# Inaccurate Beliefs and Cyclical Labor Market Dynamics

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**Abstract**

This paper examines how systematic biases and imprecise beliefs about the state of the economy shape wage dynamics, labor market flows, and aggregate responses to shocks. I present evidence that households form dispersed, backward-looking expectations about macroeconomic conditions, with more optimistic workers demanding higher wages. Motivated by these findings, I develop a search-and-matching model in which workers have noisy beliefs about aggregate productivity and update them through adaptive learning. Firms are homogeneous and are better informed than workers. Wages are bargained based on workers' subjective beliefs. Staggered renegotiation and two-sided lack of commitment create wage rigidity, which in turn generates endogenous quits and layoffs. The model is disciplined with data from the Michigan Survey of Consumers and calibrated to key empirical moments. In equilibrium, the gap between firm and worker beliefs drives unemployment volatility, while firm learning raises the persistence of the economy's response to shocks but narrows belief gaps and dampens volatility. Allowing for heterogeneity in workers' learning rates explains observed differences in employment transitions: Workers with more sluggish beliefs remain overly optimistic in recessions, are hired at higher wages, and face a higher risk of separation.

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# 1 Introduction

A growing empirical literature shows that workers' labor market behaviors are shaped by subjective beliefs regarding job-finding prospects and the distribution of available wages (e.g., Conlon et al. (2018), Mueller et al. (2021), Balleer et al. (2024)). These expectations are often influenced by inaccurate perceptions of the aggregate state of the economy. In this paper, I investigate how such misperceptions about the economy affect aggregate wage dynamics, labor market flows, and the response to shocks.

Inaccurate beliefs provide insights into several key labor market phenomena. First, they offer a novel explanation for the volatility and persistence of unemployment observed in the data. Second, cross-sectional dispersion in household beliefs helps explain the compositional shift in the pool of unemployed workers toward higher-wage workers during recessions. Finally, heterogeneity in workers' beliefs helps explain why observably similar workers experience substantially different job-finding rates and separation risks. The standard Diamond-Mortensen-Pissarides (DMP) model assuming full information struggles to simultaneously account for these empirical patterns.

The first part of my paper presents evidence from survey data showing systematic bias and substantial dispersion in household beliefs about the aggregate state of the economy. Using the Michigan Survey of Consumers, I document that household beliefs about changes in unemployment systematically lag realized changes. Consequently, households are systematically too optimistic at the onset of recessions and too pessimistic in the early stages of recoveries. Moreover, using the Survey of Consumer Expectations, I find that observably similar workers form substantially different beliefs about both their own job-finding prospects and future changes in the unemployment rate.

Importantly, such misperceptions about aggregate productivity shape workers' labor market decisions. Using the Survey of Consumer Expectations, I show that workers with more optimistic beliefs about their job-finding prospects report higher reservation wages. Over time, workers who become more pessimistic about future unemployment relative to the rest of the population revise their reservation wages downward by larger amounts.

Guided by this empirical evidence, the second part of my paper develops a DMP model with inaccurate beliefs about aggregate productivity. The framework nests the full-information model as a special case when all workers and firms observe true productivity.

My model features two key departures from the textbook DMP framework: First, otherwise identical workers form heterogeneous beliefs about current aggregate productivity, and the distribution of unemployed worker beliefs evolves endogenously through adaptive learning. Workers bargain for wages based on their individual beliefs, so subjective beliefs about aggregate productivity directly affect wage outcomes. As a result, sluggish belief adjustment endogenously generates wage stickiness for new hires, which amplifies volatility in job creation and unemployment.

Second, to study the role of beliefs in job separations, I incorporate endogenous separations driven by wage rigidity. Wages for new hires are fully flexible and determined through bargaining, while wages for continuing matches are renegotiated only with an exogenous probability each period. Either party can unilaterally terminate a match. The firm lays off the worker if the current wage exceeds its reservation value; conversely, the worker quits into unemployment if the current wage falls below their reservation value given their subjective belief. In this way, heterogeneity in workers' beliefs at the time of hiring translates into differences in subsequent separation risks.

The quantitative analysis calibrates the model to key features of the U.S. labor market. Household belief dispersion and learning rates are disciplined using the Michigan Survey of Consumers. Labor market parameters are calibrated such that the steady-state equilibrium matches the corresponding cross-sectional moments observed in the data. The model improves on the magnitude and sluggish responses of key labor market outcomes such as unemployment, the job-finding rate, and layoffs.

The first result is that sluggishness in household beliefs significantly increases the volatility of labor market tightness, the job-finding rate, and unemployment—features that full-information DMP models are known to struggle with. The intuition is that sluggish belief updating generates sticky wages for new hires. In a model with sluggish but homogeneous worker beliefs, the job-finding rate is seven times more volatile and the unemployment rate more than five times more volatile relative to the full-information benchmark.

However, sluggish beliefs have little impact on job separations relative to the full-information benchmark. Wage dispersion arises only from wage rigidity and remains concentrated around the mean, generating almost no layoffs in response to small negative shocks. By contrast, belief dispersion produces a broader wage distribution, placing more workers at wages near firms' layoff thresholds. When a negative shock hits, firms lay off these higher-wage workers. A model with both household learning and belief dispersion produces job-separation volatility almost three times larger than under full information. Hence, the second result is that heterogeneous worker beliefs amplify job separations while leaving the job-finding rate and labor market tightness largely unchanged.

Having examined the implications of household beliefs for labor market dynamics, a natural question is the role of firm beliefs. Empirical evidence shows that firms form backward-looking expectations that are generally more accurate and less dispersed than those of households (Meyer and Sheng (2025)). To capture this pattern, I extend the model so that all firms share a common belief that evolves through adaptive learning at a faster rate than household beliefs.

Firm learning increases the persistence of labor market dynamics but, perhaps surprisingly, dampens overall volatility. When firms learn about aggregate shocks with a lag, they adjust vacancy posting more slowly, generating hump-shaped responses in job-finding rates and layoffs, as well as a slow recovery in unemployment—features that standard DMP models have long struggled to match. For example, when the firm learning rate is reduced by 50 percent relative to full learning, the unemployment rate peaks five months later.

However, as the belief gap between firms and workers narrows, volatility in job-finding and unemployment declines. Because firms also recognize the downturn with a delay, vacancy postings fall less in response to workers' high wage demands. In the case where firms learn at the same rate as workers, both the job-finding rate and the unemployment rate display almost no volatility. This result shows that the key driver of labor market volatility is not sluggish learning per se but the disagreement in beliefs between workers and firms.

In addition to their effects on aggregate labor market outcomes, belief frictions also have cross-sectional implications. The next set of results focuses on the distributional effects. First, belief frictions help account for the compositional changes in unemployment documented by Mueller (2017): the pool of unemployed workers shifts toward those with high wages in their previous jobs during recessions, driven by differences in job separation rates rather than job-finding rates. Heterogeneity in workers' beliefs at the time of hiring translates into differences in subsequent separation risks, with workers who were more optimistic at the time of hiring facing higher layoff probabilities during recessions. Greater belief dispersion amplifies these differences in separation risks and increases the cyclicality of pre-displacement wages among unemployed workers. Hence, belief frictions generate the observed comovement between pre-displacement wages and the unemployment rate.

Finally, differences in household learning rates help explain why observably similar workers experience substantially different job-finding rates and separation risks (Hall and Kudlyak (2019), Ahn and Hamilton (2020), Gregory et al. (2025), Ahn et al. (2023)). Workers with slower learning rates remain more optimistic at the onset of recessions, enabling them to extract higher wages when hired but also exposing them to higher subsequent layoff probabilities. Firms are willing to hire these optimistic workers in the short run, knowing they can lay them off later if necessary. Consequently, during recessions, layoffs are disproportionately concentrated among workers with more sluggish beliefs. Comparing workers with a learning rate 0.25 times the average to those with a learning rate 2.5 times the average, the peak increase in unemployment is three times larger for the group with more sluggish beliefs.

**Literature.** My work contributes to a growing body of empirical evidence documenting that workers' subjective beliefs shape their labor market decisions and outcomes. Survey evidence shows that workers who are more optimistic about future wages or job-finding prospects report higher reservation wages, lower search intensity, and greater selectivity in job acceptance, while those who fear job loss experience lower wage growth (Campbell et al. (2007), Conlon et al. (2018), Balleer et al. (2024), Mitra (2023)). Moreover, experimental evidence shows that when workers are provided with accurate information, they adjust their search behavior and wage negotiation strategies accordingly (Jäger et al. (2024)). This paper provides additional evidence on household beliefs about aggregate labor market conditions by documenting two key facts: average household beliefs systematically lag realized changes in aggregate unemployment, and workers with more optimistic beliefs about future unemployment report higher reservation wages.

On the theoretical side, my paper contributes to the macroeconomic literature incorporating information frictions about aggregate conditions into search and matching models. Recent work demonstrates that belief distortions can significantly affect aggregate labor market outcomes through consumption and saving channels (Bhandari et al. (2025), Balleer et al. (2021)). My paper is most closely related to Morales-Jiménez (2022), Menzio (2023), and Mitra (2024), who show that inaccurate beliefs about current aggregate productivity levels affect the volatility and persistence of unemployment. Relative to these papers, I make two key contributions. First, I introduce heterogeneity in workers' beliefs about aggregate productivity and incorporate endogenous separations driven by belief dispersion. This extension allows me to study not only how information frictions influence aggregate fluctuations but also how they generate cross-sectional differences in job-finding probabilities and separation risks. Second, I discipline the model by calibrating the parameters governing household learning rates and belief dispersion directly to survey data, enabling a quantitative assessment of the importance of belief frictions for labor market dynamics.

A related but distinct literature examines information frictions in search models by focusing on agents' private information about matching quality. Azariadis and Stiglitz (1983) and Kennan (2010) focuses on private information on the firm-side, while Acharya and Wee (2020) and Birinci et al. (2025) focus private information for the workers. My contribution differs in focusing on beliefs about aggregate rather than match-specific conditions.

Finally, this paper connects to the broader literature addressing the well-known volatility and persistence puzzle in labor market dynamics. Shimer (2005) demonstrates that standard search models generate far too little volatility in unemployment and vacancies relative to the data. Subsequent research has explored various amplification mechanisms to address this puzzle.[1] One leading explanation emphasizes wage stickiness for new hires as a key source of amplification (Eg. Hall (2005), Gertler and Trigari (2009), Gertler et al. (2020)). My paper contributes to this literature by providing a micro-founded mechanism for wage stickiness: sluggish belief adjustment by workers about aggregate productivity endogenously generates sticky wages for new hires, thus amplifying the response of unemployment to productivity shocks without relying on exogenously imposed rigidities.

The rest of the paper is organized as follows: Section 2 discusses empirical evidence about beliefs and labor market outcomes from survey data. Section 3 introduces a general equilibrium search and matching model with heterogeneous beliefs, staggered bargaining and two-side lack of commitment. Section 4 discusses the calibration and estimation strategy of the model parameters. Section 5 presents results from quantitative analysis. Section 6 concludes.

# 2 Empirical Evidence

In this section, I first document a systematic lag in household beliefs about the labor market. Then, I show that workers with more optimistic expectations about the labor market demand higher wages.

## 2.1 Evidence on Household Beliefs about Unemployment

The Michigan Survey of Consumers (MSC) is a nationally representative survey that has measured U.S. household sentiment since the late 1940s, with its modern monthly format beginning in January 1978. Each month, the survey samples a new, independent cross-section of approximately 500 to 1,300 households. Although the MSC does not track individual respondents over time, it offers one of the longest and most consistent time series on population-wide expectations, making it well suited for the purposes of this study.

[1]See Rogerson and Shimer (2011) for an overview.

MSC includes a qualitative question on unemployment expectations. Respondents may answer "more unemployment," "less unemployment," or "no change". [2]Following the methods in Mankiw et al. (2003) to quantify inflation expectations, I construct a quantitative series of expectations regarding changes in unemployment rates based on these qualitative responses. This approach relies on two key assumptions. First, I assume that individuals' expectations about changes in the unemployment rate follow a normal distribution with a time-varying mean, $\mu_t$, and variance, $\sigma_t^{u2}$. Second, when households respond with "no change" in unemployment rate, I interpret it as indicating a small change within a threshold, $c$. While the mean and variance of the belief distribution vary over time, the interval width associated with "no change" is assumed to remain constant over time.

Given these assumptions, I can write the fraction of individuals expecting a rise in unemployment rate as function of the cumulative distribution function of change in unemployment rate:

$$\%Up = 1 - F\left(\frac{-c - \mu_t}{\sigma_t^u}\right) \tag{1}$$

where $F$ is the cumulative distribution of function of the expected change in unemployment.

Similarly, the fraction of individuals expecting a decrease in unemployment rate can be expressed as:

$$\%Down = F\left(\frac{c - \mu_t}{\sigma_t^u}\right) \tag{2}$$

Here, $\mu_t$ and $\sigma_t^u$ denote the mean and variance of the distribution of expected change in unemployment rate. I can solve for the mean and variance of the distribution up to a multiplicative parameter $c$:

$$\mu_t = c\left[\frac{F^{-1}(\%Down) + (F^{-1}(1 - \%Up))}{F^{-1}(\%Down) - (F^{-1}(1 - \%Up)}\right] \tag{3}$$

$$\sigma_t^u = c\left[\frac{2}{F^{-1}(1 - \%Up) - F^{-1}(\%Down)}\right] \tag{4}$$

The threshold parameter $c$ uniformly influences the scale of the distribution across all periods. To pin down the scale parameter $c$, I assume that the time average of the belief mean $\mu_t$ matches the average actual change in the unemployment rate over the sample.

[2]The data shows large fluctuations in the share expecting "more unemployment" during recessions and a consistently high fraction of respondents expecting no change. I provide a more detailed analysis of this in the Appendix.

While household beliefs systematically lag actual changes, these deviations are assumed to offset over time. As a result, the long-run average of subjective expectations align with the actual mean change in unemployment:[3]

$$\sum_t \mu_t = \sum_t \Delta u_t \tag{5}$$

I can back out $c$ as

$$c = \frac{\sum_t \Delta u_t}{\left[\frac{F^{-1}(\%Down)+(1-F^{-1}(\%Up))}{F^{-1}(\%Down)-(1-F^{-1}(\%Up)}\right]} \tag{6}$$

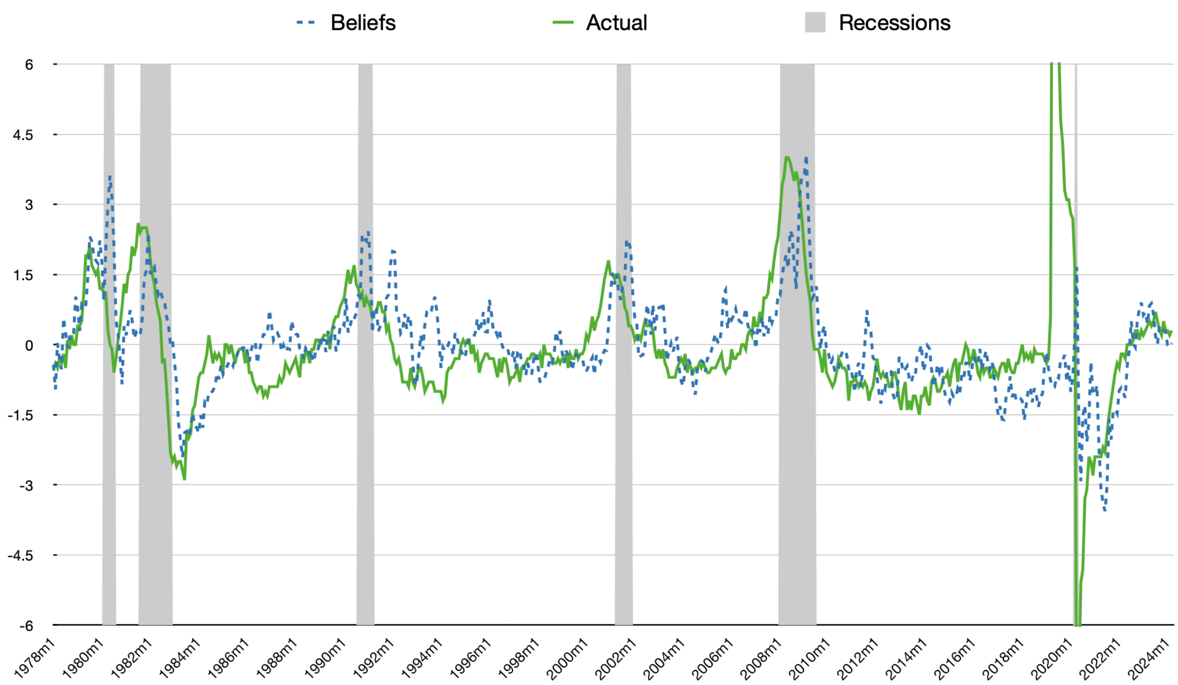
Over the sample period from 1978m1 to 2024m1, the 12-month change in the unemployment rate averages 0.0539%, which yields an estimate of the threshold parameter $c = 0.14$. This implies that households interpret changes in the unemployment rate smaller than 0.14% as "no change." This estimate is intuitively plausible. Institutions such as the Bureau of Labor Statistics (BLS), the Federal Reserve, and Bloomberg routinely describe the unemployment rate as "unchanged" when it moves by approximately 0.1 percentage points. It is reasonable to assume that households apply a slightly larger threshold in interpreting labor market changes. Using this estimate of $c$, I compute the full time series for the mean $\mu_t$ and cross-sectional standard deviation $\sigma_t^u$ of the belief distribution based on equations (3) and (4).

Figure 1 displays the evolution of the belief mean over time, alongside the actual 12-month change in the unemployment rate. Household expectations about changes in unemployment systematically lag actual changes in the economy. This is consistent with the finding of Du et al. (2024) using data from Survey of Consumer Expectations that workers' perception about their job-finding and job-separation prospects experience a lag compared to the actual variables. As a result, households tend to be overly optimistic at the beginning of recessions and overly pessimistic in early stage of recoveries.

The time series of the belief dispersion $\sigma_t^u$ is reported in Figure 15. Similar to evidence of dispersion rising in recessions for firms, households beliefs seem to become more dis-

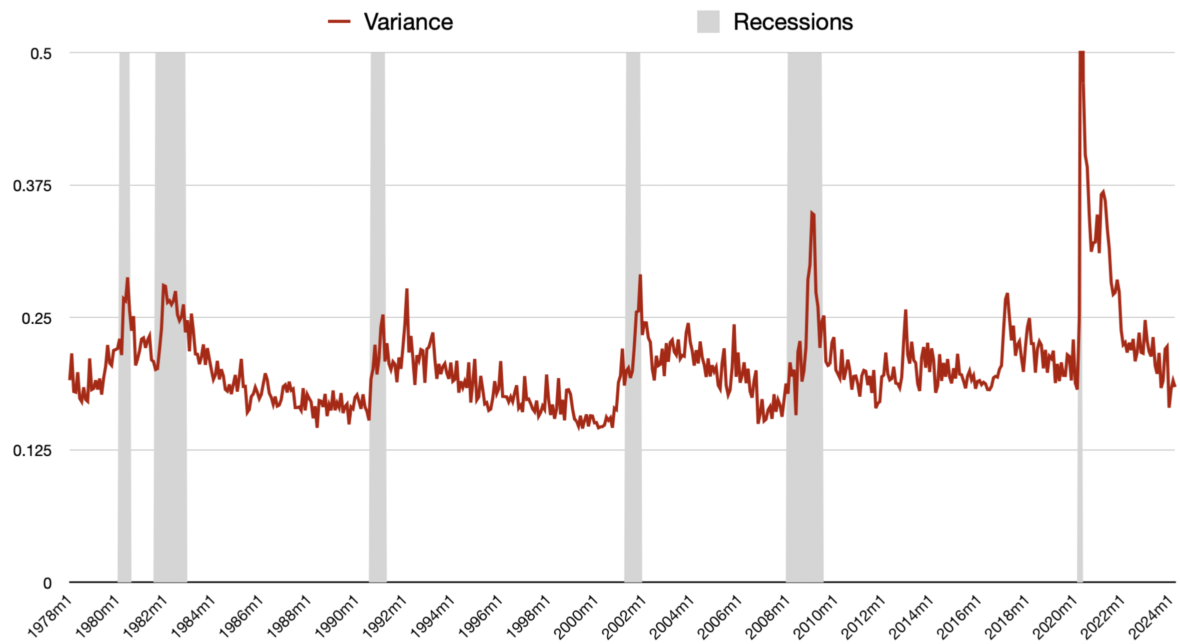
[3]Mankiw et al. (2003) adopt a slightly different approach when estimating the threshold $c$ for inflation expectations. They utilize an additional quantitative question from the Michigan Survey—"*By about what percent do you expect prices to go (up/down) on average during the next 12 months?*" This question is available for a subsample of their empirical analysis. They assume that the sample mean recovered from qualitative responses should match the quantitative median inflation forecast during the overlapping period. Since there is no quantitative question on unemployment changes, I assume that the sample mean recovered from the qualitative question should match the actual mean change in unemployment. While inflation expectations are generally positive over the long run, changes in the unemployment rate tend to average near zero..

**Figure 1:** Fluctuations in perceived and realized changes in unemployment rate




**Notes:** The blue dotted line shows the perceived change in the unemployment rate 12 months ahead, calculated using Michigan Consumer Survey. Higher values indicates optimism. The green solid line represents the actual change in the unemployment rate. Shaded areas indicate NBER recessions. Both series are standardized for comparability. Source: Michigan Survey of Consumers. FRED: UNRATE (1978m1 - 2024m1)

**Figure 2:** Dispersion in perceived changes in unemployment rate (weighted)




This figure shows the standard deviation in household beliefs about changes in unemployment rate. Details about the time-varying dispersion in beliefs is described in section 3.1. Source: Michigan Survey of Consumers.

persed in some recessions.[4]

## 2.2 Evidence on Reservation Wages

The Survey of Consumer Expectations (SCE) is a monthly, internet-based survey conducted by the Federal Reserve Bank of New York. It began in June 2013 and has been fielded on an ongoing basis since then. Each month, the survey samples a rotating panel of about 1,300 households. Respondents are asked to remain in the panel for up to twelve months, which enables researchers to observe both cross-sectional variation and individual dynamics over time. The survey covers a wide range of topics, including inflation expectations, labor market outcomes, household finance, spending, and credit access.

Active panel members who have participated in an SCE monthly survey within the prior three months are eligible for the Labor Market Survey, which focuses on expectations and behaviors related to the labor market. Fielded three times per year—in March, July, and November—the Labor Market Survey has been conducted since 2014. Each household may participate in the labor market module between one and three times. I fo-

[4]For tractability, the quantitative model keeps belief dispersion constant over time.

**Table 1:** Beliefs and Reservation Wages

| | *Exp job-finding rate* | | | *Exp unemployment rate* | | |
|---|---|---|---|---|---|---|
| | *employed* | *employed* | *unemployed* | *all* | *employed* | *non-employed* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Beliefs | 0.178*** | 0.102*** | 0.005* | -0.114** | -0.096* | -0.142 |
| | (0.032) | (0.027) | (0.003) | (0.048) | (0.047) | (0.118) |
| Household income | ✓ | | ✓ | | | |
| Worker income | | ✓ | | | | |
| Demographics | ✓ | ✓ | ✓ | | | |
| Worker FE | | | | ✓ | ✓ | ✓ |
| Observations | 19,035 | 18,989 | 802 | 28,318 | 19,049 | 8,231 |
| $R^2$ | 0.215 | 0.364 | 0.133 | 0.484 | 0.512 | 0.649 |

**Notes:** The dependent variable is the log of weekly reservation wages. The independent variable is the three-month expected job-finding rate for employed workers (Q22) in columns (1)–(2), 12-month expected job-finding rate (Q17) for unemployed workers in column (3) and the percentage chance that unemployment rate will go up in 12 months (Q4) in column (4)-(6). Household income is defined in three categories based on SCE reports in the main survey, and worker income is taken from the income level reported in the labor survey. Demographic controls include race, gender, education, and age. Column (4) also controls for employment status in addition to worker fixed effect. Robust standard errors are clustered at the individual level in columns (1)–(3). *Source: SCE 2014m3-2023m7.*

cuses on the question about individual's reservation wage. More details about the survey questions are described in the Appendix.

Table 1 reports evidence on workers' reservation wages and their beliefs, based on the SCE and estimated from equation 7:

$$\log(res\,wage)_{it} = \alpha_0 + \alpha_1 Belief_{it} + X_{it} + \epsilon_{it} \tag{7}$$

The variable *res wage* denotes the worker's weekly reservation wage, while $X_{it}$ is a vector of controls including race, gender, education, age, employment status and time fixed effects. Details on data cleaning and the coefficients associated with demographic characteristics are provided in the Appendix.[5]

First, I show that, in the cross section, greater optimism about job-finding prospects is associated with higher reservation wages. Columns (1) and (2) focus on employed workers and regress the log weekly reservation wage on the worker's three-month expected job-finding probability, defined as the chance of finding a job within three months if they were to lose their main job today. Both specifications include demographic controls; Col-

[5]The regression results indicate that workers with higher education and higher income report higher reservation wages. Prime-age workers also have higher reservation wages compared to both younger workers and those close to retirement, as one would expect. Males report higher reservation wages than females, while race explains little of the variation.

umn (1) additionally controls for household income, while Column (2) controls for the worker's own income instead.[6]

Among employed workers, a 10 percent increase in the expected job-finding rate is associated with a 10.2–17.8 percent increase in the weekly reservation wage. A worker whose expectations are one standard deviation above the median (about 30 percent) has a reservation wage that is \$32–\$57 higher than the sample median of \$1,054 per week.

Column (3) turns to unemployed workers and estimates the same relationship. The pattern remains positive, though smaller in magnitude. The median weekly reservation wage among the unemployed is \$576.9, and a one-standard-deviation increase in expected job-finding probability is associated with roughly a \$1 increase in the reservation wage.

The positive correlation between expected job-finding rates and reservation wages documented above may reflect either beliefs about aggregate labor market conditions or private information about individual circumstances. To isolate the role of beliefs about the aggregate state fo the economy, Columns (4)–(6) estimate two-way fixed-effects regressions that exploit within-person changes in reservation wages over time. The specification relates changes in reservation wages to changes in the perceived probability that the unemployment rate will be higher 12 months from now, while including both individual fixed effects and time fixed effects, as well as a control for employment status. Column (4) uses the full sample. Column (5) restricts the sample to employed workers, and Column (6) to non-employed workers.

The results show that when workers revise their expectations about unemployment rate upward, suggesting more pessimism about the labor market, they lower their reservation wages. More specifically, a 30% upward revision in the expected unemployment rate is associated with a 2.9% decline in the reservation wage. For a worker with a weekly reservation wage of \$1,054, this implies a reduction of about \$30.

# 3 Search and Matching with Imperfect Information

In this section, I develop a search-and-matching model in which workers and firms make labor market decisions based on their individual beliefs about aggregate productivity. Worker beliefs shape wage outcomes. As a result, the distribution of beliefs across workers influences firms' layoff decisions and vacancy-posting incentives. The model incorporates endogenous quits and layoffs induced by wage rigidity.

[6]Household income is grouped into three brackets: less than \$50,000;\$50,000–\$100,000; and above \$100,000.

## 3.1 Environment

Time is discrete. Agents are forward looking and discount the future at rate $\beta$. There is a continuum of infinitely lived workers and a continuum of identical firms, each of measure one. Production uses only labor. Each firm has one job that can be in one of the two states: filled and producing, or vacant and searching. Jobs that are not actively producing or searching are destroyed. Job destruction happens when the worker separates from the firm.

There are search friction in the labor market. Firms with vacancies and unemployed workers meet randomly. I assume a standard Cobb-Douglas matching function between searchers and vacancies $m(u, v) = Au^{1-\alpha}v^{\alpha}$, where $A$ is the matching efficiency, $\alpha$ is the matching elasticity to vacancies. The worker contact rate is $f(\theta) = A\theta^{\alpha}$, where $\theta = \frac{v}{u}$ denotes the labor market tightness. Similarly, the contact rate for each vacancy is given by $q(\theta) = A\theta^{\alpha-1}$. Matches formed at time $t$ become productive in the next period.

Wages for newly formed matches are flexible, whereas wages for job stayers are subject to staggered multi-period contracts, akin to Calvo (1983) pricing.[7] Both the wages of new hires and those renegotiated by incumbents are determined through a bargaining game. Workers and firms negotiate based on their respective beliefs about aggregate productivity, and negotiations between workers and firms may fail due to disagreements in their beliefs.

Figure 3 outlines the sequence of events in each period:

1. **State realization and belief formation**: The new state of aggregate productivity $z_t$ is realized. Each worker $i$ forms a belief about aggregate productivity, denoted by $\hat{z}^u_{it}$ for unemployed workers and $\hat{z}^c_{it}$ for continuing workers. Firms form belief $\hat{z}^f_t$.

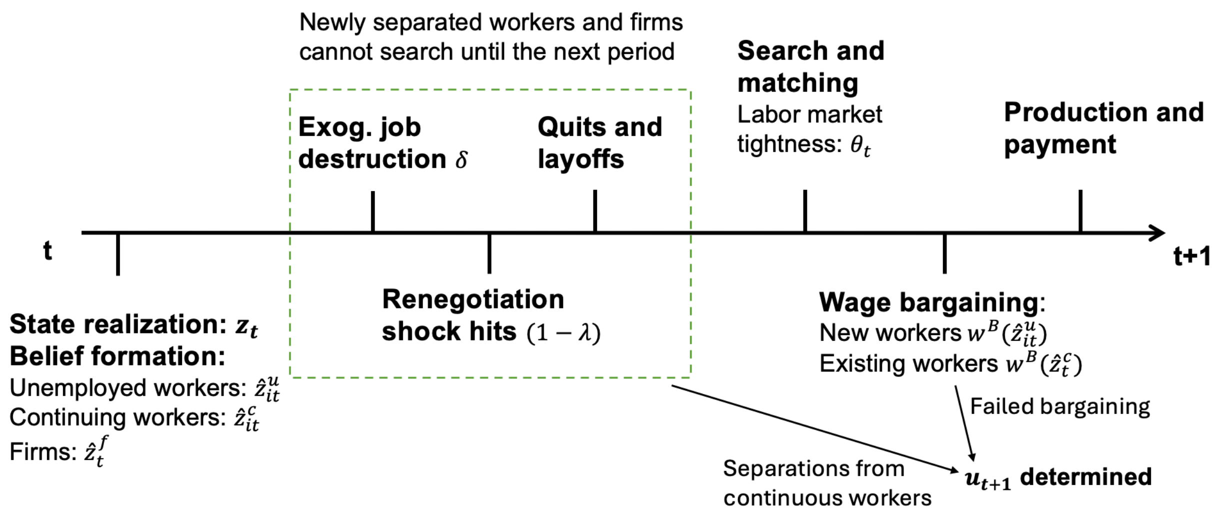
2. **Exogenous job destruction:** Existing matches are destroyed exogenously with probability $\delta$.

3. **Renegotiation shock hits:** There is a probability $\lambda$ that an existing match will be able to renegotiate their wages for the next period at the bargaining stage

4. **Quits and layoffs:** Continuing jobs that cannot renegotiate face potential endogeneous separations determined by the updated beliefs of workers and firms. Firms

[7] This is not the first paper to introduce staggered wage bargaining. For example, Gertler et al. (2020) develops a real business cycle model with search and matching friction where wages are negotiated based on staggered Nash bargaining.

**Figure 3:** Timeline




may initiate layoffs and continuing workers may choose to quit into unemployment. Workers and firms who separate must wait one period before entering the search pool.

5. **Search and matching:** Unemployed workers search for jobs. Vacancies and job searchers are randomly matched. Labor market tightness $\theta_t$ is realized, as a function of firm's and worker beliefs.

6. **Wage bargaining and job creation:** Workers and firms bargain for wages for the next period based on their expected matching surplus. All unemployed workers and continuing matches that are hit by a renegotiation shock bargain for wages. A match is formed if the new bargained wage is below the firm's reservation wage and above the worker's reservation wage for working. Matches with failed bargaining are dissolved and the worker enters unemployment for the next period. Unemployment rate $u_{t+1}$ and the distribution of wages for the next period $L_{t+1}$ are determined.

7. **Production and payments:** Firms produce output and pay their workers, unemployed workers receive unemployment benefits, and firms with vacancies incur the cost of maintaining those vacancies. Newly formed match starts producing in the next period.

### 3.2 Agents' Problem

**Workers' Problem**: Given belief $\hat{z}_{it}$ and the perceived distribution of worker beliefs, denoted by $\hat{G}^u_{it}$ for unemployed workers and $\hat{G}^c_{it}$ for continuing workers, each worker faces two potential decisions:

- An employed worker who survives exogenous job destruction and layoffs, and is not subject to wage renegotiation, solves for his reservation wage $\underline{w}^r(\hat{z}_{it}, \hat{G}^u_{it}, \hat{G}^c_{it})$ and decides whether to quit in the current period.

- An unemployed worker matched to a vacancy and an employed worker subject to a Calvo shock bargains over his perceived matching surplus to determine the wage outcome of the bargaining game. The perceived matching surplus is denoted by $S(\hat{z}_{it}, \hat{G}^u_{it}, \hat{G}^c_{it})$, and the resulting bargained wage is $w^B(\hat{z}_{it}, \hat{G}^u_{it}, \hat{G}^c_{it})$.

I discuss the belief formation process in detail later. For now, it is useful to note that each worker thinks the firms share their belief, and the perceived distributions of beliefs, $\hat{G}^u_{it}$ and $\hat{G}^c_{it}$, are both functions of the worker's current belief $\hat{z}_{it}$. Consequently, the reservation wage and the bargained wage can be written as $\underline{w}^r(\hat{z}_{it})$ and $w^B(\hat{z}_{it})$, respectively.

To compute the perceived value of working and unemployment, each worker must also solve the hypothetical firm's problem to infer the perceived job-finding rate and the firm's reservation wage. The relevant perceived job finding rate and reservation wages for unemployed and continuing workers are:

$$f(\hat{\theta}^u_{it}) = \hat{\mathbb{E}}\big(f(\theta) \mid \hat{z}^u_{it}\big), \quad \overline{w}^f(\hat{z}^u_{it}) = \hat{\mathbb{E}}\big(\bar{w}^f \mid \hat{z}^u_{it}\big),$$
$$f(\hat{\theta}^c_{it}) = \hat{\mathbb{E}}\big(f(\theta) \mid \hat{z}^c_{it}\big), \quad \overline{w}^f(\hat{z}^c_{it}) = \hat{\mathbb{E}}\big(\bar{w}^f \mid \hat{z}^c_{it}\big).$$

**Firm's problem:** Given the firm's belief $\hat{z}^f_t$ and the true distribution of beliefs for unemployed and continuing workers, $G^u_t$ and $G^c_t$, the firm solves for the strategies of the workers $\{w^B(\hat{z}^u_{it}), w^B(\hat{z}^c_{it}), \underline{w}^r(\hat{z}^c_{it})\}$, and make the following decisions:

- Firms in existing matches solve for their reservation wage $\overline{w}^f(\hat{z}^f_t, G^u_t, G^c_t)$ and decide whether to layoff their workers.

- New firms decide whether to enter and post vacancies. Their decisions determine the true market tightness $\theta_t$.

### 3.3 Perceived value functions

In this section, I describe the perceived value functions in a general form that applies to any specification of beliefs and productivity. The details of how these processes are specified and calibrated follows in the next section.

**Perceived value functions of the workers.** Given belief $\hat{z}$ and the current wage $w$, the perceived value of working is

$$\begin{aligned} W(\hat{z}, w) = w + \beta\hat{\mathbb{E}}\Big\{ & \Big[\delta + (1-\delta)\lambda\mathbb{1}\big(w \geq \overline{w}^f(\hat{z}')\big)\Big] U(\hat{z}') \\ & + (1-\delta)\lambda\mathbb{1}\big(w < \overline{w}^f(\hat{z}')\big) \max\{W\big(\hat{z}', w\big), U(\hat{z}')\} \\ & + (1-\delta)(1-\lambda)W\big(\hat{z}', w^B(\hat{z}')\big)\Big\} \end{aligned} \tag{8}$$

Conditional on the current belief $\hat{z}$, the worker forms expectations over possible future states $\hat{z}'$. If the job survives exogenous job destruction (which occurs with probability $(1-\delta)$), there are three potential outcome of an job: First, if the current wage remains in place, the firm layoffs the incumbent worker whenever the wage exceeds its reservation threshold, in which case the worker receives the value of unemployment. Second, conditional on not being laid off, the worker decides whether to continue the match by comparing the value of employment with that of unemployment. Finally, with probability $(1-\lambda)$ the worker renegotiates the wage with the firm. The new bargained wage depends on the worker's updated belief $\hat{z}'$.

Given belief $\hat{z}$, perceived value of unemployment is

$$U(\hat{z}) = b + \beta\hat{\mathbb{E}}\Big\{f(\hat{\theta})W\big(\hat{z}', w^B(\hat{z})\big) + (1-f(\hat{\theta}))U(\hat{z}')\Big\} \tag{9}$$

The worker receives the unemployment benefit $b$ in the current period. With probability $f(\hat{\theta})$, he is matched with a firm and bargains over a wage that becomes effective in the following period. Otherwise, he continues in unemployment. Because the worker believes that firms share his perception of the aggregate state, he expects all matches to result in job creation.

Equation 8 and 9 jointly determine the set of acceptable wage for the worker:

$$\{w : w \geq \underline{w}^r(\hat{z}) \quad and \quad W\big(\hat{z}, \underline{w}^r(\hat{z})\big) = U(\hat{z})\} \tag{10}$$

$\underline{w}^r(\hat{z})$ is the reservation wage of working. The worker chooses to quit to unemployment if his existing wage falls below his reservation wage.

**Perceived value functions of the firm.** Given belief $\hat{z}$, the perceived distribution of beliefs for continuing workers $\hat{G}^c$, and the current wage $w$, the perceived value function of the firm is

$$
\begin{aligned}
J(\hat{z}, w, \hat{G}^c) = \hat{z} - w + \beta \mathbb{E}\Big\{ & \delta V(\hat{z}') + (1-\delta)\lambda \int_{\hat{z}_i'^c} \mathbb{1}\big(w^r(\hat{z}_i'^c) > w\big) V(\hat{z}') d\hat{G}'^c \\
& + (1-\delta)\lambda \int_{\hat{z}_i'^c} \mathbb{1}\big(w^r(\hat{z}_i'^c) < w\big) \max\{J(\hat{z}', w), V(\hat{z}')\} d\hat{G}'^c \\
& + (1-\delta)(1-\lambda) \int_{\hat{z}_i'^c} J\big(\hat{z}', w^B(\hat{z}_i'^c)\big) d\hat{G}'^c \Big\}
\end{aligned}
\tag{11}
$$

$\hat{z} - w$ is the perceived profit of the firm in the current period. If the job survives exogenous destruction, there are three outcomes: First, with probability $\lambda$, the current wage continues to the next period. In this case, if the current wage falls below the worker's reservation wage of working, the worker quits to unemployment and the firm receives the expected value of vacancy $V(\hat{z}')$. If the worker does not quit given his updated belief, the firm then decides whether to retain or lay off the worker, comparing the expected value of a filled job to that of a vacancy. The last term represents the case that the pair renegotiates the wage.

Given belief $\hat{z}$ and the perceived distribution of beliefs for unemployed worker $\hat{G}^u$, the value of vacancy given belief $\hat{z}$ is given by

$$
V(\hat{z}, \hat{G}^u) = -\kappa + \beta \mathbb{E} q(\hat{\theta}) \Big\{ \int_{\hat{z}_i^u} \max\{J\big(\hat{z}', w^B(\hat{z}_i^u)\big), V(\hat{z}')\} d\hat{G}^u \Big\} = 0 \tag{12}
$$

where $\kappa$ is the cost of maintaining a vacancy and $q(\hat{\theta})$ is perceived probability that the vacancy is matched to a job seeker. Upon matching, the job will be formed at the bargained wage $w^B(\hat{z}_i^u)$, which depends on the belief of the worker with whom the firm is matched. For each bargained wage, the firm compares the expected value of a filled job and the expected value of vacancy. If the match is profitable, the firm proceeds with hiring; otherwise, it prefers to keep the vacancy open. The expected value of a filled job depends on the distribution of bargained wages, which is determined by the distribution of worker beliefs $\hat{G}^u$.

Free entry drives of the value of vacancy to 0 in equilibrium and pins down the labor market tightness $\theta$.

$$
V(\hat{z}, \hat{G}^u) = 0 \tag{13}
$$

Equation 11 and 12 determine the set of acceptable wages for the firm. The firm accepts all wages that makes the value of a filled job higher than the value of vacancy.

$$\{w : w \leq \overline{w}^f(\hat{z}, \hat{G}^c, \hat{G}^u) \quad \text{and} \quad J(\hat{z}, \overline{w}^f(\hat{z}, \hat{G}^c, \hat{G}^u)) = 0\} \tag{14}$$

## 3.4 Wage Negotiation

Unemployed workers who are matched to a firm and employed workers who are hit by the renegotiation shock bargain for wages with the firm. The game structure follows Figure 4.[8] A key feature of this framework is that the negotiated wage depends on the worker's belief $\hat{z}$ . As a result, matches may fail to form if workers are overly optimistic about economic conditions.

The firm and the worker negotiate over their perceived matching surplus, $\hat{S} = \hat{W} - \hat{U} + \hat{J}$, based on their respective information at the time of negotiation. Once the bargaining process begins, I assume that both parties lose contact with all other agents in the market. Additionally, I assume that the worker is truthful about his belief during the negotiation.

For simplicity in writing, in this section, I use $\hat{W}(w)$ and $\hat{J}(w)$ to represent the perceived value functions under an arbitrary wage $w$ given belief $\hat{z}$.

Wages are negotiated according to the following game:

1. The worker proposes a wage offer $x$ to the firm.

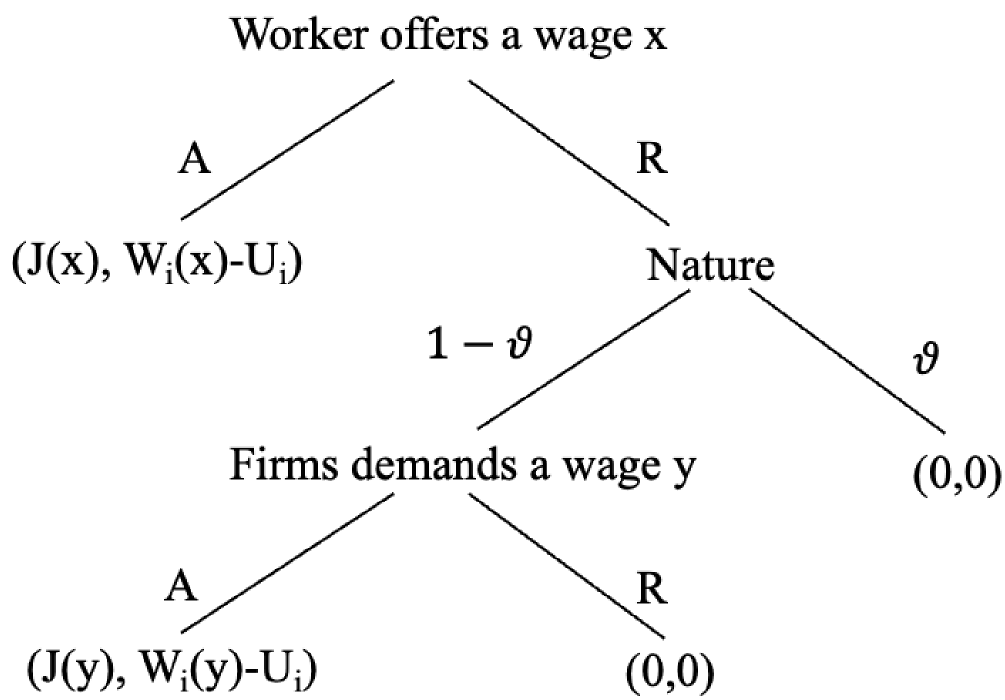
2. The firm observes the worker's offer. Upon acceptance, the game ends with payoff $\hat{J}(x)$ to the firm and $\hat{W}_i(x) - \hat{U}_i$ to the worker, where the subscript $i$ indicates that the worker's payoff depends on their individual belief.

3. If the firm rejects the worker's offer, the match is destroyed with an external probability $\vartheta$, resulting in a payoff of 0 for both the firm and the worker. If the match survives, the firm counteroffers with a wage $y$.

4. Upon the worker's acceptance of the firm's counteroffer, the game ends, and the payoffs are $\hat{J}(y)$ for the firm and $\hat{W}_i(y) - \hat{U}_i$ for the worker. If the worker rejects the firm's counteroffer, the game ends with a payoff of 0 for both parties.

[8]This setup builds on the asymmetric-information wage bargaining framework of Morales-Jiménez (2022), with two key differences. First, in my model, the worker makes the initial offer in the bargaining game, whereas the firm does so in his setup. Second, I allow for heterogeneous beliefs across workers. In related work, Menzio (2023) also study asymmetric-information bargaining using the infinite-horizon alternating-offer protocol of Binmore et al. (1986), which delivers a similar outcome.

**Figure 4:** Wage bargaining game




**Notes:** This figure shows the extensive-form of the wage bargaining game. *A* represents *accept* and *R* represents *reject*.

First, note that under full information, the outcome of the game coincide with a standard Nash Bargaining game where the bargaining power of the worker is $\vartheta$. In the case with asymmetric information, firms have an incentive to lie in order to extract all the perceived surplus of the worker when making the counteroffer. As a result, workers do not rely on the firm's offer but instead rely solely on their own beliefs when making decisions (see Appendix for more discussion). Building on this, I can characterize the equilibrium of the bargaining game.

LEMMA: If workers and firms have asymmetric beliefs about the aggregate productivity, then the following strategy constitutes a Perfect Bayesian Nash equilibrium that satisfies the Intuitive Criterion:

- The workers offers $\hat{x}_i$ in the first stage and accepts offer great then or equal to $\hat{y}_i$ in the second stage.
- The firm accepts offers less than or equal to $\hat{x}^f$ in the first stage and demands $\min\{\hat{y}_i, \hat{x}^f\}$ in the second stage.

where $\hat{x}_i$, $\hat{x}^f$, $\hat{y}_i$ and $y$ satisfy $W(\hat{x}_i) - U_i = (1-\vartheta)S(\hat{x}_i)$, $J(\hat{y}_i) = 0$, and $W(\hat{x}^f) - U = \vartheta S(\hat{x}^f)$.

See Appendix A.3.

In equilibrium, the worker makes the initial offer based on his belief. Workers recognize that if a firm makes a counteroffer, it will try to extract the entire surplus from the match. Consequently, workers do not update their beliefs based on the firm's actions during the bargaining process. From the firm's perspective, knowing that the worker's belief cannot be altered, its optimal strategy is to accept the worker's initial offer if it generates a positive payoff to the firm. Otherwise, the firm rejects, but cannot persuade the worker to lower his wage demands. Thus, the bargaining game admits two possible outcomes: (i) the firm immediately accepts the worker's offer if it implies positive value of a filled job, or (ii) the firm rejects, and the match fails to form as the worker refuses any counteroffer.

## 3.5 Aggregate Productivity and Belief Formation

Now, I outline the evolution of aggregate productivity and the belief-formation processes of workers. The framework is aimed to capture two empirical patterns regarding the distribution of worker beliefs observed in the data: substantial dispersion in expectations across workers and a systematic lag in their response to economic fluctuations.[9]

Aggregate productivity evolves according to an AR(1) process with normally distributed innovations:

$$z_t = \rho z_{t-1} + e_t, \tag{15}$$

where $e_t$ is an i.i.d. innovation drawn from a normal distribution, $e_t \sim \mathcal{N}(0, \sigma_z^2)$. All workers and firms know the persistence and variance of the aggregate productivity shock, but not the current productivity level. At the beginning of each period, firms update their beliefs about the aggregate productivity using adaptive learning. All firms share a common belief:

$$\hat{z}_t^f = \hat{z}_{t-1}^f + \gamma^f \underbrace{(z_{t-1} - \hat{z}_{t-1}^f)}_{\text{forecast error}} \tag{16}$$

where $0 < \gamma^f < 1$ denotes the learning rate of firms. A larger $\gamma^f$ corresponds to a faster learning rate.

An unemployed worker $i$ draws an individual belief from a distribution:

$$\hat{z}_{it}^u = \hat{z}_t^w + \eta_{it} \tag{17}$$

where $\hat{z}_t^w$ denotes the time-varying mean of the worker belief distribution, and $\eta_{it}$ is an idiosyncratic noise term, independently drawn across workers, with $\eta_{it} \sim \mathcal{N}(0, \sigma_s^2)$.

The mean belief $\hat{z}_t^w$ of unemployed workers evolves through an adaptive learning process:

$$\hat{z}_t^w = \hat{z}_{t-1}^w + \gamma^w \underbrace{(z_{t-1} - \hat{z}_{t-1}^w)}_{\text{forecast error}} \tag{18}$$

Workers update their beliefs based on their prior belief and an adjustment toward the true value, with $0 < \gamma^w < \gamma^f$ governing the speed of adjustment. This formulation

[9] A substantial body of research documents wide dispersion in expectations about the aggregate state of the economy. Early evidence using survey data focuses on inflation expectations (e.g., Mankiw et al. (2003); Malmendier and Nagel (2016)), while a growing literature highlights disagreement about labor market conditions among workers (e.g., Conlon et al. (2018); Mueller et al. (2021); Jäger et al. (2024); Mitman et al. (2022)) and between workers and firms (Kudlyak and Miskanic (2024)). In addition, I document a systematic lag in the average household belief about unemployment, as shown in Figure.1. Details on the construction of the beliefs measure are provided in Section3.1. This pattern aligns with the findings of Du et al. (2024), who show that household perceptions of labor market variables respond with a lag and exhibit milder fluctuations relative to the actual time series.

is motivated by the systematic lag in beliefs documented in Figure 1 and in Du et al. (2024). It captures the gradual adjustment of household beliefs about current economic conditions, which may result from information acquisition costs, limited attention, or cognitive constraints, as documented in Coibion and Gorodnichenko (2015) and Khaw et al. (2017). In addition, Carroll (2003) and Meyer and Sheng (2025) find evidence that households have a larger degree of information rigidity relative to firms.

Consequently, in each period, the cross-sectional distribution of $\hat{z}^u_{it}$ follows a normal distribution $G^u_t = \mathcal{N}(\hat{z}^w_t, \sigma^2_s)$, representing a lagged and dispersed perception of the true productivity.

Mueller et al. (2021) document that employed workers have more accurate expectations about their job-finding prospects than unemployed workers. Motivated by this evidence, a continuing worker $i$ is assumed to draw an individual belief from a distribution centered on the belief of his employer:

$$\hat{z}^u_{it} = \hat{z}^f_t + \eta_{it} \tag{19}$$

The idiosyncratic noise of continuing workers are assumed to have the same dispersion as the noise for unemployed workers: $\eta_{it} \sim \mathcal{N}(0, \sigma^2_s)$. Similarly, the cross-sectional distribution of $\hat{z}^c_{it}$ follows $G^c_t = N(\hat{z}^f_t, \sigma^2_s)$.

Workers calculate the expected labor market tightness and job-finding rate by solving a hypothetical labor market equilibrium given their own belief.[10] Thus, I need additional assumptions about how workers form beliefs about the firm and the distribution of worker beliefs: each worker $i$, independent of his employment status, assumes that firms share the same belief as him, and perceives the cross-sectional distribution of worker beliefs to be centered on his own subjective belief, which is denoted by $\hat{G}_{it}$.

## 3.6 Equilibrium

An equilibrium is a collection of perceived value functions: $\{W(\hat{z}^u_{it}, w_{it}), U(\hat{z}^u_{it}), J(\hat{z}^u_{it}, w_{it}), V(\hat{z}^u_{it})\}$ for unemployed workers, $\{W(\hat{z}^c_{it}, w_{it}),\ U(\hat{z}^c_{it}),\ J(\hat{z}^c_{it}, w_{it}), V(\hat{z}^c_{it})\}$ for continuing workers, $\{J(\hat{z}^f_t, G^c_t), V(\hat{z}^f, G^u_t)\}$ for firms, reservation wage of working $\underline{w}^r(\hat{z}^c_{it})$ for continuing workers, perceived and actual reservation wage of the firm: $\overline{w}^f(\hat{z}^u_{it}), \overline{w}^f(\hat{z}^c_{it}), \overline{w}^f(\hat{z}^f_t)$, perceived and actual labor market tightness $\hat{\theta}^u_{it}$, $\hat{\theta}^c_{it}$, $\theta_t$, such that given current productivity $z_t$

[10]In principle, agents can use other publicly available variables, such as the interest rate, output and incomes to back out the true aggregate productivity level. Here, I assume that signal extraction is costly and workers make decisions only based on his perception of the aggregate productivity.

1. The belief distributions $G_t^u$ and $G_t^c$ evolve according to 17 to 19. The belief of the firms evolve accoring to 16.
2. At each point in time, each worker $i$'s perceived distribution of beliefs $\hat{G}_{it}$ is a normal distribution centered around his own belief $\hat{z}_{it}^u$ or $\hat{z}_{it}^c$.
3. The perceived value functions of the worker follows equation 8 to 9; the perceived value functions of the firm follows equation 11 to 12.
4. The perceived and actual reservation wage of the firm $\overline{w}^f$ solves 14; The reservation wage of the worker $\underline{w}^r$ solves 10; The bargained wages $w^B$ are a solution to the bargaining game.

Suppose all workers are given the correct belief about productivity, $\hat{z}_{it} = z_t$, then given any wage $w$, their expectations about the value functions $W(\hat{z}_{it}, w)$, $U(\hat{z}_{it})$, $J(\hat{z}_{it}, w)$, $V(\hat{z}_{it})$ coincide with the true value functions $W(z_t, w)$, $U(z_t)$, $J(z_t, w)$, $V(z_t)$. Moreover, the equilibrium wage ensures that the worker obtains a share $\vartheta$ of the true matching surplus, so the bargained wage of new hires coincides with the full-information wage $w(z_t)$. It follows that the worker's perceived labor market tightness, job-finding rate, and reservation wages are also correct. Hence, when both workers and firms hold correct information about the current productivity level, the equilibrium of this model is identical to the full-information equilibrium.

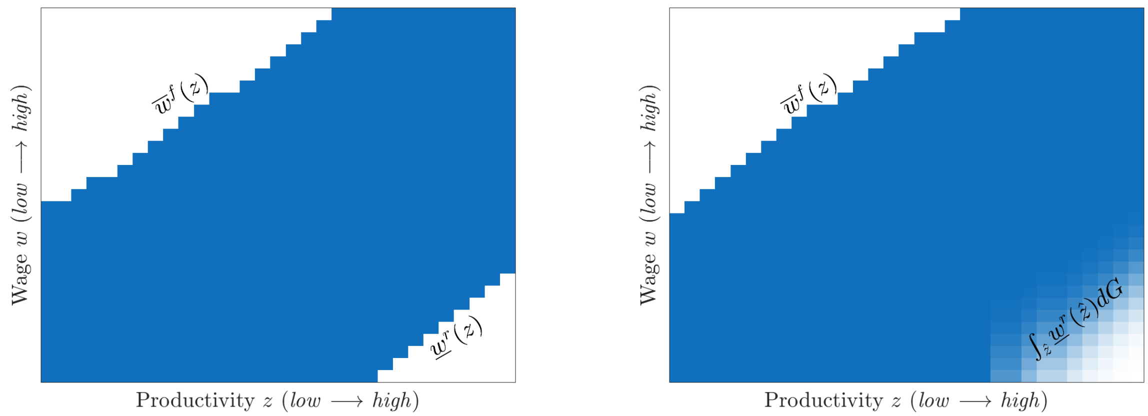
## 3.7 Steady State Job Acceptance Probability

Figure 5 illustrates the steady-state job continuation probability and the decision rule for a worker-firm match characterized by productivity $z$ and wage $w$. In steady state, the firm's belief and the mean belief of unemployed workers coincide with the true productivity level. Panel 5a shows the case for full information. The top-left region corresponds to the rejection region of the firm, where productivity is low and the wage is high. Firm's decision rule affects layoffs. The threshold line represents the firm's reservation wage $\overline{w}^f(z)$. The firm is willing to continue matches with any wage below this threshold. Analogously, the bottom-right region reflects the rejection region of the worker. Workers refuses low wages when productivity level is high. Workers accept any wage above their reservation wage $\underline{w}^r(z)$.

Panel 5b shows the case with noisy beliefs. Workers' noisy beliefs generate a distribution of bargained wages at each productivity level $z$. Some workers with overly optimistic beliefs ask for wages that the firm would not accept, resulting in a quit region where the probability of acceptance lies between zero and one.

**Figure 5:** Job continuation probability

**(a)** Full Information **(b)** Noisy Beliefs




**Notes:** Darker shades indicate higher continuation probabilities. The top-left corner corresponds to layoffs, while the bottom-right captures quits. *Source*: Model simulation. See main text for details.

## 3.8 Laws of Motion

Let $L_{t+1}(w)$ denote the measure of workers earning wage $w$ at the beginning of period $t+1$, determined at the end of last period. It includes: (i) new hires with wage $w$, (ii) job stayers with wage $w$ after surviving both exogenous and endogenous separation and not renegotiating, and (iii) workers who renegotiated and settled on wage $w$.

$$\begin{aligned} L_{t+1}(w) = \mathbb{1}(w \leq w_t^f)\Big[&\underbrace{u_t f(\theta_t) g_t^u(\hat{z}_B^{-1}(w))}_{\textit{new hires at wage } w} \\ &+ \underbrace{L_t(w)(1-\delta)\lambda G_t^c(\hat{z}_r^{-1}(w))}_{\textit{remaining workers with wage } w} + \underbrace{(1-u_t)(1-\delta)(1-\lambda) g_t^c(\hat{z}_B^{-1}(w))}_{\textit{wage renegotiation with wage } w}\Big] \end{aligned} \tag{20}$$

Here, $\hat{z}_B^{-1}(w)$ denotes the belief level that yields a bargained wage $w$, and $g_t^u(\hat{z}_B(w)) = dG_t^u(\hat{z}_B^{-1}(w))$ represents the fraction of new workers hired at wage $w$. Similarly, $\hat{z}_r^{-1}(w)$ is the belief associated with a reservation wage equal to $w$, so that $G_t^c(\hat{z}_r^{-1}(w))$ gives the cumulative fraction of continuing workers whose reservation wages are below $w$.

Equation 20 can be expressed in cumulative terms by integration. The cumulative population with wage less than $w$ at the beginning of the period $t$ can be written as

$$N_{t+1}(w) = \int_{y \leq w} L_{t+1}(y)dy \tag{21}$$

The maximum wage at the beginning of the next period is reservation wage of the firm from the current period, $\overline{w}_t^f = \overline{w}^f(\hat{z}_t^f)$. Total employment at the beginning of period $t$ is therefore:

$$N_{t+1}(\overline{w}_t^f) = 1 - u_{t+1} \tag{22}$$

The dynamics of unemployment is obtained by subtracting the outflows from the inflows of unemployment. Outflows consist of unemployed workers who successfully match with firms and receive wage offers below the firm's reservation wage, thus transitioning into employment. Inflows include exogenous job separations, endogenous layoffs, voluntary quits, and failed wage renegotiations that result in separation. Using Equation 20 to 22, I can write the unemployment rate at the beginning of the next period as

$$\begin{aligned}
u_{t+1} &= 1 - N_{t+1}(\overline{w}_t^f) = 1 - \int_{y \le \overline{w}_t^f} L_{t+1}(y) dy \\
&= 1 - \int_{y \le \overline{w}_t^f} \left[ (1-\delta) L_t(y) G_t^c(\hat{z}_r^{-1}(y)) - u_t f(\theta_t) g_t^u(\hat{z}_B^{-1}) \right] dy \\
&= \underbrace{u_t[1 - f(\theta_t)]}_{\textit{remaining unemployed}} + \underbrace{\delta(1-u_t)}_{\textit{exo separation}} + \underbrace{(1-\delta)\lambda \left[ (1-u_t) - N_t(\overline{w}_t^f) \right]}_{\textit{layoffs}} \\
&+ \underbrace{(1-\delta)\lambda [N_t(\overline{w}_t^f) - \int_{t \le \overline{w}_t^f} L_t(y) G_t^c(\hat{z}_r^{-1}(y)) dy]}_{\textit{quits}} \\
&+ \underbrace{(1-\delta)(1-\lambda)(1-u_t) \int_{y > \overline{w}_t^f} g_t^c(\hat{z}_B^{-1}(y)) dy}_{\textit{unsuccessful renegotiation}} - \underbrace{u_t f(\theta_t) \int_{y < \overline{w}_t^f} g_t^u(\hat{z}_B^{-1}(y)) dy}_{\textit{new hires}}
\end{aligned} \tag{23}$$

# 4 Calibration

In this section, I calibrate the labor market parameters and the dispersion in household belief at the steady state, targeting aggregate labor market moments and belief dispersion from Michigan Survey of Consumers (MSC). Then I simulate the model at a monthly frequency to calibrate the household learning rate, targeting its empirical counterpart in MSC.

**Table 2:** Belief Parameters

| | 1978m1-2019m12<br>(1) | 1978m1-2024m3<br>(2) |
|---|---|---|
| $\beta_1$ | 0.093*** | 0.144*** |
| | (0.019) | (0.018) |
| $\beta_2$ | 0.887*** | 0.849*** |
| | (0.018) | (0.018) |
| $R^2$ | 0.857 | 0.846 |

**Notes:** The table reports the estimates of household learning rates from MSC. The parenthesis reports the standard deviation in the estimates of $\beta$s.

## 4.1 Household Belief Dispersion and Learning Rate

I calibrate the workers' belief parameters about current level of aggregate productivity using data on household expectations from the MSC.

### 4.1.1 Belief Dispersion.

Given each worker's current belief $\hat{z}$ and the productivity process, the model implies a perceived 12-month change in the unemployment rate. Aggregating across the belief distribution in the steady state, I compute the resulting dispersion in perceived changes in unemployment over a 12-month horizon. This model-implied dispersion is directly comparable to survey-based measures from the MSC. I calibrate the belief dispersion parameter $\sigma^s$ so that the model-implied dispersion in 12-month-ahead unemployment expectations matches the cross-sectional standard deviation of household beliefs in the data, averaged over January 1978 to January 2019, $\sigma^u = 0.20$.

### 4.1.2 Household Learning

I calibrate the productivity learning gain $\gamma^w$ such that the model-implied learning rate about changes in unemployment matches its counterpart in the data. First, I estimate the learning gain for household forecasts of changes in the unemployment rate, using a constant gain learning model. This calibration ensures that the model's learning speed corresponds to the sluggish belief updating observed in survey data. The implied gain parameter suggests that households place a constant gain on recent outcomes, so that the model reproduces both the persistence and volatility of unemployment expectations

**Table 3:** Externally calibrated parameters

| Parameter | Description | Value | Source |
|---|---|---|---|
| $\rho$ | Persistence of $z$ | 0.983 | GHT |
| $\sigma_z$ | Standard deviation of $z$ | 0.007 | GHT |
| $\beta$ | Discount factor | 0.997 | Standard value |
| $\lambda$ | Renegotiation frequency | 11/12 | GHT |
| $\alpha$ | Matching elasticity to $v$ | 0.5 | Standard value |
| $\vartheta$ | Bargaining power of the worker | 0.6 | Standard value |

**Notes:** The table reports parameter values drawn from external sources in the literature, in particular Gertler et al. (2020).

documented in Figure 1.

$$UNEMPL_t^e = \beta_1 UNEMPL_{t-1} + \beta_2 UNEMPL_{t-1}^e + \epsilon_t \tag{24}$$

The estimated learning rates are reported in Table 2. Column (1) restricts the sample to the pre-Covid period (1978m1 to 2019m12), while column (2) uses the full sample through 2024m3. The post-Covid period shows substantially faster learning, with households placing greater weight on new information relative to prior beliefs. This pattern is consistent with Coibion and Gorodnichenko (2012), who show that agents pay more attention to aggregate economic conditions during periods of heightened uncertainty. Given the unprecedented labor market fluctuations during the Covid era, I calibrate the productivity learning gain $\gamma^w$ using pre-Covid data to capture typical business cycle dynamics. The calibrated value is $\gamma^w$ = 0.085, implying that information from one year ago receives an effective weight of approximately $0.085 \times (1 - 0.085)^{11} = 0.034$.

## 4.2 Labor market parameters

Table 3 reports the externally calibrated parameters set to values commonly used in the literature. The unconditional mean of aggregate productivity, $z$, is normalized to 1. The monthly persistence and standard deviation of the productivity process are set to $\rho = 0.983$ and $\sigma_z = 0.007$, following the calibration of Gertler et al. (2020). The discount factor is set to $\beta = 0.997$, corresponding to an annual real interest rate of approximately 3%. Following Hall and Milgrom (2008), the elasticity of the matching function with respect to unemployment is set to $\alpha = 0.5$. In the presence of wage rigidities, greater worker bargaining power leads to more quits, while lower bargaining power leads to more layoffs. I set the worker's bargaining power to $\vartheta = 0.6$, slightly above the value

**Table 4:** Internally calibrated parameters

| | Description | Value | Target | Model |
|---|---|---|---|---|
| $\delta$ | Exog job destruction rate | 0.021 | Unemploy. rate = 0.007 | 0.007 |
| $A$ | Matching efficiency | 0.326 | Job finding rate = 0.277 | 0.278 |
| $\kappa$ | Cost of vacancy posting | 0.283 | Labor market tightness = 0.720 | 0.719 |
| $b$ | Unemployment benefit | 0.65 | Fraction of average wage | 0.65 |
| $\sigma_s$ | Std. dev. of beliefs | 0.019 | MSC $\hat{\sigma}^u$ = 0.20 | 0.199 |
| $\gamma^w$ | Learning rate of HH | 0.085 | MSC $\hat{\beta}^1 = 0.093$ | 0.095 |

**Notes:** This table summarizes the internally calibrated parameter values.

implied by the Hosios condition, to generate a higher share of layoffs relative to quits.

Then, I jointly calibrate the four labor market parameters ($\delta$, $b$, $A$, $\kappa$) together with $\sigma_s$ that governs the belief dispersion, to match key empirical moments in the median steady state by minimizing the distance between an equal number of empirical moments and their counterparts in the model. These moments are determined simultaneously by all five parameters; however, Table 4 indicates the moment most closely associated with each parameter based on its identifying power.

The job destruction rate $\delta$ is calibrated to target a steady-state unemployment rate of 6.1%, which is the average unemployment rate between 1978 and 2019. The value of unemployment $b$ is set at 65% of the average wage. The matching efficiency is calibrated to match a monthly job-finding rate of 27.7% measured using CPS from 1990 to 2014. and reported in Fujita and Moscarini (2017). The vacancy posting cost $\kappa$ is set to 0.289 to match a labor market tightness of 0.72, as estimated by Pissarides (2009) using JOLTS data from 1960 to 2006.

# 5 Quantitative Analysis

I now quantitatively study the model implications of belief friction for labor market dynamics. I introduce the full model in steps to separate the contribution of each features. I begin by describing basic business cycle statistics. Then, I show the impulse response functions to a negative productivity shock, including a detailed description of the sources of amplification and persistence my baseline model provides. Then I discuss the compositional change in unemployment. Finally, I extend the model to incorporate two types of workers with different learning rates and study their heterogeneous transition patterns across employment states.

## 5.1 Business Cycle Summary Statistics

The main results from the baseline model are reported in Table 5. I report the standard deviation and quarterly autocorrelation of the unemployment rate, job-finding rate, job-separation rate, and labor market tightness.[11] None of these moments are targeted in the model calibration. All panels use the same labor market parameters and differ only in the belief parameters. I show that incorporating learning and dispersion in beliefs improves the model's ability to match the data. My preferred specification is Panel E, where worker beliefs are dispersed and both workers and firms adjust their beliefs with a lag.

*Empirical Benchmark*—Table 5 Panel A provides an overview of business cycle statistics for quarterly US data reported in Mercan et al. (2024). The time period covers 1976:I-2019:IV.

*Theoretical Benchmark—Full information.* Table 5 reports the cyclical behavior of the full information model with two sided lack of commitment. Relative to the standard DMP model, the model features wage rigidity induced separations. Incorporating endogenous quits and layoffs slightly increases the volatility in separation and unemployment rate relative to a model with flexible wages, but insufficiently so.

*Model with learning for workers.* Panel C reports moments from a model with only sluggish belief updating for workers. The model has over-predicts the standard deviation of unemployment rate, labor market tightness and job-finding rate, while under-predicts the volatility in job separation rates. In addition, the model does not generates enough persistence for all the variables.

*Model with learning and dispersion in beliefs for workers.* Panel D reports the cyclical summary statistics for a model with both learning and dispersion in beliefs for workers. The model significantly improves the volatility in job-separation rates, at the expense of lower persistence. The model still over-predicts the volatility in job-finding rates, leading to too much volatility for unemployment rate.

*Model with learning and dispersion in beliefs for workers, and learning for firms.* Panel E reports the moments for a model with adaptive learning for both workers and firms. I report results with firm learning rate = 0.3 and 0.5. Incorporating learning for firms

[11] In the Appendix, I report results for the model where job stayers share a common belief centered around the firm's belief.

**Table 5:** Standard Deviation and Autocorrelation for Labor Market Variables

| | $u$ | $f$ | $s$ | $\theta$ |
|---|---|---|---|---|
| *Panel A:* Data | | | | |
| Standard Deviation | 0.103 | 0.053 | 0.067 | 0.229 |
| Quarterly Autocorrelation | 0.934 | 0.871 | 0.773 | 0.936 |
| *Panel B:* Full Info | | | | |
| Standard Deviation | 0.023 | 0.020 | 0.011 | 0.040 |
| Quarterly Autocorrelation | 0.796 | 0.717 | 0.509 | 0.717 |
| *Panel C:* HH Learning | | | | |
| Standard Deviation | 0.116 | 0.148 | 0.017 | 0.296 |
| Quarterly Autocorrelation | 0.782 | 0.616 | 0.562 | 0.616 |
| *Panel D:* HH Learning + Dispersion | | | | |
| Standard Deviation | 0.125 | 0.146 | 0.032 | 0.293 |
| Quarterly Autocorrelation | 0.781 | 0.624 | 0.183 | 0.624 |
| *Panel E:* HH Learning + Dispersion + Firm Learning ($\gamma^F = 0.5$) | | | | |
| Standard Deviation | 0.100 | 0.115 | 0.023 | 0.230 |
| Quarterly Autocorrelation | 0.810 | 0.705 | 0.326 | 0.705 |
| *Panel F:* HH Learning + Dispersion + Firm Learning ($\gamma^F = 0.3$) | | | | |
| Standard Deviation | 0.081 | 0.092 | 0.017 | 0.184 |
| Quarterly Autocorrelation | 0.838 | 0.760 | 0.426 | 0.760 |

**Notes**: Results from model simulations and empirical summary statistics for aggregate productivity, labor market tightness, unemployment rate, job-finding rates and separation rates. All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600. Panel A provides value in data from 1976:I–2019:IV. Panel B reports the value for a full information model with two-sided lack of commitment. Panel C reports the values with only learning for workers. Panel D adds dispersion in beliefs to the model used in panel C. Panel E also includes learning for firms relative to the model in panel D.

dampens the volatility in all these variables, but improves the persistence.

In summary, the full-information model with wage-rigidity-induced separations fails to generate sufficient volatility and persistence in the unemployment rate, job-finding rate, separation rate, and labor market tightness. Introducing sluggish belief updating for workers increases volatility but tends to overstate fluctuations in unemployment, job finding, and market tightness. Allowing for dispersion in workers' beliefs substantially improves the volatility in job separations. Finally, a model that combines household and firm learning with belief dispersion among households significantly improves the model's ability to replicate both the volatility and persistence observed in all key labor market variables.

## 5.2 Impulse Response Functions

This section presents model-simulated impulse response functions (IRFs) following a one percent decline in aggregate productivity. I first examine the role of inaccurate worker beliefs under the assumption that firms have full information. I then incorporate sluggish belief adjustment for firms.

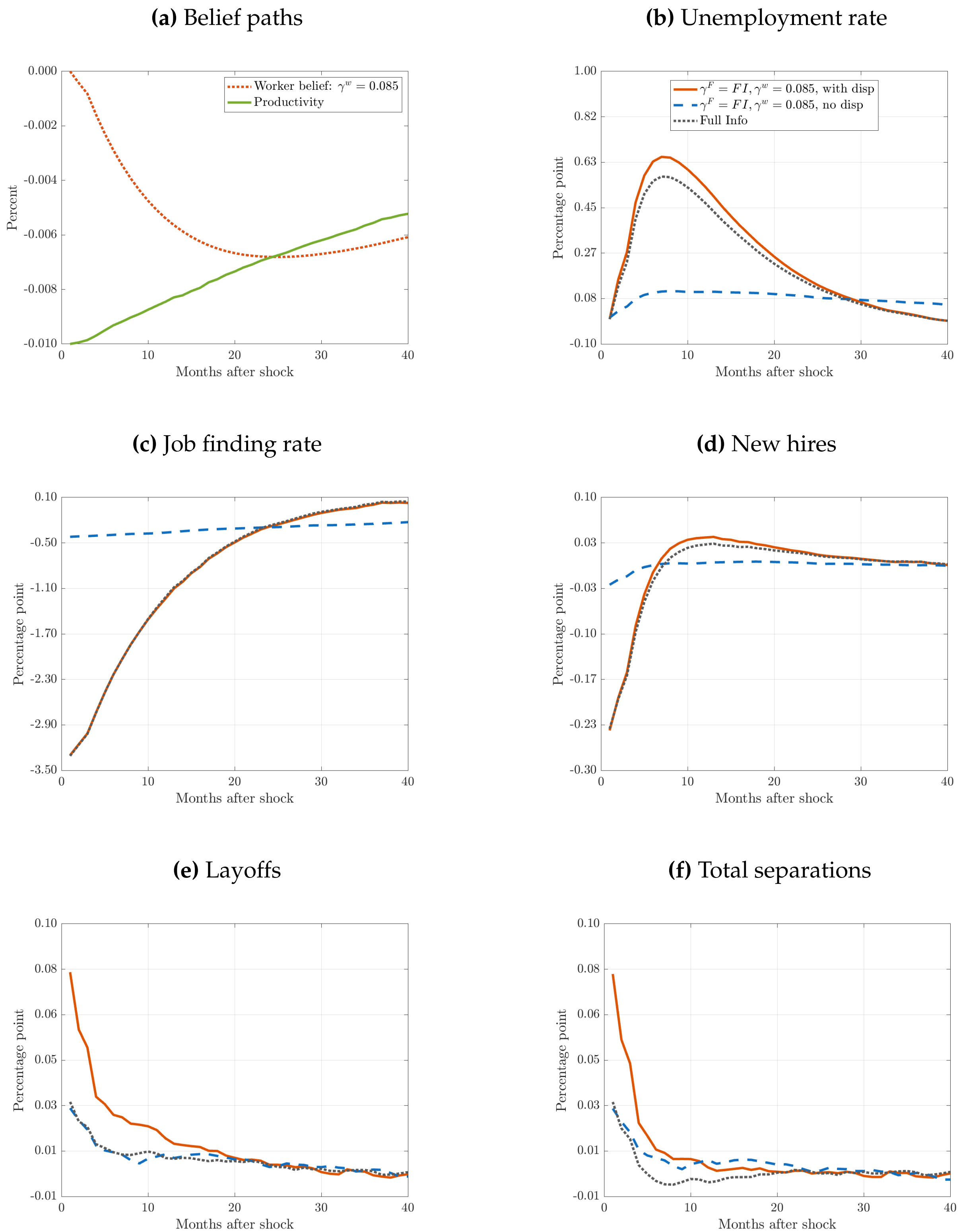
### 5.2.1 The role of sluggish belief adjustment for workers

Figure 6 reports the results from models featuring workers with imperfect information. Panel 6a plots the paths of aggregate productivity and workers' perceived productivity: the green solid line represents the actual productivity shock observed by firms, while the light blue line shows the average perceived productivity of unemployed workers. Panels (b)–(f) display the impulse responses of the unemployment rate, job-finding rate, new hires, layoffs, and total separations.

Household learning increases the volatility of job creation and unemployment but has little impact on layoffs or separations relative to the full-information benchmark. Greater dispersion in household beliefs amplifies layoffs and separations while leaving job-finding probabilities largely unchanged.

Sluggish belief adjustment endogenously generates wage stickiness for new hires and amplifies the decline in job-finding rates and the outflow from unemployment. To illustrate this mechanism, I first consider a model in which all unemployed workers share a common belief that lags behind the true state, while firms have full information (red solid lines in Figure 6). Because workers update their expectations gradually through adaptive learning, their beliefs are both dampened and delayed relative to true productivity.

**Figure 6:** IRFs of key labor market variables: only household learning




**Notes:** Model simulations. This figure presents the impulse response functions of aggregate labor market variables under different belief specifications. Solid and dashed lines denote mean responses across 20,000 simulated paths. The blue dashed line represents the full-information benchmark; the red solid line corresponds to the model with worker learning only; and the yellow dotted line depicts the model incorporating worker learning and belief dispersion. Source: Model simulations.

The intuition is as follows. At the onset of a recession, workers remain overly optimistic compared with firms and continue to demand higher wages. This rigidity reduces firms' incentives to post vacancies, thereby amplifying the declines in job-finding rates and new hires. Quantitatively, the job-finding rate falls by more than 3 percentage points under adaptive learning, compared with less than 0.5 percentage points under full information (Panel 6c).

During the recovery, workers slowly adjust their beliefs upward, thus remain overly pessimistic relative to firms. Consequently, they demand wages below firms' willingness to pay, leading to a temporary overshoot in the job-finding rate.

In contrast, sluggish belief adjustment by unemployed workers has little effect on layoffs and job separations. Layoffs are determined by firms' decisions based on the distribution of continuing wages. Two factors explain why separations remain close to the full-information benchmark. First, continuing workers adopt their employer's belief with some noise, resulting in few failed renegotiations. Second, the sluggishness in new hires' beliefs is insufficient to generate large differences in the mass of workers near the firm's layoff threshold following a small negative productivity shock.

#### 5.2.2 The role of dispersion in worker beliefs

Dispersion in worker beliefs gives rise to dispersion in wages and amplifies both layoffs and inflows into unemployment. The black dotted line represents the model with heterogeneous beliefs, where unemployed workers' beliefs are centered around a lagged mean and the beliefs of incumbent workers are centered around the firm's belief, which coincides with the true state.

With heterogeneous beliefs, the wage distribution becomes more dispersed relative to the case with homogeneous beliefs. Figure 11 in the Appendix compares the wage distribution under full information and dispersed beliefs. Under common beliefs, wage variation arises from aggregate productivity fluctuations and wage rigidity among job stayers, keeping the distribution concentrated around its mean. Belief dispersion causes the negotiated wages to spread more widely, placing a larger share of workers near firms' layoff thresholds.

Greater belief heterogeneity thus widens the wage distribution and increases separation volatility. Optimistic workers negotiate higher wages and are more likely to be laid off when conditions deteriorate, while firms accept these matches knowing they can easily terminate them. As a result, layoffs rise during recessions, amplifying inflows into unemployment relative to the full-information benchmark. Quantitatively, layoffs increase by 0.15 percentage points with heterogeneous beliefs, compared with 0.02 under common beliefs and 0.04 under full information.

Importantly, noisy beliefs do not alter the average wage of new hires faced by firms, so the responses of job-finding rates and new hires remain similar to the model without belief dispersion.

### 5.2.3 The role of sluggish belief for firms

I now extend the model to incorporate sluggish belief adjustment for firms. All firms share a common belief that evolves through an adaptive learning process, with a faster learning rate than that of households.

Figure 7 presents the results when firm learning is introduced. Panel (a) plots the average belief of workers, assuming a learning rate of $\gamma^w = 0.085$, alongside the firm's belief path with a learning rate of $\gamma^f = 0.5$. Panels (b)–(f) display the corresponding impulse responses of the same aggregate variables.

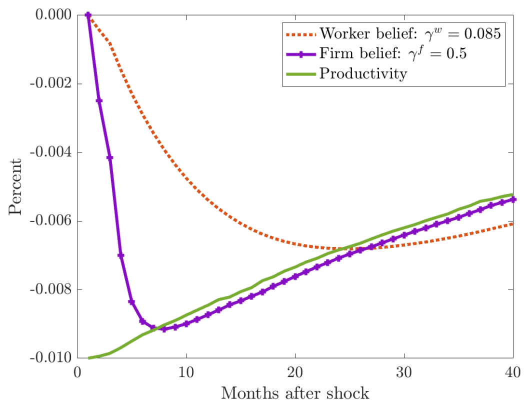
Firm learning increases the persistence of labor market dynamics. Both the inflows to and outflows from unemployment exhibit more prolonged responses compared to the case when firms have full information. However, firm learning also dampens overall volatility.

The firm learning rate, $\gamma^f$, governs the persistence of aggregate labor market dynamics. The intuition is straightforward: when firms adjust their beliefs about the aggregate state sluggishly, vacancy postings and layoffs respond with a delay. Consequently, the job-finding rate no longer drops fully following a negative productivity shock but continues to decline for several months, while layoffs keep rising until firms internalize the downturn. With $\gamma^f = 0.5$, the job-finding rate continues to fall for about five months before recovering (panel c), and layoffs rise for roughly three months after the initial shock (panel e). This delayed adjustment generates greater persistence in unemployment: under full information, the unemployment rate peaks about seven months after the shock, whereas with firm learning the peak occurs roughly after ten months.

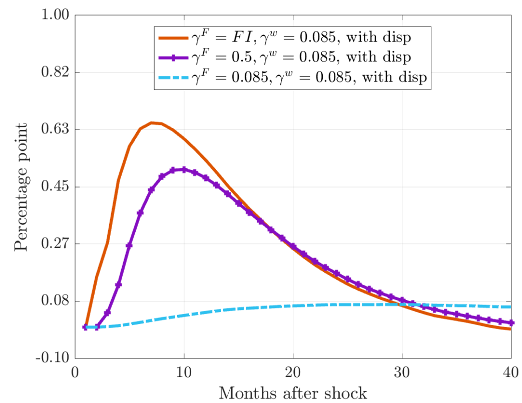
At the same time, sluggish firm learning dampens the overall magnitude of responses to shocks. Because firms never perceive the full extent of the downturn, they shed fewer workers than they would under full information, and the contraction in job creation is smaller. At its peak, job separations rise by only 0.018 percentage points, compared with nearly 0.05 percentage points in the model without firm learning. Similarly, the job-finding rate falls by about 2 percentage points, compared with over 3 percentage points in the baseline. As both inflows to and outflows from unemployment respond less sharply, the overall increase in the unemployment rate is attenuated—rising by less than 0.5 percentage points when firm learning is included, compared with 0.6 percentage points un-

**Figure 7:** IRFs: Household and firm learning

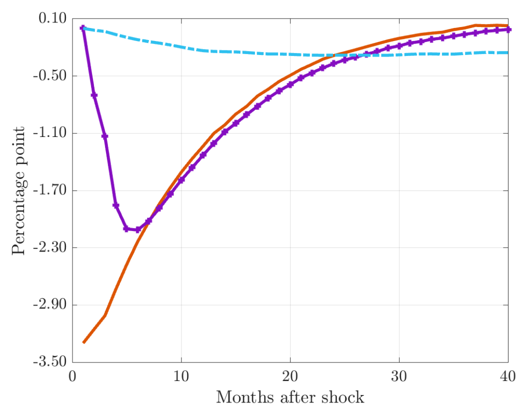
**(a)** Belief paths



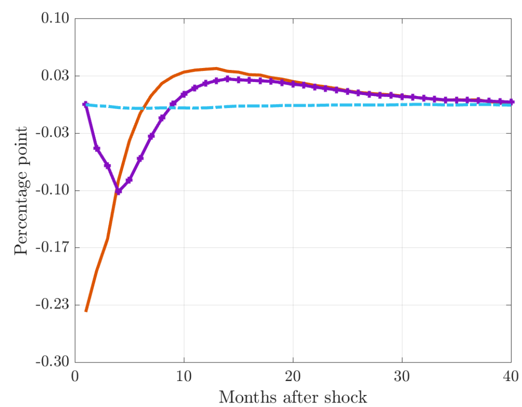

**(b)** Unemployment rate



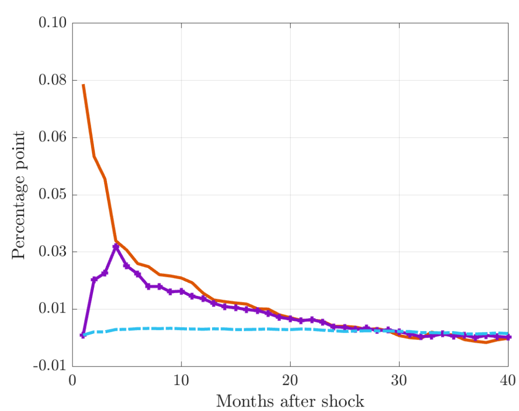

**(c)** Job finding rate



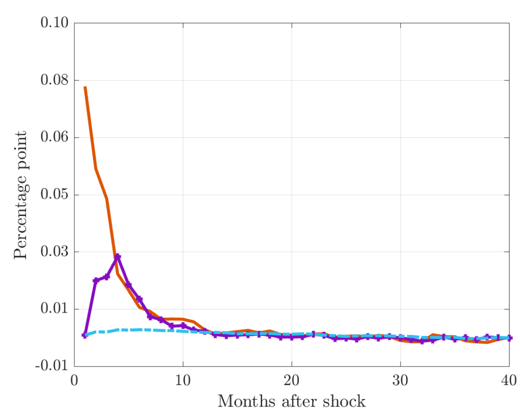

**(d)** New hires




**(e)** Layoffs




**(f)** Total separations




**Notes:** Model simulations. This figure presents the impulse response functions of aggregate labor market variables under different belief specifications. Solid and dashed lines denote mean responses across 20,000 simulated paths. The red solid line replicates the results from Figure 6 and serves as the benchmark in which workers hold lagged and dispersed beliefs while firms have full information. The purple diamond line represents a model in which firms learn with rate $\gamma^f = 0.5$ while workers follow the same belief process as before. The black dotted line illustrates an extreme case in which firms learn at the same slow rate as workers, $\gamma^w = \gamma^f = 0.085$.

der household learning alone. When firms update beliefs at the same rate as workers, disagreement during wage negotiation disappears, and labor market dynamics become nearly stationary, showing small responses to shocks. This joint sluggishness generates macroeconomic inefficiency: firms over-employ and over-produce during downturns and fail to expand sufficiently during booms, leading to misallocation of labor over the business cycle.

### 5.3 Compositional changes in unemployment

Mueller (2017) documents a compositional shift in the pool of unemployed workers toward those with higher pre-displacement wages during recessions. He finds that the average pre-displacement wage of unemployed workers is strongly and positively correlated with the aggregate unemployment rate. This cyclical pattern remains robust after controlling for workers' observable characteristics and is driven almost entirely by job separations. Job separations are substantially more cyclical for high-wage workers, whereas job-finding rates display similar cyclicality across wage groups.

Moreover, Mueller (2017) shows that a standard Mortensen–Pissarides model with endogenous job destruction and sticky wages generates only negligible compositional shifts.[12] In this section, I show that belief frictions combined with wage-rigidity-induced separations can replicate the observed compositional changes in unemployment—particularly the strong cyclicality of high-wage separations during downturns.

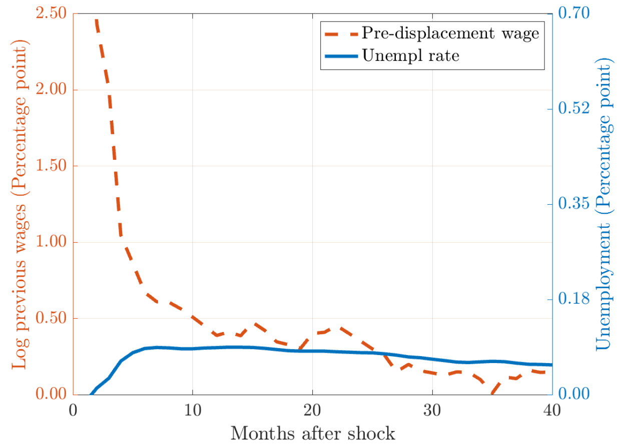
Heterogeneity in worker beliefs at the time of hiring generates dispersion in negotiated wages. Workers with more optimistic beliefs are hired at higher wages but also face higher separation risks because their wages lie closer to the firm's reservation threshold. Following a negative productivity shock, layoffs disproportionately affect these high-wage workers. As a result, the pool of unemployed shifts toward higher-wage individuals, causing the average pre-displacement wage to rise.

By contrast, individual beliefs play a smaller role in shaping job-finding rates, which are primarily determined by firms' vacancy-posting decisions based on the overall distribution of wages among potential new hires. Because workers differ only in their beliefs at the time of bargaining, their job-finding rates remain largely similar across belief types.

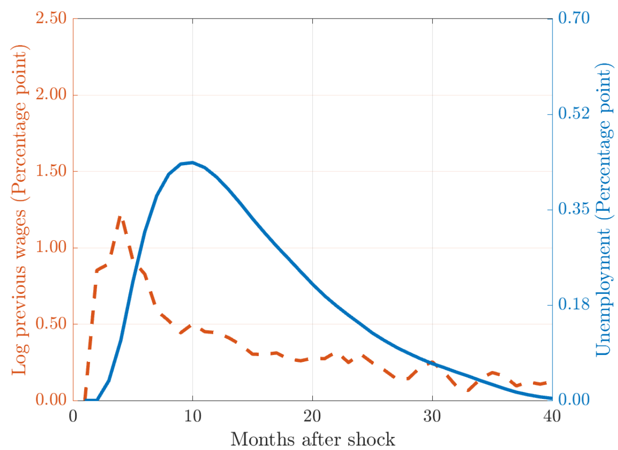
[12] Mueller (2017) evaluates several theoretical explanations, including models with match-specific productivity and endogenous separations, wage rigidity and inefficient separations, and compensating differentials for unemployment risk. Among these, models featuring lower match-specific productivity for high-ability workers or tighter credit constraints during recessions can replicate the qualitative pattern observed in the data, though both have important limitations.

**Figure 8:** Pre-displacement wage and unemployment

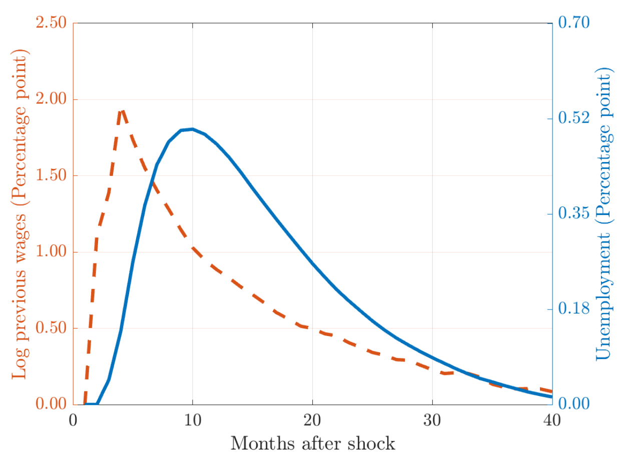
**(a)** Full information




**(b)** Only learning




**(c)** Dispersion + learning




**Note:** This figure illustrates the comovement between the unemployment rate and pre-displacement wages. The blue solid line plots the impulse response of the unemployment rate, and the red dashed line plots the impulse response of the log of average pre-displacement wages among workers who separate endogenously. All lines represent mean responses across 10,000 simulated paths. The left panel presents the full-information benchmark. The middle panel shows the case without belief dispersion, with worker learning rate $\gamma^w = 0.085$ and firm learning rate $\gamma^f = 0.5$. The right panel incorporates belief dispersion under the same learning rates.

Figures 8 and 9 compare impulse responses across three model specifications: full information, worker and firm learning, and learning with dispersion in beliefs. Figure 8 plots the pre-displacement wage of workers who experienced endogenous separations alongside the unemployment rate. Figure 9 shows the responses of quits, layoffs, and exogenous job destruction. In all specifications, quits play a negligible role in total separations. Exogenous job destruction (green shaded area) decreases during the recession as employment declines and fewer workers remain at wages above the exogenous separation threshold.

Even without dispersion in worker beliefs, wage rigidity generates a distribution of wages, and firms begin laying off high-wage workers as the economy enters a recession. However, dispersion in worker beliefs substantially amplifies the cyclicality of layoffs. Greater dispersion increases the share of layoffs in total separations, thereby strengthening the cyclical correlation between pre-displacement wages and unemployment.

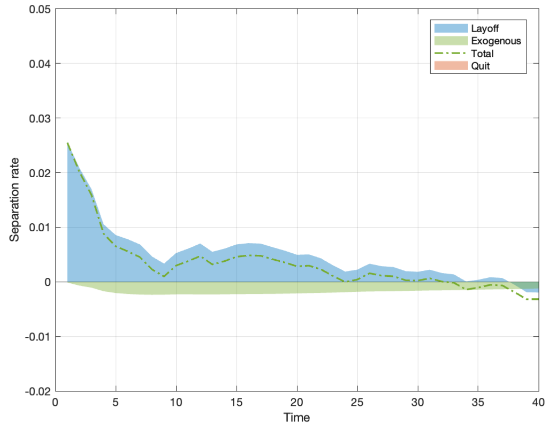
Under full information, the pre-displacement wage jumps up immediately after the negative shock hits, then declines steadily, while unemployment rises slowly for a few months before recovering. This pattern generates a negative correlation between pre-displacement wages and unemployment at the onset of the recession—the opposite of what we observe in the data. After incorporating learning for both workers and firms, the pre-displacement wage and unemployment rate move in the same direction as firms adjust layoffs with a lag. However, the contribution of layoffs to total job separations remains moderate. Once I include dispersion in worker beliefs, layoffs of high-wage workers become substantially more important, thereby explaining the compositional shifts toward high-wage workers during recessions.

## 5.4 Heterogeneous Transition Patterns

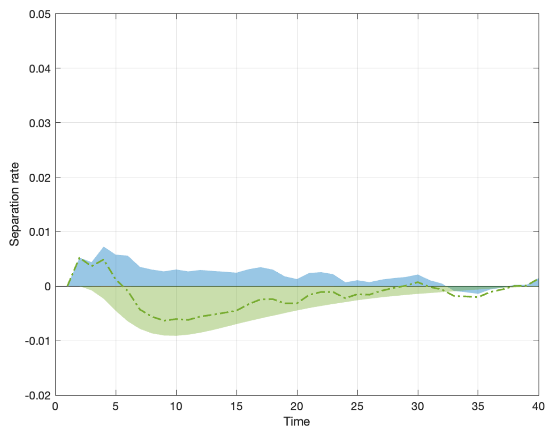
Recently, a growing literature find evidence for substantial heterogeneity across workers using a range of statistical methods (Hall and Kudlyak (2019), Ahn and Hamilton (2020), Gregory et al. (2025), Ahn et al. (2023)). Both survey and administrative data show that fluctuations in the aggregate unemployment rate are disproportionately driven by a small segment of the population. While most individuals are consistently employed, a subset of workers experiences frequent transitions between employment and unemployment. These workers have lower job-finding rates and are more likely to separate from jobs once hired, making them significantly more vulnerable to unemployment. Importantly, observable industry affiliations and demographic characteristics explain only a small fraction of this variation, suggesting that unobserved heterogeneity plays a central

**Figure 9:** Composition changes in job separations

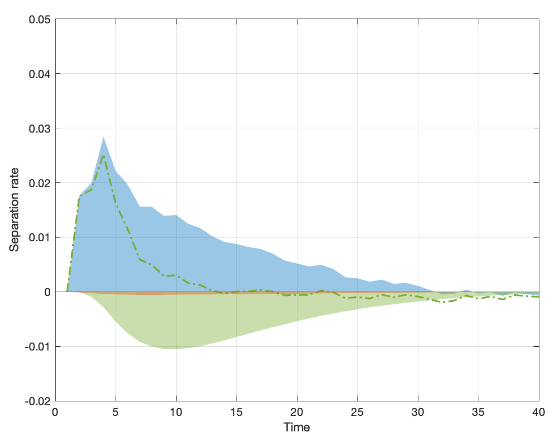
**(a)** Full information




**(b)** Only learning




**(c)** Dispersion + learning




*Note:* This figure illustrates the fraction of job separations that come from layoffs, quits and exogenous job destruction. The blue green and red shaded area indicates layoffs, exogenous job destruction and quits, respectively. The green dash-dotted line represents total job separation. All lines represent mean responses across 10,000 simulated paths. The left panel presents the full-information benchmark. The middle panel shows the case without belief dispersion, with worker learning rate $\gamma^w = 0.085$ and firm learning rate $\gamma^f = 0.5$. The right panel incorporates belief dispersion under the same learning rates.

role. I propose that differences in beliefs about aggregate productivity help explain this residual heterogeneity.

### 5.4.1 Model with two types of workerss

Workers may update their beliefs about aggregate productivity at different speeds due to variation in information frictions or inattention to economic news. To capture this, I extend the baseline model to allow for heterogeneity in learning rates and examine the resulting implications for labor market dynamics.

I introduce two groups of workers: one with a higher learning rate, $\gamma^{high} = 0.2$, representing 64% of the labor force, and another with a lower learning rate, $\gamma^{low} = 0.02$, comprising the remaining 36%. The weighted average learning rate across these two groups equals 0.085, consistent with the baseline calibration. Firms update their beliefs with $\gamma^f = 0.5$. Let $\hat{z}^{high}$ and $\hat{z}^{low}$ denote the mean beliefs of the two groups, respectively. As in the baseline model, each worker $i$ receives an idiosyncratic belief draw $\eta_{it}$ centered around the time-varying mean of their group:

$$\hat{z}_{it}^{fast} = \hat{z}_{t-1}^{fast} + \gamma^{fast}(z_{t-1} - \hat{z}_{t-1}^{fast}) + \eta_{it} \tag{25}$$

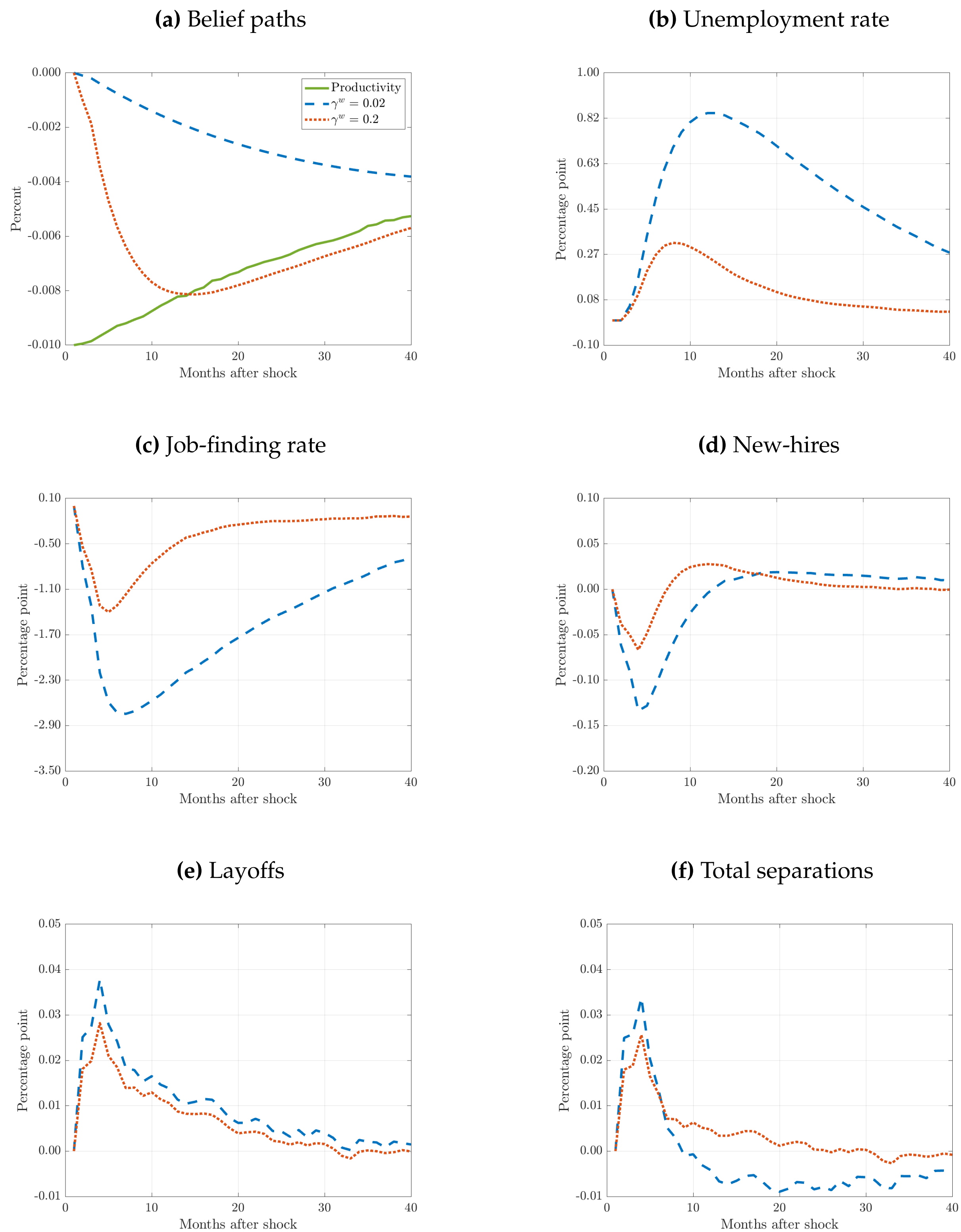
$$\hat{z}_{it}^{slow} = \hat{z}_{t-1}^{slow} + \gamma^{slow}(z_{t-1} - \hat{z}_{t-1}^{slow}) + \eta_{it} \tag{26}$$

### 5.4.2 Heterogeneous response in layoffs and job finding rates

Panel (a) of Figure 10 plots the evolution of average beliefs following a negative productivity shock. The blue dashed line corresponds to workers with a lower learning rate ($\gamma^w = 0.02$), while the red dotted line corresponds to workers with a higher learning rate ($\gamma^w = 0.2$). Workers with slower belief updating experience larger layoffs, sharper declines in job-finding probabilities, and higher unemployment rates.

At the onset of a recession, workers with slower belief adjustment remain overly optimistic about aggregate conditions and consequently demand higher wages. This behavior has two main effects. First, when new matches form, these workers negotiate higher wages and capture a larger share of the surplus from firms. Second, because such high-wage contracts are less sustainable during downturns, they face a higher likelihood of subsequent layoffs. Firms are willing to hire these workers initially, anticipating that they can terminate the match later if conditions deteriorate. Quantitatively, workers with slower belief updating experience an increase in job separation rates approximately 0.01 percentage point higher than the other group.

**Figure 10:** IRF: heterogeneous learning Rates




*Note:* This figure presents the impulse response functions of aggregate labor market variables in a model featuring heterogeneous household beliefs and learning. Dashed and dotted lines denote mean responses across 10,000 simulated paths. The red dotted line represents workers with a learning rate of $\gamma^w = 0.2$, while the blue dashed line depicts workers with a slower learning rate of $\gamma^w = 0.02$. Firms also update their beliefs sluggishly, with a learning rate of $\gamma^f = 0.5$. Source: Model simulations.

Differences in belief updating also influence job-finding dynamics. When workers are overly optimistic, their wage demands may exceed firms' reservation wages, leading to rejected offers. Consequently, workers with slower belief updating rates face lower job-finding rates and longer unemployment durations. Quantitatively, the drop in job-finding rates for the low–learning-rate group is more than twice that of the high–learning-rate group.

Driven by differences in both job separations and job-finding rates, unemployment becomes increasingly concentrated among workers with lower learning rates. On average, their unemployment rate is about 0.5 percentage points higher than that of workers with higher learning rates.

# 6 Conclusion

There is ample empirical evidence that workers' and firms' beliefs about the state of the economy often deviate from reality. To understand how systematic biases and idiosyncratic noise in beliefs shape wage dynamics, labor market flows, and aggregate responses to shocks, this paper develops a general equilibrium search-and-matching model with two key departure from standard DMP models: (1) heterogeneity and asymmetry in beliefs, (2) wage-rigidity-induced endogeneous separations.

The model accounts for several empirical patterns that standard frameworks struggle to explain. First, it offers a novel mechanism to address the Shimer puzzle, demonstrating how asymmetric information between firms and workers—combined with adaptive learning—amplifies the responses of labor market variables to productivity shocks. Second, the model predicts a gradual decline in the job-finding rate and replicates the observed persistence of unemployment following transitory shocks. These dynamics emerge from gradual belief updating and endogenous separations. Third, the model helps explain the compositional shift in unemployment observed in the data, where the pool of unemployed becomes increasingly concentrated among workers with high residual wages.

The framework also sheds light on heterogeneous employment transitions across individuals. Workers with more sluggish beliefs tend to demand higher wages during recessions and are therefore more likely to be laid off during recessions. Consequently, these individuals experience higher unemployment rates compared to other workers.

The insights that the model delivers open several promising avenues for future research. For example, empirical evidence suggests that worker beliefs affects their job-search intensity (Mitra (2024)). It would be interesting to consider on-the-job search and heterogeneous searching intensity in this model. Mukoyama et al. (2018) documents that search intensity is countercyclical. Then at the beginning of the recessions, workers who remain optimistic take time to increase their searching intensity, thus further reduces the job-finding rates and amplifying the response in unemployment.

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# 7 Model Appendix

## 7.1 Wage Bargaining Proofs

### 7.1.1 LEMMA 1.

Under perfect information, the following strategy constitute the unique subgame perfect Nash equilibrium of the wage determination game:

- The worker offers wage $x^*$ in the first stage, and accepts all wages higher than or equal to $y^*$ in the second stage.
- The firm accepts all wages less than or equal to $x^*$ in the first state, and demand wage $y^*$ in the second stage.

where $x^*$ and $y^*$ satisfy $W(x^*) - U = \vartheta S$ and $W(y^*) - U = 0$. Hence, the solution to this game coincide with a standard Nash Bargaining game such that the worker's bargaining power is equal to $\vartheta$. Note that I omit the subscript $i$ here, since under perfect information, all workers hold the same belief, which aligns with the true state $z$.

PROOF: I begin at the third stage of the game, when the firm makes an counter-offer. At this stage, the worker accepts all wages higher than or equal to $y$, as long as $W(y) - U \geq 0$. Thus, the firm will demand a wage $y^*$ such that $W(y^*) - U = 0$ to keep the entire matching surplus. Hence, at the second stage, the firm knows that if it rejects the offer, the expected payoff to the firm is $(1 - \vartheta)S$. Therefore, in the second stage, the firm only accepts wage offers that are greater than or equal to $x^*$, where $J(x^*) \geq (1 - \vartheta)$. Finally, at the first stage of the game, knowing that the firm will not accept any wage higher than $x^*$, the worker offers exactly $x^*$ to get a positive payoff $W(x^*) - U$.

LEMMA 2: Firms has incentive to lie when making the counteroffer. As a result, workers do not rely on the firm's offer but instead rely solely on their own beliefs when making decisions.

PROOF: Suppose there is an equilibrium in which the firm always truthfully reveal the current state when making a counteroffer. In this scenario, the firm would make a small offer $y$ such that $W(y) - U$ is close to zero. This strategy ensures that the worker always accepts the offer, while allowing the firm to extract the maximum surplus. Consequently, the worker would perfectly infer the true current state based on the firm's wage offer and always accept the offer in the final stage.

However, the firm is always better offer with a even lower offer. By deviating to a lower counteroffer $y^* < y$, the firm gets more surplus from the match $J(y^*) > J(y)$. In this case, the worker may be better off remaining unemployed. The worker, assuming the firm is truthfully revealing the state, would still accept the offer, lacking additional information to judge whether the firm is telling the truth. Thus, it's not an equilibrium that the firm truthfully reveal the current state when making a counteroffer. Therefore, the worker must rely on her own individual belief when making decisions.

LEMMA 3: If workers have idiosyncratic noisy belief as described in section 2.2, then the following strategy constitutes a Perfect Bayesian Nash equilibrium that satisfies the Intuitive Criterion:

- The workers offers $\hat{x}_i^{**}$ in the first stage and accepts offer great then or equal to $\hat{y}_i^{**}$ in the second stage.
- The firm accepts offers less than or equal to $x^{**}$ in the first stage and demands $min\{\hat{y}_i^{**}, x^{**}\}$ in the second stage.

where $\hat{x}_i^{**}$, $x^{**}$, $\hat{y}_i^{**}$ and $y^{**}$ satisfy $W(\hat{x}_i^{**}) - U_i = (1-\vartheta)S(\hat{x}_i^{**})$, $W(x^{**}) - U = \vartheta S$ , and $J(y^{**}) = 0$, respectively.

PROOF: I begin at the third stage of the game when the firm makes a counteroffer. At this stage, the worker will accept any wage $y$ as long as its expected net value of working $\mathbb{E}[W_i(y) - U_i]$ is positive. The firm can infer the worker's belief from her offer in the first stage and deduce her lowest acceptable wage. If the lowest acceptable wage of the worker $\hat{y}_i^{**}$ gives positive payoff to the firm, the firm will demand exactly $\hat{y}_i^{**}$. However, there may be the case in which the worker is overly optimistic about the current state such that $J(\hat{y}_i^{**}) < 0$. In this case, the firm is better off keeping the vacancy open and search again in the next period. As a result, the firm will demand $y^{**} > \hat{y}_i^{**}$ such that $J(y^{**}) = 0$. Since the worker only rely on her own belief when making the decision, she will reject the offer and the match will be dissolved.

Knowing that the expected payoff of rejecting the offer is $(1-\vartheta)$ of the total surplus given the worker's belief if a match is formed, the firm accepts all wages greater than or equal to $\hat{x}_i^{**}$ in the second stage, where $J(\hat{x}_i^{**}) = (1-\vartheta)S(\hat{x}_i^{**})$. Given the firm's strategy, the worker will offer exactly $\hat{x}_i^{**}$ in the first stage.

However, $\hat{x}_i^{**}$ is not the lowest offer that the firm accepts. In the case where the worker is overly optimistic and $J(\hat{x}^{**}) < 0$, the firm rejects the offer. The game goes to the third stage and firms accepts all $x^{**}$ such that $J(x^{**}) = 0$. As a result, the firm accepts all wages greater than or equal to $x^{**}$.

## 7.2 Full Information Model with Two-sided Lack of Commitment

$$J(z,w) = z - w + \beta(1-\delta)\mathbb{E}\Big[\lambda \mathbb{1}(w^r(z') < w) max\{J(z',w),0\} + (1-\lambda)J(z',w^B(z'))\Big] \tag{27}$$

$$V(z) = -\kappa + \beta \mathbb{E} q(\theta) J\big(z', w^B(z')\big) = 0 \tag{28}$$

$$\begin{aligned} W(z,w) = w + \beta \mathbb{E}\bigg\{ & \Big[\delta + (1-\delta)\lambda \mathbb{1}\big(w > \overline{w}^f(z')\big)\Big] U(z') \\ & + (1-\delta)\lambda \mathbb{1}\big(w < \overline{w}^f(z')\big) \max\{W\big(z',w\big), U(z')\} \\ & + (1-\delta)(1-\lambda) W\big(z', w^B(z')\big) \bigg\} \end{aligned} \tag{29}$$

$$U(z) = b + \beta \mathbb{E}\Big\{ f(\theta) W\big(z', w^B(z)\big) + (1 - f(\theta)) U(z') \Big\} \tag{30}$$

## 7.3 Solution Algorithm

**Worker's Problem.**

1. **Initialization.** Discretize beliefs over the same grid as productivity and make an initial guess for the wage schedule $w(\hat{z})$, defined as a function of workers' perceived productivity $\hat{z}$.

2. **Value Function Iteration.** Given the current wage schedule $w(\hat{z})$ and the belief distribution, solve the worker's and firm's joint value functions by iterating on the Bellman equations to obtain

$$J(\hat{z},w), \quad W(\hat{z},w), \quad \text{and} \quad U(\hat{z}),$$

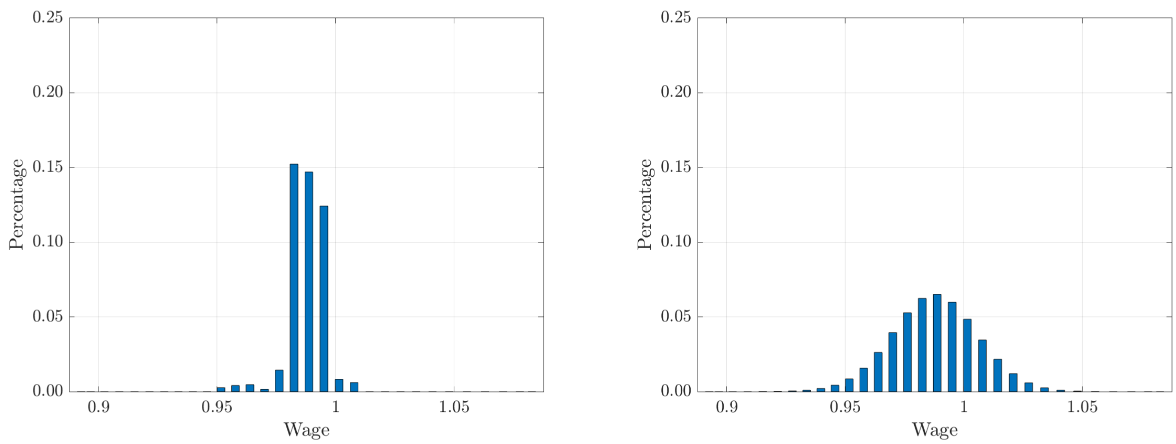
   where $J$ denotes the firm's match value, $W$ the employed worker's value, and $U$ the unemployed worker's value.

3. **Wage Adjustment.** The diagonal elements of the value matrices correspond to newly formed matches. Check the surplus-sharing condition:

$$W(\hat{z}, w(\hat{z})) - U(\hat{z}) \;\gtrless\; \vartheta\big(J(\hat{z}, w(\hat{z})) + W(\hat{z}, w(\hat{z})) - U(\hat{z})\big),$$

**Figure 11:** Wage distribution under full information and dispersed beliefs

**(a)** Belief paths | **(b)** Unemployment rate




*Note:* This figure presents wage distribution of a simulation. Source: Model simulations.

where $\vartheta$ denotes the worker's target surplus share.

- If the worker's share exceeds the target, lower $w(\hat{z})$.
- Otherwise, increase $w(\hat{z})$.

4. **Convergence.** Repeat steps 2 and 3 until the wage schedule $w(\hat{z})$ and the value functions jointly converge.

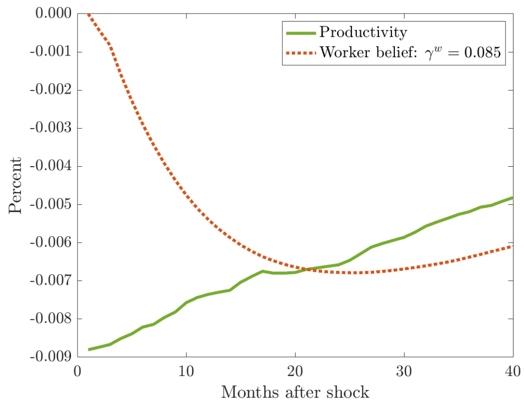
**Firm's Problem.** Given the productivity grid $z$ and wage schedule $w(z)$, solve the firm's Bellman equation for $J(z, w)$ using value function iteration. Because the belief distribution in the worker's problem is centered around perceived productivity $\hat{z}$, while the true distribution is centered around actual productivity $z$, the two coincide in steady state, implying

$$J(z, w) = J(\hat{z}, w).$$

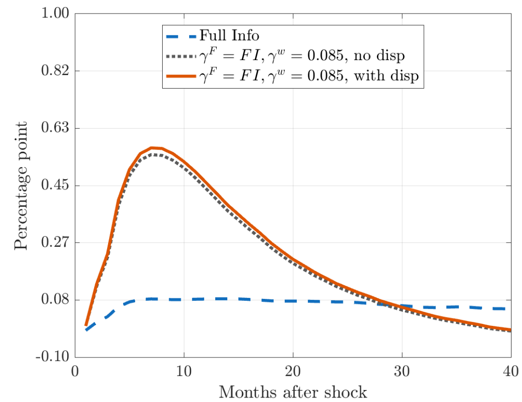
## 7.4 No dispersion in beliefs for job stayers

**Figure 12:** IRF of key labor market variables: Only HH Learning

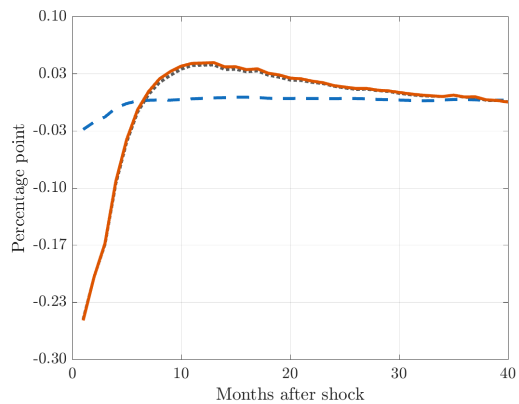
**(a)** Belief paths



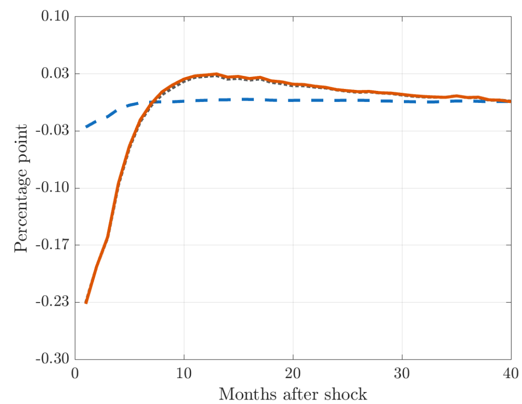

**(b)** Unemployment rate



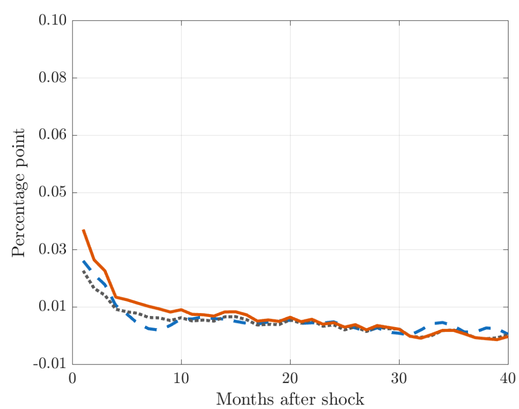

**(c)** Job-finding rate



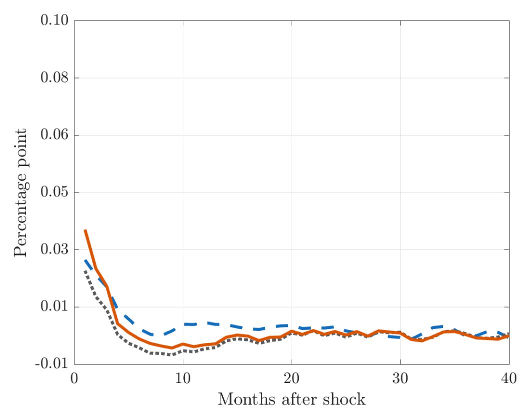

**(d)** New-hires




**(e)** Layoffs




**(f)** Total separations




This figure presents the impulse response functions of aggregate labor market variables where job stayers share a common belief with the firm. Solid and dashed lines denote mean responses across 10,000 simulated paths. The blue dashed line represents the full-information benchmark; the red solid line corresponds to the model with worker learning only; and the yellow dotted line depicts the model incorporating both worker learning and belief dispersion. Source: Model simulations.

**Table 6:** Standard Deviation and Autocorrelation for Labor Market Variables

| | $p$ | $u$ | $f$ | $s$ | $\theta$ |
|---|---|---|---|---|---|
| *Panel A:* Data | | | | | |
| Standard Deviation | 0.010 | 0.103 | 0.053 | 0.067 | 0.229 |
| Quarterly Autocorrelation | 0.746 | 0.934 | 0.871 | 0.773 | 0.936 |
| *Panel B:* Full Info | | | | | |
| Standard Deviation | 0.014 | 0.023 | 0.020 | 0.011 | 0.040 |
| Quarterly Autocorrelation | 0.724 | 0.796 | 0.717 | 0.509 | 0.717 |
| *Panel C:* HH Learning | | | | | |
| Standard Deviation | 0.014 | 0.113 | 0.145 | 0.015 | 0.291 |
| Quarterly Autocorrelation | 0.724 | 0.782 | 0.616 | 0.598 | 0.616 |
| *Panel D:* HH Learning + Dispersion | | | | | |
| Standard Deviation | 0.014 | 0.115 | 0.145 | 0.017 | 0.289 |
| Quarterly Autocorrelation | 0.724 | 0.784 | 0.624 | 0.449 | 0.624 |
| *Panel E:* HH Learning + Dispersion + Firm Learning ($\gamma^F = 0.5$) | | | | | |
| Standard Deviation | 0.014 | 0.093 | 0.113 | 0.013 | 0.226 |
| Quarterly Autocorrelation | 0.724 | 0.813 | 0.705 | 0.568 | 0.705 |
| *Panel F:* HH Learning + Dispersion + Firm Learning ($\gamma^F = 0.3$) | | | | | |
| Standard Deviation | 0.014 | 0.076 | 0.090 | 0.009 | 0.180 |
| Quarterly Autocorrelation | 0.724 | 0.841 | 0.760 | 0.648 | 0.760 |

**Notes**: Results from model simulations and empirical summary statistics for aggregate productivity, labor market tightness, unemployment rate, job-finding rates and separation rates. All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600. Panel A provides value in data from 1976:I–2019:IV. Panel B reports the value for a full information model with two-sided lack of commitment. Panel C reports the values with only learning for workers. Panel D adds dispersion in beliefs to the model used in panel C. Panel E also includes learning for firms relative to the model in panel D.

# 8 Empirical Appendix

I draw on micro-level evidence from the Michigan Survey of Consumer (MSC) and Survey of Consumer Expectations (SCE) in the paper. In this section, I describe the variables that I used from each data and additional results.

## 8.1 Additional results from MSC

The Michigan Survey of Consumers (MSC) is a nationally representative survey that has measured U.S. household sentiment since the late 1940s, with its modern monthly format beginning in January 1978. Each month, the survey samples a new, independent cross-section of approximately 500 to 1,300 households. Although the MSC does not track individual respondents over time, it offers one of the longest and most consistent time series on population-wide expectations, making it well suited for the purposes of this study. MSC includes a qualitative question on unemployment expectations:

> *"How about people out of work during the coming 12 months — do you think that there will be more unemployment than now, about the same, or less?"*

Respondents may answer "more unemployment," "less unemployment," "no change," or "don't know."

### 8.1.1 Raw responses

Figure 13 and 14 reports the proportion of households reporting each answer from January 1978 to March 2024, and the latter considers sample weights from the survey. I restrict my calibration sample to January 1978 through January 2020. The data reveal large fluctuations in the share expecting "more unemployment" during recessions and a consistently high fraction of respondents expecting no change.

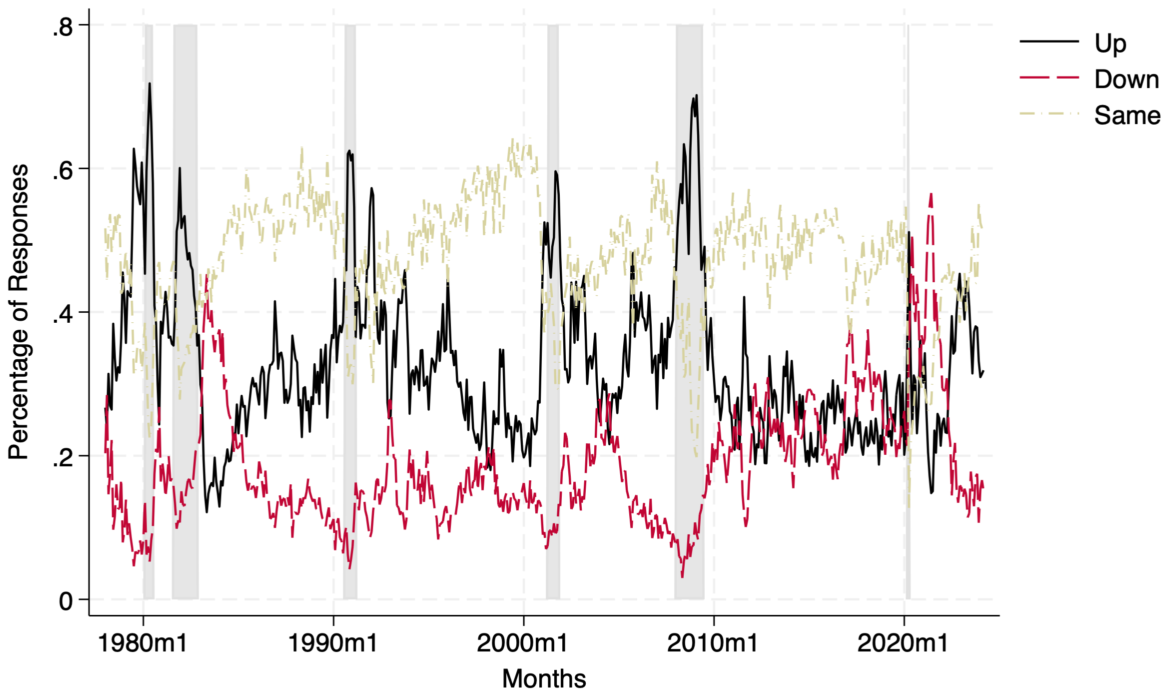
### 8.1.2 Time-varying dispersion in beliefs

Figure 15 plots the time-varying dispersion in household beliefs. The construction of this variable is detailed in Section 2 of the main paper. The figure shows that disagreement about expected changes in the unemployment rate tends to rise during downturns and gradually decline until the next recession. If excluding periods of the recession, dispersion in beliefs remain relatively stable over the past few decades. As expected, the highest level of disagreement occurred during the unprecedented COVID-19 recession. However, not all periods of elevated disagreement coincide with recessions.

## 8.2 Survey of Consumer Expectations

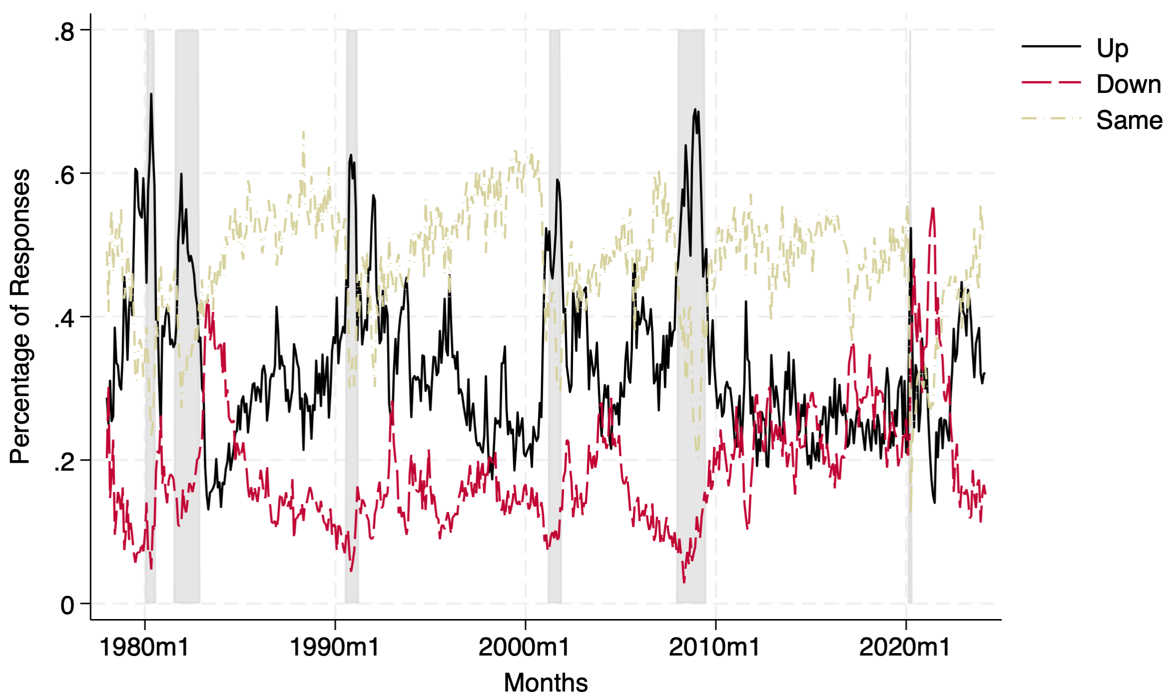
The Survey of Consumer Expectations (SCE) is a monthly, internet-based survey conducted by the Federal Reserve Bank of New York. It began in June 2013 and has been fielded on an ongoing basis since then. Each month, the survey samples a rotating panel

**Figure 13:** Qualitative Responses to Changes in Unemployment Rate (unweighted)



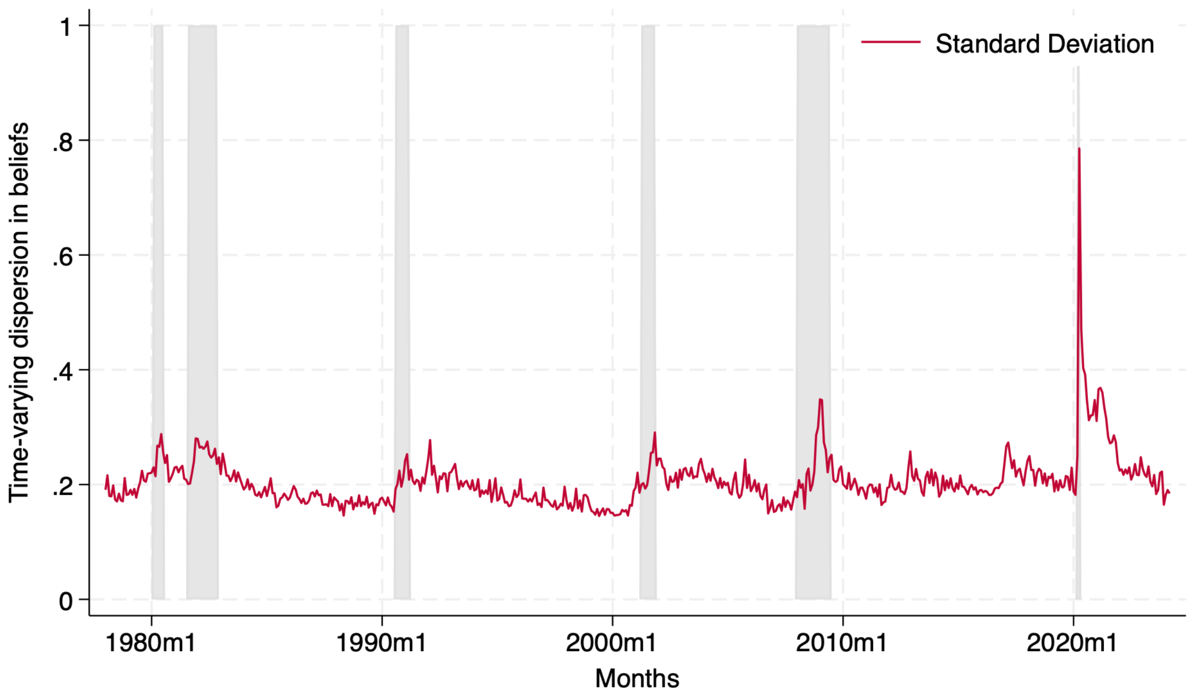

This figure shows the monthly share of respondents expecting unemployment to rise, fall, or remain the same from January 1978 to March 2024. Each survey answer is unweighted. Source: Michigan Survey of Consumers.

**Figure 14:** Qualitative Responses to Changes in Unemployment Rate (weighted)



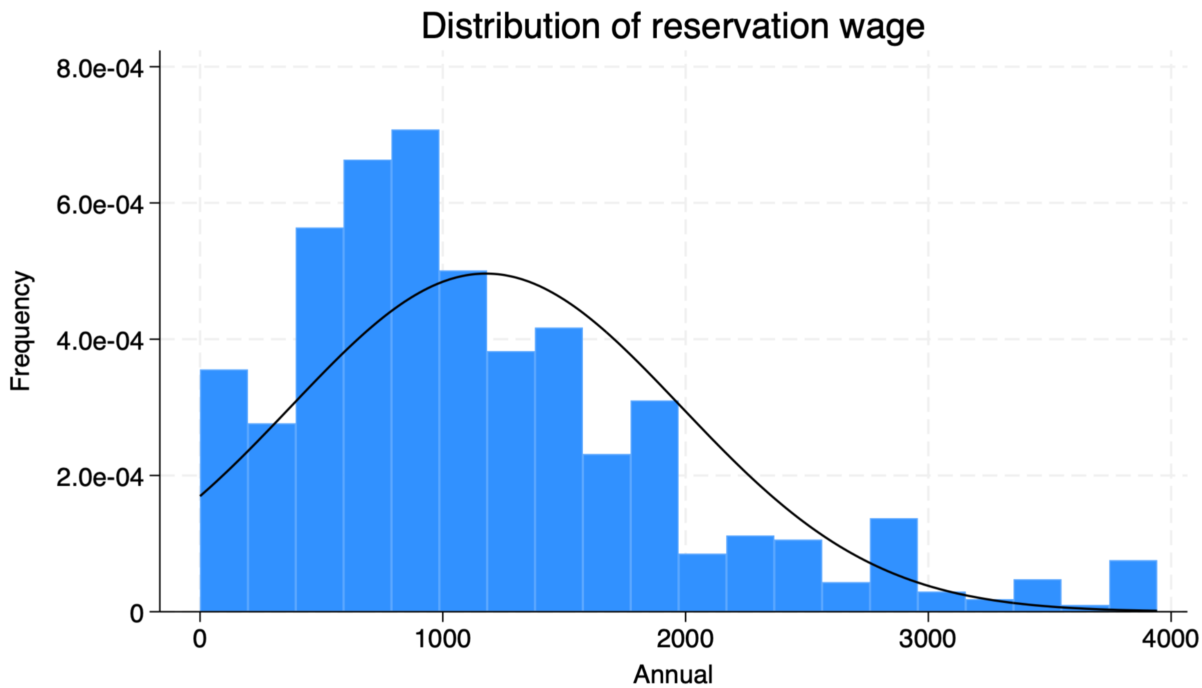

This figure shows the monthly share of respondents expecting unemployment to rise, fall, or remain the same from January 1978 to March 2024. Each survey answer is weighted by the weight variable in the data. Source: Michigan Survey of Consumers.

**Figure 15:** Qualitative Responses to Changes in Unemployment Rate (weighted)




This figure shows the standard deviation in household beliefs about changes in unemployment rate. Details about the time-varying dispersion in beliefs is described in section 3.1. Source: Michigan Survey of Consumers.

**Figure 16:** Qualitative Responses to Changes in Unemployment Rate (weighted)




This figure shows distribution of reservation wages from the SCE Labor Market Survey.

of about 1,300 households. Respondents are asked to remain in the panel for up to twelve months, which enables researchers to observe both cross-sectional variation and individual dynamics over time. The survey covers a wide range of topics, including inflation expectations, labor market outcomes, household finance, spending, and credit access.

Active panel members who have participated in an SCE monthly survey within the prior three months are eligible for the Labor Market Survey, which focuses on expectations and behaviors related to the labor market. Fielded three times per year—in March, July, and November—the Labor Market Survey has been conducted since 2014. Each household may participate in the labor market module between one and three times. The questions I used from SCE are listed in table 7.

I begin with 32,178 observations from the labor market survey that contain valid (non-missing) reservation wage information. All reported wages are converted into weekly amounts, and any observations with missing reservation wages are removed from the sample. The distribution of reservation wages below 4,000 per week is shown in Figure 16. For respondents who report hourly wages, I assume a standard work schedule of 40 hours per week when converting to weekly income.

**Table 7:** Questions used from the Main Survey and Labor Market Survey, with respondent types.

| Survey | Question | Question text | Respondent type |
|---|---|---|---|
| Main Survey | Q4new | 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? | All respondents |
| | Q10 | What is your current employment situation? | All respondents |
| | Q13new | Percent chance you will lose your main/current job in the next 12 months | Employed, not self-employed |
| | Q14new | Percent chance you will leave your main/current job voluntarily in the next 12 months | Employed, not self-employed |
| | Q15 | Are you currently looking for a job? | Unemployed workers |
| | Q16 | How long have you been unemployed? | Unemployed workers |
| | Q17new | Percent chance you will find an acceptable job within 12 months | Unemployed workers |
| | Q18new | Percent chance you will find an acceptable job within 3 months | Unemployed workers |
| | Q22new | If you lost your job this month, percent chance you find an acceptable job within 3 months | Employed, not self-employed |
| Labor Market Survey | L3 | Annual earnings before taxes/deductions at main/current job (incl. bonuses, overtime, tips, commissions) | Employed workers |
| | L4 | Rough annual earnings before taxes/deductions at current/main job | Employed workers |
| | RW2 | Lowest wage/salary you would accept today for a job you consider | All workers |