Perceived Unemployment Risks over Business Cycles*

William Du
Johns Hopkins University

Adrian Monninger
Johns Hopkins University

Xincheng Qiu
Peking University

Tao Wang
Bank of Canada

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Abstract

We backcast subjective expectations on job finding and separation in the Survey of Consumer Expectations to 1978, and use real-time machine learning forecasting to proxy their objective counterparts. We document stickiness in job finding and separation expectations in reflecting changes in real-time job finding and separation risks and their substantial heterogeneity across observable and unobservable dimensions. Calibrating these facts into a heterogeneous-agent consumption-saving model reveals that belief stickiness attenuates the precautionary saving channel. As a result, workers underinsure during recessions, leading to a more sluggish recovery afterwards. The combination of high risk exposure and underinsurance due to belief stickiness operates as a novel amplification mechanism over the business cycle.

Keywords: Risks, Uncertainty, Incomplete Market, Unemployment Risks, Business Cycles, Machine Learning, Expectation Surveys

JEL Codes: D14, E21, E71, G51

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1 Introduction

In state-of-the-art incomplete markets models with search and matching frictions, countercyclical unemployment amplifies business cycle fluctuations through two key channels.[1] The first is an expectations-driven precautionary channel, whereby heightened *fears* of unemployment prompt households to increase savings and cut consumption, which depresses aggregate demand. The second is an income channel, where realized income losses due to actual unemployment directly reduce consumption.[2]

These two channels are typically disciplined by the observed rate at which workers transition between employment and unemployment. However, the true flow of workers moving from employment to unemployment does not necessarily reflect the true ex-ante risk of job loss that governs workers' precautionary behavior. Realized separation rates are shaped by unforeseen macroeconomic shocks. For instance, workers in 2019 did not anticipate the COVID-19 pandemic, so their perceived risk of job loss for 2020 was far lower than the separation rate realized that year.

Furthermore, the job-loss risk perceived by households does not necessarily align with the actual real-time job-loss risk given prevailing macroeconomic conditions. A large literature documents systematic deviations between household expectations and full-information rational expectations (FIRE). These patterns raise a natural question: do households accurately perceive their risk of job loss? If households underreact to rising unemployment risk, they may fail to adequately insure themselves against income shocks, leading to insufficient consumption smoothing. Conversely, an overreaction could trigger a sharper decline in aggregate demand (e.g., Den Haan et al., 2018).

This paper separately measures (a) perceived unemployment risk, (b) objective unemployment risk, and (c) realized job transition rates over the business cycle, and shows that these measures exhibit different cyclical dynamics. The conventional approach to studying expectation formation using survey data compares (a) subjective expectations with (c) realized outcomes and calculates the forecast errors to identify deviations from FIRE. By incorporating measure (b), we can characterize the gap between subjective perceptions of unemployment risk and their ex-ante rational benchmark. This extends existing studies that identify biases in labor market expectations based solely on comparisons with ex-post outcomes (Stephens, 2004; Spinnewijn, 2015; Mueller et al., 2021; Balleer et al., 2021).

[1] Bayer et al. (2019); Den Haan et al. (2018); Broer et al. (2021b); Graves (2020) show that counter-cyclical unemployment risks are important drivers of aggregate business cycle fluctuations. McKay and Reis (2021); Boone et al. (2021); Kekre (2023) study the role of unemployment insurance in stabilizing such fluctuations and its distributional consequences.

[2] The distinction between *ex-ante* and *ex-post* responses is also relevant for the dynamics of durable consumption (Harmenberg and Öberg, 2021).

Our measure of perceived unemployment risk (a) is derived from responses to questions on labor market expectations in the Survey of Consumer Expectations (SCE), produced by the Federal Reserve Bank of New York and available only since 2013. We employ machine learning algorithms trained on a rich set of expectation-related indicators from the Michigan Survey of Consumers (MSC) to extend the series back to 1978.[3] We externally validate our imputation method by confirming that the backcasted versions of several benchmark series, generated using the same procedure, align closely with their actual observed values. This backcasted series allows us to analyze multiple business cycles and to empirically assess the role of precautionary behavior over a much longer period.

We construct a proxy for (b) objective unemployment risk using a real-time machine learning forecasting framework, following the methodology of Bianchi et al. (2022). Specifically, at each point in time in our sample, we apply LASSO (least absolute shrinkage and selection operator) regression to select a subset of predictors from a pool of 600 real-time macroeconomic indicators and forward-looking expectations from both households and professional forecasters that best predict subsequent labor market flows. We then generate a one-step-ahead forecast using the machine-efficient model selected from cross-validation. These real-time predicted job transition rates approximate the best possible forecast of the labor market risks, hence serving as a good proxy for the objective ex-ante unemployment risks.

Two main findings emerge from comparing these measures. First, the comparison between (a) perceived unemployment risk and (c) realized job transition rates shows that households' ex-ante subjective beliefs, especially regarding job-finding probabilities, are strong predictors of actual labor market transitions. This finding suggests that individuals form expectations using meaningful information, consistent with micro-level evidence that workers possess advance knowledge about their employment prospects (e.g., Hendren, 2017). Second, the comparison between (a) and (b) reveals a systematic gap between subjective beliefs and machine-learning-based forecasts: perceptions respond sluggishly to changes in real-time job risk. While the algorithmic forecasts accurately predict job transitions over a three-month horizon—except during an abrupt crisis, such as the onset of COVID—average subjective expectations underreact and fail to incorporate available predictive signals, indicating a deviation from rational expectations.

We propose two explanations for why average perceived unemployment risks underreact to real-time macroeconomic labor market conditions. First, information rigidity: households update their beliefs about the macroeconomy sluggishly. Second, risk heterogeneity: households face varying levels of unemployment risk, either conditionally or unconditionally, implying that households respond differentially to aggregate labor market fluctuations. We find that workers

[3] Many series from the Michigan Survey of Consumers began in 1978.

across the distribution of perceived unemployment risks respond to true real-time risks with varying intensity and degrees of stickiness. This pattern underscores the importance of heterogeneity in both actual and perceived unemployment risks over the business cycle. It aligns with a growing body of research showing that heterogeneity in unemployment risk exposure amplifies aggregate demand fluctuations through unemployment risk channels. Since households are unevenly affected by rising unemployment risks during recessions, the unequal mapping from aggregate labor market flows to individual risk perceptions helps explain why average perceived unemployment risks respond less than one-for-one to actual labor market dynamics.

Lastly, we incorporate our measures of perceived and objective unemployment risk, along with observed job transition rates, into a heterogeneous agent model with idiosyncratic unemployment risks where job-finding and separation governs the transitions between employment and unemployment. This framework allows us to quantify the extent to which fluctuations in aggregate consumption over the business cycle are driven by precautionary saving versus income losses caused by actual changes in unemployment risks. We simulate the path of aggregate consumption under three scenarios. In all three, actual job transition rates evolve according to (c) the realized data; however, workers' perceptions of unemployment risks differ. In the first, perceptions follow our empirical measure of perceived unemployment risk (a). In the second, perceptions are aligned with our measure of rational (objective) unemployment risk (b). In the third, we assume households perfectly anticipate the actual realizations of transition rates from (c). The first scenario serves as our factual decomposition of consumption fluctuations onto the part stemming from precautionary responses and the other from actual income losses. The latter two are our counterfactual quantification of such mechanisms if perceptions of job risks were ex-ante or ex-post correct.

Our simulations of aggregate consumption beginning in 1988 show that the precautionary channel is sharp and substantial when workers are assumed to hold rational (objective) perceptions of unemployment risk. In contrast, when we use workers' actual risk perceptions—which tend to underreact to macroeconomic dynamics—the strength of the precautionary channel is significantly attenuated. This underreaction leads workers to under-insure, resulting in a smaller initial drop in consumption during recessions. But the subsequent recovery is more sluggish, as there is less precautionary saving to draw down.

We also highlight the important interaction between job risk heterogeneity and belief distortions. Low-educated workers, who are disproportionately exposed to cyclical unemployment risks, exhibit the stickiest beliefs and, as a result, are the most underinsured when unemployment shocks materialize. This underinsurance amplifies the effects of unemployment risk over the business cycle.[4] Taken together, this evidence suggests that the extent to which unemploy-

[4]For example, Patterson (2023) shows that workers with the most cyclical incomes also have the highest

ment risks act as an amplification channel depends crucially on how heterogeneous households perceive fluctuations in unemployment risk.

Related Literature

Our paper builds on the empirical evidence of biases in job-finding expectations as documented by Mueller et al. (2021), who study the microdata on job-finding expectations in the SCE. In comparison to their work, we study the job-finding expectations at the macro level. We corroborate their finding by showing that individuals' job-finding expectations underreact to changes in the actual job-finding probability over business cycles, in addition to the underreaction to changes over the unemployment duration. In addition, several other studies based on a comparison of the perceived job risks and realized job transitions, as surveyed in Mueller and Spinnewijn (2023), provide divergent evidence between over-optimism and over-pessimism in job expectations. For instance, Arni (2013), Spinnewijn (2015), Conlon et al. (2018), and Mueller et al. (2021) all found that workers over-perceive probability of finding jobs, with a stronger bias with longer duration of unemployment. Conlon et al. (2018) show such bias is due to over-optimism in perceived offer arrival rates and wage offers. Balleer et al. (2021) explore the consequences of over-optimism bias. Unlike these papers, we focus primarily on the variability of the business cycle fluctuations of these perceptions relative to their realizations, instead of a possibly constant bias.

On job-separation perceptions, the evidence of Stephens (2004) suggests that workers over-perceive the job-loss probability compared to its realization. However, the author advises caution regarding possible selection bias in interpreting this finding, as higher perceived job-loss probability might induce workers to opt out of high-risk jobs, lowering the realized job-loss probability. The same issue may also be relevant to the scenario of overoptimism in job findings. A few follow-up studies suggest similar upward biases in job-loss perceptions (Dickerson and Green, 2012; Balleer et al., 2023). Despite such biases, Dickerson and Green (2012); Hendren (2017); Pettinicchi and Vellekoop (2019) and Hartmann and Leth-Petersen (2024) suggest that workers' perceived job risks predict the unemployment outcome reasonably well, indicating they had advance information about future job events.

This paper builds on the literature that adopts real-time forecasting to approximate ex-ante uncertainty/risks. Our approach is also closely related to using machine-efficient forecast as a rational benchmark instead of a constructed benchmark under a specific assumption of data-generating process (Bianchi et al., 2022). Our use of the approach in Bianchi et al. (2022) is to proximate not just FIRE, but also *ex-ante* job risks. The notion that ex-ante risks are different

marginal propensities to consume. Similarly, Guerreiro (2023) identifies the conditions under which the interaction between belief disagreement and heterogeneity amplifies business cycle dynamics.

from ex-post outcomes is also made clear by Jurado et al. (2015) and Rossi and Sekhposyan (2015) in measuring the macroeconomic uncertainty instead of specifically labor income risks.

Our paper contributes to a growing literature that incorporates subjective job risk perceptions into otherwise standard macroeconomic models with uninsured job risks (Pappa et al., 2023). Most closely related is Bardóczy and Guerreiro (2023), which shares both our focus and computational approach. Like their study, we use expectations data to quantify the precautionary saving channel in a heterogeneous agent framework. A key distinction is our use of household expectations about job transitions from the *Survey of Consumer Expectations*, rather than forecasts of the unemployment rate from the *Survey of Professional Forecasters*. Since households are the ones making precautionary saving decisions, we argue that household expectations provide a more relevant measure. Furthermore, to assess the role of imperfect expectations on consumption, we go beyond ex-post forecast errors by also comparing subjective beliefs to objective ex-ante benchmarks.

In addition, Morales-Jiménez (2022), Menzio et al. (2022) and Rodrıguez (2023) incorporate informational frictions in standard search and matching models to resolve the volatility puzzle in the aggregate unemployment rate. In a departure from their work, we explore the implications of perceived unemployment risks on consumption/saving and aggregate demand fluctuations. Our findings of the heterogeneity in job expectations also relate to Broer et al. (2021a), which relies on endogenous information choice to account for empirical evidence that information frictions in household macroeconomic expectations non-monotonically depend on their wealth. Our finding—that rigidity in job beliefs of workers does not often decrease with the cyclical exposure of their job risks—seems to suggest that mechanisms beyond optimal information choices may play a role in causing such belief stickiness.

2 Perceived job risks predict realized job transitions

2.1 Data

The data on perceived job risks are derived from the SCE, a nationally representative online survey conducted with a rotating panel of approximately 1,300 household heads. The specific questions used to elicit perceived job-finding and job-separation probabilities are as follows:

> *What do you think is the percent chance that you will lose your main (for those with multiple jobs) or current (for those with single job) job during the next 12 months?*

> *Suppose you were to lose your main job this month, what do you think is the percent chance that you will find a job within the following 3 months?*

The realized rates of job transitions are calculated using data from the Current Population Survey (CPS) (e.g., Fujita and Ramey, 2009), which tracks the movement of workers between unemployment, employment, and non-participation statuses based on panel records of individual work histories. The job-finding (JF_t) and job-separation (JS_t) rates are defined as

$$JF_t = \frac{UE_t}{U_{t-1}}, \quad JS_t = \frac{EU_t}{E_{t-1}},$$

where UE_t is the number of transitions from unemployment to employment in month t, EU_t is the number of transitions from employment to unemployment in month t, U_{t-1} is the number of individuals unemployed in month $t-1$, and E_{t-1} is the number of individuals employed in month $t-1$. We directly obtain the data on realized transition rates across various demographic groups, such as by education and income, from the labor market tracker provided by the Federal Reserve Bank of San Francisco.[5]

Time Aggregation. The perceived transition probabilities are reported for different horizons from the realized flow rates. For consistency, we convert all these rates into 3-month horizons using the following procedure. Consider the flow rates for three consecutive months, denoted p_1, p_2, and p_3. The aggregated flow rate over the 3-month window is then given by $1-(1-p_1)(1-p_2)(1-p_3)$. For the 1-year horizon job-separation probability, we first convert it into a continuous-time Poisson rate and then re-convert it into a 3-month horizon.

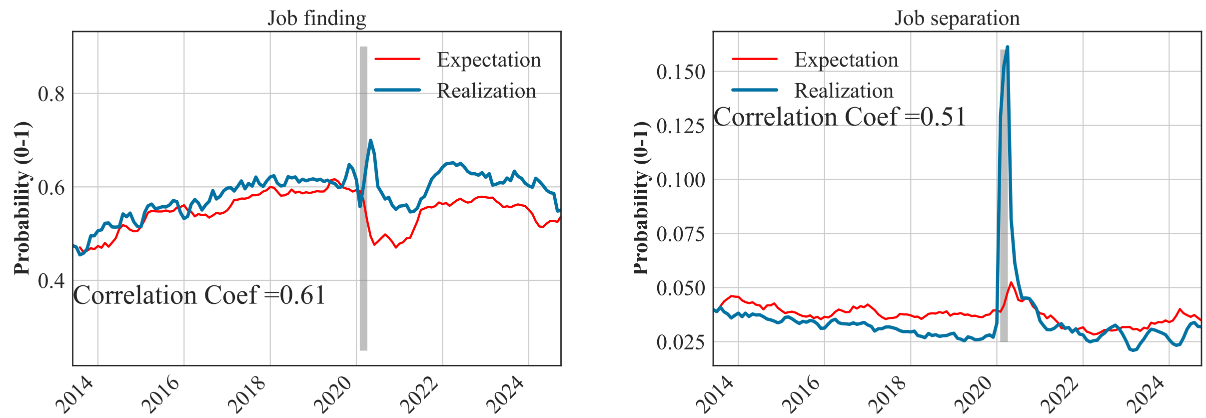
2.2 Perceived risks versus realized outcomes

Figure 1 directly compares perceived risks and realized job transitions for the sample period since 2013. It shows that perceptions predict realizations reasonably well at the aggregate level. This is evident not only in the similarity of the magnitudes of the two series but also in the highly positive correlation coefficients between them. Specifically, the 3-month-ahead perceived job-finding rate accounts for approximately 70% of realized job transitions, while the perceived job-separation rate accounts for 37% of its realization.

The correlation between perceived risks and realized flow rates would have been even higher without the COVID pandemic crisis, which introduced the most significant deviations of perceived risks from subsequent realizations. At the onset of the pandemic, the perceived job-finding rate dropped sharply, but the actual job-finding rate increased initially. This discrepancy was partly driven by the rehiring of previously laid-off workers through recalls (Gertler et al., 2022). Similarly, while perceived separation risk spiked at the onset of the crisis, the spike was dwarfed by a much higher increase in the realized job-separation rates. Such deviations

[5] Available at www.frbsf.org/research-and-insights/data-and-indicators/sf-fed-data-explorer/.

Figure 1: Perceived versus realized job transitions



Notes: This figure plots the perceived job transition probabilities over next three months, $\widetilde{JF}_{t+3|t}$ and $\widetilde{JS}_{t+3|t}$ and the realized job flow rates three months later, JF_{t+3} and JS_{t+3}.

highlight the unexpected nature of the COVID shock. However, the dynamics of perceived risks and corresponding realizations moved in tandem again within two months following the initial outbreak. The unusual labor market dynamics during the COVID crisis were unprecedented even for professional economists in real time, and continue to be a subject of current and future studies. Therefore, it is noteworthy that average perceptions of job risks could still partially predict ex-post labor market flow rates, despite the unprecedented crisis.

The fact that perceived risk predicts subsequent changes in the labor market is, on one hand, surprising, and on the other hand, reassuring. Growing survey evidence suggests that households' macroeconomic expectations, especially regarding inflation and unemployment rates, tend to contain systematic forecast errors. However, the average perceived job risks reported based on individuals' situations appear to capture predictable movements in subsequent labor market flows. This is encouraging for our analysis of perceived job risks, as it suggests that these measured beliefs contain meaningful time variations that reflect the underlying state of the economy. On the other hand, the correlation between ex-ante perceived job risks and ex-post realized transitions, while positive, is far from perfect, indicating a deviation from perfect foresight. Regardless of what the ex-ante perceptions are, realized job flow rates inevitably incorporate the realization of ex-ante unexpected macroeconomic shocks or idiosyncratic shocks.

Within-Group Comparison. The results presented above are based on average rates across all households in the survey. One potential concern when generalizing these findings is how perceptions and realizations compare within demographic groups. Several studies such as Hall and Kudlyak (2019); Gregory et al. (2021), and Patterson (2023) show the importance of heterogeneity in job risks in driving aggregate labor market dynamics, while Broer et al. (2021a) provide indicative evidence that information frictions are heterogeneous along the wealth distribution. Therefore, we also calculate both perceptions and realizations separately for low, middle, and high education groups, separately, as plotted in Figure 2.[6] The figure reveals that, within each education group, the dynamics of perceived risk and realized rates closely mirror those observed at the aggregate level, exhibiting a high correlation during normal times. There is, however, substantial heterogeneity by education level in the realized rates, both in terms of overall levels and time-series volatility. Not surprisingly, low-education workers face higher job-separation and lower job-finding rates than high-education ones. The differences in perceived job risks, especially in job-separation rates, are relatively small across education groups. Interestingly, low-education workers appear to particularly underforecast their job-separation rates at the onset of the pandemic, with the subsequent increase in separation rates being much larger than for the other two groups. Additionally, while low-education workers were notably more pessimistic about their job-finding prospects, the dynamics of realized job-finding rates were similar across all education groups. These patterns underscore the importance of considering heterogeneity in both the job risks faced by different groups and the perceptions of those risks. We explore these two points in the later part of the paper.

2.3 Forecast errors of perceived job risks

To systematically assess the relationship between perceived risks and realized job transitions, we adopt a widely used metric in the literature: forecast errors (FE), defined as the difference between the perceived risk and realized flow rate.

$$\mathrm{FE}^{JF}_{t,t+3} = \widetilde{\mathrm{JF}}_{t+3|t} - \mathrm{JF}_{t,t+3} \tag{1}$$

where the expectation is formed over a 3-month horizon. Here, $\widetilde{\mathrm{JF}}_{t+3|t}$ represents the perceived job-finding rate for 3 months ahead at time t and $\mathrm{JF}_{t,t+3}$ is the realization over the same horizon.

To test the informational efficiency of perceived job risks, we perform a 3-month-apart autoregression of forecast errors with an intercept term, which is commonly used in the literature on expectation formation, e.g., Coibion and Gorodnichenko (2015), Fuhrer (2018), and Coibion et al. (2018).

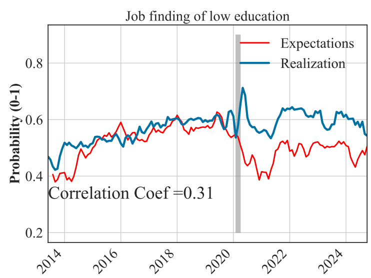
$$\mathrm{FE}^{JF}_{t,t+3} = \alpha + \beta \mathrm{FE}^{JF}_{t-3,t} + \gamma X_{t-3} + \epsilon_t \tag{2}$$

where X_{t-3} denotes information available at time $t-3$. A key null hypothesis under FIRE is that agents fully react to new shocks to the underlying variable. A significantly positive β

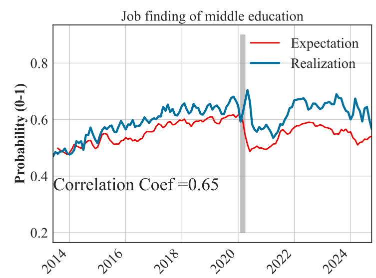
[6] We follow the definition applied by the SCE and Federal Reserve Bank of San Francisco defining high school or less as low education, some college as middle education, and bachelor degree or more as high education.

Figure 2: Perceived versus realized job transitions by education

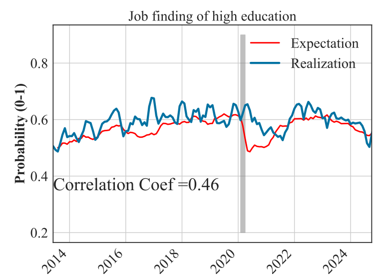
(a) JF of Low Education



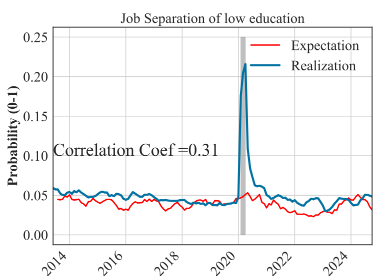
(b) JF of Middle Education



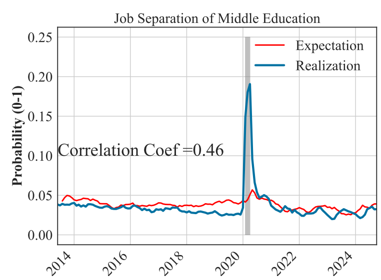
(c) JF of High Education



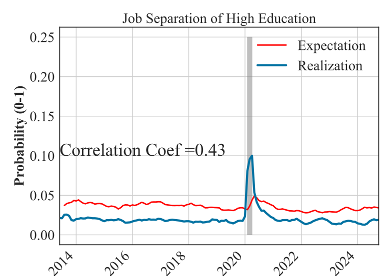
(d) JS of Low Education



(e) JS of Middle Education



(f) JS of High Education



Notes: This figure plots the 3-month-ahead job risk expectations, measured as perceived job-finding and -separation rates in the SCE, by different education groups, $\widetilde{JF}^{Educ}_{t+3|t}$ and $\widetilde{JS}^{Educ}_{t+3|t}$ $\forall Educ \in \{High, Mid, Low\}$, along with their respective realization 3 months later obtained from the Federal Reserve Bank of San Francisco, JF^{Educ}_{t+3} and JS^{Educ}_{t+3} $\forall Educ \in \{High, Mid, Low\}$. All rates are in the units of percent chance.

Table 1: Forecast Error Regression

	JF	JF LowEdu	JF MidEdu	JF HighEdu	JS	JS LowEdu	JS MidEdu	JS HighEdu
Constant	-0.027***	-0.027***	-0.038***	-0.024***	0.003*	0.076***	0.079***	0.051***
	(0.004)	(0.007)	(0.005)	(0.004)	(0.002)	(0.009)	(0.010)	(0.009)
lag_FE_jf	0.256***	0.545***	0.272***	0.183**				
	(0.087)	(0.076)	(0.084)	(0.088)				
lag_FE_js					0.131	0.202**	0.267***	0.554***
					(0.091)	(0.089)	(0.088)	(0.075)
Observations	121	124	124	124	121	124	124	124
R^2	0.068	0.295	0.079	0.034	0.017	0.040	0.070	0.308
Adjusted R^2	0.060	0.289	0.071	0.026	0.009	0.032	0.062	0.302
F Statistic	8.628***	51.049***	10.452***	4.297**	2.062	5.103**	9.197***	54.322***

*p<0.1; **p<0.05; ***p<0.01

Notes: The table reports the auto-regression results of average and various education groups' respective average forecast errors of expectations of job-finding and job-separation rate with their respective 3-month-lagged values, as defined in Equation 2.

implies predictable forecast errors based on past forecast errors.[7] In particular, $\beta > 0$ suggests that past errors persist into future forecasts in the same direction, reflecting the presence of information rigidity.

The estimation results for forecast errors in job-finding and separation perceptions are reported in Table 1. They overwhelmingly reject the null hypothesis of full efficiency ($\beta = 0$). Specifically, the 3-month-apart auto-regression coefficient of average forecast errors in job-finding is 0.256. Education-specific estimates range from 0.183 for the high-education group to 0.535 for the low-education group. For job separation, although the auto-correlation of average forecast errors is not significant, forecast errors of education-specific perceptions all show significantly positive auto-correlations, with regression coefficients ranging from 0.20 for the low-education group to 0.55 for the high-education group.

These estimates of auto-correlation of non-overlapping forecast errors suggest the presence of information rigidity in perceived job transition risks. However, the fact that the estimates are not close to one indicates that the information rigidity is moderate. This is particularly the case if the shocks to job finding and separation are relatively persistent, which means that only a mild degree of information rigidity sufficiently leads to non-zero auto-correlation of forecast errors.

Besides a non-zero serial correlation of forecast errors, as revealed in estimated β, it is worth noting that the constant term α in the auto-regression is also informative. Under FIRE, a positive (negative) α indicates an upward (downward) bias in the average forecasts. Its estimates

[7] A related null hypothesis in the same spirit is based on a regression of forecast errors on past information X_{t-3}, which states that γ being statistically different from zero means information available at $t-3$ predicts future forecast errors, implying that they are not fully utilized when the forecasts are made. We provide additional results of such tests in the Appendix **??**.

in Table 1 are significantly different from zero. Forecast errors of job-finding perceptions are on average positive and that of job separation is negative. At face value, this implies that ex-ante perceptions of job risks underestimates the job-finding, and overforecasts the job-separation, rates. Although it is tempting to conclude that job risk perceptions are biased based on such evidence, as is argued in several papers, in this paper we focus on only the dynamic rigidity of risk perceptions instead of its constant bias in levels, with a cautionary note that the sign of the latter is sensitive to the exact procedure of aggregation of individual beliefs.[8]

3 Measuring subjective versus objective risks

3.1 Proxy of objective job risks using real-time machine-learning

In the previous section, we directly compare perceived risks with the ex-post realization of job transitions. We reject the perfect foresight assumption, as ex-ante perceived risks differ from realized job flow rates. However, this gap cannot be fully interpreted as a deviation from a FIRE benchmark from an ex-ante point of view. Even if perceived job risks are fully rational ex ante, conditional on real-time economic conditions, newly realized shocks due to changes in the macroeconomy may still induce a gap between them. We would need a proxy for true ex-ante job risks to characterize the deviations of perceived job risks from a FIRE benchmark.

We adopt the methodology of Bianchi et al. (2022) to use machine-learning efficient forecasts of labor market transition rates to proxy the true ex-ante job transition risks. Specifically, for each month t in our historical sample, we use a LASSO model to select the set of variables that makes the best in-sample prediction of realized flow rates over a 10-year window up to t, as defined in Equation 3. Note that the coefficients are time-specific due to the real-time nature of this estimation procedure, i.e., the prediction model is estimated using only historical information up to time t.

$$\begin{aligned} JF_{t+3|t} &= \beta_0^t + \sum_{i=1}^{p} \beta_i^t X_{t,i} + \epsilon_t, \\ \text{subject to} \quad & \sum_{i=1}^{p} |\beta_i^t| \leq \lambda. \end{aligned} \tag{3}$$

Next, we generate a 3-month-ahead out-of-sample predicted value, $\widehat{\mathrm{JF}}^*_{t+3|t}$, based on the

[8] Arni (2013), Conlon et al. (2018), and Mueller et al. (2021), based on a comparison of average survey perceptions and realization, concluded that workers overperceive job finding probability. Meanwhile, Stephens (2004), Dickerson and Green (2012), and Balleer et al. (2023) found that workers overperceive job-separation probabilities relative to their realizations.

optimally chosen coefficient estimates, β^{t*}, obtained through k-fold cross-validation. (Equation 4)

$$\widehat{JF}^{*}_{t+3|t} = \beta_0^{*t} + \sum_{i=1}^{p} \beta_i^{*t} X_{t,i} \tag{4}$$

Approximately 600 time series are considered as candidate predictors of job flow rates. They include not only real-time macroeconomic variables but also forward-looking expectations of households and professional forecasts. Specifically, the following categories of predictors are included:

- real-time macroeconomic data, such as inflation, unemployment rate, GDP growth, etc. We ensure that these series are real-time data rather than retrospectively revised figures.
- household expectations from the MSC.[9] We use disaggregated indices instead of composite indices in the survey. These indices contain rich information on how average households perceive the macroeconomy and their personal finances. Notably, we include survey questions that elicit respondents' recent exposure to macroeconomic news, their intentions to purchase durable goods, and the reasoning behind their reported expectations (e.g., "it is not a good time to buy a car because the price is too high").[10]
- realized job-finding and separation rates calculated from the CPS (Fujita and Ramey, 2009). Given the persistence of flow rates, recent job flow realizations may serve as strong predictors of future transitions.
- consensus professional forecasts of the macroeconomy from the Survey of Professional Forecasters (SPF). Even professional forecasters have often been shown to deviate from the FIRE benchmark due to information rigidity and overreaction (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020; Bianchi et al., 2022). Nonetheless, professional forecasts' views reflect one of the most sophisticated and informed perspectives on the macroeconomy in real time. Indeed, Carroll (2003) treats professional forecasts as a proxy for real-time rational forecasts. Here, however, we do not make such an assumption, instead recognizing their potential as part of the broader real-time information set.

In theory, there is no restriction to what series we can use as long as it was measured in real time and could have been, in principle, in the information set of agents making forecasts standing at t. In practice, we cannot exhaustively account for all potentially relevant real-time information. However, given the extensive coverage of our selected series, they collectively serve as a reasonable proxy for the hypothetical complete real-time information set.

[9]Codebook: `https://data.sca.isr.umich.edu/subset/codebook.php`.

[10]Survey questions that ask about not only "what" but also "why" contain useful information in understanding household expectations (Colarieti et al., 2024; Haaland et al., 2024).

One particularly important input in real-time forecasting is directly reported perceived job risks. A large body of literature has shown that individuals have advance information, or superior information, about their future job changes that economists bystanders might have otherwise attributed to unexpected shocks (Hendren, 2017). Using average perceived risks is therefore meant to take care of this fact. If household expectations indeed predict subsequent labor market transition rates, as shown in the previous section, our machine-learning model would identify them as useful predictors.

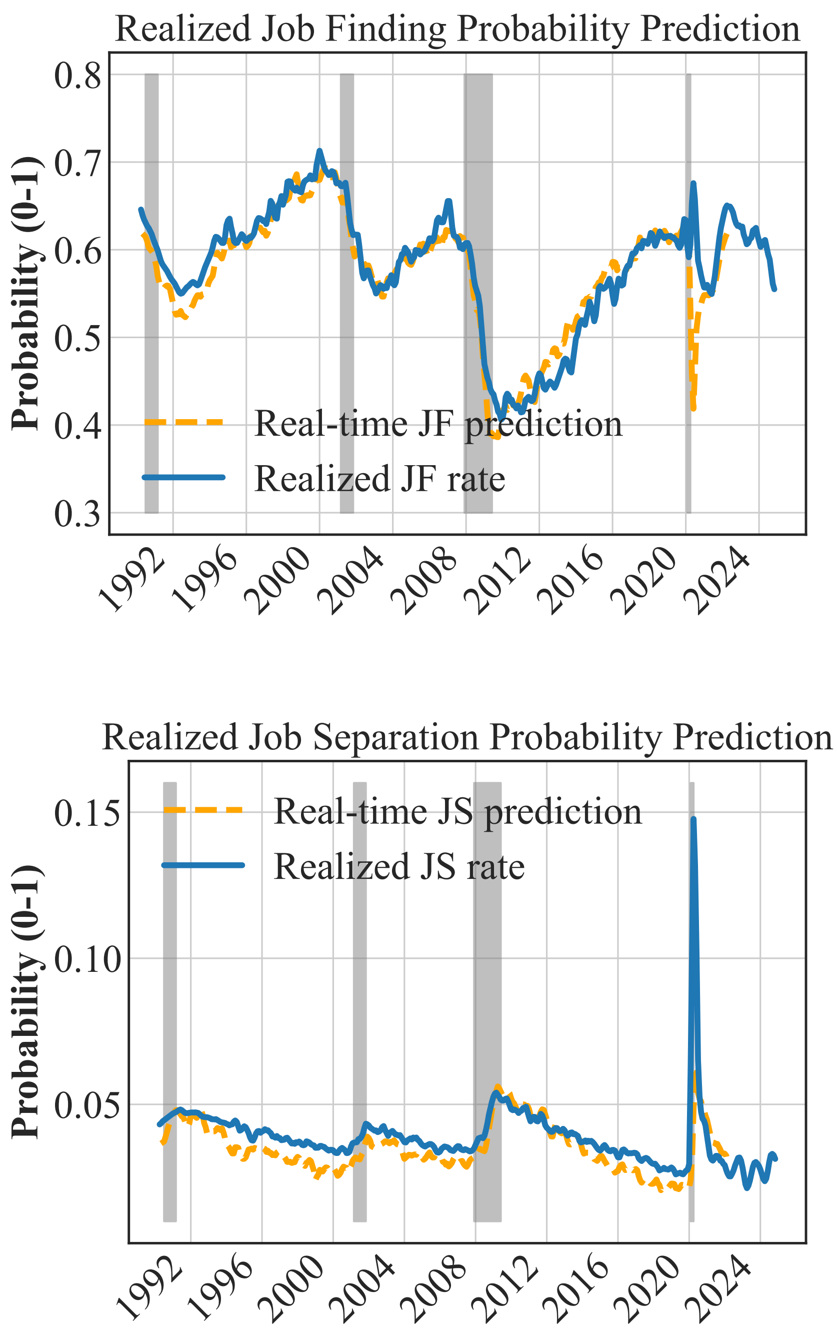
In practice, however, we cannot always rely on perceived risks by households, as such data have been available in the SCE only since 2013. Instead, we indirectly include all time series on household expectations in the MSC, assuming that perceived job risks are ultimately correlated with other household expectations. Alternatively, we also explicitly impute perceived risks using such an assumption in Section 3.2. Both approaches yield similar results.

Real-time job risks. The real-time machine-efficient prediction of job transition rates is plotted in Figure 3 against the realized job transition rates. Each point on the real-time forecast risk line corresponds to a forecast generated using only the information up to that point in time, based on a selected set of predictors with the optimally chosen penalty to prevent overfitting. Overall, the machine-efficient forecasts predict subsequent labor market movements with a high degree of accuracy, with the notable exception of major recessions, particularly the COVID-19 crisis in the first quarter of 2020.

This suggests that near-horizon labor market flow rates are highly predictable as long as all the relevant information is used, especially during normal times. When it comes to sudden crisis episodes such as the COVID pandemic outbreak, machine-efficient forecasts fail to anticipate the resulting labor market disruptions, consistent with the unexpected nature of such events. Nonetheless, once the initial shock unfolds, the machine-efficient forecasts are able to predict the subsequent changes in job flows with reasonable accuracy.

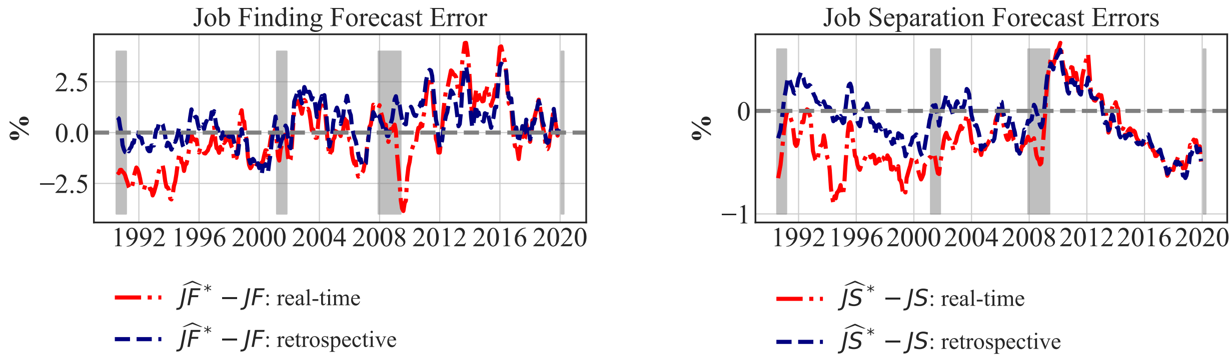
Figure 4 highlights the importance of using real-time forecasts without relying on hindsight. In most of the sample periods, the machine-efficient real-time forecasts of job-finding and separation rates exhibit non-zero forecast errors, implying even the rational ex-ante job risks would not have perfectly anticipated the subsequent realization of macro flow rates. In contrast, one-shot retrospective machine-learning forecasts, by which we mean the forecasts made based on the hindsight of the entire sample period, produce a forecast of job transition rates that have on average zero forecast errors. This was essentially due to overfitting to latter realizations of the history. This suggests that compared to a well-informed benchmark of ex-ante risks, unexpected shocks to realized job flow rates inevitably occur.

Figure 3: Machine prediction of labor market outcomes



Notes: 3-month-ahead job risks generated from real-time machine-learning forecasts using real-time data for each 10-year rolling window.

Figure 4: Forecast errors of real-time versus retrospective job risks



Notes: This figure compares the forecast errors of the machine-learning predictions of job-finding and job-separation rates generated by two different approaches: real-time versus retrospective forecasting. All rates are in the units of percent chance.

What predicts labor flows? One of the commonly selected predictors in real-time forecasting is the unemployment rate. A higher current unemployment rate predicts a higher separation rate and a lower job-finding rate. This is not surprising, as the unemployment rate reflects the overall state of the labor market and affects the subsequent transition rates.

In addition, many forward-looking variables in the MSC consistently predict future labor market outcomes. The fact that many expectational variables can predict labor transitions suggests that households possess meaningful forward-looking views on job risks. It is worth noting that such predictability should not be interpreted as causal. We take it as evidence that information available ex ante and predictable for macroeconomic outcomes is indeed incorporated into households' expectations about their future employment prospects.

In particular, three types of household expectations commonly show up in the LASSO model selections. The first set of variables directly relates to the self-reported exposure to labor market news. In particular, we find that when households report having heard favorable (unfavorable) news about the labor market, it predicts subsequent increases (decreases) in job finding and decreases (increases) in job separation. The second group of expectational variables is broadly about future personal finance and its recent realizations. The third set of predictors that are constantly selected across real-time forecasting samples is forward-looking actions by households, the most notable of which is the durable goods purchase intentions. Several papers (Carroll and Dunn, 1997; Harmenberg and Öberg, 2021) have empirically established the negative relationship between job risk and the propensity to purchase durable goods, consistent with structural models predicting that costly adjustments in durable goods are highly sensitive to income uncertainty, due to both precautionary saving motives and "wait-and-see" mechanisms.

Therefore, the correlation between intentions of future durable purchasing and subsequent labor market movements is likely driven by their respective correlation with ex-ante perceived job risks. In addition, durable goods demand plays a crucial role in aggregate fluctuations through general-equilibrium forces, as shown in McKay and Wieland (2021). Interestingly, survey questions that directly elicit rationales from households on their expectations, such as "not buying a durable due to high uncertainty," also help predict future job transition rates. This confirms the finding by Leduc and Liu (2016) that is also based on the uncertainty question elicited in the MSC.

Comparing machine-learning forecasts with simple time series models. Are these predictions as good as simply one univariate time series prediction? Given the persistence and time-series correlation of flow rates, the answer is not necessarily yes. We therefore compare the mean squared errors (MSE) of real-time forecasts using all datasets with a real-time forecast that uses only an AR(1) model. We show that the LASSO prediction based on a large time series dataset slightly outperforms the AR(1) model in terms of MSEs. Figure A.1 in the Appendix compares the risk forecast based on LASSO and AR(1). In most of the sample period, the two track each other quite well. The most noticeable divergence occurred during the pandemic where AR(1) forecast overforecast job separations due to the historical persistence of the separation rate, while LASSO model-based separation risk is predicted to have a more temporary reversal, following the initial dramatic spike.

3.2 Backcasting perceptions: what were people thinking then?

Directly observed perceived risks have been available in the SCE only since 2013. Meanwhile, a wide range of expectations have been surveyed in the MSC for a much longer time span, some of which go back to as early as the 1960s. Under the assumption that the correlations between different expectations have been stable[11], we can utilize the estimated correlation between perceived job risks in the SCE and other expectations in the MSC in the overlapping sample period to impute the out-of-sample perceived risks back in earlier history. We use a LASSO model to select among many contemporaneous variables that best predict the measured perceived job risks, as specified below.

$$\begin{aligned} \widetilde{\mathrm{JF}}_{t+3|t} &= \gamma_0^t + \sum_{i=1}^{p} \gamma_i^t X_{t,i} + \epsilon_t, \\ \text{subject to} \quad & \sum_{i=1}^{p} |\gamma_i^t| \leq \lambda. \end{aligned} \tag{5}$$

[11] We reject the null hypothesis of a structural break based on the test by Andrews (1993).

where $\widetilde{JF}_t$ is the average 3-month job-finding expectations at month t. The regressor vector X_t includes both EXP_t, a vector of contemporaneous belief variables, and REAL_t, a vector of real-time macro aggregates. The reason why we also include real-time aggregate realizations, not just expectational variables, is that in theory, this information may have been in the information set of the agents forming expectations. We again use cross-validation to determine the optimal degree of regularization of the LASSO model and obtain the optimal model coefficients of the selected list of predictors that we denote as $\gamma_i^{*t} \forall i = 1, 2...p$.

We externally validate our imputation methodology utilizing the fact that the expectations about 1-year-ahead inflation and 5-year horizon job-separation probability are measured in the MSC for a much longer period. Figure A.2 in the Appendix suggests that the imputation based on only 2013-2022 in-sample data can generate out-of-sample backcasts of these two expectations that almost mimic the observed data by a correlation of 80%-99%.

What are the most important covariates of the perceived risks? It turns out that they are numerous expectation variables in the MSC, such as durable purchase, news heard about economic conditions, recent experience, and future expectations of personal finance. In Figure A.5 in the Appendix, we list the top predictors of perceived finding and separation rates, respectively. The directions of these correlations all have sensible and intuitive interpretations.

In addition to expectations, real-time macroeconomic realizations are also found to be important covariates of perceived job risks. In particular, the recent unemployment rate stands out as the most important variable that comoves with the contemporaneous perceived separation rate. The roles of inflation and inflation expectations also deserve a special discussion. For instance, a higher recent realization of inflation is positively associated with a higher perceived separation rate. Meanwhile, higher inflation expectations, as measured by the share of those who expect higher inflation above 15%, are also associated with lower job-finding perceptions. The positive association of inflation (and inflation expectations) with job risks is consistent with the finding by Hou and Wang (2024).

Figure 5 plots the in-sample and out-of-sample imputation model fit from the optimal LASSO model selected from such a procedure. One of the advantages of a LASSO model is that it optimally penalizes over-fitting in the sample, as indicated by the difference between the in-sample prediction of the belief and the actual belief. We favor this approach over traditionally used linear models such as OLS because of our primary focus on achieving a great prediction of the beliefs even out of the sample. The backcast of perceived risks before 2013 exhibits reasonable cyclical movements. Throughout most of the five recessions since the 1980s, the imputed perceived job-finding rate dropped significantly compared to normal times, and the perceived job-separation rate significantly increased.

With the imputed belief, we confirm the findings in Section 2.2 based on directly observed beliefs that job-finding perceptions predict job-finding outcomes quite well, while the job-separation expectations are much less predictive of realized outcomes. The imputed belief on job finding and separation have a correlation coefficient of 0.81 and 0.16, respectively, with their realization 3 months later.

Our benchmark imputation in-sample includes the 2013-2022 period, which witnessed drastic movements in the labor markets. In Appendix A.2.3, we examine if the choice of including the Covid era has significant impacts on the dynamics of the imputed beliefs. In particular, we show that the belief imputation based on pre-Covid sample would have implied a much more dramatic drop in the job-finding perceptions than the actual perceptions observed in the SCE during this period, and the imputed job-separation perceptions turned out to be overly optimistic compared to the actual perceptions. Since our final goal in this exercise is to produce the best backcast of the belief to an earlier period in which such beliefs are not observed, we decided to maximize the in-sample size to include the variations in beliefs during this period, despite its possible peculiarity.

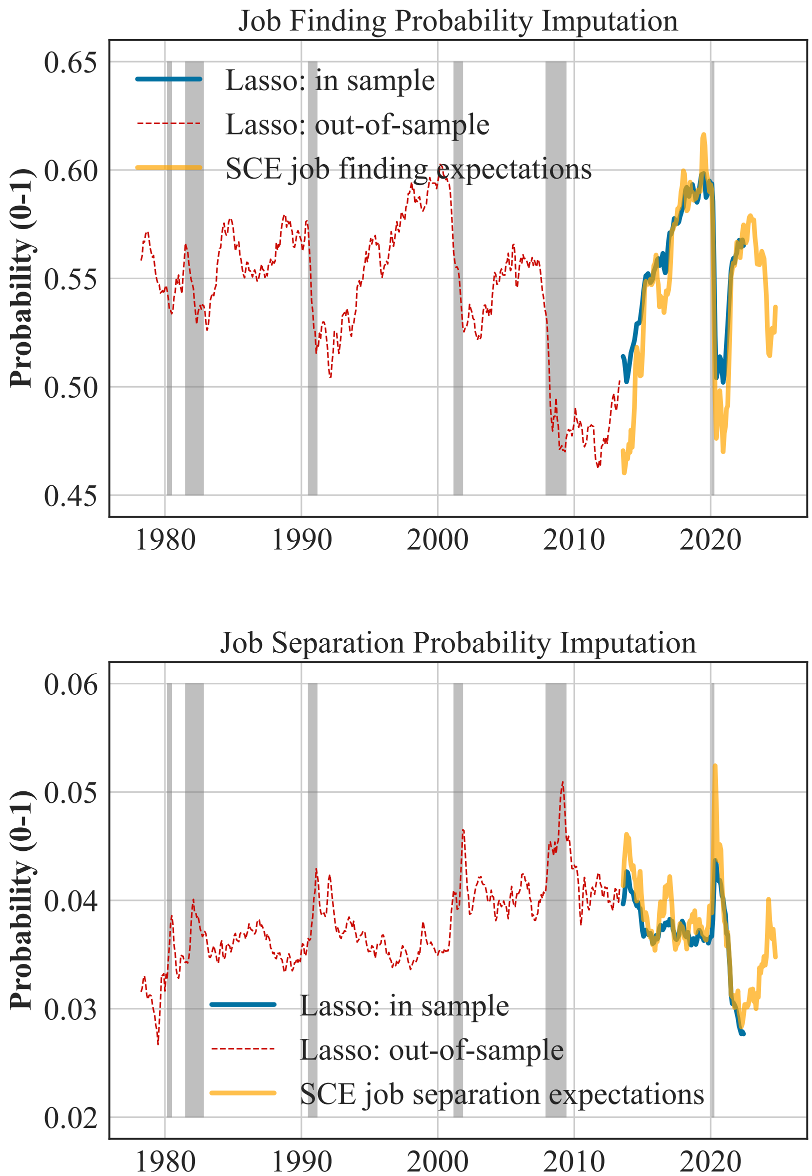
4 Perceived versus "true" risk

With the true risk proxy from the real-time machine-learning forecasting, denoted as $\widehat{JF}^*$ and $\widehat{JS}^*$, respectively, we can directly estimate the degree of belief distortion, namely the extent to which perceived job risks $\widetilde{JF}$ and $\widetilde{JS}$ deviate from rational ex-ante job risks. In particular, we regress $\widetilde{JF}$ and $\widetilde{JS}$ on the machine-efficient risk forecasts, $\widehat{JF}^*$ and $\widehat{JS}^*$, respectively. We use the log values in both sides of the equation so that the coefficient can be interpreted as the elasticity of beliefs with respect to changes in real-time risk. A coefficient with a size of unity corresponds to the situation where perceived job risks fully react to real-time rational risk, e.g., no under/overreactions.

Our estimates suggest that for each one percentage point increase in a real-time job-finding forecast, the average perceived job-finding rate increases by 0.5 percentage points, as reported in Equation 6.[12] On one hand, the significantly positive coefficient estimate suggests that perceived job finding somewhat comoves with real-time job-finding rate. On the other hand, a coefficient of half is indicative of underreaction in job-finding expectations. Figure 6 plots the perceived risk against real-time machine-efficient risk forecasts, in addition to ex-post realized transition rates, which visually exhibit such patterns.

[12] These regression coefficients are all statistically significant, as reported in Table A.1 and Table A.2. Estimates using the post-2013 sample without imputed beliefs show a higher sensitivity for job finding perceptions (0.81) and a lower one for job separation perceptions (0.14).

Figure 5: Imputed perceived job risks



Notes: The two charts plot imputed perceived job risks (on a scale of of 0-100) that are predicted using the selected LASSO model based on in-sample cross-validation.

$$\log(\widetilde{JF}_{t+3|t}) = 1.92 + \mathbf{0.51}\log(\widehat{JF}^*_{t+3|t}) + \epsilon_t \tag{6}$$

Perceived job-separation probabilities are less correlated with real-time risk, with a regression coefficient $\widehat{JS}^*_{t+3|t}$ of 0.19 (equation 7), implying only a 20-cents increase in perceived job separation in response to one percentage point increase in machine forecasts. Perceived job separation fails to incorporate about 81% of the predictable job-separation transitions.

$$\log(\widetilde{JS}_{t+3|t}) = 1.13 + \mathbf{0.19}\log(\widehat{JS}^*_{t+3|t}) + \epsilon_t \tag{7}$$

Information rigidity in the form of Sticky Expectations. As an extension, we re-estimate the job risk perception equations, now including a 3-month lag of perceived job risks. This approach allows us to test whether the underreaction in perceived job risks can be explained by the canonical recursive structure of the Sticky Expectations model, [13] as represented in Equation 8. Following Mankiw and Reis (2002), Carroll (2003), and Coibion and Gorodnichenko (2015), this formulation posits that a fraction λ of agents updates their beliefs fully and rationally, while the remaining fraction $1-\lambda$ continues to rely on outdated beliefs due to infrequent updating.

$$\widetilde{JF}_{t+3|t} = \lambda JF^*_{t+3|t} + (1-\lambda)\widetilde{JF}_{t+3|t-3} \tag{8}$$

Table A.3 and A.4 report the estimates for job finding and separation perceptions, respectively. It seems that the actual patterns of perceptions do not fully comply with the canonical SE formulation, since the coefficients of 3-month lag perceptions are not often statistically significant. Nevertheless, when the lagged perceptions are controlled for, the coefficient of JF^*_t and JS^*_t remain in a similar range as reported above, indicating a similar degree of underreaction of perceived risks to real-time risks.

4.1 Heterogeneity in job risks

Our analysis so far assumes homogeneous job risks, which means that the perceived job risks assumed by different workers are supposed to react to the true aggregate risk to the same degree, in the absence of belief distortion. But in reality, job risks are widely heterogeneous across workers; see Hall and Kudlyak (2019); Ahn and Hamilton (2020); Gregory et al. (2021). So are

[13] A number of studies have estimated the updating rate λ to be significantly lower than one, based on survey expectations of inflation, unemployment and other macroeconomic variables, e.g., see Mankiw and Reis (2002), Carroll (2003), Coibion and Gorodnichenko (2012), etc. In the literature, such information rigidity can be also microfounded by another class of models, namely the noisy information, where agents learn about the true state of the world via noisy public and private signals. Like SE, it generates a serial correlation of forecast errors as shown at the beginning of the paper, but it does not exactly have a prediction as in Equation 8.

Figure 6: Survey perceived job risks versus machine-efficient risk forecasts

Notes: The charts plot perceived job risk, real-time machine-efficient forecast, and realized job flow rates.

the perceived risks, as shown in Mueller et al. (2021); Wang (2023). Guvenen et al. (2014) show that heightened income risks during recessions can be, in part, predicted by observable factors measured prior to recessions. Patterson (2023) shows that the positive correlation between workers' marginal propensity to consume (MPC) and the cyclicality of their income amplifies recessions compared to a world with equal income exposure. A similar argument can be made in the space of job risks. We therefore consider it important to study ex-ante heterogeneity in job risks. Unlike the common countercyclical risks that drive time-varying fluctuations, the presence of risk heterogeneity causes business cycle fluctuations via its heterogeneous incidences.

Meanwhile, the fact that workers face different degrees of job risks is naturally another important reason for why average perceptions underreact to real-time conditions. To see this point clearly, assume an individual worker i's JF has an idiosyncratic loading $\eta_{i,t}$ from the aggregate job-finding rate JF_t. (Equation 9), where each individual i has their respective expectations of their own heterogeneous risk $\widetilde{JF}_{i,t}$. We further make the assumption that people know perfectly about their heterogeneous factor $\eta_{i,t}$, which makes the last equality hold in the second line of the Equation 9.

$$\begin{aligned} &\mathrm{JF}_{i,t} = \eta_{i,t}\mathrm{JF}_t \\ &\widetilde{\mathrm{JF}}_{i,t} = \mathbb{E}_i(\mathrm{JF}_{i,t}) = \mathbb{E}_i(\eta_{i,t}\mathrm{JF}_t) = \eta_{i,t}\mathbb{E}_i(\mathrm{JF}_t) \end{aligned} \tag{9}$$

If the following equation holds, namely if average perceived job risks across agents converge to the aggregate job risks, JF_t depends on at least two factors. The first is the cross-sectional distribution of $\eta_{i,t}$. The second is the expectation patterns of individuals toward aggregate job risk. Even if all workers correctly perceive JF_t, which implies $\mathbb{E}_i(\mathrm{JF}_{i,t}) = JF_t \forall i$, the heterogeneity in job risks still matter for the behaviors of average perceived job risk.

$$\widetilde{JF}_t = \frac{\sum \mathbb{E}_i(\mathrm{JF}_{i,t})}{N} = \frac{\sum \eta_{i,t}}{N} JF_t \stackrel{?}{=} \mathrm{JF}_t \tag{10}$$

Such an aggregation through the distributional effects of aggregate job risk on individual workers, even in the absence of belief distortion, would also potentially imply a wedge between average perception and true aggregate risk. Imagine the shocks to JF_t are highly persistent while the idiosyncratic loadings $\eta_{i,t}$ are entirely transitory and agents perceive these components correctly. That would imply that the average perceived risks $\widetilde{JF}_t$ are less responsive to aggregate risks JF_t by a degree less than unity.

The importance of heterogeneity in job risks in understanding perceived job risks is emphasized by Mueller et al. (2021). They show that both ex-ante heterogeneity and underreaction to variations in job-finding rate *across workers* and *over unemployment spells* are important to explain the patterns of job-finding perceptions. To the extent that such beliefs induce self-insurance behaviors through job search, underreaction to the heterogeneity and duration-dependent variations results in a larger dispersion in job-finding outcomes. What this paper has shown so far is essentially that such underreaction to variations in job risks also exists along the variations of job risks over business cycles at the aggregate level.

To formally shed light on the role of heterogeneity, we estimate the belief-distortion regression for different percentiles of the perceived job risks. The key assumption is that at any point in the business cycle, workers face different degrees of job risks and are affected by the same aggregate conditions unevenly.

In particular, instead of the mean perceived job risks in the survey as in Equation 6, we regress the q-th percentile perceived job risks $\widetilde{JF}^q$ and $\widetilde{JS}^q$ $\forall q = \{25, 50, 75\}$ (Equation 11) on the same aggregate common real-time risk measure. By doing so, we are asking a very intuitive question: whose expectations are the most reactive to the change in real-time risks? Our estimated sensitivities are reported below and Table A.1 and Table A.2 report more in details.

$$\begin{aligned} \log(\widetilde{JF}^{0.25}_{t+3|t}) &= -1.55 + \mathbf{1.22} \log(\widehat{JF}^{*}_{t+3|t}) + \epsilon_t \\ \log(\widetilde{JF}^{0.5}_{t+3|t}) &= 1.54 + \mathbf{0.63} \log(\widehat{JF}^{*}_{t+3|t}) + \epsilon_t \\ \log(\widetilde{JF}^{0.75}_{t+3|t}) &= 3.62 + \mathbf{0.20} \log(\widehat{JF}^{*}_{t+3|t}) + \epsilon_t \end{aligned} \tag{11}$$

The job-finding perceptions of the 25th percentile worker react to the real-time job-finding rate by a much larger degree than the rest, as implied by the coefficient estimates of 1.22 for this group, as opposed to a 0.63 for the median worker and 0.20 for the worker at the 75th percentile. To put it bluntly, those who usually believe that they cannot easily find a job are the marginal workers whose belief reacts to the real-time job-finding rate the most. A higher-than-one elasticity of beliefs suggests that the beliefs are overreactive to the market finding conditions.

$$\begin{aligned} \log(\widetilde{JS}^{0.25}_{t+3|t}) &= -0.42 + \mathbf{0.46} \log(\widehat{JS}^{*}_{t+3|t}) + \epsilon_t \\ \log(\widetilde{JS}^{0.5}_{t+3|t}) &= 1.06 + \mathbf{0.68} \log(\widehat{JS}^{*}_{t+3|t}) + \epsilon_t \\ \log(\widetilde{JS}^{0.75}_{t+3|t}) &= 2.57 + \mathbf{0.27} \log(\widehat{JS}^{*}_{t+3|t}) + \epsilon_t \end{aligned} \tag{12}$$

In terms of job separation, it is the median-risk workers that have the most sensitive reactions to aggregate real-time job-separation rate. The estimates of responses range from 0.46 for 25th percentile workers (almost a non-reaction) to 0.68 and 0.27 for the median and 75th percentile workers, respectively.

Taken all together, these estimates suggest that, conditional on individual heterogeneity in risk exposures, the information rigidity is not as severe as the average perceived job risks. Both overreaction and underreaction in perceptions exist, depending on where the worker is located in the distribution of heterogeneous job risks.

The heterogeneous sensitivities of perceptions with respect to common aggregate risk are probably sensible. In particular, the perceptions of those who perceive high job risks (high separation and low finding risk perceptions) show the highest sensitivity. Business cycles are not just characterized by the change in aggregate job risks; they are probably more accurately seen as a shift in the location of the marginal workers who face the job risks. For instance, in recessions, the marginal worker who faces job-loss risk shifts downward from the top 10th percentile of perceived job risk to the 50th percentile. The sensitivity in perceptions helps reveal who the marginal workers are.

The idea that distributional expectations contain information about the aggregate economy also echoes a few papers that show that distributional expectations of households/firms improve the predictions of subsequent aggregate outcomes. It is not always the average agent, but the *marginal* one, whose expectations matter for macroeconomic outcomes, because the same aggregate shock has different footprints on heterogeneous agents in the economy.

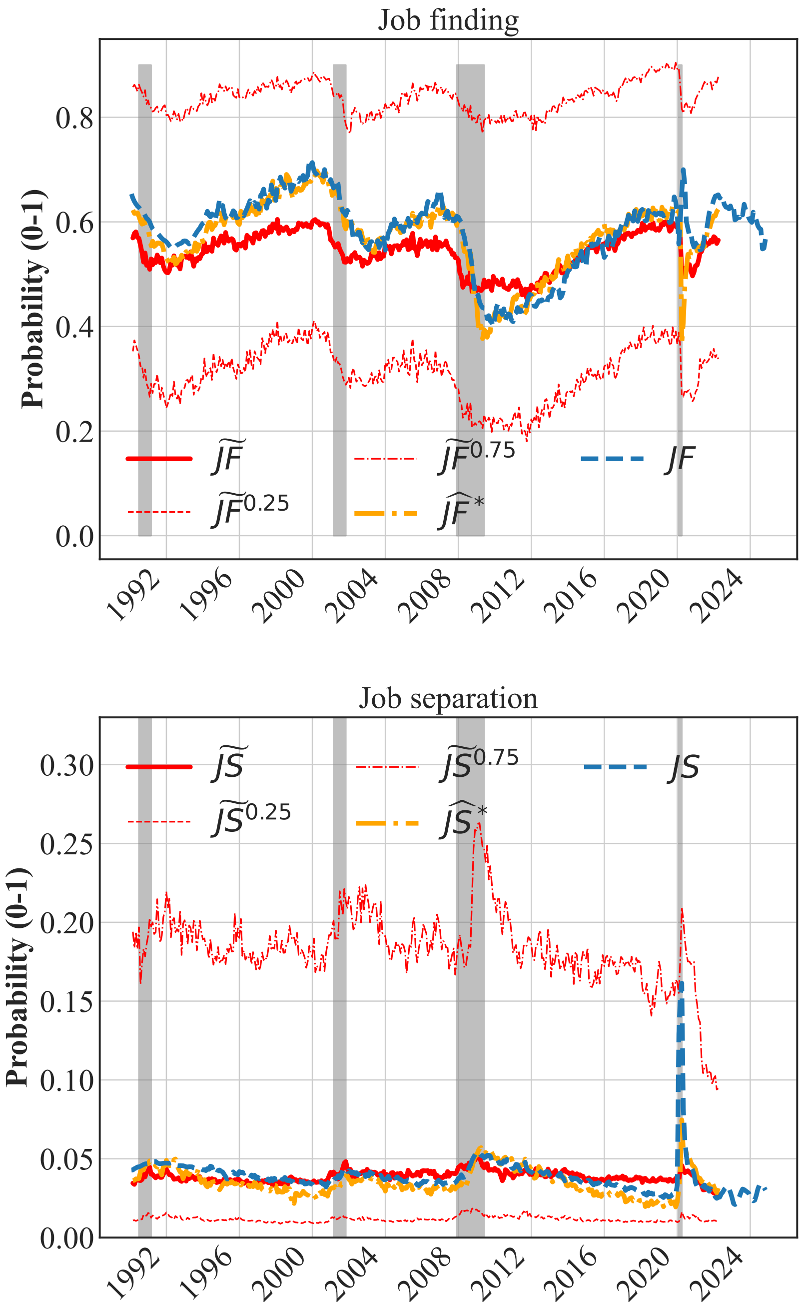
4.2 Heterogeneous perceptions of job risks

Is there heterogeneity in terms of belief distortions, in addition to the heterogeneity in true job risks faced by different workers? If the workers who face the most cyclical movements in job risks tend to underperceive such movements—and therefore underinsure themselves—total consumption fluctuations amplify, due to the heterogeneous footprints of uninsured job risks.

We can shed light on this question along a few observable dimensions, such as education, relying upon the fact that we can create group-specific risk forecasts specifically for each education group, e.g., $\widehat{JF}^{HighEdu*}$,$\widehat{JF}^{MidEdu}$,$\widehat{JF}^{LowEdu*}$, respectively. Using group-specific risk forecasts admits the ex-ante heterogeneous risk exposures of different education groups.

The estimates are reported below. In terms of job finding, the middle-education group is the most rigid, relative to their real-time risk, than the low- and high-education groups. Meanwhile, with job separation, low-education workers underreact to the real-time risks the most, exhibiting the largest degree of information rigidity. Such patterns are consistent with the patterns in Figure 2, i.e., that different low-education groups underestimate the spike in job-separation rate and react more strongly to the decline in job finding at the outbreak of

Figure 7: Survey perceived job risks versus machine-efficient risk forecasts by distribution



Note: The figures plot the average and heterogeneous perceived job risks at different quantiles, real-time job risks, and realized job transition rates.

the pandemic compared to the high-education group. Assuming a strong correlation between education and liquid wealth, Broer et al. (2021a) would predict a U-shaped pattern, as poor and rich households have the highest incentives to know the current state of the world. Our results support such a claim for job finding, but contradict it for job-separation rates. In fact, workers without a high school degree have the weakest reaction in beliefs to changes in realized job-separation rates, even though they would have the largest utility penalties of non-optimal precautionary savings.

Despite the differences across workers, however, it is worth emphasizing that overall, all beliefs by all types of groups exhibit rigidity, with the coefficient always below 60 percent.

$$
\begin{aligned}
\log(\widetilde{JF}^{LowEdu}_{t+3|t}) &= 1.28 + \mathbf{0.66}\log(\widehat{JF}^{*LowEdu}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JF}^{MidEdu}_{t+3|t}) &= 2.53 + \mathbf{0.36}\log(\widehat{JF}^{*MidEdu}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JF}^{HighEdu}_{t+3|t}) &= 1.87 + \mathbf{0.53}\log(\widehat{JF}^{*HighEdu}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JS}^{LowEdu}_{t+3|t}) &= 1.1 + \mathbf{0.17}\log(\widehat{JS}^{*LowEdu}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JS}^{MidEdu}_{t+3|t}) &= 0.95 + \mathbf{0.35}\log(\widehat{JS}^{*MidEdu}_{t+3|t}) + \epsilon_t \\
\log(\widetilde{JS}^{HighEdu}_{t+3|t}) &= 1.08 + \mathbf{0.33}\log(\widehat{JS}^{*HighEdu}_{t+3|t}) + \epsilon_t
\end{aligned}
\tag{13}
$$

5 Macro implications of perceived job risks

5.1 Shocks or risks?

In the previous sections, with the three measures in hand, namely (a) perceived risks $\widetilde{JF}/\widetilde{JS}$, (b) objective risks $\widehat{JF}^*/\widehat{JS}^*$, and (c) realization of job flow rates JF/JS, we have established two major findings. The first is a rejection of perfect foresight, in that even ex-ante rational and fully informed forecasts of risks don't fully predict ex-post realizations. The rejection is indicated by the gap between (b) and (c). The second is the deviation of ex-ante perceived job risks from its true ex-ante counterpart, at least partially due to information rigidity.

But do the distinctions between (a), (b), and (c) matter for aggregate fluctuations? We can assess empirically the relative importance of ex-ante precautionary saving motives resulting from perceived job risks (a), responses due to misperceived risk ((a)- (b)), and ex-post responses due to truly unexpected income shocks ((b)-(c)), by comparing the cyclical properties of (a), (b) and (c) across business cycles.

We use two sets of metrics to evaluate the relative importance of the three channels. The first one is the unconditional standard deviation of (a), (b), and (c). The second metric is the ratio between the onset and the end of each recession in our sample. More intuitively, these ratios reflect the changes in these rates from the peak to the trough of each cycle.

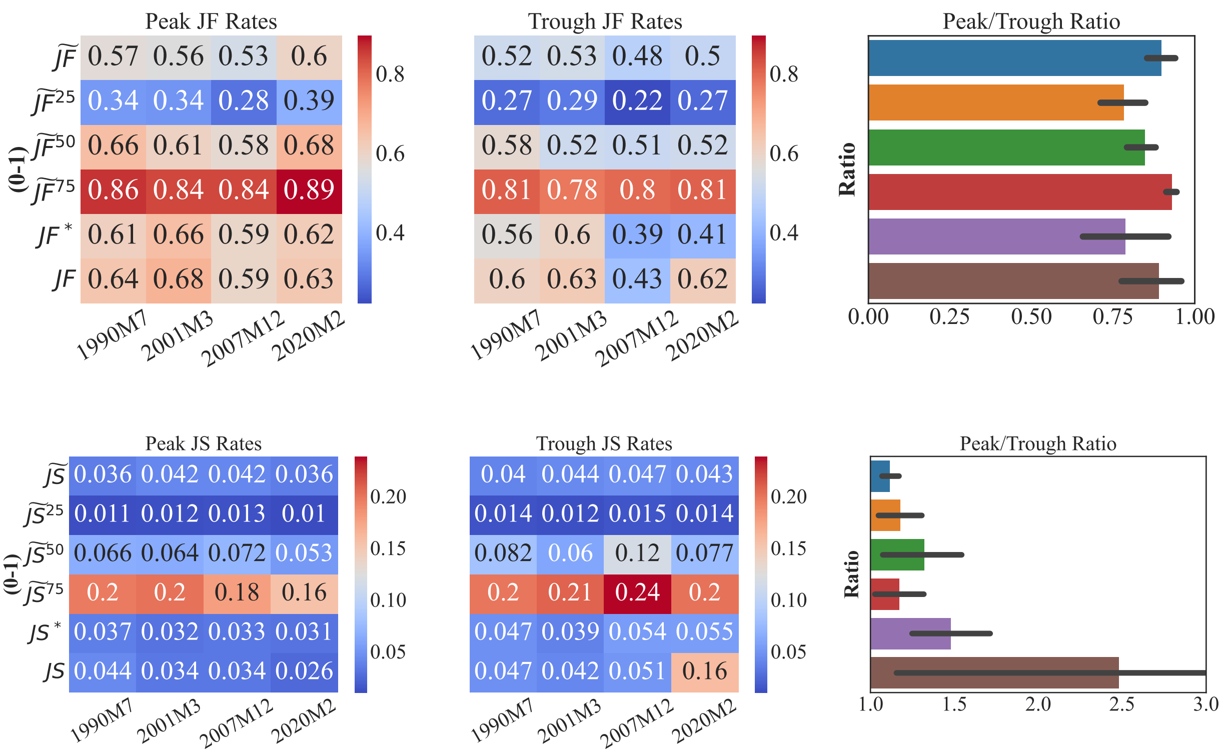
Throughout our data sample of 1990-2024, which covered four recessions and experienced sizable cyclical movements of unemployment risks, the unconditional standard deviation of realized job-finding rates is approximately 7.2 percentage points. Most of these variations are reflected in real-time job-finding probabilities, whose standard deviation was about 6.9 percentage points. In contrast to these cyclical movements of realized job-finding rates, the perceived finding rates exhibit milder fluctuations and have a standard deviation of 4 percentage points. In the domain of job separation, the unconditional standard deviations of perceptions, risk forecast, and realizations are 1.0, 0.9, and 0.3 percentage points, respectively. Both finding and separation perceptions move significantly less than the realized job risks.

Such rankings of the relative volatility of perceptions and realizations also can be seen in Figure 8, which reports the peak and trough rates in each of the four recessions in the sample period. From the onset of each recession to its end month, the real-time job finding drops by 25%, while the perceptions of job finding decrease by only 15%.

Meanwhile, average job-separation perceptions are much more sluggish than job-finding expectations, which is again confirmed by, on average, a 16% increase from the start to the end of each recession, as opposed to a 50% average increase in job-separation risk forecast and 150% in realized job-separation rates. The increase in realized job-separation rates remains high with the pandemic recession excluded, which was not reflected in the change in perceptions.

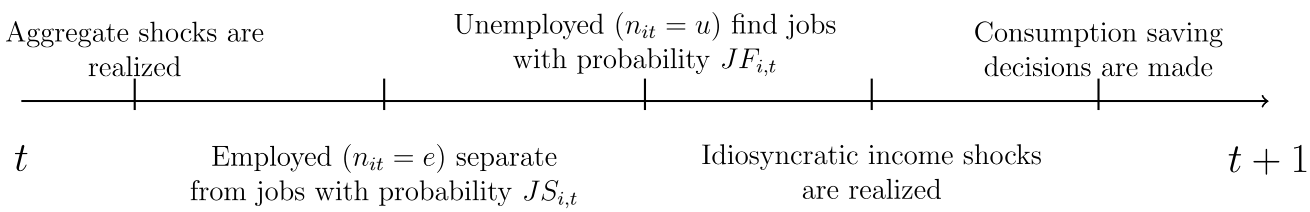
Such average patterns mask substantial heterogeneity in job risks and perceptions. Figure 8 also plots the movements of perceptions over business cycles by agents at different percentiles of perceived job risks. In terms of job-finding, although an average worker's perceived job-finding probability drops by 15% from the peak to the trough of a recession, which is more or less comparable to the realized job finding, it is the low-finding rate worker at the 25th percentile who perceives a much sharper drop of about 25%, compared to a drop of 10% for the worker at the 75th percentile. In terms of job separation, although an average worker's job-loss perceptions increase by only 15 percentage points in recessions, the *median* worker's perceptions increased much more sharply, by about 35 percentage points. Recessions hit agents in the economy unevenly in terms of their job risks. Such heterogeneity in perceptions reveals the uneven footprints of business cycle fluctuations via job risk changes. Heterogeneity in risk exposure implies different degrees of ex-ante precautionary saving behaviors and their consequent ex-post shock responses, a topic we turn to in the next section.

Figure 8: Business cycle patterns of risks and perceptions: start versus end of recessions



Note: The left tables report the perceived job risks, perceived job risks at different quantiles, real-time job risks, and realized job transition rates at the beginning and the end month of each one of the four recessions. The bar charts on the right plot the peak-to-trough ratios of these rates. The sample period is 1990-2024.

Figure 9: Timeline of the model



5.2 Quantifying the aggregate consumption impacts of unemployment risks

In this section, we show that the strength of the unemployment risk channel changes substantially when household beliefs are disciplined by survey data on workers' expectations of finding and losing jobs, instead of by the realized counterparts of these probabilities, or the proxy of their rational ex-ante counterparts. Furthermore, we demonstrate that the magnitude of this channel differs significantly across education groups.

To assess the extent to which consumption fluctuations are driven by precautionary behavior versus realized income losses from unemployment, we simulate the path of aggregate consumption dynamics by feeding our time series of perceived and objective unemployment risk, and our measures of actual job transition rates, into a standard heterogeneous agent model with persistent unemployment.

The model is set to a monthly frequency. In the model, workers make a consumption-saving decision in the face of both idiosyncratic productivity shocks and stochastic transition between employment and unemployment. Transitions between (un)employment states are dictated by the job-separation and job-finding probabilities. Workers' perceptions of job finding and separation probabilities are distinct states, separate from the probabilities that govern their actual transitions between employment and unemployment. Households achieve self-insurance through saving money on a risk-free asset. Finally, during unemployment, households receive unemployment insurance. Figure 9 illustrates the timeline of the model. Details of the model specifications are found in Appendix B.1. The calibration of the model can be found in table A.5. Crucial to our quantification, we assume an unemployment insurance replacement ratio of 50 percent. In addition, we indirectly calibrate a homogeneous discount factor to be 0.98 per year to target an average quarterly MPC of 0.21, a value reported by Fuster et al. (2021) based on the SCE.[14] To the extent that a higher MPC stems from a larger fraction of low liquidity or hand-to-mouth households, this disciplines the degree to which households react to heightened risks in future.

[14] In particular, this is the average elicited MPC out of a hypothetical income loss of 500 USD among respondents in the SCE. We use the same study to calibrate education-specific MPCs in the next section.

Decomposition of Consumption Jacobians

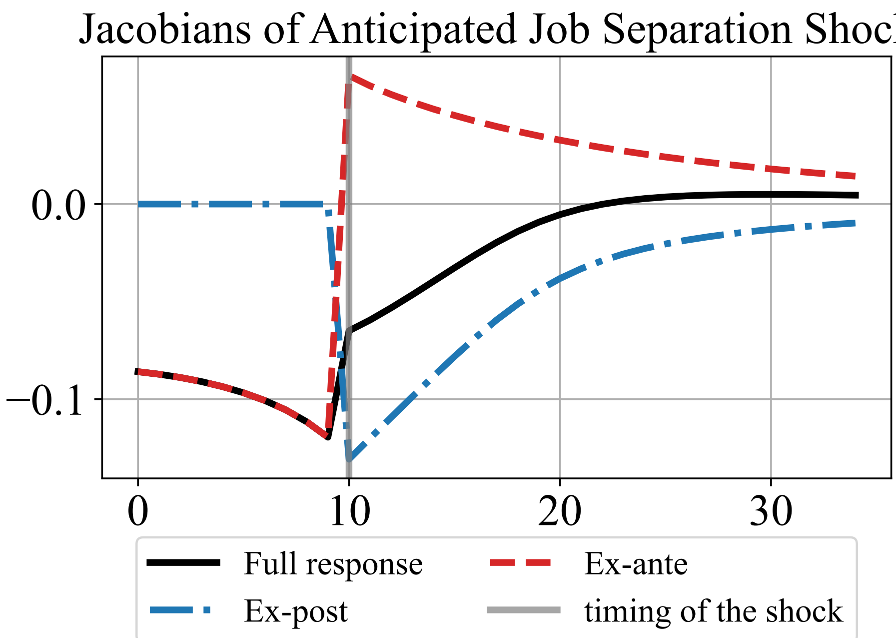
Following the approach of Auclert et al. (2021) and Auclert et al. (2020), we first decompose the aggregate consumption Jacobians with respect to a given shock to the future job-separation and finding probability into ex-ante and ex-post channels. The first channel operates through precautionary effects and the second channel stems from income effect due to changes in actual unemployment. The two components are distinctive from each other, but are interconnected in the sense that a greater degree of aggregate ex-ante precautionary response dampens the actual consumption impacts of income losses following a realized unemployment shock. Furthermore, we utilize these decomposed Jacobians to simulate the path of aggregate consumption under different counterfactual assumptions regarding job risk perceptions.

Taking job-separation as an example, Figure 10 illustrates the consumption response to an increase in the job-separation probability at horizon $t+h$, with $h = 10$. The black line corresponds exactly to the 10$^{\text{th}}$ column of the consumption Jacobian with respect to the job-separation probability. The *ex-ante* component captures the anticipatory behavior reflected in the black line—that is, the self-insurance response of workers leading up to the increase in separation risk at $t = 10$, under the assumption that the risk itself does not actually materialize. Since the hypothetically heightened job loss risk affects every worker in the economy as long as they face the potential risk of losing the job, such aggregate responses entails heterogeneous changes in consumption/savings by all agents in the model and their resulting changes in the evolution of the distribution of liquid wealth between period 0 to 10. Such self-insurance responses prior to the shock's actual realization also implies positive surprise from the period 10 onward if the fears of job loss does not actually realize. In contrast, the *ex-post* Jacobian captures the consumption response to the realized increase in unemployment resulting from an actual rise in the separation probability, assuming workers do not anticipate this change. Note that such a channel only impacts those who unexpectedly lose the job due to such a shock.

Figure 11 illustrates how underreactive beliefs—as documented in survey expectations about both job-finding and job-loss probabilities—weaken the precautionary channel while amplifying the income loss channel associated with unemployment. The figure includes two additional consumption responses under the assumption of sticky belief updating.[15] The purple line shows the *subjective* consumption response to an increase in the job-separation probability at $t = 10$, assuming that in each period from $t = 10$ onward, 3% of workers update their expectations. The red line shows the same response with the additional assumption that the job-separation probability never effectively increases. The ex-ante component of the response is significantly

[15] While Figure 11 presents the subjective Jacobian decomposition to illustrate the underinsurance mechanisms arising from sticky job risk beliefs, the model experiments in the following section rely directly on the empirically estimated patterns of $\widetilde{JF}_t$ and $\widetilde{JS}_t$.

Figure 10: Consumption Jacobian with respect to an anticipated 10-period-ahead shock to the job separation probability



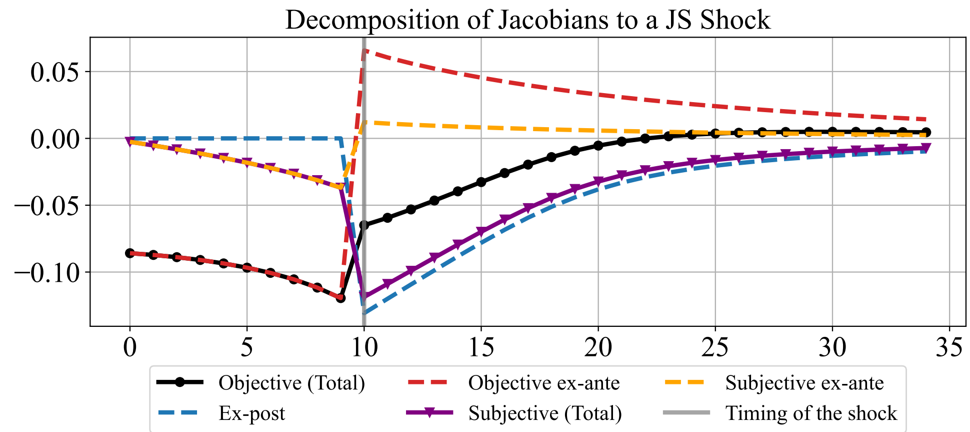
Notes: This figure plots the total and decomposed Jacobians of the aggregate consumption with respect to an anticipated shock to job-separation probability at $t + 10$. The Jacobian is defined exactly as in Auclert et al. (2021).

muted relative to the full (objective) response shown in black. However, the consumption drop at $t = 10$ and beyond is substantially larger, reflecting a lack of precautionary saving and thus a lack of self-insurance.

Quantifying the Impacts of Fear of Unemployment in Driving Consumption Fluctuations

With the decomposed Jacobians, we simulate of the path of aggregate consumption from 1988 to 2020. Specifically, we estimate AR(1) processes for both our survey-based expectations and the constructed rational expectations of job-separation and job-finding probabilities, and recover the corresponding shocks that replicate their observed paths from 1988 to 2020. We apply the same procedure to the realized job-finding and job separating probabilities estimated from the CPS. These shocks are then fed into the model: household perceptions evolve according to the respective perception shock series, while actual job transition rates follow the shocks estimated from realized data. This approach generates a simulated path of aggregate consumption that reflects the assumptions underlying each scenario.

Figure 11: Subjective consumption Jacobians with sticky expectations



Note: The figure shows the aggregate consumption Jacobian concerning a future shock to job-separation rate. The Jacobian is broken down into those driven by ex-ante perceived risk and that is caused by ex-post shock response in full-information versus subjective/sticky perceptions of job-separation risk.

We conduct this simulation under four different scenarios. The first assumes that workers do not perceive any changes to the job finding and job separation ex-ante and the they are only hit by unexpected shocks to the actual job finding and separations by shocks as estimated from JF_t and JS_t. This simulation isolates the income loss channel of consumption induced from an increase in the unemployment rate. The second assumes that workers' expectations follow our survey-based measure of job-finding and job-loss perceptions and they acted upon such perceptions, in addition to the ex-post income losses. The third assumes that workers expectations follow our constructed measure of rational expectations. Finally, the fourth simulation assumes workers have perfect foresight and perfectly anticipate the actual shocks to the job transition probabilities.

Figure 12 shows simulated paths of aggregate consumption from the 1980s through 2020. The first two panels isolate the effects of fluctuations in the job-separation and job finding probabilities, respectively. The third panel presents the combined effect of both on aggregate consumption.

Three key findings emerge from the figure. First, when considering job separation alone, the stickiness in separation beliefs leads to a minimal ex-ante precautionary saving response during recessions. Consequently, the total consumption response based on subjective perceptions closely mirrors the ex-post impact and falls short of the response implied by objective risk. Finally, as workers engage in a substantially smaller magnitude of precautionary saving, the recovery of consumption exhibits a more sluggish recovery under subjective beliefs.

Second, in the case of job-finding risk, precautionary saving plays a non-trivial role in driving consumption. However, because beliefs about job finding adjust only partially to the true underlying risk, there is a large gap between the simulation with objective risk or perfect foresight versus subjective expectations. In the Great Recession, the objective response implies an even larger drop—roughly one percentage point more—than the subjective estimate. Just as sluggish job-separation beliefs induce a slower recovery, the slow adjustment in job-finding beliefs also contributes to a delayed recovery in aggregate consumption.

Third, the combined impact of job separation and job finding—shown in the bottom panel of Figure 12—is largely driven by the job-finding channel. This reflects two main factors. First, consistent with Fujita and Ramey (2009) and the broader search and matching literature, fluctuations in job finding account for a larger share of unemployment dynamics over the business cycle, though the precise contribution is debated. For instance, Broer et al. (2021b) argue that job separations shape the short-term response, while job finding drives longer-term dynamics. Second, in our model, job-finding risk matters not only for the unemployed but also for the employed, as workers face the possibility of job loss followed by difficulty finding re-employment. Importantly, beliefs about job finding are also more responsive than those about separation, amplifying the precautionary saving motive. Since our model focuses on non-durable consumption, these estimates likely represent a lower bound. As noted by Carroll and Dunn (1997) and Harmenberg and Öberg (2021), the impact of unemployment risk on durable goods consumption is considerably larger.

Allowing for Heterogeneous Risks and Beliefs

Figure 13 simulates consumption fluctuations for each education group separately, under the alternative assumption that job risks vary ex-ante by education level. This assumption is motivated by the findings in Section 4.2, which show that lower-education groups are slower to adjust their perceptions of separation risk, despite facing larger fluctuations in those risks. In contrast, it is the middle-education group whose beliefs about job finding are the most sluggish in responding to real-time changes. We quantify the role of both misperceived risks and overall precautionary saving motives for each group. We calibrate the discount factor of low- and middle-education groups to target a quarterly MPC of 0.34, the MPC reported by Fuster et al. (2021) for individuals with less than a bachelor's degree. The discount factor of the high education group is calibrated to target a quarterly MPC of 0.27, the MPC reported by Fuster et al. (2021) for bachelor's degree holders and above.

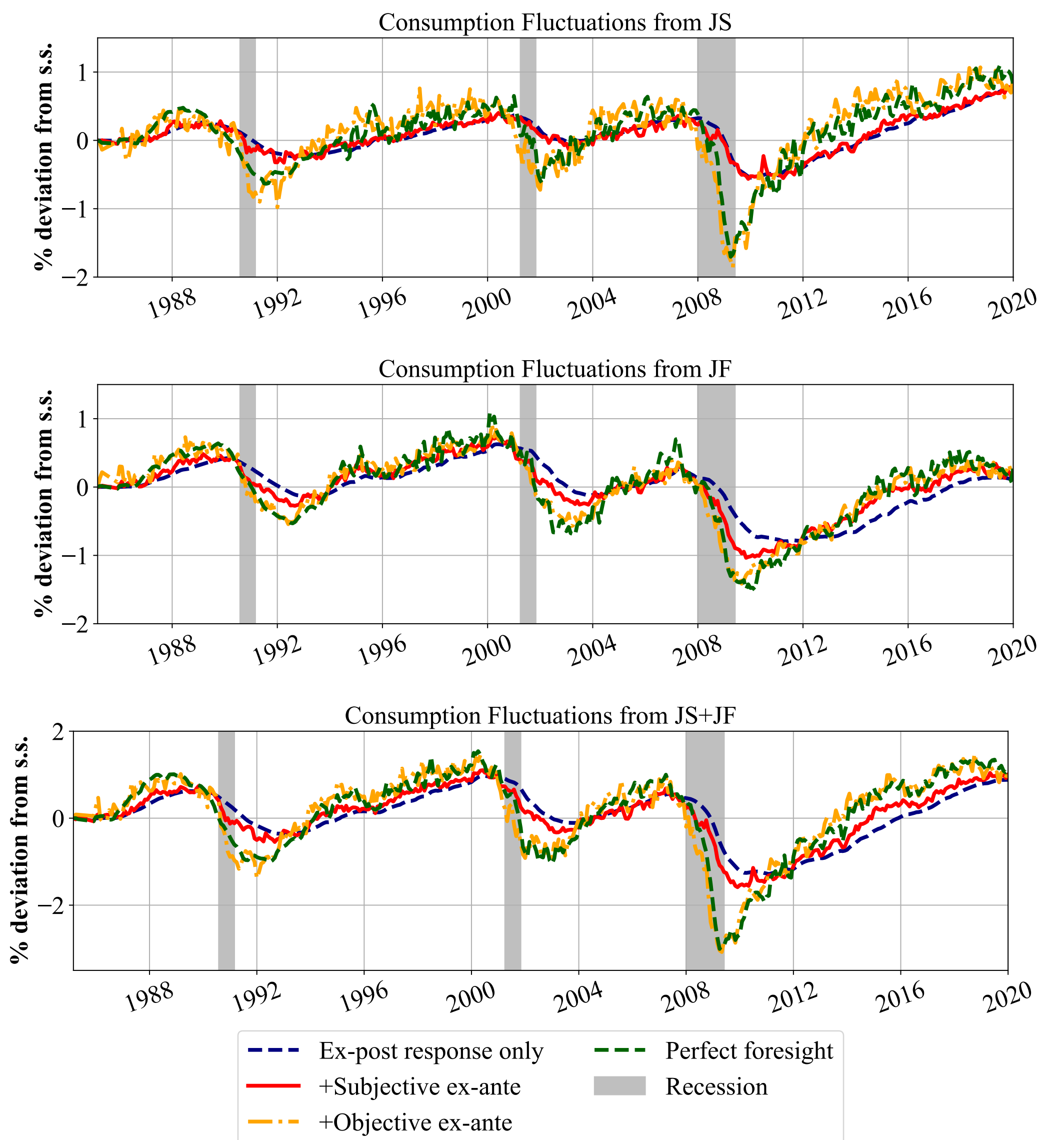
Two key findings emerge. First, as expected, the low-education group exhibits the largest ex-post consumption response during recessions, reflecting the interaction between the higher volatility of their realized job transitions and their higher MPC. Second, the high-education group shows a stronger precautionary response overall, driven by their greater sensitivity in updating beliefs. This pattern is evidenced by a smaller gap between their subjective and objective responses, and a larger gap between their subjective and ex-post responses.

Our group-specific analysis has an aggregate implication. When the workers most exposed to cyclical job risks are also the least responsive in updating their beliefs and engaging in self-insurance, the result is a sharper drop in consumption at the onset of shocks. Such interaction of risk exposure and underinsurance due to sticky risk perceptions creates a potential amplification mechanism for aggregate consumption—not through its overall cyclicality, but through the uneven distribution of responses across groups. While heterogeneous risk exposure does not inherently amplify the aggregate impact of job risks, it can do so when exposure is positively correlated with underinsurance. Our findings suggest this condition holds empirically, as those facing more cyclical risks appear especially prone to underreacting to changes in job risk.

6 Conclusion

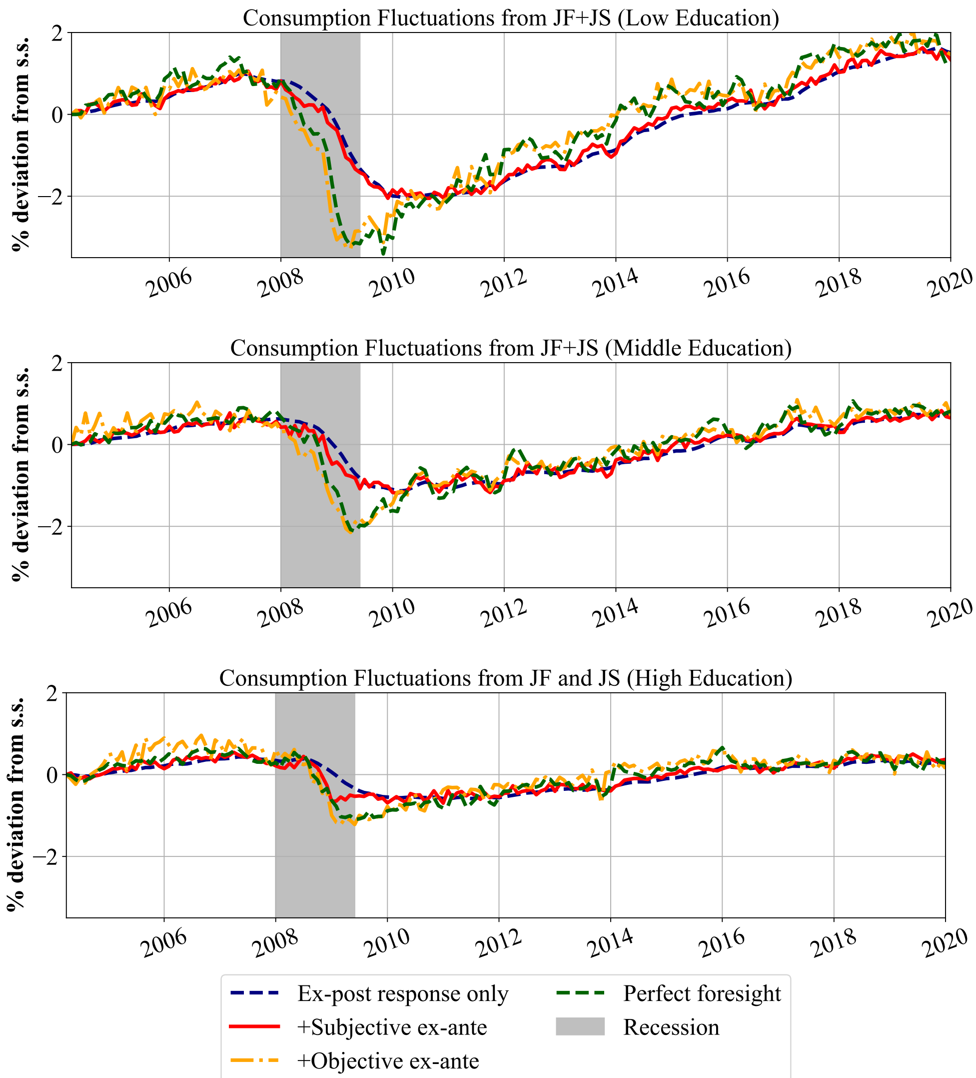
More people lose jobs and fewer people find jobs in recessions than in normal times. But do people see these changes coming? This paper asks if business cycle movements in job risks are perceived by the average and heterogeneous households who are exposed to different degrees of job risks. The answer to such a question matters because it affects the relative importance of consumption slump in recessions due to ex-ante heightened risks or unexpected ex-post shocks. This paper finds that the average risk perceptions, primarily those regarding job loss, are slow to reflect the unfolding job risk movements along business cycles, therefore limiting the ex-ante channel in driving consumption response and the degree of self-insurance, resulting in a larger impact by ex-post shock response. Meanwhile, job-finding beliefs are less rigid and even overreactive, inducing sizable precautionary saving responses. In addition, the footprints of aggregate market labor conditions are widely heterogeneous, as revealed by substantial heterogeneity in perceived job risks. It is not the average worker, but the marginal one, who is particularly exposed to business cycle fluctuations that matter for aggregate demand fluctuations due to counter-cyclical job risks. We show the quantitative importance of aggregate and distributional consumption drop due to precautionary savings, misperceived risks, and unexpected income shock response.

Figure 12: Consumption Fluctuations due to Unemployment Risks



Note: The figure compares the partial-equilibrium aggregate consumption deviations from the model's steady state, simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition rates. We also plot dynamics implied from the perfect foresight, where agents fully anticipate the actual realized shocks to job flow rate.

Figure 13: Consumption Fluctuations due to Unemployment Risks by Education



Note: The figure compares for each education group their partial-equilibrium aggregate consumption deviations from the model's steady state, simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition rates. In addition, we also plot dynamics implied from perfect foresight, where agents fully anticipate the actual realized shocks to job flow rate.

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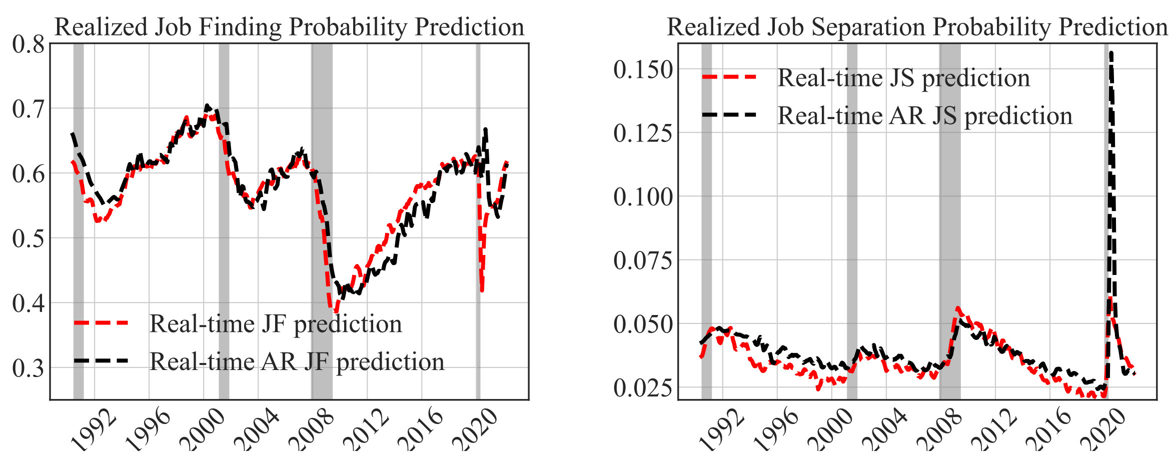
A Additional Empirical Results

A.1 Additional results with real-time forecasting of job risks

Figure A.1 compares the real-time machine-efficient forecasts of job risks based on the LASSO with one from an AR(1) model using only the 3-month lag of the realized job flow rate. The two closely move with each other. The mean square errors (MSE) from the two are almost equal for both job finding and separation. This indicates that near-term job risks are highly predictable, especially in normal times. The major exceptions occurred during the Covid era.

Figure A.1: Real-time machine-efficient risks from LASSO and AR(1)



Note: Multi-variate LASSO real-time forecasts versus one from AR(1) model.

A.2 Additional results with imputation of perceived job risks

A.2.1 Cross-validation of the imputing methodology

We evaluate the performance of imputing methods used to backcast SCE job beliefs by examining if the imputed beliefs based on the 2013-2022 in-sample can successfully generate belief backcasts that match the observed expectations in the MSC. In particular, Figure A.2 plots the imputed beliefs for two series of expectations on median inflation expectations and 5-year-ahead job-separation expectations in the MSC based on 2013-2022 in-sample. They have an impressively large degree of co-movement with the observed data. We are particularly careful to exclude any indices in the MSC that are directly correlated to the target expectation series. They provide a strong external validation of our belief imputation methods.

Figure A.2: Imputed beliefs versus observed expectations in the MSC

Note: the figure plots the imputed beliefs in the MSC regarding job-loss probability over the next five years, the inflation over the next year, interet rate expectation index and unemployment rate expectation index, relative to their actual series in the MSC, respectively.

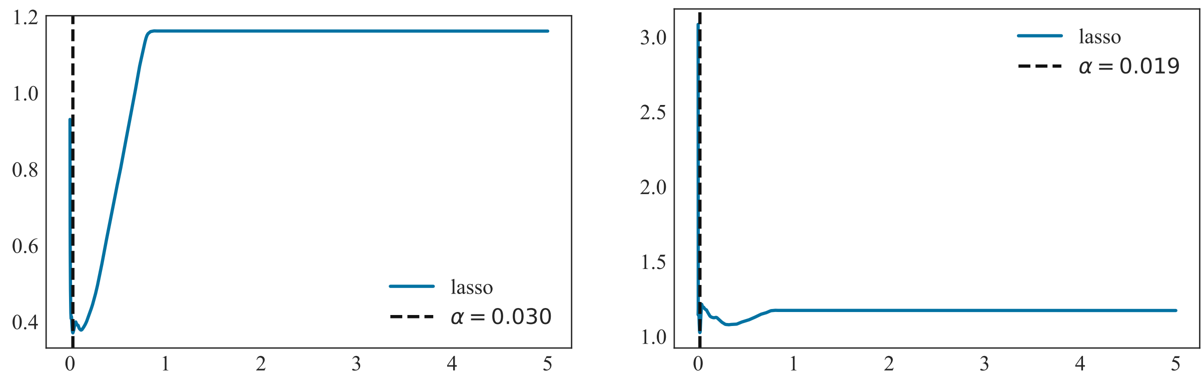
A.2.2 Hyper-parameter tuning of the LASSO model using cross-validation

Figure A.3 plots the model score, i.e., out-of-sample average MSE from k-fold samples, under various values of α.

A.2.3 Inclusion of the pandemic era

Figure A.4 compares the imputed job risk belief relied upon pre-2020 sample as the in-sample of the LASSO model, with one relied upon as an extended sample covering the Covid era (2020-2022). The gap between the two series reveals a possible structural break in the relationship between job perceptions and other household expectations and macroeconomic conditions. However, such a different choice of in-sample period of the belief imputation does not significantly alter the patterns of the imputed out-of-sample job beliefs. The major exception was the job-separation perceptions in the early 1980s.

Figure A.3: Model selection using cross-validation



Note: Mean square error scores under different penalization parameters α of the LASSO model.

A.2.4 Selected covariates of perceived risks

Figure A.5 reports the 10 most important variables selected from the LASSO model of imputation of perceived job risks, ranked by the absolute value of their estimated coefficients associated with the normalized value of each variable.

A.2.5 Imputed beliefs by education group

Figure A.7 plots the in-sample fitted and out-of-sample imputed perceptions of the job-finding and job-separation rates for low-, middle-, and high-education groups, versus the realized rates for each group.

A.3 Additional evidence for belief distortions over business cycles

Instead of calculating peak-to-trough values of job risks as in Figure 8, Figure A.8 plots the average job-finding/separation rates in normal times versus recessions and their average ratios, which show largely similar business cycle patterns of realized transition rates, risk forecasts and perceived job risks.

Figure A.4: Imputing beliefs including or excluding Covid era

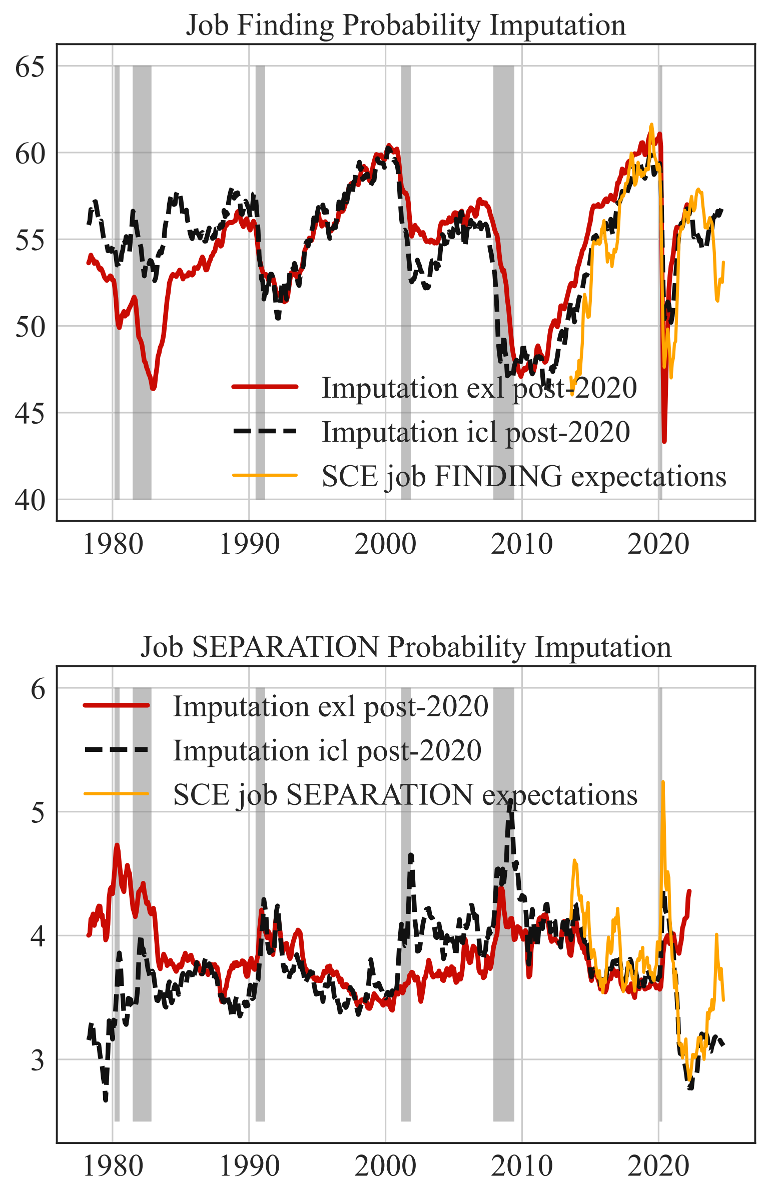
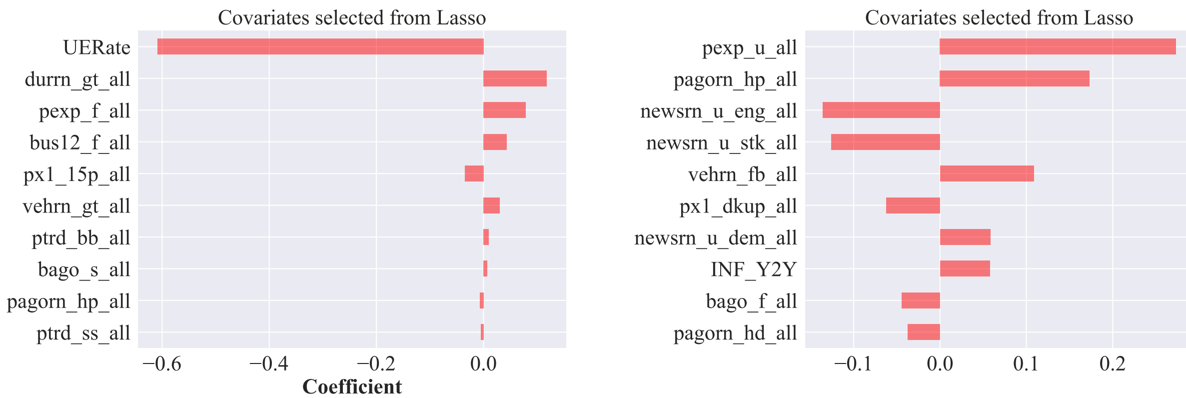


Figure A.5: Selected variables of LASSO model of perceived job risks



Note: selected variables ranked by the absolute value of their estimated coefficients in the LASSO imputation model for perceived job finding (left) and job separation (right). The in-sample is between 2013-2020. UERate: real-time unemployment rate. Durrn_gt_all: good time to buy durables. Pexp_f_all: expecting better personal finance one year from now. Bus12_f_all: better nationwide business conditions a year from now. Px1_15p_all: expected inflation above 15 percent. Vehrn_gt_all: good time to buy vehicles. ptrd_bb_all: better off financially a year ago and better off a year from now. bago_s_all: same business conditions compared to a year ago. Pagorn_hp_all: worse financial situation than a year ago due to higher prices. Ptrd_ss_all: same personal finance compared to a year ago and will be the same a year from now. Pexp_u_all: worse personal finance one year from now. Newsrn_u_eng_all: heard unfavorable news about the energy crisis. Newsrn_u_stk_all: heard about unfavorable news regarding the stock market. Vehrn_fb_all: a bad time to buy vehicles due to uncertain future. Px1_dkup_all: do not know about future inflation. Newsrn_u_dem_all: heard unfavorable news about lower consumer demand. INF_Y2Y: real-time annual realized inflation rate. Bago_f_all: better business conditions compared to a year ago. Pagorn_hd_all: worse personal finance due to higher debt.

A.4 Additional regression results

Table A.1: Regression results of realized on perceived job finding probability

	$\widetilde{JF}$	$\widetilde{JF}^{p25}$	$\widetilde{JF}^{p50}$	$\widetilde{JF}^{p75}$	$\widetilde{JF}^{LEdu}$	$\widetilde{JF}^{MEdu}$	$\widetilde{JF}^{HEdu}$
$\widehat{JF}$	0.471***	1.234***	0.623***	0.204***	0.573***	0.313***	0.484***
	(0.028)	(0.071)	(0.039)	(0.014)	(0.060)	(0.032)	(0.043)
Const	2.088***	-1.542***	1.572***	3.608***	0.190***	0.359***	0.275***
	(0.113)	(0.291)	(0.160)	(0.054)	(0.029)	(0.017)	(0.025)
Adj. R^2	0.791	0.801	0.748	0.564	0.522	0.567	0.575
N	386	386	386	386	218	218	218

Notes: The table reports the regression results of equation 6, 11, 13. *, **, and *** represent significance of the coefficient at the 10%, 5%, and 1% levels. Note that $\widehat{JF}$ for education levels is the machine efficient forecast of the job finding rate by education level.

Table A.2: Regression results of realized on perceived job separation probability

	$\widetilde{JS}$	$\widetilde{JS}^{p25}$	$\widetilde{JS}^{p50}$	$\widetilde{JS}^{p75}$	$\widetilde{JS}^{LEdu}$	$\widetilde{JS}^{MEdu}$	$\widetilde{JS}^{HEdu}$
$\widehat{JS}$	0.192***	0.451***	0.684***	0.297***	0.155***	0.282***	0.217***
	(0.028)	(0.037)	(0.073)	(0.047)	(0.046)	(0.068)	(0.057)
Const	1.110***	-0.420***	1.063***	2.504***	1.090***	0.992***	1.151***
	(0.034)	(0.045)	(0.088)	(0.057)	(0.080)	(0.086)	(0.041)
Adj. R^2	0.225	0.538	0.514	0.197	0.326	0.428	0.378
N	386	386	386	386	218	218	218

Notes: The table reports the regression results of equation 7, 12, 13. *, **, and *** represent significance of the coefficient at the 10%, 5%, and 1% levels. Note that $\widehat{JS}$ for education levels is the machine efficient forecast of the job separation rate by education level.

Table A.3: Regression results of realized on perceived job finding probability (with lags)

	$\widetilde{JF}$	$\widetilde{JF}^{p25}$	$\widetilde{JF}^{p50}$	$\widetilde{JF}^{p75}$	$\widetilde{JF}^{LEdu}$	$\widetilde{JF}^{MEdu}$	$\widetilde{JF}^{HEdu}$
$\widehat{JF}$	0.435***	1.064***	0.588***	0.192***	0.657***	0.349***	0.533***
	(0.085)	(0.239)	(0.115)	(0.040)	(0.221)	(0.076)	(0.156)
$\widehat{JF}_{t-3}$	0.039	0.182	0.035	0.013	-0.092	-0.038	-0.053
	(0.083)	(0.226)	(0.111)	(0.039)	(0.213)	(0.077)	(0.152)
Const	2.078***	-1.593***	1.569***	3.605***	0.194***	0.360***	0.277***
	(0.110)	(0.258)	(0.155)	(0.054)	(0.028)	(0.017)	(0.023)
Adj. R^2	0.790	0.804	0.748	0.562	0.520	0.566	0.575
N	383	383	383	383	215	215	215

Notes: The table reports the regression results of equation 6, 11, 13 with lags. *, **, and *** represent significance of the coefficient at the 10%, 5%, and 1% levels. Note that $\widehat{JF}$ for education levels is the machine efficient forecast of the job finding rate by education level.

Table A.4: Regression results of realized on perceived job separation probability (with lags)

	$\widetilde{JS}$	$\widetilde{JS}^{p25}$	$\widetilde{JS}^{p50}$	$\widetilde{JS}^{p75}$	$\widetilde{JS}^{LEdu}$	$\widetilde{JS}^{MEdu}$	$\widetilde{JS}^{HEdu}$
$\widehat{JS}$	0.271***	0.493***	0.511***	0.383***	0.108***	0.219***	0.162**
	(0.055)	(0.080)	(0.099)	(0.110)	(0.041)	(0.072)	(0.076)
$\widehat{JS}_{t-3}$	-0.090*	-0.048	0.200**	-0.100	0.072***	0.096	0.083
	(0.047)	(0.070)	(0.095)	(0.106)	(0.026)	(0.066)	(0.074)
Const	1.125***	-0.412***	1.029***	2.520***	1.048***	0.949***	1.128***
	(0.032)	(0.044)	(0.090)	(0.056)	(0.070)	(0.077)	(0.034)
Adj. R^2	0.240	0.541	0.524	0.200	0.363	0.452	0.406
N	383	383	383	383	215	215	215

Notes: The table reports the regression results of equation 7, 12, 13 with lags. *, **, and *** represent significance of the coefficient at the 10%, 5%, and 1% levels. Note that $\widehat{JS}$ for education levels is the machine efficient forecast of the job separation rate by education level.

B Additional Model Results

B.1 Heterogeneous Agent Model with Persistent Unemployment

The model is partial equilibrium and consists only of households. In particular, there is a continuum of workers of mass 1 indexed by i who face both idiosyncratic shocks to labor productivity, and stochastic transitions between employment states. A worker is either employed or unemployed. Their employment state is indexed by n_{it}. Employed households ($n_{it} = 1$) separate from employment with probability JS_t. Unemployed workers find a job with probability JF_t. Workers receive unemployment insurance.

The Bellman problem is:

$$v_t\left(\mathbf{m}_{it}, e_{it}, n_{it}\right) = \max_{\{\mathbf{c}_{it}, \mathbf{a}_{it}\}} \left\{U\left(\mathbf{c}_{it}\right)\right) + \beta \mathrm{E_t}\left[v_{t+1}\left(\mathbf{m}_{t+1}, e_{it+1}, n_{it+1}\right)\right]\}$$

subject to the budget constraint

$$
\begin{aligned}
\mathbf{a}_{it} &= \mathbf{m}_{it} - \mathbf{c}_{it} \\
\mathbf{a}_{it} + \mathbf{c}_{it} &= \mathbf{z}_{it} + (1 + r_t)\mathbf{a}_{it-1} \\
\mathbf{a}_{it} &\geq 0
\end{aligned}
$$

where $\mathbf{m}_{it}$ denotes market resources to be expended on consumption or saved into a risk free asset, $\mathbf{a}_{it}$. $\mathbf{c}_{it}$ is the level of consumption and the return to the asset at time t is r_t. $\mathbf{m}_{it}$ is determined by labor income, $\mathbf{z}_{it}$, and the gross return on assets from the last period, $(1+r_t)\mathbf{a}_{it-1}$. β is the discount factor.

Worker i's at time t labor income is composed of their labor productivity e_{it} and of their un(employment) income ζ_{it}. In particular, labor income, $\mathbf{z}_{i,t}$, follows

$$
\begin{gathered}
\mathbf{z}_{i,t} = e_{i,t}\zeta_{it} \\
\log e_{i,t} = \rho_e \log e_{i,t-1} + \eta_{i,t}, \quad \eta_{i,t} \sim \mathcal{N}(0, \sigma_e^2)
\end{gathered}
$$

We assume labor productivity, e_{it}, follows an AR(1) process with persistence ρ_e and a standard deviation σ_e.

(Un)Employment income, $\zeta_{i,t}$ depends on the employment status $n_{i,t}$ between employment and unemployment.

$$
\zeta_{it} = \begin{cases} \theta_{it}, \text{ if employed} : n_{i,t} = e \\ \\ \theta_{it}\gamma, \text{ if unemployed} : n_{i,t} = u \end{cases}
$$

where θ_{it} is i.i.d mean one lognormal with standard deviation σ_θ. γ is the replacement ratio of an unemployment insurance.

Transitions between employment states follows a Markov process. In particular, the e-to-u and u-to-e probabilities are, respectively, the following.

$$
\begin{aligned}
p(n_{i,t} = e | n_{i,t-1} = u) = JF_t \\
p(n_{i,t} = u | n_{i,t-1} = e) = JS_t
\end{aligned}
$$

where JF_t and JS_t are the probability of finding and losing a job, as actually *realized* at t.

We calibrate these probabilities using the observed transition rates between employment and unemployment estimated from the CPS.

Law of Motion of Subjective, Objective and Actual Job Transitions

Workers understand that the job transitions occur through job-finding and separation following the Markov; however, their perceived probabilities of finding and separating may differ. In particular, we denote variables with a $\sim$ as workers' subjective beliefs are possibly different from their objective beliefs on those variables.

$$
\begin{aligned}
\tilde{p}(n_{i,t+1} = e | n_{i,t} = u) &= \widetilde{JF_t} \\
\tilde{p}(n_{i,t+1} = u | n_{i,t} = e) &= \widetilde{JS_t}
\end{aligned}
$$

We also define the ex-ante objective counterparts of these two probabilities as $\widehat{JF_t}^*$ and $\widehat{JS_t}^*$.

Note that both $\widetilde{JF_t}/\widetilde{JS_t}$ and $\widehat{JF_t}^*$ / $\widehat{JS_t}^*$ are forward-looking probabilities between t to $t+1$. They have not yet realized as of t and their corresponding realizations are JF_{t+1} and JS_{t+1}. We calibrate these two pairs with our measure of perceived risk or objective risk, respectively.

We assume that the job finding and job separation probabilities–subjective, objective, and actual realization–each follow distinct AR(1) processes. They differ from each other in terms of both the persistence and the realized shocks.

$$
\begin{aligned}
JF_t &= \rho_{JF} JF_{t-1} + \varepsilon_{JF,t} \\
JS_t &= \rho_{JS} JS_{t-1} + \varepsilon_{JS,t} \\
\widetilde{JF}_t &= \rho_{\widetilde{JF}} \widetilde{JF}_{t-1} + \varepsilon_{\widetilde{JF},t} \\
\widetilde{JS}_t &= \rho_{\widetilde{JS}} \widetilde{JS}_{t-1} + \varepsilon_{\widetilde{JS},t} \\
\widehat{JF}^*_t &= \rho_{\widehat{JF}^*} \widehat{JF}_{t-1} + \varepsilon_{\widetilde{JF},t} \\
\widehat{JS}^*_t &= \rho_{\widehat{JS}^*} \widehat{JS}^*_{t-1} + \varepsilon_{\widehat{JS}^*,t}
\end{aligned}
$$

In the model experiments, we estimate each equation and then recover the sequence of shocks that replicates the respective time series. We then feed these AR(1) shocks to the model to simulate time series of aggregate consumption.

Table A.5: Household Calibration in the Baseline Monthly Model

Description	Parameter	Value	Source/Target
CRRA	CRRA	2	Standard
Real interest rate	r	$1.05^{\frac{1}{12}} - 1$	5% annualized real rate
UI replacement rate	γ	0.5	50% replacement rate
Persistence of idiosyncratic income process	ρ_e	0.997	Kekre (2023)
Std dev of idiosyncratic income process	σ_e	0.057	Kekre (2023)
Std dev of log transitory shock	σ_θ	0.244	Kekre (2023)
Steady state job-finding rate	JF	0.25	CPS
Steady state job-separation rate	JS	0.017	CPS
Discount factor	β	0.988	Quarterly MPC = 0.21

$$\{\hat{\varepsilon}_{JF,t}, \quad \hat{\varepsilon}_{JS,t}, \quad \hat{\varepsilon}_{\widetilde{JF},t}, \quad \hat{\varepsilon}_{\widetilde{JS},t}\} \quad \text{for } t = 1, \ldots, T.$$

The calibration of the model is described in table A.5.

B.2 Details of the model experiments

B.2.1 Baseline model

The model experiments in Figure 12 are based on directly estimated shocks to JF/JS, $\widetilde{JF}/\widetilde{JS}$ and JF^*/JS^*. To obtain such shocks, we estimate, respectively, a monthly AR(1) model of each one of these sequences in the sample period up to the 2020 M1. The predicted residuals are the estimated shocks to realized rates, beliefs, and rational job risk, which are plotted in Figure A.9.

Figure A.10 complements Figure 13 by showing the education-specific consumption aggregation fluctuations due to job-separation and job-finding risks, separately.

B.2.2 Alternative model experiment at quarterly frequency

In this section, we report results from the baseline model experiments with a quarterly version of the model with several modifications.

Labor income is composed of permanent income p_{it} and (un)employment income ζ_{it}.

$$\mathbf{z}_{it} = \mathbf{p}_{it}\zeta_{it}$$

Permanent income is subject to shocks, $\mathbf{p}_{it+1}$ where ψ_{it} is iid mean one lognormal with standard deviation σ_ψ .

$$\mathbf{p}_{it+1} = \mathbf{p}_{it}\psi_{it+1}$$

(Un)Employment income, $\zeta_{i,t}$ depends on the employment status $n_{i,t}$ between employment and unemployment.

$$\zeta_{it} = \begin{cases} \theta_{it}, \text{ if employed} : n_{i,t} = e \\ \\ \gamma, \text{ if unemployed} : n_{i,t} = u \end{cases}$$

where θ_{it} is iid mean one lognormal with standard deviation σ_θ. γ is the replacement ratio of an unemployment insurance, which is set to be 0.5. Our benchmark model does not consider the expiration of unemployment insurance as in Kekre (2023).[16]

The employment status $n_{i,t}$ transitions between two states following a 2-state Markov process. Unlike the monthly model in baseline, the employment-to-unemployment transition probability is now jointly determined by job-finding $JF_{i,t}$ and job-separation $JS_{i,t}$ rates. The u-to-e probability is solely from job-finding probability JF.

$$\begin{aligned} p(n_{i,t+1} = e | n_{i,t} = u) &= JF_t \\ p(n_{i,t+1} = u | n_{i,t} = e) &= JS_t(1 - JF_t) \end{aligned}$$

It is also worth noting that we target a slightly lower MPC of 0.16 for this model variation. Other calibration of the quarterly version of the model is described in the table below:

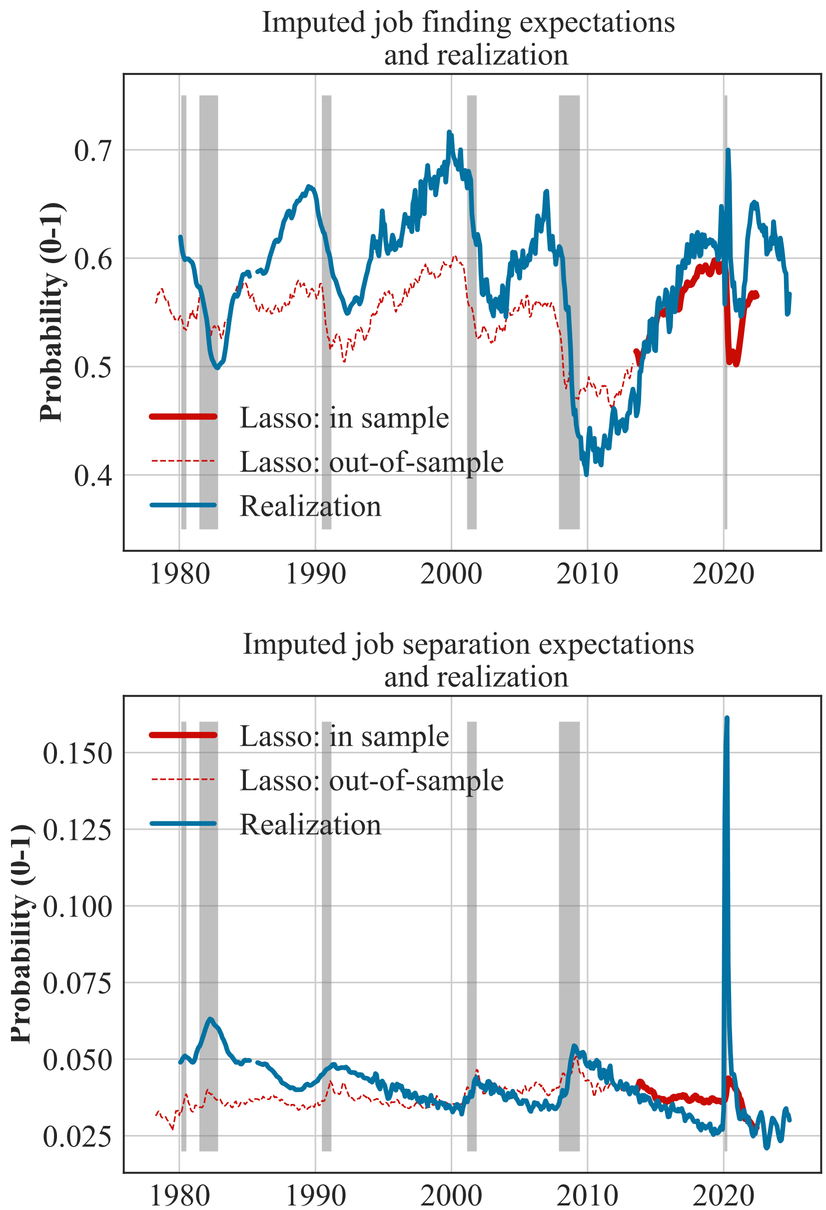
Figure A.11 and Figure A.12 plot the model results for the aggregate consumption and education-specific consumption impacts. Figure A.13 plot the underlying shocks used for the experiments.

[16] Kekre (2023) estimates the income ratios during unemployment relative to pre-displacement with and without unemployment insurance to be 0.76 and 0.55, respectively.

Table A.6: Household calibration in model at quarterly frequency

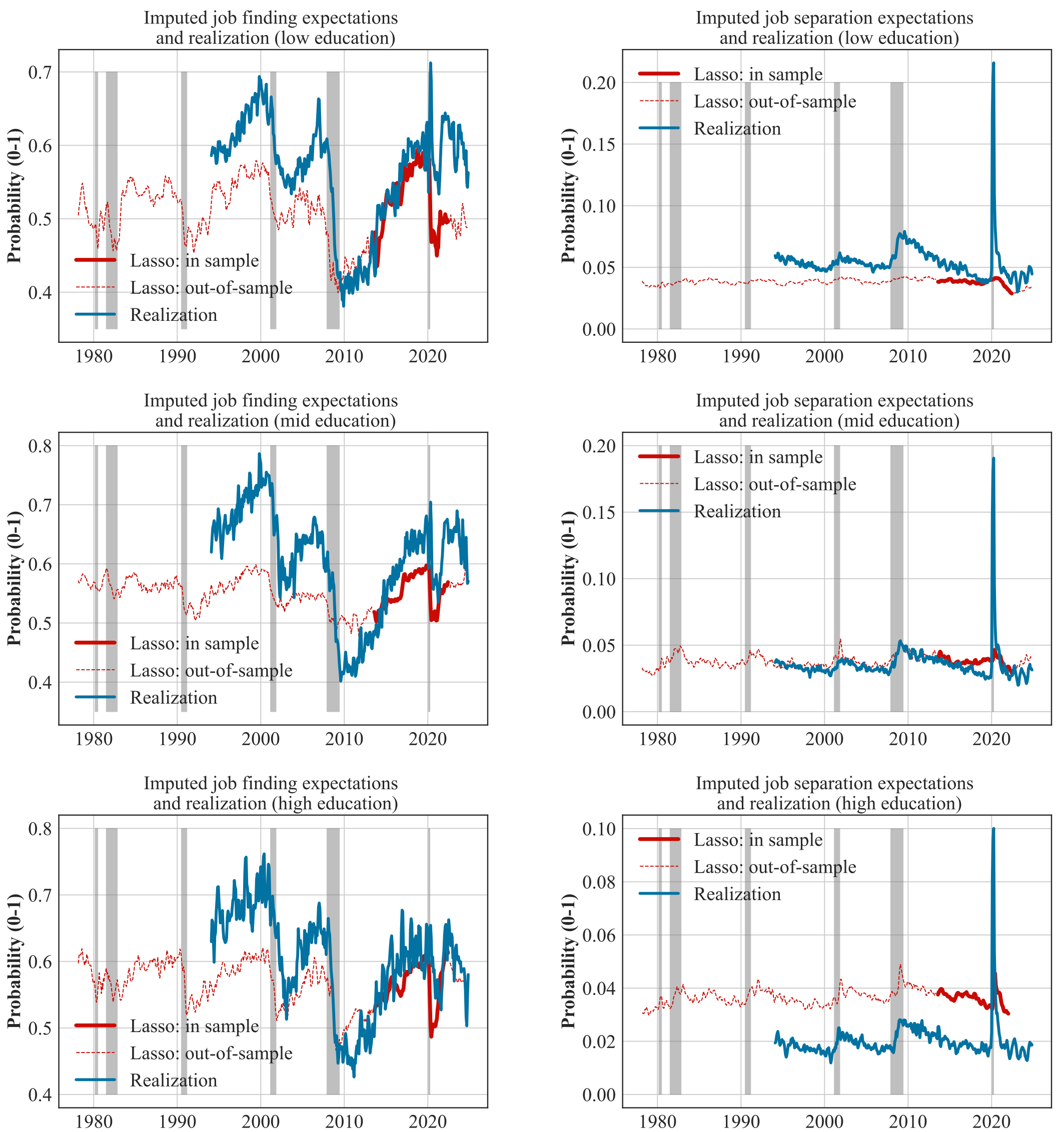
Description	Parameter	Value	Source/Target
CRRA	CRRA	2	Standard
Real Interest Rate	r	$1.03^{.25} - 1$	3% annualized real rate
Probability of Death	D	0.00625	Carroll et al. (2017)
UI replacement rate	γ	0.5	50% income drop at unemployment
Std Dev of Log Permanent Shock	σ_ψ	0.06	Carroll et al. (2017)
Std Dev of Log Transitory Shock	σ_θ	0.2	Carroll et al. (2017)
Steady state Job-Finding Rate	JF	0.58	CPS
Steady state Job-Separation Rate	JS	0.070	steady state unemployment rate=0.05
Discount Factor	β	0.976	Quarterly MPC = 0.16

Figure A.6: Imputed job-finding rate and realizations



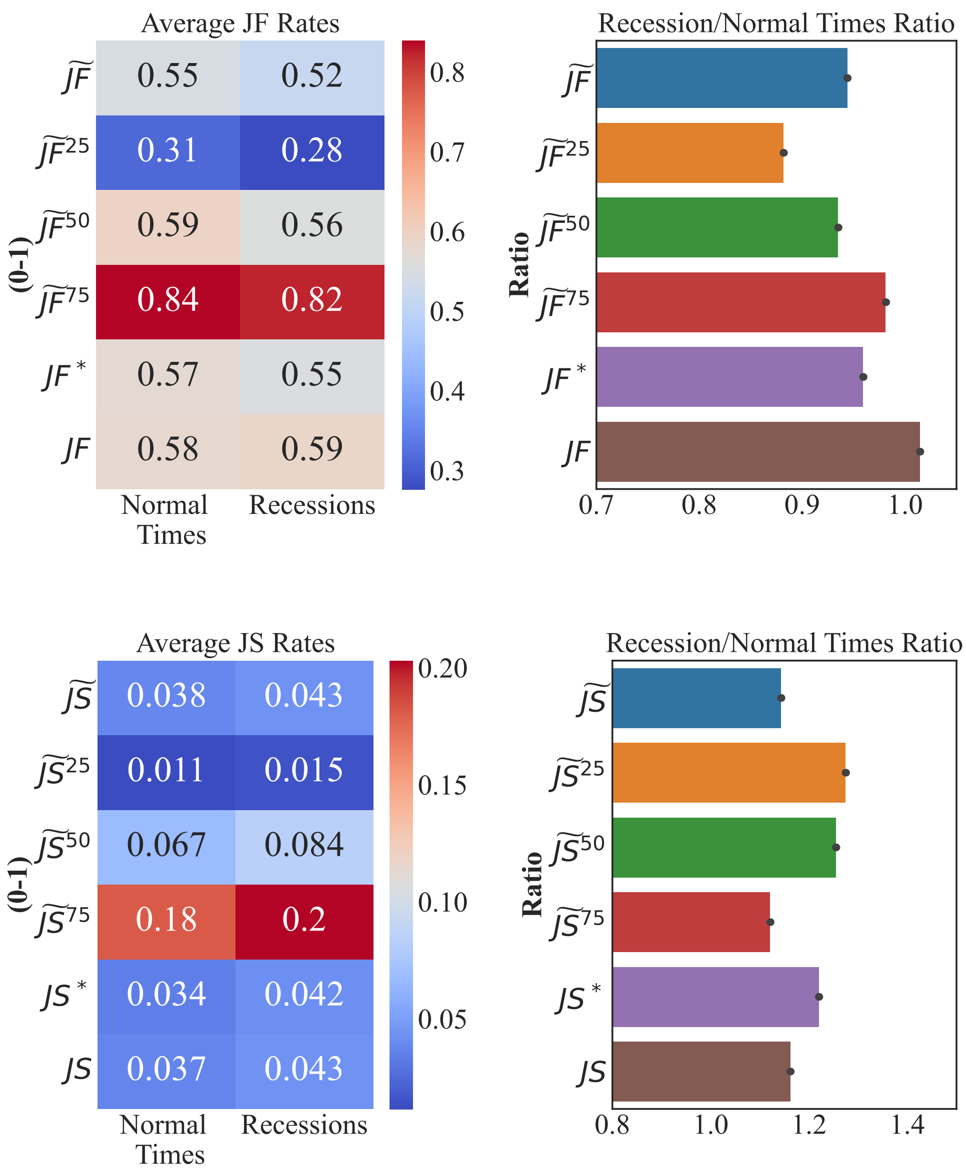
Note: Imputed perceived risks in the sample (2013-2022) and out of the sample (1980-2013) compared to realized job flow rates.

Figure A.7: Imputed beliefs by education



Note: These figures plot the imputed perceived job-separation and job-finding rates by low, middle and high educations, respectively, using the same methodology and the education-specific expectations in the MSC.

Figure A.8: Business Cycle Patterns of Risks and Perceptions: Normal Times versus Recessions

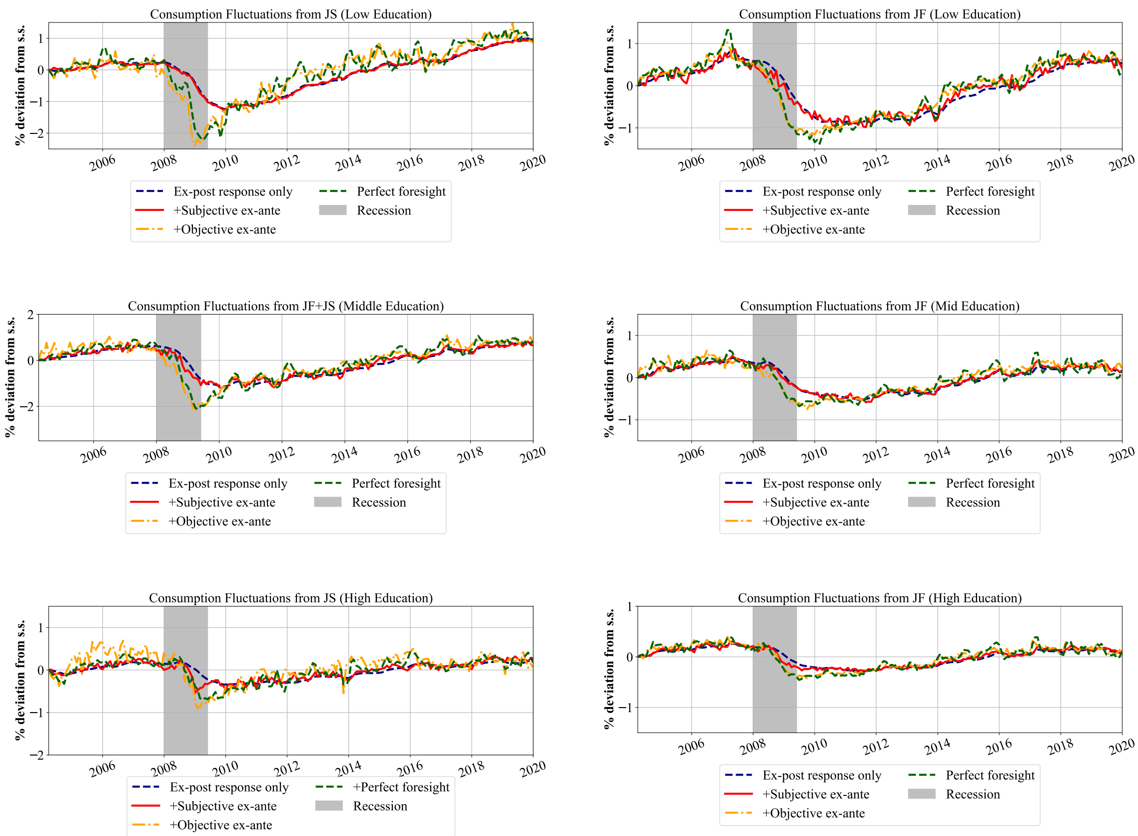


Note: The left tables report the average perceived job risks, perceived job risks at different quantiles, real-time job risks, and realized job transition rates in normal times and NBER-labeled recessions. The right figures plot the ratio of these rates between recessions and normal times. The sample period is 1990-2024.

Figure A.9: Shocks to realized job transitions, perceptions and rational forecasts

Note: The figure plots the estimated shocks used for the experiments in Figure 12, based on an estimation of a monthly AR(1) model on demeaned $JS_t \& JF_t$, $\widetilde{JS}_t \& \widetilde{JF}_t$, and $JS^*_t \& JF^*_t$. The sample period is between 1984 and 2020.

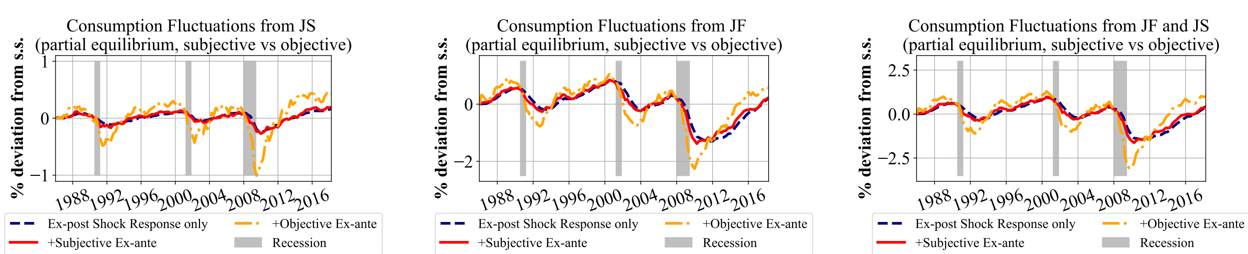
Figure A.10: Consumption Fluctuations due to JS and JF Risks: by Education



Note: The figure compares for each education group their partial-equilibrium aggregate consumption deviations from the model's steady state by simulations based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition rates.

Figure A.11: **Quarterly** Consumption Fluctuations due to Unemployment Risks

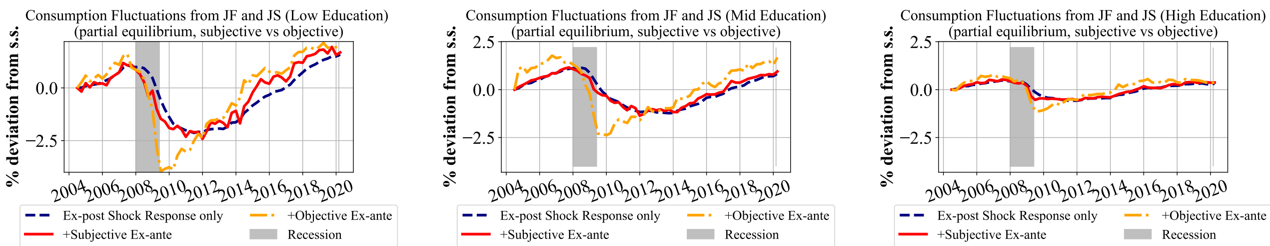
Job separation | Job finding | Combined



Note: The figure compares the partial-equilibrium aggregate consumption deviations from its steady state simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition rates. The results are from a quarterly variation of the baseline model set at the monthly frequency.

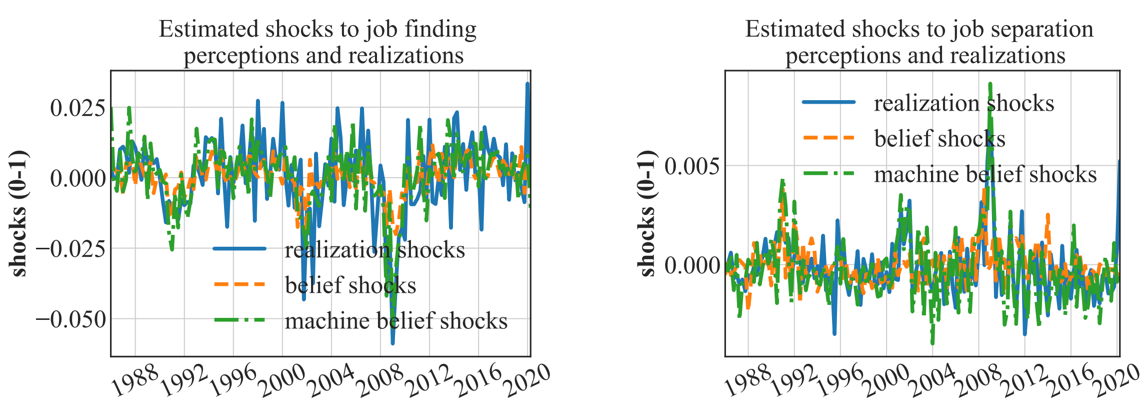
Figure A.12: **Quarterly** Consumption Fluctuations due to Unemployment Risks: by Education

Low Education | Middle Education | High Education



Note: The figure compares for each education group their partial-equilibrium aggregate consumption deviations from its steady state simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition rates. The results are from the quarterly version of the baseline model with modified assumptions.

Figure A.13: **Quarterly** shocks to realized job transitions, perceptions and rational forecasts



Note: The figure plots the estimated shocks used for the alternative experiments with the quarterly model, based on an estimation of a quarterly AR(1) model on demand $JS_t\&JF_t$, $\widetilde{JS}_t\&\widetilde{JF}_t$, and $JS^*_t\&JF^*_t$. The sample period is between 1984 and 2020.