Perceived Unemployment Risks over Business Cycles*

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Abstract

We backcast subjective expectations on job finding and job loss 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 loss expectations in reflecting changes in real-time job risks and their substantial heterogeneity across observable and unobservable dimensions. Calibration of these facts to a heterogeneous-agent consumption-saving model with unemployment suggests that about one-third of the drop in aggregate consumption during the Great Recession stemmed from precautionary responses to heightened perceived job risks, although belief stickiness limited the role of ex-ante self-insurance.

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 the state-of-the-art macroeconomic model of incomplete markets with search and matching frictions, countercyclical unemployment risk amplifies business cycle fluctuations.[1] This amplification stems from two channels. The first is a precautionary saving channel whereby heightened fears of unemployment dampen consumption further reducing aggregate demand. The second is an income channel, where a reduction in consumption occurs due to realized income losses from unemployment.

Both these channels are typically disciplined by the realized probability of unemployment calculated from microdata. However, given the large body of evidence on how households' macroeconomic expectations deviate from the full-information-rational-expectations (FIRE), it is natural to ask whether perceptions of unemployment risk align with the true probability of losing a job. An underreaction to increased unemployment risk could lead to under-insurance, leaving households vulnerable as they are unable to smooth their consumption in response to shocks. In contrast, an overreaction to increased unemployment risk may induce a substantial fall in aggregate demand.[2]

This paper measures how (a) perceived, (b) objective, and (c) realized unemployment risks evolve over the business cycle. The first two measures capture ex-ante expectations of unemployment risks, while the third is the ex-post realization of the fraction of individuals transitioning into unemployment. Under rational expectations, models of the business cycle featuring countercyclical unemployment risk assume that (a) and (b) are identical. Moreover, the assumption of perfect foresight, commonly used in the empirical implementation of this class of models, implies that (b) and (c) are equivalent. We show that neither assumption proves consistent with the data.

In particular, survey expectations of job transition probabilities are used to measure (a), while the method of real-time machine learning forecasting is used to create a proxy of (b). Separately measuring these two allows us to characterize the difference between subjective job risk perceptions and their ex-ante rational benchmark. The conventional approach of studying expectation formation relies upon a direct comparison of (a) and (c), i.e. the forecast errors, to provide evidence for deviations from FIRE. The existence of ex-post forecast errors, however, does not necessarily imply ex-ante deviations in expectations as the ex-post realizations may contain realized shocks that could not have been expected even by rational agents. This complements several existing studies that document biases in job beliefs by only comparing (a) and

[1] Counter-cyclical idiosyncratic job risks are one of the important drivers of aggregate business cycle fluctuations(Bayer et al., 2019; Den Haan et al., 2018; Broer et al., 2021b; Graves, 2020). Other papers study the effect of unemployment insurance in stabilizing such fluctuations and its distributional impacts(McKay and Reis, 2021; Boone et al., 2021; Kekre, 2023).

[2] See, for instance, Den Haan et al. (2018).

(c).[3]

Although the perceived job risks in survey data directly measure (a), such data is not available until the most recent decade. Therefore, we backcast the series of perceived job risks back to 1978 when there were no directly surveyed beliefs of the same kind. Utilizing the correlation between perceived job risks in New York Fed's *Survey of Consumer Expectations* (SCE) since 2013 and the Michigan Survey of Consumers (MSC) in which numerous other expectations have been measured for a much longer history, we backcast the perceived job risks into the past four decades. This allows our analysis to span multiple business cycles and empirically measure the strength of precautionary motives, circumventing the assumption that ex-post outcomes are equal to ex-ante perceived risks.

To measure (b), we adopt a real-time machine-learning forecast framework following the methodology of Bianchi et al. (2022). In particular, we generate real-time forecasts of labor market transition rates using numerous real-time variables that include economic conditions, household expectations on the future of the macroeconomy, and personal finance. We also incorporate professional forecasts and other macroeconomic series that may predict subsequent labor market changes. Real-time predicted job transition rates approximate the best possible risk forecast of the labor markets, hence, serving as a good proxy for the objective ex-ante risks.

Specifically, for each point of the time in the sample, we perform a LASSO (least absolute shrinkage and selection operator) estimation to select a subset of variables from a set of 600 time series of real-time macroeconomic conditions and other forward-looking expectations that best predict subsequent labor market flows. We then generate a one-step-ahead forecast using the machine-efficient model. We include survey perceptions of job risks in the prediction model to account for the fact that ex-ante perceptions reported in surveys, although measures of perceptions, turn out to be predictive of ex-post transition rates. This also nests a special case where perceptions perfectly predict ex-post transition rates. Household expectations in MSC are strongly predictive of labor market transition rates, suggesting agents do incorporate useful information in forming expectations on unemployment risk. In addition, not only do real-time conditions correlate with expectations; but also forward-looking economic decisions, such as durable spending intentions. Finally, several series in the MSC provide causal attributions, e.g. not a good time to buy durables because one cannot afford them, are also important predictors.

With direct measures of (a) and (c) and a good proxy for (b), we document two main findings. First, ex-ante subjective job risks, especially regarding job-finding rates, are highly predictive of ex-post job transition rates. This suggests that average households incorporate useful information to form views about their job risks. It is also consistent with the finding in the literature that agents possess advance information about future job transitions. Second,

[3] See for instance, Stephens Jr (2004), Spinnewijn (2015), Mueller et al. (2021), Balleer et al. (2021), etc.

perceived risks do not perfectly coincide with machine-efficient forecasts in that the former are upward biased and underreactive to the changes in the latter. Machine-efficient forecasts produced by the aforementioned procedure are found to be highly accurate in forecasting labor transition rates in the 3-month horizon. Average subjective perceptions of job risks, despite their predictive power, do not fully update synchronously with rational ex-ante risks, suggesting that they fail to efficiently incorporate all the information that predicts subsequent labor market changes.

The sluggish response in perceived job risks limits the ex-ante precautionary saving channel's role while amplifying the ex-post shock response channel. In addition, there is an important difference between normal times and crisis episodes in terms of the relative importance of two contributors of ex-post channel, one from misperceived risks, namely the gap between (a) and (b), and the truly unexpected unemployment shocks, namely the gap between (b) and (c). During normal times, the former was the key. This means households do not see the risks that are actually already unfolding and are therefore under-prepared when the unemployment happens. In a few crisis episodes such as the outbreak of the COVID-19 crisis, in contrast, it is the latter that matters more. The sudden increase in unemployment was a truly unexpected shock and could not have been perceived ex-ante even by the most informed forecasters in the economy.

We provide two explanations for why average perceived risks underreact to real-time macroeconomic labor risks. The first is information rigidity, in that households sluggishly learn about macroeconomic conditions. The second is heterogeneity, in that households face either conditional or unconditional heterogeneity in job risks. This implies that households do not need to react equally to aggregate labor market conditions. In particular, we find that workers across the distribution of perceived job risks react to true real-time risks by different degrees and exhibit various biases. This highlights the role of heterogeneity in true and perceived job risks workers face over business cycles. It is consistent with an increasing number of studies that emphasize the role of heterogeneity in job risks in amplifying aggregate demand fluctuations via unemployment risk channels.[4] Households are unevenly affected by increasing job risks in recessions. The heterogeneity in the effects of aggregate labor market flow rates on individual job risks, therefore, helps explain why average perceived job risks do not one-to-one react to the true real-time job risks.

Lastly, we quantify the aggregate demand fluctuations due to unemployment and unemployment risk allowing for sticky and heterogeneous risk perceptions in a standard Heterogeneous-agent model with persistent unemployment. Our empirical measures of perceptions and out-

[4] For instance, Patterson (2023) shows that the group of workers whose income has the largest cyclical movements also have high marginal propensities to consume.

comes tell their time-series volatility per se, but it is together with the heterogeneous households' consumption/saving sensitivity with respect to risks and shocks that governs the degree of aggregate demand fluctuations. We therefore decompose the aggregate consumption Jacobians (in the terminology of Auclert et al. (2021)) to a given shock of future job-separation and finding probability onto the ex-ante precautionary response given perceptions of such a shock, under-insurance due to misperceived risk, and ex-post shock responses. Then the decomposed Jacobians are combined with the empirically estimated shocks to perceived risk, objective risk, and realized job transitions to quantify the consumption impacts of these three channels. The second channel largely contributes to the ex-post drop in consumption. We show that allowing for subjective and heterogeneous perceptions of risks yields a more persistent drop in aggregate consumption during recessions than a model assuming rational expectation and perfect foresight. This result suggests that the strength of unemployment and unemployment risk channel in amplifying business cycles crucially depend on how risks are perceived.

Related Literature

Our paper builds on the empirical evidence of biases in job-finding expectations as documented by Mueller et al. (2021), which studies 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), Mueller et al. (2021) all found that workers over-perceive the job-finding probability, with a stronger bias with longer duration of unemployment. Conlon et al. (2018) shows such bias is due to over-optimism in perceived offer arrival rates and wage offers. Balleer et al. (2021) explores the consequences of over-optimism bias. Unlike these papers, we primarily focus 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, Stephens Jr (2004)'s evidence suggests that workers over-perceive the job loss probability compared to the realization. However, the author cautions on the 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 in 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); Hartmann and Leth-Petersen (2024) suggest that workers' perceived job risks predict the unemployment outcome reasonably well indicating advance information.

This paper builds on the literature that adopts real-time forecasting to approximate ex-ante uncertainty/risks. This is also closely related to using machine-efficient forecast as the 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 from ex-post outcomes is also made clear by Jurado et al. (2015); Rossi and Sekhposyan (2015) in measuring the macroeconomic uncertainty instead of specifically labor income risks.

Our paper directly contributes to several papers that incorporate subjective job risk perceptions in otherwise standard macroeconomic models featuring uninsured job risks. (Pappa et al., 2023; Bardóczy and Guerreiro, 2023). In addition, Morales-Jiménez (2022); Menzio et al. (2022); Rodrıguez (2023) incorporate informational frictions in standard search and matching models to resolve the volatility puzzle in the aggregate unemployment rate. Different 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 is derived from the Survey of Consumer Expectations (SCE) by the Federal Reserve Bank of New York. The SCE is 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, 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.

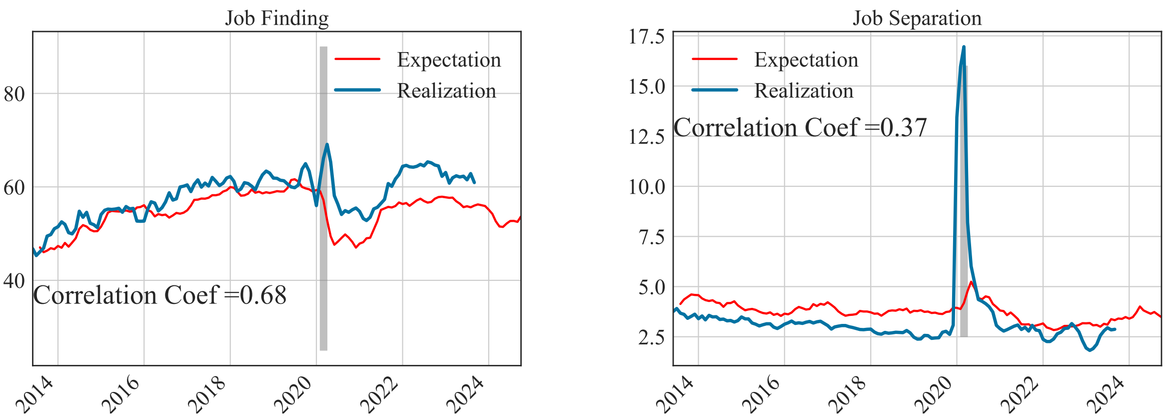
2.2 Perceived risks versus realized outcomes

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. 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 highlight the unexpected

[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}.

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); 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. 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).

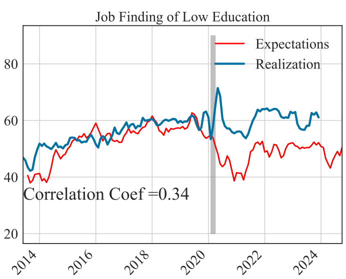
$$\mathrm{FE}^{JF}_{t,t+3} = \alpha + \beta \mathrm{FE}^{JF}_{t-3,t} + \gamma X_{t-3} + \epsilon_t, \tag{2}$$

where X_{t-3} denotes information available at time $t-3$. A key null hypothesis under FIRE is that agents do not fully react to new shocks to the underlying variable. A significantly positive β implies predictable forecast errors based on past forecast errors.[6] In particular, $\beta > 0$ suggests

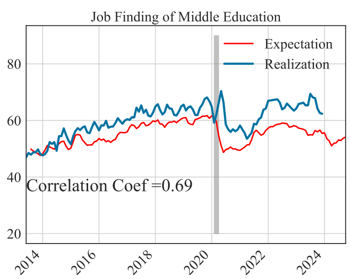
[6]A related null hypothesis in the same spirit is based on a regression of forecast errors on past information X_{t-3}, which states that γ being statistically different from zero means information available at $t-3$ predicts

Figure 2: Perceived versus realized job transitions: by education

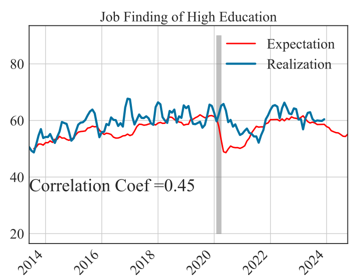
(a) JF of Low Education



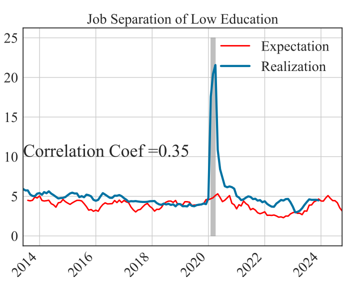
(b) JF of Middle Education



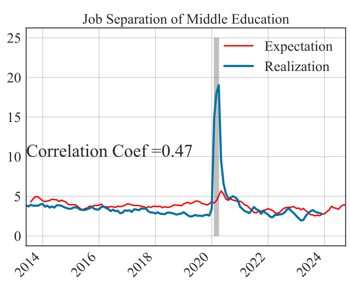
(c) JF of High Education



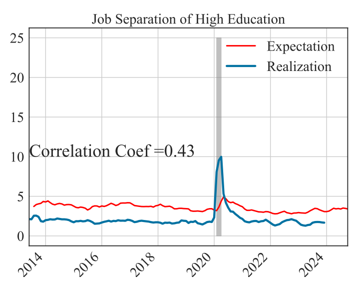
(d) JS of Low Education



(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 SCE, by different education groups, $\widetilde{JF}^{Educ}_{t+3|t}$ and $\widetilde{JS}^{Educ}_{t+3|t}$ $\forall Educ \in \{High, Mid, Low\}$, compared to their respective realization 3 months later obtained from the San Francisco Fed, JF^{Educ}_{t+3} and JS^{Educ}_{t+3} $\forall Educ \in \{High, Mid, Low\}$.

that past errors persist into future forecasts in the same direction, reflecting the presence of information rigidity.

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 separation rate with their respective 3-month-lagged values, as defined in Equation 2.

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 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

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 A.3.

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 argued in several papers, we only focus in this paper on 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.[7]

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 full-information-rational-expectations 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 optimally chosen coefficient estimates, β^{t*}, obtained through k-fold cross-validation. (Equation

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

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 Michigan Survey of Consumers (MSC).[8] 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.").[9]
- Realized job-finding and separation rates calculated from the Current Population Survey (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.

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

[9] 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 the 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 which 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.

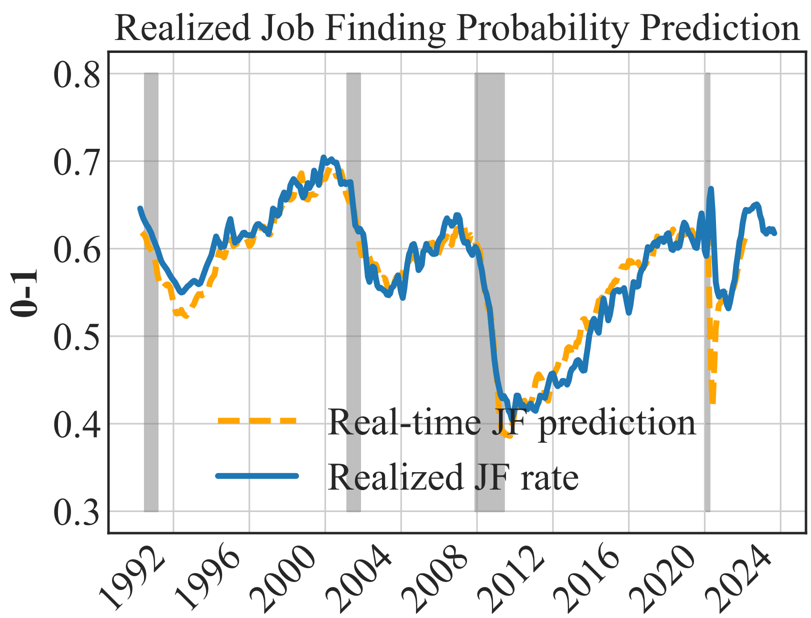
In practice, however, we cannot always rely on perceived risks by households, as such data have only been available in SCE since 2013. Instead, we indirectly include all time series on household expectations in MSC, assuming that perceived job risks are ultimately correlated with other household expectations.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

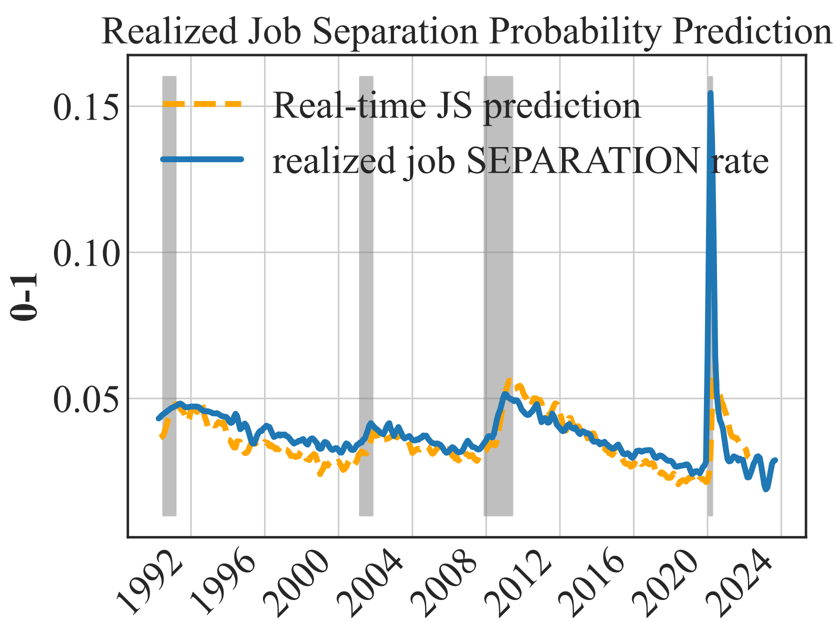
Real-time job risks. The real-time machine-efficient prediction of job transition rates is plotted in Figure 3 against the realized job transition rates. Each point on the real-time forecast risk line corresponds to a forecast generated using only the information up to that point in time, based on a selected set of predictors with the optimally chosen penalization to prevent overfitting. Overall, the machine-efficient forecasts predict subsequent labor market movements with high 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.

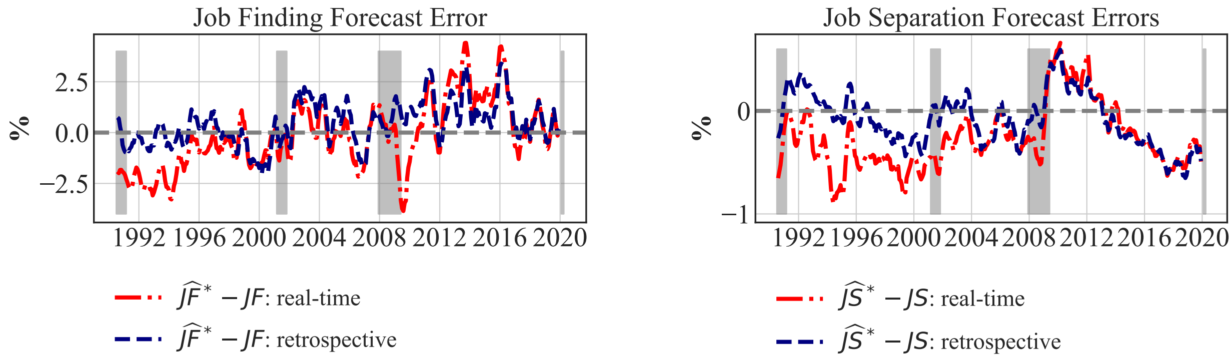
Figure 3: Machine prediction of labor market outcomes





Notes: 3-mouth-ahead job risks generated from real-time machine-learning forecasts using real-time data for each 10-year rolling window (in scale of 0-100).

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 separation rates generated by two different approaches: real-time versus retrospective forecasting.

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 impacts the subsequent transition rates.

In addition, many forward-looking variables in 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 by 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) 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 is only using 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 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 only been available in SCE since 2013. Meanwhile, a wide range of expectations have been surveyed in 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[10], we can utilize the estimated correlation between perceived job risks in SCE and other expectations in 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.

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

[10]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, 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 MSC for a much longer period. Figure A.2 in the Appendix suggests that the imputation based on only 2013-2022 in-sample can generate out-of-sample backcasts of these two expectations that almost mimic the observed data by a correlation of 80%-99%. [11]

What are the most important covariates of the perceived risks? It turns out that numerous expectation variables in MSC, such as durable purchase, news heard about economic conditions, recent experience, and future expectations of personal finance. In Figure A.6 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 role of inflation and inflation expectations also deserves 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 the 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

[11] Figure A.3 further validates that the imputed unemployment rate expectation in SCE almost perfectly correlates with the unemployment rate expectation index in MSC, although the two are not measured in the same way. This suggests that even across the two surveys the imputation methods yield valid backcasts of beliefs.

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 findings 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 SCE during this period, and the imputed job-separation perceptions turned out to be overly optimistic than 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 decide to maximize the in-sample size to include the variations in beliefs during this period, despite its possible peculiarity.

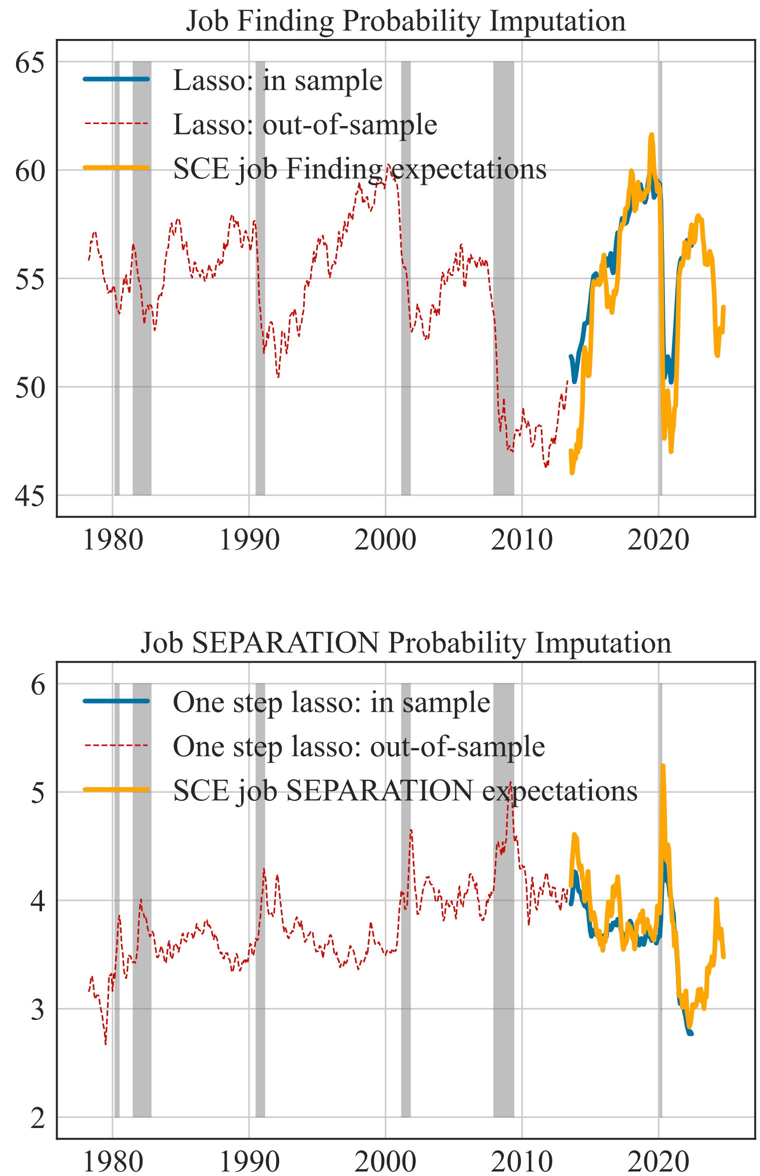
4 Perceived versus "true" risk

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 of unity corresponds to the situation where perceived job risks fully react to real-time rational risk, e.g. no under/overreactions.

For each one percentage point increase in real-time job-finding forecast, the average perceived job-finding rate increases by 0.5 percentage points. This suggests that perceived job finding follows real-time job finding rate forecasts relatively well. But a coefficient of only half is still indicative of underreaction in job finding expectations. Figure 6 plots the perceived risk, real-time machine-efficient risk forecasts, and ex-post transition rates.

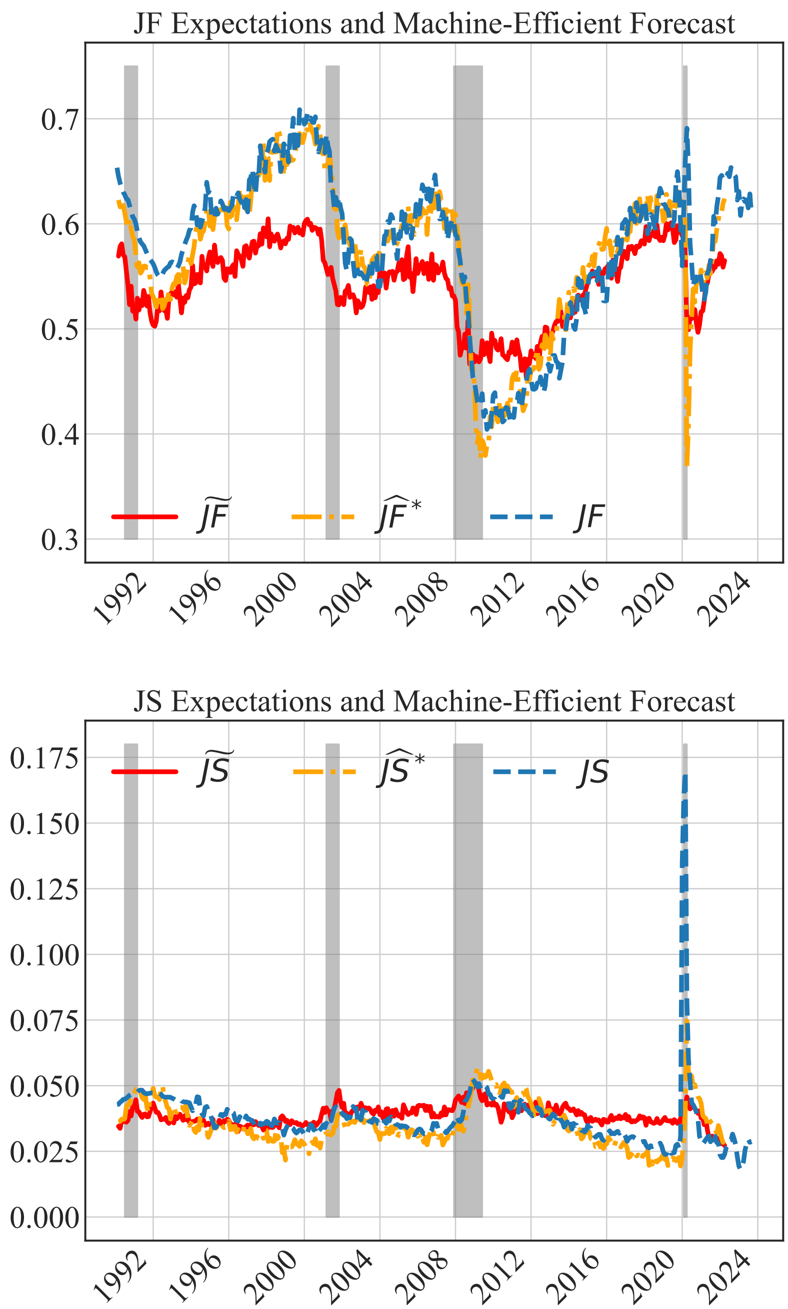
$$\log(\widetilde{JF}_{t+3|t}) = 1.92 + \mathbf{0.51}\log(\widehat{JF}^*_{t+3|t}) + \epsilon_t \tag{6}$$

Figure 5: Imputed Perceived Job Risks



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

Figure 6: Survey perceived job risks versus machine-efficient risk forecasts (0-1)



Perceived job-separation probabilities are less correlated with the real-time risk, with a regression coefficient $\widehat{JS}^*_{t+3|t}$ being 0.31, implying a one-third percentage point increase in response to each one percentage point increase in machine forecasts. Perceived job separation fails to incorporate about 80% of the predictable job separation transitions.

In addition, similar to perceived job finding, the constant term of the regression is positive, implying on average an upward bias in the perceived job separation rate.

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

4.1 Information rigidity in job beliefs

The tests presented in the previous section using forecast errors reject the null of FIRE and imply information rigidity, but it does not give us an exact degree of information rigidity that can be used to generate quantitative model implications. To do so, we follow a large body of literature to specify a widely used model of expectation formation capturing information rigidity: Sticky Expectations (SE).[12]

Sticky Expectation posits a very tractable mechanism of underreaction mechanism of beliefs in the population average. In particular, in each period, each agent learns about the most up-to-date information regarding the aggregate economy (the true underlying real-time job-finding probability) at a constant and time-independent rate of λ. Therefore, the average belief under SE mechanism follows a recursive formula as below.

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

The intuition behind this equation is that the average expectation depends on both the average expectation of the $(1-\lambda)$ fraction of agents who did not update at time t and the FIRE expectation of the λ fraction of updated agents. In the special case of full-updating, $\lambda = 1$, the above equation collapses into the FIRE case.[13]

Our estimated Equation 6 and Equation 7 can be almost squarely interpreted within the SE framework. In particular, the updating rate of job-finding expectations is about $\widehat{\lambda}^{JF} = 0.51$ and $\widehat{\lambda}^{JS} = 0.19$ for job separations. Both are significantly different from unity, rejecting the

[12] Mankiw and Reis (2002), Carroll (2003), and Coibion and Gorodnichenko (2015).

[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. 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.

null hypothesis of perfect updating.

When the lagged perceived job risks are controlled in the same regression, the coefficient remains in a similar range. In addition to the true real-time risks, we also control past information such as the realized job finding and separation flow rates or aggregate economic variables. The estimated rigidity does not vary much.

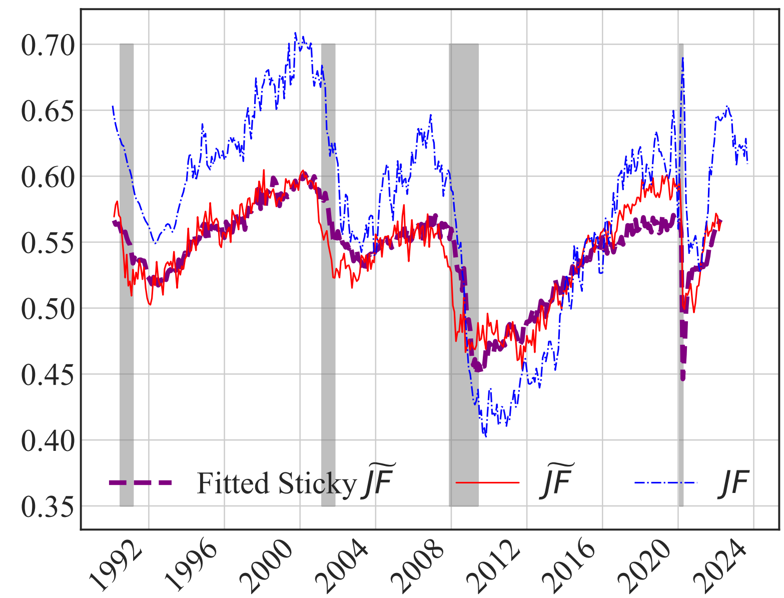
Although the information rigidity as formulated by SE model fits the correlation between perceived job risks and true real-time risks well, there remains the big gap between the SE-model-implied time series of perceived job risks $\widetilde{JF}^{SE}$ versus the observed perceived job risks $\widetilde{JF}$ as plotted in Figure 7 where we plug in the estimated $\hat{\lambda}^{JF}$ and $\hat{\lambda}^{JS}$ into the Equation 8. The perceived job risk sequences more or less center around the true real-time risks, with mild deviations. It shows less time-variations, which does capture the underreaction of perceptions to real-time conditions.

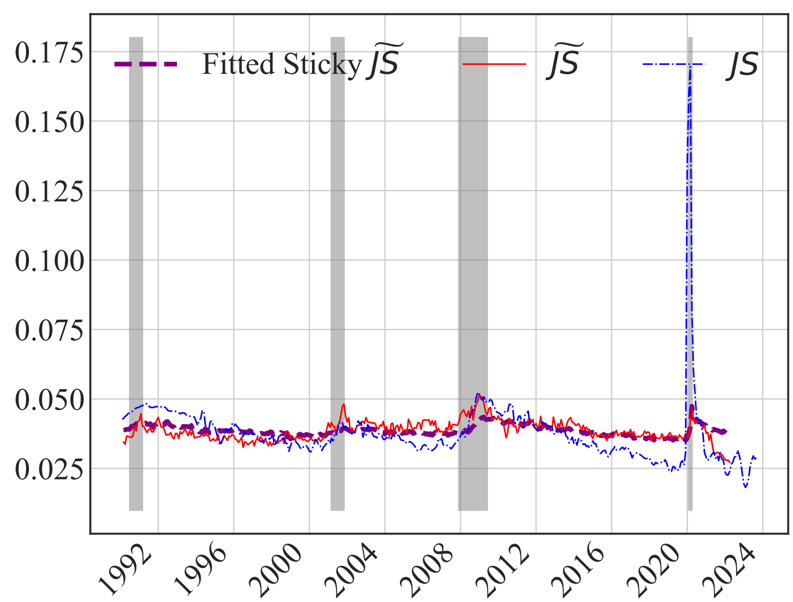
4.2 Heterogeneity in job risks

Our analysis so far assumes homogeneous job risks, which means that the perceived job risks by different workers are supposed to react to the true aggregate risk by the same degree in the absence of belief distortion. But in reality, job risks are widely heterogeneous across workers Hall and Kudlyak (2019); Ahn and Hamilton (2020); Gregory et al. (2021). So are the perceived risks, as shown in Mueller et al. (2021); Wang (2023). Guvenen et al. (2014) shows 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 (MPCs) 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 to be 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 the 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.

Figure 7: The Estimated Sticky Expectation Model of Perceived Job Risks (0-1)





Note: The figures plot the perceived job risk ($\widetilde{JF}$ and $\widetilde{JS}$) versus their fitted value based on the estimation of Equation 6 and 7, in addition to the realized job transition rates (JF and JS.), respectively.

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

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?

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

The job-finding perceptions of the 25 percentile worker in terms of their perceptions 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 75 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 25 percentile workers (almost non-reaction) to 0.68 and 0.27 for the median and 75 percentile workers, respectively.

Taken all together, these estimates suggest 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, it is 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 10 percentile of perceived job risk to the 50th percentile. The sensitivity in perceptions helps reveal who is the marginal worker.

The idea that distributional expectations contain information about the aggregate economy also echoes a few papers that show 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 the macroeconomic outcomes, because the same aggregate shock has different footprints on heterogeneous agents in the economy.

4.3 Heterogeneous perceptions of job risks

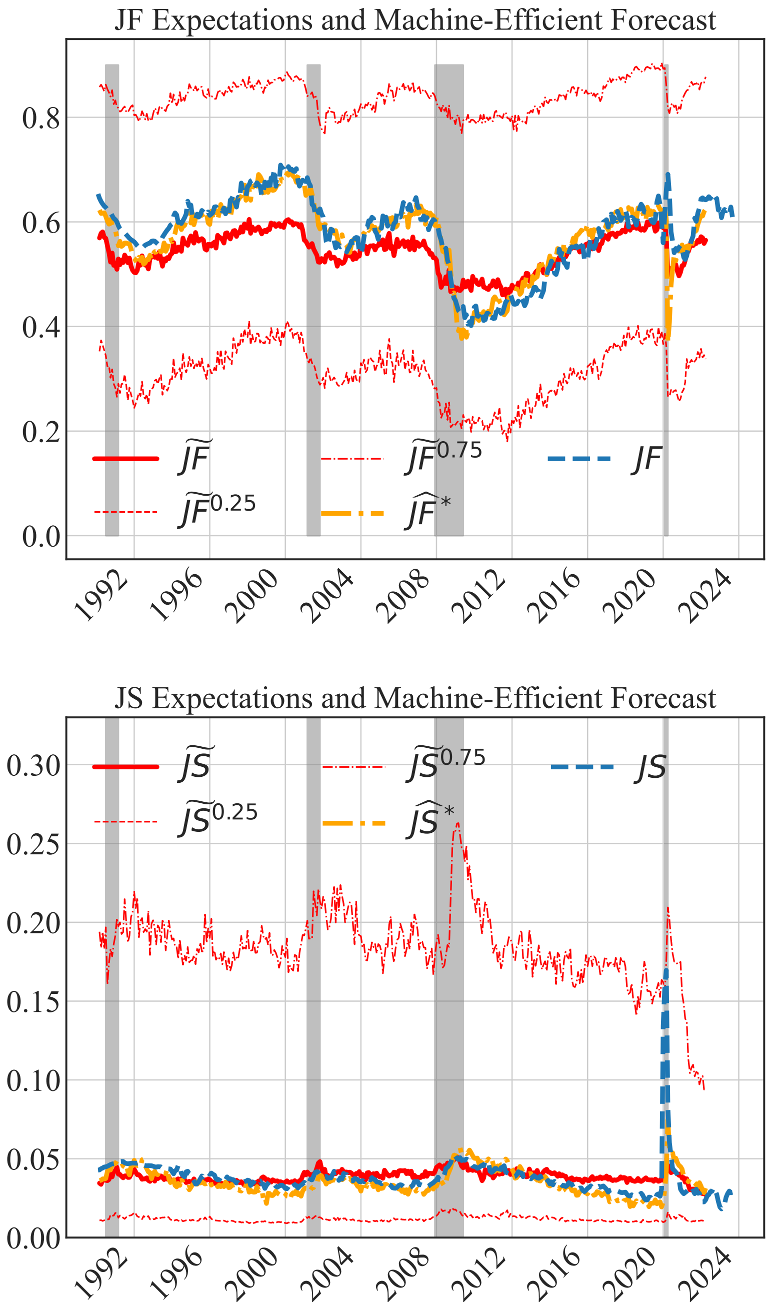
Is there heterogeneity in terms of belief distortions in addition to the heterogeneity in true job risks faced by different workers? If the workers who face the most cyclical movements in job risks tend to underperceive such movements – therefore underinsure – total consumption fluctuations amplify due 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 workers. 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 that different low-education groups underestimate the spike in job separation rate and more strongly react to the decline in job finding at the outbreak of the pandemic than 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.

Figure 8: 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.

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

5 Macro implications of perceived job risks

5.1 Shocks or risks?

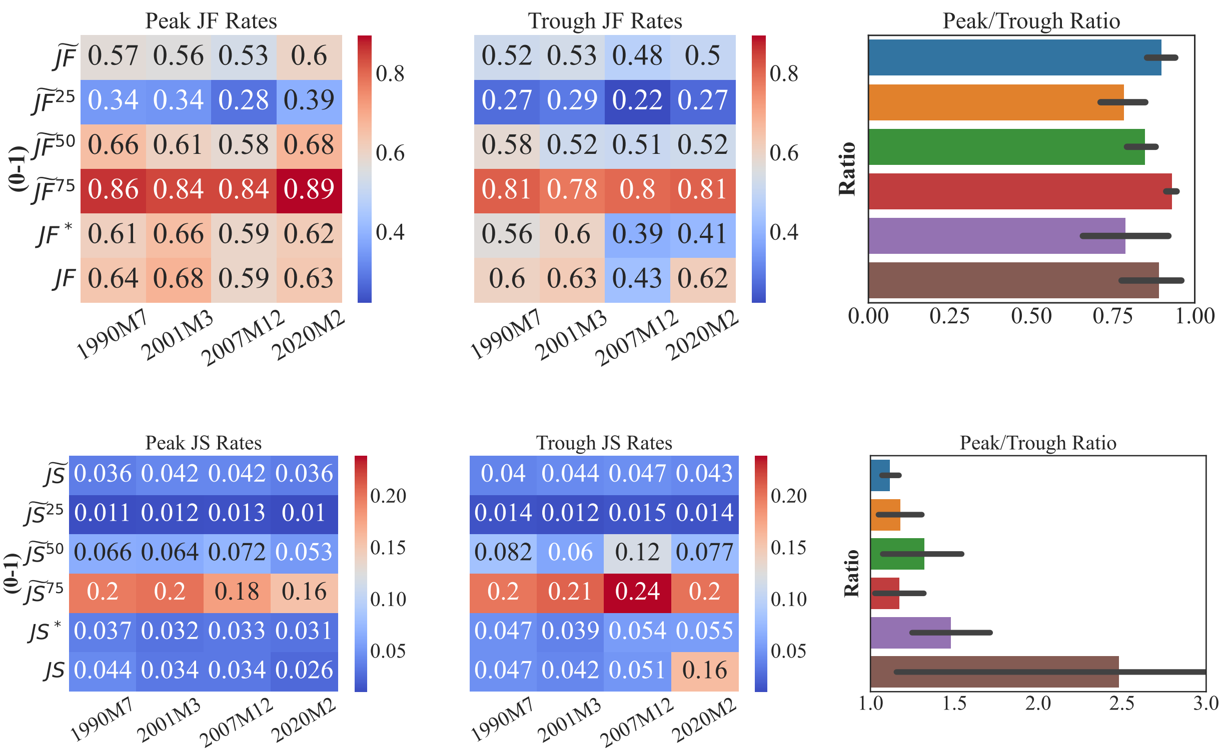
In the previous sections, with the three measures in hand, namely (a) perceived risks, $\widetilde{JF}/\widetilde{JS}$, (b) objective risks $\widehat{JF}^*/\widehat{JS}^*$, and (c) realization of job flow rates JF/JS, we have established two major findings. The first is a rejection of perfect foresight, in that even ex-ante rational and fully informed forecasts of risks don't fully predict ex-post realizations. This 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, they reflect the changes in these rates from the peak to the trough of each cycle.

Throughout our data sample 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 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,

Figure 9: 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 chart on the right plots the peak-to-trough ratios of these rates. The sample period is 1990-2024.

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 9 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 only decrease by 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 9 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 trough of a recession, more or less comparable to the realized job finding, it is the low-finding rate worker, at 25 percentile who perceive a much sharper drop by 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 only increase by 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.

5.2 Quantifying the aggregate consumption impacts of unemployment risks

Despite its debatable quantitative importance, an expanding literature has demonstrated that counter-cyclical unemployment risk is an important mechanism that amplifies business cycle fluctuations.[14] Almost all of these models, however, assume perfect foresight and full-information-rational expectations. That is, (a), (b), and (c) are assumed to be the same object.[15] Unlike them, we pay special attention to implications of the fact that it is subjectively perceived job risks, as we measured separately, that effectively govern ex-ante precautionary saving behaviors. We show in this section that the quantitative importance of the unemployment risk channel crucially depends on how such risks are perceived by the households.

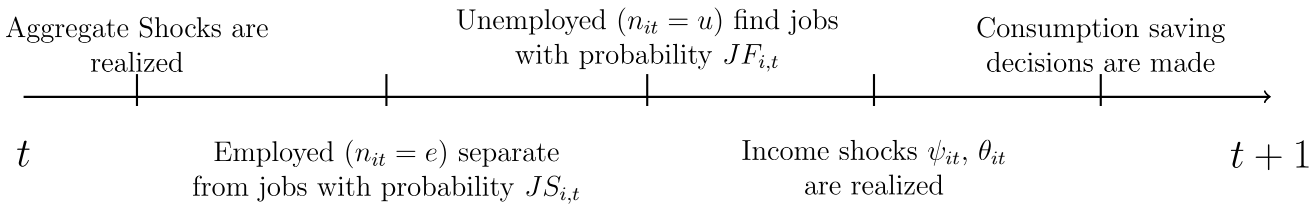
Decomposition of consumption Jacobians

The overall impacts of unemployment risks on consumption not only depend on how big the fluctuation of the actual and perceived risks is, which is the primary focus of the paper but also the sensitivity of the aggregate consumption response to changes in unemployment risks. We discipline such sensitivity with a heterogeneous-agent consumption-saving model featuring persistent unemployment under a set of standard calibrations commonly seen in the literature. In our model, households make a consumption-saving decision in the face of both productivity shocks and unemployment risk. Unemployment risk is dictated by the job separation and job finding probability. Self-insurance is achieved by saving money on a risk-free bond. Figure 10 illustrates the timeline of the model and we document other model specifications in the Appendix B.1. Table A.1 reports all the parameter calibrations. What's particularly important is the unemployment insurance replacement ratio, which we set to be 0.5. We indirectly infer

[14] Challe and Ragot (2016), McKay (2017), Bayer et al. (2019), Ravn and Sterk (2021).

[15] Bardóczy and Guerreiro (2023) is an exception, which incorporates deviation in perceived job risks in an otherwise standard HANK model.

Figure 10: Timeline of the Model



the discount factor β to be 0.97 to match a steady state quarterly MPC of 0.16, which falls well in the median range of the estimates seen in the literature. The model is set at a quarterly frequency. footnote [16]

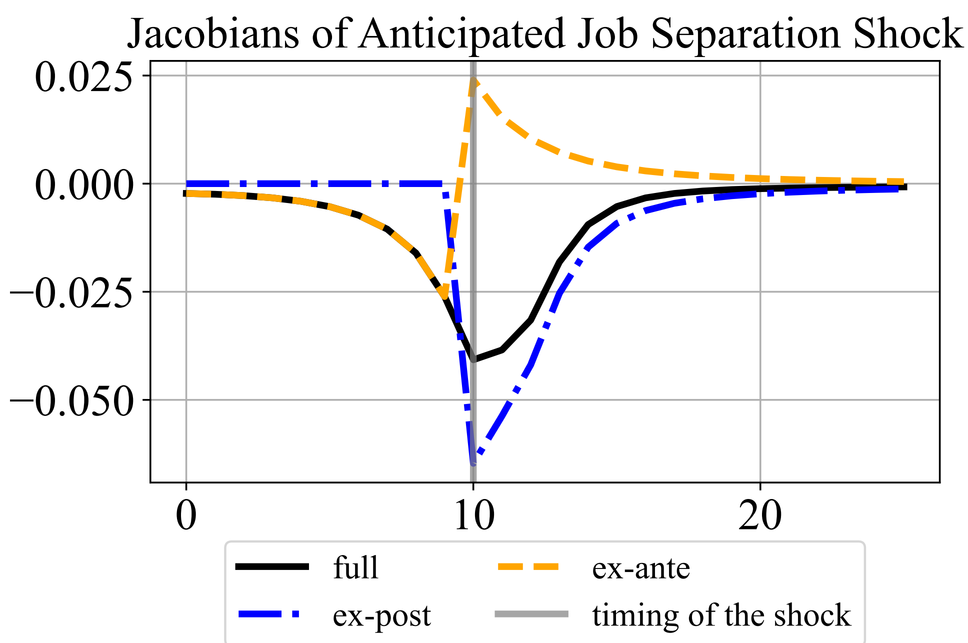
In the model, the dynamic aggregate consumption response comes from both the optimally chosen consumption policies of heterogeneous households given their perceived risks and the resulting changes in the wealth distribution, which come from both choices and the realized unemployment shocks. We summarize such responses using the Sequence Space Jacobian method by Auclert et al. (2021).

As an illustration, the consumption Jacobians concerning a future positive shock to job separation rate at a given horizon are shown in Figure 11 under the standard perfect foresight assumption, in that the shock to future job risks at $t + h$ (h=10 here) is perfectly anticipated by agents at the time t. The ex-ante component Jacobians include both the consumption response between t and $t + h$ and the subsequent impacts of such self-insurance behaviors on the consumption response after the shock realization. The ex-post Jacobians capture the consumption impacts in effect from $t+h$ when the shock happens. It is calculated by fixing the consumption policy of the agents but unexpectedly increasing the job risks at $t+h$. Essentially, it measures the aggregate consumption impacts of a higher share of people who unexpectedly find or lose their jobs. The total Jacobians consist of both the ex-ante and ex-post responses. Intuitively, because of the ex-ante responses before the realization of the shock, the hypothetical ex-post responses to the realized shock at t+h are partially insured, resulting in a more moderate total response at the moment of the shock.

With the same logic, we can decompose the aggregate consumption Jacobians into ex-ante and ex-post responses under subjective perceptions of job risks, as shown in Figure 12. The total response with belief rigidity differs from its objective benchmark, which ultimately comes from a different ex-ante response. In particular, the ex-ante subjective response is entirely based on how the imagined shock at $t + h$ is perceived by the agent at time t. Because of belief stickiness, subjective ex-ante Jacobian jumps downward less than the full-information one. This also results in a more drastic drop in consumption following the shock at $t + h$ than

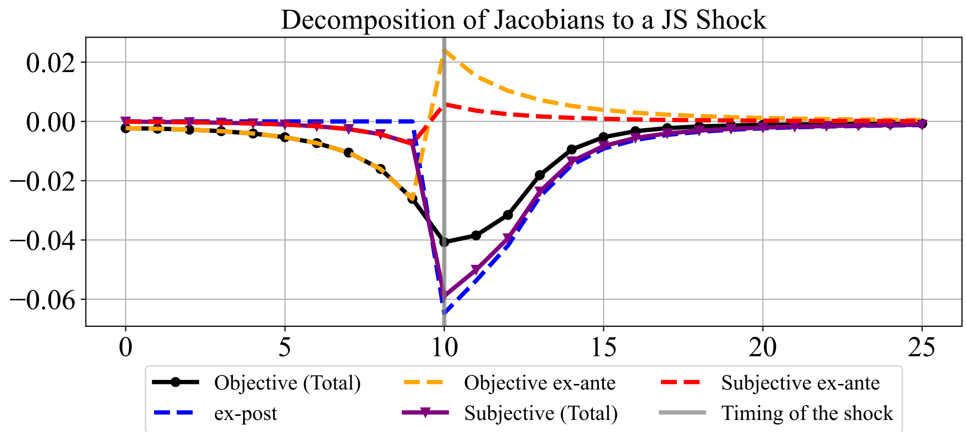
[16] In the Appendix, we reproduce our experiments with a monthly model with several modifications. The main messengers to be conveyed in the following discussions remain intact.

Figure 11: Consumption Jacobian to an anticipated 10-period-ahead shock to the job finding



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 that in Auclert et al. (2021).

Figure 12: Subjective Consumption Jacobians with Sticky Expectations



Note: The figure shows the aggregate consumption Jacobian concerning a future shock to job-separation rate that 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.

in the full-information case ("Subjective (Total)"), simply because the consumption insurance induced by ex-ante response was more limited ("Subjective ex-ante") to counteract the impacts of uninsured ex-post shock ("ex-post").

What is more interesting is that we can understand the difference between the objective and subjective perceptions of job risks through the lens of ex-ante/ex-post decomposition. In particular, the total subjective responses ("Subjective (Total)") can be further thought of as a combination of the contributions from the ex-ante response under sticky expectations ("Subjective ex-ante"), underinsurance due to misperceived risks due to stickiness (the area between "Subjective ex-ante" and "Objective ex-ante"), and the responses under full-information ("Objective (Total)"). Due to the under-insurance toward the increased job separation risk, the consumption drop following the shock is bigger than that under full information.

Quantification of consumption impacts

With the decomposed Jacobians, we simulate the path of aggregate consumption from 1988 to 2020 due to unemployment and unemployment risk fluctuations. For this simulation, expectations are disciplined by the beliefs series we have estimated, and the unemployment rate is disciplined by the realized path of job transition rates.

In particular, we empirically estimate the persistence and realized shocks to job flow rates JS_t and JF_t using an AR(1) model. We confirm that the unemployment rate dynamics implied by such an estimated law of motion and shocks to separation and finding match the empirical patterns of the realized unemployment rate reasonably well. Such shocks, combined with the ex-post Jacobians in Figure 12 yield the consumption deviations that only come from ex-post shock responses.

Next, respectively, we add to the ex-post response the ex-ante precautionary response stemming from either objective job risks according to rational expectation as measured by real-time risk forecast or measured subjective perceptions to obtain the total simulated path of consumption deviation from its steady state. We combine the estimated perceived law of motion and the realized shocks to the perceived job finding and separation rates ($\widetilde{JF}_t/\widetilde{JS}_t$), and $\widehat{JF}^*_t/\widehat{JS}^*_t$.) with the ex-ante Jacobians to obtain such responses.

Figure 13 plots the results from such comparisons based on only job separation, job finding, and the combined impacts of both. Three findings are worth discussing. First, with only a separation rate, the stickiness in job separation beliefs induces a very limited degree of ex-ante precautionary saving responses during each recession. This explains why the total consumption fluctuations according to subjective perceptions fall short of objective perceptions and are very close to the ex-post impacts. Intuitively, consumption drops mostly due to the realized job losses, instead of precautionary responses.

Second, with job-finding beliefs, however, the subjective total response indeed largely precedes that of ex-post shock response, suggesting an important role of precautionary saving behaviors. Take the Great Recession as an example, such precautionary responses imply an additional 1.5-2 percentage point drop in aggregate consumption at the onset of the crisis compared to the drop that solely stems from realized lower job-finding rates. Furthermore, because of the partial response in job finding beliefs to true finding risk, there is also a sizable gap between subjective and objective responses throughout the sample. During the Great Recession, for instance, the objective response implies an even sharper drop in consumption by an additional 1 percentage point. Meanwhile, the slowly reacting job beliefs induce a slower recovery from the recession, a defending feature of the post-crisis consumption patterns.

Lastly, the combined impacts of job finding and separation, shown at the bottom of Figure 13, are primarily driven by the impacts of job finding. This is due to two reasons. First, as established by Fujita and Ramey (2009) and a few follow-up studies, job finding overall contributes more than job separation to the business cycle fluctuations of the unemployment rate, although the exact relative importance is debated in the literature. For instance, Broer et al. (2021b) argue that job separations are important for the immediate impact and job finding rates have a long lasting effect. Second, our model assumes that job finding affects not only people currently unemployed but also those currently employed. The unemployment risk a worker faces stems from the possibility of losing their current job and being unable to find a new job. In addition, the importance of job finding also comes from a higher sensitivity in perceptions in the former than that in separation. This makes the precautionary saving behaviors due to unemployment risk quantitatively significant. Note that this model focuses on non-durable consumption. As Carroll and Dunn (1997) and Harmenberg and Öberg (2021) argue that the unemployment risk channel for durable goods is much stronger than for non-durables, our estimates provide rather a lower bound.

Allowing for heterogeneous risks and beliefs

Figure 14 simulates consumption fluctuations for each education group, separately, under the alternative assumption of ex-ante heterogeneity in job risks along education level. This is motivated by the results in section 4.3, which suggests that compared to the higher separation risk fluctuations than the others, the low education groups' perceptions are particularly sluggish in reacting to such changes. Meanwhile, it is the middle-education group whose beliefs on job finding are the most underreactive to real-time changes. We quantify the importance of misperceived risks and overall precautionary saving motives for each group, respectively. It should be noted that the Jacobians we used to calculate such responses are identical for all groups. This means that we do not assume any other heterogeneity by education besides the one on the objective risks they face and on those as perceived.

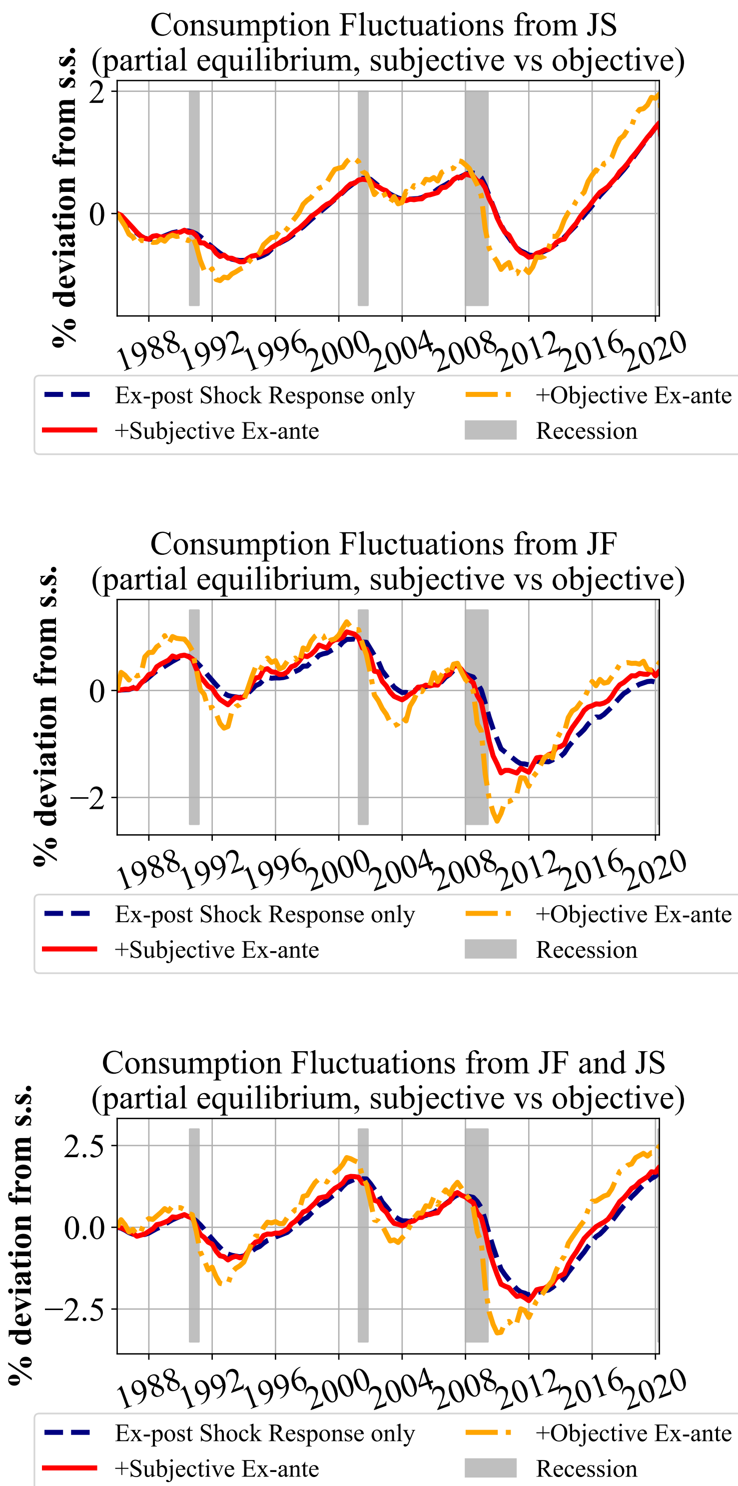
Two findings emerge. First, not surprisingly, the ex-post shock response by the low education group was the biggest in recessions, which is attributable to an overall higher volatility of realized job transitions of this group. Second, because the group with the highest education also has the highest sensitivity of the beliefs, they overall have a larger precautionary response. This is indicated by a smaller gap between the subjective and objective response and a larger gap between the subjective and ex-post response for the high-education group.

Our group-specific anatomy bears aggregate implications. To the extent that the most cyclically exposed groups in job risks are also the ones that have the least sensitivity in reacting to their beliefs and carrying out self-insurance behaviors, which means a larger cut in spending at the moments of the shock, this introduces a potentially important amplification mechanism in the aggregate consumption that is not via its counter-cyclicality per se, but via its heterogeneous footprints. Although heterogeneous risk exposures do not, in general necessarily amplify job risks' impacts on aggregate consumption, they could do so when the heterogeneous workers' risk exposures are positively correlated with their degree of underinsurance. Our results seem to suggest this mechanism is empirically feasible, particularly because workers facing more cyclical risks tend to underreact to such movements in job risks.

6 Conclusion

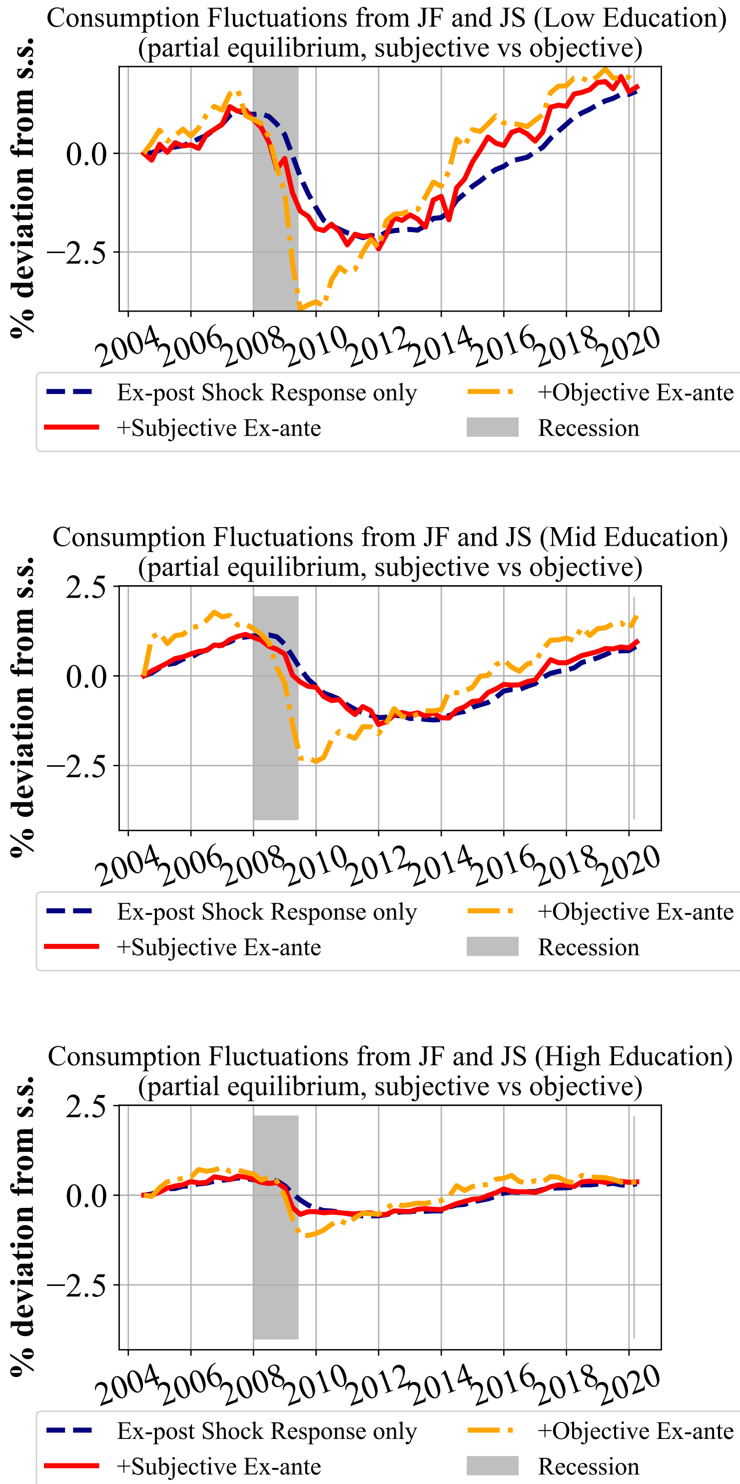
More people lose jobs and fewer people find jobs in recessions than in normal times. But do people see these changes coming? This paper asks if business cycle movements in job risks are perceived by the average and heterogeneous households who are exposed to different degrees of job risks. The answer 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 13: Consumption Fluctuations due to Unemployment Risks



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.

Figure 14: Consumption Fluctuations due to Unemployment Risks: by 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.

References

Ahn, Hie Joo and James D Hamilton, "Heterogeneity and unemployment dynamics," *Journal of Business & Economic Statistics*, 2020, *38* (3), 554–569.

Andrews, Donald WK, "Tests for parameter instability and structural change with unknown change point," *Econometrica: Journal of the Econometric Society*, 1993, pp. 821–856.

Arni, Patrick, "Whats in the Blackbox? The Effect of Labor Market Policy on Search Behavior & Beliefs. A Field Experiment," Technical Report, IZA Working papers 2013.

Auclert, Adrien, Bence Bardóczy, Matthew Rognlie, and Ludwig Straub, "Using the sequence-space Jacobian to solve and estimate heterogeneous-agent models," *Econometrica*, 2021, *89* (5), 2375–2408.

Balleer, Almut, Georg Duernecker, Susanne Forstner, and Johannes Goensch, "The Effects of Biased Labor Market Expectations on Consumption, Wealth Inequality, and Welfare," 2021.

_ , _ , _ , and _ , "Biased expectations and labor market outcomes: Evidence from German survey data and implications for the East-West wage gap," 2023.

Bardóczy, Bence and Joao Guerreiro, "Unemployment Insurance in Macroeconomic Stabilization with Imperfect Expectations," Technical Report, mimeo 2023.

Bayer, Christian, Ralph Lütticke, Lien Pham-Dao, and Volker Tjaden, "Precautionary savings, illiquid assets, and the aggregate consequences of shocks to household income risk," *Econometrica*, 2019, *87* (1), 255–290.

Bianchi, Francesco, Sydney C Ludvigson, and Sai Ma, "Belief distortions and macroeconomic fluctuations," *American Economic Review*, 2022, *112* (7), 2269–2315.

Boone, Christopher, Arindrajit Dube, Lucas Goodman, and Ethan Kaplan, "Unemployment insurance generosity and aggregate employment," *American Economic Journal: Economic Policy*, 2021, *13* (2), 58–99.

Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer, "Overreaction in macroeconomic expectations," *American Economic Review*, 2020, *110* (9), 2748–2782.

Broer, Tobias, Alexandre Kohlhas, Kurt Mitman, and Kathrin Schlafmann, "Information and wealth heterogeneity in the macroeconomy," 2021.

_ , Jeppe Druedahl, Karl Harmenberg, and Erik Öberg, "The unemployment-risk channel in business-cycle fluctuations," 2021.

Carroll, Christopher D, "Macroeconomic expectations of households and professional forecasters," *the Quarterly Journal of economics*, 2003, *118* (1), 269–298.

— **and Wendy E Dunn**, "Unemployment expectations, jumping (S, s) triggers, and household balance sheets," *NBER macroeconomics annual*, 1997, *12*, 165–217.

Carroll, Christopher, Jiri Slacalek, Kiichi Tokuoka, and Matthew N White, "The distribution of wealth and the marginal propensity to consume," *Quantitative Economics*, 2017, *8* (3), 977–1020.

Challe, Edouard and Xavier Ragot, "Precautionary saving over the business cycle," *The Economic Journal*, 2016, *126* (590), 135–164.

Coibion, Olivier and Yuriy Gorodnichenko, "What can survey forecasts tell us about information rigidities?," *Journal of Political Economy*, 2012, *120* (1), 116–159.

— **and —** , "Information rigidity and the expectations formation process: A simple framework and new facts," *American Economic Review*, 2015, *105* (8), 2644–78.

— **,** — **, and Saten Kumar**, "How do firms form their expectations? new survey evidence," *American Economic Review*, 2018, *108* (9), 2671–2713.

Colarieti, Roberto, Pierfrancesco Mei, and Stefanie Stantcheva, "The how and why of household reactions to income shocks," Technical Report, National Bureau of Economic Research 2024.

Conlon, John J, Laura Pilossoph, Matthew Wiswall, and Basit Zafar, "Labor market search with imperfect information and learning," Technical Report, National Bureau of Economic Research 2018.

Dickerson, Andy and Francis Green, "Fears and realisations of employment insecurity," *Labour economics*, 2012, *19* (2), 198–210.

Fuhrer, Jeffrey C, "Intrinsic expectations persistence: evidence from professional and household survey expectations," *Available at SSRN 3296152*, 2018.

Fujita, Shigeru and Garey Ramey, "The cyclicality of separation and job finding rates," *International Economic Review*, 2009, *50* (2), 415–430.

Graves, Sebastian, "Does Unemployment Risk Affect Business Cycle Dynamics?," *International Finance Discussion Paper*, 2020, (1298).

Gregory, Victoria, Guido Menzio, and David G Wiczer, "The alpha beta gamma of the labor market," Technical Report, National Bureau of Economic Research 2021.

Guvenen, Fatih, Serdar Ozkan, and Jae Song, "The nature of countercyclical income risk," *Journal of Political Economy*, 2014, *122* (3), 621–660.

Haaland, Ingar K, Christopher Roth, Stefanie Stantcheva, and Johannes Wohlfart, "Measuring what is top of mind," Technical Report, National Bureau of Economic Research 2024.

Haan, Wouter J Den, Pontus Rendahl, and Markus Riegler, "Unemployment (fears) and deflationary spirals," *Journal of the European Economic Association*, 2018, *16* (5), 1281–1349.

Hall, Robert E and Marianna Kudlyak, "Job-finding and job-losing: A comprehensive model of heterogeneous individual labor-market dynamics," Technical Report, National Bureau of Economic Research 2019.

Harmenberg, Karl and Erik Öberg, "Consumption dynamics under time-varying unemployment risk," *Journal of Monetary Economics*, 2021, *118*, 350–365.

Hartmann, Ida Maria and Søren Leth-Petersen, "Subjective unemployment expectations and (self-) insurance," *Labour Economics*, 2024, p. 102579.

Hendren, Nathaniel, "Knowledge of future job loss and implications for unemployment insurance," *American Economic Review*, 2017, *107* (7), 1778–1823.

Hou, Chenyu and Tao Wang, "Uncovering Subjective Models from Survey Expectations," Technical Report, mimeo 2024.

Jr, Melvin Stephens, "Job loss expectations, realizations, and household consumption behavior," *Review of Economics and statistics*, 2004, *86* (1), 253–269.

Jurado, Kyle, Sydney C Ludvigson, and Serena Ng, "Measuring uncertainty," *American Economic Review*, 2015, *105* (3), 1177–1216.

Kekre, Rohan, "Unemployment insurance in macroeconomic stabilization," *Review of Economic Studies*, 2023, *90* (5), 2439–2480.

Leduc, Sylvain and Zheng Liu, "Uncertainty shocks are aggregate demand shocks," *Journal of Monetary Economics*, 2016, *82*, 20–35.

Mankiw, N Gregory and Ricardo Reis, "Sticky information versus sticky prices: a proposal to replace the New Keynesian Phillips curve," *The Quarterly Journal of Economics*, 2002, *117* (4), 1295–1328.

McKay, Alisdair, "Time-varying idiosyncratic risk and aggregate consumption dynamics," *Journal of Monetary Economics*, 2017, *88*, 1–14.

— **and Johannes F Wieland**, "Lumpy durable consumption demand and the limited ammunition of monetary policy," *Econometrica*, 2021, *89* (6), 2717–2749.

— **and Ricardo Reis**, "Optimal automatic stabilizers," *The Review of Economic Studies*, 2021, *88* (5), 2375–2406.

Menzio, Guido et al., "Stubborn Beliefs in Search Equilibrium," *NBER Chapters*, 2022.

Morales-Jiménez, Camilo, "The Cyclical Behavior of Unemployment and Wages under Information Frictions," *American Economic Journal: Macroeconomics*, 2022, *14* (1), 301–331.

Mueller, Andreas I and Johannes Spinnewijn, "Expectations data, labor market, and job search," *Handbook of Economic Expectations*, 2023, pp. 677–713.

— **, — , and Giorgio Topa**, "Job seekers' perceptions and employment prospects: Heterogeneity, duration dependence, and bias," *American Economic Review*, 2021, *111* (1), 324–63.

Pappa, Evi, Morten O Ravn, and Vincent Sterk, "Expectations and incomplete markets," in "Handbook of Economic Expectations," Elsevier, 2023, pp. 569–611.

Patterson, Christina, "The matching multiplier and the amplification of recessions," *American Economic Review*, 2023, *113* (4), 982–1012.

Pettinicchi, Yuri and Nathanael Vellekoop, "Job loss expectations, durable consumption and household finances: Evidence from linked survey data," 2019.

Ravn, Morten O and Vincent Sterk, "Macroeconomic fluctuations with HANK & SAM: An analytical approach," *Journal of the European Economic Association*, 2021, *19* (2), 1162–1202.

Rodrıguez, Marta Garcıa, "The Role of Wage Expectations in the Labor Market," 2023.

Rossi, Barbara and Tatevik Sekhposyan, "Macroeconomic uncertainty indices based on nowcast and forecast error distributions," *American Economic Review*, 2015, *105* (5), 650–655.

Spinnewijn, Johannes, "Unemployed but optimistic: Optimal insurance design with biased beliefs," *Journal of the European Economic Association*, 2015, *13* (1), 130–167.

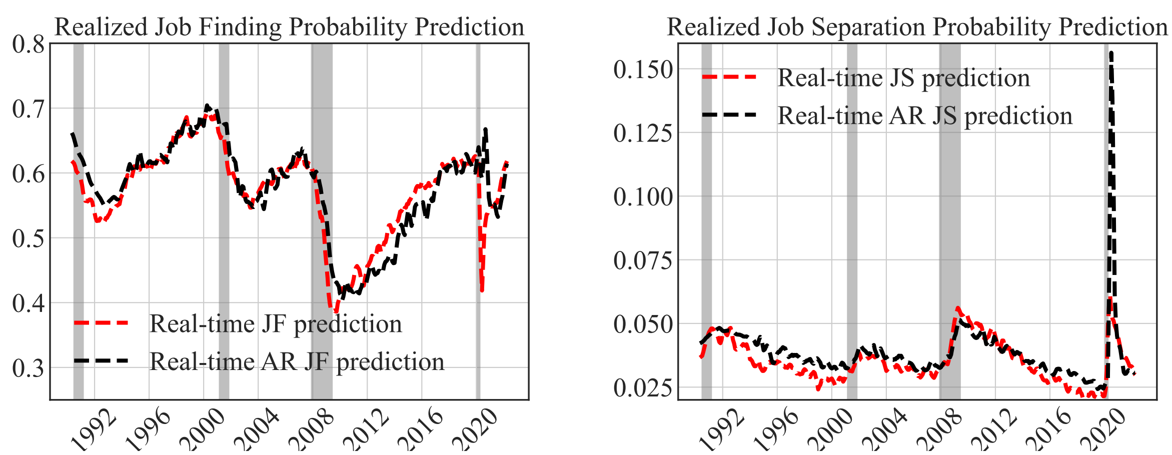
Wang, Tao, "Perceived versus calibrated income risks in heterogeneous-agent consumption models," Technical Report, Bank of Canada 2023.

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 were during the Covid era.

Figure A.1: Real-time Machine-efficient Risks from Lasso and AR(1)



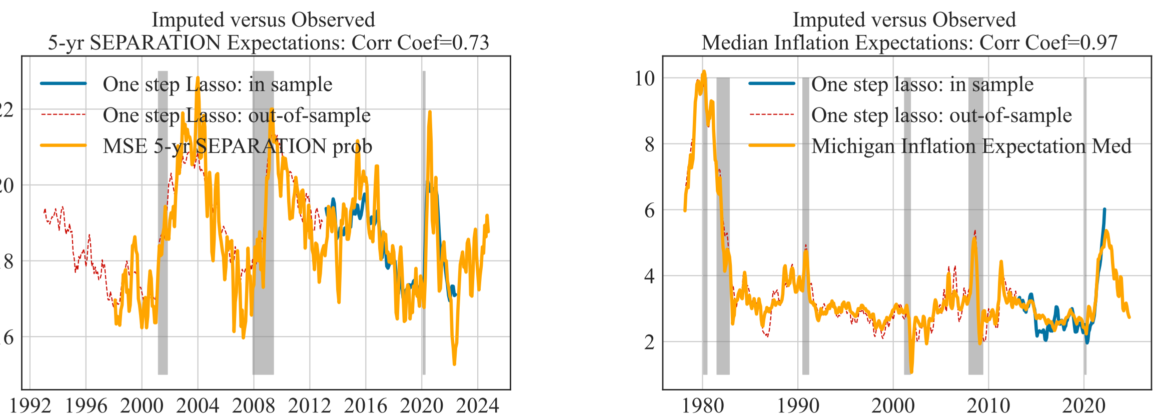
Note: Multi-variate Lasso real-time forecasts versus one from AR(1) model.

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 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 MSC based on 2013-2022 in-sample. They have an impressively large degree of comovement with the observed data. We are particularly careful to exclude any indices in 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 MSC



Note: the figure plots the imputed beliefs from SCE regarding the percent chance the nationwide unemployment rate will be higher in the next year relative to the unemployment expectation index in MSC.

As a further validation of the imputation methodology across surveys, Figure A.3 plots the imputed expectations in SCE regarding the median percent probability of nationwide unemployment rate to be higher, against the series of Michigan index regarding the direction of unemployment rate, which was observed for a much longer period. Again, in our in-sample Lasso imputation, we particularly exclude all Michigan indices regarding unemployment expectations to make it a fair test of the validity of our imputation methods. Because the SCE unemployment expectations are expressed as a percent probability while the MSC index is measured as the share of respondents expecting higher unemployment rates minus those expecting lower, we can not directly compare the imputation errors out-of-sample. We nevertheless show that the correlation between imputed expectations and the observed index in MSC is as high as 0.99. This suggests that our imputation method is able to do a great job of backcasting beliefs.

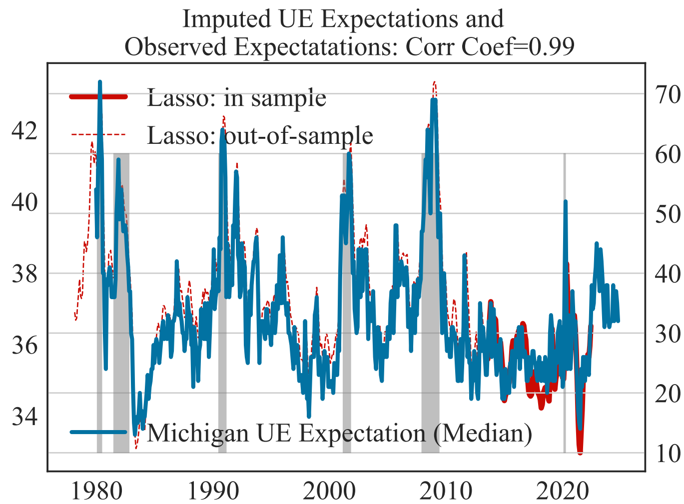
A.2.2 Hyper-parameter tuning of the Lasso model using cross-validation

Figure A.4 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.5 compares the imputed job risk belief relied upon pre-2020 sample as the in-sample of Lasso model with one relied on an extended sample covering the Covid era (2020-2022). The

Figure A.3: Imputed SCE versus Observed UE Expectations in MSC



Note: the figure plots the imputed beliefs from SCE regarding the percent chance the nationwide unemployment rate will be higher in the next year relative to the unemployment expectation index in MSC.

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.

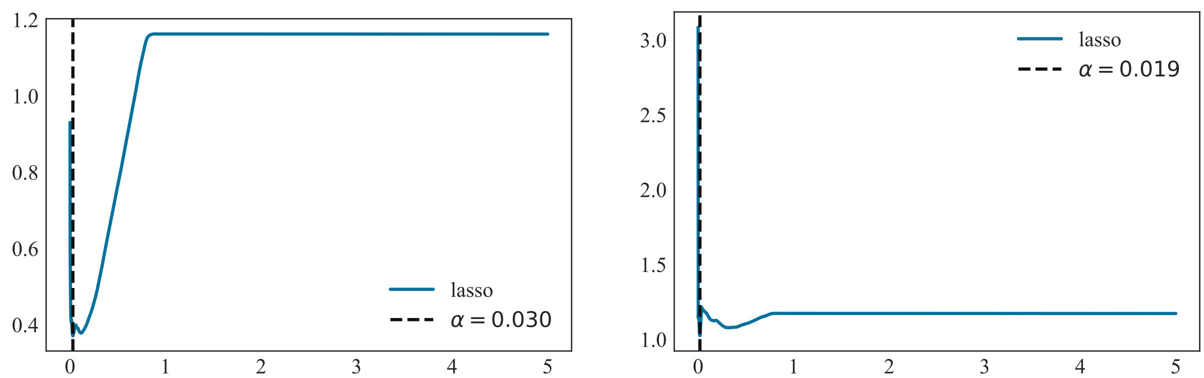
A.2.4 Selected covariates of perceived risks

Figure A.6 report 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.8 plots the in-sample fitted and out-of-sample imputed perceptions of the job finding and separations rates for low, middle, and high education groups, versus the realized rates for each group.

Figure A.4: Model Selection using Cross-Validation



Note: mean square error scores under different penalization parameter α of the Lasso model.

A.3 Additional results with forecast errors

The upper panel in Figure A.9 plots the FEs using two alternative series as realizations of job findings. During the majority of times in the sample, FEs lie in the negative domains, suggesting that on average, household beliefs underpredicted the realization of job-findings. This is consistent with the observation in Figure A.7 that the imputed beliefs are below the realization most of the time. The periods with notable exceptions were the 1981-1982 recession and the Great Recession.

The lower panel plots the size of (absolute values) of the FEs. The size of FEs seemed to dramatically drop during recessions, compared to normal times. Some research has found that information-rigidity is counter-cyclical.[17]

A.4 Additional evidence for the belief distortions over business cycles

Instead of calculating peak-to-trough values of job risks as in Figure 9, Figure A.10 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.

[17]See Coibion and Gorodnichenko (2015) for the evidence with inflation expectations.

Figure A.5: Imputing Beliefs Including or Excluding Covid Era

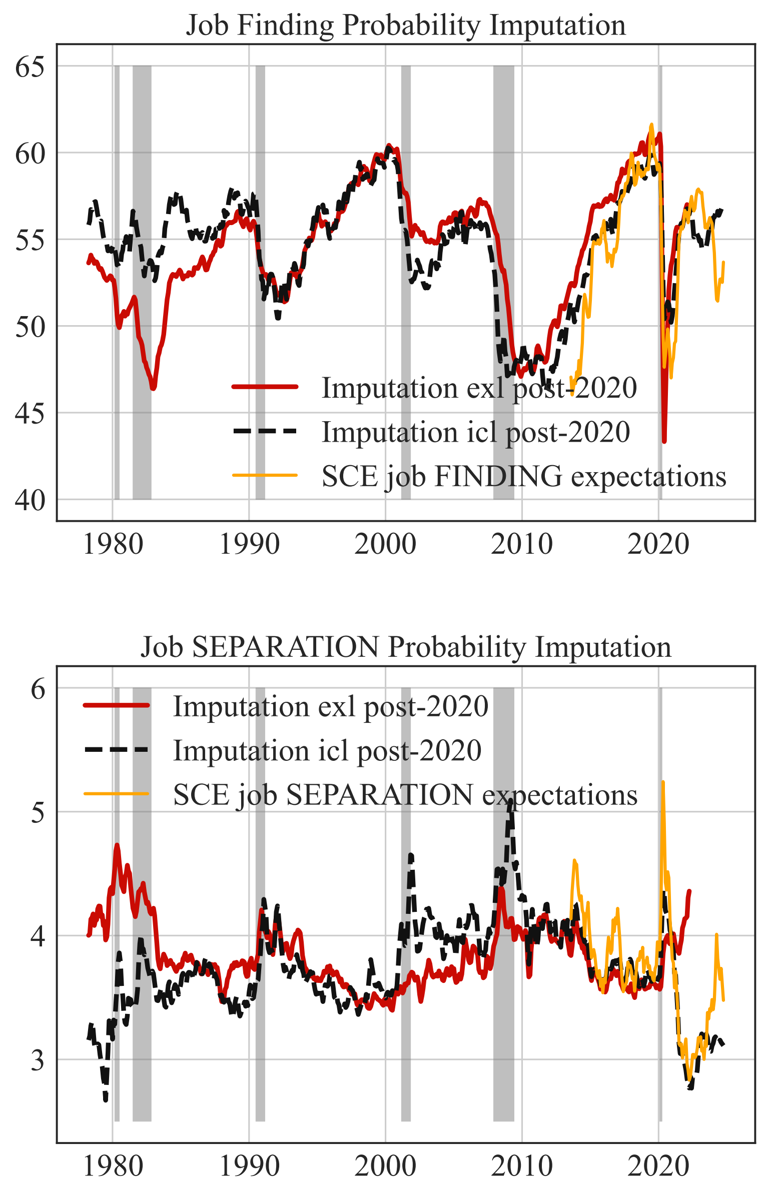
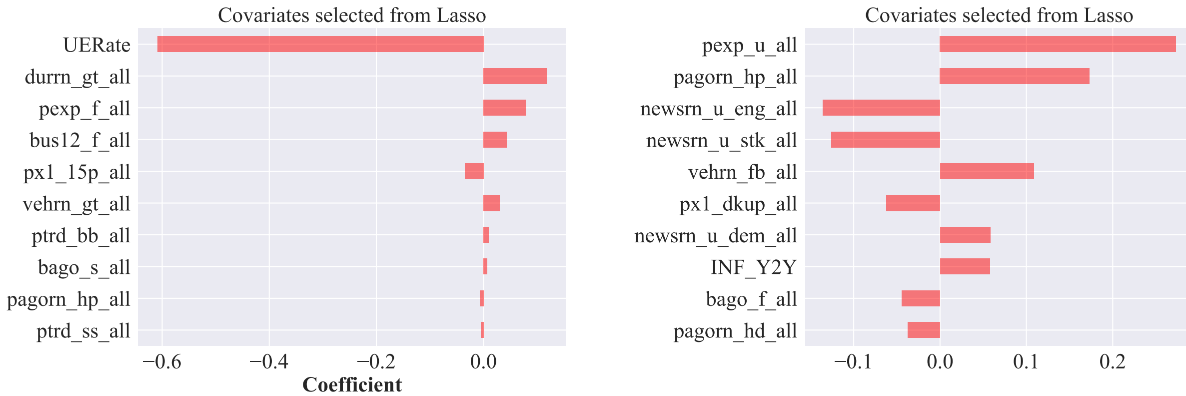


Figure A.6: Selected variables of Lasso model of perceived job risks



Note: selected variables ranked by the absolute value of their estimated coefficients in the Lasso imputation model for perceived job finding (left) and 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.

B Additional Model Results

B.1 Household block of a HANK model

There is a continuum of households of mass 1 indexed by i who face both idiosyncratic permanent and transitory income shocks, and stochastic transitions between employment states. A household is either employed or unemployed and is indexed by n_{it}. Employed households ($n_{it} = 1$) separate from employment with probability JS_t. Households separated this period who fail to find a job enter unemployment in the next period. Unemployed workers find a job with probability, JF_t. Households receive unemployment insurance for two quarters. During unemployment, households find employment with probability η_t. Finally, households are subject to a constant probability of death D.

The Bellman problem is:

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

subject to the budget constraint

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

where $\mathbf{m}_{it}$ denotes market resources to be expended on consumption or saved into government bonds. $\mathbf{c}_{it}$ is the level of consumption and $\mathbf{a}_{it}$ is the value of government bonds where the return is r^a_{t+1}. $\mathbf{m}_{it}$ is determined by labor income, $\mathbf{z}_{it}$, and the gross return on assets from the last period, $(1 + r^a_t)\mathbf{a}_{it-1}$. D is the probability of death and β_i is the discount factor.

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).[18]

[18] 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.1: Household Calibration

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

The employment status $n_{i,t}$ transitions between two states following a 2-state Markov process. Its transition probabilities are jointly determined by job-finding $JF_{i,t}$ and job separation $JS_{i,t}$ rates. The e-to-u and u-to-e probabilities are, respectively the following.

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

B.2 Model experiment

B.3 Baseline

The model experiments in Figure 13 are based on directly estimated shocks to JF/JS, $\widetilde{JF}/\widetilde{JS}$ and JF^*/JS^*. To obtain such shocks, we estimate, respectively, a quarterly AR(1) model of each one of these sequences in the sample period up to the 2020 Q1. The predicted residuals are the estimated shocks to realized rates, beliefs, and rational job risk, which are plotted in Figure A.11.

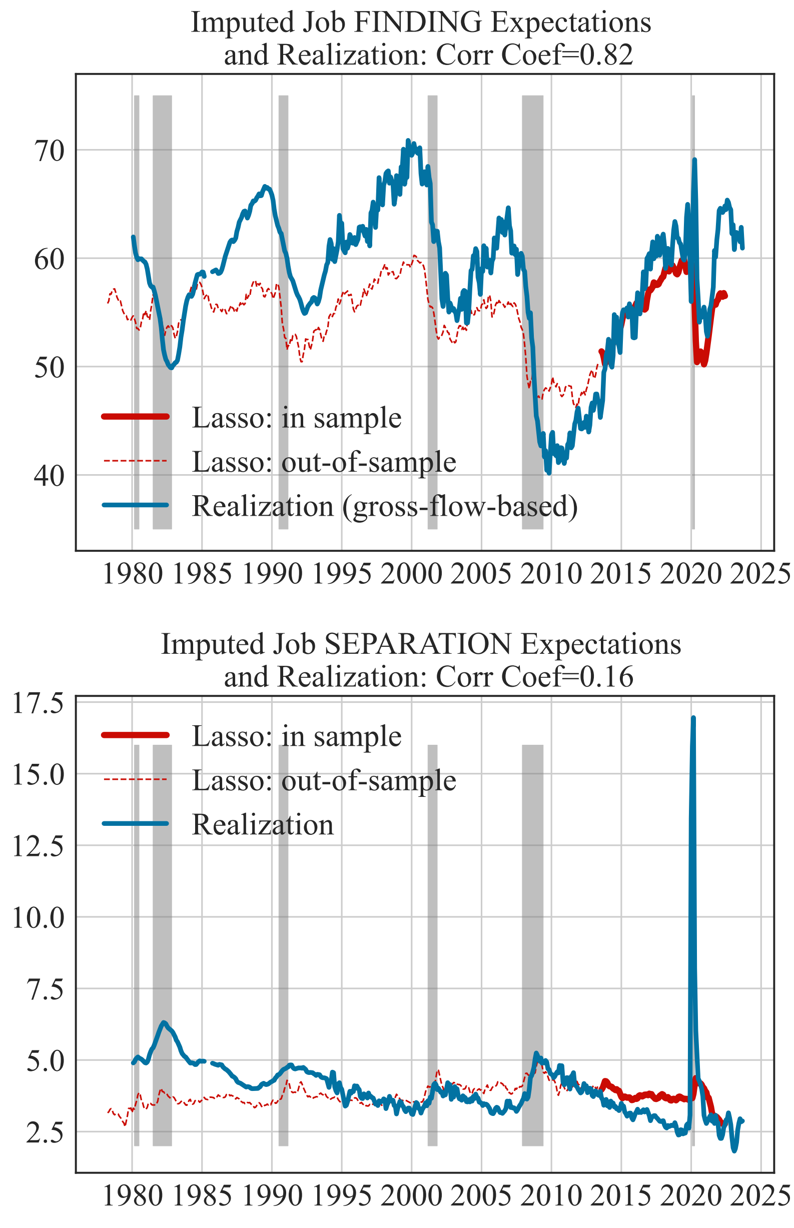
Figure A.12 complements Figure 14 by showing the education-specific consumption aggregation fluctuations due to job separation and finding risks, separately.

B.3.1 Alternative model experiment at monthly frequency

In this section, we report results from the baseline model experiments with a monthly version of the model with several modifications, which is calibrated similarly to Kekre (2023). Since working with a quarterly model inevitably involves time-aggregation of monthly job flow rates and their belief counterparts, we see a monthly model as more robust to our assumptions on the time-aggregation. In particular, we replace the permanent wage component with a persistent component with a monthly AR(1) coefficient of 0.997, and a standard deviation of the shock of 0.057. We use steady-state monthly job finding rate to be 0.2517, the sample average from CPS before Covid era.

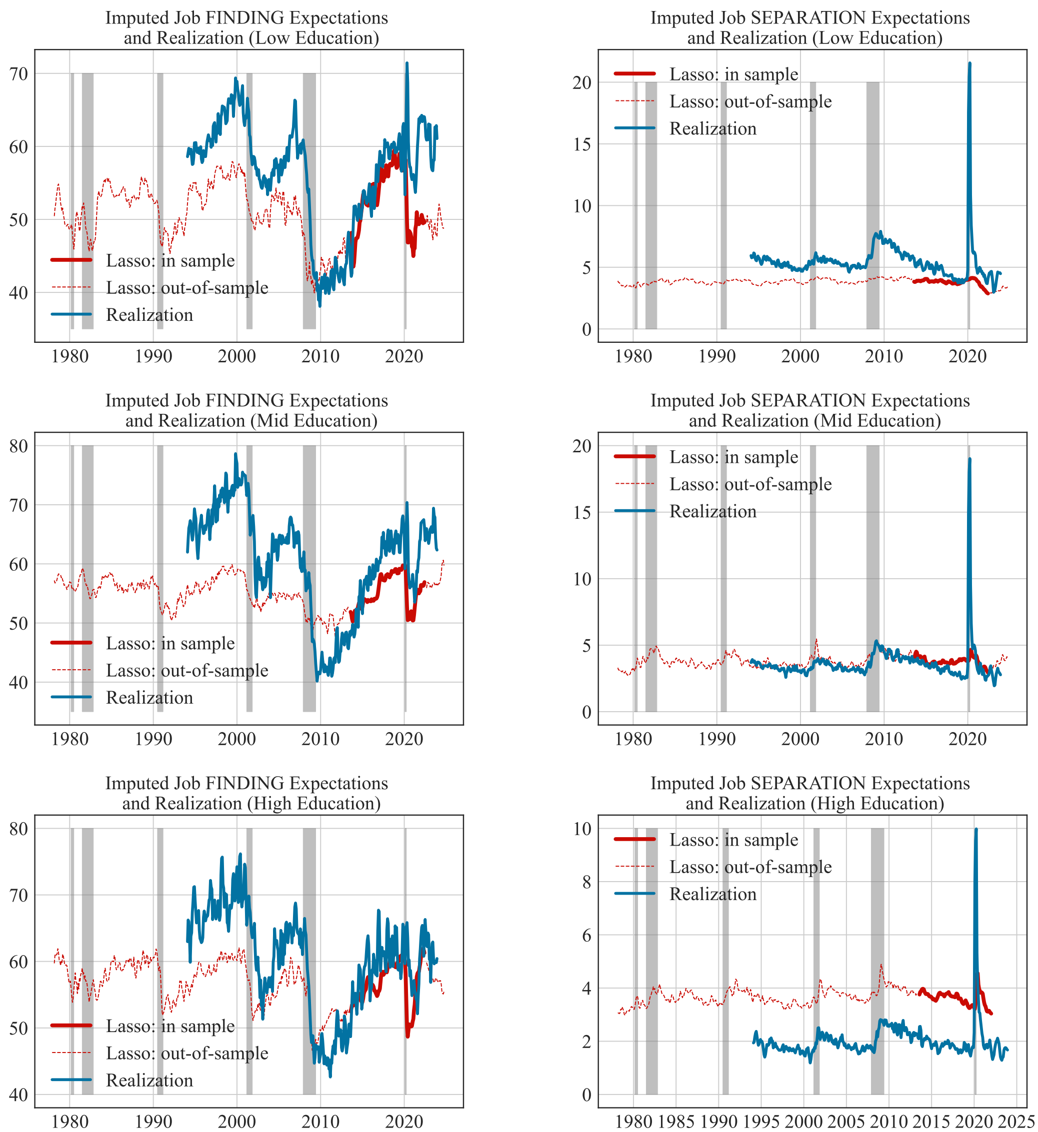
Modifying the quarterly model assumption, we also assume that employment-to-unemployment transition is entirely driven by job separations, e.g. $p(n_{i,t+1} = u | n_{i,t} = e) = JS_t$). We set its average to be 0.017. The discount factor beta is estimated to yield a quarterly MPC of 0.21, a la Kekre (2023). Figure A.13 shows the results with homogeneous workers, and Figure A.14 shows that with heterogeneous risks by education.

Figure A.7: Imputed job finding rate and realizations



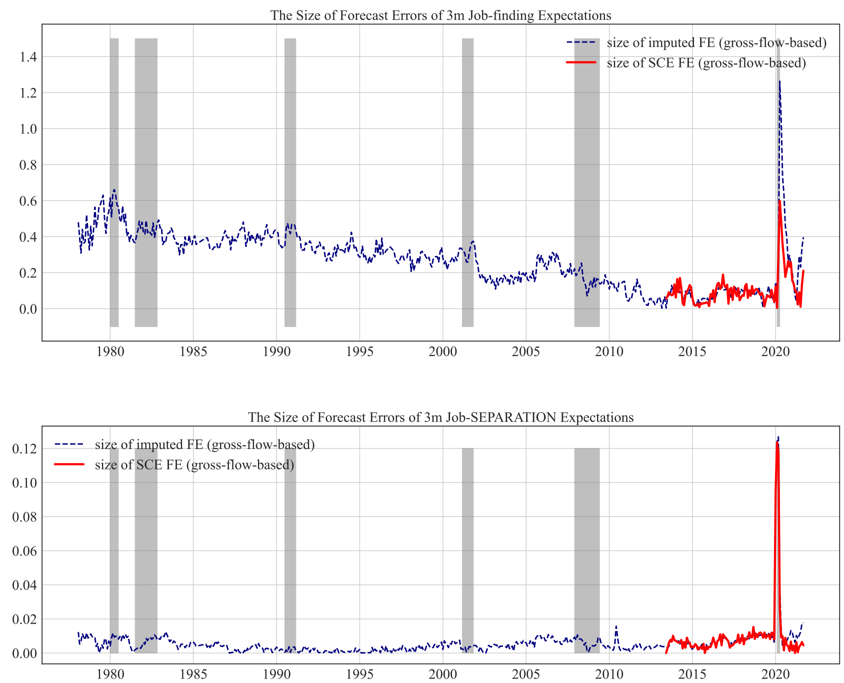
Note: imputed perceived risks in the sample (2013-2022) and out-of-sample (1980-2013) compared to realized job flow rates.

Figure A.8: Imputed beliefs by education



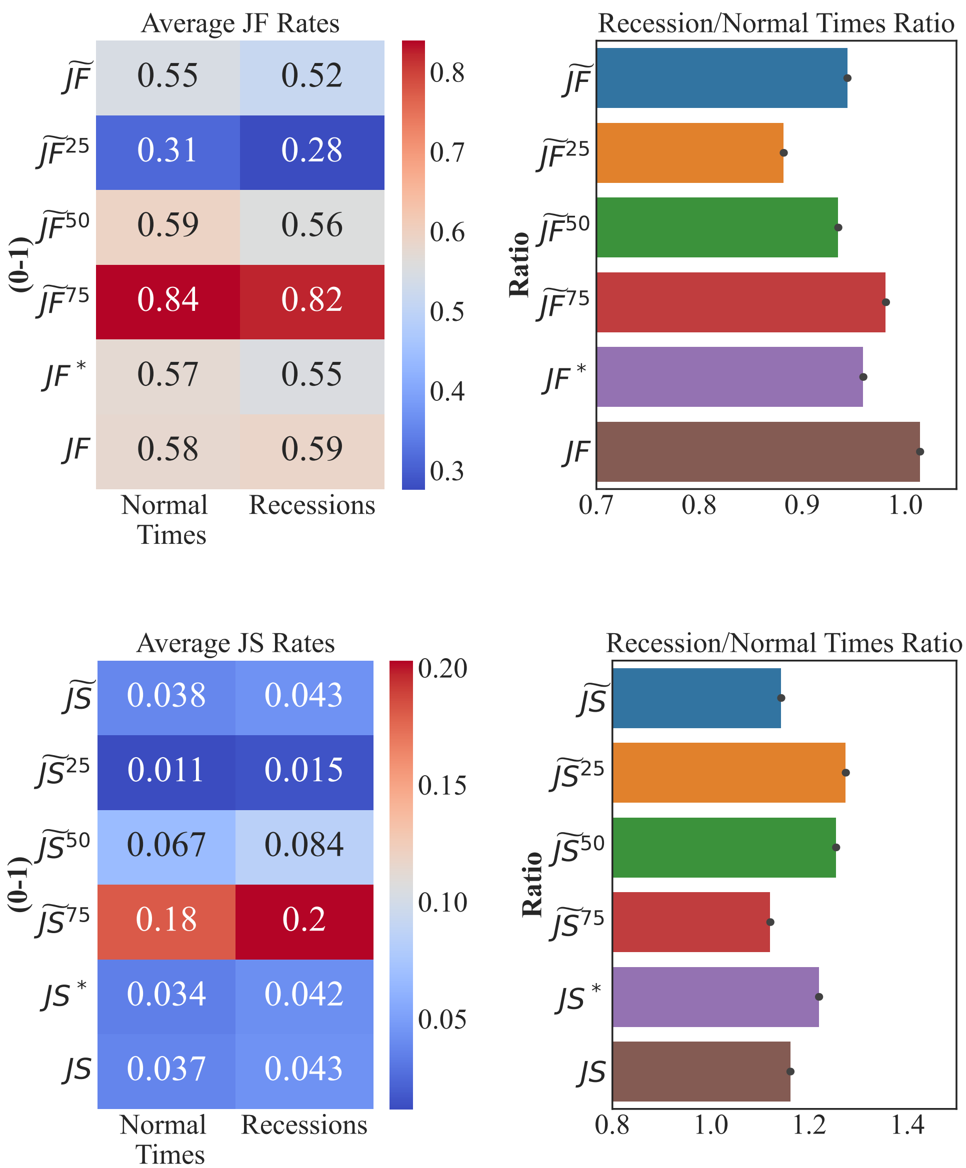
Note: these figures plot the imputed perceived job separation and finding rates by low, middle and high educations, respectively, using the same methodology and the education-specific expectations in MSC.

Figure A.9: Forecast errors of job-finding and separation expectations



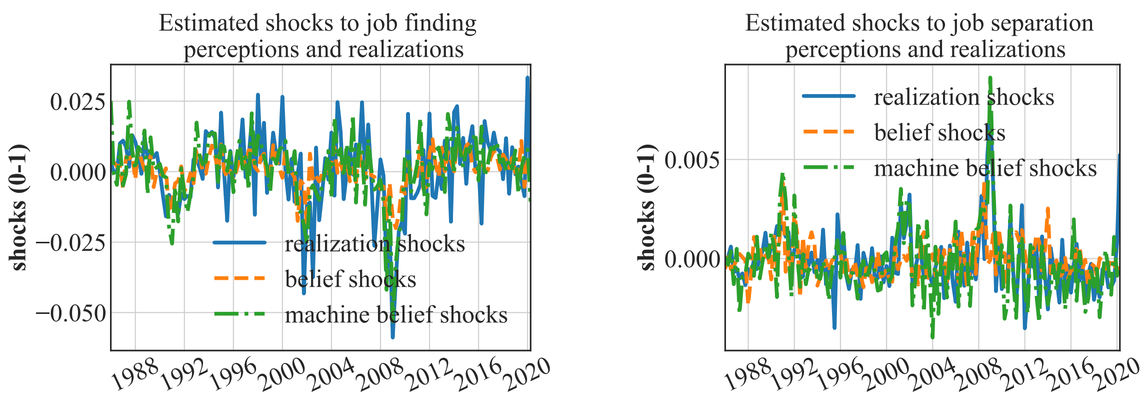
Note: the absolute value of forecast errors of job finding and separation rates, defined as the difference both imputed/or observed perceived risk and the realized job transition rates.

Figure A.10: Business Cycle Patterns of Risks and Perceptions: Normal Times versus Recessions



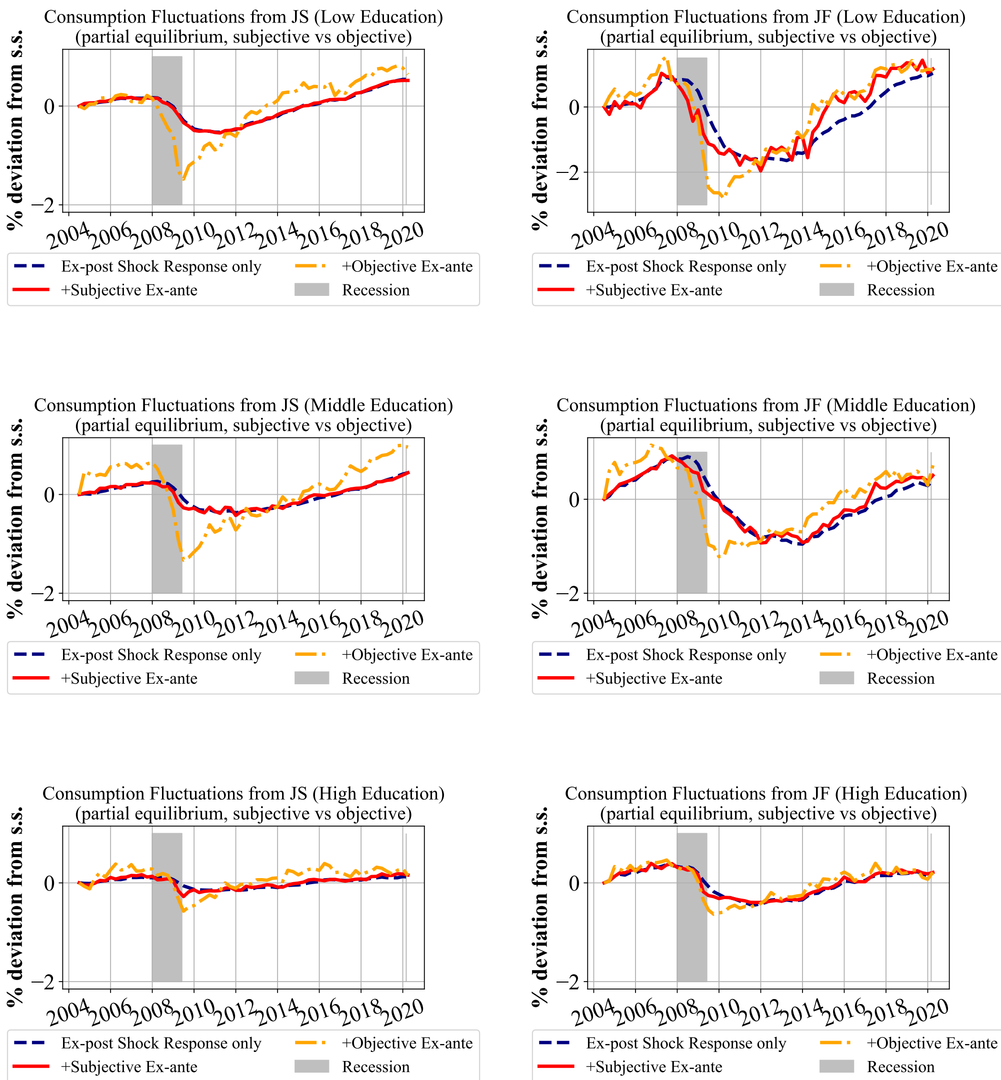
Note: The left tables report the average perceived job risks, perceived job risks at different quantiles, real-time job risks, and realized job transition rates in normal times and NBER-labeled recessions. The right figures plot the ratio of these rates between recessions and normal times. The sample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

Figure A.11: Shocks to realized job transitions, perceptions and rational forecasts



Note: The figure plots the estimated shocks used for the experiments in Figure 13, based on an estimation of a quarterly 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 1987 and 2020.

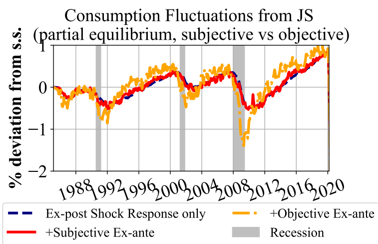
Figure A.12: Consumption Fluctuations due to JS and JF Risks: by Education



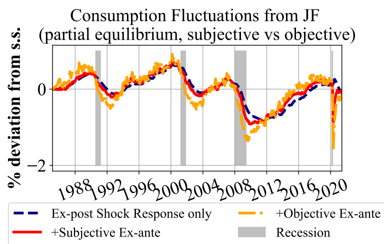
Note: The figure compares for each education group their partial-equilibrium aggregate consumption deviations from its steady state simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks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

Figure A.13: **Monthly** Consumption Fluctuations due to Unemployment Risks

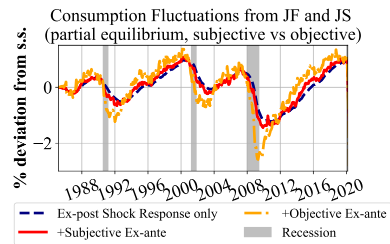
Job separation



Job finding



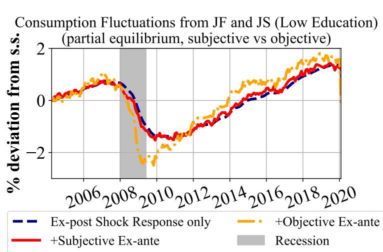
Combined



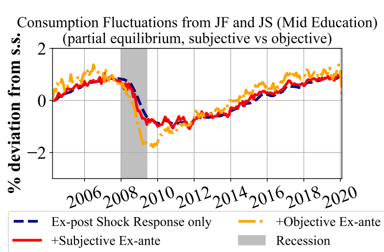
Note: The figure compares the partial-equilibrium aggregate consumption deviations from its steady state simulated based on empirically estimated shocks to perceived job risk (subjective) and the real-time forecast risk (objective), in addition to the ex-post response to shocks to the realized job transition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

Figure A.14: **Monthly** Consumption Fluctuations due to Unemployment Risks: by Education

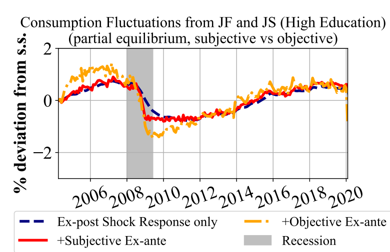
Low Education



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 monthly version of the baseline model with modified assumptions.