Expectations Data, Labor Market and Job Search*

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Abstract

This chapter reviews how expectations data can inform theories of the labor market and job search. The main focus of the chapter is on expectations data regarding outcomes of the job search process, such as expectations related to the chances of finding a job or expectations about job offers. We review the evidence and highlight challenges and opportunities using expectations data in the labor market context. A key advance using expectation data is the identification of biases in beliefs and learning, and we illustrate their importance in a model of labor market search. We also present recent work demonstrating how expectations data can be leveraged to identify unobserved heterogeneity across job seekers. Throughout the chapter we highlight promising areas for future research.

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1 Introduction

Individuals' beliefs about their labor market prospects are an important determinant of their search behavior. In search-theoretic models of the labor market, job seekers balance the present costs of their search effort with the uncertain benefit of receiving a job offer. And when presented with an offer, job seekers trade off the value of the offer with the uncertain value of future offers they may receive if they reject the current offer and continue to search. Typically, search and acceptance decisions in the labor market context are viewed through the lens of models that impose rational expectations and assume that job seekers' know their labor market prospects or, at least, learn more about them through the process of job search.

In this chapter, we shed light on how expectations data can inform theories of the labor market and job search, but also on how expectations data can be used to test and relax the rational expectation assumptions in prior work. The chapter starts by reviewing existing surveys with data regarding job search expectations. An immediate observation is that these type of expectations are still relatively rare and only recently research started to use them more widely. While many surveys have adopted questions about job loss, only few data sources have adopted questions about the process of job search. This focus is often dictated by the sample frame of general population surveys and the associated small sample sizes of unemployed workers. One exception is the Survey of Consumer Expectations (SCE), which has collected by now a relatively large sample of unemployed job seekers along with their elicited beliefs (Federal Reserve Bank of New York [2012-2019]). Building on our own prior work, we will use the data from the SCE for the years 2012-2020 throughout the chapter to provide supporting evidence or illustrate specific methods. We start by illustrating a number of measurement issues that arise when eliciting beliefs about employment prospects. We stress the importance of panel data to measure beliefs and outcomes for the same individuals and ideally over the same horizon. This is critical to evaluate the predictive power of beliefs, but also to measure potential biases in the elicited beliefs. We also illustrate the usefulness of collecting beliefs over different horizons or using alternative measures to deal with issues of bunching and other forms of measurement error.

An often cited advantage of expectations data is that it can help informing structural models and overcoming the challenge to separate the role of preferences and expectations in explaining individuals' behavior [Manski, 2004]. This ambition has also been put forward in the context of models about the labor market (e.g., Manski and Straub [2000], Van der Klaauw [2012]). However, the multi-faceted nature of the job search environment and the interdependence between beliefs and behavior make it difficult to put the theory into practice. We set up a stylized model of job search to highlight some key issues concerning beliefs about job finding and how they influence search behavior and outcomes. In practice, surveys often elicit individuals' *baseline* beliefs about their employment prospects or the unemployment risk they are facing. In theory, we would like to understand their impact on search behavior and for that we would need their *control* beliefs instead. Indeed, an important challenge in the context of job finding is that it is difficult to elicit beliefs about primitives such as the marginal return to search effort or the distribution of potential job offers. Instead, surveys have elicited beliefs about, for example, the probability of finding a job in a given time interval. While this is a relatively simple question to ask to a survey respondent, it mixes behavior and primitives, which makes it difficult in practice to identify the impact of beliefs on behavior. E.g., job seekers may be optimistic about their job finding prospects because they search hard or they search hard because they are optimistic. We argue that instrumental variable approaches or field experiments that vary the information environment and that measure beliefs and behavior before and after treatment can address these issues of reverse causality. We see this as a promising avenue for future research and potentially a critical step towards embracing expectations data in our models of job search and the labor market.

We argue that a key benefit of expectations data in the labor market context so far has been in the identification of biases in beliefs and learning. The evidence strongly rejects the hypothesis of rational expectations - a standard assumption in models of labor market search. We focus our discussion on expectations data regarding outcomes of the job search process, such as expectations related to the chances of finding a job or expectations about job offers, and show how expectations data can be used to identify biases in job seekers' beliefs about their job finding prospects. We argue that one can identify biases for groups of individuals, but this requires panel data that elicits beliefs and outcomes for the same risk, over the same horizon and for the same set of individuals. We review recent evidence that consistently shows over-optimistic beliefs about job finding starting with Spinnewijn [2015] and also indicates a lack of updating in these beliefs. We specifically show evidence on how beliefs evolve over the unemployment spell, as studied by Mueller et al. [2021], and use the SCE to illustrate how beliefs respond to macro-economic indicators when employed and unemployed. Importantly, if beliefs are biased and learning is limited, we expect this to affect the job seekers' search and acceptance behavior, with important implications for labor market policies such as unemployment insurance and job training programs. We discuss recent work that has extended the standard models of labor market search to study the importance of biases and learning for employment outcomes and policies.

While we argue that job seekers' beliefs are biased, this should not preclude researchers to use expectations data to learn about the labor market and search environment more generally. Pioneering research by Stephens [2004] has shown how individuals' expectations about their employment prospects are predictive of later outcomes. Following up on this, Hendren [2017] has shown how the relation between ex-ante expectations and ex-post realizations can be used to infer the extent of heterogeneity in ex-ante risk. Typically, this is a challenging task as ex-ante separation risk is not observed but only its random realization ex-post. With expectations data, to the extent that it is predictive of outcomes, one can leverage it to estimate the extent of heterogeneity in ex-ante risks. More recently, Mueller et al. [2021] apply this idea to the context of job finding and find substantial predictive power of beliefs about the probability of finding a job. They go one step further in showing how one can identify the extent of heterogeneity in the presence of biases either through non-parametric lower bounds or by jointly estimating it with a well-specified model of beliefs. These new methods have documented substantial heterogeneity across employed and unemployed workers and shed new light on long-standing questions regarding adverse selection in UI markets and the decline in job finding over the unemployment spell.

We hope that this chapter can serve as a guide for future research. To do so, we are (i) presenting methods that use expectations data in labor and search theory, (ii) describing existing data sources and their comparative advantage to implement these methods, and (iii) trying to highlight some promising avenues and open questions for future research. Throughout we are heavily relying on our own work and experiences. This is an active research agenda with lots of excellent work of which providing a comprehensive and balanced overview is impossible. We refer interested readers to recent and related reviews by Cooper and Kuhn [2020] and Santos-Pinto and de la Rosa [2020].

The outline of this chapter is as follows: Section 2 describes existing data sources and discusses measurement issues. Section 3 sets up a framework that illustrates how beliefs influence search behavior and outcomes. Section 4 discusses how to empirically identify the impact of beliefs on behavior. Section 5 discusses how to identify biases in beliefs, their determinants and policy implications. Section 6 discusses how to leverage beliefs to identify heterogeneity in ex-ante risks in the context of the labor market. Section 7 concludes and outlines promising areas for future research.

2 Measurement

This section reviews a series of existing measures of expectations about labor market outcomes and highlight some measurement issues that arise.

2.1 Data Sources

One of the first surveys that systematically collected information on expectations regarding job loss and job finding is the *Survey of Economic Expectations* (SEE). It was designed by Jeff Dominitz and Charles F. Manski and, running from 1994 to 2002, it randomly sampled nearly 10,000 respondents. It asked a question about job loss over the next 12 months to individuals with a job, as well as a question about job finding in the event of job loss. Table 1 provides the exact wording of the questions.[1] The SEE also asked questions about job finding to those looking for a job. Interestingly, it probed respondents first on how long they think it will take at most to find a job and then asked the probabilistic question about job finding over three different horizons, ranging from 2 weeks to 1.5 years.

Many surveys have adopted similar questions about job loss as the SEE. This includes the *Health and Retirement Survey* (HRS), which asked about the perceived probability of job loss over the next 12 months, and the job finding probability in the event of job loss. The *Survey of Consumer Expectations* (SCE) adopted a similar structure, though it also probed respondents on what they think is their likelihood of leaving the current job. Examples in Europe are the *British Household Panel Survey* (BHPS) and, more recently, the survey of the *Copenhagen Life Panel* (CLP). Both ask directly about the mutually exclusive events of losing and quitting a job. Typically, the horizon for the job loss question is 12 months, except for the *German Socio-Economic Panel* (GSOEP), which asked about job loss over the next two years. It is likely that there are many other surveys that ask questions about job loss, though we focus here the attention on data sources that have been used for academic studies.

Surveys with questions about expectations related to job finding are more rare. While the SEE did ask questions about the probability of re-employment to non-employed job seekers, many other data sources do not include this type of question. A likely reason is that the sample of unemployed workers is typically just a small sub-sample of the surveyed population and thus sample size may be a limiting factor. The Survey of Unemployed Workers in New Jersey, also known as the *Krueger-Mueller*

[1] See also Table 1 in Chapter 1 "Household Surveys and Probabilistic Questions" (Bruine de Bruin et al.) for a list of surveys with probabilistic elicitations not restricted to the labor market.

Table 1: Selected Data Sources on Expectations about Job Loss and Job Finding

Panel A. U.S. Data Sources

Survey	Years	Panel	Universe	Selected Survey Questions
SEE	1994-2002	None	Employed	"I would like you to think about your employment prospects over the next 12 months. What do you think is the PERCENT CHANCE that you will lose your job during the next 12 months?" "If you were to lose your job during the next 12 months... What do you think is the PERCENT CHANCE (or CHANCES OUT OF 100) that the job you eventually find and accept would be at least as good as your current job, in terms of wages and benefits?" "What do you think is the PERCENT CHANCE that you will leave your job voluntarily during the next 12 months?"
			Unemployed	"What is the PERCENT CHANCE (or what are the chances out of 100) that it will take you less than [X] to find a job that you will accept?" *Asked for three different X, ranging from 2 weeks to 1.5 years.*
HRS	1991-	Biennial	Individuals over 50 yrs old and their spouses	"What is the percent chance (0-100) that you will lose your job in the next 12 months?" "What do you think are the chances that you could find an equally good job in the same line of work within the next few months?"
KM	2009-10	Weekly	UI recipients in New Jersey	"What do you think is the percent chance that you will be employed again within the next 4 weeks?" "How many weeks do you estimate it will actually take before you will be employed again?" "Do you think your chances of finding a job would increase if you spent more time searching for a job?" "How many weeks do you estimate it would take to become employed again if you spent an additional hour searching for a job every day?"
SCE	2012-	Monthly	Employed household heads	"What do you think is the percent chance that you will lose your current/main job during the next 12 months?" "What do you think is the percent chance that you will leave your current/main job voluntarily during the next 12 months?" "Suppose you were to lose your job this month. What do you think is the percent chance that within the following 3 months, you will find a job that you will accept, considering the pay and type of work"
			Unemployed household heads	"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?"
SCE LMS	2014-	Quadri-mesterly	Household heads	"What do you think is the percent chance that four months from now you will be: (1) Employed (2) Employed and working for the same employer (3) Employed and working for a different employer (4) self-employed (5) Unemployed and looking for work (6) Unemployed and NOT looking for work " "What do you think is the percent chance that within the coming 4 months, you will receive at least one job offer?" "Over the next 4 months, how many job offers do you expect to receive?" "Think about the job offers that you may receive within the coming four months. Roughly speaking, what do you think the average annual salary for these offers will be for the first year?" "Think about the job offers that you may receive within the coming four months. Roughly speaking, what do you think the annual salary for the best offer will be for the first year? "If you were to receive a job offer from another employer at a higher salary, what do you believe is the percent chance your current employer will match the salary offer?"

Panel B. Selected Data Sources in Other Countries

Survey (Country)	Years	Panel	Universe	Selected Survey Questions
HUS (Sweden)	1984-1998	Yearly	Employed	"How likely is it that you will keep your current job? Respond with a number between 0 and 100, where 100 means that it is completely certain that you will keep your job, 0 means that it is inconceivable and 50 means that both alternatives are equally likely."
GSOEP (Germany)	1999-	Yearly	Employed	"Do you expect to lose your job within the next two years?"
			Unemployed	"What is the probability of taking up a paid job within the next two years?"
BHPS (UK) Waves 6-7	1996-1997	Yearly	Employed	"In the next twelve months how likely do you think it is that you will: - Become unemployed? - Get a better job with your current employer? - Start a new job with a new employer? - Take up any work related training or education? - Start up your own business?"
LISS (Netherl.)	2008-	Quarterly/ Yearly	Employed	"Do you think that there is any chance that you might lose your job in the coming 12 months? You can indicate this in terms of a percentage. 0% means that you are sure that you will not lose your job, and 100% means that you are sure that you will lose your job." *Option for answering that "N/A since I am voluntarily leaving job."*
			Unemployed	Do you think that you have a chance of finding a job in the coming 12 months? You can indicate this as a percentage. 0% means that you are sure that you will not find a job, and 100% means that you are sure that you will find a job between now and 12 months.
DHS (Netherl.)	2005-	Yearly	Employed	"What do you think is the probability that you lose your jobin the next 12 months? You can fill in a number between 0 and 100."
CLP (Denmark)	2020-2021	Yearly	Employed	"Please think about your possible relationship with your current employer in 2021. Assign the probability in each possible case. The sum of the probabilities should be 100. 1. Staying with the current employer during 2021 2. Laid-off from current employer at some point during 2021 3. Quit from the current employer at some point during 2021 4. Separation for other reasons during 2021"

Notes: The table shows questions related to expectations about job loss and job finding in the Survey of Economic Expectations (SEE), Health and Retirement Survey (HRS), the Krueger-Mueller (KM) survey, the Survey of Consumer Expectations (SCE), the Labor Market Survey (LMS) module of the SCE, the The Household Market and Nonmarket Activities panel survey (HUS), the German Socio-Economic Panel (GSOEP), the British Household Panel Survey (BHPS), the Longitudinal Internet Studies for the Social sciences survey (LISS), the DNB Household Survey (DHS), and the Copenhagen Life Panel (CLP). For the GSEOP, the panel structure is annual, but expectation questions are asked only every two years.

Table 2: Means of Elicited and Realized Probabilities

Variable	**Sample**	**N**	**Mean**	**S.e.**
3-Month Realized Job-Finding Rate	Unemployed	1,720	0.403	0.011
3-Month Job-Finding Probability	Unemployed	1,720	0.482	0.007
3-Month Job-Finding Probability in Event of Job Loss	Employed	44,466	0.553	0.001
3-Month Realized Job-Separation Rate	Employed	44,466	0.027	0.001
12-Month Realized Job-Separation Rate (Imputed)	Employed	44,466	0.103	0.003
12-Month Probability of Losing a Job	Employed	44,466	0.148	0.001
12-Month Probability of Leaving a Job	Employed	44,466	0.208	0.001

Notes: Survey weights are used for all estimates. Sample is restricted to unemployed or employed workers, ages 20-65, with three consecutive follow-up surveys in the SCE. The table shows the sample averages of some elicited and realized probabilities. The 3-Month Job Finding Probability for the employed refers to the elicited probability of finding a new job within 3 months in the event if job loss.

(KM) survey (Krueger and Mueller [2011]), directly targeted the universe of UI recipients in 2009-10 in New Jersey and thus does not suffer from small sample issues. We received the opportunity to add questions to the KM survey that elicit beliefs about employment prospects in alternative ways. In particular, we asked unemployed job seekers both about their perceived probability of finding a job in the next 4 weeks as well as the expected remaining time it would take them to find a job. We also added questions directly eliciting their beliefs about the returns to search, asking how much faster they would expect to find a job when searching more. The *Survey of Consumer Expectations* (SCE) asks all unemployed individuals about their perceived probability of finding a job in the next 3 and 12 months. It also does not suffer from small sample size as it has been continuously running since December 2012 and thus by now contains a relatively large sub-sample of unemployed workers. The GSOEP and the *Longitudinal Internet Studies for the Social Sciences Survey* (LISS) also ask belief questions about job finding, though the horizons for these questions seem long (12-24 months) given that most unemployed job-seekers typically find a job in less than a year. The *SCE Labor Market Survey* (LMS) is a special module of the SCE, which is administered in July, November and March of every year since 2014, and asks questions about the perceived probability of a job offer as well as the expected number of job offers within the next four months. It asks these questions to all respondents, which makes sense to us, given the recent findings by Faberman et al. [Forthcoming] that many job seekers are actually employed, receiving a majority of job offers received. The SCE LMS also asks questions about expected offered wages. We found a few other surveys in other countries that ask questions about their expected wage in relation to their reservation wage, which are not included here.

While the seminal SEE sampled repeated cross-sections, most of the more recent studies have a panel dimension and/or are merged to administrative employment records. This is important because it allows (1) to compare elicited beliefs to actual outcomes and/or (2) to study the evolution of beliefs over time at the individual level.

2.2 Descriptive Statistics

In this subsection, we provide some descriptive statistics with data from the SCE for the years 2013-2020. While the results here have been documented elsewhere, it is useful to illustrate these results in the SCE and we provide the references where applicable.

Table 2 reports the means of the elicited probabilities along with their realizations. Note that we restricted the sample of the SCE to responses with three consecutive follow-up interviews with information on labor force status. This is important since attrition would lead to under-counting of job finding.[2] The restriction to three consecutive follow-up interviews thus allows us to measure realized job finding as precisely as possible. We define the 3-month realized job-finding rate as the fraction of unemployed job seekers who reported being employed in at least one of the following three interviews. This limits any issues related to time aggregation, i.e. the possibility that someone finds a job but becomes unemployed again within the 3 month horizon.[3] Regarding job loss, we cannot compare the elicitation of the job loss probability to its realization over the same time horizon, since each individual has at most 11 follow up interviews. Instead, we decided to compute the average realization of the 3-month job loss probability, s_3, defined as the fraction of employed job seekers who were not employed in at least one of the following three interviews. We then impute the average realized 12-month probability as $s_{12} = 1 - (1 - s_3)^4$.

Table 2 shows that the unemployed tend to be over-optimistic in their job finding prospects, with the elicited 3-month job finding probability being $8p.p.$ above the realized job-finding rates. Overoptimism among the unemployed has first been documented by Spinnewijn [2015] and been confirmed in other settings (see Section 5 for more details). The overoptimism seems even larger when comparing the unemployed's 3-month probability to the hypothetical job-finding probability elicited of the employed (in the event of job loss), but this could of course be explained by the negative selection into unemloyment.

The employed appear to be over-pessimistic when it comes to their probability of job loss, as the imputed 12-month realization of job loss – measured as the rate of transition from employment to unemployment – is $4.5p.p$ below the perceived one. The perceived probability of leaving the job is substantial, as 21% of employed expect to leave their job voluntarily over the next 12 months. There is no natural counter-part for the realization of job leaving in the SCE, as most quitters likely transition directly to a new job or to out of the labor force instead of becoming unemployed.

Panels a and b of Figure 1 show the expected and realized job finding rate and job loss rate by year from 2013 to 2020. There is some positive co-movement between realized and expected job finding, though perceptions appear somewhat more rigid than the realizations. This is even more apparent, when looking at the expectations of job loss, which appear to be completely stable in 2020. This latter finding seems puzzling, as job loss spiked up to unprecedented levels during the pandemic recession. Note, however, that the big waves in job loss in March and April 2020 were to a large degree unexpected and thus not captured by the elicitations of job loss in January and February of 2020. Moreoever, these patterns may reflect selection as the pools of employed and unemployed changed rapidly over this period.

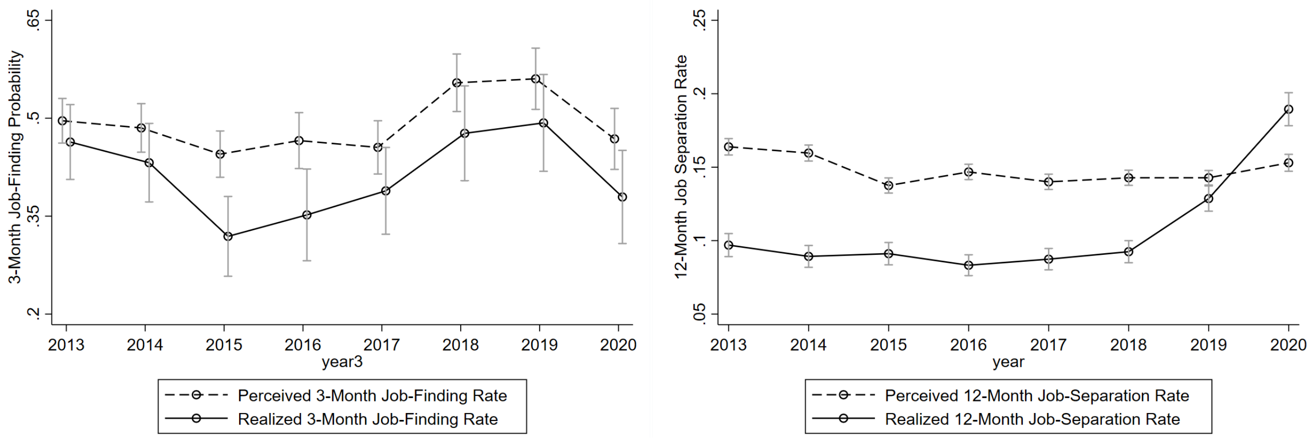
[2] The SCE suffers from relatively little attrition and thus is well suited to compare elicitations with their realizations.

[3] In addition, we exclude survey answers where the answer to the elicited 12-month job finding question was smaller than (and thus inconsistent with) the 3-month job-finding probability, which amounts to about 12% of the sample.

Figure 1: Expectations and Realizations of Job Finding and Job Loss, By Year in SCE

a. 3-Month Job-Finding Probability

b. 12-Month Job-Loss Probability



Notes: Survey weights are used for all estimates. Sample is restricted to unemployed or employed workers, ages 20-65, with three consecutive follow-up surveys in the SCE. Panel A shows the perceived and realized job-finding probability and Panels B and C show the perceived and realized job-loss probability. In Panel B, the 12-Month separation rate is imputed based on realized 3-month transitions as explained further above in the text.

2.3 Predictive Power of Elicited Beliefs

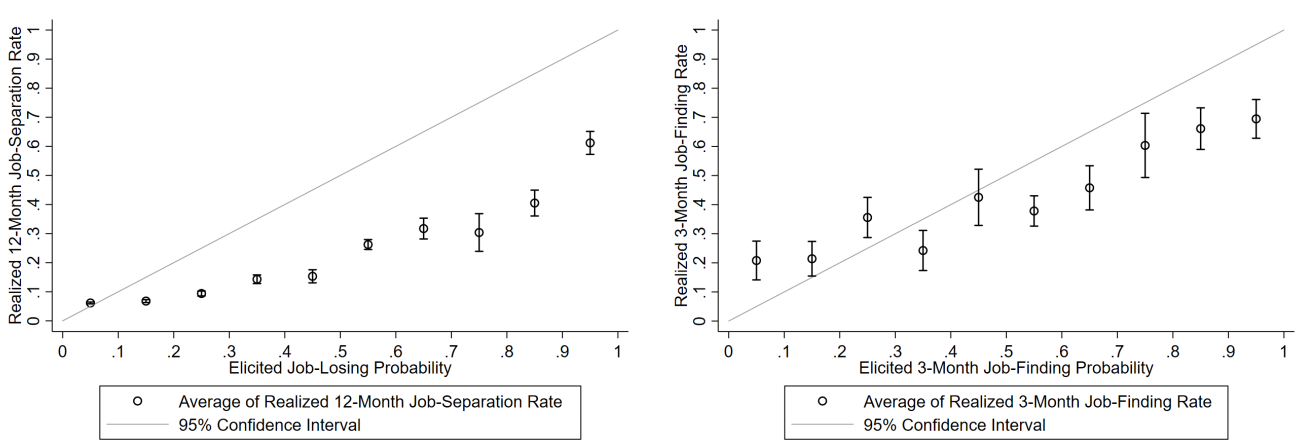
A central question regarding elicitations about labor market prospects is whether they predict actual job finding and job loss. Stephens [2004], Campbell et al. [2007] and more recently Hendren [2017] all look at the predictive value of beliefs about job loss in the HRS and find strong positive correlations with realizations. Mueller et al. [2021] look at the predictive power of beliefs about job finding and also find strong correlations between beliefs and realizations in the SCE. Relatedly, Conlon et al. [2018] show a strong positive correlation between the realized and expected number of job offers. With recent data from the SCE, we illustrate these sets of findings in Figure 2. A common theme about both panel a, which illustrates the predictive power of job loss expectations, and panel b, which illustrates the predictive power of job finding expectations, is that the gradient between realized and elicited probabilities is less than one. This could be in principle the result of a systematic bias in the beliefs, where individuals overestimate how different their employment prospects are. The evidence that we discuss later in this chapter suggests that the opposite is true, with individuals' beliefs responding less than one-to-one to differences in their employment prospects. However, a slope of less than one can also arise due to random error in the beliefs.[4] Still, one should be cautious interpreting the muted slope as evidence against rational expectations as it can also be due to noise in the elicitation procedure, in particular when the concept covered by the elicitation question does not overlap perfectly with its realization. For example, job loss refers to the idea of losing the current job, whereas its realization – measured as the probability of transitioning from employment to unemployed – misses transitions of individuals who got an advance notice but found a new job before the previous one ended, but also includes some individuals who left their job voluntarily. In addition, our imputation of the 12-month

[4]A slope of less than one has been found in other contexts such as survival and retirement, see Chapter 10 "Mortality and Health Expectations" (Hudomiet et al.) and Chapter 12 "Retirement Expectations" (Kezdi and Shapiro) respectively.

Figure 2: Realized Job Finding and Job Loss, By Bins of Elicited Beliefs

a. 12-Month Job-Loss Probability

b. 3-Month Job-Finding Probability



Notes: Survey weights are used for all estimates. Sample is restricted to unemployed or employed workers, ages 20-65, with three consecutive follow-up surveys in the SCE. Figures shows the 12-Month E-to-U transition and the 3-Month U-to-E rate by bins of the elicited beliefs about the probability of job loss (Panel a) and job finding (Panel b). Note that the 12-Month job-separation rate is imputed based on realized 3-month transitions as explained further above in the text.

transition rate based on the 3-month transition rate does not work if there is mean reversion of 3-month transition rates over the next 12 months. We turn to the issue of biases in more detail in Section 5.

2.4 Measurement Issues

While qualitative questions about expectations may be useful in some contexts, we focus here on the quantitative questions, i.e. questions which ask the respondent to indicate a percent chance (or other quantitative measure) over a well-defined horizon. Of course, as mentioned in the previous paragraph about the predictive power of beliefs, issues related to the measurement of such elicitations are an important concern and we'd like to elaborate on some of these issues here.

Non-classical measurement error. Measurement errors in expectations may be of classical or non-classical nature, with the latter especially likely at or near the bounds as individuals with a 0 cannot err on the negative and individuals with a true probability of 100 cannot err on the positive. Non-classical measurement error introduces a number of problems, including potentially, on average, a positive or negative error. This is important when inferring biases in elicited expectations from the data, and it is thus advisable to probe the robustness of results by excluding surveys with expectations at or near 0 and/or 100.

Horizon. Individuals may find it difficult to think about a certain probability over horizons that are either too short or too long. Moreover, issues related to non-classical measurement error are likely to be less common when choosing a horizon of the expectation question such that answers of 0 and 100 are uncommon. The SEE addressed this problem by probing respondents first about the maximum and minimum time till employment and then picking a horizon for the probability question based on the answer to these preliminary questions. Alternatively, a survey may just ask about different horizons for all respondents, which makes it easier to compare the elicitations to realizations. E.g., the SCE asked about the probability of job finding over the next 12 and 3 months. This is a relatively simple approach and useful, because it also allows to detect inattentive survey answers. E.g., if someone indicates that the probability of finding a job is 50 percent over the next 12 months but 60 percent over the next 3 months, it suggests that the person did not put much effort into filling out the survey questionnaire or has some fundamental difficulties with understanding the concept of probability.[5]

Bunching. A common source of measurement error is bunching in survey answers, which is most common at 50 for probability questions. While bunching per se is not necessarily a big issue when driven simply by rounding up or down, it may reflect a bigger problem of individuals indicating a percent chance of 50 if they have difficulty assessing the degree of risk. Multiple questions at different horizons, or questions about the expected remaining duration of the job or unemployment (as in KM survey) may be useful in this respect as they allow to see whether respondents who respond 50 percent on one question provide a different answer on the other question. Eliciting probabilities has the statistical advantage that it avoids ambiguity regarding the distributional moment one is hoping to elicit, but the disadvantage that individuals may not reason in probabilistic terms. We find in the SCE and in the KM survey that the alternative elicitations - either at different horizons or eliciting the expected remaining duration instead - are highly correlated, which is reassuring and suggests that many survey respondents submit responses that are consistent with each other (see Appendix D in Mueller et al. [2021] for details).

3 Illustrative Framework

Individuals' beliefs about their employment prospects affect their search behavior and vice versa. We can use the elicited beliefs discussed in the previous section to help understanding this relationship. In this section, we present a conceptual framework to highlight the key issues concerning beliefs and search behavior and how they affect employment outcomes. We refer to this framework in later sections.

We consider a stylized search model in which agents decide how much to consume, how hard to search for jobs and how to set their reservation wage. We define a vector of state variables, $h_{i,t}$, which captures both individual-specific characteristics *and* the agent's relevant employment and search history. For parsimony, we also include the stock of savings in the variable $h_{i,t}$. The arrival rate of job offers depends on the individual's search efforts $e_{i,t}$, but this mapping may be specific to the individual and dependent on her history, $\lambda\left(e_{i,t}|h_{i,t}\right)$. Job offers are drawn from a wage distribution $F\left(w|h_{i,t}\right)$, which again can be individual-specific and history-dependent. The unemployed agent's value at time t is

$$U\left(h_{i,t}\right) = u\left(c_{i,t}, e_{i,t}|h_{i,t}\right) + \beta E\Bigg[U\left(h_{i,t+1}\right) + \lambda\left(e_{i,t}|h_{i,t}\right)\int_{R_{i,t}}\left[V\left(w|h_{i,t+1}\right) - U\left(h_{i,t+1}\right)\right]dF\left(w|h_{i,t}\right)\Bigg],$$

determined by her chosen search effort $e_{i,t}$, reservation wage $R_{i,t}$ and consumption $c_{i,t}$. $u(\cdot)$ denotes

[5] As mentioned earlier, we exclude these survey answers from figures and tables in this section.

the per-period utility flow. The state vector $h_{i,t+1}$ builds on $h_{i,t}$, but depends on the agent's decisions (e.g., search, savings) at time t and shocks (e.g., productivity) at the start of $t+1$. The corresponding uncertainty is captured by the expectation operator E. $V(w|h_{i,t+1})$ denotes the value of being employed at wage w in state $h_{i,t+1}$, including the agent's employment history. The continuation value when employed can be written in an analogue way with an additional term for separation into unemployment.

We now turn to the beliefs, referred to with a hat. The agent's job search behavior depends on her *beliefs* about the arrival rate and wage distribution. The perceived arrival rate $\hat{\lambda}\left(e|h_{i,t}\right)$ and wage distribution $\hat{F}\left(w|h_{i,t}\right)$, however, may differ from the true arrival rate and wage distribution respectively. A job seeker thus sets her reservation wage $R_{i,t}$ to maximize her perceived continuation value at any time of the unemployment spell. At this reservation wage, the agent is indifferent between accepting a job and remaining unemployed, $\hat{U}\left(h_{i,t+1}\right)=\hat{V}\left(R_{i,t}|h_{i,t+1}\right)$. The job seeker also chooses to exert search effort $e_{i,t}$, trading off the cost of search and the perceived returns to search. Finally, the job seeker chooses her consumption $c_{i,t}$ depending on the perceived employment prospects, which in turn affect the continuation value when employed and unemployed.

The different dimensions of behavior and beliefs are intertwined. The resulting actual and perceived employment probability for unemployed agent i at time t given history $h_{i,t}$ equals respectively

$$T\left(h_{i,t}\right) = \lambda\left(e_{i,t}\left(h_{i,t}\right)|h_{i,t}\right)\left(1-F\left(R_{i,t}\left(h_{i,t}\right)|h_{i,t}\right)\right), \tag{1}$$

$$\hat{T}\left(h_{i,t}\right) = \hat{\lambda}\left(e_{i,t}\left(h_{i,t}\right)|h_{i,t}\right)\left(1-\hat{F}\left(R_{i,t}\left(h_{i,t}\right)|h_{i,t}\right)\right). \tag{2}$$

We can construct similar expressions to describe the job loss probability or the job to job transitions for employed workers. Note that, if individuals are uncertain about their beliefs and thus hold beliefs about the entire probability distribution, then equation (2) will have an additional co-variance term. This is not relevant here, since we observe $\hat{T}$ rather than the objects on the right hand side.

This stylized framework allows us to highlight some important factors determining the relationship between expectations and job search more generally:

Beliefs affect Search. A job seeker's search strategy does not only depend on her preferences and the cost of search, but crucially depends on her beliefs, too. The decision to put in more effort depends in the first place on how much it will increase her chances to get an offer, $\hat{\lambda}'(e)$. The decision how to set her reservation wage depends in the first place on how it affects the share of acceptable job offers, $\hat{F}'(R)$. The different job search decisions also interact. In particular, when deciding how much effort e to put in, one needs to form beliefs about the type of wage offers one can expect, $\hat{F}\left(w|h_{i,t}\right)$. When deciding whether to accept a job or where to set one's reservation wage R, one needs to form beliefs about one's chances to get new job offers in the future, $\hat{\lambda}\left(e|h_{i,t+k}\right)$. In practice, job search is very diverse, requiring job seekers to make decisions in various dimensions. It is not just about how much time to spend, but also on the different modes of search to spend time on, e.g., through specific search platforms or through informal networks.[6] Similarly, it is not just about the wage one hopes for, but also about the types of jobs to search for. In principle, to understand the role of beliefs for job search, we would need to have a comprehensive understanding of individuals' beliefs on all of these dimensions.

[6] E.g., see Holzer [1988] who argues that channel choices should relate to their costs and expected productivities.

Search affects Beliefs. Not only do job seekers' choices depend on their beliefs, their beliefs will also depend on their choices. An agent will search more, the more she believes this increases her chances to get an offer. However, the overall effort she puts in will also affect her beliefs about her chances to get an offer. The endogenous relation between behavior and beliefs makes it challenging to separate the impact of beliefs on behavior and vice versa. This challenge gets worse as we move away from primitives and consider beliefs at a higher level. Differences between the perceived and true employment probability $\hat{T}(h_{i,t}) - T(h_{i,t})$ could be driven by biases in the primitive beliefs, but then further magnified or mitigated by the choices made. To unpack the two channels in an empirical setting, we would need some exogenous variation that induces individuals to change their behavior and evaluate the impact on their beliefs, or that induces individuals to change their beliefs and evaluate the impact on their behavior. In both cases, we would also need to rely on an exclusion restriction that excludes any direct effect of the source of variation on the beliefs or the behavior respectively.

Baseline vs. Control Beliefs. Given the multi-faceted nature of job search and job seekers' beliefs, it is useful to distinguish between *baseline* and *control* beliefs as in Spinnewijn [2013, 2015]. An individual's baseline beliefs refer to the risk an individual is facing, given her search behavior. For example, an individual is baseline-optimistic when she overestimates the probability to leave unemployment, conditional on her search effort and reservation wage, i.e., $\hat{T}(h_{i,t}) > T(h_{i,t})$. An individual's control beliefs refer to how much she can reduce her risk through her own behavior. For example, an individual is control-optimistic when she overestimates the impact of her own search effort on leaving unemployment, i.e., $\frac{\partial \hat{T}(h_{i,t})}{\partial e_{i,t}} > \frac{\partial T(h_{i,t})}{\partial e_{i,t}}$. The perception of the baseline unemployment risk is crucial to evaluate how much individuals would value any protection, mitigating the consequences of unemployment through unemployment benefits or precautionary savings. A baseline optimist would under-appreciate the value of unemployment insurance and invest too little in precautionary savings as a consequence. The control beliefs are crucial for understanding individuals' search behavior and how much they would respond to changes in policy. While a control-pessimist exerts too little effort, financial incentives are ineffective when she believes to have little control over her employment prospects.

Heterogeneity. Beliefs and potential heterogeneity therein introduce another factor affecting individuals' behaviors differentially. However, beliefs also allow us to shed light on the importance of other dimensions of heterogeneity. A fundamental challenge is to understand how much of the heterogeneity in ex-post outcomes could be anticipated ex-ante. Some individuals receive job offers, while others do not. Some of them are offered higher wages, while others are offered lower wages. But could they anticipate these differences ex ante? While we only observe the distribution of ex-post outcomes in the data, an individual's choice depends on the job offer probability, $\lambda(e|h_{i,t})$, and wage distribution, $F(w|h_{i,t})$, she is facing ex-ante. The predictive value of ex-ante elicited beliefs help us understand how much of the heterogeneity in ex-post outcomes was anticipated and allows to provide a lower bound on the overall importance of ex-ante heterogeneity in employment prospects.

Learning. Beliefs are not static, but evolve over time. Individuals learn. They respond to news or changes in the environment and update their beliefs accordingly. Like for heterogeneity, individuals' beliefs provide an opportunity to learn about the dynamics that are inherent to the search environment, but they also introduce their own dynamics that in practice may not be easily captured by standard models of learning. In a similar spirit, agents take search and consumption decisions jointly and their histories may influence future behavior. For example, if the job seeker is optimistic about the chances of finding a job, she will consume more than otherwise, but if she fails to find a job, the lack of savings may drive her to search more. Understanding how beliefs change and what they respond to is thus important, too.

4 Beliefs and Behavior

Our conceptual work has illustrated how expectations wield a big influence on choices such as search effort and the reservation wage. But so do preferences. It is generally difficult to separate the role of preferences and expectations in explaining choice data [Manski 1993, 2002, 2004]. For example, a job seeker may search little because she is impatient and thus discounts heavily the expected gain from search or because she perceives the returns to search to be low. Similarly, a job seeker may set a low reservation wage because she is impatient and thus discounts the value of future offers or because she believes that the probability of sampling better offers is low (i.e., the option value of remaining unemployed is low). Expectations data about job finding are useful in this respect as they can help distinguish between preferences and expectations in explaining job search behavior. Alternatively, one can try to directly measure preferences, eliciting them through experiments or experimentally-validated survey questions.[7]

4.1 Structural Models with Expectations Data

Despite the promise for expectations to help understanding job search behavior and separate the role of preferences, only a few papers have combined expectations data with data on search behavior and/or labor market transitions to inform structural models of job search. We already highlighted some challenges before, which can help explain why expectations data have not been embraced more in the structural labor literature. But there are definitely opportunities to be further exploited going forward.[8]

A first opportunity is to use expectations data in labor market models to improve the precision of estimated parameters. Van der Klaauw [2012] shows this in the context of occupational choice. Assuming that the model underlying expectations data and choices are the same and that expectations data reflect optimal future behavior, he uses data on the expected future occupation to estimate a structural model of career choice and argues that a big gain in the efficiency stems from the fact that expectations allow to identify better unobserved types. We will return to this latter point in Section 6.

A second opportunity is that expectations data allow to drop the assumption of rational expectations. Conlon et al. [2018] and Mueller et al. [2021] estimate structural models of the labor market using data on both transitions *and* expectations. Their purpose is to show how deviations from rational expectations distort job seekers' behavior and affect employment outcomes. We will come back to this in Section 5.

[7] E.g., DellaVigna and Paserman [2005] show that measures of impatience are negatively correlated with search effort.
[8] See also Chapter 19 "Expectations Data in Structural Microeconomic Models" (Kosar and O'Dea).

A third opportunity lies in the combined use of expectations data and data on search behavior for the estimation of structural models of job search. Note that traditionally choice data such as search effort or the reservation wage are typically not directly observed and structural models infer behavior from transitions between labor market states and accepted wages. Recently, researchers have also started to use self-reported data on reservation wages and search effort (measured typically as time spent on job search activities) to estimate search models (e.g., Hall and Mueller [2018]; Potter [2021]), though they do not use elicitations of beliefs to inform the model. An interesting direction for future research would be to estimate search models with transition data, beliefs *and* behavior data on self-reported search effort and reservation wages. For example, DellaVigna et al. [2020] and Marinescu and Skandalis [2021] show that data on search effort informs the degree of reference-dependence in models of job search. Similarly, Ganong and Noel [2019] find that a model with present bias or myopia can account for the large consumption drops at UI exhaustion. Data on expectations about job finding or job offer arrival could further discipline the identification in this context, both increasing the precision of the estimates (as in Van der Klaauw [2012]) and allowing for deviations from rational expectations (as in Conlon et al. [2018] and Mueller et al. [2021]).

A final opportunity for expectations data in labor markets models is to shed light on general equilibrium forces, as they interact with beliefs and are important in shaping labor market outcomes more broadly. While this issue receives increasing attention in macroeconomics more generally, little work exists to date in the context of the labor market models, which typically rely on the rational expectations assumption. There are again a few exceptions. One is the recent paper of Menzio [2020] who shows that rigid beliefs about the probability of job finding lead to rigidity in bargained wages and amplify fluctuations in vacancy creation and unemployment. Also Mitra [2021] introduces biased beliefs about job finding in a search-and-matching model with endogenous search effort. In her framework, biased beliefs and shocks therein change job seekers' search effort, which in turn feeds into firms' incentives for vacancy creation. Finally, Balleer et al. [2021] introduce over-optimism about labour market prospects in a quantitative model of consumption and saving and explore the implications for aggregate wealth inequality. While we haven't found other papers that use general equilibrium models, which deviate from rational expectations in the context of job search and job finding, we believe this is a promising avenue for future research.

4.2 Identification and Empirical Evidence

Separating the causal pathways between beliefs and behavior is challenging. An additional complication is that in practice it is difficult to elicit beliefs about primitives such as the returns and the shape of the wage offer distribution. Instead, researchers have resorted to elicit beliefs about job finding or the arrival rate of job offers, which reflect an amalgam of search inputs and beliefs about primitives. E.g., the elicited job-finding probability reflects both search inputs and beliefs about the job-offer production function. To address these issues, one would like ideally to rely on exogenous variation in search behavior to study its impact on beliefs and exogenous variation in beliefs to study its impact on behavior. We address both causal pathways – the perceived returns to search and the impact of beliefs on search behavior – in what follows.

4.2.1 The Perceived Return to Job Search

We first consider different strategies to identify the perceived effect of search on employment prospects.

Exogenous Variation. In an ideal experiment, we obtain exogenous variation in search behavior and study the impact on the perceived employment prospects. Following an instrumental variable (IV) approach, one can exploit variation in the costs of search related to instruments such as, e.g., differences in UI eligibility or the presence of severance pay, and then analyse the impact of resulting search behavior. This can in principle inform the primitives of the model (i.e., the beliefs about the marginal returns to search), but only if the exclusion restriction holds. In this spirit, Spinnewijn [2008] leverages the non-linearity in unemployment benefits to estimate the impact of search efforts on both the perceived and actual remaining unemployment duration. An important complication in this respect is that the instrument may affect different behavioral dimensions, so that we cannot single out the impact of one specific behavior. The costs of search for example are likely to affect both search effort and the reservation wage and thus it is not possible to identify the marginal effect of either on job finding.[9]

A possible solution is to elicit beliefs about more narrow job search outcomes for which the exclusion restriction arguably holds. One example is to collect data on beliefs and realizations of job offer arrivals (such as in the SCE LMS) rather than job finding (as in the SCE and KM survey). Assuming that job offer arrival is only affected by search effort but not the reservation wage, one can then use the IV strategy to analyze the impact of search effort on beliefs about job offer arrival (the probability of receiving at least one offer or the number of offers). This assumption, however, holds only in a random search context, where job seekers' contact rate is independent of the reservation wage. If job seekers, however, apply to jobs that are acceptable, the reservation wage may affect the offer rate.

Another approach is to use multiple instruments, which allow to identify the marginal impacts of the different search behaviors when providing independent variation. This approach is illustrated in Table 3 with data from the KM survey, which contains information on both search efforts and the reservation wage. The table shows the results of linear regressions, which relate elicitations about job finding to self-reported measures of search effort and the reservation wage. Ordinary least square estimation in columns (1) and (3) shows that search effort is positively associated with the perceived probability of job finding whereas the reservation wage is negatively correlated with perceived job finding. As noted above, these coefficients may be biased due to endogeneity of search effort and the reservation wage to the perceived probability of finding a job. For this reason, we instrument search effort and the reservation wage with a dummy for the receipt of severance pay, a measure of impatience and a measure of self-reported risk aversion. These instruments should provide independent variation for search effort and the reservation wage. The exclusion restriction is now that all instruments affect elicited expectations only through these two behavioral dimensions. The results show big differences between the OLS and IV regressions in the relationship between the self-reported behavioral variables and the perceived job-finding probability. The contrast is particularly stark in the relationship for search effort, where 10 hours of additional job search have a 10-12 p.p. effect on the perceived job-finding probability

[9] Another complication that violates the exclusion restrictions is when individuals learn about the uncertain search environment by engaging in search activities. For example, Banerjee and Sequeira [2021] find in a field experiment that unemployed youth in South Africa update their beliefs about job finding more if they are induced to search more.

Table 3: Linear Regressions of Elicitations on Time Spent on Job Search and the Reservation Wage

	Elicited 1-Month Job-Finding Probability		Elicited Remaining Duration (Inverted)	
	OLS	IV	OLS	IV
Hours Spent on Job Search, Last Week/10	0.013**	0.118*	0.009	0.102*
	(0.006)	(0.065)	(0.006)	(0.059)
Log Hourly Reservation Wage	-0.061*	-0.160**	-0.085***	-0.280***
	(0.033)	(0.080)	(0.027)	(0.071)
Demographic Controls	X	X	X	X
Observations	4,031	4,031	3,939	3,939
R^2	0.128	0.103	0.099	0.102

Notes: Survey weights are used in all regressions. All samples are restricted to unemployed workers, ages 20-65, in the KM survey. Expected remaining duration (inverted) is calculated as $1-(1-\frac{1}{x})^4$, where x is the elicited expected remaining duration of unemployment (in weeks). The columns (1) and (3) show results of OLS, whereas columns (2) and (4) use the following three variables as instruments: a dummy for whether the unemployed worker received severance pay, a measure of patience (i.e., based on choice of 20 now vs. 40 in 12 weeks) and a measure of self-reported risk aversion. Demographic controls include age, age squared, dummies for gender, race, ethinicity and educational attainment. Robust standard errors (clustered at the individual level) are in parentheses. Asteriks indicate statistical significance at the *0.1, **0.05 and ***0.01 level.

in the IV specification compared to a 1 p.p. effect in the OLS specification. For the reservation wage, the IV specification also shows a substantially stronger effect, with a decrease of the perceived job-finding probability of between 1.6% and 2.8% for a 10 percent increase in the hourly reservation wage. The wedge is consistent with individuals who are more optimistic about their employment prospects searching less and setting their reservation wages higher, which attenuates the OLS estimates relative to the IV estimates. In future research, it would be valuable to refine these instruments, further gauge the plausibility of the exclusion restriction and compare the perceived returns to search to the actual returns to search.[10,11]

Direct Elicitations. Another way to address the endogeneity issue is to elicit beliefs directly about primitives. For example, how much do workers believe they improve their employment prospects by searching more or by lowering their reservation wage? This type of direct elicitations is clearly challenging, but we believe it is an avenue worth exploring more.

We briefly illustrate the potential of direct elicitations studying the following question we added to the KM survey:[12] "Do you think your chances of finding a job would increase if you spent more

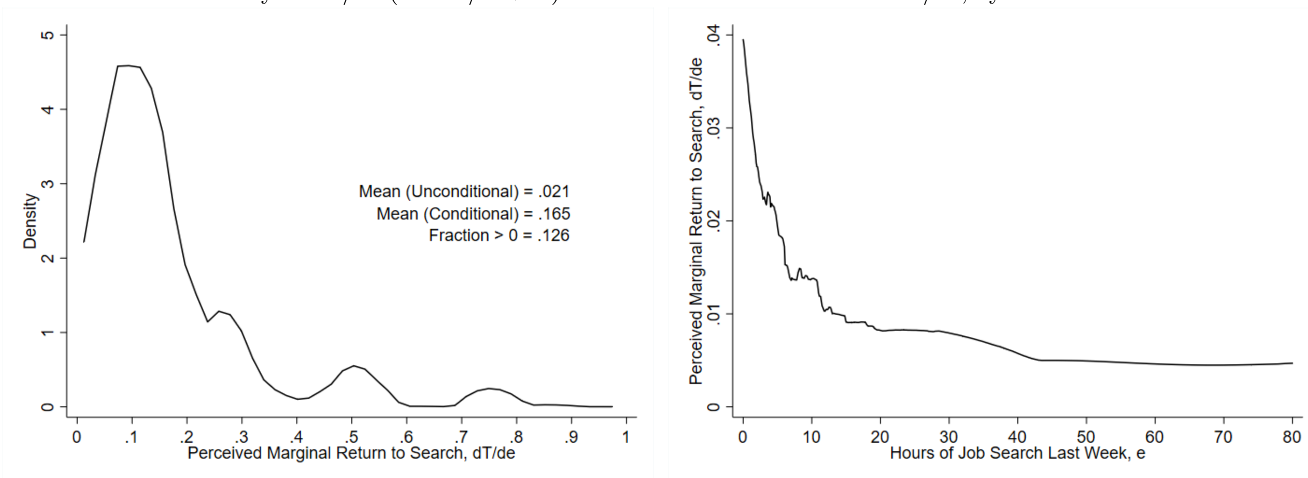
[10] As argued by DellaVigna and Paserman [2005], search effort is influenced more by present-bias whereas the reservation wage decision is a more forward-looking decision and influences the degree of impatience. Therefore, if one had some experimental measures of both present bias and impatience, this could provide a useful set of instruments for search effort and the reservation wage.

[11] The KM survey suffers from substantial attrition, in particular, for the sub-sample of observations with the belief questions and, thus, it is challenging to estimate the returns to search for the same sample.

[12] For eliciting the returns to search, we are only aware of our own attempt in the KM survey. Another paper directly eliciting perceived returns - not to search, but to training - is Alfonsi et al. [2020]. They elicit job seekers' beliefs about their employment chances and expected earnings, both given their current skills and when following a training program. Interestingly, Bandiera et al. [2021] find that, on average, the beliefs elicited under the hypothetical training scenario and after having followed the training program coincide.

Figure 3: Elicitations of the Marginal Return to an Additional Hour of Search, $\partial\hat{T}/\partial e$

a. Kernel Density of $\partial\hat{T}/\partial e$ (for $\partial\hat{T}/\partial e > 0$) b. Lowess of $\partial\hat{T}/\partial e$, by Hours of Job Search



Notes: Survey weights are used for all estimates. Sample is restricted to unemployed workers, ages 20-65, in the KM survey. Panel a shows the Kernel density estimate for the perceived marginal return to an additional hour of search per day. Panel b shows the fitted value of a locally weighted regression (Lowess) of elicited marginal return to an additional hour of search per day by time spent on job search last week. Note that marginal return to search is derived from a question about how the expected remaining duration is reduced by an additional hour of job search per day (if at all), which is then inverted and expressed as the perceived increase of monthly job-finding probability, $\partial\hat{T}/\partial e$.

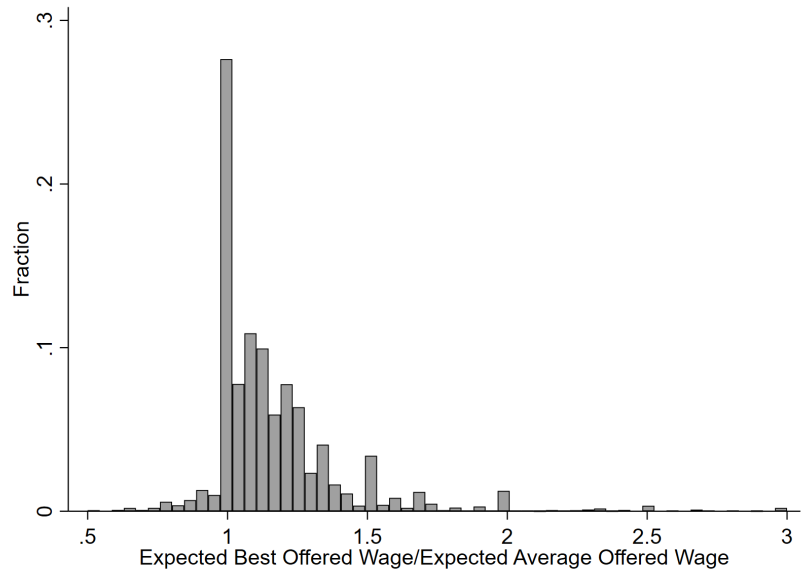
time searching for a job?", followed by a question "How many weeks do you estimate it would take to become employed again if you spent an additional hour searching for a job every day?" for those who answer with yes in the first question. One can compare the answer to the latter question to the baseline question about the expected remaining duration as shown in Table 1 to gauge the perceived return to one additional hour of job search per day, $\frac{\partial\hat{T}}{\partial e}$.[13] An important caveat is that only 12.6% of unemployed workers in the KM survey perceive there to be a positive return to job search at the margin. This is a striking observation by itself, but in hindsight we expect it would have been more informative to elicit the impact of searching less rather than searching more, or eliciting the marginal returns to search starting from a hypothetical number of hours.

Panel a of Figure 3 shows the Kernel density of $\frac{\partial\hat{T}}{\partial e}$ for those with a non-zero perceived marginal return along with descriptive statistics. For those with a positive perceived return, the return to 1 hour of job search is substantial with an average increase in the perceived job-finding probability of $16.5p.p.$. Unconditionally, however, given the large fraction of zeros, the average return to job search is moderate with an increase in the perceived job-finding probability of $2.1p.p.$ for 1 hour of job search per day. This is substantially lower than the IV estimates of the perceived marginal return to job search in Table 3, which is estimated at $7.1 - 8.3p.p.$ for 1 hour per day.[14] Clearly, the IV estimates are identified of compliers that may differ from the average job seeker. Moreover, individuals may perceive the marginal

[13] To make this comparable to the perceived monthly job-finding probability in Table 3, we invert the expected remaining duration as $1-(1-\frac{1}{x})^4$, where $x = \hat{D}$ is the elicited expected remaining duration of unemployment in weeks (baseline) and $x = \hat{D}'$ the elicited expected remaining duration of unemployment in weeks (with 1 additional hour of job search per day). For those who say no to the first question, we assume that $\hat{D}' = \hat{D}$. The perceived return to 1 hour of job search per day in terms of the monthly job-finding probability, then is $\frac{\partial\hat{T}}{\partial e} = \hat{T}' - \hat{T}$.

[14] To get to these estimates, we multiply the estimates in Table 3 by 7/10.

Figure 4: Histogram of the Ratio of Best over the Average Expected Offered Wage



Notes: Survey weights are used. Sample is restricted to ages 20-65, in the SCE LMS survey. The figure shows the histogram of the ratio of the elicitated expectation of the best wage offer received over the next 4 months over the elicited expectation of the average wage offer received over the next 4 months. Answers with values of less than 0.5 or more than 3 are trimmed from the sample.

returns to search as rapidly declining, potentially lowering the estimate using the direct elicitations. Interestingly, in Panel b we find substantial heterogeneity in the perceived marginal return to search based on how much the job seekers searched in the last week, suggestive of strongly declining marginal returns to search.[15] This further illustrates the challenge to eliciting beliefs about primitives in the context of job finding, as it suggests that even the elicitation of the perceived marginal return to job search is endogenous to search effort.

A related identification issue arises when relating elicited beliefs about future wages to the elicited reservation wage. As recognized by the long literature on search-theoretic models of the labor market and put into sharp focus by Hornstein et al. [2011], the distribution of potential wage offers is critical for the reservation wage decision: unemployed job seekers who face a wide dispersion of potential offers will set a high reservation wage to increase the likelihood to sample a high-paying offer. Hornstein et al. [2011] argue, however, that search models calibrated with empirical measures of wage dispersion imply counter-factually long unemployment spells or low flow values of unemployment. A potential caveat, however, is that empirical measures of wage dispersion, inferred from wage realizations, may over-state the wage dispersion for the job offers individuals expect to receive. In particular, the measure of wage dispersion based on cross-sectional comparisons may reflect partly unobserved heterogeneity. Elicitations of the *distribution* of potential wage offers could address this issue.

The SCE LMS asks about the *average* expected offered wage, which under the assumption of random search is a primitive and thus can be related directly to reservation wages. Conlon et al. [2018] report that reservations wages are significantly related to their expectations about future offers, indicating that

[15]Note that if the marginal returns were constant, but heterogeneous (while marginal costs are homogeneous) we would expect the reverse relation with individuals perceiving higher returns searching more.

individuals who expect higher future wages, have a higher reported reservation wages. The SCE LMS also collects elicitations of the expected *best* offered wage and Figure 4 plots the ratio of the best over the average expected wage offer. While it is not exactly clear what point in the distribution the 'best' offer corresponds to, the figure suggests that a substantial fraction of job seekers do not perceive any or very little dispersion in potential wage offers, with the ratio of the two being less than 1.1 for about 50% of job seekers.[16]

4.2.2 Estimating the Effect of Beliefs on Behavior

We now turn to the opposite causal pathway and consider methods for estimating how beliefs affect search and other behavior. To empirically isolate the effect of beliefs on behavior, one ideally has information on the relevant beliefs and plausibly exogenous variation in those beliefs.

Direct Elicitations. A first step is to elicit beliefs about primitives relevant for the behavior of interest. The second step is to relate those beliefs to behavior. This is a challenging task in the context of job finding, since elicitations are usually endogenous to search behavior as argued above. This is more feasible in the context of job loss, as layoffs are arguably exogenous, but still relevant for various dimensions of workers' behavior. Therefore, one can relate these elicitations directly to worker decisions. Stephens [2004] relates job loss expectations in the HRS to the consumption drop after job displacement and finds no effect. Hendren [2017] extends this by studying how job loss expectations and consumption evolve prior to displacement, finding some anticipation effects. Campbell et al. [2007] find that qualitative measures of fear of job loss in the BHPS are associated with less subsequent wage growth. More recently, Lizama and Villena-Roldán [2021], find with data from the SCE that individuals who perceive a high likelihood of job loss are more likely to search for a new job, likely because they want to avert unemployment.[17] Pettinicchi and Vellekoop [2019] show that workers with higher job loss expectations reduce durable consumption such as cars, but also have more precautionary savings and less exposure to risky assets. Of course, it is possible that these cross-sectional comparisons are biased due to unobserved factors that are correlated both with the primitive and the worker search or consumption decision.

Exogenous Variation. An alternative approach to gauge the role of beliefs for job search is to study how behavior responds to the arrival of new information. For example, one can look at search behavior before and after random events that shift expectations. In this spirit, Mitra [2021] uses data from the SCE and SCE LMS for an event study of the 2016 U.S. presidential election. She shows that after Trump's surprise election perceived labor market prospects improved in Republican relative to Democratic states, while time spent on job search activities declined in Republican states relative to Democratic ones, suggesting that search effort responds negatively to labor market prospects. Relatedly, Potter [2021] shows that search behavior increases after receiving (and rejecting) a job offer in the KM

[16]The SCE LMS asks follow-up questions on the percent chance that the best offer is more than 20% below or more than 20% above a critical value. While this is valuable, the reference value is the best offer, but – at least for the purposes here – it seems preferable to anchor these questions on the expected average wage offer.

[17]Similarly, Stephens [2004] shows that a higher probability of job-loss is associated with a higher likelihood of a job-to-job transition.

survey and he uses a structural model of job search to infer the impact on beliefs from the behavioral responses.[18] Conlon et al. [2018] document that expectations about the wage offer increase significantly if the respondent received a job offer with a wage that was above the previous expectation, though they do not look at the impact on search behavior associated with this change in expectation.

In the same vein, one can estimate the impact of beliefs on behavior through randomized information treatments, which affect behavior only through changes in beliefs. Card et al. [2012] study the effects of information provided about peer salaries on job satisfaction and the decision to engage in on-the-job search. Altmann et al. [2018] study the effects of information provided about job search strategies and the consequences of unemployment and find moderate treatment effects, which are concentrated among those at risk of long-term unemployment. Belot et al. [2019] find that information provided to job seekers on alternative occupations broadened their applications and increased the number of interviews attained. Finally, Roussille [2021] shows that, when a recruitment platform for engineers provided candidates with suggestions on what salary to ask for, the gender wage gap went to zero.

A common theme in this literature that uses event-study or information treatment designs to study the effect of beliefs on behavior is that typically it focuses either on elicitations of beliefs *or* behavior. More precisely, papers that employ structural techniques use empirical evidence on either and then use the structure of the model to infer the other, and papers that use information treatments typically estimate the reduced form of the information treatment on behavior. For future research, we believe it would be interesting to build on these papers and infer the impact of beliefs on job search in settings where both beliefs *and* behavior are elicited before and after the event or information treatment. This will allow to estimate the impact of beliefs on behavior directly from the data.

5 Beliefs and Biases

Traditional models of labor markets assume that workers have rational expectations about the risks they face. The direct measurement of workers' expectations through the elicitation of their beliefs allows to relax this assumption. The previous section discussed how beliefs affect behavior and how elicited beliefs can help separating its role from preferences. Importantly, if workers' beliefs are biased, these biases distort workers' behavior. Understanding these biases is therefore key for designing effective labor market policies. This section discusses the identification of biases in beliefs, the empirical evidence on biases in beliefs and its determinants, and the implications for policy.

5.1 Identification

The direct measurement of expectations allows to overcome important challenges when trying to identify how workers perceive the risk they face. First, it allows to relax the assumption of rational expectations. Second, it avoids the reverse mapping from ex post outcomes to ex ante expectations, which requires strong assumptions when risks are heterogeneous and dynamic as we discuss further in Section 6. However, the identification of biases poses some practical and conceptual challenges as well.

[18] The KM survey also collects information on beliefs about job finding but only for a sub-sample of observations, see Mueller et al. [2021] for details.

In the conceptual framework we introduced in Section 3, we consider an invidual's beliefs to be optimistically biased if $\hat{T}(h_{i,t}) > T(h_{i,t})$ and vice versa.[19] The challenge in evaluating the accuracy of one's beliefs is that we cannot directly observe an individual's risk type, $T(h_{i,t})$. We can, however, observe realizations of the risk. Let us denote this by $R(h_{i,t})$, which equals 1 with probability $T(h_{i,t})$ and 0 otherwise. We can then construct a simple test for the bias in beliefs by comparing ex ante beliefs and ex post realizations, since

$$E_I(\hat{T}(h_{i,t})) = E_I(T(h_{i,t})) \Rightarrow E_I(\hat{T}(h_{i,t})) = E_I(R(h_{i,t})). \tag{3}$$

Here I refers to the specific group of individuals and time range over which we take the expectation. When rejecting the equality $E_I(\hat{T}(h_{i,t})) = E_I(R(h_{i,t}))$, we can conclude that expectations are on average biased in this group. Otherwise, expectations are on average correct, but can still be biased for any given individual in this group.

To implement this test, it is critical to compare the beliefs and realizations for the same risk. That is why it is very important to have elicitations of workers' beliefs and the corresponding labor market outcomes for the same workers. As discussed in Section 2, this requires not only quantitative elicitations of the beliefs about a well-defined risk for which the outcome is actually measurable. This also requires a panel survey or a survey that is linkable to other data to measure the relevant outcomes. Ideally, the outcome can be measured at the same horizon as the one used in the elicitation. Relatedly, it is important to use a time frame where differences between ex ante beliefs and ex post realizations cannot be rationalized by unexpected shocks at the macro level. E.g., in the months right before the pandemic, individuals did not correctly anticipate the huge waves of job losses over the next months (see Figure 1). To sum up, at the individual level, we cannot expect workers to fully anticipate what will happen to them as individual outcomes as the random realization of a probability. However, at the group level, there is no reason for them to over- or underestimate their employment prospects, except when the studied group is subject to an aggregate shock.

For the interpretation of the test, we should also try to minimize the potential for elicitation noise to be systematic. As mentioned earlier, individuals may report a belief of 50% when their *true* belief is somewhere between $50 - x\%$ and $50 + x\%$. Hence, if their risk type is in that interval, the measured bias may be simply due to the rounding that individuals do. Eliciting the beliefs in different ways or at different horizons will help in making a more compelling case that beliefs are indeed biased. Similarly, we want to avoid experimenter effects where individuals report beliefs to please the experimenter or the elicitation of beliefs is known to be linked to specific interventions. It is common in experimental belief elicitation to provide incentives to elicit participants' 'true' beliefs, by mapping the ex-ante beliefs and ex-post realizations in a scoring rule (see Schlag and van der Weele [2015] or Schlag et al. [2015] for a review). However, from a policy perspective, the goal is to measure the beliefs that are underlying individuals' behavior, potentially distorted for motivational reasons or to overcome other behavioral frictions. Hence, the 'true' beliefs identified by providing incentives are not the most relevant ones.

[19] Moore and Healy [2008] refer to such types of overconfidence as *overestimation* and distinguish it from *overplacement* – the tendency to overestimate one's relative skills or performance – and *overprecision* – the tendency to overestimate the precision of one's beliefs.

We note that economists tend to trust more what individuals do than what they say in the spirit of the influential revealed preference paradigm. An alternative to using elicited beliefs is to look at the choices individuals make, like insurance or savings decisions. For example, Malmendier and Tate [2008] show how CEOs hold on for too long to their stock options as evidence for optimistic beliefs about their (firm) performance. In general, it is challenging to exclude that these choices cannot be rationalized by specific preferences rather than by specific beliefs. Recent work started studying how variation in the choice environment allows to separate preferences and perceptions (e.g., Ericson et al. [2021]).

5.2 Empirical Evidence

A large body of work in psychology and a rapidly growing literature in economics has documented substantial biases in beliefs (see, for example, Moore and Healy [2008] or Santos-Pinto and de la Rosa [2020] for reviews). People are shown to have overly optimistic beliefs in a variety of applications, both in experimental contexts and in the field. A number of recent papers have been documenting the importance of optimistic biases in labor markets as well.

To our knowledge, the first test for bias in labor market expectations was implemented by Spinnewijn [2015], who used a survey ran by a team of psychologists studying how couples handle depression during unemployment [Price et al., 1998].[20] A sample of 1,487 unemployed job seekers in Michigan and Maryland were surveyed repeatedly between 1996 and 1998 and asked about their expectations in the question: "How many weeks do you estimate it will actually be before you will be working more than 20 hours per week?" In follow-up interviews, subjects were then asked when they actually started working. Spinnewijn [2015] simply links the reported expectations of unemployed job seekers to the actual outcomes of their job search to reveal a striking optimistic bias. On average, accounting for censored unemployment spells, the average remaining duration for the same sample of job seekers exceeded 23 weeks, which was more than three times longer than expected. This is a substantial wedge on average, with more than 80% of the job seekers underestimating the length of their unemployment spell. This wedge is unlikely to be rationalized by unexpected changes in the aggregate labor market conditions. However, the test is implemented for a specific sample in a specific context. The wording in the elicitation questions also leaves some ambiguity about whether the average number of weeks is what individuals are expected to report.

The optimistic bias in the beliefs held by unemployed job seekers is, however, corroborated using different types of elicitations and in different macro-economic contexts. Mueller et al. [2021] report on the optimistic bias in beliefs from the KM survey and the SCE survey. As mentioned before, the KM survey elicited beliefs asking for the expected remaining duration and for the job finding probability. The optimistic bias is similar and very large again for both elicitation methods. In the SCE, probabilistic beliefs are elicited both at the three month and twelve month horizon. As shown in Table 2, at the three month horizon, we find an average optimistic bias (8 p.p.) indicating that job seekers perceive their chances to be 20 percent higher than they are. The overall bias is smaller than in the KM survey, but the optimistic bias is substantially larger for the long-term unemployed in both surveys. A number

[20] We also refer to the interested reader to the earlier version Spinnewijn [2008], which contains a more comprehensive empirical analysis of the elicited beliefs, including an estimation of the perceived returns to search.

of recent papers (Abebe et al. [2020]; Alfonsi et al. [2020]; Bandiera et al. [2021]; Banerjee and Sequeira [2021]) have fielded job search interventions in developing countries and also elicit job seekers' beliefs about their employment prospects. Despite the difference in contexts, all these papers consistently document optimistic biases in job seekers' expectations.

The elicited beliefs in Spinnewijn [2015] and Mueller et al. [2021] correspond to the baseline probabilities T in our conceptual framework. However, these optimistic beliefs could correspond to optimism about the specific dimensions of job search underlying these employment prospects. In particular, Conlon et al. [2018] have studied job seekers' expectations regarding the number of job offers they would receive and the wages that they would be offered, corresponding to the arrival rate λ and the wage offer distribution $F(w)$ in our conceptual framework. Conlon et al. [2018] find using the SCE that in general, workers tend to expect a much higher number of job offers than what they receive. The wage expectations are more accurate with only a small optimistic wedge between the average expected wage of \$32.30 and average received wage offer of \$30.40. Using similar elicitations in Switzerland, Arni [2017] reports overly optimistic beliefs on both the arrival rate and wage offers. Moreover, using an RCT intervention with coaching and counseling, he finds that job seekers' optimistic bias can be reduced. Relatedly, using the Linked IZA/IAB Evaluation Dataset from Germany, Drahs et al. [2018] look at the wages job seekers expect to be re-employed at and find that unemployed individuals over-estimate their future net re-employment wage by 10% on average. Almost 40% expect to earn a wage which is very close to their last wage, but the average and the median job seeker obtain only 90% of their expected wage. Jäger et al. [2021] elicit workers' beliefs about their outside options in a special questionnaire in the GSOEP and find that most workers think their next-best job will pay exactly the same as their current one. Comparing the expected to actual wage changes associated with job transitions, they find that low-paid (high-paid) workers are overly pessimistic (optimistic) about their outside options. With correct beliefs, 13% of jobs would become non-viable (i.e. negative worker rent) at current wages. Finally, Cortés et al. [2021] find that among business majors men exhibit higher levels of optimism about their post-graduation earnings than women, and show that in a model of job search with biased beliefs this contributes to the realized gender earnings gap.

The above evidence mostly relates to the employment prospects of unemployed job seekers. However, also employed workers face the risk of unemployment. As reported in Table 2, in the SCE the perceived probability of losing a job is high relative to the separation rate to unemployment. However, it is substantially lower than the combined transition rate from employment to unemployment and non-employment and does not account for immediate job-to-job transitions after job loss. Therefore, it is not clear whether these differences reflect biases in the perceived probability of job loss or simply the imperfect overlap between the concept covered in the elicited probability and the realized transition. The HRS includes a question on involuntary job loss that relates more directly to the elicited beliefs. While focused on the predictive power of job loss expectations, Stephens [2004] finds a positive wedge between the perceived probability of job loss and the observed probability of job loss. This wedge is even more pronounced for later waves in the HRS, as reported in Hendren [2017]. Both authors, however, caution the reader in interpreting this wedge as a pessimistic bias in beliefs.

Finally, employed workers do not only form beliefs about their unemployment risk, but also about their future productivity at a firm. These expectations affect the value of staying on a job and investing in firm-specific capital at this job or whether to consider alternative jobs. For example, Hoffman and Burks [2017] compare weekly productivity and productivity beliefs data for truckers in the US over two years and finds that workers' beliefs tend to systematically exceed realized productivity.

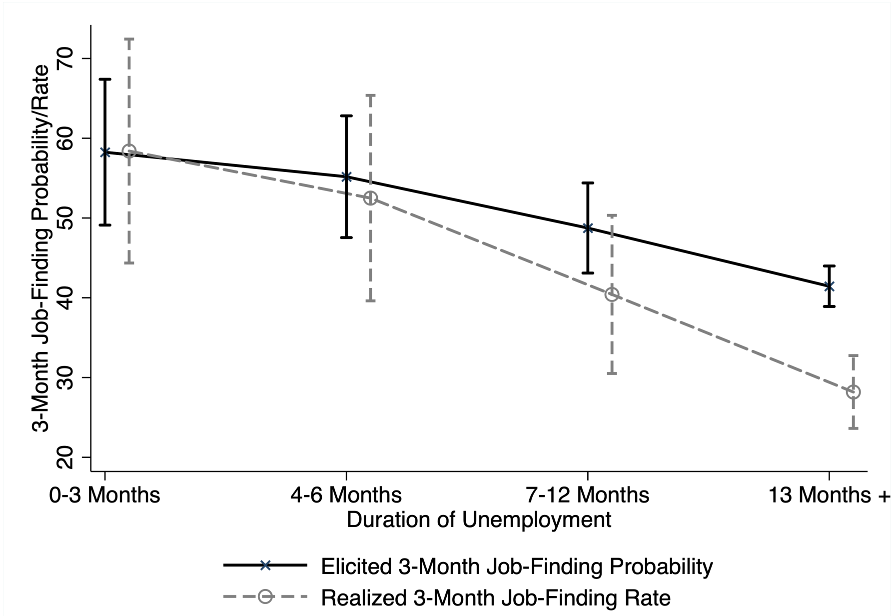
5.3 Determinants of Biased Beliefs

Since the seminal work by Kahneman and Tversky, psychologist and economists have formulated theories and collected evidence about how individuals form beliefs and update their beliefs based on personal observations and experience. Santos-Pinto and de la Rosa [2020] provide an excellent overview of explanations for overly optimistic beliefs. Individuals may prefer to have an optimistic belief about about their own ability [Kunda, 1990], even though this could distort their decisions (e.g., Brunnermeier and Parker [2005]). Or individuals may distort their beliefs to mitigate the distorting impact of other behavioral biases like present bias or lack of self-control (e.g., Bénabou and Tirole [2002], Heifetz [2007a], [2007b]). These motivational effects may also affect how individuals' process information and update their beliefs. Understanding the sources of biases in beliefs is of course very challenging, but can be key to learn how to overcome these biases and reduce the potential behavioral distortions.

A first natural way to further our understanding of biases in beliefs in labor markets is to study observable factors they correlate with. Some prior work has studied how elicited beliefs themselves change with observables. Early examples are Manski and Straub [2000] and Stephens [2004]. The notion that beliefs are responding to observables that are known to affect employment prospects is often seen as prima facie evidence that beliefs are predictive. However, there is relatively limited work that relates biases in beliefs to individuals' observable characteristics (e.g., Spinnewijn [2015], Balleer et al. [2021]). While more work would be valuable, for example to inform the targeting of information treatments or de-biasing policies, we need to be careful how to interpret differences in wedges for workers with different observables X. One interpretation is that *all* individuals in the population over- or underestimate the employment 'returns' to individuals with these observables X and not just the individuals with these observables X. Therefore, policy makers may want to correct the population beliefs rather than the beliefs of individuals with those observables X. The alternative interpretation is that individuals with different observables are subject to different biases. This could be due to motivational reasons. Under this alternative interpretation targeting individuals with larger biases may not necessarily result in larger behavioral responses.

Unemployment Duration. In the context of unemployment, Spinnewijn [2008, 2015] and Mueller et al. [2021] link the biases in job seekers' beliefs to their reported search behavior and the duration of their unemployment spell. Spinnewijn [2008, 2015] finds that individuals who report higher search intensity experience significantly shorter unemployment spells, while the relation between search and the elicited expected duration of unemployment is smaller. This could indicate that job seekers under-estimate the returns to search and thus are subject to biases in both their baseline and control beliefs. The relation with reported search efforts also points to another potential source of bias in beliefs, which is that individuals wrongly anticipate their behavior. For example, hyperbolic discounting or self-control issues imply that job seekers can over-estimate their future search efforts when they are naive about

Figure 5: Perceived and Realized Job Finding in the SCE, by Duration of Unemployment



Notes: Survey weights are used for all estimates. Sample is restricted to unemployed workers, ages 20-65, with 3 consecutive follow-up surveys in the SCE.

their biases [DellaVigna and Paserman, 2005]. The bias in beliefs about future behavior could explain why individuals who end up exerting less effort are more optimistic.

Mueller et al. [2021] show that the optimistic bias in baseline beliefs among job seekers is driven by the long-term unemployed. This observation is repeated in Figure 5 with more recent data from the SCE, where we compare the beliefs and job finding of the short- and long-term unemployed respectively. This links to two other potential sources of biases in beliefs. The first is a simple selection effect. Individuals with worse employment prospects may not perceive this as such, resulting in more optimistic individuals selecting into longer unemployment. This selection effect can interact with job seekers' behavior, for example, when optimistic job seekers are more selective or put in less effort and thus are more likely to remain unemployed. These type of selection effects underlying optimistic biases have been discussed in other contexts (e.g., Van den Steen [2004], Spinnewijn [2017]). Mueller et al. [2021] show that this type of dynamic selection is important for explaining the optimistic bias among long-term unemployed.

The second potential source is a lack of updating of beliefs. When job seekers have imprecise priors about their employability, we expect them to learn from prolonged spells of unemployment and revise their beliefs downward.[21] However, with data from the SCE and KM survey, Mueller et al. [2021] find that job seekers do not revise their beliefs downward as they remain unemployed. The lack of updating is surprising, but several explanations can be put forward. A first explanation is motivated beliefs where job seekers want to keep a positive self-image or value optimistic expectations even more as the lasting unemployment causes hardship. Biases in information processing and statistical reasoning can explain the persistence in beliefs, too. In particular, unemployed job seekers may be subject to the gambler's fallacy. By applying the law of small numbers, unsuccessful job seekers may infer from a series of

[21]See Bikhchandani and Sharma [1996] and Dubra [2004] for an analysis of learning with biased beliefs in standard search models.

bad draws (as their unemployment spell lasts) that the probability of a good draw increases [Rabin and Vayanos, 2010]. Alternatively, the lack of of updating may simply reflect stationary employment prospects over the spell of unemployment, see more on this in the next section. Stationary employment prospects also are consistent with Krueger and Mueller [2016], who show – using data from the KM survey – that reservation wages are nearly constant over the spell, and also with Marinescu and Skandalis [2021] and DellaVigna et al. [2020], who find that search activity is constant or even increasing, at least prior to the exhaustion of unemployment benefits.

The lack of learning and persistence in beliefs has been documented in other contexts. A large literature has studied the updating of beliefs in experimental settings more generally. Falk et al. [2006] study how beliefs evolve in a search experiment where the returns to search depend on subjects' relative performance on an initial task. Individuals update their beliefs depending on the success of their search efforts, but less than what would be predicted by Bayes' rule. A few papers have studied how beliefs evolve 'in the field' in a labor market context.[22] Banerjee and Sequeira [2021] find in a field experiment that unemployed youth in South Africa update their beliefs about job finding more if they are induced to search more. This suggests that the lack of updating could be explained by inefficiently low search effort due to over-optimistic beliefs. Hoffman and Burks [2017] provide compelling evidence that truck drivers are not only overly optimistic about their productivity, but also that these optimistic beliefs are very persistent, up to two years after the first elicitations. Conlon et al. [2018] study workers' wage expectations and how they respond to a wage offer. They find that higher than expected salary offers cause workers' to update their beliefs about future wages upward and vice versa. Estimating a structural model of learning, they show that this response is substantially stronger than what Bayesian updating would predict. They also elicit a direct measure of individuals' priors and they do not find that individuals with more precise priors update their beliefs less.

Business Cycles. In addition to knowing how workers' beliefs respond to their personal circumstances, it is also important to understand how workers' beliefs and thus their behavior respond to aggregate circumstances. We already showed the time series of the perceived and realized job finding for the SCE in Figure 1. Table 4 illustrates their relation further by showing how workers' perceptions respond to macroeconomic indicators.[23] The table shows that there is a clear and significant relationship between the monthly national unemployment and vacancy statistics and the elicited beliefs about job finding. Note that these regressions include both the employed and unemployed, and for the employed this refers to the probability of job finding in the event of job loss. We find a very similar relationship with the state unemployment rate, also when controlling for state fixed effects. Overall, the relationship between the beliefs and macroeconomic indicators seems less pronounced for the unemployed than the employed job seekers, though standard errors are very large. Compared to the employed job seekers, the relationship between the unemployed job seekers' beliefs and the national job openings rate is small and insignificant (Column 1 in Table 4). Column 2 even indicates no relationship with the unemployment rate, once we control for the perceived impact of the Pandemic. This deserves further attention in the

[22] See Chapter 5 "Survey Experiments and Economic Expectations" (Fuster and Zafar) for a thorough analysis of this topic.

[23] Mueller et al. [2021] have reported a version of this table for the unemployed job seekers (see Appendix Table D.10).

future, as the pattern is surprising; for the employed job seekers the elicited beliefs are only relevant conditional on becoming unemployed. The accuracy of beliefs thus matters more for the unemployed individuals, but they may have specific motivations to distort their beliefs. In spite of this difference, we do find a similar relationship for the employed and unemployed job seekers between the job seekers' beliefs and their elicited expectation that the unemployment rate will rise (Column 5 in Table 4). This suggests that although the unemployed appear to be less informed about aggregate unemployment, they take into account their own perceptions about aggregate conditions.[24]

To unpack the correlation between macroeconomic expectations and personal expectations, Roth and Wohlfart [2020] vary exposure to expert forecasts and show how this exogenous variation changes macroeconomic and personal expectations. Moreover, the personal expectations respond more for individuals with higher exposure to macroeconomic risk. Emmler and Fitzenberger [2021] consider the German reunification and find even an over-response in personal job loss expectations held by workers in East-Germany. Kuchler and Zafar [2019] study the opposite direction and show that individuals who personally experience unemployment become more pessimistic about future nationwide unemployment.

While the over-responses in beliefs are seemingly opposite in nature to evidence for persistence in beliefs or lack of learning, prior work in psychology and experimental economics has also shown the tendency of individuals to rely too heavily on recent information, referred to as the "representative" heuristic [Kahneman et al., 1982]. How the multitude of biases and heuristics can lead to persistence in beliefs in some settings vs. over-responses in others shows the importance of studying beliefs in a variety of contexts.

5.4 Policy Implications

Understanding the biases in beliefs is important for designing effective labor market policies. The biases may affect the evaluation of standard labor market policies, but also open the door for information policies that help workers to correct these biases. While workers' perceived risks determine their decisions and their so-called 'decision utility', the true risks will determine their so-called 'true utility' and could be deemed more relevant to evaluate welfare. Hence, a policy maker who cares about workers' true utility needs to know the bias in beliefs to evaluate welfare. While most of the papers discussed above use workers' 'true utility' to evaluate welfare, there is discussion in the literature regarding the appropriate welfare criterion (see Bernheim and Taubinsky [2018]).

Spinnewijn [2015] shows how biases in beliefs and the behavioral distortions they cause affect the evaluation of labor market policies. He starts from the Baily-Chetty formula (Baily [1978], Chetty [2006]), which characterizes the optimal unemployment insurance (UI) generosity as a function of the consumption smoothing gains and the moral hazard costs. While both can be estimated empirically, this type of sufficient-statistics representation critically relies on the envelope theorem. This implies that any behavioral response to a change in the policy only has second-order impacts on the welfare of optimizing agents. However, when beliefs are biased and thus decisions are distorted, the behavioral response to a change in the policy and how this affects 'true utility' can be of first-order. Spinnewijn

[24] See also Curtin [2003] who finds that expectations about changes in the unemployment rate are correlated with actual changes in the unemployment rate.

Table 4: Linear Regressions of Elicitations on Aggregate Labor Market Variables

Dependent Variable: Elicited 3-Month Job-Finding Probability	(1)	(2)	(3)	(4)	(5)
National Unemployment Rate	-1.582***	-0.588***			
	(0.161)	(0.175)			
× Unemployed	0.200	0.513			
	(0.638)	(1.194)			
National Job Openings Rate	3.351***	5.743***			
	(0.664)	(0.712)			
× Unemployed	-2.541	-1.726			
	(2.283)	(3.228)			
Pandemic		-0.067***			
		(0.013)			
× Unemployed		-0.018			
		(0.067)			
State Unemployment Rate			-1.891***	-1.884***	
			(0.141)	(0.145)	
× Unemployed			0.628	0.578	
			(0.527)	(0.505)	
Elicited Prob(Rise in Stock Prices)					0.220***
					(0.013)
× Unemployed					-0.127***
					(0.044)
Elicited Prob(Rise in US Unemployment)					-0.089***
					(0.012)
× Unemployed					0.004
					(0.045)
Demographics	×	×	×	×	×
State FE				×	
Observations	73080	73080	73792	73792	73344
R^2	0.057	0.058	0.054	0.062	0.064

Notes: The sample period is 2012:12 to 2021:02. All samples are restricted to workers in the SCE, ages 20–65. Robust standard errors (clustered at the individual level) are in parentheses. Survey weights are used in all regressions.

[2015] shows how the moral hazard cost needs to be scaled by the bias in control beliefs, to account for the underlying distortion in search efforts, and how the consumption smoothing gain needs to be scaled by the baseline bias, to account for the underlying distortion in intertemporal consumption smoothing. This type of internality corrections have been useful for standard policy formulae in other contexts too (e.g., Baicker et al. [2015], Allcott et al. [2019], Farhi and Gabaix [2020]). Moreover, biased beliefs may not only distort workers' choices, but also change the bargaining and interactions with potential employers. For example, Fang and Moscarini [2005] analyze the impact of biased beliefs on optimal wage-setting by firms. De la Rosa [2011] and Santos-Pinto [2008] show how biased beliefs affect both the wages and the power of incentives used by firms.

The presence of biases in beliefs that affect welfare also calls for policies that directly target these biases. Conlon et al. [2018] find sizeable welfare costs due to belief-induced search distortions, but show that the estimated learning process mitigates these distortions. Hoffman and Burks [2017] show that the optimistic bias in truckers' beliefs has only moderate impacts on their own welfare, but substantially increases firm profits. Moreover, as discussed in Section 4, a number of recent papers have studied the impact of specific policy interventions, either to provide information or additional job search assistance to improve job search outcomes. These interventions have had some mixed success and hopefully more general lessons can be learned in future work.

6 Beliefs and Heterogeneity

This final section outlines how elicited beliefs can be used constructively to learn about the environment, above and beyond workers' expectations. We illustrate how beliefs can help uncover both heterogeneity and dynamics in employment risk - across and within job seekers respectively - that is otherwise unobservable. Building on Hendren [2013; 2017], we start by writing down non-parametric lower bounds on heterogeneity in employment risk and then discuss issues related to biases and persistence in beliefs. We also discuss how beliefs can be leveraged to identify the scope for adverse selection in unemployment insurance markets and to separate dynamic selection from true duration dependence underlying the decline in job finding rates over the unemployment spell.

6.1 Identification

The prior section showed how subjective expectations can be used to relax the rational expectations assumptions commonly assumed in models of the labor market. What sometimes gets overlooked is that even when assuming rational expectations, one needs strong assumptions to infer ex-ante risk types from ex-post risk realizations. The challenge is most easily illustrated for binary risks. In Table 2 we reported that among the unemployed job seekers 40 percent enter employment again over the next three months. However, from the employment outcomes alone it is impossible to infer whether all of them faced a 40 percent probability to become employed, or whether 40 percent were certain to become employed and the remaining 60 percent were certain to remain unemployed. One solution is to have repeated employment observations for the same individual. For identifying income risk for employed workers, this would require a long time series of income observations for each individual (e.g., Chamberlain [1984]). Identifying the job finding probability for unemployed job seekers is even more challenging, because – as shown by Heckman and Singer [1984] – with single-spell data estimates are sensitive to assumptions about functional form of the distribution of types. Put more generally, the identification problem for an individual's risk translates to the identification of any heterogeneity or dynamics in individuals' risk. Honoré [1993] provided a proof that identification can be obtained with multiple-spell data without relying heavily on functional form assumptions, and recently Alvarez et al. [2016] estimate a model with multiple-spell data from Austria. One potential limitation of this approach, however, is that it abstracts of any changes in types across spells (e.g., due to changes in savings, skills, health, ...) and thus, only identifies the extent of heterogeneity that is fixed across spells.

Individuals' subjective expectations about these risks can help overcoming this identification challenge. For the estimation of income processes and for example tests of consumption smoothing hypotheses, it has been known for a while that subjective expectations can be useful, but there is some apparent reluctance in relying on subjective expectations in standard modelling, which could be explained by data availability, but also by the alternative assumptions that are required (see Jappelli and Pistaferri [2010]). For example, Pistaferri [2001] has shown how the extent to which innovations in income do not translate in updating of subjective income expectations can be used to identify transitory shocks and separate them from persistent shocks to income. However, to learn about the true income process, this requires again that expectations are rational. More recently, Hendren [2013; 2017] shows how we can use beliefs to learn about heterogeneity in employment risks – focusing on the risk of job loss for employed workers. Mueller et al. [2021] extend Hendren's approach for when expectations are not rational – focusing on the re-employment risk for unemployed job seekers.

The basic idea in Hendren [2013] relies on the variance decomposition. Presented in the context of our illustrative framework on job finding, we have

$$Var(T_{i,t}) \geq Var(E(T_{i,t}|X_{i,t})) \text{ for any } X_{i,t} \Rightarrow Var(T_{i,t}) \geq Var(E(R_{i,t}|\hat{T}_{i,t})). \tag{4}$$

Any predictable variation in job-finding outcomes $R_{i,t}$ provides a non-parametric lower bound on the variance in job-finding probabilities $T_{i,t}$. While this holds for any set of observables $X_{i,t}$, job seekers' beliefs $\hat{T}_{i,t}$ may prove to be particularly predictive.

If individuals had perfect information about their employment prospects, the heterogeneity in job finding chances would be fully captured by the variance in elicited beliefs. That is, $Var(T_{i,t}) = Var(\hat{T}_{i,t})$. In general, beliefs can be subject to bias and elicited with error. Still, the predictive value of individuals' elicitations can help uncover the heterogeneity in true job-finding probabilities. For binary risks, the covariances of beliefs with ex-post job finding realizations and with ex-ante job-finding probabilities simply coincide, $cov\left(\hat{T}_{i,t}, T_{i,t}\right) = cov\left(\hat{T}_{i,t}, R_{i,t}\right)$. Hence, when elicited beliefs provide an unbiased – but potentially noisy – measure of individuals' job finding probabilities, the covariance between these beliefs and ex-post job finding outcomes exactly identifies the variance in ex-ante job-finding probabilities. That is, $var\left(T_{i,t}\right) = cov\left(\hat{T}_{i,t}, R_{i,t}\right)$, as shown by Hendren [2013]. When beliefs are biased, we can still bound this variance using the Cauchy-Schwarz inequality (see Morrison and Taubinsky [2019]),

$$var\left(T_{i,t}\right) \geq \frac{cov\left(\hat{T}_{i,t}, R_{i,t}\right)^2}{var\left(\hat{T}_{i,t}\right)}. \tag{5}$$

For a given variance in elicitations, a larger covariance between elicitations and realizations indicates less noise underlying the elicitations, and thus a larger variance in the job-finding probabilities themselves.[25]

The non-parametric bounds in (5) is robust to biases in beliefs. One can now go beyond partial

[25] Note that when the elicited beliefs are subject to noise, one can further tighten the bound by using multiple elicitations, $\hat{T}^k_{i,t}$ (see Morrison and Taubinsky [2019] and Mueller et al. [2021]).

identification by specifying a model of how beliefs relate to observable variation in job finding, as shown by Mueller et al. [2021]. They consider the following linear model of job seekers' elicited beliefs,

$$\hat{T}_{i,t} = b_0 + b_1 T_{i,t} + \varepsilon_{i,t}. \tag{6}$$

In this model, $\varepsilon_{i,t}$ captures random error in the elicited beliefs (with $E(\varepsilon_{i,t}|T_{i,t}) = 0$), the intercept b_0 captures a bias in the elicitations that is common to all individuals, and the slope parameter b_1 captures the extent to which elicitations reflect the underlying job-finding rates. As a result, the covariance between the beliefs and actual job finding scales the variance in true job-finding rates with the slope parameter b_1,

$$cov(\hat{T}_{i,t}, R_{i,t}) = b_1 var(T_{i,t}). \tag{7}$$

Hence, if job seekers' elicitations under-react to variation in job finding ($b_1 < 1$), the covariance underestimates the variance in true job finding, and vice versa. Now one can leverage the variation in job-finding rates across individuals with different observable characteristics to learn about the slope parameter. Intuitively, this parameter is revealed by the compression of the differences in $\hat{T}$'s relative to the differences in T's across observable groups. For the linear model, this becomes

$$b_1 = \frac{E\left(\hat{T}_{i,t}|X_{i,t}\right) - E\left(\hat{T}_{i,t}|X'_{i,t}\right)}{E\left(R_{i,t}|X_{i,t}\right) - E\left(R_{i,t}|X'_{i,t}\right)}. \tag{8}$$

This relies on the assumption that the average bias is constant across workers with different observables (i.e., $E(\varepsilon_{i,t}|X_{i,t}) = E(\varepsilon_{i,t}|X'_{i,t}) = 0$), but this can be tested or relaxed if we can observe the same individual under different X's.[26]

6.2 Applications

We discuss two recent applications using the beliefs of job seekers to shed new light on two long-standing questions in economics.

Adverse Selection in UI. A long-standing question in the unemployment literature is whether adverse selection can explain the absence of private markets for unemployment insurance (UI) and therefore rationalize the use of universal mandates in UI (see also Landais et al. [2021]; Hendren et al. [2020]). To shed light on this, Hendren [2017] uses the elicited beliefs of employed workers in the HRS to estimate the heterogeneity in job loss probabilities and thus measure the scope for adverse selection. Building on Hendren [2013], this requires an estimate of the pooled-price ratio, i.e., $\frac{E(T_{i,t}|T_{i,t}\geq\bar{T})}{1-E(T_{i,t}|T_{i,t}\geq\bar{T})}$. Leveraging again the relationship between the elicited job-loss probabilities and the actual outcomes, Hendren [2017] provides non-parametric and parametric estimates of this statistic, which just like the variance crucially depends on the heterogeneity in job-loss probabilities. This relationship, also documented in Figure 2, is very strong, even when controlling for a rich set of demographics and employment variables. The strong relationship translates into estimates for the pooled-price ratio that are as high as

[26] Mueller et al. [2021] use how individuals' job finding changes over the unemployment spell and show how the assumption that beliefs respond in the same way to variation in job finding across and within job seekers can be relaxed.

300%. This indicates that for a private market to exist workers at the margin of buying UI would need to be willing to pay a mark-up of 300% relative to their cost in order to compensate private insurers for insuring individuals with even higher unemployment risk and who would be selecting the UI, too.[27]

Interestingly, Hendren [2017] also shows that individuals act on their elicited beliefs and self-insure against their perceived risk of job loss: spousal labor supply and consumption dynamics both significantly correlate with elicited unemployment risk. In particular, as individuals are surveyed closer to the moment they end up losing their job, they report higher perceived probabilities of job loss and they also report lower consumption levels. Hendren [2017] shows how these dynamics in self-insurance, scaled by the anticipated change in unemployment risk, can be used to infer how much workers value UI and finds that workers' willingness-to-pay is lower than a mark-up of 60% relative to their cost.

Duration Dependence vs. Dynamic Selection. A long-standing question in macro- and labor economics is why employment prospects are worse for the long-term unemployed. Is it because long-term unemployment reduces a given worker's chances to find a job (e.g., due to skill depreciation)? Or is it because less employable workers select into long-term unemployment? Separating the role of duration-dependent forces from heterogeneity across job seekers has been a major empirical challenge (see Heckman and Singer [1984]; Machin and Manning [1999]). To shed light on this, Mueller et al. [2021] use the elicited beliefs of unemployed job seekers in the SCE to estimate the heterogeneity in job finding probabilities and measure the scope for dynamic selection.

Expressed in our stylized model, we have

$$E_t(T_{i,t}) - E_{t+1}(T_{i,t+1}) = E_t(T_{i,t} - T_{i,t+1}) + \frac{cov_t(T_{i,t}, T_{i,t+1})}{1 - E_t(T_{i,t})}, \tag{9}$$

where the subindex t denotes the duration at which the job seekers are sampled to evaluate the corresponding moment. The challenge is thus to separate the true duration dependence in job finding, $E_t(T_{i,t} - T_{i,t+1})$, from dynamic selection of job seekers with worse re-employment prospects into prolonged unemployment, $cov_t(T_{i,t}, T_{i,t+1})$. When cross-sectional differences in job finding are persistent over the unemployment spell, the dynamic selection term fully depends on the variance in job-finding probabilities, which can be estimated again using the covariance between elicited beliefs and actual job finding. This variance, however, tends to overestimate the role of dynamic selection when some of the differences are transitory in nature. To separate the persistent differences in job finding, Mueller et al. [2021] show how one can use the relationship between realized job finding and the lagged rather than the contemporaneous beliefs. Furthermore, as discussed before, when job seekers under- or overestimate their differences, we need to scale the covariance by $1/b_1$ to obtain the variance in job finding. Comparing the difference in perceived and true job finding probabilities for the short- and long-term unemployed, they obtain an estimate of about .5 for b_1.

Putting these empirical moments together, Mueller et al. [2021] find that dynamic selection explains most of the observed negative duration dependence in job finding. A full parametric estimation of their

[27] As mentioned, Hendren [2017] allows for beliefs to be elicited with noise, but not for them to be biased. Moreover, to translate the pooled-price ratio into a measure of adverse selection, one needs to assume that other dimensions of heterogeneity driving the selection of UI are orthogonal to the heterogeneity in risk.

model estimates this share to be 85 percent, leaving only 15 percent to be explained by true duration dependence. As mentioned before, Mueller et al. [2021] also find that job seekers are not significantly revising their beliefs downward as they remain unemployed. Simply using repeated elicitations of individuals' beliefs could have been a more direct solution to the challenge of identifying the dynamics of an individual's risk. This only works if individuals are not subject to biases more generally, but in this application also requires that individuals have perfect information. When job seekers have imperfect information instead, they should also learn about their employability from remaining unemployed and revise their beliefs downward. So it remains a puzzle why their perceived job finding does not decrease more rapidly as they remain unemployed. This persistence in their beliefs could also be part of the reason of why some job seekers remain unemployed for so long, as argued in Mueller et al. [2021].

7 Conclusion

We hope this chapter provides a stimulating guide for further work on belief elicitations in labor markets.

First, we have argued that an important advantage of belief elicitations is to shed light on biases in perceptions and the resulting distorted search behavior. Existing research shows a clear optimistic bias in elicited beliefs about job finding, which in turn raises questions about its sources as well as its implications. We believe it is important to better understand how biases distort search behavior. While existing research often relies on structural models to draw implications of distorted beliefs for behavior, we see promise in the instrumental variable approaches and field/natural experiments that rely on exogenous variation in beliefs or the information environment.

Second, and related to the discussion above, we believe that it is important to understand how beliefs about job prospects respond to changes in the macroeconomic environment as well as to study beliefs in equilibrium models of the labor market. E.g., in a typical search-and-matching model with vacancy creation, if beliefs about job finding are sticky, then so will be bargained wages, which in turn may depress vacancy creation in response to a negative aggregate shock. While we present some evidence on the cyclicality of beliefs from the SCE in the present paper, a more systematic analysis with a longer time series and one that includes a comparison to actual outcomes would be of great value. The dynamics of beliefs over the business cycle may also inform macroeconomic models of aggregate consumption dynamics and the effects of stimulus policies. For all these reasons, it would be highly valuable if surveys aimed at collecting consistent time series of labor market expectations.

Third, a growing literature recognizes the importance of on-the-job search for labor market outcomes, yet with the exception of the SCE, elicitations about job prospects are typically limited to unemployed job seekers. Eliciting beliefs about job-to-job transitions and potential wages on other jobs, documenting potential biases and effects on search behavior thus seems a fruitful direction for future research.

Finally, despite the documented biases, we argued that one can leverage beliefs to learn about aspects of the job seekers' environment that are not observed otherwise. Elicited beliefs have a high predictive power for job finding, above and beyond the typical observable characteristics, suggesting that these elicitations reveal information that are typically private to the job seeker or, at least, not observable to the econometrician. This can be leveraged to learn about ex-ante heterogeneity in various settings, including but not limited to ex-ante heterogeneity in job loss, job finding and wage offers.

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