questions in the SCE LMS (Section 5.1). We also show that the model reveals similar anticipated declines when applied to very different belief questions in the KM survey (Section 5.2). We find such anticipation also in our online survey where we rely minimally on additional assumptions (Section 5.3). For the second, we show reported job-finding probabilities for workers without positive surprise about the unemployment rate and for workers in the Covid recession (Section 5.4). We also rule out a version of reverse causality (Section 5.5) and briefly discuss that job seekers’ self-selection to be out of the labor force is unlikely to explain the empirical pattern (Section 5.5).

5.1 Statistical Model and Numerical Calculation Ability

Our simple statistical model of geometric beliefs implicitly assumes that participants can do numerical calculations including compounding probabilities. To assess this, we analyze their responses to a set of numerical questions in the SCE. Our findings indicate that a majority (approximately 71%) of job seekers in our sample demonstrate the ability to numerical calculations. Moreover, we do not find significant differences in perceived job-finding probability projections between job seekers who provide accurate answers and those who provide inaccurate answers to the compounding questions. Appendix A.4.1 provides more details.

Even if participants can do numerical calculations properly, is our geometric model in (4.1) and (4.2) a reasonable way to capture their beliefs? To answer this, we rely on an infrequent question in the SCE LMS that asks about the probability of holding a job in 4 months. The question is not exactly the same as the 3-months and 12-months perceived job-finding probability, but we view it as close enough.[25] We focus on individuals in our consistent SCE sample who answer the 3 and 12 months questions and this additional question. First we replicate the exercise of Figure 1 where we take the 12-month perceived job-finding probability of each individual and impute the 3-month horizon under the assumption that job seekers perceived a constant job-finding probability in the

[25]The answer to the 4-month question in the SCE LMS can be lower, since an individual may accept a job and then loose it again, in which case he would no longer hold that job at the 4-month mark. Since job-losing rates in the data are much smaller than job-finding rates, we suspect that the difference is minimal.

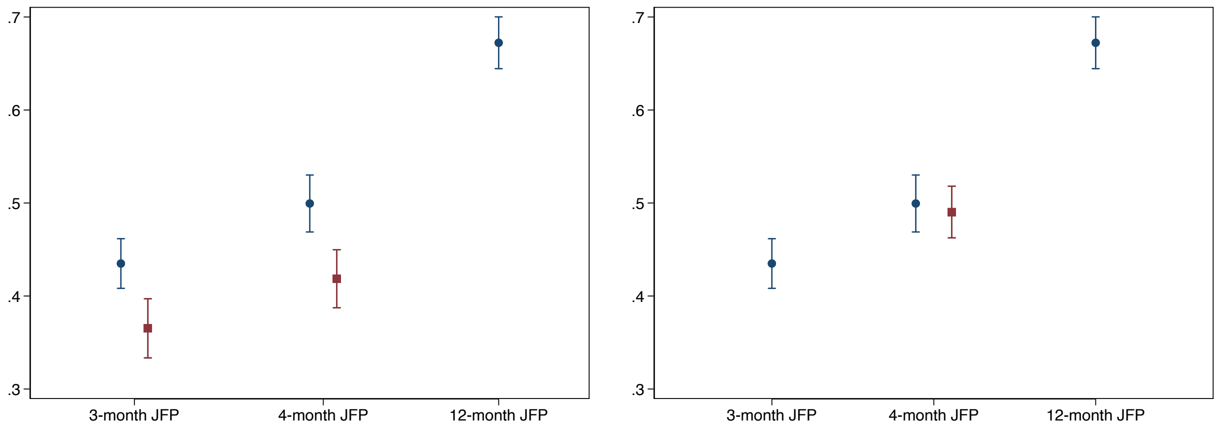

Figure 6: Comparison: 3, 4 and 12 Month Perceived Job-finding Probability

Notes: We focus on respondents who report consistent answers in the SCE who also reported their 4-month perceived job-finding probability in the SCE LMS. In both figures, we plot average 3, 4 and 12 months perceived job-finding probability (solid circles) with their 90% confidence intervals. In the left panel, we plot imputed 3 and 4 month perceived job-finding probability (solid squares) with their 90% confidence intervals using $1-\left(1-FindJob12_t^i\right)^{1/4}$ and $1-\left(1-FindJob12_t^i\right)^{1/3}$. In the right panel, we plot the 4 month imputed job-finding probability (solid squares) with their 90% confidence intervals imputed using estimated $F_t^i\hat{X}_t^i$ and $\hat{\beta}_{i,t}^x$.

future. The left panel in Figure 6 shows that the averages of the imputed probabilities are much lower than the average of the actual reports for both 3 and 4 month horizons. This replicates the stronger optimism for the early months in unemployment shown in Figure 1.

Next, we take the estimated initial perceived job-finding probability ($F_t^i\hat{X}_t^i$) and the anticipated decline ($\hat{\beta}_{i,t}^x$) (from Section 4.1) to impute the 4-month perceived job-finding probability for each individual. The solid square in the right panel reports the average together with its 90% confidence interval. We find that it exactly hits the average responses to the 4 month question in the SCE LMS, which is visible by comparing the circles (reported values) and square (imputed values) in the middle. This provides evidence that our statistical model (4.2) and its assumption on individual numerical calculation ability are not at obvious odds with the data.[26] Moreover, individual-level answers to the 4-month question are highly correlated with the imputed 4-month values (cor=0.77). Appendix A.4.1 provides more details.

5.2 KM Survey

We investigate 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

[26] In the Appendix A.4.1, we provide more detailed statistics on this.

job-finding probability ($FindJob4_t^i$) and their expected unemployment duration in weeks ($\hat{\tau}_i$).[27]

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 $\hat{\beta}_{i,t}$. The expected duration of unemployment ($\hat{\tau}_i$) and 4-week job-finding probability are given by

$$\hat{\tau}_i = \hat{X}_t^i + \sum_{\tau=2}^{T} \tau(\hat{\beta}_{i,t})^{\tau-1}\hat{X}_t^i \prod_{k=2}^{\tau}\left(1-(\hat{\beta}_{i,t})^{k-2}\hat{X}_t^i\right) \quad T\to\infty, \qquad FindJob4_t^i = 1-\prod_{\tau=0}^{3}\left(1-\left(\hat{\beta}_{i,t}\right)^{\tau}\hat{X}_t^i\right) \tag{5.1}$$

Since we observe both $FindJob4_t^i$ and $\hat{\tau}_i$ in 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.[28] 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.

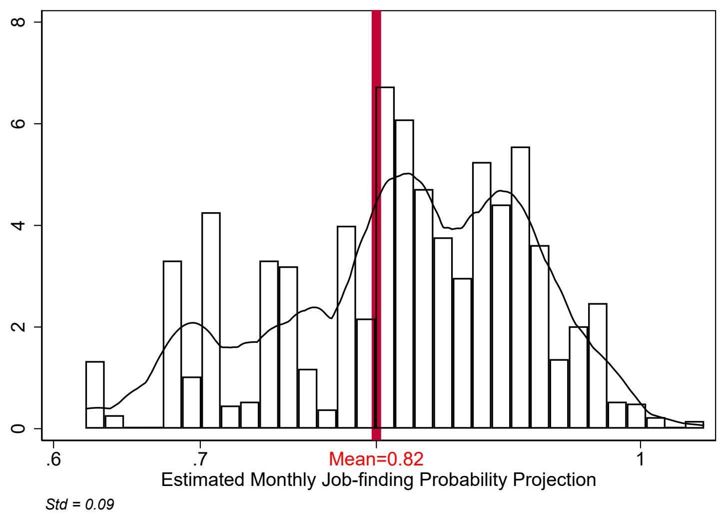

Figure 7: Histogram of Job-finding Probability Projection $\hat{\beta}_{i,t}$ (KM survey)

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 (5.1). The line connects the fitted kernel density estimates using the Epanechnikov kernel. The samples are restricted to unemployed workers ages 20–65 who report consistent answers for weekly job-finding probability and expected unemployment duration in weeks.

We estimate the monthly $\hat{\beta}_{i,t}$ for each job seeker in the KM survey and plot the histogram in Figure 7.[29] We find that job seekers believe their job-finding probability will depreciate by an

[27] We exclude job seekers who report obviously contradictory answers, i.e., we drop job seekers who report a 4-week perceived job-finding probability equal to 1 while their reported 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.

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

[29] There are 3039 consistent observations. After the simulation exercise, we are left with 1995 estimated $\hat{\beta}_{i,t}$. The numerical solver cannot find a solution for the rest of the observations. In Online Appendix O.7.4, we provide evidence that job seekers perceive their job-finding probabilities to decline in the future using an alternative method.

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.

5.3 The Online Survey

Analyzing the SCE and KM survey requires statistical models to filter the data due to the question design. Our online survey elicits more directly how job seekers perceive their future job-finding probabilities and the aggregate economy, even though it does not have the same representativeness or coverage as the SCE or the KM survey.

5.3.1 Online Survey: Anticipated Duration Dependence

Survey results present clear evidence that unemployed job seekers perceive a duration dependence in job search. The majority (79%) of respondents in our main survey sample (comprising 272 unemployed job seekers) believes that job seekers with longer unemployment durations have a lower chance of finding a job.

We then ask respondents how unemployment duration affects their own perceived job-finding probability. In a pair of questions, we elicit respondents' perceived job-finding probability in two scenarios: *Q1: What do you think is the percent chance that within 3 months, you will find a job (job offer) that you will accept, considering the pay and type of work? Imagine that 3 months have passed and you still have not found a job, which means that you are unemployed for an additional 3 months. Q2: Now, thinking about the following 3 months, what do you think is the percentage chance that you will find and accept a job considering both the pay and the type of work?* Through this pair of questions, we can directly compare perceived job-finding probability over different time horizons.

We denote $FindJob3^i_t$ as the current perceived 3-month job-finding probability and $FindJob3^i_{t+3}$ as the perceived 3-month job-finding probability 3 months later. In our sample, 66.9% of unemployed job seekers reported $FindJob3^i_t \geq FindJob3^i_{t+3}$, which supports that most people perceive duration dependence in their own job-finding prospects. The first row of Table 3 shows that the raw difference between $FindJob3^i_t$ and $FindJob3^i_{t+3}$ is significantly negative.

It can be misleading to use the ratio $\frac{FindJob3^i_{t+3}}{FindJob3^i_t}$ or the simple growth rate $\frac{FindJob3^i_{t+3}-FindJob3^i_t}{FindJob3^i_t}$ because both statistics are asymmetric, leading to outliers when the earlier probability ($FindJob3^i_t$) is close to zero.[30] Specifically, although both statistics are bounded below, they become unbounded

[30]Our registered pre-analysis plan (see registry https://osf.io/wx3ub) before obtaining the unemployed sample

when the earlier probability ($FindJob3_t^i$) is closer to zero, leading to outliers. Similarly, the alternative growth rate $\frac{FindJob3_{t+3}^i - FindJob3_t^i}{FindJob3_{t+3}^i}$ introduces a similar issue, producing outliers when the later period probability ($FindJob3_{t+3}^i$) is close to zero. Therefore, we opted for the symmetric growth rate $\frac{FindJob3_{t+3}^i - FindJob3_t^i}{0.5(FindJob3_{t+3}^i + FindJob3_t^i)}$, which is based on the average of two probabilities ($FindJob3_{t+3}^i$, $FindJob3_t^i$) and can effectively address outliers.[31] We registered these tests for our sample with both employed and unemployed job seekers (see Online Appendix O.3 for results). The results are very similar for our unemployed sample as shown in the second row of Table 3. The symmetric growth rate ($\frac{FindJob3_{t+3}^i - FindJob3_t^i}{0.5(FindJob3_{t+3}^i + FindJob3_t^i)}$) is significantly negative, with a large magnitude.

We also convert the 3-month probability to a monthly basis and show that the implied $\hat{\beta}_{i,t}^x$ is around 0.9 and is statistically significantly smaller than 1 (Figure A.3.1 in Appendix A.3).

Table 3: Perceived Job-finding Probability: Survey Analysis

Variables	Mean	SE	T-statistics
$FindJob3_{t+3}^i - FindJob3_t^i$	-0.037	0.011	-3.469
$\frac{FindJob3_{t+3}^i - FindJob3_t^i}{0.5(FindJob3_{t+3}^i + FindJob3_t^i)}$	-0.119	0.027	-4.465
$\widetilde{FindJob3_t^i} - FindJob3_t^i$	-0.134	0.011	-12.420
$\frac{\widetilde{FindJob3_t^i} - FindJob3_t^i}{0.5(\widetilde{FindJob3_t^i} + FindJob3_t^i)}$	-0.400	0.029	-13.707

Notes: we restrict survey responses to respondents (ages 20-65) who are unemployed and looking for jobs. The median of the standard growth rate $(FindJob3_{t+3}^i - FindJob3_t^i)/(FindJob3_t^i)$ is -0.1. While the median of $(\widetilde{FindJob3_t^i} - FindJob3_t^i)/(FindJob3_t^i)$ is -0.3.

5.3.2 Online Survey: Aggregate Unemployment and Individual Job-finding Prospects

Another part of the survey examines how unemployed job seekers perceive the impact of national unemployment rate on individual job search. In a general question that we ask, the majority of

proposes comparing $\frac{FindJob3_{t+3}^i}{FindJob3_t^i}$ with 1. This ratio is 0.991 (SE = 0.034). The large number is driven by a small number of outliers where the earlier probability ($FindJob3_t^i$) is closer to zero. The median of $FindJob3_{t+3}^i/FindJob3_t^i$ is 0.9. After removing a limited number of outliers, the mean of $\frac{FindJob3_{t+3}^i}{FindJob3_t^i}$ is 0.893, which is statistically significantly smaller than 1. However, we prefer the symmetric growth rate as it automatically addresses the outlier problem. We registered to comparing the symmetric growth rate in our setting with 1 in the pre-analysis plan (see registry `https://osf.io/6de43`) before obtaining the sample with both employed and unemployed job seekers. Findings are very similar when we conduct the same set of tests using both samples (Table 3 and Table O.3.3).

[31]The issues of zero's in the first vs the second period are reminiscent of issues in the analysis firm growth with entry (firms size of zero in initial period) and exit (firm size of zero in subsequent period), where the symmetric growth rate is common. See Davis and Haltiwanger (1992) for a careful discussion.

respondents (75%) report that the national unemployment rate matters.

We elicit respondent's perceived US unemployment rate for October 2024 (denoted as $F_t^i U_t$). Subsequently, we elicit each respondent's perceived 3-month job-finding probability given a hypothetical 10% increase in the US unemployment rate ($\widetilde{FindJob3}_t^i$). *Suppose the economy is not doing as good as you thought. The US unemployment rate for October is 10% higher than the value that you just reported. What do you think is the percent chance that within 3 months, you will find a job (job offer) that you will accept, considering the pay and type of work?*

A majority (79.04%) of the respondents perceive a lower job-finding probability given this unexpected hypothetical US unemployment rate increase. In Table 3, we show two statistics for the absolute ($\widetilde{FindJob3}_t^i - FindJob3_t^i$) and relative ($\frac{\widetilde{FindJob3}_t^i - FindJob3_t^i}{0.5(\widetilde{FindJob3}_t^i + FindJob3_t^i)}$) change in first-period job-finding probabilities induced by the hypothetically lower unemployment rate. Both of them are statistically significantly smaller than 0 based on T-tests.[32] Moreover, the magnitude of the response is large. The elasticity $\frac{\widetilde{F_t^i \hat{X}_t^i} - F_t^i \hat{X}_t^i}{10\% \times F_t^i U_t}$ equals -26.3 (SE 2.6), consistent with what we found in Table 2 using the SCE.[33]

5.4 SCE Job Seekers without Positive Unemployment " Surprise" in the SCE

Our empirical analysis indicates that because job seekers are often "surprised" by the low realizations of the US unemployment rate compared to their last period beliefs, they update their perceived job-finding probability. However, what did job seekers report when they are not positively surprised by the aggregate unemployment rate? According to our theory, if they anticipate a decline in their job-finding probability, they should report such a decline when they are asked next period. Focusing on job seekers in the SCE who perceive $U_t \geq \hat{\beta}_{i,t}^u U_{t-1}$ (no positive "surprise"), we find that they anticipate a decline of approximately 11% in their job-finding probability from period $t-1$ to period t, denoted as $\hat{\beta}_{i,t-1}^x = 0.888$. Moreover, upon reaching period t, their perceived job-finding probability declines by an average of around $1 - \frac{F_t^i \hat{X}_t^i}{F_{t-1}^i \hat{X}_{t-1}^i} \approx 12\%$, which aligns with our hypothesis. Figure 8 illustrates the decrease of within-spell perceived job-finding probability for job seekers without any "surprise" concerning the US unemployment rate. It provides a sharp contrast to Figure 5.

Moreover, in the Appendix O.7.1, we use one episode in which aggregate labor market conditions declined: the Covid-Recession. Although observations during this period are limited, they

[32] Table O.3.2 reports the mean and standard deviation of $\widetilde{FindJob3}_t^i$.

[33] It is statistically significantly smaller than 0. We convert the 3-month probability to a monthly basis using $\widetilde{FindJob3}_t^i = 1 - (1 - \widetilde{F_t^i \hat{X}_t^i})^3$.

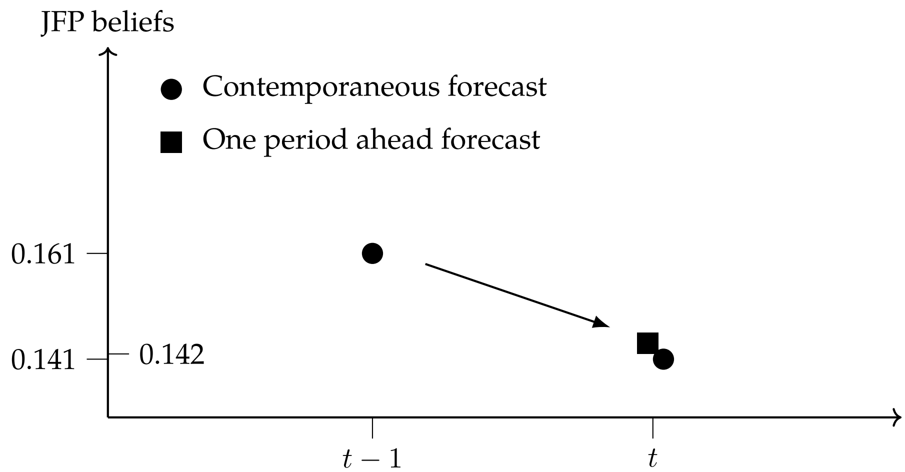

Figure 8: Job-finding Probability Updates of Individuals Without Belief “Surprise"

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.

do suggest that job seekers reduced their beliefs over time, in a pattern that was exceedingly rare during our main sample period.

5.5 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. Another possible explanation is that job seekers who get favorable private signals about their job-finding chances update their beliefs about the US unemployment rate, i.e., an instance of reverse causality. We investigate this using the SCE LMS, which elicits individual past experiences in job search: *whether the individual had a job interview or not*. In the Appendix A.4.3, we show empirical evidence that individual job-finding experience (i.e., being interviewed in the past four weeks) is associated with increased job-finding perceptions but has no effect on their beliefs about the US unemployment rate. So learning about own chances does not seem to generate updates about the unemployment rate.

Another possible explanation for why job seekers perceive an 18% decline in the job-finding probability conditional on being unemployed in the next month is that they expect some probability of being out of the labor force (OLF).[34] Nevertheless, the average one-month unemployment to OLF transition probability decreases with duration and is usually lower than 10% and in later months lower then 5%, which is inconsistent with an average $\hat{\beta}^x_{i,t}$ of 18% remaining con-

[34]For example, if $F^i_t\hat{X}_{i,t} = 0.2$ and the probability of being OLF is 0.18% per month, this could result in an 18% $\hat{\beta}^x i, t$.

stant throughout the unemployment duration. See Online Appendix Figure O.1.4 for empirical evidence.

6 A Belief Model of Job Search

In this section, we setup a job search model of beliefs to explore with more structure the potential mechanisms that could explain the pattern we uncover, in which job seekers anticipate a negative evolution of their job-finding chances but update their assessment strongly in light of unexpected developments in the unemployment rate.

Model Setup. We assume that 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 models. 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, as in Den Haan et al. (2000) and Hagedorn and Manovskii (2008).[35]

To introduce potential behaviorial responses by job seekers to the change of the aggregate economy, we assume that job seeker i faces an unemployment rate $U_{i,t}$ that is relevant for his/her job-finding probability. The intuition behind $U_{i,t}$ can be viewed from different perspectives in labor economics. For example, one may 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. $U_{i,t}$ is presumed to be the aggregate unemployment rate (i.e., the fundamental) plus a normally distributed shock $\eta_{i,t} \sim N(0, \sigma_\eta^2)$, i.e., $U_{i,t} = U_t + \eta_{i,t}$. Consistent with the maintained assumption in the previous empirical exercise, we assume that job seeker i knows the unemployment rate U_t at period t. However, neither job seeker i nor the researchers know the individual unemployment rate $U_{i,t}$.

Following recent developments in expectation formation in Bordalo et al. (2019, 2020, 2022), we

[35]We use this matching function as it naturally provides probabilities between zero and one, but note that the main idea is robust to other choices of matching functions, such as a Cobb-Douglas matching function.

formally introduce "Diagnostic Expectation" when job seekers use information about the aggregate unemployment rate to infer their individual unemployment rate ($U_{i,t}$). Based on the presumed structure of $U_{i,t}$, a rational job seeker solves this problem by using the true conditional distribution of $h(U_{i,t}|U_t)$ with mean U_t. A behavioral job seeker subject to representativeness bias overweights the probability of individual unemployment realizations $U_{i,t}$ that are representative (or "diagnostic") of the aggregate unemployment rate U_t relative to the background context. The relevant comparison is the state that there is no new information at period t, i.e., $F^i_{t-1}U_t = \beta^u_{i,t-1}U_{t-1}$. In particular, the most representative state is the one exhibiting the largest increase in its likelihood based on recent information. A surprisingly low U_t raises in particular the likelihood of a low $U_{i,t}$, and the individual overweighs this in the current period.

This intuition is captured by a distorted subjective distribution $h^\theta_{i,t}(U_{i,t})$, which is assumed to be $h(U_{i,t}|U_t) \times \left[\frac{h(U_{i,t}|U_t)}{h(U_{i,t}|F^i_{t-1}U_t)}\right]^\theta \frac{1}{Z_{i,t}}$. $Z_{i,t}$ is a normalizing constant ensuring $h^\theta_{i,t}(U_{i,t})$ integrates to 1. θ measures the degree of representativeness bias. When $\theta = 0$, the model reduces to the rational expectation benchmark. When $\theta > 0$, the model departs from rational expectation to the direction of overreaction. Intuitively, a large θ implies that job seekers overreact to the most recent news in the sense that they expect changes in the national unemployment rate are particular relevant for their own "island". Formally, we derive the following result by arguments similar to Bordalo et al. (2019):

$$E^\theta_{i,t}(U_{i,t}) = E_{i,t}(U_{i,t}) + \theta\left[E_{i,t}(U_{i,t}) - E_{i,t-1}(U_{i,t})\right] = U_t + \underbrace{\theta\left[U_t - \beta^u_{i,t-1}U_{t-1}\right]}_{\text{overreaction to recent "surprise"}} \tag{6.2}$$

Another issue we need to address is that none of the available survey questions 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., $F^i_tV_{i,t} = b(F^i_tU_{i,t})^k$ for each t.[36] We obtain estimates of b and k by a linear regression ($log(V_t) = log(b) + klog(U_t)$) using the true US unemployment rate and US vacancy rate. We use this as our baseline specification for individual vacancy beliefs, but alternative versions did not qualitatively alter our conclusions regarding overreaction and perceived duration dependence.[37] With a specified Beveridge curve $F^i_tV_{i,t}(F^i_tU_{i,t})$, we can derive the beliefs about future job-finding probabilities using solely the perceived dynamics of the unemployment rate.

After linearly approximating the perceived job-finding probability, we obtain the forecast in

[36] During the sample period, the US economy experienced a long recovery, leading to a downward sloping Beveridge curve. Figure O.1.2 shows that a log-normal Beveridge curve can well approximate the trend in the data.

[37] In the Online Appendix O.8, we conduct two exercises to show that alternative specifications of obtaining parameter k and b does not materially change the estimation results.

period t of next period's job-finding probability $F_t^i \hat{X}_{t+1}^i$ by

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

Notice that we have $E_{i,t}^{\theta}(U_{i,t+1}) = \beta_{i,t}^{u} U_t$ here, i.e., there is no bias when forecasting the future since U_{t+1} has not realized yet. That is, over-reaction parameter θ has no impact on future predictions because these predictions operate on average, but once the new aggregate unemployment rate has realized it affects the immediate assessment by overweighting the more chances of the more extreme outcomes on the job seeker's island.

The model no longer restricts the perceived job-finding probability to preserve a geometric increase or decrease as in as in equation (4.1) and (4.2).[38]

Lemma 1 *The job search model (equation 6.1) implies* $\frac{F_t^i \hat{X}_{t+2}^i}{F_t^i \hat{X}_t^i} \neq \left(\frac{F_t^i \hat{X}_{t+1}^i}{F_t^i \hat{X}_t^i}\right)^2$.

In sum, the model can account for flexible belief patterns and incorporates the following mechanisms: (1) a perceived duration dependence, (2) the standard matching function when individuals correctly perceive the empirical Beveridge curve and respond to the aggregate economic conditions without overreaction, (3) an overreaction where individuals think that surprises in the aggregate unemployment rate matter particularly for the situation on their own "island". We also discuss the possibility for a misperception of the Beveridge curve that links the level of unemployment to the associated vacancies.[39]

We normalize the individual efficiency $A_i = 1$ because only the average individual efficiency matters in the calibration (see Online Appendix O.4 for the reason).[40] We therefore focus on parameter vector $\Theta = \{\gamma_d, \theta, l\}$, which we estimate via simulated generalized method of moments (GMM). The minimization problem can be expressed as follows:

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

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

[39] 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. Online Appendix O.8 presents the results.

[40] In the Appendix O.9, we examine the role of individual efficiency heterogeneity (the dispersion of A_i) in a simulation. While the perceived job-finding probability model indicates a significant response to U_t, results show that the response is unlikely to be detected with statistical precision when incorporating the heterogeneous individual efficiency as calibrated from the data. This finding aligns with evidence in Mueller et al. (2021); Mueller and Spinnewijn (2021); Menzio (2022).

The estimation result is presented in Table 4.[41] We present model-fit in the lower panel of Table 4. We demonstrate the model matches the constant within-spell job-finding beliefs and the 18% perceived future job-finding probability decline simultaneously.

In the upper panel of Table 4, we report all estimates. Consistent with empirical patterns presented in Figure 2, the negative value of $\gamma_d = -0.144$ indicates that job seekers believe their job-finding probability will decrease as unemployment duration becomes longer. However, a large and negative γ_d not only implies a significantly smaller anticipation in period t of the job-finding probability in period $t+1$ according to equation 6.3, but also implies that in period $t+1$ the individual indeed reports a lower job-finding probability in the absence of other mechanisms that counteract this. Since the job-finding probability in $t+1$ is not much smaller as is visible in our calibration targets and already demonstrated by Mueller et al. (2021), we aim to understand which mechanism within the model explains this phenomenon.

Table 4: Calibration with Micro-data

Parameters:	γ_d	θ	l
Value	-0.144	1.356	0.612
(SE)	(0.000)	(0.000)	(0.000)
Model-fit:	$\frac{1}{N}\sum_i log(1-FindJob3^i_t)$	$\frac{1}{N}\sum_i log(1-FindJob12^i_t)$	$\frac{1}{N}\sum_i log(1-FindJob3^i_{t+1})$
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 the 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 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.5.1 provides additional details regarding the sample.

One candidate is the perceived job-finding probability elasticity within the matching function (l). When the unemployment rate improves in a matching model, this improves job-finding probabilities. 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. However, matching function elasticity l alone cannot account for a flat perceived job-finding probability

[41] Appendix A.5.1 shows details about the estimation process. We construct three moment conditions based on 3-month beliefs in period t, $t+1$ and 12-month beliefs in period t. We interact U_t with residuals of first two moment conditions to create two additional moments. We use identity matrix as the weight matrix. Results are robust to using other weighting matrices. We also conduct an aggregate version for a calibration: we use a representative agent who faces possible future changes of aggregate conditions. We find similar results as in Table A.5.1.

within-spell even with a unreasonably large l (e.g., $l = 20$).[42]

Our attention now turns to how overreaction manifests in a job-search context. We obtain $\theta = 1.356$, indicating that job seekers exhibit a strong representativeness bias and overreact to the most recent news about the aggregate labor market. Specifically, job seekers react to surprises about the unemployment rate 2.4 times as much as to older information. This can be seen in (6.2) where the plain change of unemployment rate receives a factor of 1, and the additional increment associated with the most recent forecast error is multiplied by θ. This overreaction $(\theta > 0)$ in the job search model helps rationalize a flat within-spell job-finding probability beliefs, despite the presence of negative duration dependence. It occurs because the expectation from a distorted distribution, $E^{\theta}_{i,t}(U_{i,t})$, significantly elevates the perceived job-finding probability when θ is positive.

An other important feature of our paper is that when forecasting future perceived job-finding probability, the bias is not present because no news about future unemployment rates has arrived. Consequently, after a positive surprise, job seekers elevate their current perceived chances of finding a job but do not expect future probabilities to remain similarly elevated. In other words, effects of unemployment rate for the period carry the standard factor (of 1). This is part of the reason why the term γ_d accounts for an approximately 14.4% decrease in perceived job-finding probabilities, even though the model has to rationalize on average an 18% reduction in beliefs (see Figure 2). The difference arises because the overreaction observed in the present is short-lived and is not expected to persist.

Empirical evidence supports these important feature of our model. Table 2 provides evidence that surprises in the unemployment rate induce large and statistically significant updates to the immediate perceived job-finding probability. Additionally, Table A.1.3 provides further evidence supporting the short-lived nature of overreaction in line with the model. Specifically, we show that the unemployment rate surprises from period $t - 1$ have an insignificant effect — an order of magnitude smaller — on forecasts of future job-finding probabilities $(F^i_{t-1}\hat{X}^i_t)$ and future job-finding probability updates $(F^i_{t-1}\hat{X}^i_t - F^i_{t-2}\hat{X}^i_t)$. Furthermore, surprises from earlier periods have a minimal impact on perceived future job-finding probabilities $(F^i_t\hat{X}^i_t)$.

We also calibrate θ using our online survey sample, where we directly ask individuals how

[42]With $F^i_{t-1}\hat{X}^i_t \approx 0.154$ and $F^i_t\hat{X}^i_t \approx 0.204$ from Table A.1.2, the perceived job-finding probability has an increase of $\frac{F^i_t\hat{X}^i_t - F^i_{t-1}\hat{X}^i_t}{F^i_{t-1}\hat{X}^i_t} \approx 0.325$. When $\theta = 0$, 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, model depicted in equation (6.1) cannot produce $\frac{F^i_t\hat{X}^i_t - F^i_{t-1}\hat{X}^i_t}{F^i_{t-1}\hat{X}^i_t}$ close to 0.325 even with a $l = 20$.

a hypothetical deterioration in the unemployment rate would affect their perceived job-finding probability. Appendix A.3 provides details. Results show that online survey respondents exhibit an even stronger overreaction with $\theta = 2.44$, which further support that job seekers overreact to the unexpected change in the aggregate environment.

7 Implications for Unemployment Insurance and Moral Hazard

In this section, we show that the implications of the pattern of perceived job-finding prospects can have big impact on job search. The empirical evidence shown in section 4 suggests that job seekers seem to expect low chances in the future, but they are again more optimistic when the future arrives and there is a positive shock. Because search efforts today and tomorrow are substitutes, the empirical evidence suggests that job seekers exert more efforts initially than they would have if they had anticipated the better times ahead.[43] Appendix A.4.4 provides supporting evidence for this intuition: using the SCE LMS we show that job seekers who expect larger declines in future job-finding probabilities tend to apply to more jobs. Similarly, evidence from the online survey Appendix A.3.3 shows that job seekers tend to increase their job search hours now if they are told about worse prospects in future periods.

How large could these effects be? We conduct a rough assessment to demonstrate that this channel might be nontrivial. Our focus is on a representative unemployed job seeker i who searches for a job for up to T periods (and then, for simplicity, finds a job for sure).[44] We assume that job seekers can search for 30 total periods. For simplicity, we normalize job seeker's search efficiency by setting $A_i = 0$. We introduce a search effort $e_{i,t} \geq 0$ to the perceived job-finding probability.

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

Equation (7.1) indicates that higher job search effort leads to higher perceived job-finding probability. Following the works of Christensen et al. (2005), Lise (2013), and Gomme and Lkhagvasuren (2015), we presume a quadratic search cost function ($\frac{c}{2}(e_{i,t})^2$) and the monthly discount factor is set to be $\delta = (0.99)^{1/12}$. 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 calibrate the remaining parameters to target the average monthly perceived job-finding probability and the perceived job-finding probability projection. Compared to estimates obtained in Section 6, we find a big overreaction (θ)

[43]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)

[44]We extend the calibration based on a representative job seeker in Section 6 (Table A.5.1).

but a smaller perceived duration dependence which is due to some part of the effect being picked up by anticipated reductions in search effort. Appendix A.6 shows more details.

We aim to understand the choice of search effort by job seeker i in period 1, given various beliefs about the future evolution of the US unemployment rate. Table 5 reports the result. We find that, a job seeker i who perceives that her future job-finding probability will decrease by 18% per month her first period search effort $(e_{i,1})$ decreases by 4.34% when she correctly anticipates the expected the future evolution of US unemployment rate. 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.

Table 5: Belief Dynamics and Search Effort

Perceived future U_t dynamics :	Rational Expectation (RE)	Data $(\hat{\beta}^u_{i,t})$
% change of $e_{i,1}$ relative to a RE	0%	4.34%
% of $e_{i,1}$ relative to $e^{sp}_{i,1}$ with RE	66.05%	69.04%

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 U_t. $e^{sp}_{i,1}$ is the social planner's search effort choice under rational expectation of U_t.

The model-implied effect of pessimism about future US unemployment rate on search effort is substantial, and is broadly consistent with the magnitude of the effects that we find in the SCE LMS.[45] The impact of non-rational beliefs on job search effort is equivalent to the effect of a 6.8% unemployment benefit cut for a person with rational expectations on future US unemployment rate evolution, holding everything else constant. The perception of a worse future mitigates the usual moral hazard in job search. Considering the associated problem of a social planner who maximizes a similar problem as that of the individual job seeker, but correctly expects future U_t evolution. The first period search effort $(e_{i,1})$ of the individual is around 69.04% of the optimal effort level $(e^{sp}_{i,1})$ that the planner would like. Her first period search effort $(e_{i,1})$ falls to only 66.05% of the optimal effort level $(e^{sp}_{i,1})$ when she correctly perceived future U_t. So the fear of a worse aggregate labor market closes the efficiency gap by 4.5%.

While more work on this domain is needed, this rough calculation highlights that understanding the beliefs of job search prospects and their dynamics is important for the correct design of

[45]The search effort increase is consistent with the supporting empirical evidence shown in the Appendix A.4.4, 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. Moreover, we find in our online survey sample that job seekers will significantly increase their search effort 16.3% when they are told that their job-finding probability will be lower in the future. The magnitude is also consistent with our calibration.

unemployment benefits. It is 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. 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.

8 Conclusion

Understanding how job seekers form beliefs about their job-finding probability is a burgeoning topic in the literature on job search. Using multiple survey samples, this paper investigates the dynamics of such beliefs, and decouples the anticipation of future trends from the dynamics that arise when beliefs are elicited again in the future. 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.

Our findings emphasize the importance and benefit of investigating belief interactions: While job seekers seem non-optimistic about their own future job-finding prospects and stubborn about how the unemployment rate will develop, they seem to very positively update about their own prospects when the aggregate labor market does improve. We find that theories in behavioral economics about overreactions, specifically diagnostic expectations, can explain these belief patterns.

The sheer size of these effects make them a promising target for future work, and might affect policy decisions. Whether to correct erroneous expectations in not obvious, as we show when we analyze possible impacts on job search: The threat of an unattractive future can act as a source of incentives that counteracts classical moral-hazard problems of unemployment insurance at least during the time of economic expansion covered in most of the Survey of Consumer Expectations. Effects might possibly revert in recessions, and more work on this is needed.

Overall, our research underscores the importance of studying the learning and updating process of job seekers, both their initial anticipation and how they adjust expectations as unemployment progresses. We anticipate that more research will follow, utilizing 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 and Tables

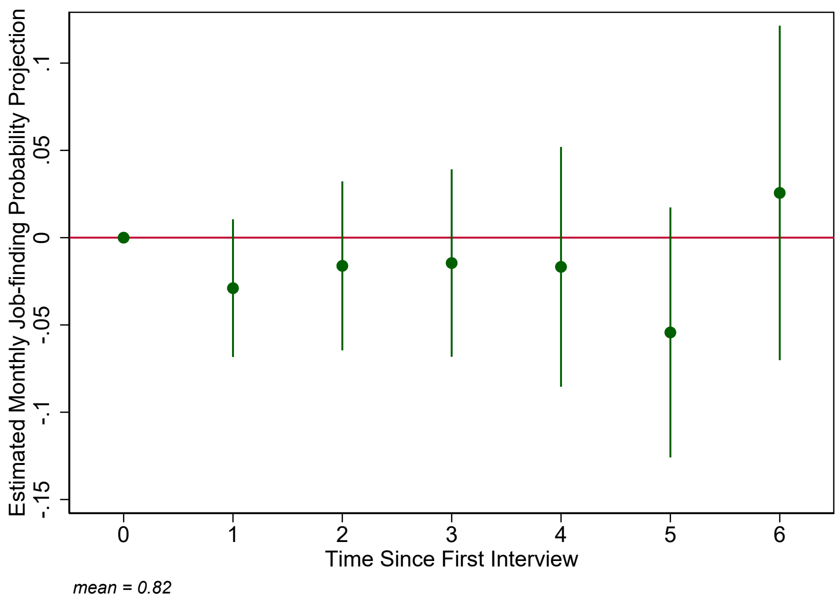


Figure A.1.1: Estimated $\hat{\beta}^{x}_{i,t}$ by Time since First Interview

Notes: We plot the estimated job-finding probability projection $\hat{\beta}^{x}_{i,t}$ by months since first interview. 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 the 12-month job-finding probability (the consistent sample).

Table A.1.1: Estimated Monthly Job-finding Probability Projection and Individual Characteristics

	(1)	(2)
	Estimated Monthly Job Finding Prob Projection	
Age	-0.0000145	-0.0000525
	(0.000437)	(0.000440)
Female	-0.00540	-0.00694
	(0.0112)	(0.0113)
High School	0.0321	0.0320
	(0.0271)	(0.0272)
Some College	0.0636**	0.0638**
	(0.0278)	(0.0279)
College	0.0696**	0.0701**
	(0.0273)	(0.0274)
Post Graduate	0.0630**	0.0623**
	(0.0313)	(0.0313)
Other Education	-0.0402	-0.0336
	(0.0587)	(0.0591)
Household income 30000-59999	0.000479	0.000442
	(0.0128)	(0.0128)
Household income 60000-100000	0.0305*	0.0313*
	(0.0179)	(0.0180)
Household income 100000+	0.0179	0.0172
	(0.0210)	(0.0211)
White	0.0478***	0.0486***
	(0.0125)	(0.0126)
US unemployment rate		-0.282
		(0.805)
State unemployment rate		-0.105
		(0.648)
Obs	1,345	1,343

Notes: 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 the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.1.2: Job-Finding Probability Updates Induced by Belief Surprise of Unemployment Rate

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

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

Table A.1.3: Testing Short-lived Overreactions

	(1)	(2)	(3)
	$F^i_t \hat{X}^i_t$	$F^i_{t-1}\hat{X}^i_t$	$F^i_{t-1}\hat{X}^i_t - F^i_{t-2}\hat{X}^i_t$
Belief Surprise: US Unemployment rate $(t-1)$	-5.119	1.381	0.102
	(6.566)	(2.431)	(3.662)
Person FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
U Duration	Yes	Yes	Yes
Cluster SE	Person	Person	Person
Obs	307	343	343

Notes: "Belief Surprise: US Unemployment Rate $(t-1)$" is $U_{t-1} - \hat{\beta}^u_{i,t-2} U_{t-2}$. 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 the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2 Omitted Proofs and Derivations

A.2.1 Proof for Proposition 1

We can first write

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

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 obtain Equation 4.4 in Proposition 1

A.2.2 Derivations for lemma 1 and equation (A.5.1)

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

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

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

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

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

A.3 The Online Survey: Details

We fielded two rounds of online survey in early October of 2024. The survey questionnaire was distributed through Prolific.com. Please refer to our registry (https://osf.io/6de43) for more details about hypothesis, survey implementation, survey questionnaire, power analyses and analysis plan.

In early September 2024, we conducted an initial round of the study, which results in noisy data because of a few several design issues. For example, results are also potentially unreliable due to the potential interference of non-human responses. We offered more details in Online Appendix O.3.3. We subsequently redesigned the survey questions to prevent those problems. We launch the second round of survey in October 2024. We submitted a registry before we obtain the sample with unemployed workers (see `https://osf.io/wx3ub`), which is closely related to our final registry at `https://osf.io/6de43` which was submitted before we obtain the sample with both employed and unemployed workers. The main difference between the two registries is that we proposed several additional tests, including the symmetric growth rate.

A.3.1 More Results: Job-finding Probability Projection

We ask respondents about how unemployment duration affects job search prospects in general: *Consider two unemployed job seekers A and B. Job seeker A has been unemployed for 3 months. Job seeker B has been unemployed for 6 months. Job seeker A and B are identical in all other aspects. Who do you think has a higher probability of finding a job within the next month?* Majority (79% of unemployed job seekers) reported that job seeker A has a better chance in finding a job, providing strong evidence that people in general perceive a duration dependence in job search.

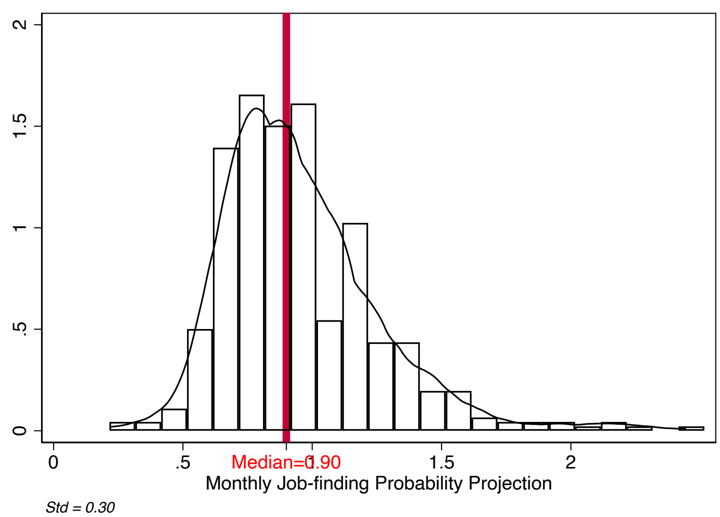


Figure A.3.1: Histogram of Job-finding Probability Projection $\hat{\beta}^x_{i,t}$

Notes: We plot the histogram of job-finding probability projection estimates for all respondents in both rounds of our survey. The line connects the fitted kernel density estimates using the Epanechnikov kernel. We distribute survey to respondents ages 20-65.

We transfer the 3-month perceived job-finding probability into a monthly basis using the equality $FindJob3^i_t = 1 - (1 - F^i_t \hat{X}^i_t)^3$, with the implicit assumption that there is a constant monthly job-finding probability within the 3 month. Then $\hat{\beta}^x_{i,t} = \left(\frac{F^i_{t+3}\hat{X}^i_{t+3}}{F^i_t\hat{X}^i_t}\right)^{\frac{1}{2}}$. We plot the histogram in Figure A.3.1 using two rounds of our survey (both employed and unemployed workers), which can be used to compare with Figure 2 and 7. We find that the median $\hat{\beta}^x_{i,t}$ we obtained from the survey sample is around 0.9, and $\hat{\beta}^x_{i,t}$ is statistically significantly smaller than 1 (t-statistics= -3.201). This result is consistent with the numbers from both the SCE and the KM survey. One difference is that $\hat{\beta}^x_{i,t}$ from the online survey exhibit a slight long and thin tail.

Alternatively, we use the statistical framework proposed in Equation 4.2 to convert the current and future 3-month perceived job-finding probability into a monthly basis. The model implied perceived job-finding probabilities are

$$FindJob3^i_t = 1 - \prod_{\tau=0}^{2}\left(1 - F^i_t X^i_{t+\tau}\right), \quad FindJob3^i_{t+3} = 1 - \prod_{\tau=0}^{2}\left(1 - F^i_{t+3} X^i_{t+3+\tau}\right).$$

In Figure A.3.2, we plot the histogram of estimated job-finding probability projection ($\beta^x_{i,t}$). Both figures exhibit similar empirical pattern.

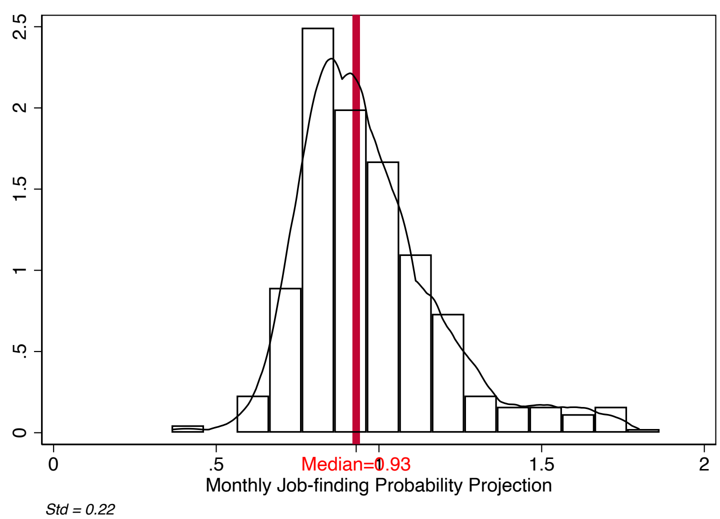


Figure A.3.2: Histogram of Job-finding Probability Projection $\hat{\beta}^x_{i,t}$

Notes: We plot the histogram of job-finding probability projection estimates for all respondents in both rounds of our survey. The line connects the fitted kernel density estimates using the Epanechnikov kernel. We distribute survey to respondents ages 20-65.

A.3.2 More Results: Aggregate Condition and Perceived Job-finding Probability

We obtain $\widetilde{F^i_t\hat{X}^i_t}$ using the equality $\widetilde{FindJob3^i_t} = 1 - (1 - \widetilde{F^i_t\hat{X}^i_t})^3$ and calculate the change of perceived job-finding probability in reaction to a this hypothetical shock on US unemployment rate: $\frac{\widetilde{F^i_t\hat{X}^i_t} - F^i_t\hat{X}^i_t}{10\% \times F^i_t U_t} = -26.097$. Alternatively, the effect can be interpreted as a 10% increase of US unemployment rate leads to a 27.5 % decrease of perceived job-finding probability. The response is very large, which is hard to be rationalized by a standard matching function even with extreme parameter values.

We calibrate the overreaction parameter θ using the survey sample. We calculate the percentage change of individual perceived job-finding probability given the hypothetical shock using $\frac{\widetilde{F_t^i\hat{X}_t^i}-F_t^i\hat{X}_t^i}{F_t^i\hat{X}_t^i}$. The Diagnostic Expectation representation in this context is

$$E_{i,t}(U_{i,t}) + \theta\left[E_{i,shocked}(U_{i,t}) - E_{i,t}(U_{i,t})\right] = U_t + \underbrace{\theta\left[110\% \times U_t - U_t\right]}_{\text{overreaction to recent hypothetical ``shock''}}$$

Using the job search model as in Equation 6.1, we can calibrate θ by matching the model implied $\frac{\widetilde{F_t^i\hat{X}_t^i}-F_t^i\hat{X}_t^i}{F_t^i\hat{X}_t^i}$ and the data. Note that other parameters (k, b and l) of the model are taken from our main calibration. Results show that online survey respondents also exhibit overreaction with $\theta = 2.44$.

A.3.3 Survey Results: Search Efforts

Another part of the survey focuses on search efforts approximated by hours spent (denoted as $e_{i,t}$) per week in job search. We directly elicit respondent's job search hours when unemployed by asking (*Suppose you were to lose your job now*) *How many hours per week do you intend to spend on job search activities in October.* On average, the reported hours spent on job search per week is 12.118 hours (See Table O.3.2).

In the second step, we ask how respondents were to change their job-search hours per week given a negative shock to their future job-finding prospects:

(*Suppose you were to lose your job now and*) *Suppose a job search expert tells you that the chances of finding a job 3 month later is lower than what you expected. How would that affect how many hours you search right now relative to what you planned before knowing this?* (*select one of the following*)*: I would* (*A*) *I would increase my hours of search by* [ ]%*;* (*B*) *I would spend the same hours on job search in August;* (*C*) *I would decrease my hours of search by* [ ]%

A majority (55.51%) of the respondents react to this unexpected decline of future job search prospects by increasing their job search hours now, with an average increase 32.60%. 38.24% of respondents report that they will not change search hours and 6.25% report a decrease of their job search hours (with average decrease 28.41%). Results indicates that job seekers increase their search effort in response to a looming job search prospect, which are consistent with what's found in our model presented in Section 7.

A.4 Additional Empirical Results

A.4.1 Perceived Job-finding Probability: Numerical Calculation Abilities

We conduct a tests to demonstrate that the job seekers in our sample are able to perform numerical calculations, which supports the framework outlined in Equation 4.2.

The SCE includes 5 questions designed to assess respondents' proficiency with numbers and calculations in everyday contexts. We determined the proportion of job seekers who answered this question accurately within our consistent SCE sample. Our findings reveal that 72% of the respondents in our consistent sample answered 80% of the questions. This suggests that a majority of the job seekers in our sample possess the ability to correctly perform number calculations. Furthermore, when comparing the responses of unemployed job seekers with those of employed individuals, we find that 78% of the employed respondents answered the question accurately. This percentage is slightly higher than that of the unemployed job seekers. Moreover, based on a slightly different sample (the public version of the SCE) that spans from slightly different years, we find that job seekers who provide 80% accurate answers to all questions report a perceived job-finding projection $\beta^x_{i,t} = 0.856$. Those who provide less than 80% answers to the numerical questions report a perceived job-finding projection $\beta^x_{i,t} = 0.845$. The two numbers are very close and cannot be distinguished statistically.

Moreover, if we look at one of the 5 numerical questions that is about calculating compound interest rates, we find that job seekers who provide accurate answers to this questions report a perceived job-finding projection $\beta^x_{i,t} = 0.85$. Those who provide inaccurate answers to the compounding questions report a perceived job-finding projection$\beta^x_{i,t} = 0.84$. The two numbers are very close and cannot be distinguished statistically.

The SCE LMS surveys a subset of respondents from the main SCE survey to obtain their perceived probability of having a job in four months. The survey question is stated slightly differently than the 3-month and 12-month job-finding probability. The exact survey question is copied here for comparison: *What do you think is the percent chance that four months from now you will be employed?* The answer to this is technically a lower bound to the question about the probability of being offered and accepting a job in 4 months, since an individual can take a job and then loose it again. While we acknowledge the difference, we do not think that this distinction matters much in reality since the monthly job-losing rate in the US is low. In the absence of a better measure, we use the

Table A.4.1: Estimated and Reported 4-month Job-finding Probability

	$\widehat{FindJob4_t^i}$	$FindJob4_t^i$
Average	0.499	0.490
SE	(0.019)	(0.017)
Observations	245	245
T-test of the two variables:		
H0: $\widehat{FindJob4_t^i} \neq FindJob4_t^i$	P-value 0.512	

Notes: We only use the job seekers who are surveyed in both 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.

answer to this question as a proxy for the perceived 4-month job-finding probability.

Using the estimates $\hat{\beta}^x_{i,t}$ and $F^i_t \hat{X}^i_t$, we can calculate the individual perceived probability of finding a job in four months, denoted as $\widehat{FindJob4_t^i}$. We also have the reported probability of finding a job within four months for the same job seeker in the SCE LMS at the same t, denoted as $FindJob4_t^i$. Table A.4.1 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.

Finally, we report how much the constructed 4-month job-finding probability ($\widehat{FindJob4_t^i}$) can explain the reported 4-month job-finding probability ($FindJob4_t^i$). Regressing $FindJob4_t^i$ on $\widehat{FindJob4_t^i}$ and a constant yields a regression coefficient of 0.77 and R-square 0.49.

A.4.2 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) from the Federal Reserve Bank of Philadelphia. 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 un-

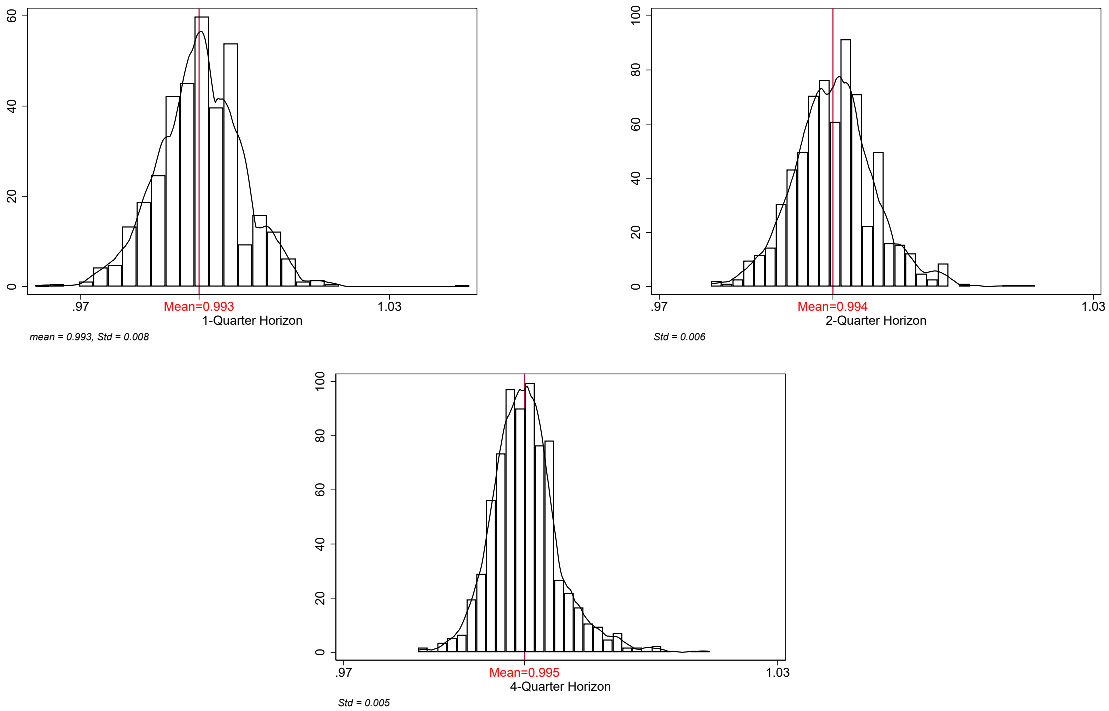


Figure A.4.1: Histogram of Perceived US Unemployment Rate Dynamics (SPF)

Notes: 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 $\left(\frac{U4}{U-1}\right)^{1/12}$. We use the SPF sample from 2012 to 2019 to match with the year span of our main SCE sample.

employed job seekers $\hat{\beta}^u_{i,t}$, we calculate the ratios of unemployment rate level forecast to obtain its dynamics.

In Figure A.4.1, 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%).

A.4.3 Perceptions and Job Search Experience

To examine the relationship between perceptions on job search and job search experience, we employ two sets of empirical results derived from the SCE 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. We also control for the US unemployment rate and job seeker's unemployment duration.

In Table A.4.2, we find that the contemporaneous perceived job-finding probability ($F^i_t \hat{X}^i_t$) is

Table A.4.2: Job Search Beliefs and Job Search Activities

	(1)	(2)
	$F_t^i \hat{X}_{i,t}$	$\hat{\beta}^u_{i,t}$
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 the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

positively statistically significantly correlated 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 perception of the aggregate market based on their own job search experience.

Table A.4.3: 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)
Unemployment Duration	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 the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.4.3 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 having 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 find 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.

A.4.4 Perceptions and Job Search Effort

Here, we demonstrate empirical evidence in alignment with the arguments in section 7. We use the SCE and the SCE LMS for this exercise.[46]

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 is the count of job search activities that a job seeker has engaged in during the last 4 weeks. The third measure estimates the number of hours that a job seeker has allocated towards job search activities in the past 7 days.

Table A.4.4: Belief on Job Search and Job Search Activities

	(1)	(2)	(3)
	Applied Jobs (last 4 weeks)	JS Activities (last 4 weeks)	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 the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The findings are presented in Table A.4.4. 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

[46]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.

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%.

A.5 Main Calibration: Additional Details and Results

A.5.1 Calibration: Sample Construction

Here, we introduce in detail how we construct the sample for the calibration exercise. Specifically, we keep unemployed workers who reported at least 3 times about their perceived job-finding probabilities consecutively. This is because calculating model predicted $F^i_t \hat{X}^i_t$ and $F^i_{t+1}\hat{X}^i_{t+1}$ rely on survey responses of the current period (t) and the immediate future period ($t+1$) from the same job seeker.

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

Additionally, model predicted $F^i_t \hat{X}^i_{t+\tau}$ requires calculating $E_{t-1}U_t$, which elicited $\hat{\beta}^{u}_{i,t-1}$ 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.

The three main moments that we construct are:

$$\frac{1}{N}\sum_i \left(FindJob3^i_t - 1 + \prod_{\tau=0}^{2}\left(1 - F^i_t \hat{X}^i_{t+\tau}\right)\right) = 0, \quad \frac{1}{N}\sum_i \left(FindJob3^i_{t+1} - 1 + \prod_{\tau=1}^{3}\left(1 - F^i_{t+1}\hat{X}^i_{t+\tau}\right)\right) = 0,$$
$$\frac{1}{N}\sum_i \left(FindJob12^i_t - 1 + \prod_{\tau=0}^{11}\left(1 - F^i_t \hat{X}^i_{t+\tau}\right)\right) = 0 \quad \text{(A.5.1)}$$

Model implied 3 and 12 month job-finding probabilities are calculated using $F^i_t \hat{X}^i_{t+\tau}$. We interact residuals of the first two moments with unemployment rate U_t to create two additional moment conditions. U_t is the most important state variable and should be mean independent to the residuals. It provides additional information to help identify the elasticity of unemployment rate and overreaction parameter. We choose not to interact U_t with the 12-month beliefs because the 12 month beliefs is mostly helping us to identify γ (perceived duration dependence).

We also conduct a version of the calibration based on a representative agent faces average aggregate labor market conditions and holds average beliefs. Here, we hit three different moments.

We show results in Table A.5.1, which are qualitatively similar to those found in Table 4 but inpute an even larger role for over-reaction.

Table A.5.1: Calibration with Representative Agent

Parameters:	γ_d	θ	l
Value	-0.082	3.332	0.612
Model-fit:	$\frac{1}{N}\sum_i F_t^i \hat{X}_t^i$	$\frac{1}{N}\sum_i F_{t+1}^i \hat{X}_{t+1}^i$	$\frac{1}{N}\sum_i \hat{\beta}_{i,t}^x$
Data	0.200	0.193	0.826
Model	0.200	0.193	0.826

Notes: k and b are estimated by a linear regression ($log(V_t) = log(b) + klog(U_t)$) using the 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 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.

A.5.2 Long-term Updating under the model

Although the model we estimate in the main part of the paper assumes that each job seeker only reacts to one period of recent "surprise", here we illustrate that the mode allows for infrequent updates as well. Given that in reality, people may update their beliefs about the aggregate environment less than 1 month or more than a month, estimates in table 4 serve as an average.

A.6 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 if s/he is still unemployed in period $t \in \{0, 1, 2, ..., T-1\}$ can be recursively formulated as follows:

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

where the first summand B represents the immediate unemployment benefit, the second summand captures the probability of successful job search which leads to permanent employment at wage W with current net present value of $\delta W/(1-\delta)$, while the third summand captures unsuccessful job search which leads the individual to enter next period as unemployed. The final summand captures the search cost in the current period. Since a job seeker is assumed to find a job for sure in period T that starts in $T+1$, there is no point to search in period T, and the terminal value V_T is provided by

$$V_T = B + \delta W/(1-\delta).$$

Since the payoff after period T is a constant, one obtains equal choices when omitting the payments after period T from the value functions, in which case the system reduces to final value

$\hat{V}_T = B$ and otherwise:

$$\begin{aligned}
\hat{V}_t(U_t, \hat{\beta}^u_{i,t}U_{t-1}) = \quad & \max_{e_{i,t}} B + E^\theta \left[F^i_t \hat{X}^i_t(e_{i,t}) \mid U_t, \hat{\beta}^u_{i,t}U_{t-1} \right] \delta W \sum_{\tau=t+1}^{T} \delta^{\tau-(t+1)} \\
& + (1 - E^\theta \left[F^i_t \hat{X}^i_t(e_{i,t}) \mid U_t, \hat{\beta}^u_{i,t}U_{t-1} \right]) \delta E \left[V_{t+1}(U_{t+1}, \hat{\beta}^u_{i,t}U_t) \mid \hat{\beta}^u_{i,t}U_t \right] - \frac{c}{2}(e_{i,t})^2 \\
= \quad & \max_{e_{i,t}} B + E^\theta \left[F^i_t \hat{X}^i_t(e_{i,t}) \mid U_t, \hat{\beta}^u_{i,t}U_{t-1} \right] \delta W \frac{1-\delta^{T-t}}{1-\delta} \\
& + (1 - E^\theta \left[F^i_t \hat{X}^i_t(e_{i,t}) \mid U_t, \hat{\beta}^u_{i,t}U_{t-1} \right]) \delta E \left[V_{t+1}(U_{t+1}, \hat{\beta}^u_{i,t}U_t) \mid \hat{\beta}^u_{i,t}U_t \right] - \frac{c}{2}(e_{i,t})^2.
\end{aligned}$$

Job seeker's effort choice ($e_{i,1}$) can be solved via backward induction, anticipating future job search prospects. The expected future job search prospect depends on job seeker perceived evolution of US unemployment rate, i.e., $E_t(U_{t+k}) = \left(\hat{\beta}^u_{i,t}\right)^k U_t$. Nevertheless, when forming the current period job-finding probability, job seeker i overreacts to the most recent change of US unemployment following the Diagnostic Expectation formulated in 6.2.

We conduct the calibration based on a representative agent, who is an "average" job seeker in the data living under average US unemployment environment U_τ ($\tau = t, t+1$), having an average duration $D_{i,t}$ and perceiving average unemployment rate duration $\hat{\beta}^u_{i,t}$. The cost function of search effort is presumed to be quadratic $c(e_{i,1}) = \frac{c}{2}(e_{i,t})^2$ following Christensen et al. (2005), Lise (2013), and Gomme and Lkhagvasuren (2015). We fix $T = 30$ and set the discount factor δ at $(0.99)^{1/12}$, aligning with Hagedorn and Manovskii (2008). Using UI data released by the United States Department of Labor, we set 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.6.1: Calibration: Search Effort

Parameters:	γ_d	θ	c
Estimates	-0.050	1.906	2.838

We solve the model and calibrate three parameters by targeting three data moments. The parameters are: (1) γ_d that determines how job-finding probability decreases with duration on top of other mechanisms in the model (e.g., search effort decline); (2) the parameter θ that governs the magnitude of overreaction; (3) the scalar of the search effort function c. The first and second moments are average perceived first-period job-finding probability in two consecutive periods taken from the data. The third moment is average perceived job-finding probability projection taken from the data. The calibrated parameters are presented in Table A.6.1. We choose the elasticity of unemployment rate $L = 0.404$ from the literature because we only have 3 moments. Using our own estimates $L = 0.606$ shown in Table 4 does not change the resulting patterns significantly.

The calibrated γ_d is smaller than that in Table A.5.1. This is expected since the two parameters have slightly different interpretations. The γ_d in Table 4 nests the potential decline of search efforts in the future, whereas the γ_d in Table A.6.1 is the additional negative effects of unemployment duration on top of endogenous search effort response which takes into the future decline as well. Nevertheless, the magnitude of γ_d is still substantial (half of the value of Table A.5.1). The overreaction parameter remains large in the calibration.

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 the job seeker's perceived evolution of US unemployment rate aligns with the actual realization $\hat{\beta}^u_{i,t} = \frac{U_{t+1}}{U_t}$, i.e., when the job seeker is not pessimistic about the future anymore. We discover that $e^{'}_{i,1}$ is approximately 4.34% smaller than $e^*_{i,1}$. This result is in line with the intuition that job seekers lower their search efforts when they perceive their job-finding prospects to be better in the future. Moreover, this surge in effort can be equivalently achieved by a 6.8% reduction in UI benefits (B) when job seekers remain pessimistic about the future as in the data.

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 $(e^p_{i,1})$. In this exercise, we assume that the planner correctly anticipates the future US unemployment rate and does not utilize the unemployment benefit $(B = 0)$. We find that $\frac{e^*_{i,1}}{e^p_{i,1}}$ is 66.05% while $\frac{e^{'}_{i,1}}{e^p_{i,1}}$ is roughly 69.04%, suggesting that the belief pattern we uncover drives the first period job search effort closer to the first best search effort level.

Online Appendix: Not for Publication

O.1 Additional Figures

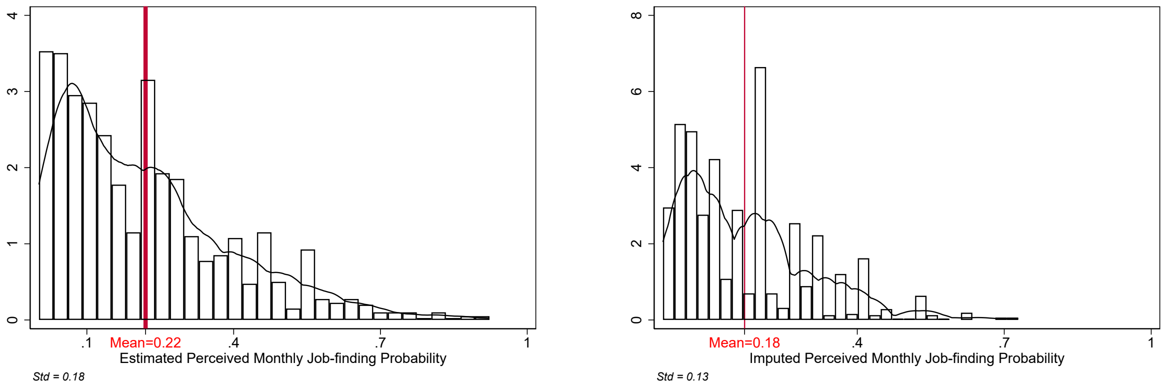


Figure O.1.1: Histogram of Job-finding Probability $F_t^i \hat{X}_t^i$

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 the 12-month job-finding probability (the consistent sample).

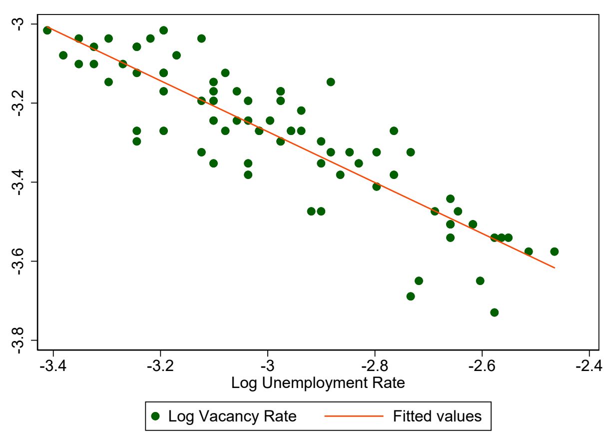


Figure O.1.2: Beveridge Curve with a Log-linear Fit

Notes: The figure shows the plot of $Log(V_t)$ and $log(U_t)$ together with the linear fit.

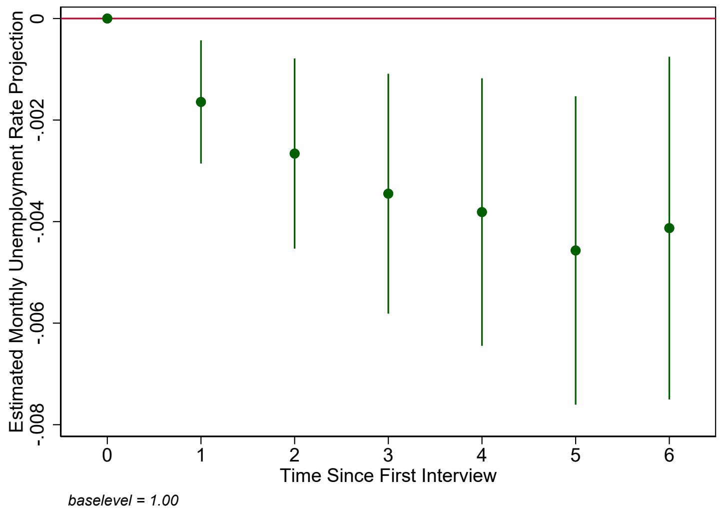


Figure O.1.3: Estimated $\hat{\beta}^u_{i,t}$, by Time since First Interview

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 the 12-month job-finding probability (the consistent sample).

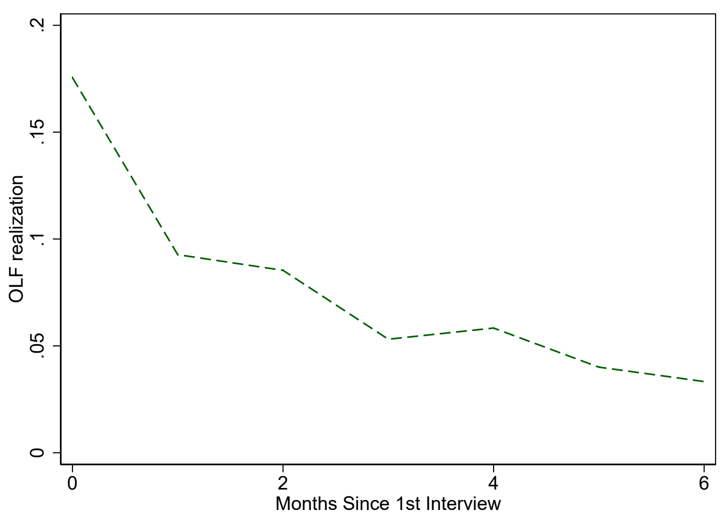


Figure O.1.4: Estimated U to OLF Transition Probability by Time since First Interview

Notes: We calculate the average one month U-OLF transition rate by months since 1st interview. 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 the 12-month job-finding probability (the consistent sample).

O.2 Additional Table

Table O.2.1: Belief Change of US Unemployment on Job-finding Probability Update

	(1) Job Finding Prob Update	(2) Job Finding Prob Update
$F_t^i \Pr(U_{t+12} > U_t) - F_{t-1}^i \Pr(U_{t+11} > U_{t-1})$	-0.000653*	-0.000648*
	(0.000344)	(0.000371)
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 $F_t^i \hat{X}_t^i - \hat{\beta}_{i,t}^x F_{t-1}^i \hat{X}_{t-1}^i$. $F_{t-1}^i \hat{X}_t^i$ and $F_t^i \hat{X}_t^i$ are taken directly from the survey. 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 the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

O.3 Additional Results of the Online Survey

In this section, we show more details about our online survey. First, we show summary statistics of two survey samples we obtained in October 2024. Second, we show empirical results based on the survey sample that has both employed and unemployed people. Third, we discuss the survey sample obtained in August 2025.

O.3.1 Summary Statistics

In October 2024, we distribute our survey to both employed and unemployed workers. For employed respondents, questions about perceived job-finding probability is hypothetical. Specifically, we state the following before eliciting their perceived job-finding probability: *In the following questions, we would like you to consider you own job search in the future months suppose you were to lose your job now. Please answer those questions as accurately as possible.* We also give respondents similar reminders in other question contexts. For specific survey questions, please refer to our registry (https://osf.io/6de43) for more details.

Table O.3.1 reports basic demographics of our two rounds of our online survey sample obtained in October 2024. In the second round, 37% of respondents indicate that they are currently unemployed.

Table O.3.1: Descriptive Statistics For the Online Survey: Demographics

	U	E & U
High school degree or less	23.2%	10.7%
Some college education:	40.8%	30.0%
College Degree of More:	36.0%	59.3%
Ages 20–34	48.2%	25.4%
Ages 35–49	36.0%	33.5%
Ages 50–65	15.8%	41.1%
Female	61.3%	59.9%
Black	24.3%	14.4%
Number of respondents	272	187

Notes: in column U, we present basic demographics with the online survey sample where we distribute the survey to respondents who are unemployed, ages 20-65. In column E& U, we present basic demographics with the online survey sample where we distribute the survey to respondents who ages 20-65. Whenever we survey an employed respondent, questions about perceived job-finding probability is hypothetical.

Table O.3.2 presents summary statistics of perceived job-finding probability reported by respondents in each round of our survey.

Table O.3.2: Descriptive Statistics For the Online Survey: Perceived Job-finding Probability

U Sample:	$FindJob3_t^i$	$FindJob3_{t+3}^i$	$e_{i,t}$	$\widetilde{FindJob3}_t^i$	$F_t^i U_t$
Mean	0.490	0.453	12.118	0.356	0.042
Std	(0.263)	(0.258)	(11.730)	(0.245)	(0.005)
E & U Sample:	$FindJob3_t^i$	$FindJob3_{t+3}^i$	$e_{i,t}$	$\widetilde{FindJob3}_t^i$	$F_t^i U_t$
Mean	0.626	0.551	18.358	0.466	0.043
Std	(0.220)	(0.247)	(11.757)	(0.243)	(0.005)

Notes: in the upper panel, we present summary statistics with the online survey sample where we distribute the survey to respondents who are unemployed, ages 20-65. In the lower panel, we present the summary statistics with the online survey sample where we distribute the survey to respondents who ages 20-65. For employed respondents, questions about perceived job-finding probability is hypothetical.

We launch the second round of survey in October 2024. Before we obtained the sample of unemployed workers, we submitted a registry at https://osf.io/wx3ub, which is closely related to our final registry at https://osf.io/6de43 which was submitted before we obtained the sample of both employed and unemployed workers. The main difference between the two registries is that we proposed several additional tests, including the tests shown in Table 3 and Table O.3.3. The results in both tables are similar, which confirms that this is not an ex post selection of results.

O.3.2 Survey Results: E & U Sample

Results from the survey sample focusing both unemployed and employed workers are very similar to the round where we only focus on unemployed workers. Here, we present key results for the second round for comparison.

Majority (77.01% of respondents) reported that job seeker A (who is designed to have a shorter unemployment spell) has a better chance in finding a job, providing strong evidence that people in general perceive a duration dependence in job search.

In Table O.3.3, we show that the two statistics that we construct, i.e., $FindJob3_{t+3}^i - FindJob3_t^i$ and $\frac{FindJob3_{t+3}^i - FindJob3_t^i}{0.5(FindJob3_{t+3}^i + FindJob3_t^i)}$ are statistically significantly smaller than 0 using T-tests.

Majority of the respondents (66.31%) report that the national unemployment rate matters. We elicit respondent's perceived US unemployment rate in October, November and December of 2024. We denote their responses as $F_\tau^i U_\tau$ ($\tau = t, t+1, t+2$).

A majority (82.89%) of the respondents perceive a lower job-finding probability given this unexpected hypothetical US unemployment rate increase. In Table O.3.3, we show that the two statistics that we construct, i.e., $\widetilde{FindJob3}_t^i - FindJob3_t^i$ and $\frac{\widetilde{FindJob3}_t^i - FindJob3_t^i}{0.5(\widetilde{FindJob3}_t^i + FindJob3_t^i)}$ are statistically

Table O.3.3: Perceived Job-finding Probability: Survey Analysis (2nd Round)

Variables	Mean	SE	T-statistics
$FindJob3^i_{t+3} - FindJob3^i_t$	-0.075	0.016	-4.808
$\frac{FindJob3^i_{t+3} - FindJob3^i_t}{0.5(FindJob3^i_{t+3} + FindJob3^i_t)}$	-0.175	0.030	-5.810
$\widetilde{FindJob3^i_t} - FindJob3^i_t$	-0.160	0.014	-11.460
$\frac{\widetilde{FindJob3^i_t} - FindJob3^i_t}{0.5(\widetilde{FindJob3^i_t} + FindJob3^i_t)}$	-0.374	0.032	-11.767

Notes: we distribute the survey to respondents who ages 20-65. Whenever we survey an employed respondent, questions about perceived job-finding probability is hypothetical.

significantly smaller than 0 using T-tests.

Similarly, we obtain $\widetilde{F^i_t \hat{X}^i_t}$ and calculate the change of perceived job-finding probability in reaction to a this hypothetical shock on US unemployment rate: $\frac{\widetilde{F^i_t \hat{X}^i_t} - F^i_t \hat{X}^i_t}{10\% \times F^i_t U_t} = -33.24$. The calculated elasticity is very large, which is hard to be rationalized by a standard matching function even with extreme parameter values.

Majority (65.78%) of the respondents react to the unexpected decline of future job search prospects by increasing their job search hours now. 28.88% of respondents report that they will not change their search hours and 5.35% report a decrease of their job search hours.

O.3.3 Online Survey Sample: Initial Round

In early September 2024, we conducted an initial round of the study. Our registry at https://osf.io/q4yhu provides additional details about the survey design.The survey result is very noisy. For example, the average ratio of perceived current and next month job-finding probability is centered around 1 with a 95% confidence interval (0.836, 1.244). We ended up not using the sample from the first round survey because of the following two reasons.

We view that a potential reason is that asking about the one-month job-finding probability might be problematic, because individuals might be confused between accepting a job and starting a job. This motivates us following more closely with the SCE and aske about 3-month job finding probability in the second round of the survey.

Another potential reason that leads to the noisy result is that we did not design questions to exclude non-human respondents (or robots). It turns out the robots are prevalent in online survey platforms. Specifically, in the second round of survey, we detected 44 (15% of the targeted sample) non-human respondence through our screening questions. This percentage is only a lower-bound because some responses are excluded by the platform due to incomplete answers. The potential interference of non-human responses is a major reason why we chose to not use the survey sample. We introduced three checks against bots in our revised survey later: (1) a check-box to declare that the respondent is a human, (2) a visual puzzle to detect robots, (3) a question that specifically asks a "large language model" to reveal itself.

O.4 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

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

Now we move on to the empirical moments shown in A.5.1. 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.5 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:

$$S_{t+1} = \hat{\beta}^s_{i,t} S_t + \hat{\epsilon}^s_{i,t+1}, \quad \hat{\epsilon}^s_{i,t+1} \sim N(0, \hat{\sigma}^2_{s,\epsilon}). \tag{O.5.1}$$

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

Table O.5.1 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 $\left(S_t^i - F_{t-1}^i S_t\right)$, is close to zero and statistically insignificant in both specifications, indicating that job seekers do not update their job-finding probability based on the US stock market.

Table O.5.1: 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 the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

O.6 Perceived US Unemployment Rate Projection: Robustness

O.6.1 The Level of Unemployment Rate

In Section 4, we assume 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. Here, we relax our the 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.

We alternatively allow job seeker i to enter our sample with an incorrect belief about the unemployment rate U_t. Specifically, we assume 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 $\hat{U}_t \in [0.9 \times U_t, 1.1 \times U_t]$.[47] 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 calculate 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 that the estimated US Unemployment rate projection ($\hat{\beta}^{u}_{i,t}$) remains constant, irrespective of whether job seekers have misconceptions about the level of the US unemployment rate.

O.6.2 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 4 remains robust when employing this alternative belief model.

[47] Results remain robust when we allow job seekers to misperceive the US unemployment rate to be 20% higher or lower than the actual US unemployment rate.

O.6.2.1 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:

$$U_{t+1} - U^n = \hat{\beta}^u_{i,t}(U_t - U^n) + \hat{\epsilon}^u_{i,t+1}, \quad \hat{\epsilon}^u_{i,t+1} \sim N(0, \hat{\sigma}^2_{u,\epsilon}). \tag{O.6.1}$$

$\hat{\beta}^u_{i,t}$ represents 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 $U_t - U^n$.[48] 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.6.2.2 Empirical Results

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

$$\left(F^i_t \hat{X}^i_t - F^i_{t-1} \hat{X}^i_t\right) = \vartheta \left(U_t - F^i_{t-1} U_t\right) + \delta_i + \delta_u + \varepsilon_{i,t} \tag{O.6.2}$$

The dependent variable is the update of job-finding probability $F^i_t \hat{X}^i_t - F^i_{t-1} \hat{X}^i_t$. The parame-

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

ter 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.[49] 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.6.1: Belief Surprise of US Unemployment on Job-finding Probability Update

	(1) Job-Finding Prob Update	(2) 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.6.1. We use specification O.6.2 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 the 12-month job-finding probability (the consistent sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table O.6.1 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 A.1.2. We 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.6.2 shows that incorporating the impact of perceived unemployment rate "surprise" helps mitigate the empirical puzzle. The adjusted job-finding probability forecast

[49]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.

$(\widehat{F^i_t\hat{X}^i_t})$ is around 0.188, which is statistically significantly larger than the period $t-1$ perceived job-finding probability forecast $(F^i_{t-1}\hat{X}^i_t)$. 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.6.2: Job-finding Probability Updates Induced by Belief Surprise of Unemployment Rate

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

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

The empirical results shows that the empirical pattern highlighted in section 4 is robust to an alternative specification of how the job seekers perceive the dynamics of US unemployment rate.

O.7 Additional Empirical Results

O.7.1 Perceived Job-finding Probability during the COVID-19 Pandemic

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 $FindJob3^i_t = 0.480$, $FindJob3^i_{t+1} = 0.357$, and $FindJob3^i_{t+2} = 0.174$ for all six job seekers in the sample, who all under-estimate how quickly the US unemployment rate evolves during the pandemic period and therefore clearly do not receive a positive surprise about unemployment. Figure O.7.1 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 O.7.1).

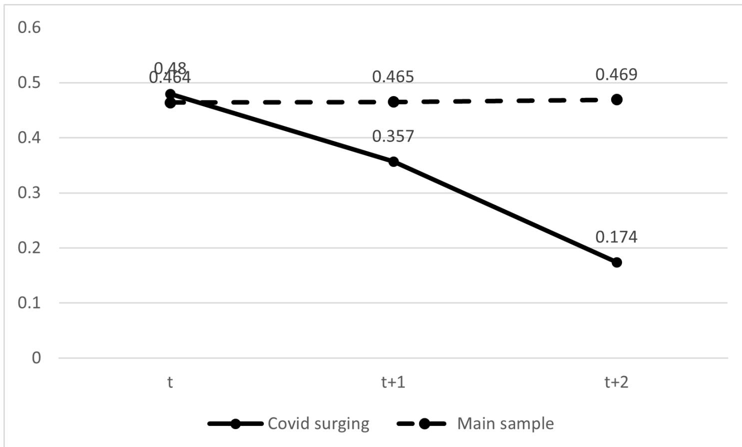


Figure O.7.1: Perceived 3-month Job-finding Probability During COVID Pandemic

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.

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 at least as much as the Covid sample is less than 1%. Specifically, we calculate the probability that the average $\frac{FindJob3_t^i}{FindJob3_{t-1}^i}$ and $\frac{FindJob3_{t+1}^i}{FindJob3_t^i}$ calculated by 6 job seekers randomly drawn from our main sample is smaller than average $\frac{FindJob3_t^i}{FindJob3_{t-1}^i}$ and $\frac{FindJob3_{t+1}^i}{FindJob3_t^i}$ from the 6 job seekers from our Covid sample respectively. This exercise shows that when job seekers believe their unemployment opportunities are deteriorating, they perceive their job-finding probabilities to decrease sharply.

O.7.2 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 ($\hat{\beta}^u_{i,t}$) 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 ($F^i_t \hat{X}^i_t$ and $\hat{\beta}^u_{i,t}$). 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.7.1. 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 ($\hat{\beta}^u_{i,t}$), is associated with a decrease in actual job-finding probability. Specifically, a 0.01 increase in $\hat{\beta}^u_{i,t}$ 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.

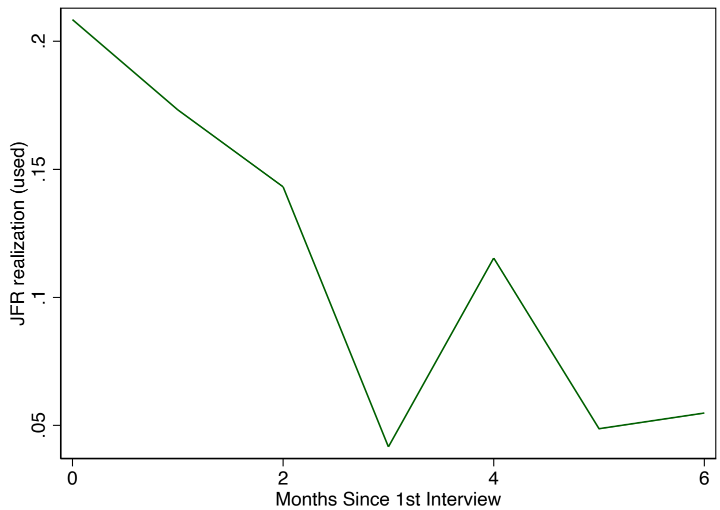
Table O.7.1: The Effect of Beliefs on Job-Finding Outcomes

	(1)	(2)
	Realized Job Finding	Realized Job Finding
Estimated Job-Finding Probability	0.433***	
	(0.143)	
Estimated US Unemployment Rate Projection		-9.036**
		(4.290)
Person FE	Yes	Yes
Month FE	Yes	Yes
Cluster 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 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.7.3 Job-finding Outcomes

Here, 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 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.



Notes: We calculate the average one month U-E transition rate by months since 1st interview. The line connects average U-E transitions rates that are calculated using the consistent 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 the 12-month job-finding probability (the consistent sample).

Figure O.7.2: U-E Transition Rate by Months Since 1st Interview

Figure O.7.2 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.

O.7.4 KM Survey: An Alternative Specification

In subsection 5.2, we proposed a method to estimate job seekers' perceived job-finding probability projection $\hat{\beta}^x_{i,t}$ using the KM survey. Here, we use an alternative approach to show that job seekers in the KM survey perceive a lower job-finding probability in the future. First, we calculate the inverted one-week job-finding probability using the inverse of the reported expected duration.[50] It should be noted that this inversion assumes a constant job-finding probability for the entire future duration. Second, we calculate the elicited one-week perceived job-finding probability from the 4-week perceived job-finding probability ($FindJob4^i_t$) using $1 - \sqrt[4]{1 - FindJob4^i_t}$. This calculation assumes that the weekly perceived job-finding probability is constant within 4 weeks. The inverted one-week job-finding probability should be interpreted as the average job-finding probability for the forthcoming 4 weeks.

Table O.7.2: 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.

In Table O.7.2, we find that the elicited job-finding probability is statistically significantly larger than the inverted one-week job-finding probability. This indicates that job seekers perceive a decline of their future job-finding prospects. This finding is consistent with Figure 7.

O.8 Subjective Beveridge Curve

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

In the first exercise, we estimate the model as in the main micro calibration by using the same set of moments defined in equation (A.5.1). However, we independently vary the value of the

[50] The calculation uses the the expectation of a negative binomial distribution.

elasticity of individual unemployment rate on individual vacancy rate (k) and the constant of individual unemployment rate on individual vacancy rate (b). Figure O.8.1 presents the estimated θ with different values of ks and bs.

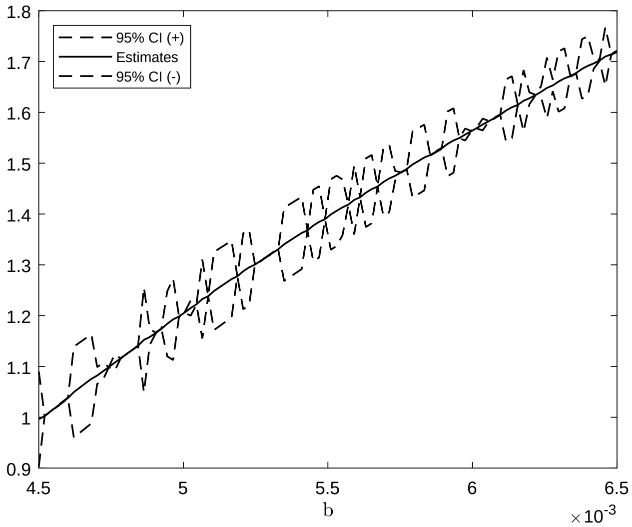
In the left panel of Figure O.8.1, we fix k to be the value estimated from the linear regression $(\log(V_t) = \log(b) + k\log(U_t))$ and vary b from 0.0045 to 0.0065 (the estimated value of b from $\log(V_t) = \log(b) + k\log(U_t)$ is around 0.0055). We find that the estimated θ values given different 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.8.1, 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.

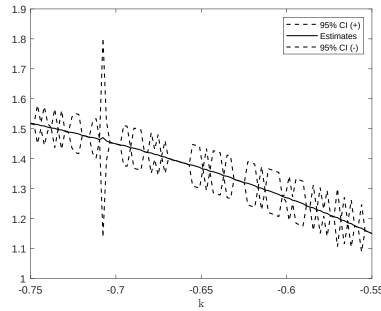
In the second exercise, we estimate k together with other model parameters γ_d, θ, and l, allowing job seekers to have subjective beliefs on the elasticity of individual unemployment rate on individual vacancy rate. We choose not to estimate the level effect b since the elasticity k can better reflect 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.8.1. 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.

Table O.8.1: Calibration with Micro-data (with k)

Parameter:	γ_d	θ	l	k
Estimate	-0.141	1.794	0.329	-1.387
Model-fit:	$\frac{1}{N}\sum_i log(1 - FindJob3^i_t)$	$log(1 - FindJob3^i_{t+1})$	$\frac{1}{N}\sum_i log(1 - FindJob12^i_t)$	
Data	-0.532	-1.199	-0.539	
Model	-0.532	-1.199	-0.539	

Notes: b is estimated by a linear regression $(log(V_t) = log(b) + klog(U_t))$ using the 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 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.





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 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.8.1: θ with Different Values of k and b

O.9 Response to Unemployment Rate U_t

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

To begin, we 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:

$$\tilde{X}_t^i = \exp(A_i) \underbrace{\exp\left(\gamma_d D_{i,t}\right) \times F_t^i \frac{M(U_{i,t}, b(U_{i,t})^k)}{U_{i,t}}}_{\hat{X}_t^i} \tag{O.9.1}$$

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, $VAR(A_i)$.[51]

We proceed by simulating individual monthly job-finding probabilities using the model given in equation (O.9.1), 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 O.9.1 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.

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

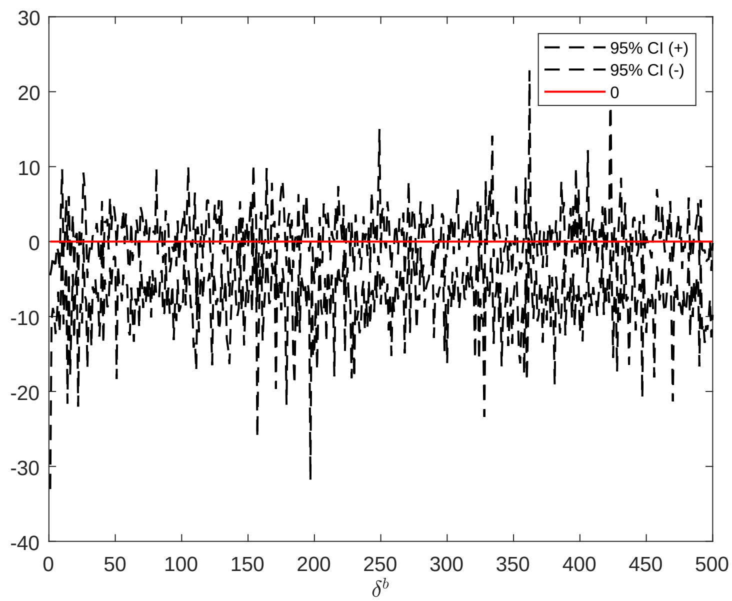


Figure O.9.1: Simulated Correlation Between $\tilde{X}_t^i$ and U_t

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 exercise.