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# **Essays on Information in Frictional Labor Markets**

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*To my loved ones,  
the kindest of mirrors and the steadiest of compasses.*

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# Introduction

This dissertation comprises three essays centered around the role of subjective expectations and information in labor markets. In equilibrium search models of the labor market, processes such as wage formation, job creation, offer acceptance, among others, largely depend on agents' expectations. Throughout these essays, I research how workers form expectations about aggregate and idiosyncratic factors that determine their behavior, with an emphasis on job search.

In the first chapter, I quantify the pass-through from inflation expectations to job search behavior by designing and implementing a survey of United States workers. The second chapter studies whether workers' perceived unemployment risk (i.e. their beliefs about job loss) responds to public information about mass lay-offs. The last chapter empirically contrasts individuals' job loss beliefs with their realized employment outcomes and investigates how overestimation of unemployment risk affects on-the-job search decisions.

Overall, this thesis shows that workers' expectations about the idiosyncratic and aggregate risk they face predicts their decisions in the labor market. Workers incorporate information about local idiosyncratic events and other macroeconomic variables, such as inflation, when forming expectations about future unemployment. There is vast heterogeneity in expectations, which is only partially explained by factors such as demographics, job related characteristics or location. Together, the chapters in this dissertation provide foundations for future research on various fronts, such as the design of optimal unemployment insurance or employment protection policies, as well as how Central Bank communication can be used as a tool for expectations' management. I leave these ventures for the very near future.

## Chapter 1

# Inflation Expectations, Wages and On-the-Job Search

### Abstract

In this paper, I design and implement a survey of United States workers to study the causal effect of higher inflation expectations on workers' job search decisions. I use hypothetical scenarios to decompose and quantify the impact of inflation expectations into direct and indirect effects: Direct effects are those caused by changes in inflation expectations, keeping other expectations constant. Indirect effects are caused by spill-overs from inflation expectations to expectations about the real economy. Through a within-subject design, I identify each of these effects at the individual and aggregate levels. I find that, on average, the direct effects of inflation expectations are positive and statistically significant. On average, workers associate higher inflation with higher unemployment. This produces an indirect effect that mutes average intentions to search. Workers' responses to higher expected inflation are heterogeneous with respect to age, gender and job tenure.

## 1.1 Introduction

The 2021-2022 inflationary episode saw the highest inflation rates in decades across many advanced economies. In countries such as the United States, the United Kingdom, and throughout the euro area, the surge in inflation occurred against a backdrop of tight labor markets. This situation raised concerns that workers, in attempting to catch up with unexpected price increases and to mitigate further expected real income losses, would exacerbate price pressures. Workers' demands could materialize either through direct requests for pay raises or by increasing their job search efforts to find higher-paying positions. By 2024, while inflation rates have cooled, real wages have not yet returned to pre-inflation levels.

How do inflation expectations affect employed workers' search behavior? In this paper, I design and implement a survey of employed workers in the United States. I first elicit workers' one-year ahead macroeconomic expectations, their plans to search for a higher-paid job in the near future, and their demographic and job-related characteristics. Then, I induce changes in their macroeconomic expectations by presenting hypothetical scenarios in which the Central Bank announces forecasts for inflation and unemployment rates. I focus on short-term inflation expectations, given their importance for price and wage setting (Weber et al., 2023) and their predominant role in the recent inflation episode (Hajdini, 2023; Werning, 2022). In particular, I assess how each announcement translates into a change in expectations. Workers adjust their inflation expectations towards the information provided in Central Bank announcements, and adjust their planned behavior in line with these posteriors.

I separately identify the effects of higher inflation expectations on planned search behavior into direct and indirect effects. The direct effect represents the impact of higher inflation expectations when labor market expectations remain constant. In practice, however, changes in inflation expectations can spill over into unemployment expectations. The indirect effect, therefore, arises from updated labor market expectations in response to inflation expectations. In canonical job search models, workers optimally decide on their search effort by equating the marginal cost with the expected marginal benefit. This expected benefit includes the value from switching jobs, weighted by the probability of receiving an offer. When the labor market is slack, the probability of finding a job for a given search effort is lower, reducing incentives to search. Depending on how workers perceive the co-movements between inflation and unemployment,

these spillovers could either offset or amplify the direct effects of inflation expectations.

My survey design accounts for these potential dynamics. Decomposing and quantifying changes in behavior into direct and indirect effects provides a more comprehensive understanding of the mechanisms through which inflation expectations influence behavior. On average, a 1 percentage point increase in inflation expectations raises intentions to search for a higher-paying job by 1.2 percentage points. However, workers tend to associate higher inflation with higher unemployment, which dampens average intentions to search. This “supply-side” view of inflation provides a potential reason for why real wages have not grown as much as initially anticipated at the onset of the inflationary surge.

My within-subject design enables me to go beyond average effects and to characterize the cross-sectional distribution of individual-level effects. First, it allows me to examine the distribution of the effects of Central Bank announcements on inflation and labor market expectations, providing direct evidence on heterogeneous effects of Central Bank communication on household expectations. Second, it captures the distribution of the effects of these expectations on behavior across heterogeneous workers. This distribution is relevant, as shifts in the composition of job seekers play a significant role in aggregate wage cyclicality (Gertler et al., 2020; Grigsby et al., 2021; Bauer and Lochner, 2020; Black and Figueiredo, 2022).

To validate respondents’ intentions to search, I re-contact survey participants three months after the initial survey to assess their actual behavior. Reported intentions to search effectively predict whether employed workers pursued a higher-paying job, confirming that *ex-ante* planned behavior aligns closely with *ex-post* realized behavior.

**Related literature.** This paper contributes to a broad literature on the formation of macroeconomic expectations and its impact on household behavior (see Candia et al. (2020) or Fuster and Zafar (2022) for a review). In particular, this paper is most closely related to a nascent strand of the literature that leverages survey data to study the impact of inflation expectations on labor market expectations and actions. Several studies show that households associate higher expected inflation to expected losses in income (Hajdini et al., 2022; Stantcheva, 2024; Baek and Yaremko, 2022). These studies show how, given higher inflation expectations, workers choose whether to engage in costly wage bargaining (Guerreiro et al., 2024), adjust reservation wages (Baek and Yaremko, 2022) or intensify on-the-job search (Pilossoph and Ryngaert, 2024). Georgarakos et al.

(2024) focus on the impact of inflation uncertainty, and find that reducing inflation uncertainty increases planned search intensity. These papers present complementary methodologies and datasets, offering a thorough understanding of worker behavior in an inflationary environment. This paper adds to this body of evidence by documenting the individual-level heterogeneity of behavioral responses of workers employed in a variety of occupations, industries and states, and by explicitly accounting for the role of unemployment expectations.

Secondly, this paper contributes to a growing literature on the links between business cycle dynamics and labor market transitions. Job-to-job transitions matter for reallocation, wage growth and productivity growth. Several papers explore the theoretical links between business cycle fluctuations and job ladder dynamics that take place through on-the-job search (Faccini and Melosi, 2023; Moscarini and Postel-Vinay, 2022; Trigari, 2009; Krause and Lubik, 2007). Empirically, there is contrasting evidence of countercyclical search among the employed (Bransch et al., 2024; Ahn and Shao, 2021; Elsby et al., 2015). Some studies highlight that different motives for searching on-the-job can generate offsetting cyclical properties, depending on whether employed workers search for a job to avoid unemployment or to climb the job ladder (Fujita, 2010; Simmons, 2023). Other studies use survey design to recover perceived returns or costs of on-the-job search (Adams-Prassl et al., 2023; Miano, 2023). I contribute to this literature by providing empirical evidence on on-the-job search given workers' different perceived stages of the business cycle, accounting for both the effects of perceived labor market slack and inflation.

By measuring the spill-overs of inflation expectations to unemployment expectations and its effects on behavior, this work is related to a strand of literature that examines the joint formation of macroeconomic expectations through mental models of the macroeconomy and perceived sources of fluctuations. This literature draws on both cross-sectional and time series data on expectations (Bhandari et al., 2019; Hou, 2020; Jain et al., 2022; Ferreira and Pica, 2024) as well as experimental methods (Andre et al., 2022; Binetti et al., 2024).

Methodologically, measuring the causal effect of *one* macroeconomic expectation is challenging - macroeconomic variables, as well as their expectation counterparts, are correlated and likely to jointly impact behavior. Depending on the underlying economic shocks, the magnitude and sign of the correlation between macroeconomic variables may differ not only across individuals, but across time and within-individuals, limiting the use of observational data on choices and

expectations. This simultaneity also poses challenges under experimental settings - Fuster and Zafar (2022) or Coibion et al. (2023) discuss how an “exclusion restriction” problem arises when an information treatment is used to instrument for changes in expectations and behavior is regressed on this instrument.

To address these challenges, I build on the literature on survey measurement of expectations (see Manski (2018); Bachmann et al. (2022) for a review). I elicit subjective choice probabilities under incomplete scenarios, following the stated preference literature (Manski, 1999) and estimate treatment effects based on conditional expectations as in Giustinelli and Shapiro (2024), Wiswall and Zafar (2021), Ameriks et al. (2020) or Arcidiacono et al. (2020). Hypothetical scenarios, beyond having a causal interpretation, allow for specification of environments that may not be observable in practice (Armantier et al., 2022). I specify scenarios where the Central Bank makes different announcements of economic forecasts with no policy commitment, akin to what is usually referred to as “Delphic” forward guidance (Campbell et al., 2012). The within-individual comparison of how expectations update in response to different types of Central Bank announcements contributes to the empirical literature studying how Central Banks can use communication to affect agents’ expectations (Coibion et al., 2022, 2020; Haldane and McMahon, 2018; Binder, 2017).

**Paper structure** The rest of the paper is structured as follows: Section 1.2 explains the analytical framework underlying the survey design. Section 1.3 describes the empirical strategy. Section 1.4 presents the survey results. Section 1.5 presents the results from a follow-up survey that validates respondents’ planned actions. Section 1.6 and Section 1.7 showcase further robustness checks and discussion. Finally, Section 1.8 concludes.

## 1.2 Conceptual framework

This section explains how I measure the individual subjective effect of an increase in inflation expectations on behavior. Let  $Y$  denote a binary outcome: to search or not for a higher-paid job (denoted by “search” or  $S_i$ ).

At time  $t$ , individual  $i$  forms expectations about macroeconomic variables (in particular, inflation  $\pi$  and unemployment  $u$ ) at  $t + j$ . These  $j$  periods ahead expectations are used to formulate a

subjective probability of an outcome  $Y$  at time  $t+k$ , with  $k \leq j$ . Let the probability of individual  $i$  taking action  $Y$  be a linear function of individual fixed and time-varying characteristics  $(\alpha_{i1}, v_{it})$ , as well as of macroeconomic expectations:

$$P_{it}(Y_{it+k} = 1) = \alpha_{i1} + \beta_{i1}\pi_{it+j,t}^e + \beta_{i2}u_{it+j,t}^e + v_{it} \quad (1.1)$$

Where  $P_{it}(Y_{it+k} = 1)$  is the subjective probability that individual  $i$  searches for a higher-paid job in period  $t+k$ ,  $\pi_{it+j,t}^e$  is the expected inflation at  $t+j$  evaluated at time  $t$ ,  $u_{it+j,t}^e$  is expected unemployment at time  $t+j$  evaluated at time  $t$ .

As mentioned previously, while realized inflation and unemployment rates co-move, this is also the case for their expectation counterparts. In reduced form, this can be expressed as:

$$u_{it+j,t}^e = \alpha_{i2} + \gamma_i \pi_{it+j,t}^e + \varepsilon_{it} \quad (1.2)$$

A positive shock to inflation expectations may lead to a contemporaneous revision in unemployment expectations, which is captured by  $\gamma_i$ . As indicated by the subscript  $i$ , the sign of this revision can be heterogeneous across individuals.

These individual-level regressions are unobserved. In this paper, I design hypothetical scenarios that generate controlled variation in inflation expectations and assess how planned behavior responds. In doing so, I assume that unemployment expectations are a sufficiently good instrument for individuals' expectations about the real economy and labor markets, such that no "spill-overs" from higher inflation expectations to other macroeconomic variables would have a first-order effect on search behaviors.<sup>1</sup>

Stated preference methods allow the researcher to generate controlled exogenous variation and measure responses that could not be identified from variation in actual choices (or revealed preferences) alone.<sup>2</sup> The elicitation of choice probabilities, a particular type of stated preference,

---

<sup>1</sup>This assumption is supported both by my data collection and other existing surveys. In particular, other macroeconomic expectations have no predictive power over individuals' realized search efforts, once unemployment and inflation expectations are controlled for. Note that this assumption is made with regards to search behaviors only.

<sup>2</sup>These encompass methods such as conditional probability elicitation (Giustinelli and Shapiro (2024)), vignettes or strategic surveys (Ameriks et al., 2020; Armantier et al., 2022).

allows respondents to express uncertainty about factors that can affect decision-making.<sup>3</sup> In this paper, I elicit choice probabilities conditional on different hypothetical scenarios. Conceptually, hypothetical scenarios correspond to a function assigning an environment to each member of the population (Manski, 1999). In practice, I partially specify the environment by fixing a state of the world such that the Central Bank communicates their predictions. This is akin to what is described in the Central Bank communication literature as Delphic forward guidance (Campbell et al., 2012), whereby the Central Bank announces their expected future economic conditions without making any binding promises on future policy. Individuals' baseline expectations are made conditional on a state of the world that *differs* from the one I describe in the scenarios. The within-subject design controls for unobserved heterogeneity and the effects of inflation expectations on planned behavior can be point identified at the individual level.

For the remainder of this paper, let  $j = 12$  and  $k = 3$ .<sup>4</sup> Changes in planned behaviour caused by changes in inflation expectations can be decomposed into a direct effect - if labor market conditions and unemployment expectations were unchanged - and an indirect effect - driven by revisions in unemployment expectations. I can manipulate individuals' inflation expectations and identify both effects solely using the elicitation (i.e. without resorting to regression estimation). Let subscripts 0 and 1 be used to denote prior and posteriors, respectively. I can retrieve the subjective treatment effect for individual  $i$  of a 1 percentage point increase in her inflation expectations by eliciting the following objects:

1. Priors:

- Inflation expectations  $\mathbb{E}_{it}(\pi_{t+12}) \equiv \pi_{i0}^e$
- Unemployment expectations  $\mathbb{E}_{it}(u_{t+12} | \pi_i^e = \pi_{i0}^e) \equiv u_{i0}^e$
- Probability of searching for a higher-paid job given inflation and unemployment expectations  $P_{it}(Y_{it+3} = 1 | \pi_{i0}^e, u_{i0}^e) \equiv S_i$

2. Expectations under hypothetical scenario:

---

<sup>3</sup>For a discussion see, for example, Blass et al. (2010)

<sup>4</sup>Empirical work by Glick et al. (2022) shows that while one-year ahead inflation expectations impact wage inflation, long-term expectations play no role. Furthermore, Armantier et al. (2022) find evidence that long-term expectations are irresponsive to persistent inflation shocks

- Inflation expectations:  $\pi_{i1}^e$
- Change in inflation expectations under the scenario:  $\pi_{i1}^e - \pi_{i0}^e \equiv \Delta$
- Expected unemployment rate conditional on  $\pi_{i1}^e$ :  $\mathbb{E}_{it}(u_{t+12} | \pi_{i1}^e) = u_{i1}^e$

3. Planned behavior under hypothetical scenario:

- Probability to search conditional on higher expected inflation, keeping expected unemployment constant:  $P_{it}(Y_{it+3} = 1 | \pi_{i1}^e, u_{i0}^e) \equiv S_i^D$
- Probability to search conditional on unemployment expectations  $u_{i1}^e$ :  
 $P_{it}(Y_{it+3} = 1 | \pi_{i0}^e, u_{i1}^e) \equiv S_i^I$

Given these objects, we can retrieve  $\beta_{i1}$ ,  $\beta_{i2}$  and  $\gamma_i$  from Equations 2.1 and 2.2 as:

$$\beta_{i1} \equiv \frac{S_i^D - S_i}{\pi_{i1}^e - \pi_{i0}^e} \quad \beta_{i2} \equiv \frac{S_i^I - S_i}{u_{i1}^e - u_{i0}^e} \quad \gamma_i \equiv \frac{u_{i1}^e - u_{i0}^e}{\pi_{i1}^e - \pi_{i0}^e}$$

The total individual treatment effect can therefore be estimated as the sum of the direct effect of inflation expectations and the indirect effect of unemployment expectations that changed in response to higher inflation expectations ( $\beta_{i1} + \gamma_i \beta_{i2}$ ). This treatment effect is subjective, in the sense that it is evaluated by the individual. It is also *ex-ante*, as it is evaluated prior to the treatment.<sup>5</sup>

### 1.3 Research design

The survey is composed of 6 blocks. Participants are first asked about their economic expectations. Secondly, they are asked to report the percent chances of taking different actions given their current expectations. Then, respondents are shown hypothetical scenarios. The hypothetical scenarios describe a situation where a source discloses information about the expected evolution of an aggregate variable - namely, price inflation and the national unemployment rate. To isolate the variation of interest, the scenario pins down other macroeconomic variables that could otherwise be expected co-move with the main variable. Table 1.1 maps the theoretical objects described in Section 1.2 into the different survey blocks.

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<sup>5</sup>Some papers, such as Arcidiacono et al. (2020) and Giustinelli and Shapiro (2024) have used the term subjective ex-ante treatment effect. Others (for example Ameriks et al. (2020)) have referred to it simply as treatment effects.

Table 1.1: Mapping: Elicitation and analytical framework

| Survey Block          | Environment specification  | Elicited objects       |
|-----------------------|--|------------------------|
| Baseline expectations | n.a.   | $\pi_{i0}^e, u_{i0}^e$ |
| Baseline behavior     | n.a.   | $S_i$                  |
| Scenario 1.           | Fed expects 7 percent inflation  | $\tilde{u}_{i1}^e$     |
| Scenario 2.           | Fed expects 7 percent inflation,<br>unemployment expectations<br>unchanged ( $u_{i0}^e$ )              | $\pi_{i1}^e, S_i^D$    |
| Scenario 3.           | Fed expects unemployment rate<br>$\tilde{u}_{i1}^e$ , expected<br>inflation unchanged ( $\pi_{i0}^e$ ) | $u_{i1}^e, S_i^I$      |
| Controls              | n.a.   | See Table ??           |

The exact phrasing of the scenarios is specified below:

**Scenario 1. Higher expected inflation**

*Suppose that, after an unexpected shock, the Fed announces that it expects the inflation rate to be 7 percent 12 months from now. In your opinion, 12 months from now, what will be the national unemployment rate?*

### Scenario 2. Higher expected inflation, *ceteris paribus*

*Suppose that, after an unexpected shock, the Fed announces that it expects the inflation rate to be 7 percent 12 months from now.*

*The job market will be just as you first thought. The expected national unemployment rate is [respondent's baseline expected unemployment] percent. It will be as easy to find or lose a job as it was before the shock.*

### Scenario 3. Higher expected unemployment, *ceteris paribus*

*Suppose that, due to an unexpected shock, the Fed announces that it expects the national unemployment rate to be [respondent's expected unemployment rate when inflation rate is 7 percent] percent 12 months from now.*

*Predictions for the inflation rate are exactly in line with your first thoughts: Prices are expected to increase by [respondent's baseline inflation expectation] percent over the next 12 months.*

After each scenario is described, I re-elicite respondents' expectations over the object described under that scenario. For example, in Scenario 1:

*How do you expect prices to evolve over the next 12 months following the Fed's announcement?  
By how much?*

By explicitly eliciting individuals' expectations under the hypothetical scenario, I make sure that the changes in behavior that I identify correspond to the changes in expectations that would happen in that scenario.<sup>6</sup>

To illustrate, consider Scenario 2, which specifies an expected inflation  $\pi^S$  and keeps labor market conditions constant. Recall that in order to identify the direct effect ( $\beta_{i1}$ ), the difference in current and hypothetical planned behaviors must be divided by the difference in inflation expectations:

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<sup>6</sup>As a robustness measure, I re-estimate these effects taking into account the scenarios and not the re-elicitations. Results do not change significantly.

$$\beta_{i1} = \frac{S_i^D - S_i}{\pi_{i1}^e - \pi_0^e}$$

If the individual's expected inflation under the scenario is  $\pi_{i1}^e \neq \pi^S$  but it is assumed to be  $\pi^S$ , then the recovered effect would be, instead:

$$\tilde{\beta}_{i1} = \beta_{i1} + \frac{\pi_{i1}^e - \pi^S}{(\pi^S - \pi_{i0}^e)(\pi_{i1}^e - \pi_{i0}^e)} (S_i^D - S_i)$$

Each scenario block concludes with the re-elicitation of planned behavior:

*In this scenario, what is the percent chance that you search for a higher-paid job to replace your current job over the next 3 months?*

Finally, the last part of the survey elicits demographic and other control variables about respondents' economic and professional characteristics that could explain heterogeneous responses to macroeconomic shocks. These include age, gender, race, education, liquidity constraints, home ownership status, commuting status to work, time and reason for last pay raise, area and state of residence, inclusion of cost of living (COLA) adjustments in pay, labor union membership, type of work contract, tenure at current job and occupation.

## 1.4 Survey results

### 1.4.1 Sample composition

The survey was administered on-line on the 24<sup>th</sup>, 25<sup>th</sup> and 30<sup>th</sup> of August 2023. Participants were recruited in Prolific through convenience sampling. In total, 722 participants started the survey and 682 individual responses were collected, which makes for an attrition rate lower than 5%. The median completion time was 9 minutes. The survey sample spans across the United States, with responses from 46 states. It also broadly captures the U.S professional fabric, covering responses from individuals employed in 18 out of 20 sectors included in the North American Industry Classification System (NAICS), and in all 23 major occupational groups of the Standard Occupational Classification System (SOC). Table 1 compares the demographic composition of my survey sample to that of the employed population in the Current Population Survey (CPS). The two are broadly aligned, with my survey sample being more educated, less female

and undersampling young individuals. A more detailed description of the sample, including occupation, area of residence, home ownership status is available in the Data Appendix.

Table 1.2: Sample comparison with Current Population Survey

|   | Survey | CPS  |
|---|--------|------|
| High-School Degree or Less                      | 12,6   | 33,8 |
| Some College Education                          | 24,7   | 25,7 |
| College Degree or More                          | 62,7   | 40,5 |
| Age 18-34                                       | 29     | 33,5 |
| Age 35-49                                       | 42,5   | 32,1 |
| Age 50-65                                       | 24     | 27,4 |
| Over 65   | 4,4    | 6,9  |
| Female  | 41,5   | 46,8 |
| White   | 77,4   | 77   |
| Part-time                                       | 15,8   | 16,7 |
| Northeast                                       | 16,7   | 17,4 |
| Midwest   | 23,2   | 21,3 |
| South   | 27,6   | 37,5 |
| West  | 32,4   | 23,8 |
| Management, professional, related               | 60,4   | 42,9 |
| Service occupations                             | 10,3   | 16,2 |
| Sales and office                                | 19,5   | 19,2 |
| Farming, fishing, and forestry                  | 0,3    | 0,6  |
| Construction, and maintenance                   | 3,9    | 8,4  |
| Production, transportation, and material moving | 5,6    | 12,7 |

Average shares for Current Population Survey computed using 2022 monthly data on employed respondents only. Survey weights used.

1.4.2 Descriptive analysis

**Prior macroeconomic expectations** Figure 1.1 shows the distribution of one-year ahead expectations for inflation and unemployment rates, respectively.

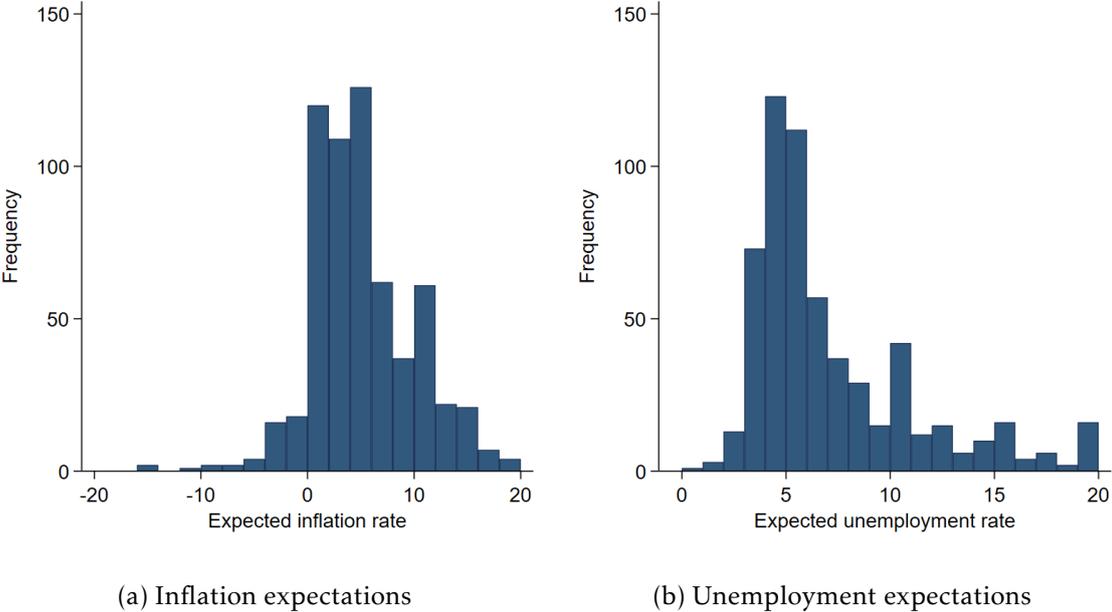


Figure 1.1: Distribution of prior macroeconomic expectations

Respondents’ one-year ahead inflation expectations are highly correlated but lower than their inflation perceptions over the previous 12 months, as can be seen from Figure 1.2. On average, respondents believed prices to have increased by 7.6 percent over the last 12 months and expected prices to increase by 3.9 percent over the next 12 months. Figure 1.3 shows the cross-sectional joint distribution between inflation and unemployment expectations.

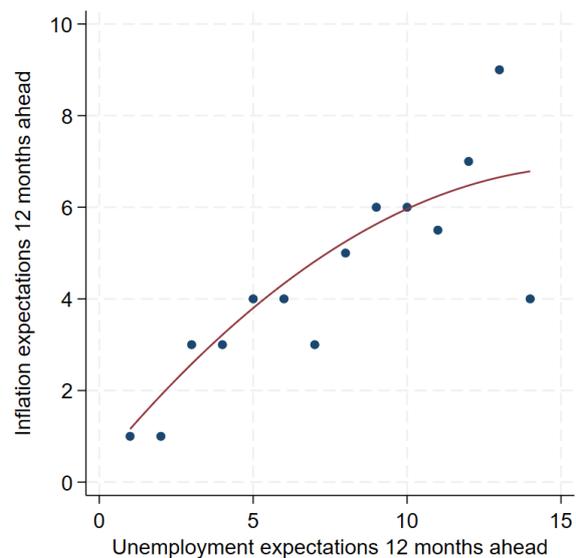
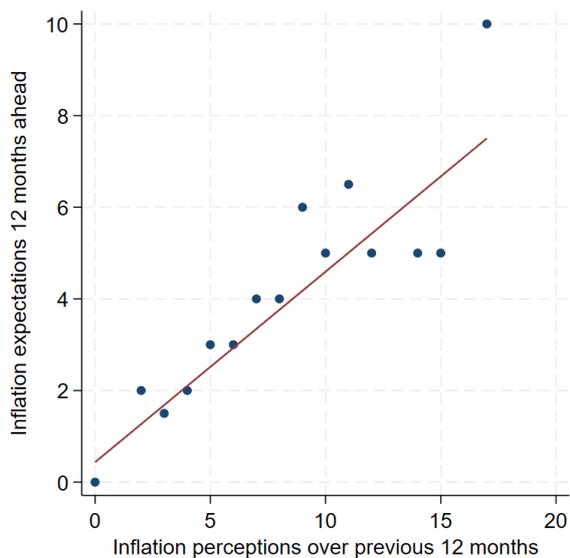


Figure 1.2: Inflation perceptions and expectations Figure 1.3: Unemployment and inflation expectations

**Prior intentions to search** Figure 1.4 shows the distribution of respondents' intentions to search on-the-job for a higher-paid job over the next 3 months. About a third of respondents report a zero percent chance of searching for a higher-paid job over the next 3 months. Around 23 percent of respondents have a 50 percent or higher chance of searching for a higher-paid job over the next 3 months. Figure 1.5 plots respondents' intentions to search for a higher-paid job against their inflation expectations. On-the-job search can be seen by respondents as either a tool to relocate to a better job, or as a way to avoid unemployment.<sup>7</sup> To gather whether these different motivations shape the relationship between search intentions and unemployment rate expectations, I divide workers into two quantiles based on the unemployment rate they report facing. I classify workers as facing below and above median unemployment risk, respectively. Figure 1.6 relates intentions to search on-the-job and unemployment rate expectations conditional on individuals' own unemployment risk. Two findings emerge: Firstly, individuals with above median unemployment risk are more likely to search for a higher-paid job while employed. Secondly, while search on-the-job increases with expected unemployment rates among workers facing high unemployment risk, the opposite relationship is present for workers

<sup>7</sup>See, for instance, Adams-Prassl et al. (2023) on main motivations for on-the-job search

in safer positions. Figure 1.7 shows how workers' self-reported reservation wages vary with intentions to search on-the-job. Workers who report higher percent chances to search on-the-job tend to have lower reservation wages, regardless of whether they face high or low unemployment risk.

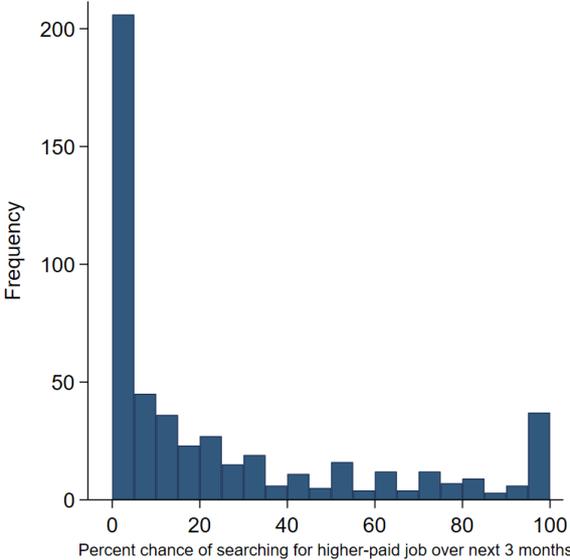


Figure 1.4: Percent chance to search on-the-job

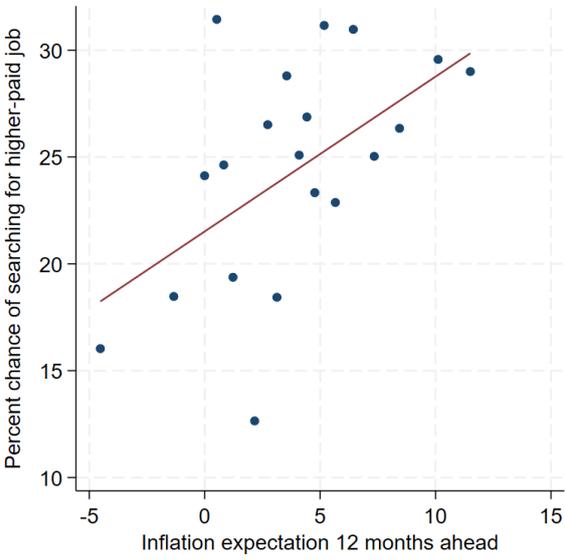


Figure 1.5: On-the-job search and inflation expectations

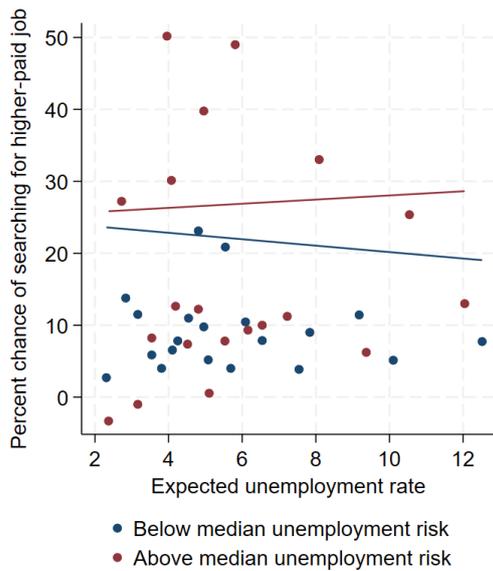


Figure 1.6: On-the-job search and expected unemployment

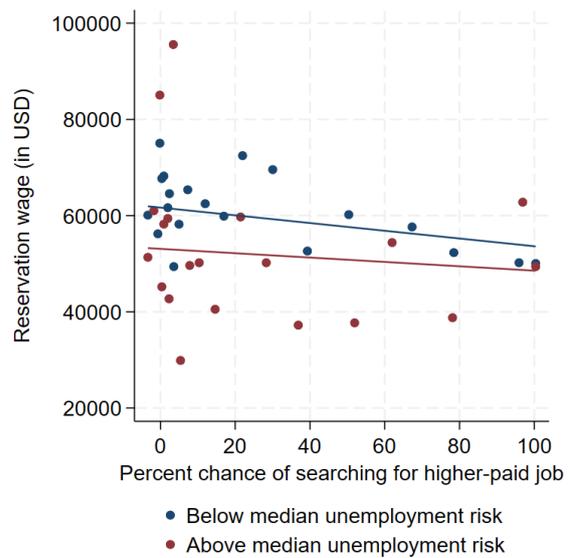


Figure 1.7: On-the-job search and reservation wages

**Effects of Central Bank communication** Figure 1.8 shows how respondents adjust their macroeconomic expectations under the direct and indirect scenarios, respectively. In particular, 1.8a plots respondents prior expected inflation rates against an orange line signaling the 7% inflation rate specified in the scenario, and their posterior inflation rates under that scenario. As can be seen, across all bins of prior expected inflation, respondents revise their expectations in the direction of the Central Bank announcement. Revisions in expectations are of larger magnitude among respondents with prior expectations much higher or lower than the ones specified in the scenario. Similarly, 1.8b plots revisions in expected unemployment under the indirect scenario where the Central Bank announces an expected unemployment rate in line with 7% inflation, but no expected changes in prices. For each bin, the figure plots respondents' prior unemployment expectations, the unemployment rate that is specified in the scenario and the posterior expectation. Here too, respondents revise their expectations toward the Central Bank forecast .

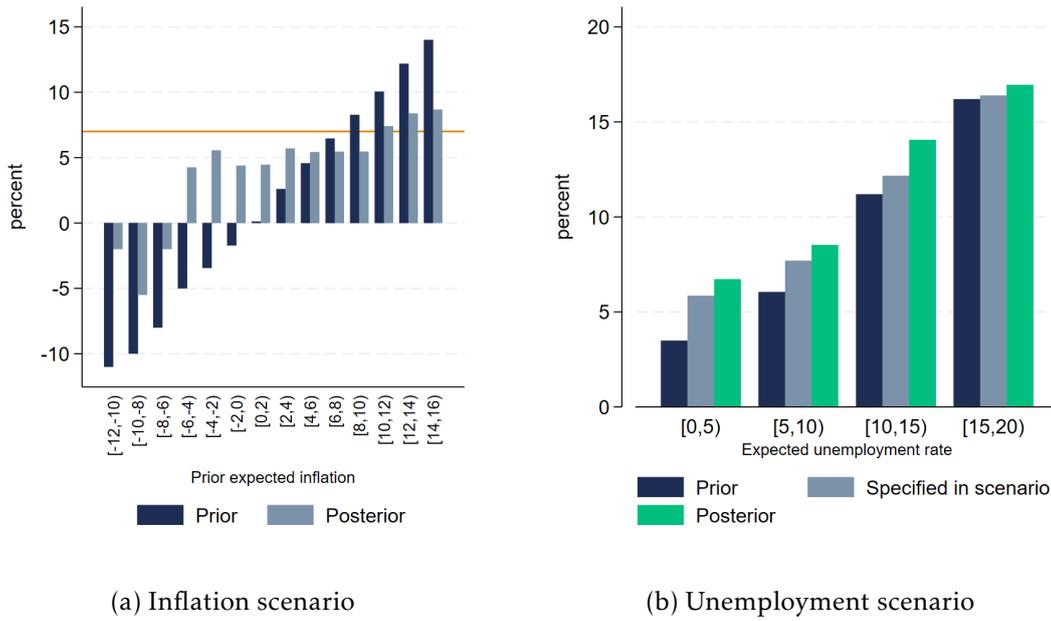


Figure 1.8: Revision in expectations under inflation and unemployment scenarios

### 1.4.3 Average treatment effects

Table 1.3 shows average treatment effects (ATE). The average magnitude and statistical significance of the effects of inflation expectations on search behavior are muted when variation is not isolated from its spill-overs through labor market expectations.

Table 1.3: Average treatment effects

|        | ATE: Inflation expectations |                                 |  |
|--------|-----------------------------|---------------------------------|--|
|        | Direct<br>( $\beta_1$ )     | Indirect<br>( $\beta_2\gamma$ ) | Total<br>( $\beta_1 + \beta_2\gamma$ ) |
| Search | 1.014***<br>(0.294)         | -0.250<br>(0.533)               | 0.764<br>(0.632)                       |

### 1.4.4 Individual treatment effects

There is rich heterogeneity behind the average treatment effects that I identify. In the following subsections, I characterize the cross-sectional distribution of each individual treatment effects (ITE) of interest. These correspond to the direct and indirect effects. These effects are identified

by comparing baseline and re-elicited behaviors under the Scenarios 2 and 3 described in Section 1.3.

Table 1.4 summarizes the distribution of individual treatment effects under the direct and indirect scenarios, as well as inflation expectations and planned search behavior before and after the scenarios were presented.

Table 1.4: Individual Treatment Effects - Search

| <i>Direct scenario</i>   |           |           |                         |                         |                      |
|--------------------------|-----------|-----------|-------------------------|-------------------------|----------------------|
|                          | $\pi_0^e$ | $\pi_1^e$ | p <sub>0</sub> (search) | p <sub>1</sub> (search) | $\beta_{i1}$         |
| Mean                     | 4.46      | 5.88      | 25.24                   | 28.94                   | 0.76                 |
| SD                       | 4.48      | 4.07      | 31.52                   | 32.15                   | 5.11                 |
| p10                      | 0         | 0         | 0                       | 0                       | -2                   |
| p25                      | 1         | 4         | 0                       | 1                       | 0                    |
| p50                      | 4         | 7         | 10                      | 16                      | 0                    |
| p75                      | 7         | 8         | 40                      | 50                      | 1.67                 |
| p90                      | 10        | 10        | 80                      | 85                      | 5                    |
| <i>Indirect scenario</i> |           |           |                         |                         |                      |
|                          | $u_0^e$   | $u_1^e$   | p <sub>0</sub> (search) | p <sub>1</sub> (search) | $\beta_{i2}\gamma_i$ |
| Mean                     | 8.98      | 11.18     | 25.24                   | 26.99                   | -0.14                |
| SD                       | 9.61      | 10.38     | 31.52                   | 30.11                   | 9.29                 |
| p10                      | 3         | 4         | 0                       | 0                       | -3                   |
| p25                      | 4         | 5         | 0                       | 1                       | 0                    |
| p50                      | 5         | 8         | 10                      | 15                      | 0                    |
| p75                      | 10        | 13        | 40                      | 45                      | 1                    |
| p90                      | 19        | 22        | 80                      | 76                      | 4.4                  |

Table 1.5 shows the share of negative, zero and positive individual treatment effects by scenario. Overall, the share of individuals revising their intentions to search upward is very similar in both scenarios.

Table 1.5: Share of search ITE, by sign

|                   | Sign of ITE |      |          |
|-------------------|-------------|------|----------|
|                   | Negative    | Zero | Positive |
| Direct Scenario   | 0.19        | 0.43 | 0.39     |
| Indirect Scenario | 0.24        | 0.40 | 0.36     |

**Heterogeneity** On average, inflation expectations directly increase workers' plans to search for higher-paid jobs. However, the indirect effect of updated unemployment expectations mitigates these revisions. Behind these findings there is wide heterogeneity.

To study heterogeneity in the magnitude and the sign of the response to the scenarios, I run OLS and ordered probit regressions reported in Table 6. The first column studies how workers' baseline probability to search on-the-job varies with respondents' characteristics; The two following columns assess heterogeneity in the magnitude of responses to direct and indirect scenarios; The last two columns study the sign (negative, null or positive) of the response to direct and indirect scenarios.

Responses to the direct scenario - recall, that induces *ceteris paribus* variation in inflation expectations - are heterogeneous across gender and education. Responses to the indirect scenario, that focuses on the *labor market*, are heterogeneous for different levels of job tenure.

The regressions are estimated with respect to a baseline category with the following characteristics: white man aged between 30 and 40 years old, college-educated, working full-time in the same city that he lives in; who has had a pay raise over the past year; employed at his current job for more than 6 years; owns a home with an outstanding mortgage; with a pay contract without cost of living adjustments and not a member of a labor union; employed in a management occupation in the South region of the United States.

Direct effects of higher inflation expectations are lower for individuals between 50 and 59 years of age. Female and non-college educated workers are more likely to reduce the percent chance of search for a higher-paid job. Indirect effects through unemployment expectations are heterogeneous across job tenures. In particular, workers with lower job tenures would increase their intentions to search for a higher-paid job more than workers who have been in their job for longer than 6 years.<sup>8</sup>

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<sup>8</sup>Note that given the large mass of zero ITEs, coefficient estimates should be interpreted with caution. Relative differences with respect to the baseline category are the focal point of this heterogeneity analysis.

Table 1.6: Heterogeneity in ITE - on-the-job search

|                              | Probability<br>to search | ITE Size - OLS             |                                      | ITE Sign - Oprobit         |                                      |
|------------------------------|--------------------------|----------------------------|--------------------------------------|----------------------------|--------------------------------------|
|                              |                          | Direct<br>( $\beta_{i1}$ ) | Indirect<br>( $\beta_{i2}\gamma_i$ ) | Direct<br>( $\beta_{i1}$ ) | Indirect<br>( $\beta_{i2}\gamma_i$ ) |
| Under 30 years old           | -3.84<br>(5.26)          | 0.19<br>(0.61)             | -3.21**<br>(1.56)                    | 0.33<br>(0.21)             | -0.03<br>(0.22)                      |
| Between 40 and 49 years old  | -0.87<br>(3.97)          | -0.33<br>(0.45)            | -1.00<br>(1.24)                      | -0.10<br>(0.15)            | 0.12<br>(0.17)                       |
| Between 50 and 59 years      | -4.13<br>(4.24)          | -0.94**<br>(0.48)          | -0.13<br>(1.33)                      | -0.23<br>(0.16)            | 0.09<br>(0.18)                       |
| Over 60 years old            | -9.96*<br>(5.16)         | -0.83<br>(0.58)            | -1.04<br>(1.66)                      | -0.13<br>(0.20)            | 0.05<br>(0.23)                       |
| Female                       | 0.96<br>(3.16)           | -0.07<br>(0.36)            | -1.06<br>(0.99)                      | -0.24**<br>(0.12)          | -0.14<br>(0.13)                      |
| No college degree            | -3.99<br>(3.40)          | -0.75*<br>(0.39)           | -1.13<br>(1.07)                      | -0.14<br>(0.13)            | -0.10<br>(0.15)                      |
| Renter                       | 8.24**<br>(3.51)         | -0.07<br>(0.40)            | -1.11<br>(1.07)                      | -0.06<br>(0.13)            | -0.14<br>(0.15)                      |
| Never had a pay raise        | 13.16**<br>(5.94)        | 0.47<br>(0.67)             | -2.09<br>(1.89)                      | -0.15<br>(0.23)            | -0.19<br>(0.27)                      |
| Tenure lower than 1 year     | 4.03<br>(6.40)           | 0.33<br>(0.72)             | 4.32**<br>(1.91)                     | 0.19<br>(0.25)             | 0.47*<br>(0.27)                      |
| Tenure between 1 and 2 years | 14.54***<br>(5.32)       | -0.64<br>(0.60)            | 4.28**<br>(1.70)                     | -0.19<br>(0.20)            | 0.40*<br>(0.24)                      |
| Tenure between 2 and 6 years | 8.07**<br>(3.54)         | -0.71*<br>(0.40)           | 2.37**<br>(1.10)                     | -0.22<br>(0.13)            | 0.28*<br>(0.15)                      |
| Constant                     | 23.41***<br>(6.10)       | 2.31***<br>(0.69)          | -0.79<br>(1.92)                      |                            |                                      |
| Other controls               | Y                        | Y                          | Y                                    | Y                          | Y                                    |
| Observations                 | 462                      | 454                        | 365                                  | 462                        | 371                                  |

“Other controls” include dummies for race, home ownership status, commuter status, residence, liquidity constraints, part-time contracts, cost of living adjustment clauses, labor union membership, occupation and region.

## 1.5 Follow-up survey: contrasting planned and realized behavior

The causal effects estimated in the previous sections are evaluated *ex-ante* by respondents. These subjective causal effects are informative to the extent that planned behavior predicts actual behavior. To test whether that is the case, I re-contacted survey participants 3 months after the original survey was fielded. The data collection took place between 29<sup>th</sup> November and December 1<sup>st</sup>. Out of 682 respondents, 500 completed the follow-up study. The follow-up study was designed to contrast reported probabilities to search for a higher-paid job with actual self-reported behavior. In this sense, respondents are asked the following questions:

*Have you searched for a higher-paid job in the last 3 months?*

Additionally, I elicit labor market outcomes:

*Have you received a pay raise in the last 3 months?*

*Have you changed jobs in the last 3 months?*

When the survey was originally fielded, the average percent chance of search on-the-job over the next 3 months was 25 percent. Three months later, 38 percent of respondents who completed the follow-up survey reported to have searched for a higher-paid job. The average search intention among respondents who ended up searching for a higher-paid job was 46 percent, compared to 12 percent among workers who did not search.

Table 1.7 contrasts realized and planned behavior in more detail. Subjective search probabilities predict ex-post search behavior.<sup>9</sup> In both cases, there is a positive correlation between planned and realized behavior.

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<sup>9</sup>Note that uncertainty and the materialization of shocks may lead to divergences between *ex-ante* assessments and *ex-post* choices.

Table 1.7: Ex-post behavior and ex-ante beliefs

|              | Searched           |
|--------------|--------------------|
| P(search)    | 0.78***<br>(0.059) |
| Constant     | 0.50<br>(0.121)    |
| Controls     | Y                  |
| Observations | 497                |
| R-squared    | 0.301              |

## 1.6 Validating direct effects of inflation expectations

### 1.6.1 A simpler scenario: The effects of housing inflation expectations

In this section, I focus on the particular role of shelter inflation expectations in affecting individuals' job search behavior. I elicit expectations of *local* rental prices.<sup>10</sup> While inflationary pressures have eased since the peak in June 2022 (9.1%), shelter inflation has been taking longer to cool off (Kmetz et al., 2023). On average, housing services account for one-third of the overall personal expenditures in the United States (Hazell et al., 2022). These facts illustrate how housing may be particularly salient to survey respondents, and how a scenario around that object may be realistic and easy to understand. Moreover, with regards to the simultaneity issue described in the introduction, a shock to local housing prices is more likely to affect agents' inflation expectations, without spilling-over to expectations about the labor market. In support of the former, Dhamija et al. (2023) find that households overweight house price expectations when thinking about their inflation expectations. With regards to the latter, Kuchler and Zafar (2019) document extrapolation from local home price changes to formation of national inflation expectations but zero effects on unemployment expectations.<sup>11</sup>

I elicit one-year ahead rent inflation expectations  $r_{i0}^e$  and  $r_{i1}^e$  based on the scenario transcribed below:

<sup>10</sup>My focus on rent inflation expectations, instead of house price expectations, is in line with the BLS methodology to measure all shelter component of housing services.

<sup>11</sup>In my survey, the cross-correlations between inflation expectations, rent inflation expectations and unemployment expectations are of 0.43, 0.32 and 0.21, respectively.

### Higher expected rent inflation, *ceteris paribus*

*Suppose the following:*

*The news report that average home rents in the city where you live are expected to increase by 9 percent over the next 12 months. This expected increase in rents is not caused by changes in jobs, wages or other prices.*

Let  $S_i$  denote the same baseline search as previously defined and  $S_i^R$  define search under the direct scenario.

*In this scenario, by what percentage do you think home rents in your area will increase over the next year?*

On average, I find that a 1 pp increase in rent inflation expectations leads to a 0.294 pp increase in intentions to search for higher-paid jobs, and this effect is significant at a 95% confidence level.

Table 1.8 shows how rent expectations change in response to a scenario where local news informs that rents are expected to increase 9% over the next year. As can be seen, rent expectations after the scenario become significantly less dispersed and concentrated around 9%. The 10<sup>th</sup> percentile increases from 0 to 6 percent and the 90<sup>th</sup> percentile decreases from 20 to 14% expected rent inflation. On average, the percent chance of searching for a higher-paid job increases from 23.7 to 26.11%, with median intentions increasing from 8.50 to 14%. On average, ITE are small and feature a significant mass around 0. As can be seen from Figure 1.9, this correspond to a large extent to respondents with baseline 0 percent chances of searching for a higher-paid job. On average, a 1 pp increase in rent inflation expectations leads to a 0.29 pp increase in intentions to search for a higher-paid job.

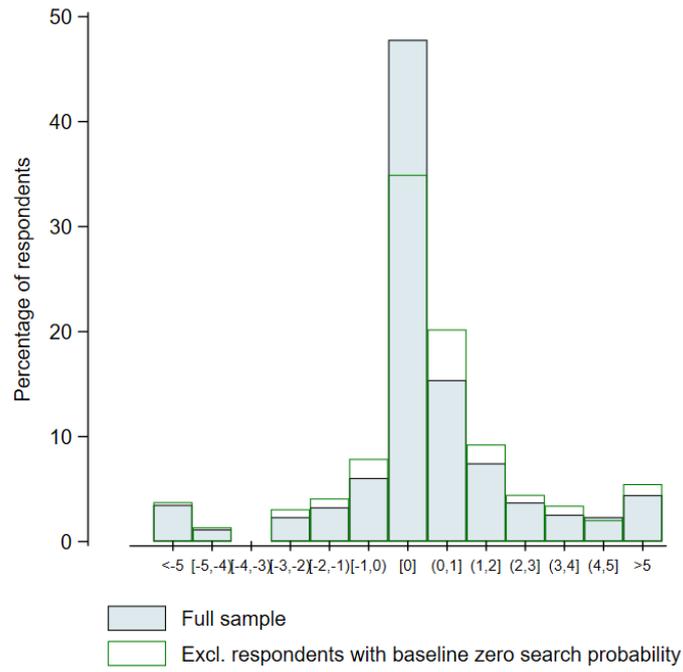


Figure 1.9: Distribution of ITEs to Rent Scenario

Table 1.8: Individual Treatment Effects - Rent scenario

|      | $r_0^e$ | $r_1^e$ | $p_0(\text{search})$ | $p_1(\text{search})$ | ITE  |
|------|---------|---------|----------------------|----------------------|------|
| Mean | 7.84    | 10.25   | 23.71                | 26.11                | 0.29 |
| SD   | 7.82    | 5.11    | 31.51                | 31.23                | 3.46 |
| p10  | 0       | 6       | 0                    | 0                    | -1   |
| p25  | 2       | 9       | 0                    | 1                    | 0    |
| p50  | 5.5     | 9       | 8.5                  | 14                   | 0    |
| p75  | 12      | 10      | 39                   | 40                   | 0.6  |
| p90  | 20      | 14      | 76                   | 81                   | 2.79 |

Table 1.9 shows nearly 48% of respondents do not change intentions to search following the rent shock, 35% increase intentions to search and 16.8% decrease search intentions.

Table 1.9: Share ITE responses, by sign

|        | Sign of ITE |      |          |
|--------|-------------|------|----------|
|        | Negative    | Zero | Positive |
| Search | 0.17        | 0.48 | 0.35     |

**Heterogeneity** Table 1.10 shows heterogeneity of individual treatment effects along observable characteristics. The baseline category is defined as previously. The first column is, as before, a regression of baseline search behavior on observable characteristics.

Consistent with the general inflation scenario (Columns 3 and 5 of Table ??), ITEs are lower for female and non-college educated individuals. However, some new results emerge compared to the direct effects estimated before. We see that renters have higher baseline search intentions, but also higher ITEs to the rent scenario; Additionally, there are heterogeneous ITEs with respect to age, with lower estimated ITEs for all age categories compared to the baseline of 30 to 40 years old. Lastly, individuals who never had a pay raise have a higher estimated ITE compared to individuals who had a pay raise sometime over the past year.

## 1.7 Further robustness, extensions and discussion

### 1.7.1 Zero individual treatment effects

As highlighted in Section 1.4, a sizeable share of respondents does not change their planned behavior in the scenarios. To respondents who, for one of the scenarios, did not change their intentions to search, the survey asks why. Respondents can select all options that apply from the following: a) Scenario is not different enough b) Chances of *finding* a higher-paid job would not be affected by the scenario c) Doesn't know how to look for a higher-paid job d) Doesn't have time to look for a higher-paid job e) Satisfied with my current job or f) The scenario was difficult to understand. In providing this list of options, I account for three main reasons behind zero-effects:

Table 1.10: Heterogeneity in ITE - on-the-job search - rent scenario

|                              | Search             | ITE               |                    |
|------------------------------|--------------------|-------------------|--------------------|
|                              |                    | Size OLS          | Sign -<br>Oprobit  |
| Under 30 years old           | -3.98<br>(5.22)    | -1.16**<br>(0.53) | -0.20<br>(0.20)    |
| Between 40 and 50 years      | 1.60<br>(4.34)     | -0.65<br>(0.44)   | -0.50***<br>(0.17) |
| Between 50 and 60 years      | -1.40<br>(4.92)    | 0.14<br>(0.50)    | -0.41**<br>(0.19)  |
| Over 60 years old            | -12.47**<br>(5.69) | -0.65<br>(0.58)   | -0.58***<br>(0.22) |
| Female                       | 2.05<br>(3.46)     | -0.66*<br>(0.35)  | -0.27**<br>(0.13)  |
| No college degree            | -1.67<br>(3.62)    | -0.52<br>(0.36)   | -0.29**<br>(0.14)  |
| Renter                       | 9.91***<br>(3.76)  | 0.75**<br>(0.38)  | 0.17<br>(0.15)     |
| Never had a pay raise        | 4.86<br>(6.72)     | 0.38<br>(0.70)    | 0.57**<br>(0.26)   |
| Tenure lower than 1 years    | 4.39<br>(7.12)     | 0.69<br>(0.72)    | -0.07<br>(0.27)    |
| Tenure between 1 and 2 years | 19.69***<br>(5.92) | 0.29<br>(0.60)    | -0.06<br>(0.23)    |
| Tenure between 2 and 6 years | 13.25***<br>(3.85) | 0.02<br>(0.39)    | 0.09<br>(0.15)     |
| Constant                     | 20.69***<br>(6.82) | -0.46<br>(0.69)   |                    |
| Other controls               | Y                  | Y                 | Y                  |
| Observations                 | 388                | 380               | 388                |

1. Scenario complexity
2. Expected returns of search relatively low
3. Expected costs of search are relatively high

Table A4 shows, for each scenario, the share of zero individual treatment effects by individuals with baseline zero or hundred percent chances of searching for a job.

Table 1.11: Zero individual treatment effects, by scenario

|                           | Scenario  |              |       |
|---------------------------|-----------|--------------|-------|
|                           | Inflation | Unemployment | Rent  |
| <i>Total Search ITE</i>   | 500       | 418          | 581   |
| of which: Zeros           | 214       | 163          | 230   |
| of which: P(Search) = 0   | 49.5%     | 55.2%        | 49.6% |
| of which: P(Search) = 100 | 15.0%     | 10.4%        | 14.3% |

Across the scenarios, the most common answer was that the scenarios were not different enough to change respondents' planned behavior. The second most frequent answer was that respondents are satisfied with their current job. Third, same chances of finding a higher-paid job - while this is correlated with the first reason, it specifically ties with the expected returns from job search under the two scenarios, rather than potential income effects. Very few respondents mention that they do not know or cannot look for a higher-paid job, and only 3 respondents select difficulty in understanding scenarios as an option for zero changes in planned behavior. Overall, this sub-section suggests that null ITEs may be more reflective of respondents' actual job constraints or non-pecuniary benefits, than of scenario complexity or confusion.

### 1.7.2 Consistency with other empirical evidence

Table 1.12: Comparison with other surveys' expectations

|   | Median one-year<br>ahead inflation expectation<br>(Aug 23) | Mean one-year<br>ahead inflation expectation<br>(Aug 23) | U.S. CPI<br>YoY<br>percent change<br>(Aug 24, BLS) |
|---|--|--|--|
| Survey of Consumer Expectations (NYFed) | 4.9%   |  | 2.5% (all items)                                   |
| Michigan Survey of Consumers            | 3.5%   | 5.6%   | 3.2% (core)  |
| This paper                              | 4%   | 4.7%   |  |

Table 1.12 compares the median and mean one-year ahead inflation expectations of my survey to those in long-running surveys established in the measurement of inflation expectations, the

Survey of Consumer Expectations of the New York Fed and the Michigan Survey of Consumers. The last column of the table shows realized inflation one year later.

My elicitations correlate positively with similar measures in more extensive and widely accepted surveys. The longitudinal nature of these surveys can be used to understand how planned job seeking behavior correlates with realized job-to-job transitions. Figures 1.10 and 1.11 illustrate how realized inflation and job-to-job transitions correlate with self-reported survey measures of on-the-job search behavior - namely, those elicited in the Labor Market Survey, the in-depth quadrimestral module in the SCE focused on job search. Figure 1.10 shows that job-to-job transitions co-move positively with realized inflation. Figure 1.11 shows, especially since 2016, a co-movement between the self-reported percent chances of switching jobs and the actual job-to-job transitions.

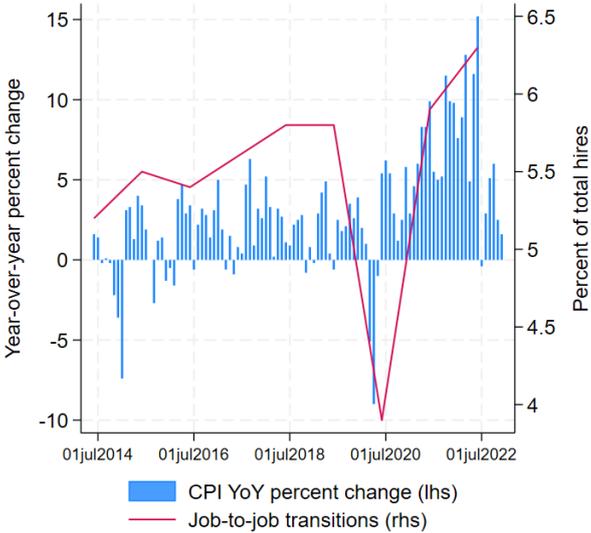
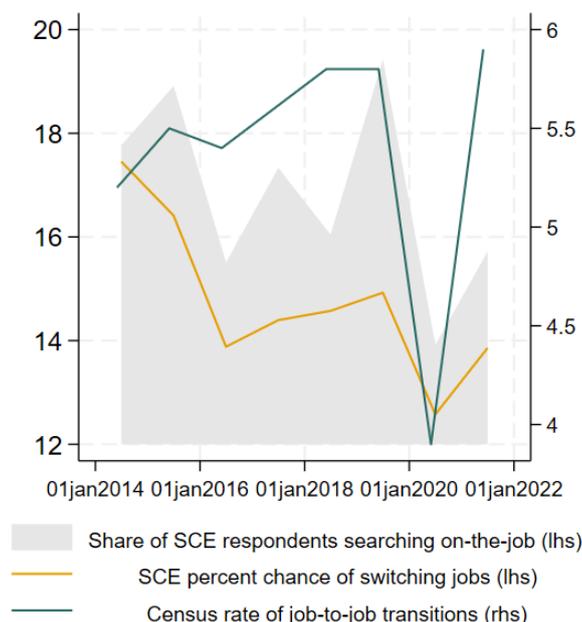


Figure 1.10: Inflation and job-to-job transitions - realizations

Source: Federal Reserve Bank of Cleveland (CPI YoY percent change) and US Census Bureau (Rate of job-to-job hires, non seasonally adjusted).

Figure 1.11: Survey measures of job search and realized job-to-job transitions



Source: Labor Market Survey, Federal Reserve Bank of New York (on-the-job search indicators and percent chance of working for a different employer in 4 months) and US Census Bureau (Rate of job-to-job hires, non seasonally adjusted).

Lastly, Figure A5 shows individual revisions in their unemployment expectations in response to higher inflation expectations. This corresponds to how I defined  $\gamma_i$  in Section 1.2. Around two thirds of respondents revise their unemployment expectations up in response to a 1 percentage point increase in inflation expectations. Most individuals (41% of respondents) revise their unemployment expectations upwards by at most 1 percentage point. For 6% of respondents the magnitude of revisions is between 1 and 2 percentage points, while 8% of respondents revise by more than 2 percentage points. Almost a fifth of respondents (19%) does not revise their unemployment expectations at all. On average, these findings are consistent with findings there is heterogeneity in belief updating even when provided with the same information about macroeconomic variables (Andre et al., 2022), and that on average individuals hold a recessionary view of inflation.

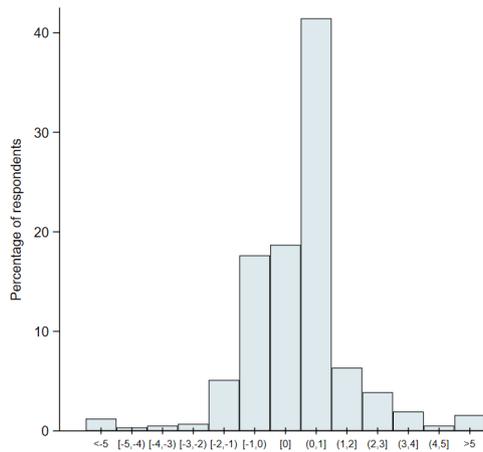


Figure 1.12: Changes in unemployment expectations (pp) given a 1 pp increase in inflation expectations

### 1.7.3 Extensions: other variables

The Data Appendix extends the analysis to workers' propensity to ask employers for a pay raise. Workers are more likely to search on-the-job than to ask for a nominal pay raise. Only a small share of workers would ask directly for a pay raise to their employer. This is compatible with workers facing some degree of nominal wage rigidity, documented in the literature. While the model I present in the next section assumes a specific form of wage rigidity (Calvo) that keeps the analysis tractable, I will comment on how inflation expectations change the wage bargaining outcome. The expected *frequency* of wage renegotiations, however, will be kept fixed by assumption.

### 1.7.4 Consistency with macroeconomic models

A recent literature has focused on effects of monetary policy on labor market flows, and how these flows can result in inflation pressures. To the extent that monetary policy affects households' expectations (Binder et al., 2022), these effects can be related to the ones of this paper. Most studies addressing the effect of monetary policy in frictional labor markets use modelling choices where transmission channels operate through labor demand. For example, when firms use wages to compete over workers, on-the-job search co-moves positively with inflation (Moscarini and Postel-Vinay, 2022). A monetary tightening increases propensity to search on-the-job and resulting job-to-job transitions (Faccini and Melosi, 2023). Graves et al.

(2023) explicitly focuses on the role of labor supply in a partial setting with sticky wages, studying the participation margin. In this stylized model, a monetary contraction produces a substitution (reduces the job finding rate and hence, returns to search) and an income effect (increases the marginal utility of consumption) on workers' decision to participate in the labor market. Cantore et al. (2022) consider a two-agent model with hand-to-mouth and saver households, but no on-the-job search. An increase in interest rates increases debt repayments and generates an income effect in labor supply. In particular, it generates an increase in working hours at the bottom of the income distribution, though on average hours and labor earnings decline. Unconstrained households reduce consumption because of intertemporal substitution, as well as higher returns to savings.

In ongoing work, I study the choice of optimal search intensity through the lens of a New Keynesian Dynamic Stochastic General Equilibrium (NK DSGE) model. The purpose of the model is to provide insight into how inflation expectations theoretically affect on-the-job search, mapping with the direct and indirect effects elicited in the survey. The model features search and matching frictions, as well as nominal price and wage rigidities. The model follows closely the works of Gertler et al. (2020) and Gertler et al. (2008). Workers search on-the-job to improve match quality, but do not directly negotiate their pay when joining a new job, joining the firms' existing payscale. Wages are negotiated in nominal terms and there are wage rigidities. Match surplus is decreasing with expected inflation across all match qualities. I describe the model framework in the Model Appendix, but leave a full-fledged theoretical exposition of the results for future work.

### **1.7.5 Experimenter demand effects**

Recent evidence that demand effects in online experiments is quantitatively small (see Fuster and Zafar (2023); De Quidt et al. (2018); Clifford et al. (2021), and in particular Roth et al. (2022) for evidence on macroeconomic information). I follow best practices to minimize concerns of experimenter demand effects (see, e.g. De Quidt et al. (2019); Falk and Zimmermann (2013)). In particular, the purpose of the survey and instructions are neutrally framed. Respondents are not primed in any direction of updating and are informed that their decisions are anonymous.

### **1.7.6 External validity and reverse causality**

The elicitation of stated choices or behavior may prompt concerns regarding the unbiasedness or external validity of the estimated effects. Evidence (for example, Fuster et al. (2021); Fuster and Zafar (2022)) suggests that if scenarios are realistic and relevant for individuals, stated choices are meaningful and retrieve similar preference estimates to actual choices. With regards to inflation expectations in particular, Coibion et al. (2023) find that transitory shocks in inflation expectations lead to persistent effects on spending. The authors argue that a potential mechanism is revision of planned behavior that is followed through even after the shock has worn out.

A final issue for discussion is that, while I explore the link from inflation expectations to unemployment expectations, it could be argued that the inverse direction also affects behavior. I focus on the causal chain from inflation expectations to unemployment expectations to study responses to inflationary shocks. Additionally, there is empirical evidence that while news about inflation move both inflation and unemployment expectations, news about real economic variables do not generate this co-movement (Hou, 2020).

## **1.8 Conclusion**

The recent inflationary period has revived interest in measuring the role of inflation expectations for nominal wage growth. Studies that take labor market frictions into account show how wage pressures can materialize, of which on-the-job search is an important mechanism. My survey sheds light on how increases in inflation expectations may have heterogeneous effects on individuals' search behavior. These behaviors are important as they could materialize into an effect on aggregate wages. Existing experimental studies contributing to measurement of this response do not take into account that individuals may hold heterogeneous views of what causes higher inflation - depending on how individuals observe or interpret shocks, some may expect unemployment and inflation to co-move positively, and others negatively. By doing that, my work allows for a more complete description, not only by identifying which individuals' responses to expected inflation are muted or exacerbated, but also why.

I find that inflationary pressures may per se increase search for higher-paid jobs. This effect, however, is counteracted by how average individuals think about the real economy in an

inflationary environment. There is rich heterogeneity behind these average effects.

The findings of this paper raise interesting policy implications with respect to Central Bank communication and its use for expectations' management. In particular, this paper highlights how managing expectations of one macroeconomic variable may spill-over to how individuals view the broader economic reality.

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# A Data Appendix

## A1 Aggregating individual treatment effects

The previous sub-sections identify average treatment effects and unpack the underlying heterogeneity at the individual level. Each of the effects is based on two observations per individual, which effectively identify how behavior would change if expectations changed from one point to the other. This change, however, may not be the same for other points of the individual's inflation expectations distribution. To evaluate this, one could elicit behavior conditional on different inflation expectations, keeping unemployment constant. An alternative approach that minimizes the burden on respondents is to interpret these effects as *local*. Under minimal assumptions, I can aggregate responses to identify a curve between expectations and planned behavior. To illustrate, consider Figure A1, that plots survey responses for four hypothetical individuals (A, B, C and D). For each individual, the survey elicitation recovers a linear relationship between two points, corresponding to prior and posterior inflation expectations, respectively.

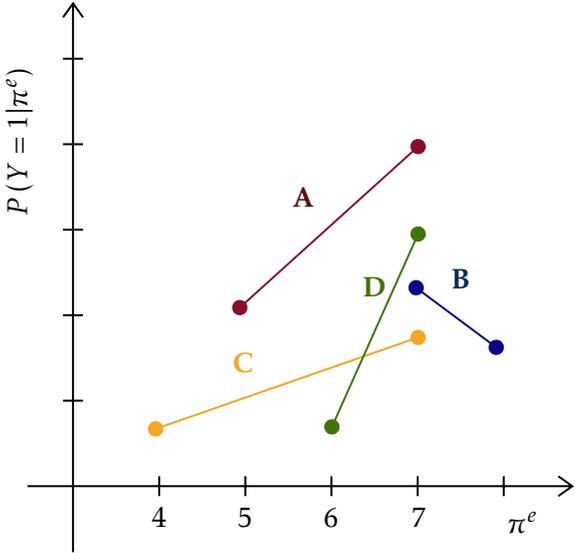


Figure A1: Illustration of hypothetical individual responses

The slope of each line is  $\beta_{i1}$ , the subjective direct effect of inflation expectations on behavior (job search or wage bargaining). A first assumption required is that this effect holds *locally*, this

is, for every point of the inflation expectation distribution between the two elicited points<sup>12</sup>.

For each integer value of inflation expectations  $j$ , let  $\mathcal{J}$  be the set of respondents such that  $j \in [\pi_i^{min}, \pi_i^{max}]$  and  $j+1 \in [\pi_i^{min}, \pi_i^{max}]$ . Let  $N_j$  be the number of respondents in that set. Then, for each  $\pi^e \in [j, j+1]$ , we can estimate an average effect  $\beta_1(j)$ , with standard deviation  $\sigma(j)$ :

$$\beta_1(j) = \frac{1}{N_j} \sum_{i \in \mathcal{J}} \beta_{i1}, \quad \sigma(j) = \sqrt{\frac{1}{N_j - 1} \sum_{i \in \mathcal{J}} (\beta_{i1} - \beta_1(j))^2}$$

As an example, in Figure **A1**, this aggregation method would imply using individual's C response to identify the effect between  $\pi^e = [4, 5)$ ; individuals A and C for  $\pi^e = [5, 6)$ ; individuals A, C and D for  $\pi^e = [6, 7)$ ; and individual B for  $\pi^e = [7, 8)$ .

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<sup>12</sup>Let  $\pi_0^e$  and  $\pi_1^e$  denote the prior and posterior inflation expectations,  $\pi^e \in [\min\{\pi_0^e, \pi_1^e\}, \max\{\pi_0^e, \pi_1^e\}] \equiv [\pi_i^{min}, \pi_i^{max}]$

Figure A2 plots the aggregate relationship between planned behavior and inflation expectations, *ceteris paribus*. In each plot, I estimate  $\beta_1(j)$  and plot 95% confidence bands. In line with previous findings, there is a positive relationship between inflation expectations and both intentions to search, as well as to bargain for a higher nominal wages.

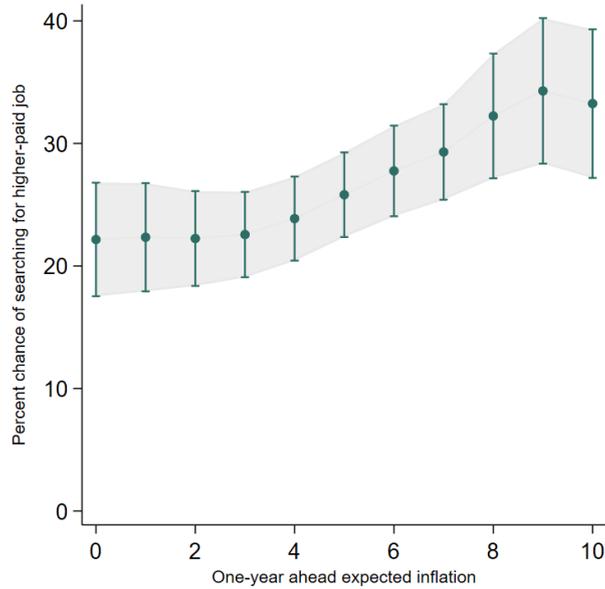


Figure A2: Average treatment effects

## A2 Inflation expectations and wage bargaining

The elicitation is done to the same individuals on the same date and session, and follows the same flow as described in the main text. The elicited objects are:

- Probability of asking current employer for a raise given inflation and unemployment expectations  $P_{it}(Y_{it+3} = 1 | \pi_{i0}^e, u_{i0}^e) \equiv W_i$
- Probability to ask for a pay raise conditional on higher expected inflation, keeping expected unemployment constant:  $P_{it}(Y_{it+3} = 1 | \pi_{i1}^e, u_{i0}^e) \equiv W_i^D$
- Probability to ask for a pay raise conditional on unemployment expectations  $u_1^e$ :  
 $P_{it}(Y_{it+3} = 1 | \pi_{i0}^e, u_{i1}^e) \equiv W_i^I$

The elicitation question is:

*What is the percent chance that you will ask your employer for a pay increase over the next 3 months?*

Table A1: Average treatment effects

|                 | ATE: Inflation expectations |                   |                             |
|-----------------|-----------------------------|-------------------|-----------------------------|
|                 | Direct                      | Indirect          | Total                       |
|                 | $(\beta_1)$                 | $(\beta_2\gamma)$ | $(\beta_1 + \beta_2\gamma)$ |
| Wage bargaining | 1.259***                    | 0.139             | 1.399*                      |
|                 | (0.399)                     | (0.552)           | (0.711)                     |

Table A2 presents similar summary statistics for the reported percent chances of asking for a pay raise following the direct and indirect scenarios. As in the previous sub-section, a scenario where the Fed reports an expected 7% inflation rate shifts the median respondents' expectations under that scenario towards that value. In terms of wage setting behavior, the median percent chance of asking for a pay raise increases from 5 to 8%. The 90<sup>th</sup> percentile also increases from 55 to 58%. On average, the percent chance of asking for a pay raise increases from 17 to 18.4%. The ITE is small on average, with significant heterogeneity.

The indirect scenario shows the effects of a change in unemployment expectations equivalent to that caused by a 1 percentage point increase in inflation expectations. An equivalent change in unemployment expectations generates a small increase on average intentions to ask for a pay raise, from 17.04 to 17.29%. While the median intention increases from 5 to 8 percent, the right-tail of the distribution decreases from 55 to 50%. The extremes of the distribution of ITE are of slightly larger magnitudes than under the inflation expectations scenario.

Table A2: Individual Treatment Effects - wage bargaining

| <i>Direct scenario</i>   |           |           |       |         |                      |
|--------------------------|-----------|-----------|-------|---------|----------------------|
|                          | $\pi_0^e$ | $\pi_1^e$ | $W_i$ | $W_i^D$ | $\beta_{i1}$         |
| Mean                     | 4.46      | 5.88      | 17.04 | 18.41   | 0.96                 |
| SD                       | 4.48      | 4.07      | 25.68 | 25.58   | 7.26                 |
| p10                      | 0         | 0         | 0     | 0       | -3.12                |
| p25                      | 1         | 4         | 0     | 0       | 0                    |
| p50                      | 4         | 7         | 5     | 8       | 0                    |
| p75                      | 7         | 8         | 25    | 25      | 1.97                 |
| p90                      | 10        | 10        | 55    | 58      | 6.67                 |
| <i>Indirect scenario</i> |           |           |       |         |                      |
|                          | $u_0^e$   | $u_1^e$   | $W_i$ | $W_i^I$ | $\beta_{i2}\gamma_i$ |
| Mean                     | 8.98      | 11.18     | 17.04 | 17.29   | 0.10                 |
| SD                       | 9.61      | 10.38     | 25.68 | 23.58   | 9.93                 |
| p10                      | 3         | 4         | 0     | 0       | -3.71                |
| p25                      | 4         | 5         | 0     | 0       | -0.14                |
| p50                      | 5         | 8         | 5     | 8       | 0                    |
| p75                      | 10        | 13        | 25    | 25      | 0.83                 |
| p90                      | 19        | 22        | 55    | 50      | 5                    |

Table A3 shows that in response to a scenario where the Fed announces 7% inflation, 48% of respondents increase intentions to ask for a higher-paid job to their current employer (9 pp higher than search behavior). A scenario focusing instead on unemployment rates increases wage bargaining intention of 37% of respondents, with a larger share of null or negative treatment effects.

Table A3: Share of wage bargaining ITE, by sign

|                   | Sign of ITE |      |          |
|-------------------|-------------|------|----------|
|                   | Negative    | Zero | Positive |
| Direct Scenario   | 0.20        | 0.31 | 0.48     |
| Indirect Scenario | 0.26        | 0.38 | 0.36     |

Participants also reported in the follow-up study actual wage bargaining behavior which can be contrasted to elicited behavior.

*Have you asked your employer for a pay raise in the last 3 months?*

The average 18.5 percent chance of asking employers for a pay raise, which aligns well with the fact that 17 percent of respondents reported having asked for a pay raise 3 months later.

Figure A3 contrasts realized and planned behavior in more detail.

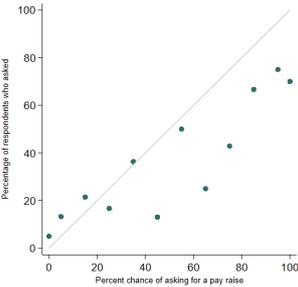


Figure A3: Wage bargaining: planned and realized behavior

Table A4: Zero individual treatment effects, by scenario

| Scenario                         | Inflation | Unemployment |
|----------------------------------|-----------|--------------|
| <i>Wage bargaining behavior:</i> |           |              |
| Zeros                            | 187       | 157          |
| of which: P(Raise) = 0           | 80.7%     | 75.8%        |
| of which: P(Raise) = 100         | 2.7%      | 2.5%         |

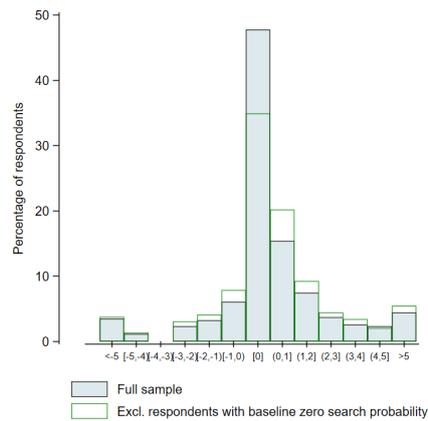
I elicit the main reasons for not asking for a pay raise for individuals with baseline zero percent chances of doing so. The most frequently mentioned reason by survey respondents is that their employer will not accept giving a pay raise (selected by 38% of respondents). A fifth of respondents mention their pay already automatically adjusts for changes in cost of living as the main reason for not asking for a pay raise. For 16% respondents, overall economic conditions are not favourable to asking; Finally, 17% respondents had already recently asked for a pay raise.

Table A5: Reasons for not asking for a pay raise

|   | Share | N  |
|---|-------|----|
| My employer will not accept it                                | 38%   | 93 |
| My pay automatically adjusts to changes in the cost of living | 20%   | 49 |
| I already asked for a pay increase recently                   | 17%   | 41 |
| The economy   | 16%   | 39 |
| My pay is negotiated in collective bargaining                 | 10%   | 23 |
| Current work contract ending soon                             | 2%    | 5  |
| My partner recently had a pay increase                        | 1%    | 2  |

### A3 Additional tables and figures

#### Rent scenario - individual treatment effects



Search

Figure A4: Individual effects of higher rent expectations on search

#### Joint unemployment and inflation expectations

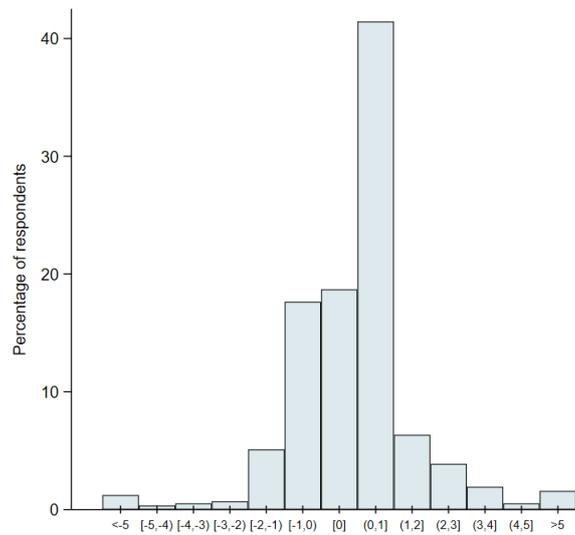


Figure A5: Individual percentage point changes in unemployment expectations in response to a 1 pp increase in inflation expectations

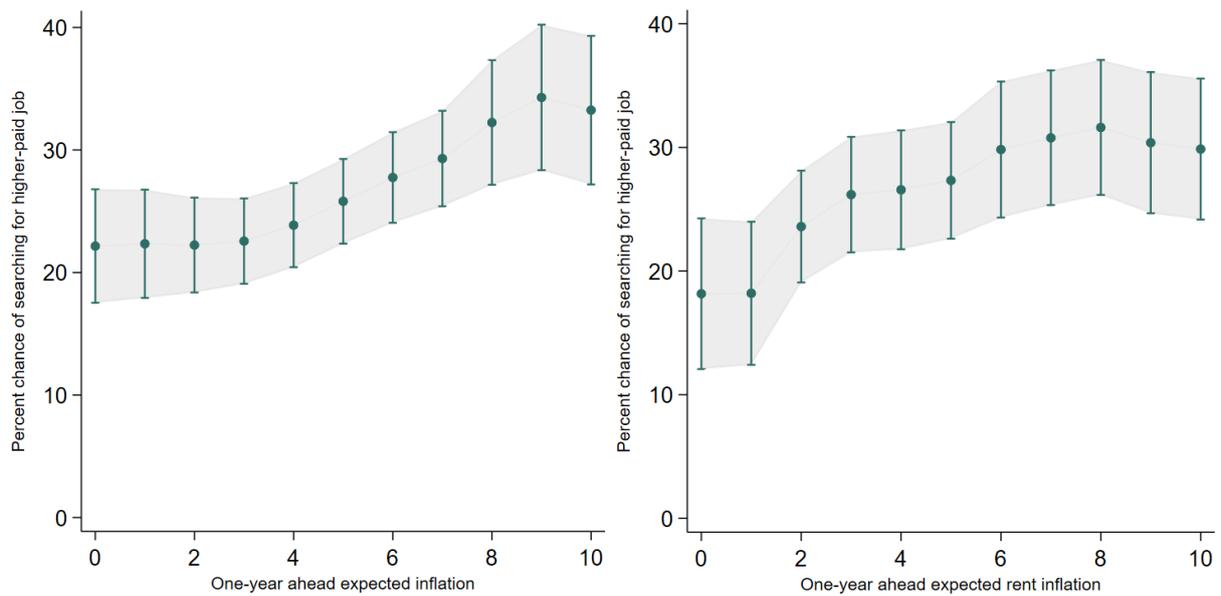


Figure A6: Search behavior and inflation expectations - general and rent inflation

## **B Model appendix**

This appendix studies the choice of optimal search intensity through the lens of a New Keynesian Dynamic Stochastic General Equilibrium (NK DSGE) model. The purpose of the model is to understand the theoretical mechanisms through which inflation expectations may affect on-the-job search, and to map these with the direct and indirect effects elicited in the survey. The model features search and matching frictions, as well as nominal price and wage rigidities. The model follows closely the works of Gertler et al. (2020) and Gertler et al. (2008). The former introduces idiosyncratic match quality and on-the-job search in a search and matching model with staggered wage bargaining. The latter estimates a New Keynesian DSGE with search and matching frictions, but does not consider on-the-job search. I first present the model extensively, but focus my analysis on the labour market block, which the main differentiating element and object of interest.

## B1 Model description

### Environment

There are three types of agents in the economy: households, wholesale firms and retailers. Households consume, save and supply labour to wholesale firms. Wholesale firms hire labour through a search and matching process with idiosyncratic match quality  $k \in \{g, b\}$  and produce intermediate goods sold at relative price  $x_t$ . Retailers operate under monopolistic competition, aggregate intermediate goods into a single final good, and sell this good to households. Retailers choose the price of the final good optimally, given Calvo nominal price rigidities. Furthermore, a monetary authority sets interest rates based on a Taylor rule and a government finances unemployment benefits through lump-sum taxes.

### Timing

Consider the following intra-period timing of events: at the beginning of the period, shocks materialize. A share  $\rho$  of the workforce exogenously separates and can only search in the next period. Wholesale firms post vacancies, workers and firms meet, and matches form. Production takes place by firms with the workforce size and composition reflecting the outcomes from the search and matching process. Firms and workers bargain on the wage with a probability  $\lambda$ . Firms produce and the household consumes and saves.

### Households

There is a representative household with a continuum of family members of measure 1 and perfect consumption insurance (Merz (1995); Andolfatto (1996)). Within the household, a measure  $g_t$  is employed in good matches,  $b_t$  is employed in bad matches, and  $1 - g_t - b_t$  collect unemployment benefits. The family pools all income and benefits before deciding how much to consume and to save. Households do not earn utility from leisure.

Let  $B_{t-1}$  be the beginning of period bonds,  $r_t$  the one-period nominal interest rate,  $p_t$  the nominal price level,  $\Pi_t$  lump-sum profits,  $T_t$  government transfers. There is a number  $l_t$  of employed workers that is determined through a search and matching process, and  $1 - l_t$  unemployed family members. The value of the representative household is  $\Omega_t$ :

$$\Omega_t = \max_{c_t, B_t} \{\log(c_t) + \beta \mathbb{E}_t \Omega_{t+1}\}$$

$$\text{s.t. } c_t + \frac{B_t}{r_t p_t} + c(\zeta_t) = w_t g_t + \phi w_t b_t + (1 - g_t - b_t) u_B + \Pi_t + T_t + \frac{B_{t-1}}{p_t} \quad (\text{c.1})$$

$$g_t = \delta_t^g g_{t-1} + \xi f_t s_t \quad (\text{c.2})$$

$$b_t = \delta_t^b b_{t-1} + \xi \bar{\varphi}_t f_t s_t \quad (\text{c.3})$$

With  $\bar{\varphi}_t$  is the quality mix of bad to good hires in the economy and the total cost of search is given by  $c(\zeta_t) = \frac{\zeta_0}{1+\eta_\zeta} \left( \zeta_g^{1+\eta_\zeta} g_{t-1} + \bar{\zeta}_{bt}^{1+\eta_\zeta} b_{t-1} \right)$ , with  $\bar{\zeta}$  the average search intensity of workers employed in bad matches. Given period employment  $l_t$ , the representative household chooses consumption  $c_t$  and savings  $B_t$  subject to a budget constraint (c.1) and to an employment accumulation equation for good and bad matches (c.2 and c.3, respectively).

### Vacancies, match quality and hires

The search and matching process is analogous to Gertler et al. (2020), with the important difference that new hires start working within the period. Match quality is idiosyncratic, with good matches occurring with probability  $\xi$  and bad matches with probability  $1-\xi$ . Bad matches produce a fraction  $\phi$  of the output produced by good matches. At the beginning of period  $t$ , the existing labour force in efficiency units of firm  $i$  is:

$$l_{it-1} = g_{it-1} + \phi b_{it-1} = (1 + \phi) g_{it-1} \quad (1.3)$$

Firms post vacancies, workers search, and they match randomly. Workers in bad matches search on-the-job with intensity  $\zeta_{bt}$  to improve match quality. Workers in good matches face probability  $\zeta_g$  to search on-the-job for any other match, allowing for relocation shocks. I normalize the search intensity of unemployed workers to 1. After meeting and randomly drawing match quality, firms and workers decide whether or not to actually form a match (i.e. a hire).

Let  $g_{t-1} = \int g_{it-1} di$  and  $b_{t-1} = \int b_{it-1} di$  denote the total of good and bad matches in the economy in the beginning of period  $t$ . Then, the number of unemployed workers in the beginning of the period is:

$$u_{t-1} = 1 - l_{t-1} \quad (1.4)$$

The total efficiency units of search in the labour market at a given time  $t$  is defined as:

$$s_t = u_{t-1} + (1 - \rho)(\zeta_g g_{t-1} + \zeta_b b_{t-1}) \quad (1.5)$$

Where  $(1 - \rho)$  is the probability that the match is not destroyed, and employed workers in good and bad matches are weighted by their respective search intensities. The matching process in the economy is described as:

$$m_t = \sigma_m s_t^\sigma v_t^{1-\sigma} \quad (1.6)$$

Where  $\sigma$  denotes elasticity of matches to units of search effort,  $\sigma_m$  the match efficiency and  $v_t$  the total number of vacancies posted.

The job-finding probability per unit of search intensity in the economy is:

$$f_t = \frac{m_t}{s_t} \quad (1.7)$$

The probabilities of finding a good and bad match are, respectively:

$$f_t^g = \xi f_t \quad f_t^b = (1 - \xi) f_t \quad (1.8)$$

Similarly, a firm that posts a vacancy will meet workers with probability  $q_t^m$ :

$$q_t^m = \frac{m_t}{v_t} \quad (1.9)$$

The probabilities of a posted vacancy resulting in bad and a good hire are, respectively:

$$q_t^b = (1 - \xi) \left( 1 - (1 - \rho) \frac{\zeta_b b_{t-1}}{s_t} \right) q_t^m \quad q_t^g = \xi q_t^m \quad (1.10)$$

These job-filling probabilities account for the fact that hires are conditional on realized match quality.<sup>13</sup> When firms post vacancies, the expected hires in efficiency units are:

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<sup>13</sup>While all good matches lead to hires, bad matches only lead to hires if the worker is either unemployed or employed in a good match and forced to search, which occurs with probability  $\zeta_g$ .

$$q_t = q_t^g + \phi q_t^b \quad (1.11)$$

The number of hires in the economy in a given period are equal to  $q_t v_t$ .

### Firms

Each period, wholesale firms produce output using only labor as an input. The ratio of bad-to-good matches in firm  $i$ ,  $\varphi_{it} \equiv b_{it}/g_{it}$ , describes the quality mix of the firm's total labor force. The stock of labor in efficiency units is:

$$l_{it} = (1 + \phi \varphi_{it}) g_{it} \quad (1.12)$$

The number of good and bad matches in the firm evolves through retentions - workers who do not separate from the firm into unemployment or into another match - and new hires. The laws of motion for good and bad matches in firm  $i$  are:

$$g_{it} = (1 - \rho)(1 - \zeta_g f_t) g_{it-1} + q_t^g v_{it} \equiv \delta_t^g g_{it-1} + q_t^g v_{it} \quad (1.13)$$

$$b_{it} = (1 - \rho)(1 - \zeta_b f_t^g) b_{it-1} + q_t^b v_{it} \equiv \delta_t^b b_{it-1} + q_t^b v_{it} \quad (1.14)$$

Matches separate exogenously with probability  $\rho$ . Retention probabilities in good and bad matches are denoted by  $\delta_t^k, k \in \{g, b\}$ . Their convex combination yields the firm's retention probability of a unit of labour in efficiency units:

$$\delta_{it} = \frac{\delta_t^g + \phi \varphi_{it-1} \delta_t^b}{1 + \phi \varphi_{it-1}} \quad (1.15)$$

The firm's hiring rate is measured with respect to its existing workforce at the beginning of time  $t$ ,  $l_{it-1}$ :

$$x_{it} = \frac{q_t v_{it}}{l_{it-1}} \quad (1.16)$$

The employment stock in firm  $i$  at the end of period  $t$  is:

$$l_{it} = (\delta_{it} + \chi_{it})l_{it-1} \quad (1.17)$$

Let  $x_t$  be the relative price of intermediate goods,  $w_{it}$  the nominal wage per efficiency unit of labour at firm  $i$ ,  $a_t$  the productivity per efficiency unit of labour ( $a_t = \frac{1-\zeta}{l_t}$ ),<sup>14</sup>  $\Lambda_{t,t+1} \equiv \beta\lambda_{t+1}/\lambda_t = \beta u'(c_{t+1})/u'(c_t)$  the firm's discount rate. Firms use their employment stock  $l_{it}$  to produce output  $y_{it} = a_t l_{it}$ . They add labour by choosing the hiring rate for labour in efficiency units,  $\chi_{it}$ . Hiring activities involve costs that are assumed to be quadratic in the hiring rate ( $\chi_{it}$ ) and linear in the existing stock of employment at the time of hiring ( $l_{it-1}$ ).

The firm value  $F$  is homogeneous in the stock of labour, due to the assumption of constant returns. The firm decides the hiring rate to maximize expected discounted profits subject to the laws of motion for labor ( $l_{it}$ ) and quality mix ( $\varphi_{it}$ ), taking as given the expected path of wages  $w_t$ . The value of each firm is:

$$F_t(l_{it-1}, \varphi_{it-1}, w_{it}) = \max_{\chi_{it}, l_{it}} \left\{ x_t a_t l_{it} - \frac{\kappa}{2} \chi_{it}^2 l_{it-1} - \frac{w_{it}}{p_t} l_{it} + E_t \Lambda_{t,t+1} F_{t+1}(l_{it}, \varphi_{it}, w_{it+1}) \right\} \quad (1.18)$$

subject to:

$$\varphi_{it} = \frac{\delta_t^b \varphi_{it-1} + q_t^b v_{it}/g_{it-1}}{\delta_t^g + q_t^g v_{it}/g_{it-1}} = \frac{\delta_t^b \frac{\varphi_{it-1}}{1+\phi\varphi_{it-1}} + \frac{\bar{\varphi}_t^h}{1+\phi\bar{\varphi}_t^h} \chi_{it}}{\delta_t^g \frac{1}{1+\phi\varphi_{it-1}} + \frac{1}{1+\phi\bar{\varphi}_t^h} \chi_{it}}$$

$$l_{it} = (\delta_{it} + \chi_{it})l_{it-1}$$

The firm's hiring decision yields:

$$\kappa \chi_{it} l_{it-1} = x_t a_t l_{it-1} - \frac{w_{it}}{p_t} l_{it-1} + E_t \Lambda_{t,t+1} \frac{\partial F_{t+1}}{\partial \chi_{it}}$$

Now, note that  $F_{t+1} \equiv F_{t+1}(l_{it}(\chi_{it}), \varphi_{it}(\chi_{it}), w_{it+1})$ . Therefore:

$$\frac{\partial F_{t+1}}{\partial \chi_{it}} = \frac{\partial F_{t+1}}{\partial l_{it}} \frac{\partial l_{it}}{\partial \chi_{it}} + \frac{\partial F_{t+1}}{\partial \varphi_{it}} \frac{\partial \varphi_{it}}{\partial \chi_{it}} = \frac{\partial F_{t+1}}{\partial l_{it}} l_{it-1} + \frac{\partial F_{t+1}}{\partial \varphi_{it}} \frac{\partial \varphi_{it}}{\partial \chi_{it}}$$

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<sup>14</sup>The productivity per efficiency unit of labour is independent of the firm and *its logarithm* is assumed to follow an autoregressive process with persistence parameter  $\rho_a$  and standard deviation  $\sigma_a$

Using that:

$$\frac{\partial F_t(l_{it-1}, \varphi_{it-1}, w_{it})}{\partial l_{it-1}} = \frac{\kappa}{2} \chi_{it}^2 + \kappa \delta_{it} \chi_{it}$$

We have:

$$\kappa \chi_{it} l_{it-1} = x_t a_t l_{it-1} - \frac{w_{it}}{p_t} l_{it-1} + E_t \Lambda_{t,t+1} \left[ \frac{\kappa}{2} \chi_{it+1}^2 + \kappa \delta_{it+1} \chi_{it+1} \right] l_{it-1} + E_t \Lambda_{t,t+1} \frac{\partial F_{t+1}}{\partial \varphi_{it}} \frac{\partial \varphi_{it}}{\partial \chi_{it}}$$

Where the second term reflects the composition effect of hiring in the future value of the firm. I follow the assumption in Gertler et al. (2020) that firm retention of good and bad matches is identical in the steady-state. As a result, the steady-state search intensity of workers in good matches will be a fraction  $\xi$  of that of workers in bad matches i.e.  $\xi \zeta_{bt} = \zeta_g$ . Under that assumption, it can be shown that  $\frac{\partial F_{t+1}}{\partial \varphi_{it}} = 0$ .<sup>15</sup> This simplifying assumption lends considerable tractability to the model and allows me to focus on the link between inflation expectations, search intensity and hiring that are not driven by quality composition adjustment motives of the firm.

Given the assumption of constant returns to scale, the firm's hiring decision can be expressed as:

$$\kappa \chi_{it}(\varphi_{it}, w_{it}) = x_t a_t - \frac{w_{it}}{p_t} + E_t \Lambda_{t,t+1} \left[ \frac{\kappa}{2} \chi_{it+1}^2 + \kappa \delta_{it+1} \chi_{it+1} \right]$$

In order to define the wage bargaining process, let the value of the firm of hiring one additional efficiency unit of labour at time  $t$  after workers have already joined the firm at time  $t$ . This is, define this value net of current adjustment costs and taking hiring and worker composition as given,  $J_t(\varphi_{it}, w_{it})$ . We have that:

$$J_t(\varphi_{it}, w_{it}) \equiv \frac{\partial (F_t(l_{it-1}, \varphi_{it-1}, w_{it}) + \frac{\kappa}{2} \chi_{it}^2 l_{it-1})}{\partial l_{it}} = x_t a_t - \frac{w_{it}}{p_t} + E_t \Lambda_{t,t+1} \frac{\partial F_{t+1}}{\partial l_{it}}$$

Where the last term is simply:

$$\frac{\partial F_{t+1}}{\partial l_{it}} = \frac{\partial F_{t+1}}{\partial l_{it}} + \frac{\partial F_{t+1}}{\partial l_{it+1}} \frac{\partial l_{it+1}}{\partial l_{it}} = -\frac{\kappa}{2} \chi_{it+1}^2 + (\delta_{it+1} + \chi_{it+1}) J_{t+1}(\varphi_{it+1}, w_{it+1})$$

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<sup>15</sup>Crucially, it holds that  $\delta + \chi = 1$  in the steady state. See Appendix of Gertler et al. (2020) for further details

This value, which corresponds to the firm's surplus, will consist of average expected profits per efficiency unit of labour:

$$J_t(\varphi_{it}, w_{it}) = x_t a_t - \frac{w_{it}}{p_t} - E_t \Lambda_{t,t+1} \frac{\kappa}{2} x_{it+1}^2 + E_t \Lambda_{t,t+1} (\delta_{it+1} + x_{it+1}) J_{t+1}(\varphi_{it+1}, w_{it+1})$$

## Workers

The value functions for unemployed workers, workers in good matches and workers in bad matches are defined in units of efficient labour. Workers in bad matches search with variable search intensity. The cost of search intensity for each match quality  $k \in \{g, b\}$  is:

$$c(\zeta_{kt}) = \frac{\zeta_0}{1 + \eta_\zeta} \zeta_{kt}^{1 + \eta_\zeta} \quad (1.19)$$

Where  $\eta_\zeta$  is the search cost elasticity and  $\zeta_0$  is a scale parameter. Let the average value of being employed in a match of quality  $k$  at the end of period  $t$  be:

$$\bar{V}_t^k = \int V_t^k(w_{it}^k, \varphi_{it}) dG_t(w, \varphi) \quad (1.20)$$

In the beginning of period  $t$ , workers in bad matches optimally choose search intensity  $\zeta_{bt}$ , taking as given the end of period wages and composition. Workers in bad matches may upgrade to a good match, with average value  $\bar{V}_t^g$ , or continue in their current match, with value  $V_t^b(\varphi_{it}, w_{it})$ . Workers in good matches do not choose their search effort, they simply observe the shock  $\zeta_g$  in the beginning of the period. The value of search for each match quality  $k$  is:<sup>16</sup>

$$S_t^b = \max_{\zeta_{bt}} \{ \zeta_{bt} f_t^g \bar{V}_t^g + (1 - \zeta_{bt} f_t^g) V_t^b - c(\zeta_{bt}) \} \quad (1.21)$$

$$S_t^g = (1 - \zeta_g f_t) V_t^g + \zeta_g (f_t^g \bar{V}_t^g + f_t^b \bar{V}_t^b) - c(\zeta_g) \quad (1.22)$$

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<sup>16</sup>Recall that workers and firms match, but not all matches lead to hires. I express the values of search, employment and unemployment in terms of the average unconditional values of good and bad matches and refer to Gertler et al. (2020, 2008); Gertler and Trigari (2009) for first-order equivalence results between values of matches conditional and unconditional on being hired.

Workers in bad matches will choose, for each given  $(\varphi_{it}, w_{it})$ , the search intensity that equalizes the marginal benefit and cost of one additional search unit:

$$\zeta_0 \zeta_{bt}^{\eta_\zeta} = f_t^g (\bar{V}_t^g - V_t^b) \quad (1.23)$$

Consider the value of being employed in a bad and a good match at time  $t$ . These values are defined after hires take place and are net of current search costs. The value of a worker hired in a bad match employed in firm  $i$  is:

$$V_t^b \equiv V_t^b(\varphi_{it}, w_{it}^b) = \left\{ \frac{w_{bt}}{p_t} + E_t \left\{ \Lambda_{t,t+1} \left[ (1-\rho)S_{t+1}^b + \rho U_{t+1} \right] \right\} \right\} \quad (1.24)$$

The value of a worker hired in a good match will be:

$$V_t^g \equiv V_t^g(\varphi_{it}, w_{it}^g) = \left\{ \frac{w_{gt}}{p_t} + E_t \left\{ \Lambda_{t,t+1} \left[ (1-\rho)S_{t+1}^g + \rho U_{t+1} \right] \right\} \right\} \quad (1.25)$$

The value of an unemployed worker is:

$$U_t = u_B + E_t \left[ \Lambda_{t,t+1} \left[ f_{t+1}^g \bar{V}_{t+1}^g + f_{t+1}^b \bar{V}_{t+1}^b + (1-f_{t+1})U_{t+1} \right] \right] \quad (1.26)$$

I now define the match surplus, which will be essential to characterize the contract wage. The match surplus for a workers in a good and bad matches will be, respectively:

$$H_t \equiv H_t(\varphi_{it}, w_{it}) = V_t^g - U_t \quad (1.27)$$

$$H_t^b \equiv H_t^b(\varphi_{it}, w_{it}) = V_t^b - U_t \quad (1.28)$$

### Wage-setting

There is staggered Nash wage bargaining, where wage contracts are negotiated in *nominal* terms. Define  $\pi_t = p_t/p_{t-1}$ . Let  $w$  denote the nominal wage per unit of labour quality. As such,  $w$  will be the nominal wage of a good match, and  $\phi w$  the nominal wage of a bad match. For simplicity, I follow Gertler et al. (2020) and assume that wage bargaining is led by workers in good matches, and workers in bad matches simply reap the quality-adjusted bargained nominal wage.

Every period, there is a probability  $1 - \lambda$  to renegotiate the wage. In other words, each period there is a share  $\lambda$  of firms that cannot renegotiate the contract wage. Firms who cannot renegotiate wages will index wages to past inflation according to the following rule:

$$w_{it} = \pi_t^\gamma w_{it-1}, \quad \gamma \in (0, 1) \quad (1.29)$$

Let  $w_{it}^*$  denote the nominal wage per unity of labour quality chosen if wage renegotiations are possible at time  $t$ . Let  $H_t$  and  $J_t$  denote the match surplus for workers employed in good matches and for firms, as defined in the previous sub-section. The optimally renegotiated wage  $w_{it}^*$  is chosen to maximize the Nash product of one unit of labour quality to a firm and a worker in a good match:

$$\max_{w_{it}^*} H_t^\eta (w_{it}^*) J_t^{1-\eta} (w_{it}^*) \quad (1.30)$$

subject to:

$$w_{it+j} = \begin{cases} w_{it+j-1} \pi_{t+j-1}^\gamma, & \text{with probability } \lambda \\ w_{it+j-1}^*, & \text{with probability } 1 - \lambda \end{cases}, \quad \text{for every } t + j, j \geq 1.$$

The expected duration of an optimally chosen contract wage will be  $\frac{1}{1-\lambda}$ , where  $\lambda$  is a measure of nominal wage stickiness in the economy. The first order condition is:

$$\chi_t^* J_t^* = (1 - \chi_t^*) H_t^* \quad (1.31)$$

$$\chi_t^* = \frac{\eta}{\eta + (1 - \eta) \mu_t^* / \epsilon_t^*} \quad (1.32)$$

Where  $\epsilon_t^* = p_t \partial H_t^* / \partial w_{it}^*$  and  $\mu_t(\varphi_{it}, w_{it}) = -p_t \partial J_t(\varphi_{it}, w_{it}^*) / \partial w_{it}^*$  will be the effects of a rise in the real wage on the worker and firm surpluses, respectively. I express  $\epsilon_t$  and  $\mu_t$  recursively as:

$$\epsilon_t = 1 + (1 - \rho) \lambda E_t \Lambda_{t,t+1} (1 - \zeta_g f_{t+1}) \pi_t^\gamma \frac{P_t}{P_{t+1}} \epsilon_{t+1} + \mathcal{O}_1 \quad (1.33)$$

$$\mu_t(w_{it}^*) = 1 + \lambda E_t \Lambda_{t,t+1} \pi_t^\gamma \frac{P_t}{P_{t+1}} \mu_{t+1}(\pi_t^\gamma w_{it}^*) + \mathcal{O}_2 \quad (1.34)$$

Where  $\mathcal{O}_1$  and  $\mathcal{O}_2$  are composition terms that are equal to zero up to a first order in the steady-state. Average nominal wages per unit of labour quality are defined as:

$$w_t = \int_{w,\varphi} w_{it} dG_t(\varphi, w)$$

To a first order approximation, the evolution of average nominal wages per unit of labour quality is equal to a linear combination of the target nominal wage contract and last period's nominal wages partially adjusted to inflation:

$$w_t = (1 - \lambda)w_t^* + \lambda \int_{w,\varphi} (\pi_t^\gamma w_{it-1}) dG_{t-1}(\varphi, w)$$

### Retailers and price-setting

There is a measure one of monopolistic competitive retailers indexed by  $j$ . These retailers repack goods produced by wholesalers into intermediate goods, and price them at nominal  $p_{jt}$ . Intermediate goods  $y_{jt}$  are purchased by a competitive final goods sector, that aggregates them into a final good  $y_t$ , taking the final price  $p_t$  as given.

$$y_t = \left[ \int_0^1 y_{jt}^{\frac{\varepsilon_p - 1}{\varepsilon_p}} dj \right]^{\frac{\varepsilon_p}{\varepsilon_p - 1}} \quad (1.35)$$

where  $\varepsilon_p$  denotes the elasticity of substitution between different varieties. The demand facing retailer  $j$  will be:

$$y_{jt} = \left( \frac{p_{jt}}{p_t} \right)^{-\varepsilon_p} y_t, \text{ with } p_t = \left( \int_0^1 p_{jt}^{1-\varepsilon_p} dj \right)^{\frac{1}{1-\varepsilon_p}}$$

Retailers are price-setters in this economy. They purchase intermediate goods at relative price  $x_t$  and choose  $p_{jt}^*$  to maximize expected discounted future profits. There are Calvo-style nominal price rigidities: every period, retailers have a probability  $1 - \psi$  of choosing  $p_{jt}^*$ . Formalizing the optimization problem of retailer  $j$ :

$$\begin{aligned} \max_{p_{jt}} \quad & \Pi_t = \left( \frac{p_{jt}}{p_t} - x_t \right) y_{jt} + \psi E_t \Lambda_{t,t+1} \Pi_{t+1} \\ \text{s.t.} \quad & y_{jt} = \left( \frac{p_{jt}}{p_t} \right)^{-\varepsilon_p} y_t \end{aligned}$$

As can be seen from the first order condition, the optimal price  $p_{jt}^*$  will be a function of  $p_t x_t$ , the nominal marginal cost faced by the retailers. This nominal marginal cost is simply the relative nominal price of the wholesale good.

From the hiring equation of wholesale firms, we can express the real marginal cost faced by retailers ( $x_t$ ) as a function of real wages and of current and expected future discounted hiring costs.<sup>17</sup>

$$x_t = \frac{1}{a_t} \left[ \kappa \chi_{it}(\varphi_{it}, w_{it}) + \frac{w_{it}}{p_t} - E_t \Lambda_{t,t+1} \left[ \frac{\kappa}{2} \chi_{it+1}^2 + \kappa \delta_{it+1} \chi_{it+1} \right] \right]$$

In this environment, the aggregate price level will be:

$$p_t = (1 - \psi)p_t^* + \psi p_{t-1} \quad (1.36)$$

**Monetary policy** There is a monetary authority that sets rates based on the following Taylor rule:

$$r_t = r(\pi_t)^\phi e^{\varepsilon_t^m} \quad (1.37)$$

Where  $\varepsilon_t^m$  is a monetary policy shock.

**Government** The government finances unemployment benefits through lump-sum transfers:

$$T_t + (1 - g_t - b_t)u_B = 0 \quad (1.38)$$

**Resource constraint** Aggregate output is equal to the total of resources allocated towards consumption, vacancy posting costs and search costs:

$$y_t = c_t + \frac{\kappa}{2} \int_0^1 \chi_t^2 l_{it-1} di + \frac{\zeta_0}{1 + \eta_\zeta} (1 - \rho) \left( \zeta_n^{1 + \eta_\zeta} g_t + \zeta_{bt}^{1 + \eta_\zeta} b_t \right) \quad (1.39)$$

**The role of prices** How do current prices  $p_t$  affect optimal search? From the optimal hiring condition, we can observe that an increase in  $p_t$  reduces unit labour costs  $\frac{w_{it}}{p_t}$  and increases  $\chi_{it}$ .

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<sup>17</sup>See ? for discussion on how search and matching frictions change the nature of the real marginal cost through use of labor.

As a result, firms post more vacancies,  $f_t$  increases, and the probability of finding a good match  $f_t^g = \xi f_t$  also increases. To assess how prices affect the flow value of improving match quality i.e.  $\bar{V}_t^g - V_t^b$ , note that we can write it as:

$$\bar{V}_t^g - V_t^b = \int \frac{w_{it}^g}{p_t} dG_t(w, \varphi) - \frac{w_{it}^b}{p_t} + E_t \left[ \Lambda_{t,t+1} \left[ (1 - \rho) \bar{S}_{t+1}^g - S_{t+1}^b \right] \right] \quad (1.40)$$

$$\bar{S}_{t+1}^g = \bar{V}_{t+1}^g + f_t^b \bar{V}_{t+1}^b - c(\zeta_g) \quad (1.41)$$

$$S_{t+1}^b = \max_{\zeta_{bt+1}} \left\{ \zeta_{bt+1} f_{t+1}^g \bar{V}_{t+1}^g + (1 - \zeta_{bt+1} f_{t+1}^g) V_{t+1}^b - c(\zeta_{bt+1}) \right\} \quad (1.42)$$

From (21) we see that higher  $p_t$  erodes the difference in flow gains from upgrading match quality

$$\int \frac{w_{it}^g}{p_t} dG_t(w, \varphi) - \frac{w_{it}^b}{p_t}$$

## B2 Expected inflation, hiring and search intensity

To deepen the intuition about the mechanisms through which expected inflation affects on-the-job search, I derive log-linear equations that describe search and hiring dynamics. A more detailed account of these results is available in the following sections. Let  $\hat{y}_t$  denote the log-deviation of any variable  $y_t$  at time  $t$  from its steady state value  $\bar{y}$ .

The loglinearized surplus for a worker in a good match is:

$$\begin{aligned}\hat{H}_t &= \frac{\bar{w}^r}{\bar{H}} (\hat{w}_t^{*r} + \lambda\beta\delta\epsilon E_t(\hat{w}_t^{*r} + \gamma\hat{\pi}_t - \hat{\pi}_{t+1} - \hat{w}_{t+1}^{*r})) + \\ &\beta(1 - \rho - \delta) \frac{\bar{H}^a}{\bar{H}} E_t(\hat{\Lambda}_{t,t+1} + \hat{H}_{t+1}^a) - f\beta \frac{\bar{H}^a}{\bar{H}} E_t(\hat{f}_{t+1} + \hat{H}_{t+1}^a + \hat{\Lambda}_{t,t+1}) + \\ &+ \beta(\delta - 1 - \rho) \left(1 - \frac{\bar{H}^a}{\bar{H}}\right) E_t \hat{f}_{t+1} + \beta\delta E_t(\hat{\Lambda}_{t,t+1} + \hat{H}_{t+1}^a)\end{aligned}$$

Where  $\epsilon = \partial H / \partial w$  evaluated at the steady state,  $w^r$  denotes *real* wages,  $H^a$  denotes the surplus in *all* matches (good and bad) and  $f_{t+1}$  denotes the probability of finding *any* match. Focusing on the first term, we can observe that surplus of workers in good matches *decreases* with expected inflation.

Similarly, the surplus of workers employed in bad matches is:

$$\begin{aligned}\hat{H}_t^b &= \frac{\phi\bar{w}^r}{H^b} (\hat{w}_t^{*r} + \beta\lambda\delta\epsilon E_t(\gamma\hat{\pi}_t + \hat{w}_t^{*r} - \hat{\pi}_{t+1} - \hat{w}_{t+1}^{*r})) + \chi_\Lambda E_t \hat{\Lambda}_{t,t+1} + \chi_f E_t \hat{f}_{t+1} \\ &+ \delta\beta E_t \hat{H}_{t+1}^b(w_{t+1}^*) + \beta(1 - \rho - \delta) \frac{\bar{H}}{H^b} E_t \hat{H}_{t+1} - \beta f \frac{\bar{H}^a}{H^b} E_t(\hat{H}_{t+1}^a)\end{aligned}$$

Where  $\chi_\Lambda$  and  $\chi_f$  are functions of the model's primitives and are reported extensively in the next subsections. As expected, expected inflation decreases the surplus of workers in bad matches as well.

The loglinearized optimal search intensity for a worker in a bad match is:

$$\eta \hat{c}_{bt}(w_t^*) = \frac{(\bar{H}\hat{H}_t - H^b\hat{H}_t^b(w_t^*))}{\bar{H} - H^b} + \hat{f}_t^g$$

Where  $\bar{H} - H^b$  is the steady-state difference in the surplus from a good and a bad match and  $\hat{f}_t^g$  denotes log-deviations from the steady-state probability of finding a good match. Search

intensity of workers in bad matches will be increasing in the surplus of good matches relative to bad matches, as well as in the probability of finding a good match. Recall that:

$$\hat{f}_t^g = \hat{f}_t = \hat{m}_t - \hat{s}_t$$

The loglinearized hiring rate is:

$$\begin{aligned} \hat{\chi}_t(w_t^*) &= \frac{xa}{\kappa\bar{\chi}}(\hat{\chi}_t + \hat{a}_t) - \frac{\bar{w}^r}{\kappa\bar{\chi}}\hat{w}_t^r + \beta\lambda E_t(\hat{\chi}_{t+1}(\pi_t^\gamma w_t^*) - \hat{\chi}_{t+1}(w_{t+1}^*)) + \frac{\beta}{2}(1 + \delta)E_t\hat{\Lambda}_{t,t+1} + \\ &\beta\delta\lambda E_t(\hat{\delta}_{t+1}(\pi_t^\gamma w_t^*) - \hat{\delta}_{t+1}(w_{t+1}^*)) + \beta\delta E_t(\hat{\delta}_{t+1}(w_{t+1}^*)) + \beta E_t(\hat{\chi}_{t+1}(w_{t+1}^*)) \end{aligned}$$

Deviations from steady-state hires are driven by expected future changes in the firm's labor force, through hires and retentions. These, in turn, can be expressed recursively, so that:

$$\begin{aligned} \hat{\chi}_t(w_t^*) &= \frac{xa}{\kappa\bar{\chi}}(\hat{\chi}_t + \hat{a}_t) - \frac{\bar{w}^r}{\kappa\bar{\chi}}\hat{w}_t^r - \frac{\bar{w}}{\kappa\bar{\chi}}\mu E_t(\gamma\hat{\pi}_t + \hat{w}_t^{*r} - \hat{\pi}_{t+1} - \hat{w}_{t+1}^{*r}) + \\ &+ \frac{1 - \rho - \delta}{\delta\eta} \frac{\phi\bar{w}^{*r}}{\bar{H} - H^b} \epsilon E_t(\gamma\hat{\pi}_t + \hat{w}_t^{*r} - \hat{\pi}_{t+1} - \hat{w}_{t+1}^{*r}) \\ &+ \frac{\beta}{2}(1 + \delta)E_t\hat{\Lambda}_{t,t+1} + \beta\delta E_t(\hat{\delta}_{t+1}(w_{t+1}^*)) + \beta E_t(\hat{\chi}_{t+1}(w_{t+1}^*)) \end{aligned}$$

On the one hand, higher expected future inflation increases current period hires ( $\frac{\bar{w}\mu}{\kappa\bar{\chi}}$ ). As can be seen by the fourth term of the equation above, this positive effect is however tapered by the changes in expected retention of matches, which depend on  $\eta$  (the cost of search elasticity).

**Discounting and expected inflation** An increase in expected inflation in  $t + 1$  decreases the marginal utility of consumption at  $t$ . Recall that the discount rate of firms in the model is  $\Lambda_{t,t+1} \equiv \beta u'(c_{t+1})/u'(c_t)$ , with  $u'(c_t) = r_t\beta E_t\left(\frac{\lambda_{t+1}}{\pi_{t+1}}\right)$ . Consequently, an increase in expected inflation will *increase* the discount rate of firms and workers use in the labor market to make search and hiring decisions. Firms discount more heavily the hiring costs they will have to pay on their next period labor force - this in turn, affects hiring decisions in the present period. Workers will discount more heavily future possible upgrades in match quality, even though inflation *erodes* the difference in flow values from good and bad matches.

In this appendix, I follow GHT20 closely and show that, under the assumption of equal retention of good and bad quality matches in the steady-state, there is no composition effect in nominal

wage setting. The proof follows the structure of the Appendix of GHT20, and is established by using a set of auxiliary results, which I also prove. The appendix is structured as follows: first, I present the set of auxiliary results which allow me to prove the lack of composition effect; then, I present two results that allow me to conveniently express the average surplus as approximately the surplus in a firm with an average wage and average composition; Finally, I derive the loglinearized equations of the labor market block of the model. Note that, while my model and results build from GHT20, it differs from the authors' model in important ways, namely *nominal* wage rigidity, model timing and the existence of within-period hires. As such, it is not straightforward that their results carry over to my setting, which justifies the need for derivations.

### B3 The average contract wage

To derive the average contract wage through the Nash Bargaining first order condition, I need the average firm surplus and the average workers' surplus in good matches in renegotiating firms. While the wage is negotiated by workers in good matches, the contract wage will depend on average retention rates, which hinge on search intensity of workers in bad matches. This, in turn, depends on the surplus of the workers employed in these bad matches.

Take a firm  $i$  renegotiating wages. With probability  $\lambda$ , next period's nominal wage  $w_{it+1}$  will be equal to this period's wage adjusted for inflation  $\pi_t^\gamma w_{it}^*$ . With probability  $1 - \lambda$ , it will be equal to next period's target nominal wage  $w_{it+1}^*$ . The Nash bargaining condition (recall,  $w^*$  is nominal) will be:

$$\begin{aligned}\chi_t^* J_t^*(\varphi_{it}, w_{it}^*) &= (1 - \chi_t^*) H_t^*(\varphi_{it}, w_{it}^*) \\ \chi_t^* &= \frac{\eta}{\eta + (1 - \eta)\mu_t^*/\epsilon_t^*}\end{aligned}$$

With:

$$\begin{aligned}\epsilon_t(\varphi_{it}, w_{it}^*(\varphi_{it})) &= p_t \frac{\partial H_t(\varphi_{it}, w_{it}^*(\varphi_{it}))}{\partial w_{it}^*(\varphi_{it})} \\ \mu_t(\varphi_{it}, w_{it}^*(\varphi_{it})) &= -p_t \frac{\partial J_t(\varphi_{it}, w_{it}^*(\varphi_{it}))}{\partial w_{it}^*(\varphi_{it})}\end{aligned}$$

In particular, we can show that these can be written recursively as:

$$\begin{aligned}\epsilon_t &= 1 + (1 - \rho)\lambda E_t \Lambda_{t,t+1} (1 - \zeta_g f_{t+1}) \pi_t^\gamma \frac{p_t}{p_{t+1}} \epsilon_{t+1} + \mathcal{O}_1 \\ \mu_t(w_t^*) &= 1 + \lambda E_t \Lambda_{t,t+1} [\delta_{it+1} + x_{it+1}] \pi_t^\gamma \frac{p_t}{p_{t+1}} \mu_{t+1}(\pi_t^\gamma w_t^*) + \mathcal{O}_2\end{aligned}$$

Where  $\mathcal{O}_1$  and  $\mathcal{O}_2$  are composition terms which will be zero in the steady-state.

The goal is to solve for the **average** contract wage  $w_t^*$ . In order to solve for the contract wage, we need the log-linearized expressions for the average firm and worker surplus. I drop the subscript  $i$  to refer to a firm with average wage and average composition. First, the log-linearized Nash bargaining condition for a renegotiating firm with average composition is:

$$\hat{J}_t(\varphi_t, w_t^*) + (1 - \chi)^{-1} \hat{\chi}_t(w_t^*) = \hat{H}_t(\varphi_t, w_t^*)$$

### Average worker surplus in good matches

$$\begin{aligned}H_t(\varphi_t, w_t^*) &= \frac{w_t^*}{p_t} - u_B + \\ E_t \Lambda_{t,t+1} &\left[ (1 - \rho)(1 - \zeta_g f_{t+1}) \left[ \lambda H_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_t^*) + (1 - \lambda) H_{t+1}(\varphi_{it+1}, w_{it+1}^*) \right] \right] + \\ &+ E_t \Lambda_{t,t+1} \left[ (1 - \rho) \zeta_g f_{t+1} \bar{H}_{t+1}^a - f_{t+1} \bar{H}_{t+1}^a \right]\end{aligned}$$

Which can be re-written as:

$$\begin{aligned}H_t(\varphi_t, w_t^*) &= \frac{w_t^*}{p_t} - u_B \\ &+ \lambda E_t \Lambda_{t,t+1} \left[ (1 - \rho)(1 - \zeta_g f_{t+1}) \right] \left[ H_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_t^*) - H_{t+1}(\varphi_{it+1}, w_{it+1}^*) \right] \\ &+ E_t \Lambda_{t,t+1} \left[ (1 - \rho)(1 - \zeta_g f_{t+1}) \right] H_{t+1}(\varphi_{it+1}, w_{it+1}^*) \\ &+ E_t \Lambda_{t,t+1} \left[ (1 - \rho) \zeta_g f_{t+1} \bar{H}_{t+1}^a - f_{t+1} \bar{H}_{t+1}^a \right]\end{aligned}$$

Using the definition of retention rate  $\delta_{t+1}^g = (1 - \rho)(1 - \zeta_g f_t)$ , log-linearizing and using  $w^r$  to express the *real* wage:

$$\begin{aligned}\bar{H} \hat{H}_t &= \bar{w}^r \hat{w}_t^r + \\ \lambda \beta \bar{\delta}^g \bar{H} E_t &(\hat{H}_{t+1}(\pi_t^\gamma w_{it}^*) - \hat{H}_{t+1}(w_{it+1}^*)) + \\ &+ \beta \bar{\delta}^g \bar{H} E_t (\hat{\Lambda}_{t,t+1} + \hat{\delta}_{t+1}^g + \hat{H}_{t+1}) + \\ &+ E_t \beta \bar{H}^a (1 - \rho - \delta^g - f) (\hat{H}_{t+1}^a + \hat{\Lambda}_{t,t+1} + \hat{f}_{t+1})\end{aligned}$$

Using  $\epsilon_t = 1 + \lambda E_t \Lambda_{t,t+1} \delta_{t+1}^g \pi_t^\gamma \frac{p_t}{p_{t+1}} \epsilon_{t+1}$ :

$$E_t[H_{t+1}(\pi_t^\gamma w_t^*) - H_{t+1}(w_{t+1}^*)] = E_t \epsilon_{t+1} \left( \pi_t^\gamma \frac{w_t^{*r}}{\pi_{t+1}} - w_{t+1}^{*r} \right)$$

Log-linearizing around the steady state, defining the steady-state values of the surplus in good matches  $\bar{H}$ , the steady-state real wage  $\bar{w}^r$  and defining  $\epsilon = \frac{1}{1-\delta^g \lambda \beta}$ :

$$E_t[\hat{H}_{t+1}(\pi_t^\gamma w_t^*) - \hat{H}_{t+1}(w_{t+1}^*)] = \frac{\bar{w}^r}{\bar{H}} \epsilon E_t(\hat{w}_t^{*r} + \gamma \hat{\pi}_t - \hat{\pi}_{t+1} - \hat{w}_{t+1}^{*r})$$

Substituting into the main expression, using  $\delta^g \delta^g = -(1-\rho)\zeta_g f \hat{f} = (\delta^g - (1-\rho))\hat{f}$ , rearranging and using the surplus approximation  $\hat{H}_{t+1}(\varphi_{it+1}, w_{it+1}^*) = \hat{H}_{t+1}(\varphi_{t+1}, w_{t+1}^*)$ :

$$\begin{aligned} \hat{H}_t(\varphi_t, w_t^*) &= \frac{\bar{w}^r}{\bar{H}} \left( \hat{w}_t^r + \lambda \beta \delta^g \epsilon E_t(\hat{w}_t^{*r} + \gamma \hat{\pi}_t - \hat{\pi}_{t+1} - \hat{w}_{t+1}^{*r}) \right) + \\ &\beta(1-\rho-\delta^g) \frac{\bar{H}^a}{\bar{H}} E_t(\hat{\Lambda}_{t,t+1} + \hat{H}_{t+1}^a) - f \beta \frac{\bar{H}^a}{\bar{H}} E_t(\hat{f}_{t+1} + \hat{H}_{t+1}^a + \hat{\Lambda}_{t,t+1}) + \\ &+ \beta(\delta^g - 1 - \rho) \left( 1 - \frac{\bar{H}^a}{\bar{H}} \right) E_t \hat{f}_{t+1} + \beta \delta^g E_t(\hat{\Lambda}_{t,t+1} + \hat{H}_{t+1}(\varphi_{t+1}, w_{t+1}^*)) \end{aligned}$$

### Average firm surplus in good matches

$$\begin{aligned} J_t(\varphi_t, w_t^*) &= x_t a_t - \frac{w_t^*}{p_t} - \lambda E_t \Lambda_{t,t+1} \frac{\kappa}{2} x_{it+1}^2(\varphi_{it+1}, \pi_t^\gamma w_t^*) + \\ &- (1-\lambda) E_t \Lambda_{t,t+1} \frac{\kappa}{2} x_{it+1}^2(\varphi_{it+1}, w_{it+1}^*) + \\ &+ \lambda E_t \Lambda_{t,t+1} (\delta_{it+1} + x_{it+1}) \times J_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_t^*) \\ &+ (1-\lambda) E_t \Lambda_{t,t+1} (\delta_{it+1} + x_{it+1}) \times J_{t+1}(\varphi_{it+1}, w_{it+1}^*) \end{aligned}$$

Which can be combined with the hiring condition to write:

$$\begin{aligned} J_t(\varphi_t, w_t^*) &= x_t a_t - \frac{w_t^*}{p_t} + \lambda E_t \Lambda_{t,t+1} \frac{\kappa}{2} x_{it+1}^2(\varphi_{it+1}, \pi_t^\gamma w_t^*) + \\ &+ (1-\lambda) E_t \Lambda_{t,t+1} \frac{\kappa}{2} x_{it+1}^2(\varphi_{it+1}, w_{it+1}^*) + \\ &+ \lambda E_t \Lambda_{t,t+1} \left( \delta_{it+1}(\varphi_{it+1}, \pi_t^\gamma w_t^*) \times J_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_t^*) - \delta_{it+1}(\varphi_{it+1}, w_{it+1}^*) \times J_{t+1}(\varphi_{it+1}, w_{it+1}^*) \right) \\ &+ E_t \Lambda_{t,t+1} \left( \delta_{it+1}(\varphi_{it+1}, w_{it+1}^*) \times J_{t+1}(\varphi_{it+1}, w_{it+1}^*) \right) \end{aligned}$$

Loglinearizing:

$$\begin{aligned} \hat{J}_t &= x a (\hat{x}_t + \hat{a}_t) - w^r \hat{w}_t^r + \beta \left( \frac{x}{2} + \delta \right) \hat{\Lambda}_{t,t+1} + \beta x \hat{x}_{it+1}(w_{it+1}^*) + \beta \lambda x E_t \left( \hat{x}_{it+1}(\pi_t^\gamma w_t^*) - \hat{x}_{it+1}(w_{it+1}^*) \right) + \\ &+ \beta \lambda \delta E_t \left( \hat{\delta}_{it+1}(\pi_t^\gamma w_t^*) - \hat{\delta}_{it+1}(w_{it+1}^*) \right) + \beta \lambda \delta E_t \left( \hat{J}_{t+1}(\pi_t^\gamma w_t^*) - \hat{J}_{t+1}(w_{it+1}^*) \right) + \\ &+ \beta \delta \left( \hat{\delta}_{it+1}(w_{it+1}^*) + \hat{J}_{t+1}(w_{it+1}^*) \right) \end{aligned}$$

Using  $\varkappa + \delta = 1$ :

$$\begin{aligned}\hat{J}_t(\varphi_t, w_t^*) &= xa(\hat{x}_t + \hat{a}_t) - w^r \hat{w}_t^r + \beta \left( \frac{1 + \delta}{2} \right) E_t \hat{\Lambda}_{t,t+1} + \beta \lambda E_t (\hat{x}_{t+1}(\pi_t^\gamma w_t^*) - \hat{x}_{t+1}(w_{t+1}^*)) + \\ &+ \beta \lambda \delta E_t (\hat{\delta}_{t+1}(\pi_t^\gamma w_t^*) - \hat{\delta}_{t+1}(w_{t+1}^*)) + \beta \delta E_t \hat{\delta}_{t+1}(w_{t+1}^*) + \beta E_t \hat{J}_{t+1}(\varphi_{t+1}, w_{t+1}^*)\end{aligned}$$

### Average hiring rate at renegotiating firms

Considering that the composition term will be zero up to a first order, we can express the average hiring rate at a renegotiating firm as:

$$\kappa \varkappa_t(\varphi_t, w_t^*) = x_t a_t - \frac{w_t^r}{p_t} + E_t \Lambda_{t,t+1} \left[ \frac{\kappa}{2} \varkappa_{t+1}^2 + \kappa \delta_{t+1} \varkappa_{t+1} \right]$$

Loglinearizing:

$$\hat{\varkappa}_t(\varphi_t, w_t^*) = \frac{xa}{\kappa \bar{\varkappa}} (\hat{x}_t + \hat{a}_t) - \frac{\bar{w}^r}{\kappa \bar{\varkappa}} \hat{w}_t^r + \beta(\varkappa + \delta) E_t \hat{\varkappa}_{t+1} + \beta \left( \frac{\varkappa}{2} + \delta \right) E_t \hat{\Lambda}_{t,t+1} + \beta \delta E_t \hat{\delta}_{t+1}$$

Which results in, given that  $\varkappa + \delta = 1$  in the steady state:

$$\hat{\varkappa}_t(\varphi_t, w_t^*) = \frac{xa}{\kappa \bar{\varkappa}} (\hat{x}_t + \hat{a}_t) - \frac{\bar{w}^r}{\kappa \bar{\varkappa}} \hat{w}_t^r + \beta E_t \hat{\varkappa}_{t+1} + \frac{\beta}{2} (1 + \delta) E_t \hat{\Lambda}_{t,t+1} + \beta \delta E_t \hat{\delta}_{t+1}$$

Considering nominal wage rigidity:

$$\begin{aligned}\hat{\varkappa}_t(\varphi_t, w_t^*) &= \frac{xa}{\kappa \bar{\varkappa}} (\hat{x}_t + \hat{a}_t) - \frac{\bar{w}^r}{\kappa \bar{\varkappa}} \hat{w}_t^r + \beta E_t (\lambda \hat{\varkappa}_{t+1}(\pi_t^\gamma w_t^*) + (1 - \lambda) \hat{\varkappa}_{t+1}(w_{t+1}^*)) + \frac{\beta}{2} (1 + \delta) E_t \hat{\Lambda}_{t,t+1} + \\ &\beta \delta E_t (\lambda \hat{\delta}_{t+1}(\pi_t^\gamma w_t^*) + (1 - \lambda) \hat{\delta}_{t+1}(w_{t+1}^*))\end{aligned}$$

Rearranging:

$$\begin{aligned}\hat{\varkappa}_t(\varphi_t, w_t^*) &= \frac{xa}{\kappa \bar{\varkappa}} (\hat{x}_t + \hat{a}_t) - \frac{\bar{w}^r}{\kappa \bar{\varkappa}} \hat{w}_t^r + \beta \lambda E_t (\hat{\varkappa}_{t+1}(\pi_t^\gamma w_t^*) - \hat{\varkappa}_{t+1}(w_{t+1}^*)) + \frac{\beta}{2} (1 + \delta) E_t \hat{\Lambda}_{t,t+1} + \\ &\beta \delta \lambda E_t (\hat{\delta}_{t+1}(\pi_t^\gamma w_t^*) - \hat{\delta}_{t+1}(w_{t+1}^*)) + \beta \delta E_t (\hat{\delta}_{t+1}(w_{t+1}^*)) + \beta E_t (\hat{\varkappa}_{t+1}(w_{t+1}^*))\end{aligned}$$

### Average retention rate at renegotiating firms

Recall the definition of retention rate:

$$\delta_t = \frac{\delta_t^g + \phi \varphi_{t-1} \delta_t^b}{1 + \phi \varphi_{t-1}} = (1 - \rho) \frac{(1 - \zeta_g f_t) + \phi \varphi_{t-1} (1 - \zeta_{bt} f_t^g)}{1 + \phi \varphi_{t-1}}$$

Loglinearizing around a steady-state where  $\delta^g = \delta^b = \delta$  and  $\zeta_g = \zeta_{bt} \xi$ , and recalling that  $\delta_t^g = (1 - \rho)(1 - \zeta_g f_t)$  and  $\delta_t^b = (1 - \rho)(1 - \zeta_{bt} \xi f_t)$ , we can show:

$$\delta \delta_t^g = \delta(\hat{\delta}_t^b) = -(1 - \rho) \zeta_g f (\hat{\zeta}_{bt} + \hat{f}_t)$$

Which simplifies deviations in average retention rate as:

$$\hat{\delta}_t = \frac{\delta - (1 - \rho)}{\delta} (\hat{\zeta}_{bt} + \hat{f}_t)$$

Note that:

$$E_t(\hat{\delta}_{t+1}(\pi_t^\gamma w_t) - \hat{\delta}_{t+1}(w_{it+1}^*)) = \frac{\delta - (1 - \rho)}{\delta} E_t(\hat{\zeta}_{bt+1}(\pi_t^\gamma w_t) - \hat{\zeta}_{bt+1}(w_{it+1}^*))$$

### Average search intensity at renegotiating firms

The optimal search intensity for workers in bad matches in renegotiating firms is:

$$\zeta_0 \zeta_{bt}^{\eta_\zeta}(\varphi_t, w_t^*) = f_t^g (\bar{H}_t - H_t^b(\varphi_t, w_t^*))$$

Log-linearizing and using  $f_t^g = \hat{f}_t$

$$\zeta_0 \zeta_b^\eta \eta \hat{\zeta}_{bt} = f^g (\bar{H} \hat{H}_t - H_t^b \hat{H}_t^b(w_t^*)) + f^g \hat{f}_t (\bar{H}_t - \bar{H}_t^b)$$

Which simplifies into:

$$\eta \hat{\zeta}_{bt}(w_t^*) = \frac{(\bar{H} \hat{H}_t - H_t^b \hat{H}_t^b(w_t^*))}{\bar{H} - H_t^b} + \hat{f}_t^g$$

But then:

$$\eta E_t(\hat{\zeta}_{bt+1}(\pi_t^\gamma w_t^*) - \hat{\zeta}_{bt+1}(w_{it+1}^*)) = -\frac{H^b}{\bar{H} - H^b} E_t(\hat{H}_{t+1}^b(\pi_t^\gamma w_t^*) - \hat{H}_{t+1}^b(w_{it+1}^*))$$

### Average worker surplus in bad matches

$$\begin{aligned} H_t^b(\varphi_t, w_t^*) &= \phi \frac{w_t^*}{p_t} - u_B - \underbrace{E_t \Lambda_{t,t+1} (1 - \rho) c(\zeta_{bt+1})}_{(a)} + \underbrace{E_t \Lambda_{t,t+1} (1 - \rho) (\zeta_{bt+1} f_{t+1}^g) \bar{H}_{t+1}}_{(b)} + \\ &+ \underbrace{E_t \Lambda_{t,t+1} (1 - \rho) (1 - \zeta_{bt+1} f_{t+1}^g) H_{t+1}^b(\varphi_{t+1}, w_{t+1}) - E_t \Lambda_{t,t+1} f_{t+1} \bar{H}_{t+1}^a}_{(c)} \end{aligned}$$

Now, note that  $E_t \zeta_{bt+1} = \lambda \zeta_{bt+1}(\pi_t^\gamma w_t^*) + (1 - \lambda) \zeta_{bt+1}(w_{it+1}^*)$ . As such, we can re-write (a) as:

$$\begin{aligned}
& - E_t \Lambda_{t,t+1} (1 - \rho) c(\zeta_{bt+1}) = \\
& - \lambda E_t \Lambda_{t,t+1} (1 - \rho) c(\zeta_{bt+1}(\pi_t^\gamma w_t^*)) - (1 - \lambda) E_t \Lambda_{t,t+1} (1 - \rho) c(\zeta_{bt+1}(w_{it+1}^*))
\end{aligned}$$

By a similar token, we can re-write (**b**):

$$\begin{aligned}
& E_t \Lambda_{t,t+1} (1 - \rho) (\zeta_{bt+1} f_{t+1}^g) \bar{H}_{t+1} = \\
& \lambda E_t \Lambda_{t,t+1} (1 - \rho) (\zeta_{bt+1}(\pi_t^\gamma w_t^*) f_{t+1}^g) \bar{H}_{t+1} + \\
& (1 - \lambda) E_t \Lambda_{t,t+1} (1 - \rho) (\zeta_{bt+1}(w_{it+1}^*) f_{t+1}^g) \bar{H}_{t+1}
\end{aligned}$$

Likewise, for (**c**):

$$\begin{aligned}
& E_t \Lambda_{t,t+1} (1 - \rho) (1 - \zeta_{bt+1} f_{t+1}^g) H_{t+1}^b(w_{t+1}) = \\
& \lambda E_t \Lambda_{t,t+1} (1 - \rho) (1 - \zeta_{bt+1}(\pi_t^\gamma w_t^*) f_{t+1}^g) H_{t+1}^b(\pi_t^\gamma w_t^*) \\
& (1 - \lambda) E_t \Lambda_{t,t+1} (1 - \rho) (1 - \zeta_{bt+1}(w_{it+1}^*) f_{t+1}^g) H_{t+1}^b(w_{it+1}^*)
\end{aligned}$$

Which we can re-write as:

$$\begin{aligned}
& E_t \Lambda_{t,t+1} (1 - \rho) (1 - \zeta_{bt+1} f_{t+1}^g) H_{t+1}^b(w_{t+1}) = \\
& = \lambda E_t \Lambda_{t,t+1} (1 - \rho) (H_{t+1}^b(\pi_t^\gamma w_t^*) - H_{t+1}^b(w_{it+1}^*)) \\
& - \lambda E_t \Lambda_{t,t+1} (1 - \rho) f_{t+1}^g \left( \zeta_{bt+1}(\pi_t^\gamma w_t^*) H_{t+1}^b(\pi_t^\gamma w_t^*) - \zeta_{bt+1}(w_{it+1}^*) H_{t+1}^b(w_{it+1}^*) \right) \\
& + E_t \Lambda_{t,t+1} (1 - \rho) (1 - \zeta_{bt+1}(w_{it+1}^*) f_{t+1}^g) H_{t+1}^b(w_{it+1}^*)
\end{aligned}$$

Loglinearizing and collecting terms:

$$\begin{aligned}
\hat{H}_t^b(\varphi_t, w_t^*) &= \frac{\phi}{H^b} \bar{w}^r \hat{w}_t^{*r} - \beta(1-\rho)\zeta_0 \frac{\zeta_b^{1+\eta\zeta}}{H^b} E_t \left[ \lambda \hat{\zeta}_{bt+1}(\pi_t^\gamma w_t^*) + (1-\lambda) \hat{\zeta}_{bt+1}(w_{it+1}^*) \right] - \\
&- \beta(1-\rho) \frac{c(\zeta_b)}{H^b} E_t \hat{\Lambda}_{t,t+1} + \beta(1-\rho-\delta) \frac{\bar{H}}{H^b} E_t \left[ \hat{\Lambda}_{t,t+1} + \hat{H}_{t+1} \right] \\
&- \beta f \frac{\bar{H}^a}{H^b} E_t \left( \hat{f}_{t+1} + \hat{\Lambda}_{t,t+1} + \hat{H}_{t+1}^a \right) \\
&- \beta(1-\rho-\delta) \left( 1 - \frac{\bar{H}}{H^b} \right) E_t \left( \hat{f}_{t+1} + \lambda \hat{\zeta}_{bt+1}(\pi_t^\gamma w_t^*) + (1-\lambda) \hat{\zeta}_{bt+1}(w_{it+1}^*) \right) \\
&+ \delta \beta \lambda E_t \left( \hat{\Lambda}_{t,t+1} + \hat{H}_{t+1}^b(\pi_t^\gamma w_t^*) \right) \\
&+ \delta \beta (1-\lambda) E_t \left( \hat{\Lambda}_{t,t+1} + \hat{H}_{t+1}^b(w_{it+1}^*) \right)
\end{aligned}$$

Collecting terms, this can be further simplified as:

$$\begin{aligned}
\hat{H}_t^b(\varphi_t, w_t^*) &= \frac{\phi}{H^b} \bar{w}^r \hat{w}_t^{*r} + \chi_\Lambda E_t \hat{\Lambda}_{t,t+1} + \chi_f E_t \hat{f}_{t+1} \\
&+ \beta \lambda \delta E_t [\hat{H}_{t+1}^b(\pi_t^\gamma w_t^*) - \hat{H}_{t+1}^b(w_{it+1}^*)] \\
&+ \delta \beta E_t \hat{H}_{t+1}^b(w_{it+1}^*) + \beta(1-\rho-\delta) \frac{\bar{H}}{H^b} E_t \hat{H}_{t+1} - \beta f \frac{\bar{H}^a}{H^b} E_t (\hat{H}_{t+1}^a)
\end{aligned}$$

With  $\chi_\Lambda = \left[ -\beta(1-\rho) \frac{c(\zeta_b)}{H^b} + \beta(1-\rho-\delta) \frac{\bar{H}}{H^b} - \beta f \frac{\bar{H}^a}{H^b} + \delta \beta \right]$  and  $\chi_f = \left[ -\beta f \frac{\bar{H}^a}{H^b} - \beta(1-\rho-\delta) \left( 1 - \frac{\bar{H}}{H^b} \right) \right]$ . Finally, note that:

$$E_t[\hat{H}_{t+1}^b(\pi_t^\gamma w_t^*) - \hat{H}_{t+1}^b(w_{it+1}^*)] = \frac{\phi}{H^b} \bar{w}^r (1 + \beta \lambda \delta + (\beta \lambda \delta)^2 \dots) (\gamma \hat{\pi}_t + \hat{w}_t^{*r} - \hat{\pi}_{t+1} - \hat{w}_{t+1}^{*r})$$

Using  $\epsilon = \frac{1}{1-\delta\lambda\beta}$ :

$$E_t[\hat{H}_{t+1}^b(\pi_t^\gamma w_t^*) - \hat{H}_{t+1}^b(w_{it+1}^*)] = \frac{\phi}{H^b} \bar{w}^r \epsilon (\gamma \hat{\pi}_t + \hat{w}_t^{*r} - \hat{\pi}_{t+1} - \hat{w}_{t+1}^{*r})$$

Substituting:

$$\begin{aligned}
\hat{H}_t^b &= \frac{\phi}{H^b} \bar{w}^r E_t \left( \hat{w}_t^{*r} + \beta \lambda \delta \epsilon (\gamma \hat{\pi}_t + \hat{w}_t^{*r} - \hat{\pi}_{t+1} - \hat{w}_{t+1}^{*r}) \right) + \chi_\Lambda E_t \hat{\Lambda}_{t,t+1} + \chi_f E_t \hat{f}_{t+1} \\
&+ \delta \beta E_t \hat{H}_{t+1}^b(w_{it+1}^*) + \beta(1-\rho-\delta) \frac{\bar{H}}{H^b} E_t \hat{H}_{t+1} - \beta f \frac{\bar{H}^a}{H^b} E_t (\hat{H}_{t+1}^a)
\end{aligned}$$

## B4 Auxiliary steady-state results

### Effect of composition on contract wage

A firm has composition  $\varphi_{it}$  and contract wage  $w_{it}^*(\varphi_{it})$ . Let the implicit function  $\mathbf{F}_t(\varphi_{it}, w_{it}^*(\varphi_{it})) \equiv \eta J_t(\varphi_{it}, w_{it}^*(\varphi_{it})) - (1-\eta)H_t(\varphi_{it}, w_{it}^*(\varphi_{it}))$ . By the surplus sharing rule,  $\mathbf{F} = 0$ . Applying the implicit function theorem we have that:

$$\frac{\partial w_{it}^*(\varphi_{it})}{\partial \varphi_{it}} = -\frac{\partial \mathbf{F}_t / \partial \varphi_{it}}{\partial \mathbf{F}_t / \partial w_{it}^*}$$

With

$$\begin{aligned}\frac{\partial \mathbf{F}_t}{\partial \varphi_{it}} &= \eta \frac{\partial J_t}{\partial \varphi_{it}} - (1-\eta) \frac{\partial H_t}{\partial \varphi_{it}} \\ \frac{\partial \mathbf{F}_t}{\partial w_{it}^*} &= \eta \frac{\partial J_t}{\partial w_{it}^*} - (1-\eta) \frac{\partial H_t}{\partial w_{it}^*}\end{aligned}$$

Evaluated at the steady state:

$$\frac{\partial w^*}{\partial \varphi} = -\frac{\eta \partial J / \partial \varphi - (1-\eta) \partial H / \partial \varphi}{\eta \partial J / \partial w - (1-\eta) \partial H / \partial w} \quad (\text{S1})$$

### Effect of composition and wages on worker surplus in good matches

Consider the following auxiliary expressions for average surplus in all matches, in good matches and in bad matches, respectively:

$$\begin{aligned}\bar{H}_t &\equiv \xi \bar{H}_t^g + (1 - \xi) \bar{H}_t^b \\ \bar{H}_t^g &\equiv \bar{V}_t^g - U_t \\ \bar{H}_t^b &\equiv \bar{V}_t^b - U_t\end{aligned}$$

The value of a worker in a good match will be, net of search costs:

$$V_t^g \equiv V_t^g(\varphi_{it}, w_{it}^g) = \left\{ \frac{w_{gt}}{p_t} + E_t \left\{ \Lambda_{t,t+1} \left[ (1 - \rho) S_{t+1}^g + \rho U_{t+1} \right] \right\} \right\}$$

Where, recall:

$$\begin{aligned}S_t^b &= \max_{\zeta_{bt}} \left\{ \zeta_{bt} f_t^g \bar{V}_t^g + (1 - \zeta_{bt} f_t^g) V_t^b - c(\zeta_{bt}) \right\} \\ S_t^g &= (1 - \zeta_g f_t) V_t^g + \zeta_g (f_t^g \bar{V}_t^g + f_t^b \bar{V}_t^b) - c(\zeta_g)\end{aligned}$$

The value of an unemployed worker is:

$$U_t = u_B + E_t \left[ \Lambda_{t,t+1} \left[ f_{t+1}^g \bar{V}_{t+1}^g + f_{t+1}^b \bar{V}_{t+1}^b + (1 - f_{t+1}) U_{t+1} \right] \right]$$

The surplus of workers in good matches **net of search costs** can be written as:

$$\begin{aligned}H_t &= \frac{w_{gt}}{p_t} - u_B + E_t \Lambda_{t,t+1} \left( (1 - \rho) (1 - \zeta_g f_{t+1}) V_{t+1}^g \right) + \\ &+ E_t \Lambda_{t,t+1} \left( (1 - \rho) \zeta_g (f_{t+1}^g \bar{V}_{t+1}^g + f_{t+1}^b \bar{V}_{t+1}^b) - f_{t+1}^g \bar{V}_{t+1}^g - f_{t+1}^b \bar{V}_{t+1}^b \right) + \\ &+ E_t \Lambda_{t,t+1} (\rho - 1 + f_{t+1}) U_{t+1}\end{aligned}$$

Which reduces to:

$$\begin{aligned}H_t(\varphi_{it}, w_{it}) &= \frac{w_{gt}}{p_t} - u_B + E_t \Lambda_{t,t+1} \left[ (1 - \rho) (1 - \zeta_g f_{t+1}) H_{t+1}^g \right] + \\ &+ E_t \Lambda_{t,t+1} \left[ (1 - \rho) \zeta_g f_{t+1} \bar{H}_{t+1}^a - f_{t+1} \bar{H}_{t+1}^a \right]\end{aligned}$$

Which, given the nominal wage rigidity, will be:

$$\begin{aligned}
H_t(\varphi_{it}, w_{it}) &= \frac{w_{gt}}{p_t} - u_B + \\
E_t \Lambda_{t,t+1} &\left[ (1-\rho)(1-\zeta_g f_{t+1}) \left( \lambda H_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_t) + (1-\lambda) H_{t+1}(\varphi_{it+1}, w_{it+1}^*) \right) \right] + \\
&+ E_t \Lambda_{t,t+1} \left[ (1-\rho) \zeta_g f_{t+1} \bar{H}_{t+1}^a - f_{t+1} \bar{H}_{t+1}^a \right]
\end{aligned}$$

$$\begin{aligned}
\frac{\partial H_t(\varphi_{it}, w_{it})}{\partial \varphi_{it}} &= (1-\rho)(1-\zeta_g f_{t+1}) E_t \left\{ \Lambda_{t,t+1} \left( \lambda \frac{\partial H_{t+1}(\varphi_{t+1}, \pi_t^\gamma w_t)}{\partial \varphi_{t+1}} \right) \frac{d\varphi_{t+1}}{d\varphi_t} \right\} + \\
&+ (1-\lambda) E_t \left\{ \Lambda_{t,t+1} \left( \frac{\partial H_{t+1}(\varphi_{t+1}, w_{t+1}^*(\varphi_{t+1}))}{\partial \varphi_{t+1}} + \frac{\partial H_{t+1}(\varphi_{t+1}, w_{t+1}^*(\varphi_{t+1}))}{\partial w_{t+1}^*} \frac{\partial w_{t+1}^*}{\partial \varphi_{t+1}} \right) \frac{d\varphi_{t+1}}{d\varphi_t} \right\}
\end{aligned}$$

Recall that retention of good matches is  $\delta_t^g = (1-\rho)(1-\zeta_g f_t)$ . So in the steady state,  $\partial H_t / \partial \varphi_{it}$  will be:

$$\frac{\partial H}{\partial \varphi} \left( 1 - \delta^g \beta \frac{d\varphi'}{d\varphi} \right) = \delta^g \beta (1-\lambda) \frac{\partial H}{\partial w} \frac{\partial w^*(\varphi)}{\partial \varphi} \frac{d\varphi'}{d\varphi} \quad (S2)$$

As for the effect of wages on worker surplus in good matches, we have:

$$\begin{aligned}
\frac{\partial H}{\partial w} &= \frac{1}{p_t} + E_t \Lambda_{t,t+1} \left[ (1-\rho)(1-\zeta_g f_{t+1}) \lambda \left[ \pi_t^\gamma \frac{\partial H_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_{it})}{\partial (\pi_t^\gamma w_{it})} + \frac{\partial H_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_{it})}{\partial \varphi_{it+1}} \frac{\partial \varphi_{it+1}}{\partial w_{it}} \right] \right] + \\
&+ E_t \Lambda_{t,t+1} \left[ (1-\rho)(1-\zeta_g f_{t+1})(1-\lambda) \left[ \frac{\partial H_{t+1}(\varphi_{it+1}, w_{it+1}^*)}{\partial \varphi_{it+1}} + \frac{\partial H_{t+1}(\varphi_{it+1}, w_{it+1}^*)}{\partial w_{it+1}^*} \frac{\partial w_{it+1}^*}{\partial \varphi_{it+1}} \right] \frac{\partial \varphi_{it+1}}{\partial w_{it}} \right]
\end{aligned}$$

In the steady-state:

$$\frac{\partial H}{\partial w} \left( 1 - \delta^g \beta \lambda \pi^\gamma - \delta^g \beta (1-\lambda) \frac{\partial w^*(\varphi)}{\partial \varphi} \frac{d\varphi'}{dw} \right) = 1/p + \delta^g \beta \frac{\partial H}{\partial \varphi} \frac{d\varphi'}{dw} \quad (S3)$$

### Effect of composition and wages on firm surplus

The firm surplus is, for each given composition and wage:

$$\begin{aligned}
J_t(\varphi_{it}, w_{it}) &= x_t a_t - \frac{w_{it}}{p_t} - E_t \Lambda_{t,t+1} \frac{\kappa}{2} x_{it+1}^2 (\varphi_{it+1}, w_{it+1}) + \\
&+ E_t \Lambda_{t,t+1} (\delta_{it+1}(\varphi_{it+1}, w_{it+1}) + x_{it+1}(\varphi_{it+1}, w_{it+1})) J_{t+1}(\varphi_{it+1}, w_{it+1})
\end{aligned}$$

With

$$\begin{aligned}
J_{t+1}(\varphi_{it+1}, w_{it+1}) &= \lambda J_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_{it}) + (1 - \lambda) J_{t+1}(\varphi_{it+1}, w_{it+1}^*) \\
x_{t+1}(\varphi_{it+1}, w_{it+1}) &= \lambda x_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_{it}) + (1 - \lambda) x_{t+1}(\varphi_{it+1}, w_{it+1}^*) \\
\delta_{t+1}(\varphi_{it+1}, w_{it+1}) &= \lambda \delta_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_{it}) + (1 - \lambda) \delta_{t+1}(\varphi_{it+1}, w_{it+1}^*)
\end{aligned}$$

We will use these auxiliary expressions:

$$\begin{aligned}
\frac{\partial J_{t+1}(\varphi_{it+1}, w_{it+1})}{\partial \varphi_{it+1}} &= \lambda \frac{\partial J_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_{it})}{\partial \varphi_{it+1}} + (1 - \lambda) \frac{\partial J_{t+1}(\varphi_{it+1}, w_{it+1}^*(\varphi_{it+1}))}{\partial \varphi_{it+1}} + \\
&+ (1 - \lambda) \frac{\partial J_{t+1}(\varphi_{it+1}, w_{it+1}^*(\varphi_{it+1}))}{\partial w_{it+1}^*} \frac{\partial w_{it+1}^*}{\partial \varphi_{it+1}} \\
\frac{dx_{t+1}(\varphi_{it+1}, w_{it+1})}{d\varphi_{it+1}} &= \lambda \frac{dx_{t+1}(\varphi_{it+1}, \pi_t^\gamma w_{it})}{d\varphi_{it+1}} + (1 - \lambda) \frac{dx_{t+1}(\varphi_{it+1}, w_{it+1}^*(\varphi_{it+1}))}{d\varphi_{it+1}} + \\
&+ (1 - \lambda) \frac{dx_{t+1}(\varphi_{it+1}, w_{it+1}^*(\varphi_{it+1}))}{dw_{it+1}^*} \frac{\partial w_{it+1}^*}{\partial \varphi_{it+1}}
\end{aligned}$$

We can write:

$$\begin{aligned}
\frac{\partial J_t}{\partial \varphi_{it}} &= -\kappa E_t \Lambda_{t,t+1} \left( x_{it+1}(\varphi_{it+1}, w_{it+1}) \frac{dx_{it+1}(\varphi_{it+1}, w_{it+1})}{d\varphi_{it+1}} \frac{d\varphi_{it+1}}{d\varphi_{it}} \right) + \\
&+ E_t \Lambda_{t,t+1} \left( \frac{d\delta_{it+1}}{d\varphi_{it}} + \frac{dx_{it+1}}{d\varphi_{it}} \right) J_{t+1}(\varphi_{it+1}, w_{it+1}) + \\
&+ E_t \Lambda_{t,t+1} (\delta_{it+1}(\varphi_{it+1}, w_{it+1}) + x_{it+1}(\varphi_{it+1}, w_{it+1})) \frac{\partial J_{t+1}(\varphi_{it+1}, w_{it+1})}{\partial \varphi_{it+1}} \frac{d\varphi_{it+1}}{d\varphi_{it}}
\end{aligned}$$

Note that in the steady state  $\delta + x = 1$ .

$$\frac{\partial J}{\partial \varphi} = -\beta J \left( \frac{dx}{d\varphi} \right) \frac{d\varphi'}{d\varphi} + \beta \left( \frac{\partial J}{\partial \varphi} + (1 - \lambda) \frac{\partial J}{\partial w} \frac{\partial w^*}{\partial \varphi} \right) \frac{d\varphi'}{d\varphi}$$

Which yields:

$$\frac{\partial J}{\partial \varphi} \left( 1 - \beta \frac{d\varphi'}{d\varphi} \right) = -\beta J \frac{dx}{d\varphi} \frac{d\varphi'}{d\varphi} + \beta (1 - \lambda) \frac{\partial J}{\partial w} \frac{\partial w^*}{\partial \varphi} \frac{d\varphi'}{d\varphi} \tag{S4}$$

To compute  $\partial J_t / \partial w_t$ , we will use the following expressions:

$$\begin{aligned} \frac{\partial J_{t+1}(\varphi_{it+1}, w_{it+1})}{\partial w_{it}} &= \left( \lambda \pi_t^\gamma \frac{\partial J_{t+1}(\varphi_{t+1}, \pi_t^\gamma w_{it})}{\partial \pi_t^\gamma w_{it}} \right) + \\ &+ \left( \lambda \frac{\partial J_{t+1}(\varphi_{t+1}, \pi_t^\gamma w_{it})}{\partial \varphi_{t+1}} + (1-\lambda) \frac{\partial J_{t+1}(\varphi_{t+1}, w_{t+1}^*)}{\partial \varphi_{t+1}} + (1-\lambda) \frac{\partial J_{t+1}(\varphi_{t+1}, w_{t+1}^*)}{\partial w_{t+1}^*} \frac{\partial w_{t+1}^*}{\partial \varphi_{t+1}} \right) \frac{d\varphi_{t+1}}{dw_{it}} \end{aligned}$$

$$\begin{aligned} \frac{d\chi_{t+1}(\varphi_{it+1}, w_{it+1})}{dw_{it}} &= \left( \lambda \pi_t^\gamma \frac{\partial \chi_{t+1}(\varphi_{t+1}, \pi_t^\gamma w_{it})}{\partial \pi_t^\gamma w_{it}} \right) + \\ &+ \left( \lambda \frac{\partial \chi_{t+1}(\varphi_{t+1}, \pi_t^\gamma w_{it})}{\partial \varphi_{t+1}} + (1-\lambda) \frac{\partial \chi_{t+1}(\varphi_{t+1}, w_{t+1}^*)}{\partial \varphi_{t+1}} + (1-\lambda) \frac{\partial \chi_{t+1}(\varphi_{t+1}, w_{t+1}^*)}{\partial w_{t+1}^*} \frac{\partial w_{t+1}^*}{\partial \varphi_{t+1}} \right) \frac{d\varphi_{t+1}}{dw_{it}} \end{aligned}$$

$$\begin{aligned} \frac{d\delta_{t+1}(\varphi_{it+1}, w_{it+1})}{dw_{it}} &= \left( \lambda \pi_t^\gamma \frac{\partial \delta_{t+1}(\varphi_{t+1}, \pi_t^\gamma w_{it})}{\partial \pi_t^\gamma w_{it}} \right) + \\ &+ \left( \lambda \frac{\partial \delta_{t+1}(\varphi_{t+1}, \pi_t^\gamma w_{it})}{\partial \varphi_{t+1}} + (1-\lambda) \frac{\partial \delta_{t+1}(\varphi_{t+1}, w_{t+1}^*)}{\partial \varphi_{t+1}} + (1-\lambda) \frac{\partial \delta_{t+1}(\varphi_{t+1}, w_{t+1}^*)}{\partial w_{t+1}^*} \frac{\partial w_{t+1}^*}{\partial \varphi_{t+1}} \right) \frac{d\varphi_{t+1}}{dw_{it}} \end{aligned}$$

We can express:

$$\begin{aligned} \frac{\partial J_t}{\partial w_t} &= -\frac{1}{p_t} - \kappa E_t \Lambda_{t,t+1} \chi_{it+1}(\varphi_{it+1}, w_{it+1}) \frac{d\chi_{it+1}(\varphi_{it+1}, w_{it+1})}{dw_{it}} + \\ &+ E_t \Lambda_{t,t+1} \left( \frac{d\delta_{it+1}}{dw_{it}} + \frac{d\chi_{it+1}}{dw_{it}} \right) J_{t+1}(\varphi_{it+1}, w_{it+1}) + \\ &+ E_t \Lambda_{t,t+1} (\delta_{it+1} + \chi_{it+1}) \frac{\partial J_{t+1}(\varphi_{it+1}, w_{it+1})}{\partial w_t} \end{aligned}$$

Evaluating at the steady-state yields:

$$\begin{aligned} \frac{\partial J}{\partial w} &= -\frac{1}{p} - \beta J \left( \lambda \pi^\gamma \frac{\partial \chi}{\partial w} + \left( \frac{\partial \chi}{\partial \varphi} + (1-\lambda) \frac{\partial \chi}{\partial w} \frac{\partial w^*}{\partial \varphi} \right) \frac{d\varphi'}{dw} \right) + \\ &+ \beta \left( \lambda \pi^\gamma \frac{\partial J}{\partial w} \right) + \beta \left( \frac{\partial J}{\partial \varphi} + (1-\lambda) \frac{\partial J}{\partial w} \frac{\partial w^*}{\partial \varphi} \right) \frac{d\varphi'}{dw} \end{aligned}$$

Which yields:

$$\frac{\partial J}{\partial w} \left( 1 - \beta \lambda \pi^\gamma - \beta(1-\lambda) \frac{\partial w^*}{\partial \varphi} \frac{d\varphi'}{dw} \right) = -\frac{1}{p} - \beta J \frac{d\chi}{dw} + \beta \frac{\partial J}{\partial \varphi} \frac{d\varphi'}{dw} \quad (S5)$$

## Effect of composition and wages on hiring rate

Under the assumption of equal retention of good and bad matches, we have, from the optimal hiring condition:

$$x_{it}(\varphi_{it}, w_{it}) = \frac{1}{\kappa} \left[ x_t a_t - \frac{w_{it}}{p_t} + E_t \Lambda_{t,t+1} \left[ \frac{\kappa}{2} x_{it+1}^2 + \kappa \delta_{it+1}(\varphi_{it+1}, w_{it+1}) x_{it+1}(\varphi_{it+1}, w_{it+1}) \right] \right]$$

$$\begin{aligned} \frac{dx_{it}}{d\varphi_{it}} &= E_t \Lambda_{t,t+1} (x_{it+1} + \delta_{it+1}) \frac{dx_{it+1}}{d\varphi_{it+1}} \frac{d\varphi_{it+1}}{d\varphi_{it}} + E_t \Lambda_{t,t+1} x_{it+1}(\varphi_{it+1}, w_{it+1}) \frac{d\delta_{it+1}}{d\varphi_{it+1}} \frac{d\varphi_{it+1}}{d\varphi_{it}} = \\ &= E_t \Lambda_{t,t+1} x_{it+1} \left( \frac{dx_{it+1} + \delta_{it+1}}{d\varphi_{it}} \right) \frac{d\varphi_{it+1}}{d\varphi_{it}} + E_t \Lambda_{t,t+1} \delta_{it+1} \frac{dx_{it+1}}{d\varphi_{it+1}} \frac{d\varphi_{it+1}}{d\varphi_{it}} \end{aligned}$$

Evaluated at the steady state:

$$\frac{dx}{d\varphi} \left( 1 - \beta \delta \frac{d\varphi'}{d\varphi} \right) = \beta \delta (1 - \lambda) \frac{dx}{dw} \frac{\partial w^*}{\partial \varphi} \frac{d\varphi'}{d\varphi} \quad (S6)$$

As for the effect of wages:

$$\begin{aligned} \frac{dx_{it}}{dw_{it}} &= -\frac{1}{\kappa p_t} + E_t \Lambda_{t,t+1} (x_{it+1} + \delta_{it+1}) \frac{\partial x_{it+1}}{\partial w_{it+1}} \frac{dw_{it+1}}{d\varphi_{it+1}} \frac{d\varphi_{it+1}}{dw_{it}} + E_t \Lambda_{t,t+1} x_{it+1}(\varphi_{it+1}, w_{it+1}) \frac{\partial \delta_{it+1}}{\partial w_{it+1}} \frac{\partial w_{it+1}}{\partial \varphi_{it+1}} \frac{d\varphi_{it+1}}{dw_{it}} = \\ &= -\frac{1}{\kappa p_t} + E_t \Lambda_{t,t+1} x_{it+1} \left( \frac{\partial x_{it+1}}{\partial w_{it+1}} + \frac{\partial \delta_{it+1}}{\partial w_{it+1}} \right) \frac{\partial w_{it+1}}{\partial \varphi_{it+1}} \frac{d\varphi_{it+1}}{dw_{it}} + \delta_{it+1} \frac{\partial x_{it+1}}{\partial w_{it+1}} \frac{dw_{it+1}}{d\varphi_{it+1}} \frac{d\varphi_{it+1}}{dw_{it}} \end{aligned}$$

Evaluated at the steady state:

$$\frac{dx}{dw} = -\frac{1}{\kappa p} + \beta \delta \left[ \pi^\gamma \lambda \frac{dx}{dw} + \frac{\partial x}{\partial \varphi} \frac{d\varphi'}{dw} + (1 - \lambda) \frac{dx}{dw} \frac{\partial w^*}{\partial \varphi} \frac{d\varphi'}{dw} \right]$$

$$\frac{dx}{dw} \left( 1 - \pi^\gamma \beta \delta \lambda - \beta \delta (1 - \lambda) \frac{\partial w^*}{\partial \varphi} \frac{d\varphi'}{d\varphi} \right) = -\frac{1}{\kappa p} + \beta \delta \frac{dx}{d\varphi} \frac{d\varphi'}{dw} \quad (S7)$$

## Effect of composition and wage on future composition

The law of motion for composition given  $\varphi_{it-1}, w_t$  is:

$$\varphi_{it} = \frac{\delta_t^b \varphi_{it-1} + q_t^b v_{it}/g_{it-1}}{\delta_t^g + q_t^g v_{it}/g_{it-1}} = \frac{\delta_t^b \frac{\varphi_{it-1}}{1+\phi\varphi_{it-1}} + \frac{\bar{\varphi}_t^h}{1+\phi\bar{\varphi}_t^h} \chi_{it}}{\delta_t^g \frac{1}{1+\phi\varphi_{it-1}} + \frac{1}{1+\phi\bar{\varphi}_t^h} \chi_{it}}$$

Therefore

$$\varphi_{it+1} = \frac{\delta_{t+1}^b \varphi_{it} + q_{t+1}^b v_{it+1}/g_{it}}{\delta_{t+1}^g + q_{t+1}^g v_{it+1}/g_{it}} = \frac{\delta_{t+1}^b \frac{\varphi_{it}}{1+\phi\varphi_{it}} + \frac{\varphi_{t+1}^h}{1+\phi\varphi_{t+1}^h} \chi_{it+1}}{\delta_{t+1}^g \frac{1}{1+\phi\varphi_{it}} + \frac{1}{1+\phi\bar{\varphi}_{t+1}^h} \chi_{it+1}}$$

$$\frac{d\varphi_{it+1}}{d\varphi_{it}} = \frac{\partial\varphi_{it+1}}{\partial\varphi_{it}} + \frac{\partial\varphi_{it+1}}{\partial\chi_{it+1}} \frac{\partial\chi_{it+1}}{\partial\varphi_{it}} + \frac{\partial\varphi_{it+1}}{\partial\delta_{t+1}^b} \frac{\partial\delta_{t+1}^b}{\partial\zeta_{bt+1}} \frac{\partial\zeta_{bt+1}}{\partial\varphi_{it}}$$

$$\frac{d\varphi_{it+1}}{dw_{it}} = \frac{\partial\varphi_{it+1}}{\partial w_{it}} + \frac{\partial\varphi_{it+1}}{\partial\chi_{it+1}} \frac{\partial\chi_{it+1}}{\partial w_{it}} + \frac{\partial\varphi_{it+1}}{\partial\delta_{t+1}^b} \frac{\partial\delta_{t+1}^b}{\partial\zeta_{bt+1}} \frac{\partial\zeta_{bt+1}}{\partial w_{it}}$$

From the definition of  $\varphi_{it}$ , we have:

$$\frac{\partial\varphi_{it}}{\partial\varphi_{it-1}} = \frac{\frac{\delta_t^b}{(1+\phi\varphi_{it-1})^2} \left( \frac{\delta_t^g}{1+\phi\varphi_{it-1}} + \frac{\chi_{it}}{1+\phi\bar{\varphi}_t^h} \right) + \frac{\phi\delta_t^g}{(1+\phi\varphi_{it-1})^2} \left( \delta_t^b \frac{\varphi_{it-1}}{1+\phi\varphi_{it-1}} + \frac{\bar{\varphi}_t^h}{1+\phi\bar{\varphi}_t^h} \chi_{it} \right)}{\left( \frac{\delta_t^g}{1+\phi\varphi_{it-1}} + \frac{\chi_{it}}{1+\phi\bar{\varphi}_t^h} \right)^2}$$

$$\frac{\partial\varphi_{it}}{\partial\chi_{it}} = \frac{(1+\phi\bar{\varphi}_t^h)(1+\phi\varphi_{it-1})}{[\delta_t^g(1+\phi\bar{\varphi}_t^h) + \chi_{it}(1+\phi\varphi_{it-1})]^2} (\bar{\varphi}_t^h \delta_t^g - \varphi_{it-1} \delta_t^b)$$

$$\frac{\partial\varphi_{it}}{\partial\delta_t^b} = \frac{\frac{\varphi_{it-1}}{1+\phi\varphi_{it-1}}}{\frac{\delta_t^g}{1+\phi\varphi_{it-1}} + \frac{\chi_{it}}{1+\phi\bar{\varphi}_t^h}}$$

As before, we have  $\frac{\partial\delta_t^b}{\partial\zeta_{bt}} = -(1-\rho)f_t^g$ . In addition,  $\frac{\partial\varphi_{it+1}}{\partial w_{it}} = 0$ . Although  $\bar{\varphi}_t^h$  the ratio of bad to good matches among new hires is denoted with subscript  $t$  (i.e. end of period), these new hires are made from the initial pool of searchers  $s_t$  that depends on  $g_{t-1}, b_{t-1}, u_{t-1}$ . In the steady state evaluation, the ratio of good-to-bad workers among new hires is equal to the ratio of good-to-bad workers overall i.e.  $\bar{\varphi}^h = \varphi$ .

Evaluating the expressions at the steady-state yields:

$$\frac{\partial\varphi'}{\partial\varphi} = \frac{\frac{\delta^b}{(1+\phi\varphi)^2} \left( \frac{\delta^g}{1+\phi\varphi} + \frac{\chi}{1+\phi\varphi} \right) + \frac{\phi\delta^g}{(1+\phi\varphi)^2} \left( \frac{\delta^b\varphi}{1+\phi\varphi} + \frac{\varphi\chi}{1+\phi\varphi} \right)}{\left( \frac{\delta^g}{1+\phi\varphi} + \frac{\chi}{1+\phi\varphi} \right)^2} = \frac{\delta^b}{1+\phi\varphi} \frac{1}{(\delta^g + \chi)} + \frac{\delta^b + \chi}{(\delta^g + \chi)^2} \frac{\delta^g\phi\varphi}{1+\phi\varphi}$$

$$\frac{\partial \varphi'}{\partial \kappa} = \frac{(1 + \phi \varphi)^2}{[(\delta^g + \kappa)(1 + \phi \varphi)]^2} (\varphi \delta^g - \varphi \delta^b) = \frac{\varphi \delta^g - \varphi \delta^b}{(\delta^g + \kappa)^2}$$

$$\frac{\partial \varphi'}{\partial \delta^b} = \frac{\frac{\varphi}{1 + \phi \varphi}}{\frac{\delta^g}{1 + \phi \varphi} + \frac{\kappa}{1 + \phi \varphi}} = \frac{\varphi}{\delta^g + \kappa}$$

Putting it together yields:

$$\frac{d\varphi'}{d\varphi} = \frac{\delta^b}{1 + \phi \varphi} \frac{1}{(\delta^g + \kappa)} + \frac{\delta^b + \kappa}{(\delta^g + \kappa)^2} \frac{\delta^g \phi \varphi}{1 + \phi \varphi} + \frac{\varphi \delta^g - \varphi \delta^b}{(\delta^g + \kappa)^2} \frac{\partial \kappa}{\partial \varphi} - (1 - \rho) f^g \frac{\varphi}{\delta^g + \kappa} \frac{\partial \zeta_b}{\partial \varphi}$$

Note that under the assumption that  $\delta^g = \delta^b = \delta$ , it will be that:

$$\frac{\partial \varphi'}{\partial \varphi} = \delta \quad \frac{\partial \varphi'}{\partial \kappa} = 0 \quad \frac{\partial \varphi'}{\partial \delta^b} = \varphi$$

So under that assumption we have a simplified:

$$\frac{d\varphi'}{d\varphi} = \delta - (1 - \rho) f^g \varphi \frac{\partial \zeta_b}{\partial \varphi} \quad (S8)$$

As for the effect of wages on future composition evaluated in the steady-state:

$$\frac{d\varphi'}{dw} = -(1 - \rho) f^g \varphi \frac{\partial \zeta_b}{\partial w} \quad (S9)$$

### Effect of composition and wages on search intensity

To get  $\partial \zeta_b / \partial \varphi$  and  $\partial \zeta_b / \partial w$  and complete the previous expressions we have, for any composition and wage, the search intensity can be re-written in terms of worker surplus:

$$\zeta_0 \zeta_{bt}^{\eta_\zeta}(\varphi_{it}, w_{it}) = f_t^g (\bar{H}_t - H_t^b(\varphi_t, w_t))$$

$$\frac{\partial \zeta_{bt}}{\partial \varphi_{it}} = -\frac{\zeta_{bt}^{1-\eta_\zeta}}{\eta_\zeta \zeta_0} f_t^g \frac{\partial H_t^b}{\partial \varphi_{it}}$$

Defining  $\tau \equiv \frac{\zeta_b^{1-\eta_\zeta}}{\eta_\zeta \zeta_0} f^g$  we have, at the steady state:

$$\frac{\partial \zeta_b}{\partial \varphi} = -\tau \frac{\partial H^b}{\partial \varphi} \quad (S10)$$

Similarly, we have:

$$\frac{\partial \zeta_{bt}}{\partial w_{it}} = -\frac{\zeta_{bt}^{1-\eta_\zeta}}{\eta_\zeta \zeta_0} f_t^g \frac{\partial H_t^b(\varphi_{it}, w_{it})}{\partial w_{it}}$$

Evaluating at the steady state yields:

$$\frac{\partial \zeta_b}{\partial w} = -\tau \frac{\partial H^b}{\partial w} \quad (\text{S11})$$

### Effect of composition and wages on worker surplus in bad matches

The worker surplus in a bad match will be, similar to that in a good match:

$$\begin{aligned} H_t^b(\varphi_{it}, w_{it}) &= \phi \frac{w_{it}}{p_t} - u_B - E_t \Lambda_{t,t+1} (1-\rho) c(\zeta_{bt+1}) + E_t \Lambda_{t,t+1} (1-\rho) (\zeta_{bt+1} f_{t+1}^g) \bar{H}_{t+1}^g + \\ &+ E_t \Lambda_{t,t+1} (1-\rho) (1 - \zeta_{bt+1} f_{t+1}^g) H_{t+1}^b(\varphi_{it+1}, w_{it+1}) - E_t \Lambda_{t,t+1} f_{t+1} \bar{H}_{t+1} \end{aligned}$$

This surplus is maximized given the search decision of the worker at time  $t$ . However, note that  $\zeta_{bt+1} = \zeta_{bt+1}(\varphi_{it+1}, w_{it+1})$ .

Let:

$$\frac{\partial H_{t+1}^b}{\partial \varphi_{it+1}} = \lambda \frac{\partial H^b(\varphi_{it+1}, \pi_t' \varphi_{it})}{\partial \varphi_{it+1}} + (1-\lambda) \frac{\partial H^b(\varphi_{it+1}, w_{it+1}^*)}{\partial \varphi_{it+1}}$$

Therefore:

$$\begin{aligned} \frac{\partial H_t^b}{\partial \varphi_{it}} &= (1-\rho) E_t \left[ \Lambda_{t,t+1} (1 - \zeta_{bt+1} f_{t+1}^g) \left( \frac{\partial H_{t+1}^b(\varphi_{it+1}, w_{it+1})}{\partial \varphi_{it+1}} \right) + \right. \\ &\left. (1-\lambda) \left( \frac{\partial H_{t+1}^b(\varphi_{it+1}, w_{it+1}^*(\varphi_{it+1}))}{\partial w_{it+1}^*} \frac{\partial w_{it+1}^*}{\partial \varphi_{it+1}} \right) \right] \frac{d\varphi_{it+1}}{d\varphi_{it}} + Z_\varphi \end{aligned}$$

With:

$$Z_\varphi = E_t \Lambda_{t,t+1} (1-\rho) \left[ f_{t+1}^g \left[ \bar{H}_{t+1}^g - H_{t+1}^b \right] - \zeta_0 \zeta_{bt+1}^{\eta_\zeta} \right] \frac{\partial \zeta_{bt+1}}{\partial \varphi_{it+1}} \frac{d\varphi_{it+1}}{d\varphi_{it}}$$

Substituting the optimal search intensity condition at  $t+1$ , we will simply have  $Z_\varphi = 0$ .

Let  $\tau_2 \equiv \zeta_0(\zeta_b)^{\eta_\zeta}$ . We have that:

$$\frac{\partial H^b}{\partial \varphi} = \beta(1-\rho)(1 - \zeta_b f^g) \left( \frac{\partial H^b}{\partial \varphi} + \left( (1-\lambda) \frac{\partial H^b}{\partial w} \frac{\partial w^*}{\partial \varphi} \right) \right) \frac{d\varphi'}{d\varphi}$$

Which simplifies to, given the definition of retention:

$$\frac{\partial H^b}{\partial \varphi} \left( 1 - \beta \delta^b \frac{d\varphi'}{d\varphi} \right) = \beta \delta^b \left( (1-\lambda) \frac{\partial H^b}{\partial w} \frac{\partial w^*}{\partial \varphi} \right) \frac{d\varphi'}{d\varphi} \quad (\text{S12})$$

Finally, the effect of wages on the surplus of bad matches is:

$$\begin{aligned} \frac{\partial H_t^b}{\partial w_{it}} &= \frac{\phi}{p_t} + (1-\rho)(1-\zeta_{bt+1}f_{t+1}^g)\lambda E_t \left[ \Lambda_{t,t+1} \left[ \pi_t^\gamma \frac{\partial H_{t+1}^b(\varphi_{it+1}, \pi_t^\gamma w_{it})}{\partial \pi_t^\gamma w_{it}} + \frac{\partial H_{t+1}^b}{\partial \varphi_{it+1}} \frac{d\varphi_{it+1}}{dw_{it}} \right] \right] \\ &+ (1-\rho)(1-\zeta_{bt+1}f_{t+1}^g)(1-\lambda)E_t \left[ \Lambda_{t,t+1} \left[ \frac{\partial H_{t+1}^b(\varphi_{it+1}, w_{it}^*)}{\partial \varphi_{t+1}} + \frac{\partial H_{t+1}^b(\varphi_{it+1}, w_{it}^*)}{\partial w_{t+1}^*} \frac{dw_{t+1}^*}{d\varphi_{t+1}} \right] \frac{d\varphi_{it+1}}{dw_{it}} \right] + Z_w \end{aligned}$$

With  $Z_w$ :

$$Z_w = \pi_t^\gamma \lambda E_t \Lambda_{t,t+1} (1-\rho) \left[ f_{t+1}^g \left[ \bar{H}_{t+1}^g - H_{t+1}^b \right] - \zeta_0 \zeta_{bt+1}^{\eta_\zeta} \right] \frac{\partial \zeta_{bt+1}(\varphi_{it+1}, \pi_t^\gamma w_{it})}{\partial \pi_t^\gamma w_{it}}$$

But if search is chosen optimally at  $t+1$ ,  $Z_w = 0$ . Evaluating at the steady-state:

$$\frac{\partial H^b}{\partial w} \left( 1 - \delta^b \lambda \beta \pi^\gamma - \delta^b (1-\lambda) \beta \frac{dw^*}{d\varphi} \frac{d\varphi'}{dw} \right) = \frac{\phi}{p} + \delta^b \beta \frac{\partial H^b}{\partial \varphi} \frac{d\varphi'}{dw} \quad (S13)$$

### Effect of composition and wages on retention rate

The average retention rate in firm  $i$  is:

$$\begin{aligned} \delta_{it} &= \frac{\delta_t^g + \phi \varphi_{it-1} \delta_t^b}{1 + \phi \varphi_{it-1}} \\ \delta_t^b &= (1-\rho)(1-\zeta_{bt}(\varphi_{it}, w_{it})f_t^g) \end{aligned}$$

The derivative of retention with respect to composition is:

$$\frac{d\delta_{it}}{d\varphi_{it}} = \frac{\partial \delta_{it}}{\partial \delta_t^b} \frac{\partial \delta_t^b}{\partial \zeta_{bt}} \frac{\partial \zeta_{bt}}{\partial \varphi_{it}}$$

With:

$$\frac{\partial \delta_{it}}{\partial \varphi_{it-1}} = \frac{\phi(\delta_t^b - \delta_t^g)}{(1 + \phi \varphi_{it-1})^2} \quad \frac{\partial \delta_{it}}{\partial \delta_t^b} = \frac{\phi \varphi_{it-1}}{1 + \phi \varphi_{it-1}} \quad \frac{\partial \delta_t^b}{\partial \zeta_{bt}} = -(1-\rho)f_t^g$$

Evaluating at the steady-state, this yields:

$$\frac{d\delta}{d\varphi} = -(1-\rho)f^g \frac{\phi \varphi}{1 + \phi \varphi} \frac{\partial \zeta_b}{\partial \varphi} \quad (S14)$$

As for the effect of wages:

$$\frac{d\delta_t}{dw_t} = \frac{\partial \delta_t}{\partial \delta_t^b} \frac{\partial \delta_t^b}{\partial \zeta_{bt}} \frac{\partial \zeta_{bt}}{\partial w_t}$$

Evaluating at the steady-state:

$$\frac{d\delta}{dw} = -(1-\rho)f^g \frac{\phi\varphi}{1+\phi\varphi} \frac{\partial\zeta_b}{\partial w} \quad (S15)$$

## B5 Putting it all together:

$$\frac{\partial w^*}{\partial \varphi} = -\frac{\eta \partial J / \partial \varphi - (1-\eta) \partial H / \partial \varphi}{\eta \partial J / \partial w - (1-\eta) \partial H / \partial w} \quad (S1)$$

$$\frac{\partial H}{\partial \varphi} \left(1 - \delta^g \beta \frac{d\varphi'}{d\varphi}\right) = \delta^g \beta (1-\lambda) \frac{\partial H}{\partial w} \frac{\partial w^*(\varphi)}{\partial \varphi} \frac{d\varphi'}{d\varphi} \quad (S2)$$

$$\frac{\partial H}{\partial w} \left(1 - \delta^g \beta \lambda \pi^\gamma - \delta^g \beta (1-\lambda) \frac{\partial w^*(\varphi)}{\partial \varphi} \frac{d\varphi'}{dw}\right) = 1/p + \delta^g \beta \frac{\partial H}{\partial \varphi} \frac{d\varphi'}{dw} \quad (S3)$$

$$\frac{\partial J}{\partial \varphi} \left(1 - \beta \frac{d\varphi'}{d\varphi}\right) = -\beta J \frac{dx}{d\varphi} \frac{d\varphi'}{d\varphi} + \beta (1-\lambda) \frac{\partial J}{\partial w} \frac{\partial w^*}{\partial \varphi} \frac{d\varphi'}{d\varphi} \quad (S4)$$

$$\frac{\partial J}{\partial w} \left(1 - \beta \lambda \pi^\gamma - \beta (1-\lambda) \frac{\partial w^*}{\partial \varphi} \frac{d\varphi'}{dw}\right) = -\frac{1}{p} - \beta J \frac{dx}{dw} + \beta \frac{\partial J}{\partial \varphi} \frac{d\varphi'}{dw} \quad (S5)$$

$$\frac{dx}{d\varphi} \left(1 - \beta \delta \frac{d\varphi'}{d\varphi}\right) = \beta \delta (1-\lambda) \frac{dx}{dw} \frac{\partial w^*}{\partial \varphi} \frac{d\varphi'}{d\varphi} \quad (S6)$$

$$\frac{dx}{dw} \left(1 - \pi^\gamma \beta \delta \lambda - \beta \delta (1-\lambda) \frac{\partial w^*}{\partial \varphi} \frac{d\varphi'}{dw}\right) = -\frac{1}{\kappa p} + \beta \delta \frac{dx}{d\varphi} \frac{d\varphi'}{dw} \quad (S7)$$

$$\frac{d\varphi'}{d\varphi} = \delta - (1-\rho) f^g \varphi \frac{\partial \zeta_b}{\partial \varphi} \quad (S8)$$

$$\frac{d\varphi'}{dw} = -(1-\rho) f^g \varphi \frac{\partial \zeta_b}{\partial w} \quad (S9)$$

$$\frac{\partial \zeta_b}{\partial \varphi} = -\tau \frac{\partial H^b}{\partial \varphi} \quad (S10)$$

$$\frac{\partial \zeta_b}{\partial w} = -\tau \frac{\partial H^b}{\partial w} \quad (S11)$$

$$\frac{\partial H^b}{\partial \varphi} \left(1 - \beta \delta^b \frac{d\varphi'}{d\varphi}\right) = \beta \delta^b \left(1 - \lambda\right) \frac{\partial H^b}{\partial w} \frac{\partial w^*}{\partial \varphi} \frac{d\varphi'}{d\varphi} \quad (S12)$$

$$\frac{\partial H^b}{\partial w} \left(1 - \delta^b \lambda \beta \pi^\gamma - \delta^b (1-\lambda) \beta \frac{\partial w^*}{\partial \varphi} \frac{d\varphi'}{dw}\right) = \frac{\phi}{p} + \delta^b \beta \frac{\partial H^b}{\partial \varphi} \frac{d\varphi'}{dw} \quad (S13)$$

$$\frac{d\delta}{d\varphi} = -(1-\rho) f^g \frac{\phi\varphi}{1+\phi\varphi} \frac{\partial \zeta_b}{\partial \varphi} \quad (S14)$$

$$\frac{d\delta}{dw} = -(1-\rho) f^g \frac{\phi\varphi}{1+\phi\varphi} \frac{\partial \zeta_b}{\partial w} \quad (S15)$$

Where I simplified the expressions taking  $\delta^b = \delta^g = \delta$ . In sum, we have a system of **15** equations and **15** unknowns:

$$\left\{ \frac{\partial w^*}{\partial \varphi}, \frac{\partial J}{\partial \varphi}, \frac{\partial J}{\partial w}, \frac{\partial H}{\partial \varphi}, \frac{\partial H}{\partial w}, \frac{d\varphi'}{d\varphi}, \frac{d\varphi'}{dw}, \frac{\partial \zeta_b}{\partial \varphi}, \frac{\partial \zeta_b}{\partial w}, \frac{\partial H^b}{\partial \varphi}, \frac{\partial H^b}{\partial w}, \frac{dx}{d\varphi}, \frac{dx}{dw}, \frac{d\delta}{d\varphi}, \frac{d\delta}{dw} \right\}$$

We can see that  $\partial w^* / \partial \varphi = 0$  solves the system for any given price level  $p$  (or, more simply, that  $\partial w^{*r} / \partial \varphi = 0$ , with  $w^{*r} = w/p$ ).

$$\begin{aligned}
\frac{\partial w^*}{\partial \varphi} &= \frac{\partial H}{\partial \varphi} = \frac{\partial \kappa}{\partial \varphi} = \frac{\partial J}{\partial \varphi} = \frac{\partial H^b}{\partial \varphi} = \frac{\partial \zeta_b}{\partial \varphi} = \frac{d\delta}{d\varphi} = 0 \\
\frac{\partial H}{\partial w} &= \frac{1}{p(1 - \delta^g \beta \lambda \pi^\gamma)} \\
\frac{\partial J}{\partial w} (1 - \beta \lambda \pi^\gamma) &= -\frac{1}{p} - \beta J \lambda \pi^\gamma \frac{\partial \kappa}{\partial w} \\
\frac{d\kappa}{dw} &= -\frac{1}{\kappa p} (1 - \pi^\gamma \beta \delta \lambda)^{-1} \\
\frac{d\varphi'}{d\varphi} &= \delta \\
\frac{d\varphi'}{dw} &= -(1 - \rho) f^g \frac{\partial \zeta_b}{\partial w} \\
\frac{\partial \zeta_b}{\partial w} &= -\frac{\partial H^b}{\partial w} \\
\frac{\partial H^b}{\partial w} &= \frac{\phi}{p} * (1 - \delta^b \lambda \beta \pi^\gamma)^{-1} \\
\frac{d\delta}{dw} &= (1 - \rho) f^g \frac{\phi \varphi}{1 + \phi \varphi} \frac{\partial H^b}{\partial w}
\end{aligned}$$

## B6 Composition effects: Surplus approximations

See GHT Model Appendix C.2.6 for derivations. In short, we can approximate period-ahead surplus at renegotiating firms with period-ahead surplus of a firm with average composition and average wages. Crucial to obtaining this result is a first-order Taylor expansion around the average values for composition and wages, and the results that  $\partial H / \partial \varphi = \partial w^* / \partial \varphi = 0$ , which yield  $\eta_{H\varphi} = \eta_{w\varphi} = 0$ , which my model verifies. The firm surplus approximations, instead, hinge on  $\partial J / \partial \varphi = \partial H^b / \partial \varphi = \partial w^* / \partial \varphi = 0$ , also verified by my model. In turn, these yield  $\eta_{J\varphi} = \eta_{H^b\varphi} = \eta_{w\varphi} = 0$ .

The approximations for surplus of workers in good matches in renegotiating firms:

$$\begin{aligned}
\hat{H}_{t+1}(\varphi_{it+1}, w_{it+1}^*(\varphi_{it+1})) &= \hat{H}_{t+1}(\varphi_{t+1}, w_{t+1}^*) \\
\hat{H}_{t+1}(\varphi_{it+1}, \pi^\gamma w_t^*) &= \hat{H}_{t+1}(\varphi_{t+1}, w_{t+1}^*) + \eta_{H_w}(\gamma \hat{\pi}_t + \hat{w}_t^* - \hat{w}_{t+1}^*)
\end{aligned}$$

The approximations for firm surplus:

$$\begin{aligned}
\hat{J}_{t+1}(\varphi_{it+1}, w_{it+1}^*(\varphi_{it+1})) &= \hat{J}_{t+1}(\varphi_{t+1}, w_{t+1}^*) \\
\hat{J}_{t+1}(\varphi_{it+1}, \pi^\gamma w_t^*) &= \hat{J}_{t+1}(\varphi_{t+1}, w_{t+1}^*) + \eta_{J_w}(\gamma \hat{\pi}_t + \hat{w}_t^* - \hat{w}_{t+1}^*)
\end{aligned}$$

The approximations for surplus of workers in bad matches:

$$\begin{aligned}
\hat{H}_{t+1}^b(\varphi_{it+1}, w_{it+1}^*(\varphi_{it+1})) &= \hat{H}_{t+1}^b(\varphi_{t+1}, w_{t+1}^*) \\
\hat{H}_{t+1}^b(\varphi_{it+1}, \pi^\gamma w_t^*) &= \hat{H}_{t+1}^b(\varphi_{t+1}, w_{t+1}^*) + \eta_{H_w^b}(\gamma \hat{\pi}_t + \hat{w}_t^* - \hat{w}_{t+1}^*)
\end{aligned}$$

Finally,

$$\hat{w}_{t+1}^*(\varphi_{it+1}) \approx \hat{w}_{t+1}^*(\varphi_{t+1})$$

Because we also have that  $\partial\kappa/\partial\varphi = \partial\delta/\partial\varphi = 0$ , similar approximations can be derived for log-deviations in hires and retentions.

Where  $\eta_{H_w}$  denotes the steady-state elasticity of surplus  $H$  with respect to  $w$ , and so on for  $\eta_{J_w}$  and  $\eta_{H_w^b}$ .

## Chapter 2

# The Part and the Whole: Unemployment Expectations of the Employed

### Abstract

How do workers' beliefs about idiosyncratic unemployment risk and national unemployment change with public information? In this paper I make use of expectations data representative of the United States population to measure updates in workers' beliefs following announcements about local and nationwide events. In particular, I focus on widely reported idiosyncratic lay-offs. Workers update beliefs about their own job loss risk and national unemployment, even in an expansionary period with low and stable unemployment rates. A highly salient lay-off is associated to a 3.5 percentage point increase in the average reported probability of job loss and a 2.5 percentage point increase in the average reported probability of higher national unemployment. Findings are consistent with models of imperfect information where workers observe a noisy signal of the aggregate state.

# 1 Introduction

Recent work shows how increased unemployment risk can amplify business cycle fluctuations (Broer et al., 2021; Challe, 2020; Den Haan et al., 2018; Gnocato, 2024; Oh and Rogantini Picco, 2024; Ravn and Sterk, 2021). In this paper, I provide empirical evidence that workers are imperfectly informed about their unemployment risk. Unemployment risk is linked to job creation and job destruction - I focus on *job destruction risk*. I make use of survey data representative of the United States household head population to measure whether news about large local labour shocks have an effect on individuals' perceptions of their idiosyncratic unemployment risk, as well as on the expected evolution of national unemployment. First, I use data from the Survey of Consumer Expectations to provide descriptive evidence of households' beliefs about their own job loss risk, as well as about the evolution of aggregate unemployment. Then, I match firms' advance notices of mass lay-offs made in accordance to the Federal WARN Act to a news repository database (Factiva). This allows me to identify the events with the highest number of displacements that have been reported in the news. I then use daily variation in the date of survey response to employ a high frequency identification strategy and quantify the effect of reports of mass lay-offs on average beliefs.

This paper focuses on the effects of public information on beliefs about personal job loss risk and about national unemployment. In particular, it attempts to understand whether individuals use public information when updating their beliefs about idiosyncratic and aggregate conditions. As such, it relates to the literature that uses survey data to understand belief formation. An extensive body of work has leveraged survey data to measure and understand agents' beliefs about different economic variables - from inflation to returns to education (see Bachmann et al., 2022 for a comprehensive review across different fields of economics). There are fewer studies that focus on evaluating agents' beliefs about the labour market - Mueller and Spinnewijn (2021) review the literature. Namely, empirical evidence on belief formation has mostly focused on the role of personal experiences (Kuchler and Zafar, 2019; Hartmann and Leth-Petersen, 2022; Mueller et al., 2021). In an experimental setting, Roth and Wohlfart (2020) find that information about macroeconomic variables is incorporated by individuals on their expectations about personal unemployment risk.

Secondly, this paper also contributes to the literature assessing spill-over effects of local labour shocks (Gathmann et al., 2020; Helm, 2020; Giroud et al., 2021). I focus on an outcome variable that is typically unobserved in these studies - workers' beliefs. To the extent that public information about a local event affects workers' beliefs about aggregate conditions, this may shed light on spill-over effects of local labour market shocks.

Whether public information influences beliefs carries important policy implications. The ability of a policymaker to manage or influence average beliefs is mediated by the extent to which individuals incorporate *public* information when forming their beliefs. Moreover, it matters *what* public information affects beliefs - I measure updating with respect to *local* idiosyncratic events, and later extend my analysis to official communications about *aggregate* conditions.

The remainder of the paper is structured as follows: Section 2 explains the data used and shows descriptive results about labour market beliefs. Section 3 describes the empirical strategy and identification assumptions. Section 4 presents the results from the empirical analysis, as well as robustness and validity checks. Section 5 concludes.

## 2 Data

This section describes the data I use in the empirical analysis. First, I describe the data I use on workers' beliefs about personal and national unemployment. I study how these beliefs correlate with variables frequently studied in the micro (age, race, education) and macro (job tenure, income) labor literatures. Then, I describe the events that I use as treatments.

### 2.1 Beliefs: National unemployment and idiosyncratic job loss risk

The Survey of Consumer Expectations (SCE) is an online paid survey filled in by a rotating panel of 1,000 household heads. Data for the SCE is made available by the New York Federal Reserve at a monthly frequency from June 2013 to June 2020. Data is released with a 9 month lag relative to the date of survey completion. The survey is designed to measure expectations at a high frequency on different domains, such as inflation, household finance, the labour and the housing markets. It features several probabilistic questions that are formulated so as to elicit respondents' perceived likelihood of different events.<sup>1</sup> Each respondent may be asked to complete multiple survey waves for a period up to 12 months. Most individuals respond to the survey at least twice. Nearly a quarter of individuals responds to the survey every month for a year, as can be seen in Table 1.

In total, there are 111,838 observations in the raw data, out of which 86,961 are of working-age. Survey weights are provided to make the sample representative of United States household heads and are computed based on income, education, region and age.

The Labour Market Survey (LMS) is an in-depth module which is filled by SCE respondents every four months. Data is available for the period from March 2014 to July 2019 on further labour market expectations. It follows the same elicitation processes described for the SCE and allows us to retrieve information for both unemployed and employed individuals on expected and realized wage offers, expected and realized number of offers, and reservation wages.

**Belief variables** Unemployment beliefs are reported answers to the question: *“What do you think is the percent chance that 12 months from now the unemployment rate in the U.S. will be higher than it is now?”*. Note this could mean that individuals believe that unemployment will either decrease or stay unchanged. Job loss beliefs are captured by answers to the question: *“What do you think is the percent chance that you will lose your current job during the next 12 months?”*

Figure 1 plots the distribution of responses to job loss and unemployment beliefs. For both types of beliefs there is mass in all points from 0 to 100. Own beliefs exhibit a higher share of responses equal to zero, while nearly 20 percent of reported aggregate beliefs concentrate around the 50 percent mark. Although slightly skewed to the left, reported unemployment beliefs are relatively spread out. By contrast, own beliefs are concentrated to the left of the 50 percent mark.

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<sup>1</sup>There are four types of elicitation methods i) expectations of binary outcomes; ii) pointwise expectations for continuous outcomes; iii) probability densities for forecasts of continuous outcomes and iv) qualitative questions using a point scale. See Armantier et al. (2017) for details

|                                 | N obs  | Percent |
|---------------------------------|--------|---------|
| High-School Degree or Less      | 9,542  | 10.98   |
| Some College Education          | 28,571 | 32.88   |
| College Degree or More          | 48,773 | 56.13   |
| Age under 34                    | 20,305 | 23.30   |
| Age 35-49                       | 30,690 | 35.28   |
| Age 50-65                       | 35,983 | 41.37   |
| Male                            | 43,175 | 49.65   |
| Black                           | 9,099  | 10.46   |
| White                           | 71,765 | 82.51   |
| Married                         | 8,372  | 66.6    |
| Working full-time               | 59,054 | 67.9    |
| Working part-time               | 11,243 | 12.93   |
| Not working but would like to   | 3,312  | 3.81    |
| Not working and searching       | 2,592  | 2.98    |
| Household income under 50k      | 28,730 | 33.28   |
| Household income over 100k      | 26,413 | 30.6    |
| # respondents                   | 12,570 |         |
| # respondents w/ at least 2 obs | 10,324 |         |
| # respondents w/ all 12 obs     | 3,062  |         |
| # observations                  | 86,961 |         |

Table 1: Sample characteristics of the SCE dataset, working-age population

**Data quality checks** Respondents may report rounded instead of true perceived probabilities, either to express subjective uncertainty or to simplify communication. Granularity in responses, or lack thereof, may therefore convey information about rounding practices<sup>2</sup>. I find that bunching of responses at certain percentage points is more prevalent for unemployment than for job loss beliefs (see Table A1 of the Appendix). The frequency of answers equal to 0 and 100 is significantly higher for events under the direct control of respondents - namely, starting search or voluntarily quitting their jobs. By contrast, events such as finding an admissible job offer will likely be influenced by factors outside of respondents' direct control. Interestingly, the frequencies of 0 or 100 percent responses linked

<sup>2</sup>For example, it can be used to establish an upper bound to the extent of rounding, as in Giustinelli et al. (2020).

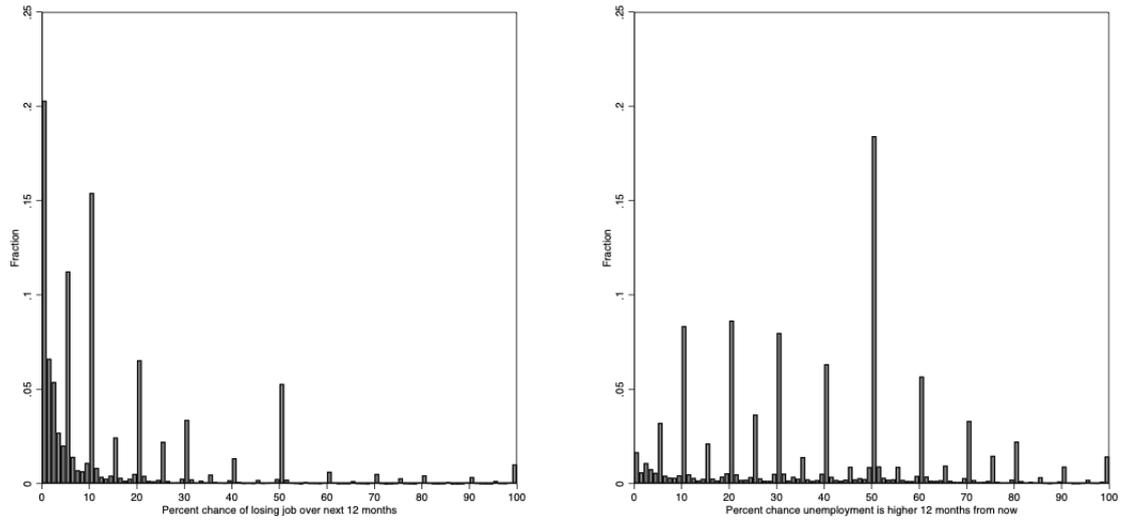


Figure 1: Sample distribution of job loss and unemployment beliefs

to the event of losing a job are placed between the former two events.<sup>3</sup>

**Best linear predictors** Given the rotating panel structure of the data and the existence of multiple observations per individual, I conduct two distinct analyses, similar to Kuchler and Zafar (2019): First, a cross-sectional analysis based on a sample that takes only one observation per respondent (Table 2) Then, the full sample of survey answers is used to understand the effects of within-individual variation in beliefs (Table 3).

*The role of socioeconomic characteristics* The analysis highlights different best linear predictors for own and aggregate beliefs. For instance, controls related to work experience are sizeable and significant predictors of individual beliefs, but not of aggregate beliefs. Indeed, longer job tenures are associated with lower subjective likelihoods of job loss, with individuals who have kept the same job for longer than 5 years reporting on average a 7.5 percentage points (pp) lower perceived job loss risk compared to individuals who have been employed for less than a month (the baseline category). Likewise, one can observe that sociodemographic covariates such as age or income are more predictive of job loss rather than national unemployment beliefs. This can be linked to the nature of the events asked to individuals - whereas the likelihood of a personal event may be informed by one's own characteristics, that is less likely the case when assessing a global event.

The sign of association between working part-time and beliefs is symmetric for national unemployment and job loss beliefs. Compared to full-time workers, part-time workers are on average expected to report a 2 pp lower perceived likelihood of an increase in unemployment, as well as a 3.5 pp higher perceived likelihood of job loss. The latter is not surprising given the lower attachment of part-time workers to the labour market. That part-time workers hold more optimistic beliefs than full-time workers regarding the evolution of national unemployment could also be reflective of how labour force attachment influences beliefs. Spinnewijn (2015) finds that unemployed individuals

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<sup>3</sup>This is in line with de Bruin et al. (2000) who document reported 50 percent subjective beliefs as a result of 'evoked feelings of less perceived control'.

hold more optimistic views than employed individuals - the attachment of part-time workers to the labour force is between these two categories, and so are their beliefs.

*Role of other beliefs* On average, individuals who assign low probabilities to losing their jobs over the next year are associated with lower reported likelihoods of higher unemployment over the same time period. A one percentage point increase in the chance of losing their job is, on average, associated with a 0.35 percentage points increase in likelihood of higher unemployment rate. The significant negative squared term on Table 2 suggests that these effects are decreasing in job loss beliefs - this is, the positive association between job loss and national unemployment is stronger for individuals with a lower subjective likelihood of losing their jobs. This non-linearity is not present on Column 2. On average, a 1 percentage point higher perceived chance of unemployment increasing next year is associated with a 0.1 percentage points higher subjective chances of getting fired in the cross-section. The analysis is robust to the inclusion of different measures of beliefs (e.g different non-parametric partitions of beliefs).

*Within-individual variation* Table 3 shows the predictive power of beliefs on within-individual variation. Estimation now includes individual-level fixed effects. An interesting result is the symmetric signs of the national unemployment rate coefficients on national unemployment and job loss beliefs, respectively. A 1 percentage point (pp) increase in the reported monthly national unemployment rate is associated with a 0.57 pp decrease in reported likelihood of higher unemployment occurring over the next year. The same increase is associated with a 0.21 pp increase in own-job loss beliefs for the same time horizon. The measure of national unemployment rate included in the regressions is the national unemployment rate from the month preceding the survey completion made publicly available by the Bureau of Labour Statistics. While one cannot assert whether individuals are *de facto* using this information when forming beliefs, one can nevertheless test if it is a relevant predictor. The resulting estimates, however, could either indicate how public information is used by individuals for belief formation, or simply capturing how public information is affecting belief formation through other unobservable channels.

Table 2: Linear prediction - cross-sectional analysis

|   | (1)                           | (2)                    |
|---|-------------------------------|------------------------|
|   | National unemployment beliefs | Job loss beliefs       |
| <i>Sociodemographic characteristics</i> |                               |                        |
| Age                                     | -0.0620**<br>(0.0224)         | 0.144***<br>(0.0198)   |
| 1.Black                                 | 0.897<br>(0.806)              | -0.219<br>(0.737)      |
| 1.Male                                  | -0.272<br>(0.498)             | 0.172<br>(0.425)       |
| 1.College=1                             | 0.756<br>(0.833)              | -0.750<br>(0.795)      |
| Middle income                           | -1.260<br>(0.645)             | -3.415***<br>(0.592)   |
| High income                             | -2.195**<br>(0.694)           | -3.540***<br>(0.622)   |
| <i>Professional characteristics</i>     |                               |                        |
| Working part-time                       | -1.996**<br>(0.763)           | 3.455***<br>(0.798)    |
| Employed between 1 and 6 months         | -1.761<br>(1.974)             | -0.676<br>(1.995)      |
| Employed between 6 months and 1 year    | -1.233<br>(1.971)             | -0.978<br>(1.956)      |
| Employed between 1 year and 5 years     | -1.392<br>(1.774)             | -4.713**<br>(1.747)    |
| Employed for more than 5 years          | -1.109<br>(1.774)             | -7.567***<br>(1.743)   |
| <i>Other beliefs</i>                    |                               |                        |
| Job loss beliefs                        |                               |                        |
| Levels                                  | 0.349***<br>(0.0331)          |                        |
| Squared                                 | -0.00223***<br>(0.000428)     |                        |
| National unemployment beliefs           |                               |                        |
| Levels                                  |                               | 0.104***<br>(0.0311)   |
| Squared                                 |                               | 0.000364<br>(0.000350) |
| <i>External information</i>             |                               |                        |
| Unemployment rate                       | -0.298<br>(0.227)             | 0.134<br>(0.170)       |
| State Fixed Effects                     | Y                             | Y                      |
| Year Fixed Effects                      | Y                             | Y                      |
| Constant                                | 47.85***<br>(10.16)           | 24.44<br>(13.64)       |
| Observations                            | 9064                          | 9064                   |
| R-squared                               | 0.042                         | 0.070                  |

Robust standard errors in parentheses, \* p<0.05,\*\* p<0.1,\*\*\* p<0.001.

|                                      | (1)                           | (2)                     |
|--------------------------------------|-------------------------------|-------------------------|
|                                      | National unemployment beliefs | Job loss beliefs        |
| <i>Job loss beliefs</i>              |                               |                         |
| Level                                | 0.319***<br>(0.0202)          |                         |
| Squared                              | -0.003***<br>(0.000232)       |                         |
| <i>National unemployment beliefs</i> |                               |                         |
| Level                                |                               | 0.083***<br>(0.0126)    |
| Squared                              |                               | -0.000116<br>(0.000147) |
| <i>External information</i>          |                               |                         |
| Unemployment rate                    | -0.586***<br>(0.0987)         | 0.214***<br>(0.0520)    |
| Constant                             | 49.52***<br>(1.119)           | 13.65***<br>(0.901)     |
| Individual Fixed Effects             | Y                             | Y                       |
| Year Fixed Effects                   | Y                             | Y                       |
| Observations                         | 64,349                        | 64,349                  |
| R-squared                            | 0.568                         | 0.634                   |

Table 3: Linear prediction - longitudinal analysis

To sum up, individuals hold heterogeneous beliefs about the probability of losing their job and the probability of an increase in the national unemployment rate. Personal and job-specific characteristics are predictive of workers' perceived probabilities of job loss, but less so of evolution of national unemployment. Individuals' job loss beliefs are predictive of their national unemployment beliefs, and vice-versa, which suggests that unobservables driving both beliefs are positively correlated.

## 2.2 Events: Publicly reported mass lay-offs

This section describes the data sources and process for the collection of publicly reported mass lay-off events. As noted before, the information set of survey respondents is *unobserved*. As such, it could be that respondents either have not observed a certain event, or that they have observed it but have not incorporated it into their belief formation process. In order to maximize the likelihood that workers know of these events, I focus on **large** and **widely reported** events.

The U.S. Federal WARN Act establishes that employers with 100 or more employees must give a 60 day notice in advance of plant closings or mass layoffs. I gather evidence of mass lay-off events from the WARN database, a publicly available <sup>4</sup> repository of firms that have filed a WARN notice across different states. In total, it consists of **44,728** events, available from July of 1998 to January 2023. The database provides information on the company name, city, number of workers affected, as well as whether the lay-offs are motivated by a plant or a firm closure, temporary lay-offs or permanent lay-offs. From 2014 to 2019, there are **11, 327** registered events across all U.S. states. Table 4 presents summary statistics by state.

| State            | Number of WARN events | Average Number of Displaced Workers |
|------------------|-----------------------|-------------------------------------|
| Alabama          | 104                   | 154                                 |
| Alaska           | 13                    | 137                                 |
| California       | 3580                  | 88                                  |
| Colorado         | 19                    | 133                                 |
| Connecticut      | 119                   | 56                                  |
| Florida          | 630                   | 106                                 |
| Georgia          | 448                   | 115                                 |
| Idaho            | 47                    | 92                                  |
| Indiana          | 221                   | 145                                 |
| Iowa             | 290                   | 60                                  |
| Kentucky         | 90                    | 120                                 |
| Maryland         | 197                   | 96                                  |
| Massachusetts    | 12                    | 53                                  |
| Minnesota        | 258                   | 39                                  |
| Missouri         | 123                   | 122                                 |
| Montana          | 10                    | 103                                 |
| Nevada           | 63                    | 196                                 |
| New Jersey       | 480                   | 130                                 |
| New Mexico       | 41                    | 173                                 |
| New York         | 2060                  | 71                                  |
| North Carolina   | 176                   | 107                                 |
| North Dakota     | 24                    | 102                                 |
| Oregon           | 202                   | 84                                  |
| Rhode Island     | 16                    | 122                                 |
| Texas            | 1068                  | 108                                 |
| Virginia         | 327                   | 125                                 |
| Washington       | 240                   | 129                                 |
| Washington, D.C. | 33                    | 113                                 |
| West Virginia    | 136                   | 119                                 |
| Wisconsin        | 300                   | 110                                 |
| US Total         | 11,327                | 95                                  |

Table 4: WARN Events - Summary statistics

I focus on the 99<sup>th</sup> percentile of worker displacements for each state. This reduces my sample of events to 379 distinct events. These events cover a variety of states (Figure 3), community zones and also industries (Figure 2). Then, I select the sub-sample of events that have been publicly covered in the news. For that, I match the company name and the event date from the WARN database to Factiva, a global news database. I consider all news classified

<sup>4</sup>Omer Arain, WARN database, last accessed on April 14 2023

as “lay-offs/redundancies” published by a United States media source around the dates of the official WARN Act files. If an event was covered in different dates, I consider the first date of publicly available news. The events are spread throughout the sample of analysis, without strong temporal clustering (Figure 4). I exclude any overlapping events from my analysis.

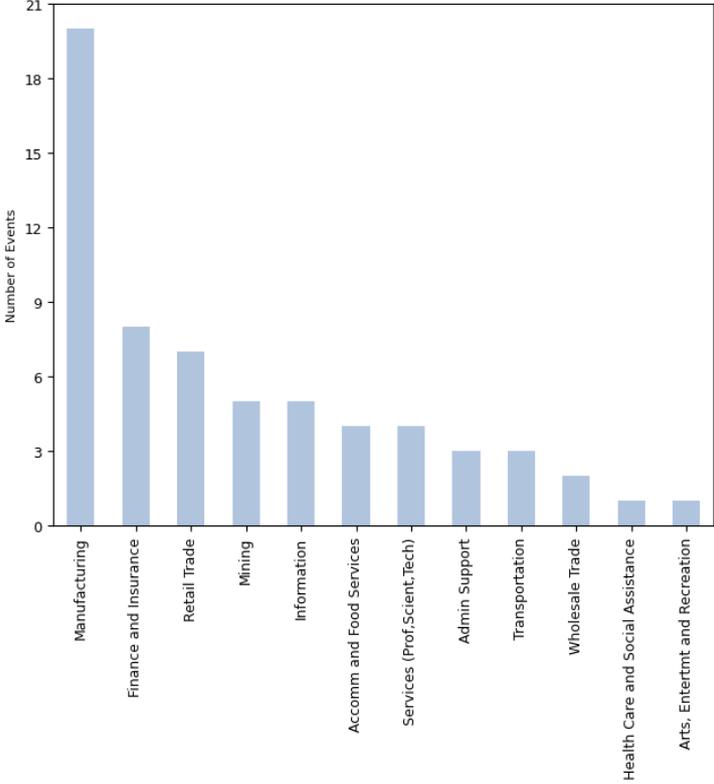


Figure 2: Industrial decomposition of all events

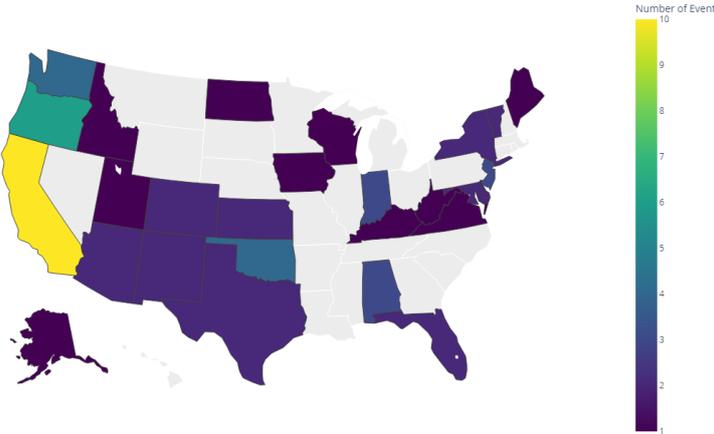


Figure 3: Spatial decomposition of all events

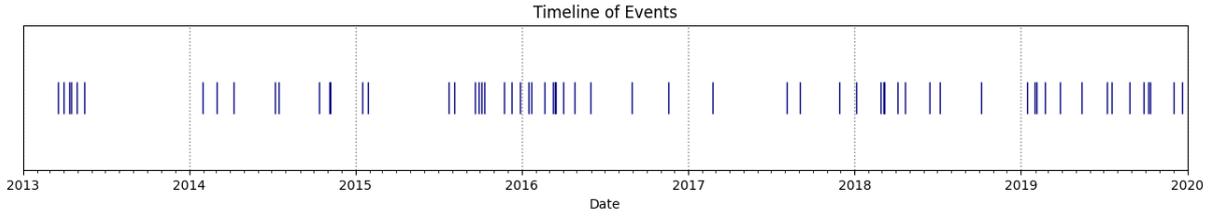


Figure 4: Timeline of all events

### 3 Empirical Strategy

I exploit the high frequency variation in the day of SCE survey responses to design an event-study specification.<sup>5</sup> For each event, I define a window  $w$  of length  $2k + 1$ . Each day within a given window is assigned a relative time-stamp  $\tau$ . Let  $y_{i,w,\tau}$  denote individual  $i$ 's perceived probability of losing their job reported at day  $\tau$  of window  $w$ . I estimate the following benchmark regression:

$$y_{i,w,\tau} = \alpha_w + \sum_{\substack{j=-k \\ j \neq -1}}^k \beta_j 1\{\tau = j\} + \Theta \mathbf{X}_i + \varepsilon_{i,w,\tau} \quad (2.1)$$

Where  $\mathbf{X}_i$  are individual time-invariant characteristics and  $\alpha_w$  are window fixed effects which capture other time-varying factors that could affect job loss beliefs. I define  $\tau = -1$  (i.e. the day prior to the event) as the benchmark period. In other words, each coefficient  $\beta_j$  tells us the average difference in job loss (unemployment) beliefs in period  $j$  compared to the average beliefs one day before a lay-off announcement. I cluster standard errors at the level which the treatment is being assigned - in this case, by window. Additionally, let  $u_{i,w,\tau}$  denote worker  $i$ 's probability that national unemployment will increase in the following year. I estimate the same regression with aggregate unemployment beliefs  $u_{i,w,\tau}$  as the dependent variable.

The coefficients estimated after the lay-off announcements can be interpreted as *causal* under two main conditions. First, that there is no omitted variable driving the dynamics of average job loss beliefs within an event window. I assess the validity of this hypothesis both by using high-frequency variation in my analysis, but also by estimating effects on the days prior to an announcement, which allows me to test for the existence of pre-trends. Second, that there is no reverse causality. My research setting minimizes reverse causality concerns - workers' beliefs are unlikely to cause mass lay-off announcements.

The baseline equation assumes that information about lay-off events is widespread - in other words, that all individuals are treated with information about a large lay-off. While this may be arguably reasonable if I focus on a small subsample of highly salient and broadcasted events (see *Salient Events*), it is unlikely to hold for extremely

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<sup>5</sup>Binder et al. (2022) also leverage daily variation in the NYFed SCE to analyse the response of inflation expectations to monetary policy news.

local shocks. As such, I consider a differences-in-differences specification which considers the treatment is assigned to the subpopulation of individuals employed in the same *state* as the lay-off announcement.<sup>6</sup>

$$y_{i,r,w,\tau} = \alpha_{w,r} + \sum_{\substack{j=-k \\ j \neq -1}}^k \beta_j^{DD} event_j^{same} + \Theta \mathbf{X}_i + \varepsilon_{i,r,w,\tau} \quad (2.2)$$

Where  $event_j^{same}$  is a dummy variable equal to 1 if  $\tau = j$  and individual  $i$  is from the same region as the region with lay-off announcement in event window  $w$ , and  $\alpha_{w,r}$  are regional-window fixed effects regional-window fixed effects which control from time-varying factors that can be affecting "treated" and "untreated" differently at a given point in time and  $\eta_\tau$  are relative event period fixed effects. Coefficients  $\beta_j^{DD}$  can be interpreted as the difference in updating behaviour between workers from treated regions ("insiders") and workers from regions that were not treated ("outsiders"). An alternative hypothesis is that treatment is assigned at the *industry* level.

$$y_{i,I,w,\tau} = \alpha_{w,I} + \sum_{\substack{j=-k \\ j \neq -1}}^k \beta_j^{DD} event_j^{same} + \Theta \mathbf{X}_i + \varepsilon_{i,I,w,\tau} \quad (2.3)$$

The specification is identical as before, only  $event_j^{same}$  is now equal to 1 if  $\tau = j$  and individual  $i$  is from the same industry as the one featured in the lay-off announcement of window  $w$ .

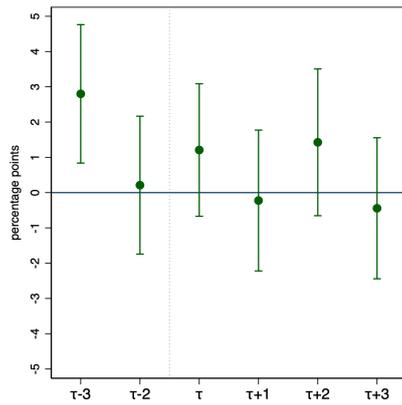
## 4 Results

### 4.1 Event-study results

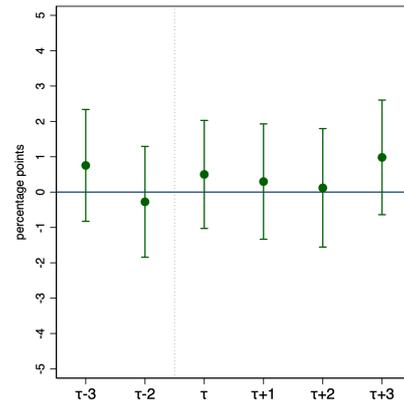
**All events** Figure 5 shows the results from estimating Equation 2.1 on the entire sample of mass lay-off events that were reported in the news. The window length is of 3 days and the reference period is the day before the first news of the event. As it can be seen, on average, workers' beliefs about their own unemployment prospects and national unemployment do not change in response to mass lay-off news in a three-day window. Figure 6 shows results when all events are considered at a weekly frequency. On average, there are no statistically significant effects of all events on workers' beliefs about their own unemployment in the weeks following announced lay-offs. While the right panel suggests a significant decrease in individuals' national unemployment beliefs on the week of the event, this appears to be part of a pre-event trend and therefore unrelated to the event itself. As discussed in the previous section, the interpretation of these results as casual is valid under the assumption of no pre-trends. While the inclusion of controls such as job tenure reduces the magnitude of the pre-trend, it does not fully eliminate it. As such, until further work and analysis disprove it, I interpret my results as correlational rather than causal.

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<sup>6</sup>A more refined specification would test whether beliefs of workers in treated commuting zones significantly differ from those in non-treated commuting zones after a mass lay-off. Although I have information on the commuting zone of workers and events, the number of observations per commuting zone is too low to have statistical power.

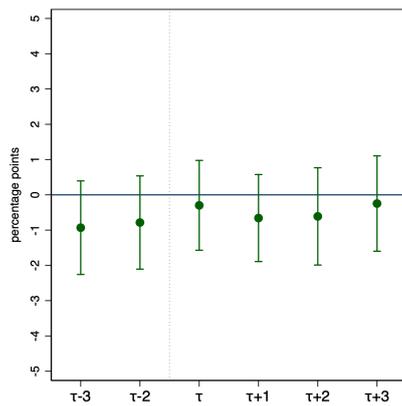


(a) Own-unemployment beliefs

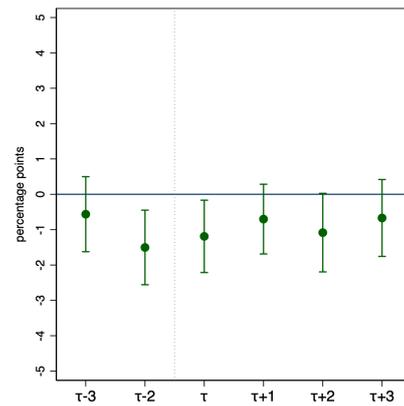


(b) National unemployment beliefs

Figure 5: Unemployment beliefs and mass-layoff events - daily frequency



(a) Own-unemployment beliefs

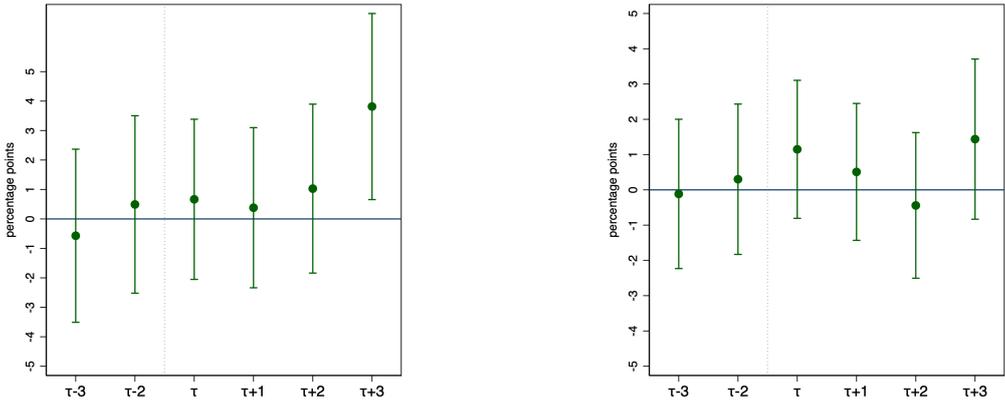


(b) National unemployment beliefs

Figure 6: Unemployment beliefs and mass-layoff events - weekly frequency

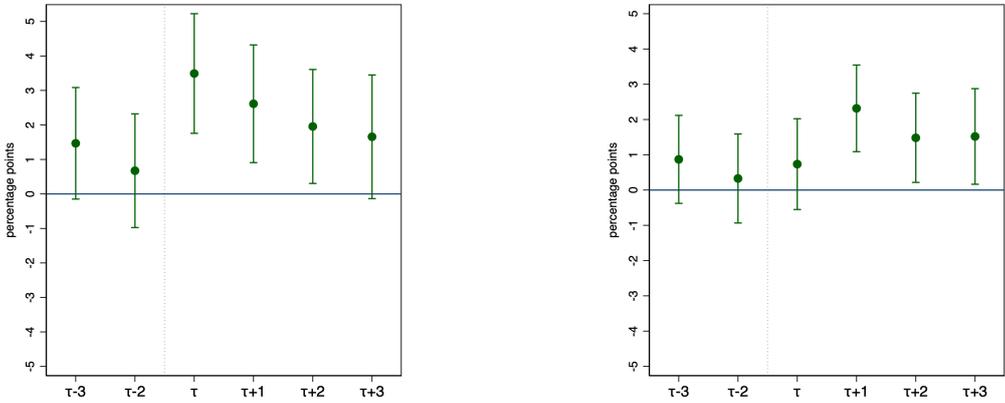
**Salient events** This section focuses on the most searched lay-off events on Google Trends during my sample period. I collect data from Google Trends to access the most searched lay-off events at a monthly frequency. I then match these lay-off events to Factiva and retrieve the precise date when they were announced. Table A2 lists these events. To the extent that Google Trends conveys a measure of public attention to events, these announcements are the most likely to be *salient* to respondents. Figure 7 shows the results of estimating regression 1 on the sample of salient events. On average, three days after a salient event is covered in the news for the first time, individuals revise their job loss beliefs up by 3.5 percentage points. In other words, highly salient lay-off events cause an average employed worker to report a subjective probability of losing their job that is 3.5 percentage points higher compared to the day before the salient event was reported. No statistically significant effect is found for beliefs about the evolution of national unemployment.

Figure 8 focuses on the effect of salient events on beliefs at a weekly frequency instead. On average, I find a positive and statistically significant effect of announced lay-offs on workers' beliefs about their own probabilities of job loss. Compared to the week prior to the announced event, workers report on average a 3.5 percentage points higher subjective probability of losing their jobs. These effects persist up to two weeks after the event, becoming non-significant on the third week. The right-panel shows that there also a statistically significant effect, albeit of a lower magnitude and delayed in timing, for beliefs about the evolution of national unemployment.



(a) Own-unemployment beliefs (b) National unemployment beliefs

Figure 7: Unemployment beliefs and salient events - daily frequency



(a) Own-unemployment beliefs (b) National unemployment beliefs

Figure 8: Unemployment beliefs and salient events - weekly frequency

### 4.2 Differences-in-Differences Specification

Figures 9 and 10 show the results from estimating Equations 2.2 and 2.3, respectively. The left panel of Figure 9 shows that, on average, lay-off announcements do not lead to differences in job loss beliefs between workers employed in the state of the lay-off *vis-a-vis* workers employed in other states. In other words, following an announced lay-off in a given state, workers from that state do not report a higher perceived probability of losing their jobs compared to workers from not affected states, *ceteris paribus*. However, as the right panel shows, differences emerge with respect to beliefs about the evolution of national unemployment. On average, workers from a treated state report a 12 percentage points higher percent chance that unemployment increases compared to workers from an untreated state, on the the day following the event announcement.

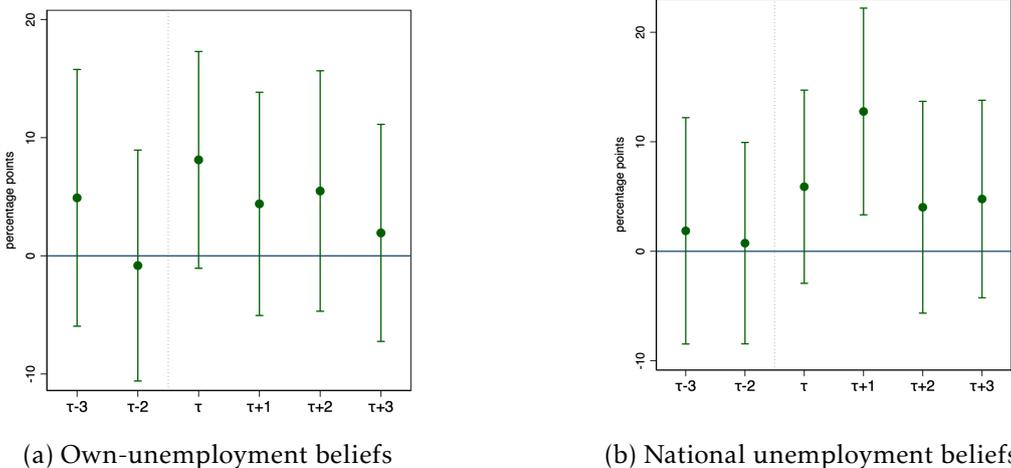
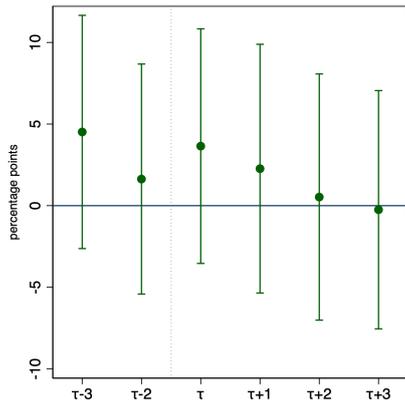
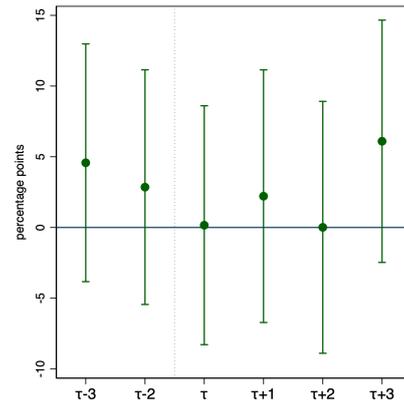


Figure 9: Diff-and-Diff: State-level analysis

As Figure 10 shows, no effects are found when I focus on insiders and outsiders with respect to the industry of the announced event. Ideally, it would be interesting to measure differential effects comparing workers in treated and untreated occupations, industries and their interaction. However, the available data is not granular enough to pursue this type of analysis.



(a) Own-unemployment beliefs



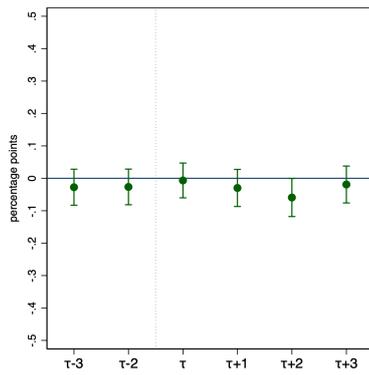
(b) National unemployment beliefs

Figure 10: Diff-and-Diff: Industry-level analysis

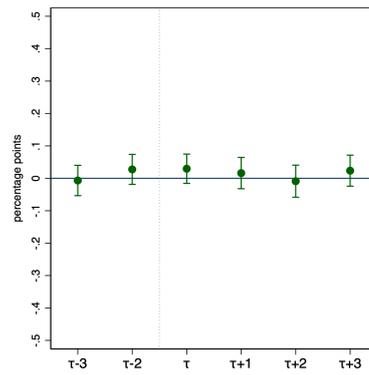
### 4.3 Robustness

I conduct three types of robustness checks to my analysis. I first verify that the sample is balanced across the event study, as well as the differences-in-differences specifications. Then, I conduct randomization inference using 1,000 samples of placebo events. Last but not least, I vary the window length in my estimation. Overall, my results are robust to all three batteries of tests.

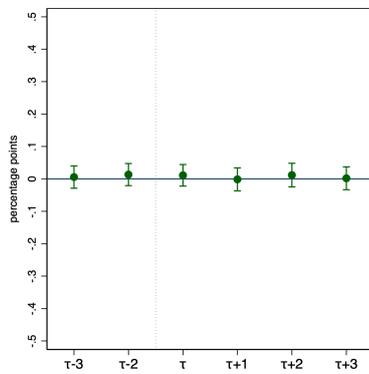
**Balanced sample checks** The first effort to probe the validity of my findings is to verify whether the composition of my treated and control groups are similar, conditional on fixed effects. In order to do that, I first regress sociodemographic characteristics on window fixed effects. I then regress the residuals on the different time-stamps of my event study. The resulting coefficients show the residualized mean differences with respect to income, education, gender and age within an event-study window between individuals in a given relative time period  $t \in [\tau - 3, \tau + 3]$  and individuals in the benchmark period ( $\tau - 1$ ). As you can see from Figure 11, these are stable throughout the event-study window.



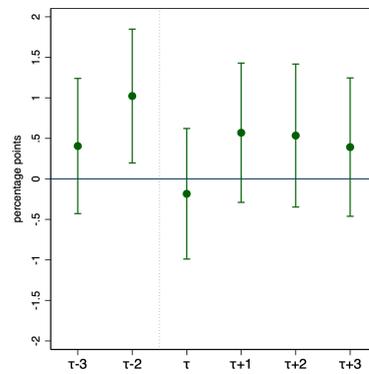
(a) Income



(b) Education



(c) Gender



(d) Age

Figure 11: Balance checks: Event-study specification

A similar regression can be run for the differences-and-differences specification. Here too, I retrieve the residuals from a regression of each sociodemographic variable on fixed effects. These residuals are then regressed on a dummy variable equal to one if an individual is part of the treatment group, and zero otherwise. The estimated residualized mean differences between treated and control groups across different sociodemographics are plotted in Figure 12

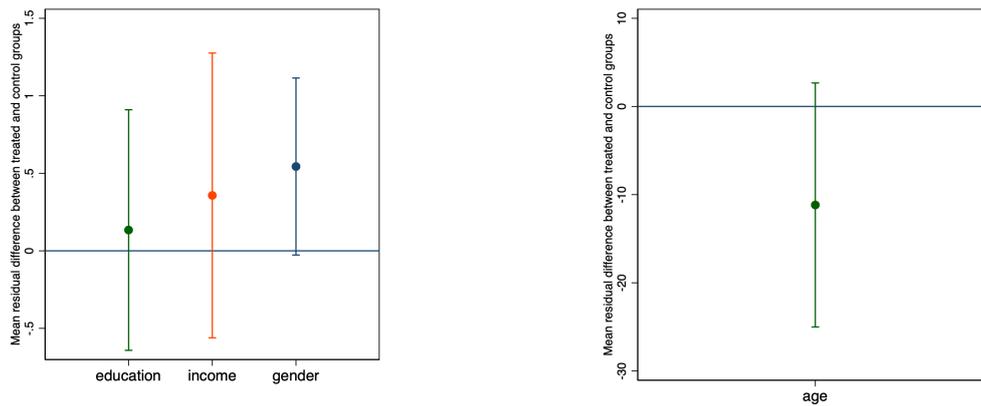


Figure 12: Balance checks: Differences-in-differences specification

### Randomization inference

I follow Imbens and Wooldridge (2009) and perform randomization inference to validate my analysis. I focus on the set of results that are significant in the main analysis - this is, responses of beliefs to *salient* events at a weekly frequency (as reported in Figure 8). For that, I generate 1,000 different samples of placebo events.<sup>7</sup> I estimate the event-study regression for each of the randomized samples and store the t-tests for each of the relative time window coefficients  $\{\tau - 3, \tau - 2, \dots, \tau + 3\}$ . I then plot the distributions of t-tests for each of these coefficients, and position the t-tests within those distributions, yielding a Fisherian p-value. Figure 13 shows results for own and national unemployment beliefs, respectively. The extremes of the box plot (in solid blue) are the 10<sup>th</sup> and 90<sup>th</sup> percentiles of each distribution. The t-statistics from the true event-study estimation are plotted as orange markers. As we can see, the t-statistics of all periods after a salient announcement are statistically significant, corroborating my initial results. In line with the main analysis, there are some subsisting issues indicative of pre-trends on the second week prior to the event. While deeper analysis and inclusion of appropriate additional controls may address this possibility, for now I present my results as correlational, rather than causal evidence.

<sup>7</sup>An illustrative example of the results generated by one of the random samples of dates is provided in the Appendix.

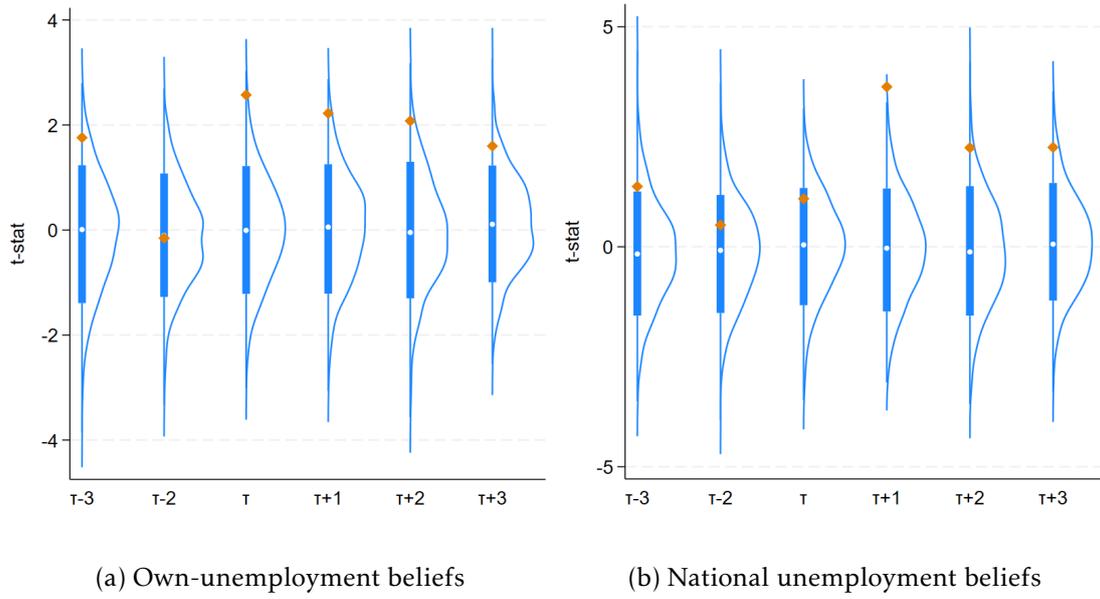


Figure 13: Balance checks: Differences-in-differences specification

**Window length** A narrow window rules out other sources of systematic variation other than the events under study. This window must be small enough to reject other sources of variation but wide enough to reasonably argue that individuals were exposed to the treatment. I estimate Equations 2.1, 2.2 and 2.3 on a four-day and five-day window, with no change in results (Figures 14, 15 and 16).

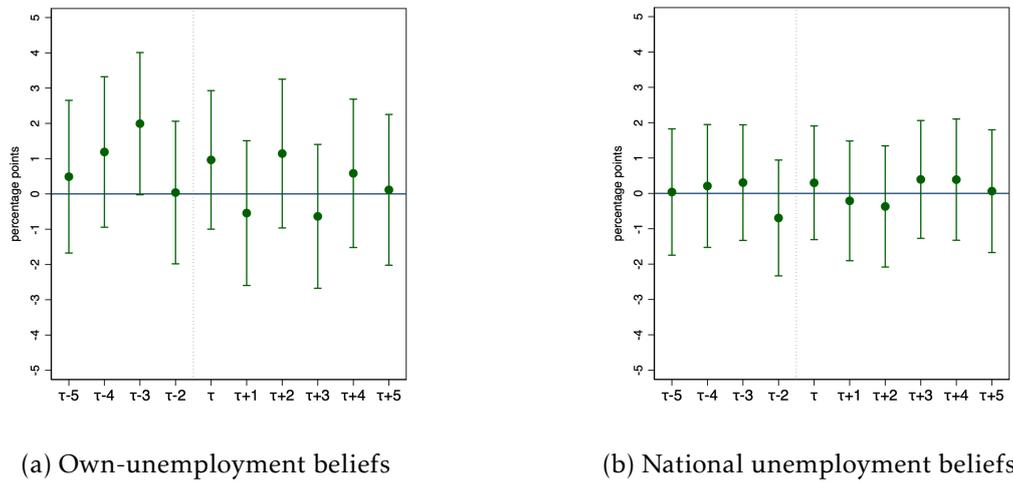
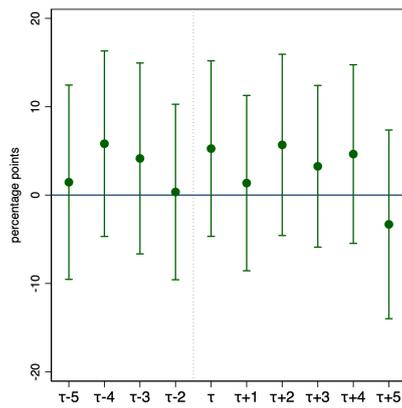
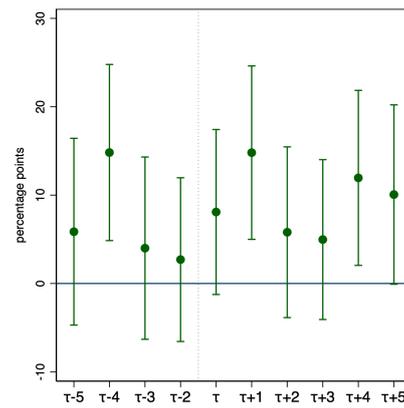


Figure 14: Event study: Extended window analysis

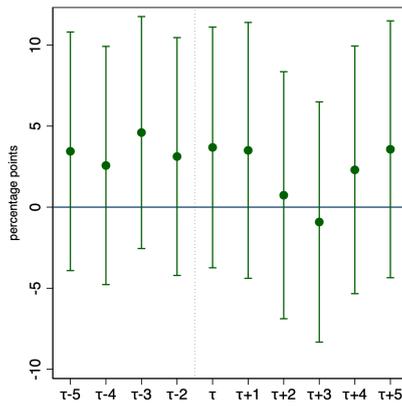


(a) Own-unemployment beliefs

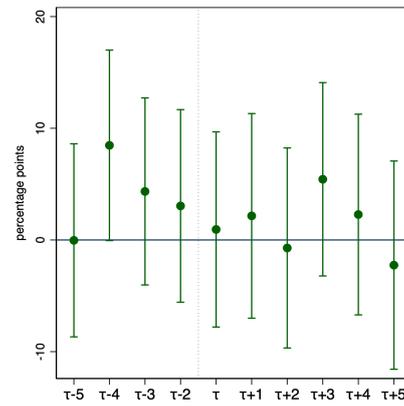


(b) National unemployment beliefs

Figure 15: Diff-and-Diff: Extended window analysis, state-level analysis



(a) Own-unemployment beliefs



(b) National unemployment beliefs

Figure 16: Diff-and-Diff: Extended window analysis, industry-level analysis

#### 4.4 Extension: learning from other events

To compare belief updating with respect to salient events other than mass lay-offs, I extend my analysis to Federal Open Market Committee (FOMC) announcements. Evidence shows that individuals on average do not update their inflation and interest rate expectations following Federal Open Market Committee (FOMC) announcements (Lamla and Vinogradov, 2019). These findings are corroborated in Binder et al. (2022). I find similar evidence for unemployment beliefs, reported in the Appendix. Note that, as aggregate unemployment was low and **decreasing** at a stable pace during my sample period, one would have to test whether these results would carry to periods with higher unemployment rates.

## 4.5 Discussion and theoretical mechanisms

The literature on **local** labour market effects of mass lay-offs highlights two competing forces when a large local displacement takes place (Gathmann et al., 2020). Importantly, these are made under the assumptions that workers have full information about the economy. On one hand, agglomeration effects are such that a mass lay-off in one firm may reduce labour demand in other firms from the same region and/or industry. On the other, if local wages are flexible and decrease after the shock, then other firms may become more willing to hire. If agglomeration forces are stronger than (downward) wage pressures, employment is expected to decrease in other firms. Therefore, *ex-ante* the probability of a worker involuntarily losing her job can either remain constant or increase following an announcement. If shocks occur in **local** labour markets, then they should not propagate to national wages and employment through general equilibrium effects. As such, under complete information, announcements should have no effect on workers' beliefs about the evolution of aggregate unemployment.

Instead, my results suggest that individuals update their beliefs about the aggregate state from idiosyncratic events. This is in line with imperfect information and models of local learning (see Baley and Veldkamp (2023) for a review). The differences-in-differences analysis cannot assert that workers geographically or occupationally *closer* to the shock revise their beliefs more strongly.

## 5 Conclusion

Workers' beliefs about idiosyncratic and national unemployment are positively correlated. Reduced form analysis sheds light on best predictors, but offers limited insight into how workers update their labour market beliefs in light of new information. To this effect, I design an empirical strategy to study how workers' update beliefs in response to a given announcement. First, I focus on reported mass lay-offs of idiosyncratic nature. Secondly, I study responses to information about the aggregate state of the economy, by focusing on FOMC announcements. I find that average beliefs about national unemployment change more markedly among workers in states where lay-offs took place. Additionally, and despite the Federal Reserve's dual mandate and commitment to pursuing maximum employment, average workers' labour market beliefs do not significantly change following announcements.

The evidence presented in this paper suggests that workers use local idiosyncratic events to update beliefs about aggregate conditions. This updating mechanism may stem either from information frictions or from an overestimation of "general equilibrium" effects of local shocks. While it is out of the scope of this paper to separate and test for these hypotheses, future work could move in this direction. In particular, these empirical findings are consistent with models of imperfect information where workers observe a noisy signal of the aggregate state - the fact that workers update beliefs about national unemployment, that mass lay-offs in the event-study are not associated to a change in unemployment rates and that national and regional unemployment rates during period of analysis were low and decreasing point are all in line with this hypothesis. Moreover, they are consistent with models where workers job destruction risk is endogenous. Future work could expand on these findings with a model with search frictions, a precautionary savings motive and imperfect information to research the macroeconomic implications of this type of belief updating.

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# A Appendix

## Bunching of variables

| <i>Percentage of responses in:</i>   |             |       |       |       |       |       |       |       |       |       |
|--|-------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| <b>Panel A. Rounding in subjective unemployment beliefs, SCE</b>                                   |             |       |       |       |       |       |       |       |       |       |
| Question: percent chance that ...  | N total obs | V50   | V100  | V25   | V10T  | V10C  | V5T   | V5C   | V1T   | V1C   |
| U.S unemployment rate higher in 12 months  | 111,532     | 0.180 | 0.031 | 0.048 | 0.208 | 0.232 | 0.058 | 0.039 | 0.099 | 0.102 |
| within the coming 12 months you will find a job that you accept                                    | 3,013       | 0.160 | 0.143 | 0.052 | 0.212 | 0.166 | 0.062 | 0.025 | 0.102 | 0.077 |
| within the coming 3 months you will find a job that you accept                                     | 3,014       | 0.151 | 0.107 | 0.064 | 0.214 | 0.181 | 0.057 | 0.032 | 0.117 | 0.077 |
| lose job during the next 12 months   | 65,064      | 0.054 | 0.215 | 0.025 | 0.228 | 0.059 | 0.136 | 0.009 | 0.248 | 0.027 |
| quit voluntarily during next 12 months   | 65,086      | 0.083 | 0.251 | 0.034 | 0.200 | 0.090 | 0.102 | 0.014 | 0.187 | 0.039 |
| start looking for a job coming next 12 months  | 27,900      | 0.038 | 0.463 | 0.015 | 0.146 | 0.048 | 0.069 | 0.004 | 0.197 | 0.020 |
| start looking for a job coming next 3 months   | 27,895      | 0.021 | 0.574 | 0.011 | 0.095 | 0.029 | 0.052 | 0.003 | 0.200 | 0.014 |
| if you were to lose job now, finding one within 3 months   | 65,282      | 0.117 | 0.130 | 0.065 | 0.234 | 0.168 | 0.070 | 0.024 | 0.121 | 0.069 |
| <b>Panel B. Rounding in subjective beliefs, LMS</b>  |             |       |       |       |       |       |       |       |       |       |
| Percent chance you receive a job offer in<br>the coming 4 months (including offers you may reject) | N total obs | V50   | V100  | V25   | V10T  | V10C  | V5T   | V5C   | V1T   | V1C   |
| unemployed respondents   | 4,829       | 0.047 | 0.488 | 0.017 | 0.126 | 0.049 | 0.059 | 0.005 | 0.183 | 0.025 |
| employed respondents   | 12,287      | 0.088 | 0.261 | 0.035 | 0.198 | 0.085 | 0.081 | 0.013 | 0.190 | 0.048 |

Table A1: Rounding patterns in aggregate- and own- subjective unemployment beliefs

Note: V  $\equiv$  {50}, V100  $\equiv$  {0, 100}, V25  $\equiv$  {25, 75}, V10-T  $\equiv$  {10, 20, 80, 90}, V10-C  $\equiv$  {30, 40, 60, 70}, V5-T  $\equiv$  {5, 15, 85, 95}, V5-C  $\equiv$  {35, 45, 55, 65}, V1-T  $\equiv$  non-round values in 1-24 or 76-99, V1-C  $\equiv$  non-round values in 26-74.

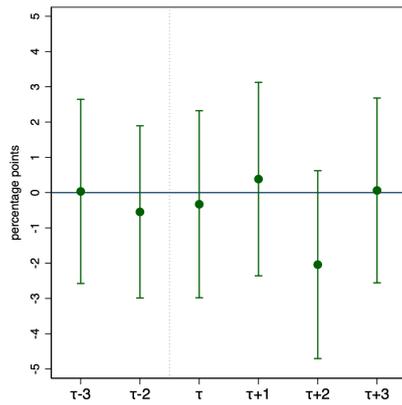
## Salient events

| Event               | Lay-offs | Date      |
|---------------------|----------|-----------|
| Best Buy            | 400      | 26feb2013 |
| IBM                 |          | 12jun2013 |
| Cisco               | 4000     | 15aug2013 |
| Wells Fargo         | 1800     | 19sep2013 |
| Merck               | 8500     | 01oct2013 |
| Teva Pharmaceutical | 5000     | 10oct2013 |
| Wal Mart Sams Club  | 2300     | 25jan2014 |
| Bank of America     | 100      | 26jan2014 |
| Kellogg             | 200      | 04feb2014 |
| JP Morgan           | 8000     | 25feb2014 |
| Poor Dart           | 325      | 04mar2014 |
| Microsoft           | 18000    | 17jul2014 |
| Target              | 1700     | 10mar2015 |
| Whole Foods         | 1500     | 28sep2015 |
| ESPN                | 300      | 21oct2015 |
| GE Transportation   | 1500     | 06nov2015 |
| Johnson and Johnson | 3000     | 19jan2016 |
| Sprint co           | 2500     | 25jan2016 |
| Yahoo               | 1700     | 03feb2016 |
| Intel               | 12000    | 20apr2016 |
| Loewe               | 2400     | 18jan2017 |
| Berkshire Hathaway  | 300      | 04apr2017 |
| State Department    | 2300     | 28apr2017 |
| Kellogg             | 300      | 03may2017 |
| ESPN                | 150      | 29nov2017 |
| Walmart             | 10000    | 12jan2018 |
| Kimberly Clark      | 5500     | 25jan2018 |
| Chesapeake Energy   | 400      | 30jan2018 |
| BP                  | 260      | 11feb2018 |
| General Motors      | 14000    | 26nov2019 |
| Tesla               | 3150     | 18jan2019 |
| Verizon             | 800      | 23jan2019 |
| Vice Media          | 250      | 02feb2019 |
| General Motors      | 4300     | 04feb2019 |
| Uber                | 400      | 29jul2019 |
| Daimler             | 900      | 02oct2019 |

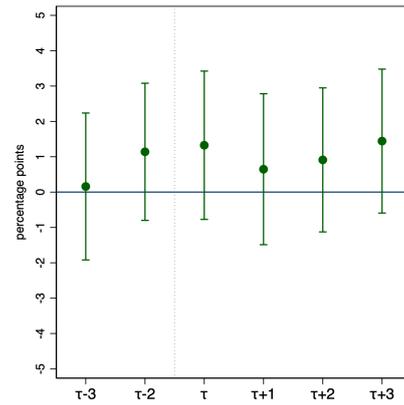
Table A2: List of salient events

## Extension: other events

Evidence shows that individuals on average do not update their inflation and interest rate expectations following Federal Open Market Committee (FOMC) announcements (Lamla and Vinogradov, 2019). These findings are corroborated in Binder et al. (2022). I test whether that is the case for unemployment beliefs. Figure A1 shows that on average, workers' beliefs about their own unemployment risk, as well as beliefs about the future evolution of national unemployment did not significantly change in the days following an announcement from the FOMC. Note that aggregate unemployment was low and **decreasing** at a stable pace during my sample period. An extension of this analysis could test whether communications during a period with historically high unemployment rates move beliefs or not.



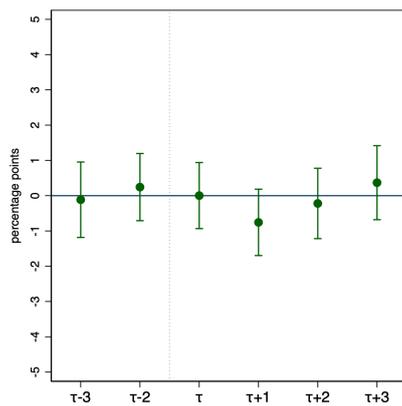
(a) Own-unemployment beliefs



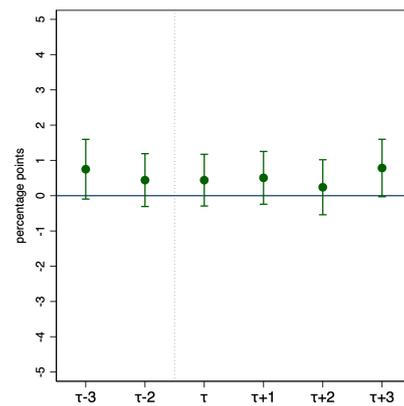
(b) National unemployment beliefs

Figure A1: Unemployment beliefs and FOMC announcements - daily frequency

Figure A2 shows that prior conclusions about the effect of FOMC announcements do not change when I take a weekly stance.



(a) Own-unemployment beliefs

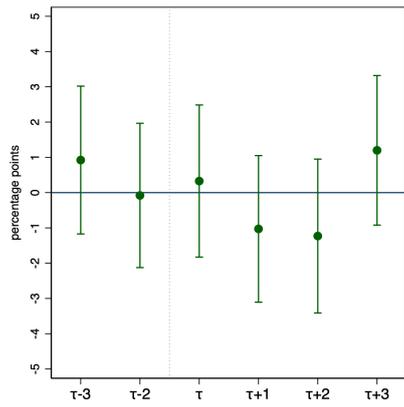


(b) National unemployment beliefs

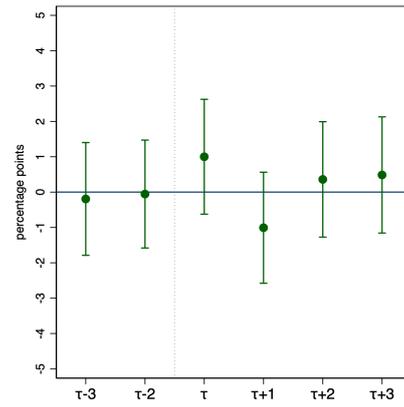
Figure A2: Unemployment beliefs and FOMC announcements - weekly frequency

## Placebo events

I conduct a placebo test by drawing a random sample of dates and estimating equation 1. As can be seen from **Figure A3**, for this random sample no effects are found in the placebo analysis with the event-study specification. In a similar fashion, no effects are found when estimating the differences-in-differences equation both at the industry (Figure A4) and at the state (Figure A5) levels.

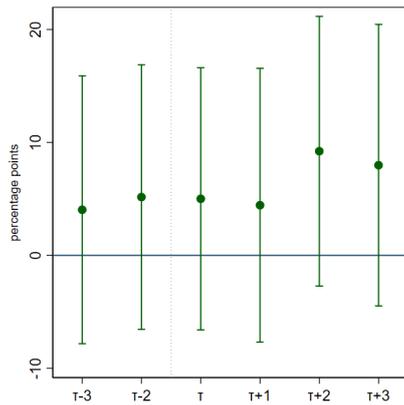


(a) Own-unemployment beliefs

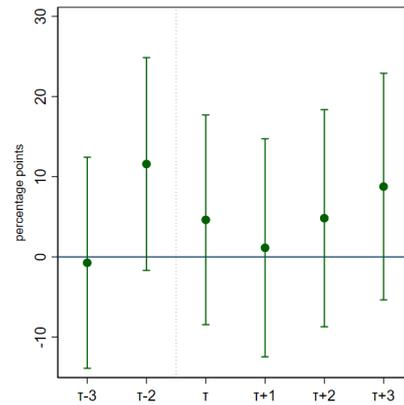


(b) National unemployment beliefs

Figure A3: Placebo tests, event-study specification

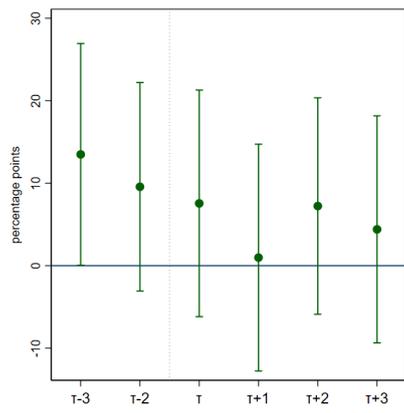


(a) Own-unemployment beliefs

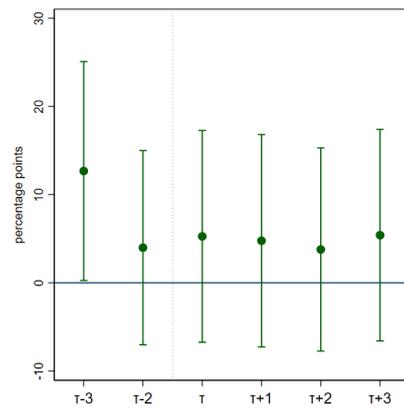


(b) National unemployment beliefs

Figure A4: Placebo tests: Differences-in-differences, industry-level analysis



(a) Own-unemployment beliefs



(b) National unemployment beliefs

Figure A5: Placebo tests: Differences-in-differences, state-level analysis

## Chapter 3

# Avoiding Unemployment: Job Loss Beliefs and On-the-Job Search

### Abstract

How do workers' perceived risk of job loss affect on-the-job search and wage growth? Using a representative survey, I show that employed workers systematically over-estimate their job loss probability compared to actual separation rates into unemployment. This is at odds with models where workers decide based on perfectly observable job values. I incorporate these findings into a partial equilibrium model of job search with heterogeneous separation risk and imperfect information. In this model, workers hold dispersed priors about the job loss risk they face and learn from survival. As time advances and individuals are not laid-off from their current jobs, they perceive their jobs to be safer, become choosier and therefore are less likely to switch to a new job. Survival and learning are determined by true job loss risk.

# 1 Introduction

*“Overall job growth has remained substantial (...) but that seems not to have relieved the fear of displacement. And that fear has doubtless played a significant role in the slowdown of the growth of wage compensation as workers have in effect sought to preserve their jobs by accepting lesser increases in wages.”*

– Alan Greenspan, Economic Club of Chicago, October 19th 1995 <sup>1</sup>

Job-to-job transitions play a key role in explaining cyclical wage dynamics and lifecycle welfare. How do workers’ perceived risk of job loss affect on-the-job search behaviour and aggregate wage growth? Using a survey representative of the United States household head population, I show that employed workers systematically over-estimate their job loss probability with respect to actual separation rates into unemployment. This is at odds with models where workers decide optimally based on job values that are perfectly observable and forecastable. Instead, this paper suggests workers are *uncertain* about the unemployment risk they face and act on this uncertainty by searching on-the-job.

Incorporating individuals’ subjective beliefs into models of job search can shed light into social mobility and inequality. Extensive evidence shows that individuals’ actions are informed by their beliefs. In this sense, systematic biases may influence workers’ search and acceptance decisions and translate into persistent labour market outcomes. To understand these links, recent studies have used increasingly available survey data that consistently elicits beliefs and outcomes to inform models of job search that relax assumptions of full information about the distribution of wage offers (Conlon et al., 2018), the arrival rate of offers (Potter, 2021), workers’ skills (Baley et al., 2022) or productivity (Venkateswaran, 2014; Di Pace et al., 2021).

I focus on employed workers’ beliefs, given the impact of job-to-job flows for lifecycle welfare, labour market efficiency and wage growth (Karahan et al., 2017). My work relates to literature examining the role of job security in search models, where individuals search for jobs not only to improve their wages but also to avoid unemployment spells (Nagypál, 2005; Jarosch, 2021; Pinheiro and Visschers, 2015). Differently from these studies, I consider unemployment risk as an unknown variable for workers on which they hold *subjective beliefs*, rather than an exogenous feature of the firm or job match.

My empirical findings are summarised as follows. First, cross-sectional heterogeneity in job loss beliefs cannot be explained by observable characteristics. In fact, individuals’ socio-demographic and professional traits explain less than 4 percent of total cross-sectional variation in beliefs. Workers who search on-the-job report on average 8 percentage points higher job loss probabilities than workers who do not search. Job loss beliefs are predictive of future realised job separations observed in the data.

Second, I find that individuals who switch to lower-paid jobs reported higher than average subjective probabilities of job loss and lower than average reservation wages prior to switching. After switching jobs, workers revise their beliefs downwards by approximately 8 percentage points. Acceptance of wage cuts is an empirical feature of 40% of

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<sup>1</sup>As cited in Manski and Straub (2000)

job-to-job transitions that current search models cannot account for (Jolivet et al., 2006; Bowlus et al., 2001). One possibility is that they accept lower wages in exchange for expected future wage growth (Postel-Vinay and Robin, 2002). Another hypothesis suggests that wage cuts are accompanied by increasing non-pecuniary benefits (Hall and Mueller, 2018). Nevertheless, recent evidence shows that the majority of earnings declines from job-to-job transitions are not offset by future increases (Sorkin, 2018) or higher non-wage values (Briggs et al., 2019) - I propose that individuals' perceived job loss risk may generate a motive for acceptance of wage cuts.

Third, I compare individuals' beliefs with observed outcomes. I find a systematic overestimation of beliefs relative to outcomes of around 10 percentage points, with very little variation across observable characteristics. I use my empirical findings to build a simple model of job search with heterogeneous job loss risk, which I modify to incorporate subjective beliefs. Future work will expand on this bare-bones model.

This paper contributes to a body of work linking wage growth, heterogeneity and on-the-job search (Carrillo-Tudela et al., 2022; Salgado et al., 2019). Compared to existing studies, I document a source of heterogeneity directly measurable from survey data that cannot be explained by other existing measures. Additionally, it speaks to the literature on uncertainty-driven business cycles. The latter has mostly emphasised how firms respond to uncertainty (Schaal, 2017; Freund et al., 2022), whereas here I consider the worker-side.

The paper is structured as follows: Section 2 describes the data and main empirical findings. Section 3 tests for rationality in workers' job loss beliefs. Section 4 proposes a simple model to illustrate how job loss risk shapes employed workers' search and acceptance decisions. Section 5 concludes.

## 2 Empirical evidence on job loss beliefs

### 2.1 Data description

This section uses data from the Survey of Consumer Expectations (SCE) to characterize workers' job loss beliefs. The Survey of Consumer Expectations is a monthly survey ran by the Federal Reserve of New York since 2012. It features a rotating panel of 1,200 individuals representative of the United States household head population. Respondents stay on the panel for up to 12 months. A complete description of the survey is provided in Armantier et al. (2016).

Individual-level responses to the SCE can be matched to responses to the Labour Market Survey (LMS). The LMS is ran every four months as a supplement to the SCE, and elicits information on workers' earnings, industry, on-the-job search behaviour, reservation wages, received and accepted offers as well as expected and actual transitions in labour force status. Matching the two surveys allows me to effectively analyse how individuals' job loss fears relate to their search behaviour and observed labour market transitions. While each individual is followed for at most one year, this high-frequency account of individual-level beliefs, search behaviour and outcomes is only possible by matching these two data sources<sup>2</sup>. Other features related to the quality of survey elicitation, such as limited attrition, add credibility to using this source for comparisons between beliefs and outcomes.

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<sup>2</sup>See Mueller and Spinnewijn (2021) for a review of surveys eliciting job loss and job finding beliefs.

In the SCE, employed individuals answer the following question: “What do you think is the percent chance that you will lose your current job during the next 12 months?”. Figure 1 plots the distribution of answers in the pooled cross-section. Job loss beliefs are strongly right-skewed, a reasonable feature given that job loss is a low-probability event. The strong prevalence of responses equal to zero is therefore unsurprising. Nevertheless, analysis of response granularity suggests that, despite some bunching of responses around multiples of 10 and 5 percent (see Appendix) akin to this type of data, the existence of mass around the entirety of the distribution of values suggests that reported beliefs represent agents’ true beliefs.

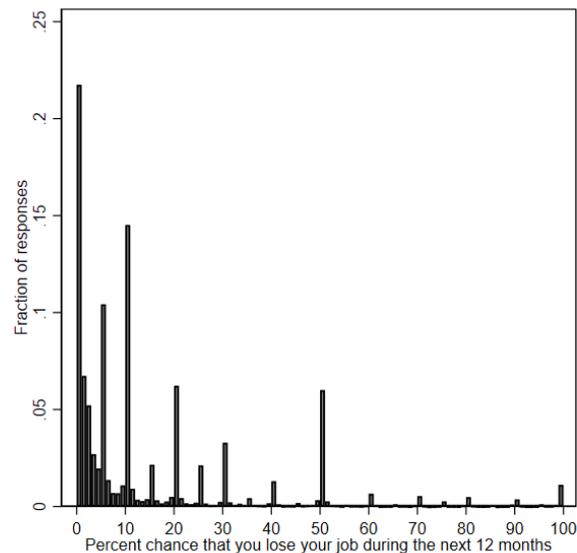


Figure 1: Distribution of job loss beliefs, Survey of Consumer Expectations

Table 1 presents descriptive statistics of job loss beliefs of working individuals aged between 20 and 65 years old. We see that mean job loss beliefs are increasing in age and decreasing in education, as well as household income. There are no significant differences across gender. Importantly, experiences of unemployment prior to belief elicitation seem to be associated with significantly higher average job loss beliefs. This is in line with a body of evidence that relates individuals’ experiences to their beliefs (Malmendier and Nagel, 2016; Kuchler and Zafar, 2019)<sup>3</sup>. Individuals with weaker labour market attachment (i.e. holding a part-time contract) also report, on average, higher subjective probabilities of job loss.

Notwithstanding, as can be seen in Table 2 workers’ observable characteristics explain very little of the cross-sample

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<sup>3</sup>I select instances where I have direct information from survey respondents in past waves that they were unemployed prior to their current employment spell and elicited beliefs. Given that I do not observe individuals’ unemployment history prior to entering the survey, it could be that I underestimate the number of individuals with past unemployment experiences.

variation in job loss beliefs.<sup>4</sup>

Table 1: Job loss beliefs and respondent characteristics

|                                | Mean percent chance<br>of losing job | Robust<br>standard errors | Nr<br>observations |
|--------------------------------|--------------------------------------|---------------------------|--------------------|
| High-School Degree or Less     | 15.16                                | (0,66)                    | 5,460              |
| Some College Education         | 14.67                                | (0,35)                    | 17,335             |
| College Degree or More         | 13.88                                | (0,24)                    | 34,947             |
| Age 20-34                      | 13.81                                | (0,44)                    | 15,401             |
| Age 35-49                      | 14.30                                | (0,41)                    | 22,447             |
| Age 50-65                      | 15.31                                | (0,44)                    | 19,937             |
| Female                         | 14.48                                | (0,35)                    | 28,631             |
| Male                           | 14.54                                | (0,35)                    | 29,148             |
| Household income < 50k         | 17.54                                | (0,51)                    | 15,874             |
| Household income ∈ [50k, 100k] | 12.95                                | (0,35)                    | 22,434             |
| Household income > 100k        | 12.80                                | (0,35)                    | 20,183             |
| Part-time workers              | 17.53                                | (0,61)                    | 8,250              |
| Full-time workers              | 13.67                                | (0,25)                    | 50,573             |
| Unemployment experience        | 25.19                                | (1,47)                    | 1,928              |
| No unemployment experience     | 13.89                                | (0,26)                    | 47,514             |

Own computations based on Survey of Consumer Expectations, sample of respondents aged 20-65 from June 2013 to December 2019. Survey weights used.

<sup>4</sup>A more in-depth analysis on the role of experiences, socioeconomic characteristics and other beliefs in predicting job loss beliefs is performed on my second-year manuscript. Here, I focus on the finding that observable characteristics explain very little of the cross-sample variation.

Table 2: Job loss beliefs: predictors

|                              | (1)    | (2)    | (3)    |
|------------------------------|--------|--------|--------|
| Sociodemographic controls    | Y      | Y      | Y      |
| Professional controls        | N      | Y      | Y      |
| Industry controls            | N      | Y      | Y      |
| Year and state fixed effects | N      | N      | Y      |
| Observations                 | 57,386 | 49,109 | 33,278 |
| R-squared                    | 0.014  | 0.025  | 0.034  |

Professional controls consist of dummies indicating whether the individual is working part-time and whether they have experienced unemployment. Sociodemographic controls include age, education, gender, household income. Standard errors are clustered at the respondent level.

Table 3 shows that job loss beliefs are, on average, predictive of actual job loss, over and above observable characteristics.<sup>5</sup> This is in line with findings based on other surveys, such as the Health and Retirement Study (Hendren, 2017) or the Australian Household Income and Labour Dynamics survey (HILDA) (Dickerson and Green, 2012). This is important for two reasons. First, it attests to the quality of the reported beliefs and to the use of survey data in the analysis. Second, together with the findings in Table 2, it suggests that beliefs incorporate private information or heterogeneity that cannot be accounted for by the characteristics elicited in the survey.

From a theoretical standpoint, most sources of heterogeneity incorporated in labour models and relevant to the job destruction probability would be subsumed in the variables that we observe - age, education, gender, race, experience, industry, local and cyclical business conditions. In that sense, it seems more likely that beliefs are incorporating private and heterogeneous information, rather than being driven by other unobservable characteristics.

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<sup>5</sup>Kuchler and Zafar (2019) present similar findings using the same data source and considering the events of job loss a different time horizons, namely within one, three, six and nine months.

Table 3: Predictive power of job loss beliefs

|   | Outcome: lost job within 12 months |          |         |         |
|---|------------------------------------|----------|---------|---------|
|   | (1)                                | (2)      | (3)     | (4)     |
| Belief: Probability of losing job in next 12 months | 0.212***                           | 0.193*** | 0.095** | 0.097** |
|   | (0.026)                            | (0.026)  | (0.033) | (0.033) |
| Sociodemographic controls                           |                                    | x        | x       | x       |
| Professional controls                               |                                    |          | x       | x       |
| Year fixed effects                                  |                                    |          |         | x       |
| Observations  | 8,254                              | 8,189    | 4,104   | 4,104   |
| R-squared   | 0.035                              | 0.049    | 0.052   | 0.058   |

Outcome variable is a dummy indicating whether the individual has lost their job within 12 months of reporting her subjective belief. Sociodemographic controls include gender, age, education and household income. Professional controls include tenure at current job and industry.

## 2.2 Job loss beliefs, prevalence of wage cuts and on-the-job search behaviour

In this sub-section, I assess how job loss beliefs correlate with workers' search behaviour and search outcomes. Data from the Labour Market Survey (LMS) is informative of workers' on-the-job search behaviour, reservation wages, as well as self-reported earnings. One can learn whether workers are searching on-the-job from the following question: "Have you done anything in the last 4 weeks to look for new work?". Information about search effort is provided by the answers to the following question: "Within the last 7 days, about how many total hours did you spend on job search activities?". An additional measure of effort is a count variable of the total number of methods selected by respondents to describe their past search behaviour. Using that measure of effort does not change the conclusions presented in this sub-section. Annual earnings are reported before taxes and deductions, and include bonuses, overtime pay, tips and commissions. Workers' reservation wage is elicited as follows: "Suppose someone offered you a job today in a line of work that you would consider. What is the lowest wage or salary you would accept (before taxes and other deductions) for this job?". This information is elicited every four months.

Table 4 shows how workers who search-on-the-job and workers who do not differ in terms of reported job loss beliefs, reservation wages and earnings. For the subsample of searching workers for whom I observe a job-to-job transition, I can compute the mean change in job loss beliefs, in reservation wages and in earnings. As it can be seen, the number of observed job-to-job transitions in the sample is quite small. This is partly due to the strict definition that I used to

identify job-to-job transitions, under which i) an individual is employed in two consecutive months and ii) in the second observed month she declares that she has switched employers since the last survey. One robustness check that I can implement is to allow for looser definitions of job-to-job transitions - for example, considering situations where the individual spends one month unemployed.

Table 4: Summary statistics

|                         | N. obs | Mean job loss beliefs<br>before transition<br>(percent) | Mean change in<br>job loss beliefs<br>after transition<br>(percentage points) | Mean<br>gross earnings<br>(USD/year) | Mean change in<br>gross earnings<br>(USD/year) | Mean<br>reservation wages<br>(USD/hour) | Mean change in<br>reservation wage<br>(USD/hour) | Mean<br>reservation wages<br>(USD/hour) |
|-------------------------|--------|---|---|--------------------------------------|--|---|--|---|
| Employed non-searching  | 12,513 | 11.44   |   | 61,067                               |  | 34                                      |  | 34                                      |
| Employed searching      | 4,972  | 19.16   |   | 65,121                               |  | 32                                      |  | 32                                      |
| of which: job-switchers | 204    | 25.37   | -8.18   | 49,472                               | 5,939.4  | 30.40                                   | 1.75   | 30.40                                   |
| of which: to higher pay | 118    | 23.05   | -7.25   | 47,123                               | 18,520.4                                       | 31.23                                   | 3.01   | 31.23                                   |
| of which: to lower pay  | 86     | 27.92   | -9.19   | 52,259                               | -8,994.6                                       | 29.40                                   | 0.26   | 29.40                                   |

Own computations based on Survey of Consumer Expectations and Labour Market Survey. Survey-weights applied. Mean change in job loss beliefs refer to sample averages of individual-level differences computed before and after the observed transition to new job. For individuals who have experienced a JTJ transition, "Mean gross earnings", "Mean job loss beliefs" and "Mean reservation wages" refer to these variables as observed prior to transitions.

Tables 5, 6 and 7 assess whether job loss beliefs are predictive of search-on-the-job, over and above socio-demographic characteristics. Table 5 regresses a binary variable indicating whether an individual has searched on-the-job over the past month on his job loss beliefs. Tables 6 and 7 regress search effort, as measured by the number of methods used and the hours spent searching, on job loss beliefs. In both instances, we see a positive association between job loss beliefs and search on-the-job. Associations are more pronounced if expressed in relative terms (i.e. comparing individuals with non-zero and zero job loss beliefs, or high and low job loss beliefs).

Note that while reverse causality may be a problem in similar settings (e.g in instances where one evaluates the relationship between the perceived probability of job finding and search effort), this is unlikely to be an issue with respect to the event of job loss<sup>6</sup>

<sup>6</sup>One can conceive a scenario of professional retaliation whereby an employer responds to knowing that the employer searches with a threat of firing her. While possible and plausible in given contexts, this should not be the main driver of my results.

Table 5: Job loss beliefs and on-the-job-search: OLS regressions

|                     | Measure of job loss beliefs  |                          |                          |                              |                        |                        |                          |                       |                       |
|---------------------|------------------------------|--------------------------|--------------------------|------------------------------|------------------------|------------------------|--------------------------|-----------------------|-----------------------|
|                     | Job loss beliefs as reported |                          |                          | 1.(Positive job loss belief) |                        |                        | 1.(High job loss belief) |                       |                       |
| Coefficient         | 0.00410***<br>(0.000299)     | 0.00419***<br>(0.000291) | 0.00419***<br>(0.000289) | 0.0770***<br>(0.00919)       | 0.0724***<br>(0.00939) | 0.0711***<br>(0.00938) | 0.113***<br>(0.00918)    | 0.113***<br>(0.00910) | 0.112***<br>(0.00905) |
| Controls            | No                           | Yes                      | Yes                      | No                           | Yes                    | Yes                    | No                       | Yes                   | Yes                   |
| Year fixed effects  | No                           | No                       | Yes                      | No                           | No                     | Yes                    | No                       | No                    | Yes                   |
| State fixed effects | No                           | No                       | Yes                      | No                           | No                     | Yes                    | No                       | No                    | Yes                   |
| Nr observations     | 11,838                       | 11,836                   | 11,813                   | 11,860                       | 11,858                 | 11,835                 | 11,860                   | 11,858                | 11,835                |

Dependent variable is a binary indicator equal to 1 if an employed individual is searching on-the-job with the intention to switch employer. Robust standard errors (clustered at the respondent level) in parentheses. Demographic controls include age, gender, race, education, income and tenure at current job. “1.(Positive job loss belief)” is a dummy variable equal to 1 if respondents report a job loss probability above 0 percent, and 0 otherwise. “1.(High job loss beliefs)” is a dummy variable equal to 1 if respondents report a job loss probability above 8 percent (sample median), and 0 otherwise. \* p<0.05, \*\* p<0.1, \*\*\* p<0.001.

Table 6: Job loss beliefs and search effort: OLS regressions

|                     | Measure of job loss beliefs  |                       |                       |                              |                  |                  |                          |                    |                    |
|---------------------|------------------------------|-----------------------|-----------------------|------------------------------|------------------|------------------|--------------------------|--------------------|--------------------|
|                     | Job loss beliefs as reported |                       |                       | 1.(Positive job loss belief) |                  |                  | 1.(High job loss belief) |                    |                    |
| Coefficient         | 0.018***<br>(0.00363)        | 0.017***<br>(0.00341) | 0.017***<br>(0.00326) | 0.254<br>(0.215)             | 0.312<br>(0.218) | 0.272<br>(0.204) | 0.533***<br>(0.159)      | 0.479**<br>(0.154) | 0.444**<br>(0.148) |
| Controls            | No                           | Yes                   | Yes                   | No                           | Yes              | Yes              | No                       | Yes                | Yes                |
| Year fixed effects  | No                           | No                    | Yes                   | No                           | No               | Yes              | No                       | No                 | Yes                |
| State fixed effects | No                           | No                    | Yes                   | No                           | No               | Yes              | No                       | No                 | Yes                |
| Nr observations     | 2096                         | 2096                  | 2091                  | 2098                         | 2098             | 2093             | 2098                     | 2098               | 2093               |

Dependent variable is number of methods used for search over the past week, as reported by survey respondents. Robust standard errors (clustered at respondent level) in parentheses. Main results do not change if measure of effort is instead number of methods used in searching over the past week, as reported by survey respondents. Demographic controls include age, gender, race, education, income and tenure at current job. “1.(Positive job loss belief)” is a dummy variable equal to 1 if respondents report a job loss probability above 0 percent, and 0 otherwise. “1.(High job loss beliefs)” is a dummy variable equal to 1 if respondents report a job loss probability above 8 percent (sample median), and 0 otherwise. \* p<0.05, \*\* p<0.1, \*\*\* p<0.001.

Table 7: Job loss beliefs and search effort: OLS regressions

|                      | Measure of job loss beliefs  |                       |                       |                              |                   |                  |                          |                  |                  |
|----------------------|------------------------------|-----------------------|-----------------------|------------------------------|-------------------|------------------|--------------------------|------------------|------------------|
|                      | Job loss beliefs as reported |                       |                       | 1.(Positive job loss belief) |                   |                  | 1.(High job loss belief) |                  |                  |
| Coefficient          | 0.033***<br>(0.00697)        | 0.025***<br>(0.00741) | 0.025***<br>(0.00722) | -0.230<br>(0.668)            | -0.131<br>(0.640) | 0.073<br>(0.659) | 0.745*<br>(0.367)        | 0.599<br>(0.374) | 0.649<br>(0.380) |
| Demographic controls | No                           | Yes                   | Yes                   | No                           | Yes               | Yes              | No                       | Yes              | Yes              |
| Year fixed effects   | No                           | No                    | Yes                   | No                           | No                | Yes              | No                       | No               | Yes              |
| State fixed effects  | No                           | No                    | Yes                   | No                           | No                | Yes              | No                       | No               | Yes              |
| Nr observations      | 2,093                        | 2,093                 | 2,088                 | 2,095                        | 2,095             | 2,090            | 2,095                    | 2,095            | 2,090            |

Dependent variable is hours spent searching over the past week, as reported by survey respondents. Robust standard errors (clustered at respondent level) in parentheses. Main results do not change if measure of effort is instead number of methods used in searching over the past week, as reported by survey respondents. Demographic controls include age, gender, race, education, income and tenure at current job. “1.(Positive job loss belief)” is a dummy variable equal to 1 if respondents report a job loss probability above 0 percent, and 0 otherwise. “1.(High job loss beliefs)” is a dummy variable equal to 1 if respondents report a job loss probability above 8 percent (sample median), and 0 otherwise.\* p<0.05,\*\* p<0.1,\*\*\* p<0.001.

**Belief updating** Individuals who stay employed and respond to the survey every month for a year update their beliefs, on average, three times. Most changes in job loss beliefs are very small in magnitude and do not statistically differ from zero. Individuals reporting to be in the same job as before present on average a monthly job loss revision of 0.12 percentage points. Instead, individuals who have changed employers report on average a downward revision of 6 percentage points. The fact that workers revise their beliefs infrequently has been documented for other labour market related beliefs, such as reservation wages or job finding probabilities. Ellison and Macaulay (2021) also find that that less 0.3% of revisions in households’ hiring expectations is explained by movements in aggregate expectations. This could be interpreted as evidence of not learning. Another explanation, given that all the cited analyses refer to a period of stable growth and unemployment, is that individuals are reporting their “stationary employment prospects” (Mueller and Spinnewijn (2021)).

In sum, I show in this sub-section that: i) On average, workers who search on-the-job report higher job loss probabilities than workers who do not search ( $\approx 8$  p.p difference); ii) about 42% of job-to-job transitions in the sample are toward lower-paid jobs; iii) on average, individuals that accept wage cuts report a 9 p.p higher subjective probability of job loss and 2.6 USD/h lower reservation wage than the average searching worker; iv) following a transition to a new job, workers revise their job loss beliefs downwards ( $\approx 8$  p.p) and v) job loss beliefs predict intensive and extensive margins of on-the-job search in the cross-section, even when controlling for observable characteristics.

## 2.3 Summary of findings

In short, this section shows that the reported beliefs correlate with search behaviour and labour market outcomes in ways akin to actual job loss risk. It explains job loss outcomes over and above usual predictors, suggesting that employed workers incorporate private information that is not captured by observable characteristics to predict the event of job loss.

## 3 Are workers' expectations about job loss accurate?

In the previous section, I have documented heterogeneity in job loss beliefs that subsists to controlling for observable characteristics. This heterogeneity in itself may shed light on differences in search behaviour across individuals by capturing ex-ante risk faced by individuals that is otherwise unobservable. Given that individuals act on these beliefs, this can also explain ex-post outcomes (Mueller et al., 2021). However, workers' beliefs could be, for the most part, pinned down by fundamentals that also determine workers' actual job loss probabilities. If so, their ability to shed light on the extent of downward wage transitions should not go beyond what a model with full information and rational expectations is able to. It is therefore crucial to understand whether these beliefs deviate systematically from observed outcomes.

### 3.1 Empirical evidence

As explained before, the rotating panel structure of the SCE allows me to observe both individuals' beliefs about job loss and whether the event of job loss has indeed materialized or not within the year. The simultaneous observation of beliefs and outcomes at the individual-level allows me to test whether beliefs are rational or not. I base my definition of rational expectations on d'Haultfoeuille et al. (2021), who establish that agents hold rational expectations if and only if the distribution of realizations is a mean-preserving spread of the distribution of beliefs. Furthermore, given beliefs  $\psi$  about a binary outcome  $Y$ , they show that testing for rational expectations is equivalent to running a "naïve" test, which is robust to classical measurement error. Under the null hypothesis of rationality, we have that:

$$H_0 : \mathbb{E}(Y) = \mathbb{E}(\psi)$$

Where, in the context of my application,  $\psi$  is the subjective probability that the worker loses her job during the next 12 months and  $Y$  is a binary variable indicating whether she actually did.

**Socio-demographic and professional characteristics** Table 8 shows the result of this test for the entire sample, as well as for selected sub-samples, in an attempt to understand whether existing biases in expectations are heterogeneous across observable dimensions<sup>7</sup>. The null hypothesis of rationality is rejected at a 95% confidence level for the full sample, as well as for all subsamples. Indeed, estimates suggest that workers are pessimistic i.e.

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<sup>7</sup>Note that from now on, I convert reported percent chances (from 0 to 100) into probabilities (from 0 to 1).

that overestimate their job loss probabilities with respect to actual separation rates over the same time-horizon. This is,  $\mathbb{E}(Y) - \mathbb{E}(\psi) < 0$ .

Individuals with lower levels of educational attainment, older, female, with lower-income or lower labour market attachment report the highest subjective probabilities of job loss, consistent with the analysis that beliefs correlate with actual probabilities. However, there is systematic overestimation of the job loss probability even for individuals with relatively lower job loss beliefs. The difference between beliefs and outcomes is larger for workers holding a college degree, male and workers aged between 35-49 years old.

Workers who previously experienced unemployment both report higher subjective job loss beliefs and a higher bias relative to workers who have not experienced unemployment. While the difference in bias between these two groups is small, note that, I am able to identify workers who experienced unemployment during the survey sample period, but not before that. So it is likely that individuals who have experienced unemployment in their lifetime prior to survey completion are currently classified under 'no unemployment experience', narrowing the differences in bias between the two types of workers. In other words, differences in biases between workers who have and have not experienced unemployment are, if anything, underestimated.

Table 8: Rational expectations tests

|                                    | $\mathbb{E}(\psi)$ | $\mathbb{E}(Y)$ | $\mathbb{E}(Y) - \mathbb{E}(\psi)$ |
|------------------------------------|--------------------|-----------------|------------------------------------|
| Full Sample                        | .161 (.004)        | .059 (.004)     | -.101 (.005)                       |
| High-School Degree or Less         | .178 (.01)         | .077 (.011)     | -.101 (.013)                       |
| Some College Education             | .159 (.005)        | .064 (.006)     | -.095 (.006)                       |
| College Degree or More             | .147 (.003)        | .039 (.003)     | -.107 (.004)                       |
| Age 20-34                          | .147 (.007)        | .067 (.009)     | -.08 (.01)                         |
| Age 35-49                          | .157 (.006)        | .046 (.006)     | -.111 (.008)                       |
| Age 50-65                          | .177 (.007)        | .068 (.008)     | -.109 (.009)                       |
| Female                             | .164 (.006)        | .064 (.006)     | -.101 (.007)                       |
| Male                               | .157 (.005)        | .055 (.006)     | -.102 (.007)                       |
| Household income < 50k             | .204 (.008)        | .099 (.009)     | -.104 (.011)                       |
| Household income $\in [50k, 100k]$ | .139 (.005)        | .042 (.005)     | -.097 (.011)                       |
| Household income > 100k            | .129 (.004)        | .026 (.005)     | -.102 (.006)                       |
| Part-time workers                  | .205 (.01)         | .104 (.013)     | -.102 (.015)                       |
| Full-time workers                  | .148 (.004)        | .044 (.004)     | -.104 (.005)                       |
| Unemployment experience            | .277 (.017)        | .175 (.021)     | -.101 (.024)                       |
| No unemployment experience         | .195 (.017)        | .105 (.025)     | -.09 (.026)                        |

Own computations based on Survey of Consumer Expectations, sample of respondents aged 20-65 from June 2013 to December 2019. Survey weights used. Reported estimates are rounded to three decimal places.

**Local business conditions** Yearly information about job destruction and job creation is available at state and industry level from the Business Dynamics Survey (U.S Census Bureau). I use this information and match it to my dataset to test whether biases are larger in individuals that work either in a state or an industry with high job destruction rates<sup>8</sup>. Namely, I identify whether the individual works (i) in a state with a yearly job destruction rate above the national average; (ii) in an industry with a yearly job destruction rate above the national average; (iii) in

<sup>8</sup>Job destruction rates at year  $t$  are defined in the Business Dynamics Survey as the “count of all employment losses within the cell from contracting and closing establishments between the week of March 12 of the prior year to the current year.” divided by “the average of employment for years  $t$  and  $t - 1$ ”.

an industry with a yearly job destruction rate above the state average. Table 9 presents the main results. While workers in high job destruction states and industries are associated with both higher reported beliefs and experienced outcomes, the pessimistic bias is larger for workers in low job destruction states and industries. Additional industry- and state-specific evidence is provided in the Appendix.

Table 9: Rational expectations tests: local business conditions

|   | $\mathbb{E}(\psi)$ | $\mathbb{E}(Y)$ | $\mathbb{E}(Y) - \mathbb{E}(\psi)$ |
|---|--------------------|-----------------|------------------------------------|
| Workers in high job destruction state             | .148 (.004)        | .081 (.008)     | -.09 (.009)                        |
| Workers in low job destruction state              | .139 (.003)        | .06 (.006)      | -.099 (.007)                       |
| Workers in high job destruction industry          | .154 (.005)        | .079 (.01)      | -.096 (.011)                       |
| Workers in low job destruction industry           | .150 (.004)        | .055 (.007)     | -.110 (.009)                       |
| Workers in high job destruction industry in state | .151 (.005)        | .082 (.011)     | -.092 (.012)                       |
| Workers in low job destruction industry in state  | .152 (.004)        | .055 (.006)     | -.112 (.008)                       |

Own computations based on Survey of Consumer Expectations, sample of respondents aged 20-65 from June 2013 to December 2019. Survey weights used. Estimates are rounded to three decimal places.

**Alternative rational expectations tests** Recall the regression estimated on Table 3. This regression was ran to test whether beliefs are predictive of outcomes, yet it can also be interpreted as a rejection of rational expectations hypothesis (Lovell, 1986). Indeed, under rational expectations, given a regression of outcomes  $Y$  on beliefs  $\psi$  such as  $Y = \alpha + \beta\psi + u$ , the null hypothesis is  $H_0 : \beta = 1$ . When outcomes  $y_i$  are binary and predictions  $\hat{p}_i$  are probabilities, Franses (2021) propose the following analogous test based on the logit model:

$$p(y_i) = \Lambda \left( \alpha + \beta \log \left( \frac{\hat{p}_i}{1 - \hat{p}_i} \right) \right)$$

The null hypothesis of rational expectations is, as before,  $H_0 : \beta = 1$ . The estimated coefficients are presented in Table 10 and well below 1, which lead me to reject the null of rational expectations at a 95% confidence level.

Table 10: Rational expectations tests: naive logit regressions (Franses, 2021)

|                                    | $\hat{\alpha}$ | $\hat{\beta}$ |
|------------------------------------|----------------|---------------|
| Full sample                        | -2.148 (.102)  | .407 (.055)   |
| High School Degree or Less         | -2.036 (.225)  | .300 (.122)   |
| Some College Education             | -2.059 (.127)  | .429 (.068)   |
| College Degree or More             | -2.389 (.113)  | .476 (.064)   |
| Age 20-34                          | -2.047 (.204)  | .410 (.125)   |
| Age 35-49                          | -2.429 (.171)  | .343 (.095)   |
| Age 50-65                          | -1.970 (.165)  | .462 (.073)   |
| Female                             | -2.150 (.131)  | .344 (.079)   |
| Male                               | -2.137 (.164)  | .485 (.076)   |
| Household income < 50 k            | -1.845(.145)   | .273 (.081)   |
| Household income $\in [50k, 100k]$ | -2.395 (.166)  | .447 (.082)   |
| Household income > 100k            | -2.683 (.206)  | .559(.098)    |
| Part-time workers                  | -1.612 (.176)  | .354 (.082)   |
| Full-time workers                  | -2.468 (.124)  | .412 (.065)   |
| Unemployment experience            | -1.373 (.202)  | .292 (.127)   |
| No unemployment experience         | -1.214 (.325)  | .408 (.143)   |

**Overestimation of small probabilities** One could argue that the bias found is induced by a response pattern whereby individuals underestimate small probabilities and overestimate big probabilities. This S-shape pattern between beliefs and outcomes has been prevalent in other domains, such as housing price or inflation expectations (Enke and Graeber, 2019). Figure 2 shows that this is not the case. In fact, across all probability bins there is overestimation of job loss probabilities relative to separation rates<sup>9</sup>. In fact, the bias between beliefs and outcomes seems to be weakly increasing in the job loss belief.

<sup>9</sup>This finding is also reported in the recent chapter for the Handbook of Economic Expectations, Mueller and Spinnewijn (2021)

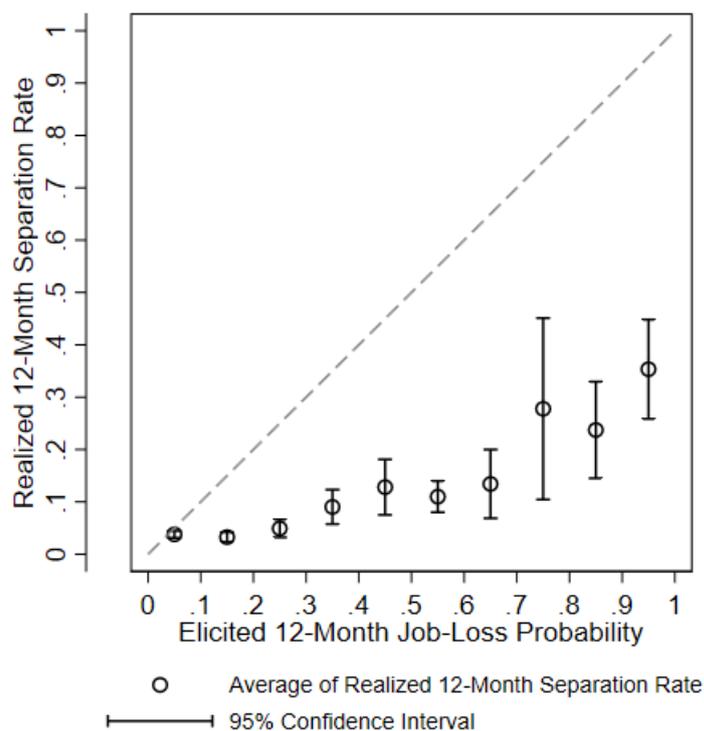
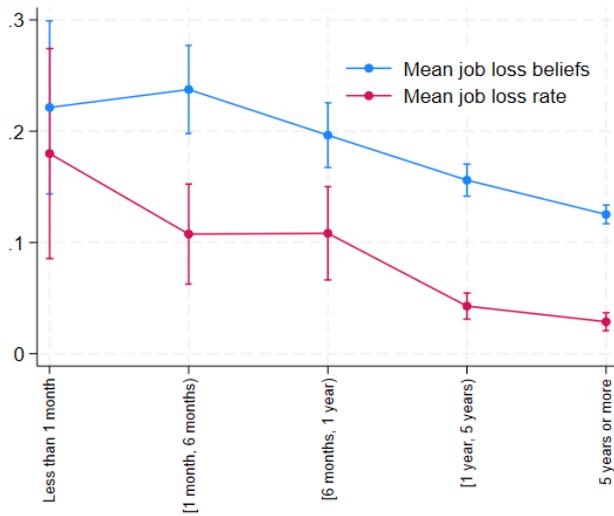


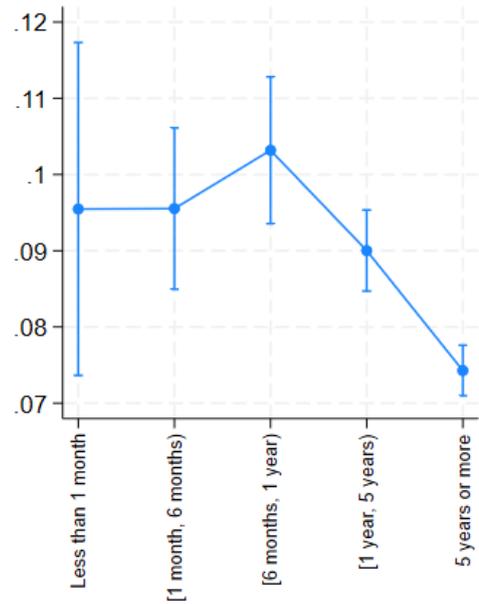
Figure 2: Job loss beliefs and average realized separation rates

### 3.2 Learning from job tenure

The left panel of Figure 3 shows that while job loss beliefs decrease with tenure, the decrease in *observed* job loss rates is more pronounced. Workers start new jobs on average with correct beliefs but revise their beliefs too little during the first year of work, resulting in pessimistic beliefs. The right panel shows that uncertainty, computed as the weighted average of individual-level uncertainty  $\delta_i(1 - \delta_i)$ , also decreases with job tenure. Figure 4 suggests that bias is gradually decreasing with tenure.



(a) Beliefs and realizations, by job tenure



(b) Belief uncertainty, by job tenure

Figure 3: Job loss beliefs, realizations and uncertainty, by job tenure

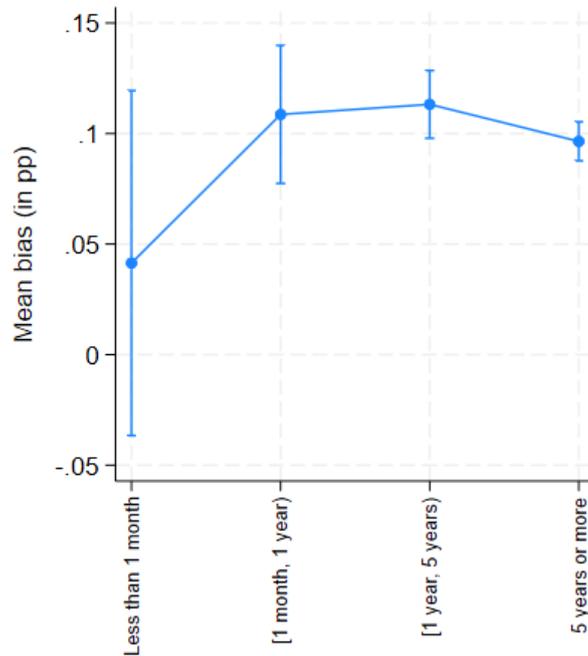


Figure 4: Difference between mean beliefs and realized job loss rate

### 3.3 Linking biases and search behaviour

As explained before, the data does not lend itself to an individual-level measure of bias. The measures of biases at levels of granularity presented in Table 10 however, provide convincing evidence that the overestimation of probabilities relative to outcomes is systematic. Given my research question, one would like to observe whether in the data individuals who move to lower-paid positions are (more) biased than individuals who move to higher-paid positions. The small sample of observed job-to-job transitions<sup>10</sup> compromises the feasibility of this task.

For now, recall that individuals who accept wage cuts have, prior to transitioning, higher job loss beliefs (Table 4), and that the magnitude of the bias seems to be increasing in job loss beliefs (Figure 2). Secondly, I can investigate who are the workers who experienced downwards wage transitions.<sup>11</sup> These consist mainly of college-educated women with low-household income (11 percent of observed downwards transitions), low-income men with some college education (11.75 percent), and low-income high-school educated women (10.58 percent). College educated individuals account for 36 percent of downward transitions observed in sample, compared to 29 percent of downward transitions from high-school educated individuals. Though power is small, this suggests that the correlation between beliefs and accepted wage changes may not fully align with the expected correlation between actual job loss probabilities and labour outcomes.

The bias for workers who ended up switching jobs is unobservable, given that the switch from job-to-job occurs prior or immediately after the actual lay-off. In other words, one cannot know if the person who switched jobs was actually going to lose their job had they not switched. What can be compared, however, is the relative bias between job-stayers who search and do not search on-the-job (Table 11). Indeed, workers who search on-the-job display a slightly higher bias than workers who do not search on-the-job.

Table 11: Bias among job-searchers and non-searchers

|                                      | $\mathbb{E}(\psi)$ | $\mathbb{E}(Y)$ | $\mathbb{E}(Y) - \mathbb{E}(\psi)$ |
|--------------------------------------|--------------------|-----------------|------------------------------------|
| Workers who do not search on-the-job | .150 (.004)        | .050 (.004)     | -.100 (.005)                       |
| Workers who search on-the-job        | .211 (.009)        | .103 (.012)     | -.108 (.014)                       |

Another element that would be interesting to assess, but unfeasible given data constraints, is whether workers' biases are attenuated following a job-to-job transition. What I do see is that average job loss beliefs are revised downwards following a transition. If biases are increasing with job loss beliefs then, by this token, the bias would be attenuated as individuals move to safer positions.

<sup>10</sup>Recall from Table 4, a total of 204, of which 118 to higher-paid positions and 86 to lower-paid positions

<sup>11</sup>The frequencies are computed using survey weights.

### 3.4 Measurement issues, robustness and discussion

Two further measurement issues arise from the fact that we only observe transitions in individuals' labour force status (namely, from employed to unemployed), but not the stated reason for that transition (i.e. whether the worker was effectively fired or decided to quit, and why). The first issue is that I am not able to identify individuals who receive an advance notice of lay-off but that are able to transition to another job without experiencing unemployment. Not accounting for these instances could result in an upward bias in estimated differences between beliefs and realizations. Evidence from Elsby et al. (2010) shows that job-to-job transitions among laid-off workers are not prevalent. Laid-off workers face on average a 91% probability of entering unemployment. The second issue is that it is not possible to disentangle individuals who have quit into unemployment from individuals who were laid-off into unemployment, hence the terminology "separation rates" rather than lay-off rates. If quits into unemployment are substantial, this could bias differences between beliefs and realizations upwards. Studies suggest that the scope for these instances is small<sup>12</sup>.

In order to probe the robustness of my findings, I consider several alternative measures of outcomes and beliefs. Namely:

1. I consider monthly job loss probabilities and monthly employment to unemployment transitions: For that, I impute monthly job loss probability from annual job loss probability  $p_m = 1 - (1 - p_y)^{\frac{1}{12}}$  and compare to observed monthly job-to-job transitions.
2. I narrow the elicitation-outcome conceptual gap by making use of elicitations that exactly correspond to observable outcomes, at a 4 month horizon. These are available in the LMS. The exact elicitation question is: "What is the probability that you are unemployed in 4 months?"
3. I extrapolate 12-month job separation rates  $s_{12}$  from 3 month separation rates from employment to unemployment  $s_3$ :  $s_{12} = 1 - (1 - s_3)^4$ .

I then run a battery of tests analogous to those in Table 8, which I present in the Appendix. The finding that workers are, on average, pessimistic is robust to the use of these alternative measures.

Another possible source of measurement error would be if individuals, when reporting their perceived job loss probabilities, integrate how their own actions shape those probabilities.<sup>13</sup> In the context of job loss, it is unlikely that one reports a very high probability of losing a job in 12 months because they are integrating some action that will increase that probability. In any case, these effects should be attenuated if the elicitation horizon is shortened.<sup>14</sup> The fact that also at shorter horizons job loss probabilities are systematically higher than job loss outcomes suggests that the original results are not driven by this possible measurement caveat.

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<sup>12</sup>Elsby et al. (2010) find a probability of 16% that a worker who quits their job subsequently enters unemployment

<sup>13</sup>See Spinnewijn (2015) for a discussion 'baseline' versus 'control' beliefs

<sup>14</sup>For example, it is less likely that one is able to increase their productivity in a way that it reduces their job loss probability if she has 3 months rather than 12 months to do so.

A related concern is whether job loss beliefs are systematically above observed outcomes simply because individuals act on their beliefs in the meantime. This would be the case, for instance, if somebody who has a high probability of losing their job increases their work effort so as to avoid being fired. First, note that individuals with very high job loss probabilities - if accurate - are unlikely to be able to control the job loss outcome. On the other hand, individuals with smaller but positive job loss probabilities may be more likely to take action that changes the job loss outcome. But, if this would be the case, we would observe more accurate correspondences between beliefs and outcomes for high-belief individuals than for low-belief individuals, which is not the case, as Figure 2 shows. The robustness check at shorter horizon elicitation also mitigates this concern.

A final caveat of the naive regression tests of rationality is that they assume the loss of the agent from positive and negative forecast errors is symmetric. If forecasters - in this case, workers - evaluate forecast errors asymmetrically, then departures from rationality can be rationalised.<sup>15</sup>

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<sup>15</sup>Using estimates from the Survey of Professional Forecasters, Elliott et al. (2008) show that output and inflation forecasts are rational under asymmetric loss.

## 4 Model

In this section, I study how the empirical findings can be rationalized through a model of job search. In particular, I am interested in accounting for the empirical patterns documented in Figures 3 and 4: i) actual job loss risk decreases with job tenure; ii) beliefs about job loss decrease with job tenure at a slower pace than actual risk, resulting in overestimation of risk; iii) uncertainty about job loss risk decreases with job tenure. In order to do that, I build from and extend the framework proposed in Pinheiro and Visschers, 2015 to incorporate incomplete information and Bayesian learning.

The fact that mean job loss rates in the data decrease with job tenure is consistent with widely documented negative duration dependence in match hazard rates. Theoretical models of turnover propose two main explanations for this negative duration dependence.<sup>16</sup> One is that workers become more productive in existing matches and accumulate job-specific human capital (learning by doing) (Parsons, 1972; Audoly et al., 2022). The other is that both workers and firms learn about the match quality as they spend time on their job (Jovanovic, 1979; Baley et al., 2022). While the latter seems like a natural candidate to my setting, note that in matching models of turnover, information and learning are symmetric. Both firm and worker learn about match quality and update their (identical) beliefs about job separation, and job separations are bilaterally efficient. As such, in this class of models, there will be no difference between actual and perceived separation risk<sup>17</sup> akin to my empirical findings. The model I propose below implicitly recognizes this *information asymmetry* between firm and worker, in that the worker cannot fully observe how her job separation risk declines with tenure. The way I model this decline in *actual* separation risk could come from either increasing on-the-job skills or from firms learning about match quality. Given that I only have data on the worker side and do not model the firm, I take the former route.

### 4.1 Model description

Time is continuous. Risk-neutral workers maximize lifetime expected discounted utility. They search on-the-job. In each period they draw wage offers  $w$  from a known distribution  $F(w)$ . They observe the value of the offer and, if better than the current offer, they accept it. Offers arrive at rate  $\lambda_e$  when employed and  $\lambda_u$  when unemployed.

There is idiosyncratic productivity risk  $z$ , which is independent and identically distributed. Productivity risk follows a normal distribution,  $z \sim \mathcal{N}(\mu_z, \tau_z^{-1})$ . The worker does not directly observe idiosyncratic productivity and holds priors  $\hat{z}_0 \sim \mathcal{N}(\mu_0, \tau_0^{-1})$ . Instead, workers observe noisy signals  $s$ , with noise parameter  $\eta$ :

$$ds(t) = zdt + \eta dW(t), \eta \sim \mathcal{N}(0, \tau_s^{-1})$$

Where  $W(t)$  is a standard Brownian motion. The signal is centered around true productivity and has precision  $\tau_s$ .

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<sup>16</sup>Nagypál (2007) explores the differences between both classes of models, theoretically and empirically.

<sup>17</sup>I use the term separation risk to acknowledge the known difficulty of this class of models of separating between quits and lay-offs

The worker updates her beliefs after receiving the signal through the Kalman-Bucy filter. The posterior distribution of beliefs about idiosyncratic productivity has mean and variance, respectively:

$$d\hat{z}(t) = \frac{\hat{\Sigma}}{\eta^2}(ds(t) - \hat{z}dt) \quad d\hat{\Sigma}(t) = -\left(\frac{\hat{\Sigma}}{\eta}\right)^2 dt$$

Workers accumulate job-specific skills while employed. These skills do not generate an increase in flow wages, but instead reduce the probability of separations.<sup>18</sup> Skills increase with time on the job:

$$dk(t) = \alpha k(t)^\beta dt$$

The output of the worker is the sum of her job specific human capital and the realized productivity shock. When output falls below the wage, the job is destroyed.<sup>19</sup> As  $z$  is independent and identically distributed across jobs, it follows that jobs with higher wages or where the worker has accumulated high level of job-specific skills will have a lower separation probability. Given posterior beliefs, the worker's subjective probability of losing her job at time  $t$  is:

$$\hat{\delta}(t) = p(w + \hat{z}(t) + k(t) \leq 0) = \Phi\left(\frac{-w - \hat{z}(t) - k(t)}{\sqrt{\hat{\Sigma}(t)}}\right)$$

The Hamilton-Jacobi-Bellman function expressing the value of employment is therefore:

$$rV(w, \hat{z}, \hat{\Sigma}) = w + \lambda_e \int_{\underline{w}}^{\bar{w}} \max\{V(w', z_0, \Sigma_0) - V(w, \hat{\delta}, \hat{\Sigma}), 0\} dF(w) + \hat{\delta}(w, \hat{z}, \hat{\Sigma})[U - V(w, \hat{z}, \hat{\Sigma})] + \frac{dV}{dt}$$

Where  $\frac{dV}{dt}$  accounts for the changes in the value function due to the evolution of the worker's beliefs ( $\hat{z}(t), \hat{\Sigma}(t)$ ).

Using Ito's lemma, we can express this term as:

$$dV/dt = \left(\frac{\Sigma}{\eta}\right)^2 \left(-\frac{\partial V}{\partial \Sigma} + \frac{1}{2} \frac{\partial^2 V}{\partial z^2}\right)$$

The value of unemployment is:

$$rU = b + \lambda_u \int_{\underline{w}}^{\bar{w}} \max\{V(w, z_0, \Sigma_0) - U, 0\} dF(w)$$

<sup>18</sup>The disconnect between wages and productivity is admittedly a large simplification, but allows workers to not learn about productivity - and hence job separation risk - from their wages. Alternatively, a combination of wage rigidity and noisy signals about output could generate similar learning dynamics.

<sup>19</sup>Although at this stage I do not model firms, this is similar to an endogenous separation decision, with the difference that the worker does not know the state  $z$ . I abstract from explicitly modelling this information asymmetry by keeping the analysis in partial equilibrium and not modelling the firm side.

The reservation wage  $w_R$  is such that it leaves workers indifferent between being unemployed or working, i.e.  $V(w_R, z_0, \Sigma_0) = U$ . As can be seen below, this reservation wage is independent of  $\hat{\delta}$ :

$$w^R = b + (\lambda_u - \lambda_e) \int_{\underline{w}}^{\bar{w}} \max\{V(w, z_0, \Sigma_0) - U, 0\} dF(w)$$

Given workers' beliefs about the separation probability  $\hat{\delta}(w, \hat{z}, \hat{\Sigma})$ , the wage that leaves a worker indifferent between her current job and an alternative offer is:

$$w^*(z_0, \Sigma_0) = w + (\delta(w^*, z_0, \Sigma_0) - \hat{\delta}(w, \hat{z}, \hat{\Sigma}))(V(w, \hat{z}, \hat{\Sigma}) - U)$$

In sum, the model features heterogeneous job loss risk, job-specific human capital accumulation and imperfect information about productivity. To build some intuition, I first describe some of the mechanics of the model under perfect information.

## 4.2 Intuition from perfect information

In this basic model, unemployed workers will accept offers with a wage higher than their reservation wage, and reject otherwise. Employed workers will move job-to-job according to a reservation policy where, given their current wage and job loss risk, they require a wage premium for riskier jobs and are willing to pay a premium for safer jobs. An extension with endogenous search effort under perfect information is presented in the Appendix, where search intensity is increasing in (observed) job loss risk. If there was no heterogeneity in job loss risk (i.e if all offers had the same  $\delta$ ), employed workers would simply accept any offer with a higher wage than their current one. As such, under full information and rational expectations, a motive for accepting wage cuts may be generated. This motive lies on the existence of job offers that are safer than the current job held by the worker. Given workers' beliefs about the layoff probability  $\delta$  (which in this case, completely align with realized  $\delta$ ), the wage that leaves a worker indifferent between her current job  $(w, \delta)$  and an alternative wage-risk pair  $(w^*, \delta^*)$  is:

$$w^*(\delta^*) = w + (\delta^* - \delta)(V(w, \delta) - U)$$

The option value of an offer while employed will be increasing with  $\delta$  and decreasing with  $w$ . If the worker draws a less secure position  $\delta^* > \delta$  such that  $\delta^* - \delta > 0$ , she will demand a higher wage to be indifferent between the current and the future position. This wage premium is increasing in the capital loss of the current job  $V - U$ . If the worker draws a more secure position, the wage that makes her indifferent is lower than her current wage. In the Appendix, I simulate the probability of transitioning to a lower-paid position for different levels of wages and job separation risk.

Given the relationship between acceptance decisions and job loss risk studied above, one can anticipate that individuals who overestimate their job loss risk will be willing to take safer jobs in exchange for larger wage cuts than they would accept had they known the true separation risk. This increases their ex-ante probability of transitioning to a lower-paid position compared to a full information rational expectations benchmark.

### 4.3 Discussion

The bias in the model is generated by slow learning, whereby “safety gains” from tenure increase at a higher pace than the worker perceives them. On-the-job search behaviour *reduces* this bias between perceived and realized job loss risk, as it gives pessimistic workers “a way out”. Workers who stay on the same job are those who enjoy a high wage and/or who have accumulated a high level of job-specific human capital. Workers who receive negative signals will be the ones looking for an outside option. While consistent with empirical evidence, this generates a selection effect such that job stayers are those who, on average, have received positive signals about productivity.

This is also the case because there is no mechanism in the model through which *optimistic* workers lose their jobs at a higher rate. To counteract that, one could extend the model to allow for feedback between skill accumulation and beliefs. The only incentive for workers to invest in on-the-job training would be to mitigate a negative signal about current productivity. For a given realized productivity, individuals who receive a signal with positive noise expect smaller expected benefits from training or search. These individuals will be less likely to train or search, and become more exposed to productivity shocks. While this is the case for all workers who observe a signal with positive noise, transitions to unemployment would only occur if the realised productivity shock is i) negative ii) larger in absolute terms than match-specific output. This in turn is more likely to be the case for low-paid and/or low tenured jobs. This selection effect is such that the noise in the sample of employed individuals at a given tenure will, on average, be *negative*. As a result, survivors would on average underestimate current productivity and overestimate job loss risk.

A general equilibrium framework will also help to shed light on the stabilizing or destabilizing effects of pessimism in recessions. Though my data sample covers only a period of “expansion”, other data suggests that pessimism may increase during recessions (Penrose et al., 2021). Intuitively, as more workers grow more pessimistic, they become more willing to accept wage cuts - this moderates the usual disincentives to job creation in a recession. On the other hand, more pessimistic workers will search more intensively and possibly crowd out unemployment individuals from the labour market, delaying recoveries.

## 5 Conclusion

In this paper, I research how perceived job loss risk impacts job search and job switching behaviours. I draw empirical evidence from survey data that measures individual-level job loss beliefs, search behaviour and accepted offers at a high frequency. I find that these beliefs are i) heterogeneous over and above observable characteristics; ii) predictive of job separation outcomes and job search behaviour; but iii) inaccurate, as individuals systematically overestimate relative to observed outcomes. These empirical insights can sustain a model of job search where workers are uncertain about the unemployment risk they face. In ongoing work, I formalize how acceptance decisions of these workers compare to a full information rational expectations benchmark.

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## A Appendix

### A1 Endogenous search effort

Consider again the case of full information. If workers choose to exert search effort  $s$  at cost  $\eta$  and if the arrival rate  $\lambda_e(s)$  is increasing with effort, then the workers' problem becomes:

$$rV(w, \delta) = \max_s \left[ w + \lambda_e(s) \int_0^1 \int_{\underline{w}}^{\bar{w}} \max\{V(w', \delta') - V(w, \delta), 0\} dF(w') dG(\delta') + \delta[U - V(w, \delta)] \right] \quad (3.1)$$

Optimally chosen effort  $s^*$  will be such that marginal cost equals the expected marginal benefit of search:

$$\eta'_e = \lambda'_e(s^*) \int_0^1 \int_{w^*}^{\bar{w}} (V(w', \delta') - V(w, \delta)) dF(w') dG(\delta') \quad (3.2)$$

Evidence shows that low-wage individuals search more intensively (Faberman et al., 2017). At the same time, I showed in Section 2.2 that higher job loss beliefs are associated with increased search intensity. The current model with endogenous search effort is able to accommodate both facts.

First, note that the workers' reservation rule does not change with the introduction of endogenous search effort. Indeed, workers will still reject or accept offers based on the mechanism described earlier. However, current  $\delta$  and  $w$ , will affect the perceived marginal benefit of exerting effort through their impact on the option value of offers. As shown earlier, the option value of offers is decreasing in  $w$  and increasing in  $\delta$ . Therefore, the marginal benefit of search (and therefore the equilibrium search intensity) will be higher for low-wage, high job loss risk individuals, and lower for high-wage, low job loss risk individuals. This is in line with empirical evidence described above.

Note that, given the value functions above, the value of a job is increasing with the wage offer and decreasing with separation risk. Indeed, Pinheiro and Visschers (2015) show:

$$\begin{aligned} \frac{\partial V(w, \delta)}{\partial w} &= \frac{1}{r + \delta + \lambda_e \int (1 - F(w^*)) dH(\delta')} > 0 \\ \frac{\partial V(w, \delta)}{\partial \delta} &= -\frac{V(w, \delta) - U}{r + \delta + \lambda_e \int (1 - F(w^*)) dH(\delta')} < 0 \end{aligned}$$

### A2 Simulations under perfect information

Let wage offers be normally distributed with mean  $\mu$  and variance  $\sigma^2$ . Define  $z = \frac{w' - \mu}{\sigma}$ . Given current job loss risk  $\delta$  and the job loss risk drawn  $\delta^*$ , the probability that a worker accepts a wage cut is therefore:

$$\begin{aligned}
p_{cut} &= P(w' \leq w | \delta, \delta^*, w) = P(w^* \leq w' \leq w) = \\
&= P\left(\frac{w^* - \mu}{\sigma^2} \leq z \leq \frac{w - \mu}{\sigma^2}\right) = \\
&= \Phi\left(\frac{w - \mu}{\sigma^2}\right) - \Phi\left(\frac{w^* - \mu}{\sigma^2}\right)
\end{aligned} \tag{3.3}$$

As expected, this probability is increasing in  $\delta - \delta^*$ : drawing a safer offer increases the probability of accepting a wage cut. I compute comparative statics that illustrate how this probability changes with  $\delta, \delta^*$  and  $w$ .

Figure **A1** plots simulated probabilities of accepting wage cuts for an individual earning a relatively low and a relatively high-wage. Given  $\delta$  and  $\delta'$ , the expected wage change is decreasing in the wage. Keeping wages constant, the expected wage change is decreasing in  $\delta$  and increasing in  $\delta'$ .

Note that, the ex-ante expected wage associated with drawing a safer position  $\delta' < \delta$  is (see Figure **A2**):

$$\mathbb{E}(w' | \delta' < \delta) = \int_0^{\delta} \int_{w^*(\delta')}^{\bar{w}} w f(w) dw d\delta' \tag{3.4}$$

Finally, the ex-ante expected wage changes from drawing an offer will depend on distributional assumptions about  $\delta'$ . For expositional purposes, assume  $\delta' \sim U(0, 1)$ . Figure **A3** displays the expected wage changes for low-wage individuals ( $w = \mu - \sigma$ ) conditional on different levels of current job loss risk  $\delta$ .

The intuition is as follows - if every  $\delta$  has an identical ex-ante probability of being drawn, then a worker employed at a job with a job loss risk very close to zero ( $\delta \approx 0$ ) will very likely draw a riskier offer next period. The wages she is willing to accept for a riskier job are higher than her current wage, so the expected wage change is positive. On the contrary, a worker currently employed at a job with a very high separation risk ( $\delta \approx 1$ ) will very likely draw a safer job which she is willing to accept at lower wages. Therefore, her expected wage change is negative.

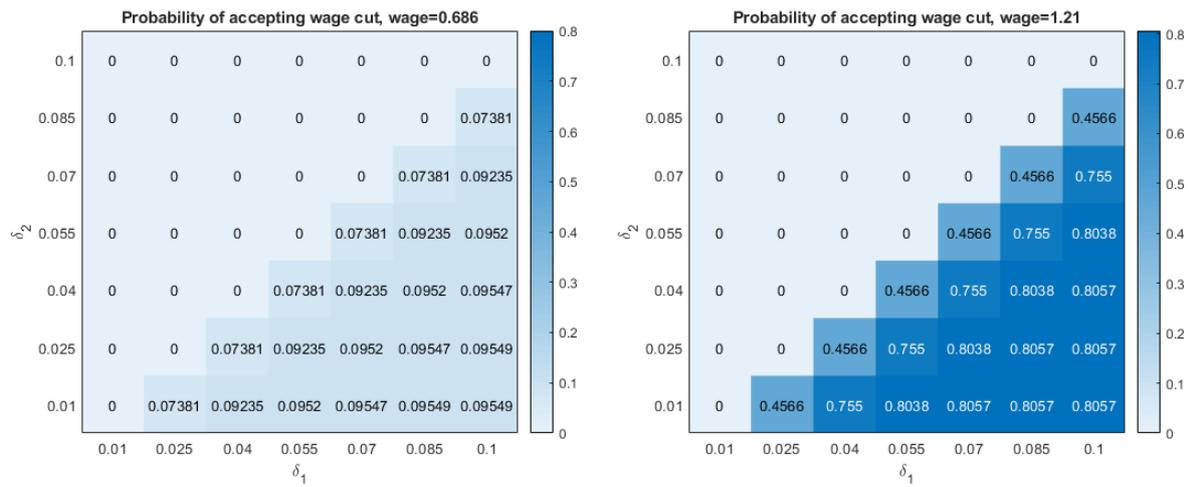


Figure A1: Workers probability of accepting a wage cut. Simulations.

Note: Simulations based on normally distributed wages with mean  $\mu = 1$  and standard error  $\sigma = 0.24$ . The horizontal axis  $\delta_1$  denotes current job loss risk. The vertical axis  $\delta_2$  denotes offered job loss risk. Cell values are the probability of accepting a wage cut.

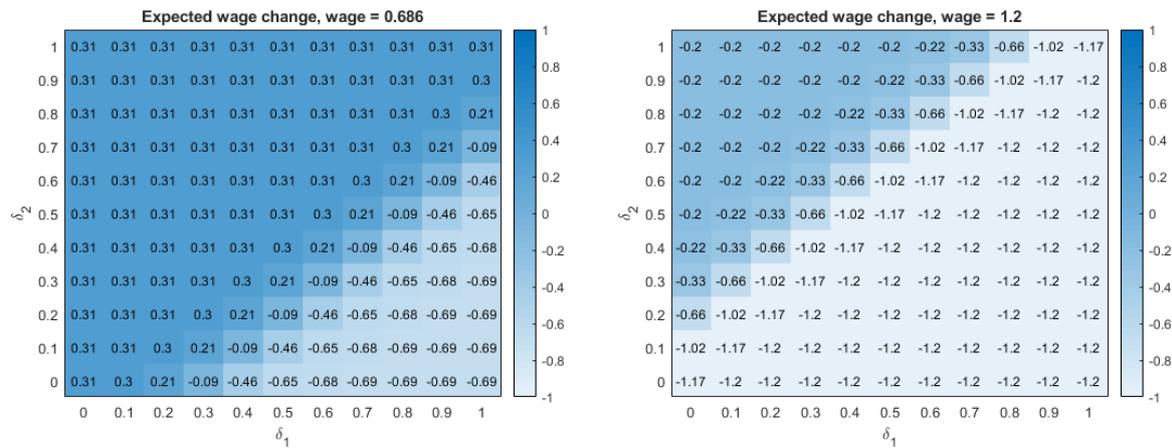


Figure A2: Ex-ante expected wage change. Simulations.

Note: Simulations based on normally distributed wages with mean  $\mu = 1$  and standard error  $\sigma = 0.1$ . The horizontal axis  $\delta_1$  denotes current job loss risk. The vertical axis  $\delta_2$  denotes offered job loss risk. Cell values are the expected wage change for every  $(\delta_1, \delta_2)$ , according to equation (8).

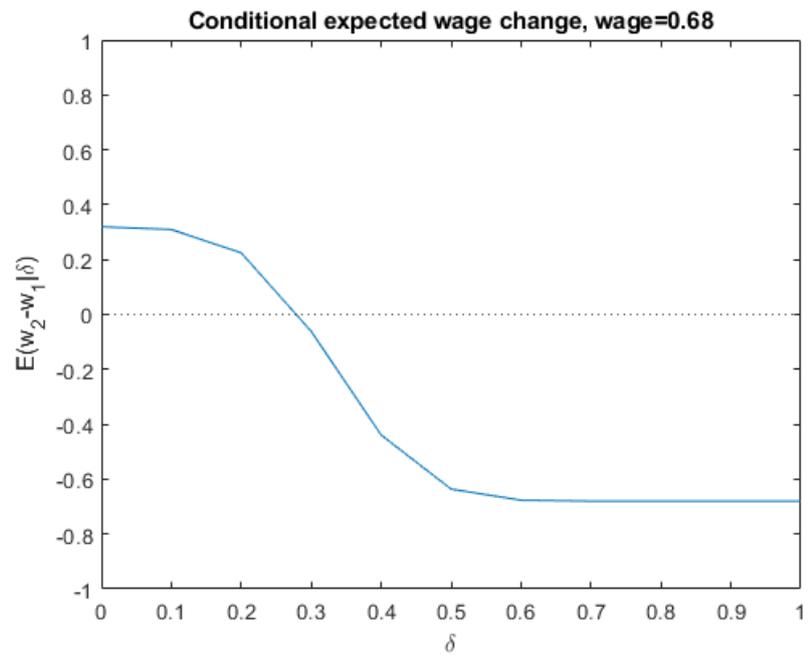


Figure A3: Conditional expected wage change. Simulations.