Perceived Unemployment Risks over Business Cycles*

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Abstract

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

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

JEL Codes: D14, E21, E71, G51

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1 Introduction

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

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

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

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

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

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

Spinnewijn, 2015; Mueller et al., 2021; Balleer et al., 2021).

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

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

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

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

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

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

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

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

We also highlight the important interaction between job risk heterogeneity and belief distortions. Low-educated workers, who are disproportionately exposed to cyclical unemployment risks, exhibit the stickiest beliefs and, as a result, are the most under-insured when unemployment shocks materialize. This under-insurance amplifies the effects of unemployment risk over the business cycle.[4] Taken together, this evidence suggests that the extent to which unemployment risks act as an amplification channel depends crucially on how heterogeneous households perceive fluctuations in unemployment risk.

Related Literature

Our paper builds on the empirical evidence of biases in job-finding expectations as documented by Mueller et al. (2021), which studied the microdata on job-finding expectations in the SCE. In comparison to their work, we study job-finding and separation expectations at the macro level. We corroborate their finding by showing that individuals' expectations underreact to changes in true probabilities over business cycles, in addition to underreacting to changes over their unemployment duration.

In addition, several studies based on a comparison of perceived job risks and realized job transitions, as surveyed in Mueller and Spinnewijn (2023), provide divergent evidence between over-optimism and over-pessimism in job expectations. For instance, Arni (2013), Spinnewijn (2015), Conlon et al. (2018), and Mueller et al. (2021) all found that workers over-perceive the probability of finding jobs, with a stronger bias for longer durations of unemployment. Conlon et al. (2018) show that 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 in an incomplete-market macro model. On job separation, the evidence of Stephens (2004) and a few follow-up studies (Dickerson and Green, 2012; Balleer et al., 2023) suggest upward biases in job-loss perceptions. Despite such biases, Dickerson and Green (2012); Hendren (2017); Pettinicchi and Vellekoop (2019), and Hartmann and Leth-Petersen (2024) suggest that workers' perceived job risks predict the unemployment outcome reasonably well, indicating they had advance information about future job events.

Our paper extends the aforementioned literature in two ways. First, we focus primarily on the business cycle fluctuations of risk perceptions relative to their realizations, instead of the level differences between them. Second, to the extent that realizations of job transitions are not necessarily identical to the ex ante rational assessment of the risks, we also construct a proxy of such a rational benchmark to evaluate the subjectivity of risk perceptions in the survey.

Beyond job transitions, recent literature follows the steps of Dominitz and Manski (1997) and Dominitz (2001), who study earning or income expectations and subjective income risks by leveraging survey data— see Wang (2023); Caplin et al. (2023); Rozsypal and Schlafmann (2023), and Koşar and Van der Klaauw (2025). What has emerged as a common theme of this

[4]For example, Patterson (2023) shows that workers with the most cyclical incomes also have the highest marginal propensities to consume. Similarly, Guerreiro (2023) identifies the conditions under which the interaction between belief disagreement and heterogeneity amplifies business cycle dynamics.

literature is that survey expectations often exhibit different patterns from the income expectations and risk profiles that are estimated and calibrated in the existing literature. Meanwhile, such subjective expectations are often shown to be highly predictive of household decisions, an assumption taken as a given by this paper.

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

In addition, Morales-Jiménez (2022), Menzio et al. (2022), Rodrıguez (2023), and Mitra (2024) incorporate informational frictions in standard search and matching models to resolve the volatility puzzle in the aggregate unemployment rate. In a departure from their work, we explore the implications of perceived unemployment risks on consumption/saving and aggregate demand fluctuations. Our findings of the heterogeneity in job expectations also relate to Broer et al. (2021a), who rely 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 the 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.

Lastly, this paper draws insights from the literature that adopts real-time forecasting to approximate ex ante uncertainty/risks and applies it to the labor market context. Our approach is also closely related to using machine-efficient forecasts as a rational benchmark rather than a constructed benchmark under a specified 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) and Rossi and Sekhposyan (2015) in measuring the macroeconomic uncertainty instead of specifically labor income risks.

2 Perceived job risks predict realized job transitions

2.1 Data

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

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

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

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

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

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

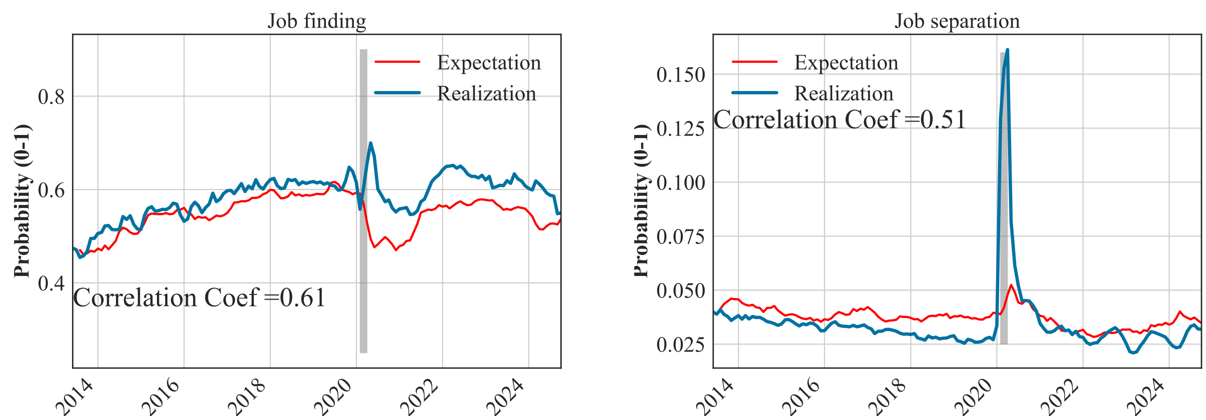
Time Aggregation. The perceived transition probabilities are reported for different horizons from the realized flow rates. For consistency, we convert all these rates into 3-month horizons using the following procedure. Consider the flow rates for three consecutive months, denoted p_1, p_2, and p_3.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

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

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.

Figure 1: Perceived versus realized job transitions



Notes: This figure plots the perceived job transition probabilities over the 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}.

The correlation between perceived risks and realized flow rates would have been even higher without the COVID pandemic crisis, which introduced the most significant deviations of perceived risks from subsequent realizations. At the onset of the pandemic, the perceived job-finding rate dropped sharply, but the actual job-finding rate increased initially. This discrepancy was partly driven by the rehiring of previously laid-off workers through recalls (Gertler et al., 2022). Similarly, while perceived separation risk spiked at the onset of the crisis, the spike was dwarfed by a much higher increase in the realized job-separation rates. Such deviations highlight the unexpected nature of the COVID shock. However, the dynamics of perceived risks and corresponding realizations moved in tandem again within two months following the initial outbreak. The unusual labor market dynamics during the COVID crisis were unprecedented even for professional economists in real time, and continue to be a subject of current and future studies. Therefore, it is noteworthy that average perceptions of job risks could still partially predict ex post labor market flow rates, despite the unprecedented crisis.

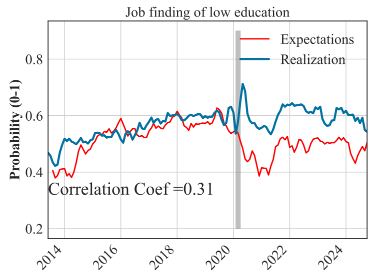
The fact that perceived risk predicts subsequent changes in the labor market is, on one hand, surprising, and on the other hand, reassuring. Growing survey evidence suggests that households' macroeconomic expectations, especially regarding inflation and unemployment rates, tend to contain systematic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

Within-Group Comparison. The results presented above are based on average rates across all households in the survey. One potential concern when generalizing these findings is how perceptions and realizations compare within demographic groups. Several studies, such as Hall and Kudlyak (2019), Gregory et al. (2021), and Patterson (2023) show the importance of heterogeneity in job risks in driving aggregate labor market dynamics, while Broer et al. (2021a) provides indicative evidence that information frictions are heterogeneous along the wealth distribution. Therefore, we also calculate both perceptions and realizations separately for low-, middle-, and high-education groups, separately, as plotted in Figure 2.[6] The figure reveals that, within each education group, the dynamics of perceived risk and realized rates closely mirror those observed at the aggregate level, exhibiting a high correlation during normal times. There is, however, substantial heterogeneity by education level in the realized rates, both in terms of overall levels and time-series volatility. Not surprisingly, low-education workers face higher job-separation and lower job-finding rates than high-education ones. The differences in perceived job risks, especially in job-separation rates, are relatively small across education groups. Interestingly, low-education workers appear to particularly under-forecast 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 latter part of the paper.

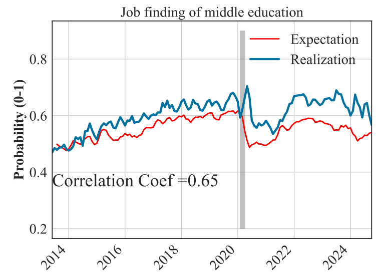
[6] We follow the definitions, applied by the SCE and Federal Reserve Bank of San Francisco, of low education as high school or less, middle education as some college, and high education as a bachelor degree or more.

Figure 2: Perceived versus realized job transitions by education

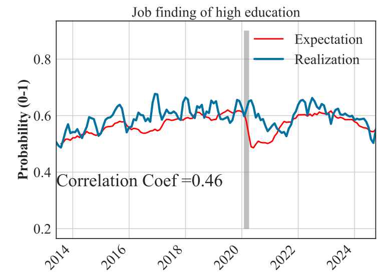
(a) JF of low education



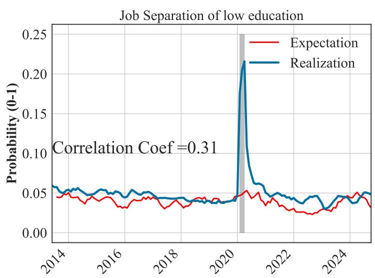
(b) JF of middle education



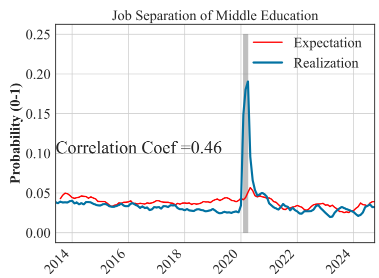
(c) JF of high education



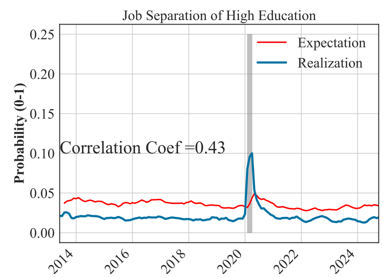
(d) JS of low education



(e) JS of middle education



(f) JS of high education



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

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 auto-regression 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).

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

Table 1: Forecast error regression

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

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

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

where X_{t-3} denotes information available at time $t-3$. A key null hypothesis under FIRE is that agents fully react to new shocks to the underlying variable. A significantly positive β implies predictable forecast errors based on past forecast errors.[7] In particular, $\beta > 0$ suggests that past errors persist into future forecasts in the same direction, reflecting the presence of information rigidity.

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

These positive and significant estimates of the autocorrelation of non-overlapping forecast errors suggest the presence of information rigidity in perceptions of job transition risks. In particular, they indicate that forecast errors made three months ago persist into current forecast errors. The fact that these estimates are well below one implies a moderate degree of information rigidity. This is especially plausible if the underlying shocks to job finding and separation are themselves persistentunder such conditions, even a mild degree of rigidity can generate non-zero autocorrelation in forecast errors.[8]

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

[8] As shown in Coibion and Gorodnichenko (2012), in models such as Sticky Expectations and Noisy Infor-

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 those of job separation are negative. At face value, this implies that ex ante perceptions of job risks underestimate the job-finding and over-forecast the job-separation rates. Although it is tempting to conclude that job risk perceptions are biased based on such evidence, as is argued in several papers, in this paper we focus on only the dynamic rigidity of risk perceptions instead of its constant bias in levels, with a cautionary note that the sign of the latter is sensitive to the exact procedure of aggregation of individual beliefs.[9]

3 Measuring subjective versus objective risks

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

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

mation, the autocorrelation of forecast errors equals the product of the degree of information rigidity and the persistence of the forecasted variable.

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

information up to time t.

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

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 4)

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

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

- real-time macroeconomic data, such as inflation, unemployment rate, GDP growth, etc. We ensure that these series are real-time data rather than retrospectively revised figures.
- household expectations from the MSC. We use disaggregated indices instead of composite indices in the survey. These indices contain rich information on how average households perceive the macro-economy and their personal finances. Notably, we include survey questions that elicit respondents' recent exposure to macroeconomic news, their intentions to purchase durable goods, and the reasoning behind their reported expectations (e.g., "it is not a good time to buy a car because the price is too high").[10]
- realized job-finding and separation rates calculated from the CPS (Fujita and Ramey, 2009). Given the persistence of flow rates, recent job flow realizations may serve as strong predictors of future transitions.
- consensus professional forecasts of the macro-economy from the 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 reflect one of the most sophisticated and informed perspectives on the macro-economy in real-time. Indeed, Carroll (2003) treats professional forecasts as a proxy for real-time rational forecasts. Here, however, we do

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

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 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.

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

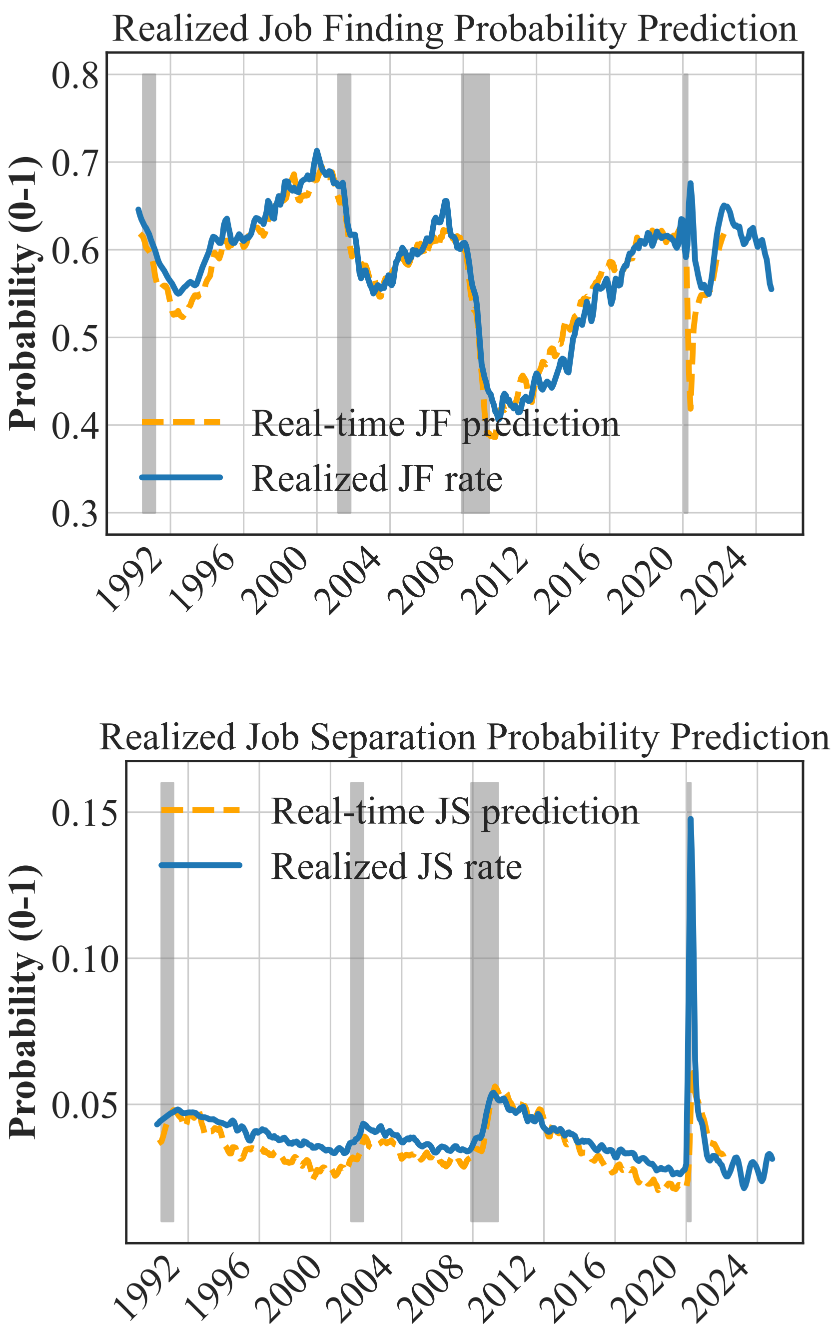
In practice, however, we cannot always rely on perceived risks by households, as such data have been available in the SCE only since 2013. Instead, we indirectly include all time series on household expectations in the MSC, assuming that perceived job risks are ultimately correlated with other household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

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

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

Figure 4 highlights the importance of using real-time forecasts without relying on hindsight. In most of the sample periods, the machine-efficient real-time forecasts of job-finding and sepa-

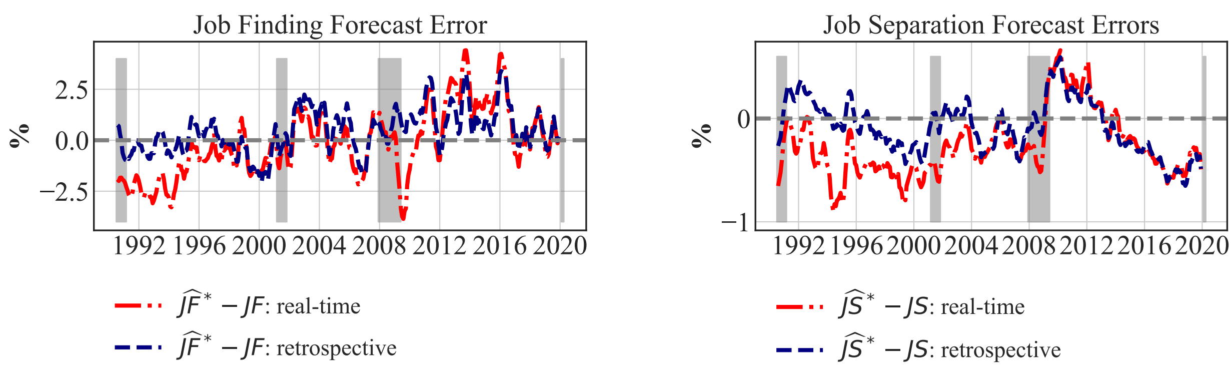
Figure 3: Machine prediction of labor market outcomes



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

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



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

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

In addition, many forward-looking variables in the MSC consistently predict future labor market outcomes. The fact that many expectations 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 a 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 the two series' respective correlation with ex ante perceived job risks. In addition, durable goods demand plays a crucial role in aggregate fluctuations through general-equilibrium forces, as shown in McKay and Wieland (2021). Interestingly, survey questions that directly elicit rationales from households on their expectations, such as "not buying a durable due to high uncertainty," also help predict future job transition rates. This pattern confirms the finding by Leduc and Liu (2016) that is also based on the uncertainty question elicited in the MSC.

Comparing machine-learning forecasts with simple time series models. Are these predictions as good as one univariate time series prediction? Given the persistence and time-series correlation of flow rates, the answer is not necessarily yes. We therefore compare the mean squared errors (MSE) of real-time forecasts using all datasets with a real-time forecast that uses only an Autoregressive model of order 1 (AR(1)). 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) forecasts over-predict job separations due to the historical persistence of the separation rate, while LASSO model-based separation risk is predicted to have a more temporary reversal, following the initial dramatic spike.

3.2 Backcasting perceptions: what were people thinking then?

Directly observed perceived risks have been available in the SCE only since 2013. Meanwhile, a wide range of expectations have been surveyed in the MSC for a much longer time span, some of which go back to as early as the 1960s. Under the assumption that the correlations between different expectations have been stable,[11] we can utilize the estimated correlation between perceived job risks in the SCE and other expectations in the MSC in the overlapping

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

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.

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

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

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

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

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

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

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

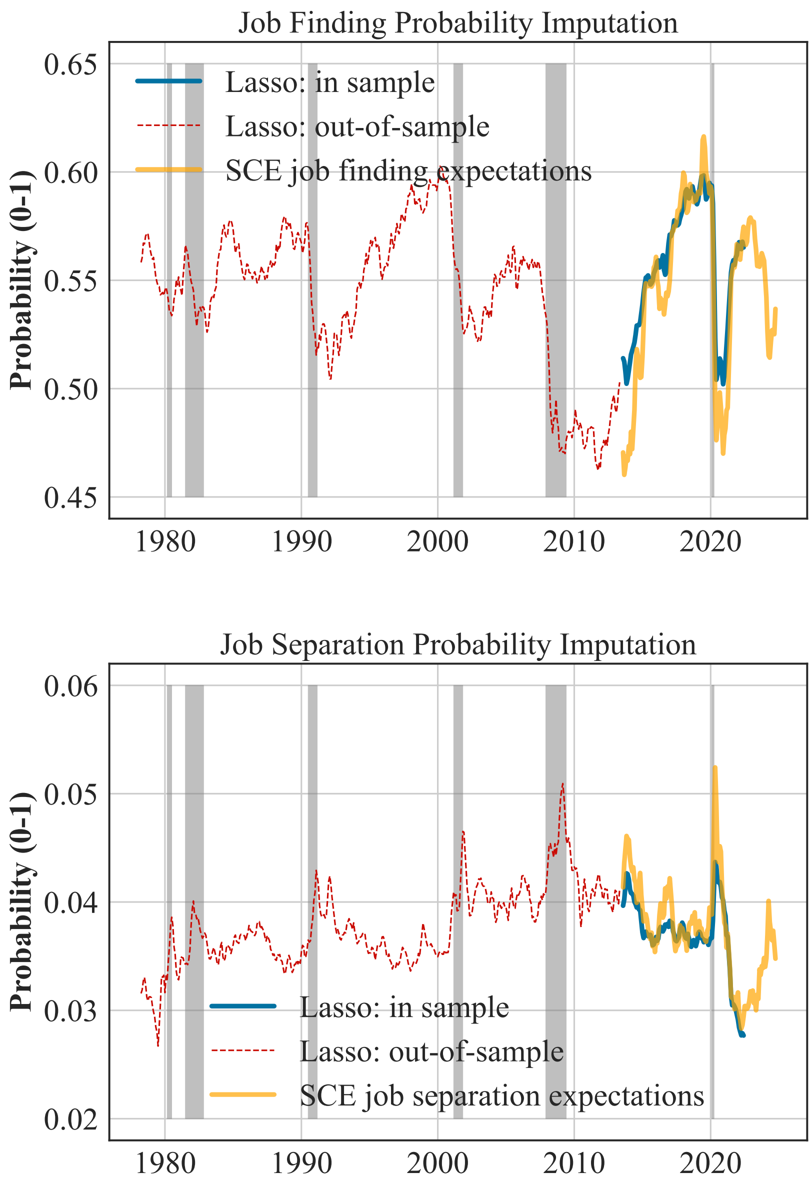
Our benchmark imputation in-sample includes the 2013-2022 period, which witnessed drastic movements in the labor markets. In Appendix A.2.3, we examine whether the choice of including the Covid era has a significant impact on the dynamics of the imputed beliefs. In particular, we show that the belief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

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 on both sides of the equation so that the coefficient can be interpreted as the elasticity of beliefs with respect to changes in real-time risk. A coefficient with a size of unity corresponds to the situation where perceived job risks fully react to real-time rational risk, e.g., no under/overreactions.

Our estimates suggest that for each one percentage point increase in a real-time job-finding forecast, the average perceived job-finding rate increases by 0.5 percentage points, as reported

Figure 5: Imputed perceived job risks



Notes: The two charts plot imputed perceived job risks that are predicted using the selected LASSO model based on in-sample cross-validation.

in Equation 6.[12] On one hand, the significantly positive coefficient estimate suggests that perceived job finding somewhat co-moves with the real-time job-finding rate. On the other hand, a coefficient of half is indicative of underreaction in job-finding expectations. Figure 6 plots the perceived risk against real-time machine-efficient risk forecasts, in addition to ex-post realized transition rates, which visually exhibit such patterns.

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

Perceived job-separation probabilities are less correlated with real-time risk, with a regression coefficient $\widehat{JS}^{*}_{t+3|t}$ of 0.19 (equation 7), implying only a 20-cent increase in perceived job separation in response to one percentage point increase in machine forecasts. Perceived job separation fails to incorporate about 80% of the predictable job-separation transitions.

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

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

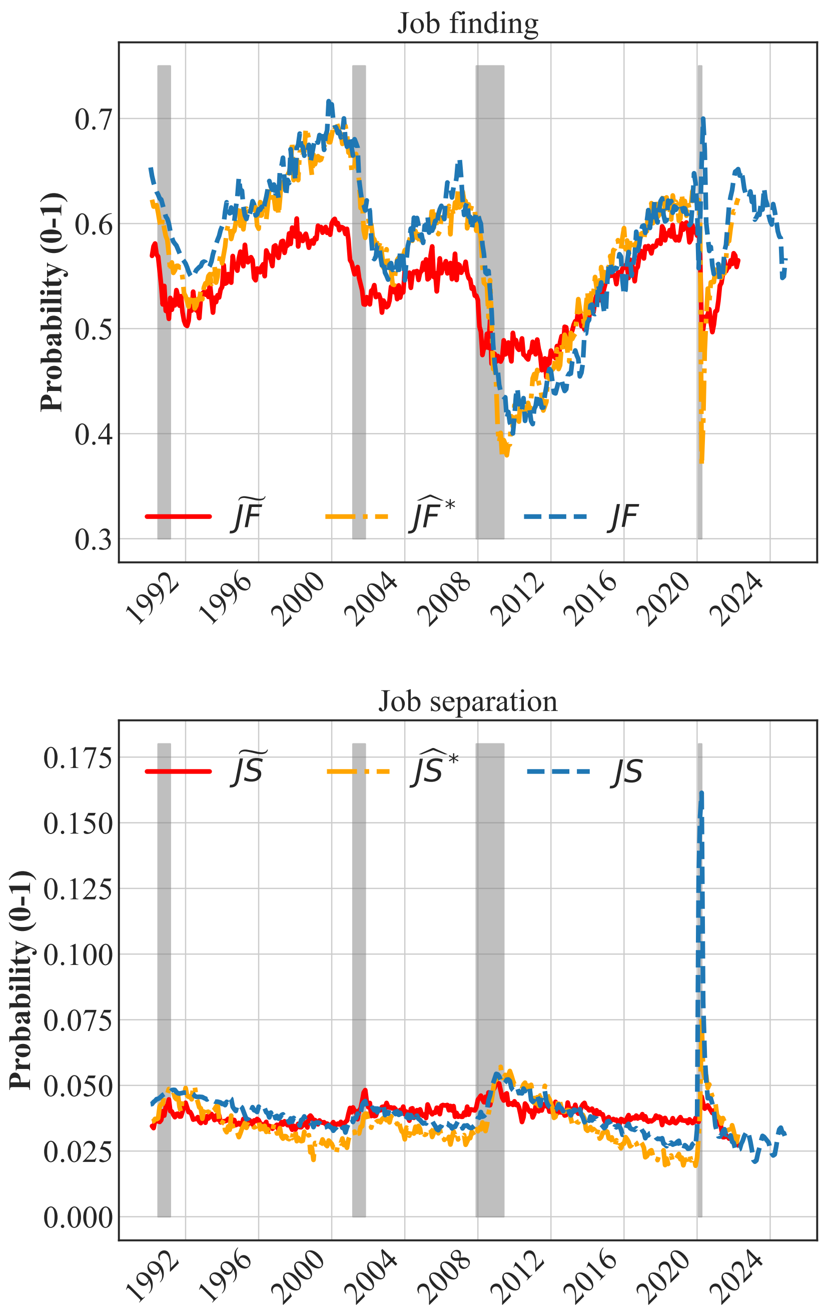
$$\widetilde{JF}_{t+3|t} = \lambda JF^{*}_{t+3|t} + (1-\lambda)\widetilde{JF}_{t+3|t-3} \tag{8}$$

Table A.3 and A.4 report the estimates for job finding and separation perceptions, respectively. It seems that the actual patterns of perceptions do not fully comply with the canonical SE formulation, since the coefficients of 3-month lag perceptions are not often statistically significant. Nevertheless, when the lagged perceptions are controlled for, the coefficient of JF^{*}_{t} and

[12] These regression coefficients are all statistically significant, as reported in Table A.1 and Table A.2. Estimates using the post-2013 sample without imputed beliefs show a higher sensitivity for job finding perceptions (0.81) and a lower one for job separation perceptions (0.14), as reported in Table A.5 and A.6. With this, we argue that our documented pattern that risk belief underreaction to real-time risks is not driven by the data patterns in imputed perceptions.

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

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



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

JS_t^* remain in a similar range as reported above, indicating a similar degree of underreaction of perceived risks to real-time risks.

4.1 Heterogeneity in job risks

Our analysis so far assumes homogeneous job risks, which means that the perceived job risks assumed by different workers are supposed to react to the true aggregate risk to the same degree, in the absence of belief distortion. But in reality, job risks are widely heterogeneous across workers; see Hall and Kudlyak (2019),Ahn and Hamilton (2020) and Gregory et al. (2021). So are the perceived risks, as shown in Mueller et al. (2021) and 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 (MPC) and the cyclicality of their income amplifies recessions compared to a world with equal income exposure. A similar argument can be made in the space of job risks. We therefore consider it important to study ex ante heterogeneity in job risks. Unlike the common countercyclical risks that drive time-varying fluctuations, the presence of risk heterogeneity causes business cycle fluctuations via its heterogeneous incidences.

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

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

If the following equation holds, namely if average perceived job risks across agents converge to the aggregate job risks, JF_t depends on at least two factors. The first is the cross-sectional distribution of $\eta_{i,t}$. The second is the expectation patterns of individuals toward aggregate job risk. Even if all workers correctly perceive JF_t, which implies $\mathbb{E}_i(\mathrm{JF}_{i,t}) = JF_t \forall i$, the heterogeneity in job risks still matters for the patterns 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 the job-finding rate *across workers* and *during unemployment spells* are important to explain the patterns of job-finding perceptions. To the extent that such beliefs induce self-insurance behaviors through job search, underreaction to the heterogeneity and duration-dependent variations results in a larger dispersion in job-finding outcomes. What this paper has shown so far is essentially that such underreaction to variations in job risks also exists along the variations of job risks over business cycles at the aggregate level.

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

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

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

The job-finding perceptions of the 25th percentile worker react to the real-time job-finding rate by a much larger degree than the rest, as implied by the coefficient estimates of 1.22 for this group, as opposed to 0.63 for the median worker and 0.20 for the worker at the 75th percentile. To put it bluntly, those who usually believe that they cannot easily find a job are the marginal workers whose belief reacts the most to the real-time job-finding rate. 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 who have the most sensitive reactions to the aggregate real-time job-separation rate. The estimates of responses range from 0.46 for 25th percentile workers (almost a non-reaction) to 0.68 and 0.27 for the median and 75th percentile workers, respectively.

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

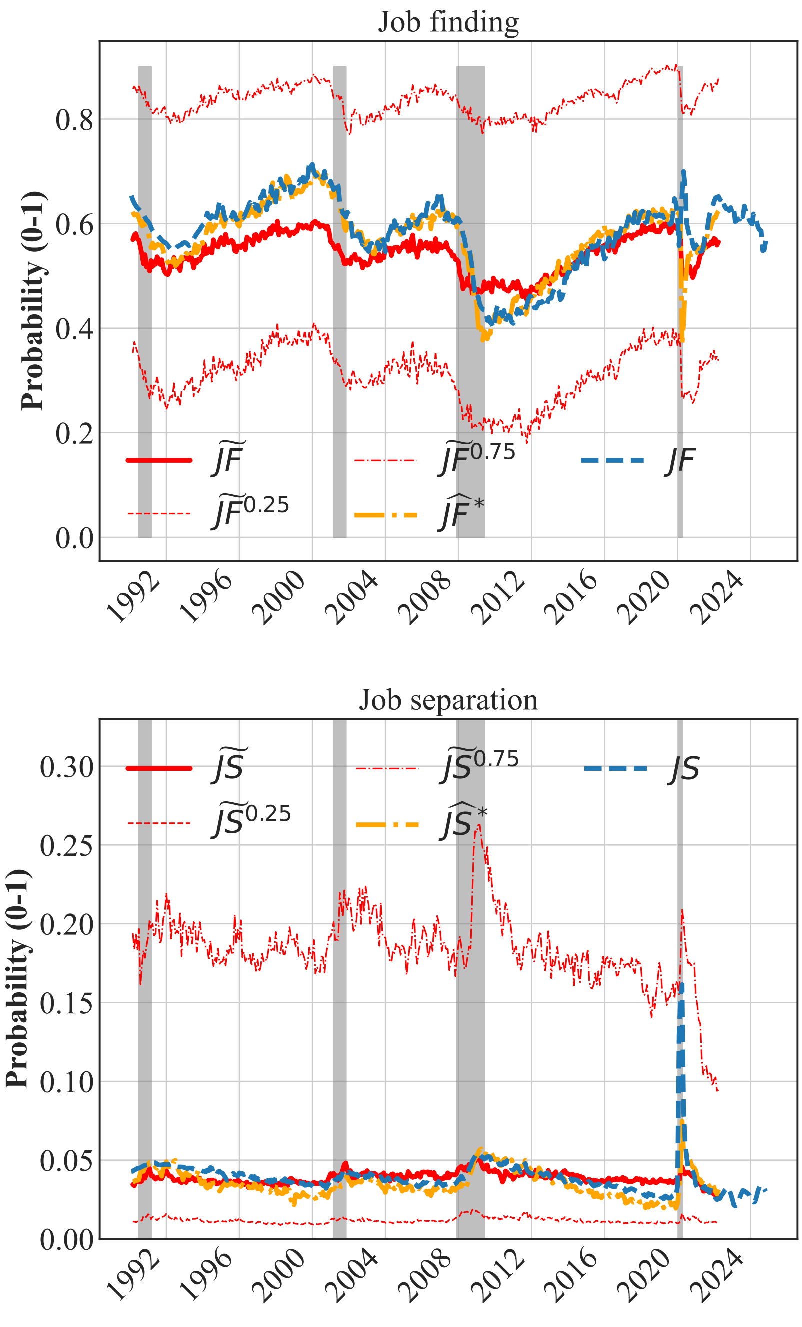
The heterogeneous sensitivities of perceptions with respect to common aggregate risk are probably sensible. In particular, the perceptions of those who perceive high job risks (high separation and low finding risk perceptions) show the highest sensitivity. Business cycles are not just characterized by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

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

4.2 Heterogeneous perceptions of job risks

Is there heterogeneity in terms of belief distortions, in addition to the heterogeneity in true job risks faced by different workers? If the workers who face the most cyclical movements in job risks tend to under-perceive such movements—and therefore under-insure themselves—total

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



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

consumption fluctuations amplify, due to the heterogeneous footprints of uninsured job risks.

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

The estimates are reported below. In terms of job finding, the middle-education group is the most rigid, relative to their real-time risk, than the low- and high-education groups. Meanwhile, with job separation, low-education workers underreact to the real-time risks the most, exhibiting the largest degree of information rigidity. Such patterns are consistent with the patterns in Figure 2, i.e., that different low-education groups underestimate the spike in job-separation rate and react more strongly to the decline in job finding at the outbreak of the pandemic compared to the high-education group. Assuming a strong correlation between education and liquid wealth, Broer et al. (2021a) would predict a U-shaped pattern, as poor and rich households have the highest incentives to know the current state of the world. Our results support such a claim for job finding, but contradict it for job-separation rates. In fact, workers without a high school degree have the weakest reaction in beliefs to changes in realized job-separation rates, even though they would have the largest utility penalties of non-optimal precautionary savings.

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

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

4.3 Business cycle patterns of (a), (b) and (c)

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

In this section, we focus on summarizing the dynamic patterns of (a), (b), and (c) over the past four business cycles in our sample, which are crucial to the consumption fluctuations due to these channels. We discuss two sets of metrics. The first one is the unconditional standard deviation of (a), (b), and (c). The second metric is the ratio between the onset and the end of each recession in our sample. More intuitively, these ratios reflect the changes in these rates from the peak to the trough of each cycle.

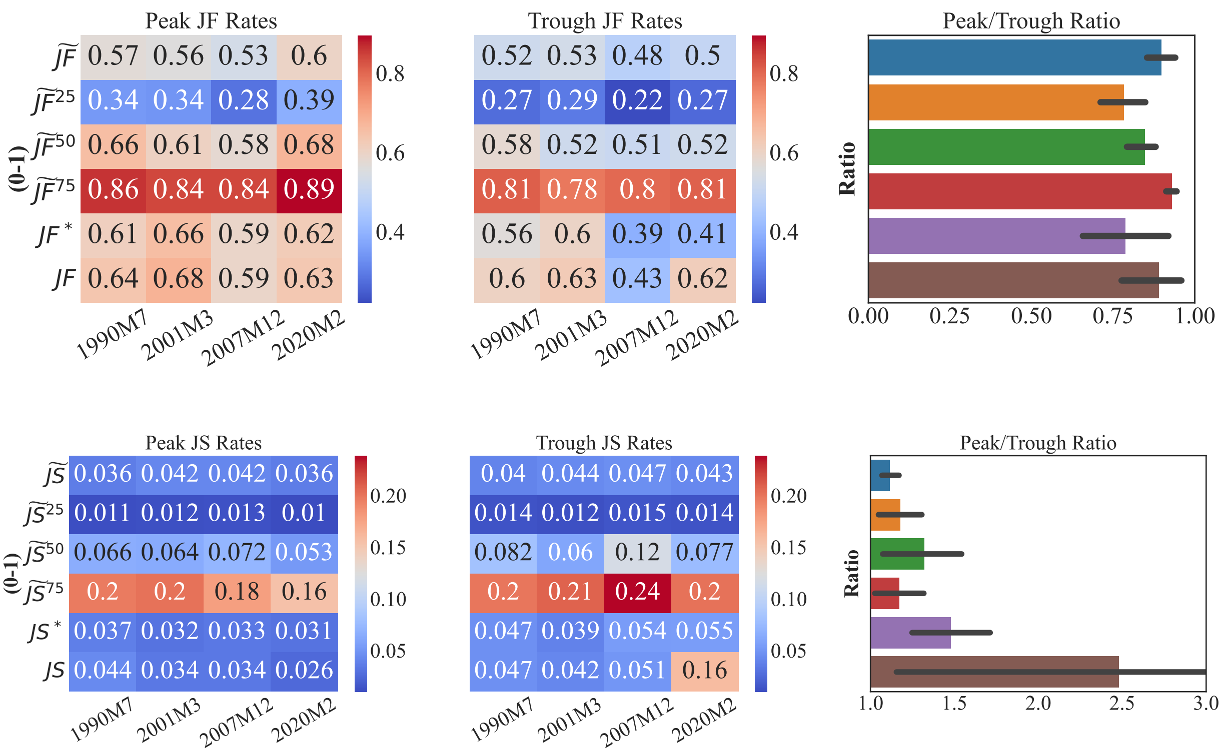
Throughout our data sample of 1990-2024, which covered four recessions and experienced sizable cyclical movements of unemployment risks, the unconditional standard deviation of realized job-finding rates is approximately 7.2 percentage points. Most of these variations are reflected in real-time job-finding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

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

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

Such average patterns mask substantial heterogeneity in job risks and perceptions. Figure 8 also plots the movements of perceptions over business cycles by agents at different percentiles of perceived job risks. In terms of job-finding, although an average worker's perceived job-finding probability drops by 15% from the peak to the trough of a recession, which is more or less comparable to the realized job finding, it is the low-finding rate worker at the 25th percentile who perceives a much sharper drop of about 25%, compared to a drop of 10% for the worker at the 75th percentile. In terms of job separation, although an average worker's job-loss perceptions increase by only 15 percentage points in recessions, the *median* worker's perceptions increased much more sharply, by about 35 percentage points. Recessions hit agents

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



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

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 Quantifying the aggregate consumption impacts of unemployment risks

In this section, we simulate the path of aggregate consumption dynamics by feeding our time series of perceived and objective unemployment risk and measures of actual job transition rates into a standard heterogeneous agent model with persistent unemployment. By doing so, we show that the strength of the unemployment risk channel changes substantially when household beliefs are disciplined by survey data on workers' expectations of finding and losing jobs, instead of by the realized counterparts of these probabilities, or the proxy of their rational ex ante counterparts. Furthermore, we demonstrate that the magnitude of this channel differs significantly across education groups.

5.1 Model

We work with a partial equilibrium model of household consumption and saving under the incomplete market at a monthly frequency. The model features a continuum of workers of unit mass indexed by i, each facing idiosyncratic labor productivity shocks and stochastic transitions between employment and unemployment. Households self-insure against these risks by saving in a risk-free asset. Preferences are represented by a standard CRRA utility function, and β denotes the discount factor.

Household Optimization Problem. Each period t, a household's state variables include market resources $\mathbf{m}_{it}$, productivity e_{it}, and employment status $n_{it} \in \{e, u\}$. The household solves the following dynamic programming problem:

$$v_t(\mathbf{m}_{it}, e_{it}, n_{it}) = \max_{\mathbf{c}_{it}, \mathbf{a}_{it}} \{U(\mathbf{c}_{it}) + \beta \mathbb{E}_t \left[v_{t+1}(\mathbf{m}_{it+1}, e_{it+1}, n_{it+1})\right]\} \tag{14}$$

subject to the constraints:

$$\mathbf{a}_{it} = \mathbf{m}_{it} - \mathbf{c}_{it} \tag{15}$$

$$\mathbf{m}_{it} = \mathbf{z}_{it} + (1 + r)\mathbf{a}_{it-1} \tag{16}$$

$$\mathbf{a}_{it} \geq 0 \tag{17}$$

Here, $\mathbf{a}_{it}$ denotes savings carried into the next period, $\mathbf{c}_{it}$ is consumption, and r is the net return on the risk-free asset. Market resources $\mathbf{m}_{it}$ consist of labor income $\mathbf{z}_{it}$ and the return on last period's assets.

Labor Income Process. Labor income $\mathbf{z}_{it}$ is given by the product of persistent productivity e_{it} and an employment-state-dependent income factor ζ_{it}:

$$\mathbf{z}_{it} = e_{it} \cdot \zeta_{it} \tag{18}$$

The persistent productivity component e_{it} follows a log-AR(1) process:

$$\log e_{it} = \rho_e \log e_{it-1} + \eta_{it}, \quad \eta_{it} \sim \mathcal{N}(0, \sigma_e^2) \tag{19}$$

The employment income component ζ_{it} depends on employment status n_{it}:

$$\zeta_{it} = \begin{cases} \theta_{it}, & \text{if } n_{it} = e \text{ (employed)} \\ \\ \gamma\theta_{it}, & \text{if } n_{it} = u \text{ (unemployed)} \end{cases} \tag{20}$$

where θ_{it} is an i.i.d. lognormal shock with mean one and standard deviation σ_θ, and γ is the unemployment insurance (UI) replacement rate.

Employment Transitions. Employment status evolves according to a Markov process:

$$\Pr(n_{it} = e \mid n_{it-1} = u) = JF_t \quad \text{(job-finding rate)} \tag{21}$$

$$\Pr(n_{it} = u \mid n_{it-1} = e) = JS_t \quad \text{(job-separation rate)} \tag{22}$$

They correspond to the realized transition rates JF_t and JS_t measured from CPS microdata.

Subjective Perceptions of Risks. While workers understand that employment transitions follow a Markov process, they may form subjective beliefs about these probabilities. Letting tildes denote subjective beliefs, we define:

$$\tilde{p}(n_{it+1} = e \mid n_{it} = u) = \widetilde{JF_t} \tag{23}$$

$$\tilde{p}(n_{it+1} = u \mid n_{it} = e) = \widetilde{JS_t} \tag{24}$$

We also define objective, forward-looking counterparts:

$$\hat{p}(n_{it+1} = e \mid n_{it} = u) = \widehat{JF_t}^* \tag{25}$$

$$\hat{p}(n_{it+1} = n \mid n_{it} = e) = \widehat{JS_t}^* \tag{26}$$

Note that both $\widetilde{JF_t}/\widetilde{JS_t}$ and $\widehat{JF_t}^*$ / $\widehat{JS_t}^*$ are forward-looking probabilities between t to $t+1$. They have not yet materialized as of t and their corresponding realizations are JF_{t+1} and JS_{t+1}. They correspond to our empirical measures of perceived risks and the objective benchmark proxies, respectively.

Calibration. Table 2 summarizes the calibration of the model. The unemployment insurance replacement rate is set to 50%. To be consistent with the paper's focus on business cycle fluctuations of perceived risks, we assume that the perceived job risks in the steady state are identical to those of actual realizations JF and JS. We calibrate the monthly discount factor $\beta = 0.988$ to match a quarterly marginal propensity to consume (MPC) of 0.21, consistent with survey evidence from Fuster et al. (2021).[14] Such MPC also indirectly disciplines the consumption sensitivity with ex ante unemployment risk, or the intensity of precautionary saving motives. Households with different liquid wealth in steady states react to an equal size of change in unemployment risk with different intensity. In particular, liquidity-constrained households have little room for adjustment in responses to a change in risk. Meanwhile, wealthy households do not react much to heightened risks, either.

Table 2: Household calibration in the baseline monthly model

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

5.2 Ex ante/ex post decomposition of aggregate consumption impacts

We start by characterizing the aggregate consumption response to changes in unemployment risks and shocks. For a given increase in the job separation and finding probability, either realized or perceived, the heterogeneous households with different levels of liquid wealth would change their consumption differently. Ex post responses differ due to heterogeneous MPCs resulting from different wealth levels. Ex ante responses differ due to different intensities of precautionary responses. The aggregate consumption impacts summarize such heterogeneous responses.

We employ the Sequence Space Jacobian method of Auclert et al. (2021) to efficiently compute the elasticities of aggregate consumption with respect to future job finding and separation probabilities as consumption Jacobians. Taking job separation as an example, the black line in Figure 9 plots the total consumption response to an increase in the job-separation probability at horizon $t+h$, with $h=10$, when it is both perceived since period 0 and realized 10 months later. It essentially corresponds exactly to the 10^{th} column of the consumption Jacobian that is usually obtained if one does not differentiate perceived risk from realized shocks.

Novel to this paper, we separately construct two Jacobians that sum up to the total Jacobian

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

above: one, when a shock to future job separation probability is perceived from period 0 but fails to materialize after 10 months, and another, when such a change is entirely unanticipated until its unexpected realization at $t = 10$. We refer to these as the *ex ante* and *ex post* Jacobians, respectively. The two channels operate through distinct mechanisms.

The *ex ante* Jacobian (the red line) captures workers' precautionary behavior before the shock at $t = 10$–that is, their self-insurance response to a perceived increase in separation risk that ultimately does not materialize. Because this risk hypothetically affects all workers, it leads to heterogeneous adjustments in consumption and savings, shifting the distribution of liquid wealth from periods 0 to 10. If the anticipated increase in risk fails to occur, these precautionary savings unwind after $t = 10$, resulting in a drop in savings or a boom in consumption.

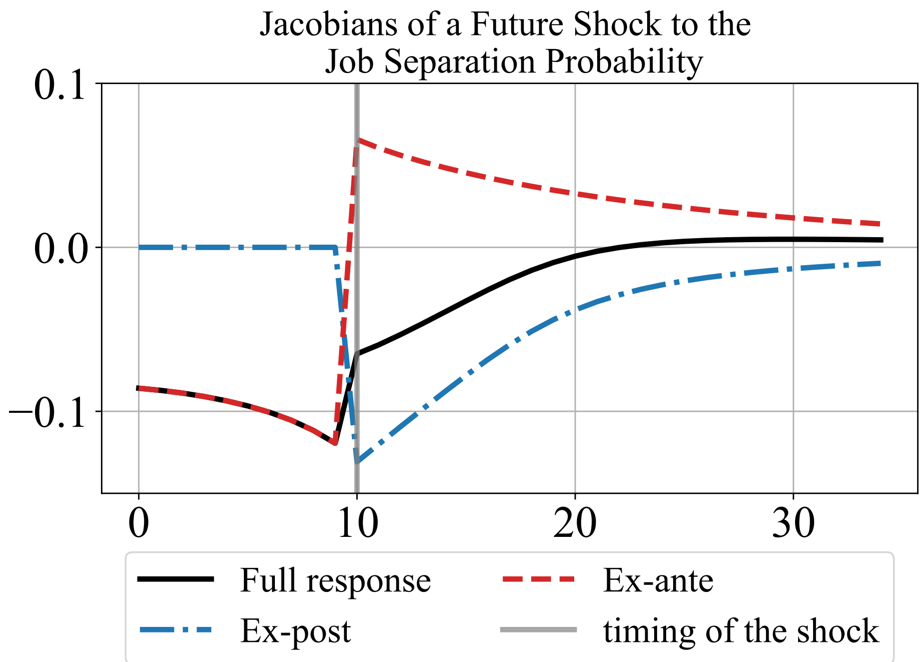
In contrast, the *ex post* Jacobian reflects the consumption response to a realized increase in unemployment when workers did not foresee the increase in job-separation risks. This channel only affects those who lose their job unexpectedly. Combining the ex ante and ex post Jacobian yields the total Jacobian corresponding to the black line in Figure 9. Notice that the actual consumption drop from $t+10$ onward, shown in the black line, is smaller than the pure ex post drop plotted in the blue line. This difference illustrates the impact of self-insurance behaviors.

Here we use t+10 as an example, but the decomposition logic holds for any horizon. Imagine a special case when h=0, meaning the shock to the job-separation probability immediately occurs. In this case, the ex ante Jacobian would be flat: no ex ante responses. The consumption impacts of such a realized shock would be entirely driven by ex post effects. It is also worth noting that the size of the ex ante adjustment varies with the horizon h, while the ex post adjustment does not. The nearer the future feared by the household is, the more dramatic is the consumption adjustment required to build buffers in response to heightened job risks in the future.

Now, let us illustrate how an arbitrary wedge between perceptions of job risk, and what would be realized subsequently, alters the ex ante responses, as well as the consumption impacts after the shock to job-separation probability is realized. Figure 10 illustrates how under-reactive beliefs—as documented in survey expectations about both job-finding and job-loss probabilities—weaken the precautionary channel while amplifying the effective income loss channel associated with unemployment. The figure includes two additional consumption responses under the assumption of sticky belief updating.[15] The purple line shows the *subjective* consumption response to an increase in the job-separation probability at $t = 10$, assuming that in each period between $t = 0$ to $t = 10$, 3% of workers update their expectations. We obtain such subjective Jacobians following the method used in Auclert et al. (2020), which essentially involves a transformation of the baseline Jacobians under perfect foresight. The ex ante com-

[15]While Figure 10 presents the subjective Jacobian decomposition to illustrate the under-insurance mechanisms arising from sticky job risk beliefs, the model experiments in the following section rely directly on the empirically estimated patterns of $\widetilde{JF}_t$ and $\widetilde{JS}_t$.

Figure 9: Consumption Jacobian with respect to an anticipated 10-period-ahead shock to the job separation probability



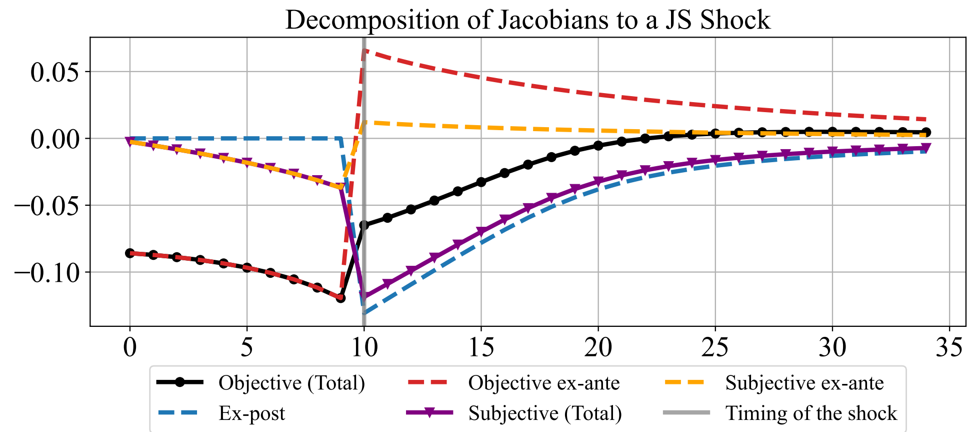
Notes: This figure plots the total and decomposed Jacobians of the aggregate consumption with respect to a shock to job-separation probability at $t + 10$. The Jacobian is defined exactly as in Auclert et al. (2021).

ponent of the response is significantly muted relative to the response under a full update of perceptions, shown in the red line. Meanwhile, under sticky beliefs, the consumption drop at $t = 10$ and beyond is substantially larger, reflecting a lack of self-insurance. This mechanism of under-insurance due to underreactive perceptions proves to be essential in driving our model results to be reported next. But instead of working with the specific formulation of Sticky Expectation, we work with a more general form of the subjective perceptions.

5.3 Quantifying the consumption fluctuations due to (a), (b), and (c)

Combining the ex ante and ex post Jacobians constructed above with the empirically observed perceptions, realizations, and objective risk proxies, we simulate the path of aggregate consumption deviations from its steady state implied by each. Our baseline analysis covers the period from 1988 to 2020. We assume that each series follows its own AR(1) process, potentially differing in both persistence and shock realizations. This general specification allows us to capture the joint dynamics of perceived and realized risks in a way that directly matches the data patterns, without imposing a specific model of expectation formation.

Figure 10: Subjective consumption Jacobians with sticky expectations



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

$$\textbf{Realizations: } JF_t = \rho_{JF} JF_{t-1} + \varepsilon_{JF,t}, \quad JS_t = \rho_{JS} JS_{t-1} + \varepsilon_{JS,t} \tag{27}$$

$$\textbf{Perceptions: } \widetilde{JF}_t = \rho_{\widetilde{JF}} \widetilde{JF}_{t-1} + \varepsilon_{\widetilde{JF},t}, \quad \widetilde{JS}_t = \rho_{\widetilde{JS}} \widetilde{JS}_{t-1} + \varepsilon_{\widetilde{JS},t} \tag{28}$$

$$\textbf{Objective risks: } \widehat{JF}^*_t = \rho_{\widehat{JF}^*} \widehat{JF}^*_{t-1} + \varepsilon_{\widehat{JF}^*,t}, \quad \widehat{JS}^*_t = \rho_{\widehat{JS}^*} \widehat{JS}^*_{t-1} + \varepsilon_{\widehat{JS}^*,t} \tag{29}$$

By estimating each equation, we filter the corresponding sequence of shocks that replicate the observed time series, as shown in Figure A.9 in the Appendix. Although our assumption completely separates the dynamics of perceived risks and realized flow rates, the empirically filtered shocks to the two are partially correlated over a common horizon. This imperfect correlation reflects the fact that there are both common and independent movements of the ex ante perceptions and ex post realizations. We then feed these shocks—accounting for their historical persistence—into the model to simulate the aggregate consumption path.

$$\{\hat{\varepsilon}_{JF,t}, \quad \hat{\varepsilon}_{JS,t}, \quad \hat{\varepsilon}_{\widetilde{JF},t}, \quad \hat{\varepsilon}_{\widetilde{JS},t}, \quad \hat{\varepsilon}_{\widehat{JF}^*,t}, \quad \hat{\varepsilon}_{\widehat{JS}^*,t}\} \quad \text{for } t = 1, \ldots, T. \tag{30}$$

The separation of ex ante and ex post Jacobians allows us to flexibly discipline the two channels in the model with respective empirical series. In particular, by combining the ex post Jacobian and the estimated realization shocks $\{\hat{\varepsilon}_{JF,t}, \hat{\varepsilon}_{JS,t}\}$, we can simulate solely the ex post consumption fluctuations. It simulates the scenario where workers did not perceive any changes to the job finding and job separation risk ex ante, and only a fraction of them, equal to the size of the estimated shock, unexpectedly faced realized job finding and separation in each month.

By combining the ex ante Jacobian defined above with the estimated shocks to either perceptions $\{\hat{\varepsilon}_{\widetilde{JF},t}, \hat{\varepsilon}_{\widetilde{JS},t}\}$, objective risks $\{\hat{\varepsilon}_{\widetilde{JF},t}, \hat{\varepsilon}_{\widetilde{JS},t}\}$, or realizations $\{\hat{\varepsilon}_{JF,t}, \hat{\varepsilon}_{JS,t}\}$, we can produce ex ante consumption fluctuations under various assumptions. While the ex post channel's impacts do not vary with the assumptions about perceived risks, the ex ante channel's quantification crucially depends on such assumptions. Adding different ex ante impacts and the same ex post one produces the overall consumption dynamics under various assumptions about perceived risks.

We start with the baseline quantification under subjective perceptions of unemployment risks, assuming that workers' expectations follow our survey-based measure of job-finding and job-loss perceptions, and that they acted upon such perceptions. The baseline experiment can be thought of as the factual decomposition. It is "factual" because we use directly observed subjective perceptions of risks to quantify the strength of ex ante impacts. The red bar, blue bar, and the black line in Figure 11 correspond to the ex ante, ex post, and total consumption dynamics, respectively.

Figure 11 shows that, while ex post impacts predominantly drove consumption fluctuations, ex ante responses to changes in perceived risks also made a sizable contribution, as indicated by the prominent red bars. This pattern confirms the importance of consumption responses to changes in perceived unemployment risks in driving business cycle fluctuations in aggregate consumption, even when such perceptions evolve sluggishly. To put it differently, it is not only the actual unemployment shocks but also the *fear of unemployment* that affect aggregate consumption dynamics over the business cycle. Notably, ex ante dynamics often preceded ex post impacts, consistent with our earlier finding that perceived job risks partially predict subsequent labor market realizations. The 2008 Great Recession illustrates this pattern: perceptions of heightened unemployment risk dampened aggregate consumption in the early phase of the downturn, while improving perceptions from 2012 onward supported the consumption recovery—even as ex-post impacts remained adverse.

Counterfactual experiments. As a comparison with the baseline simulation plotted as the black line in the figure, we also conduct the model simulation under two counterfactual scenarios based on alternative assumptions about how risks are perceived. The first (the orange line in Figure 11) assumes that workers' expectations follow our constructed measure of rational expectations $\widehat{JF^*}_t$ and $\widehat{JS^*}_t$. That is essentially equating (a) perceived risks to (b) objective risks, under the FIRE assumption. The second simulation (the green lines in the same figure) assumes workers have "perfect foresight," by which we mean that their perceived risks changed by exactly the same amount as those realized shocks to the job transition probabilities. It is essentially to assume (b) objective risks equal to (c) ex post realizations, a common implementation of the incomplete-market macroeconomic models when calibrating risks.[16]

(a) versus (b). The wedge between the baseline path and the counterfactual dynamics under objective risks reveals the effects of the deviations of the subjective risk perceptions from their ex ante rational benchmark. Throughout the sample, subjective-perception-implied consumption fluctuations are attenuated relative to their objective benchmark. For instance, in all past recessions, the objective risk dictated more drastic consumption responses at the onset of each recession than those implied by the subjective perceptions. The gap arises because of the underreactive patterns of the perceived risks relative to their rational benchmark. When recessions came along, due to the slow changes in perceiving the increases in unemployment risks, workers who ended up losing jobs had to experience a much more dramatic consumption adjustment at the moment of the shock realization. The underreactive perceptions lead to a sizable degree of under-insurance. Such underreaction also contributed to the slow recovery later.

Such a wedge is quantitatively important. For instance, the aggregate consumption at its trough during the 2008 Great Recession would have fallen below its steady state by 3 percentage points if the perceived risks had matched the true risks, given the persistently weak labor market during that time. In contrast, the negative consumption gap implied by the perceived job risks during this period was 1.5 percentage points. One may be tempted to conclude that, because of the collective underreaction to perceived risks, the aggregate consumption avoided an otherwise more dramatic drop, which seems desirable from the point of view of macroeconomic stabilization. However, such underreaction is the very reason why the consumption recovery after each recession was much slower. Also, what the aggregate underreaction masked is the fact that those who were under-insured and ended up getting hit by the unemployment shocks disproportionately bore the significant welfare losses due to under-insurance.

(b) versus (c). Comparing the two counterfactuals sheds light on the conceptual difference between ex ante risks and ex post realizations of job transitions. It turns out that the model-implied responses under the two assumptions are close to each other. This similarity is consistent with the earlier finding that machine forecasts can predict most of the subsequent labor market flows in past recessions, although the COVID crisis was a major exception. The small gap between the two suggests that the common practice in this literature of equating unemployment risks to realized job flow rates is more or less innocuous when it is used to analyze normal times or past recessions with persistent labor market conditions. We return to COVID as an exception to this statement in the next section.

[16]Note that, here, "perfect foresight" specifically refers to risk perceptions ex ante matching ex post transition rates. It does not mean that agents know the entire path of history. Nor does it mean that households face no idiosyncratic unemployment risks.

Job-finding versus job-separation. Additional insights arise when we separately assess the role of job-finding and separation risks, as shown in the bottom panels in Figure 11. First, when considering job separation alone, the stickiness in separation beliefs leads to a minimal ex ante precautionary saving response during recessions, as indicated by the nearly invisible red bars in the right bottom figure in Figure 11. Consequently, the total consumption response based on subjective perceptions closely mirrors the ex post impact and falls short of the response implied by objective risk.

Second, in the case of job-finding risk, precautionary saving plays a non-trivial role in driving consumption. However, because beliefs about job finding adjust only partially to the true underlying risk, there is still a large gap between the simulation with objective risk or perfect foresight versus subjective expectations.

Third, the combined impact of job separation and job finding—shown in the top panel of Figure 11—is driven largely by the job-finding channel. This pattern reflects three main factors. First, consistent with Fujita and Ramey (2009) and the broader search and matching literature, fluctuations in job finding account for a larger share of unemployment dynamics over the business cycle.[17] Second, in our model, job-finding risk matters not only for the unemployed but also for the employed, as workers face the possibility of job loss followed by difficulty finding re-employment. Furthermore, beliefs about job finding are also more responsive than those about separation, amplifying the precautionary saving motive. Since our model focuses on non-durable consumption, these estimates likely represent a lower bound. As noted by Carroll and Dunn (1997) and Harmenberg and Öberg (2021), the impact of unemployment risk on durable goods consumption is considerably larger.

5.4 Allowing for heterogeneous risks and perceptions

Figure 12 simulates consumption fluctuations for each education group separately, under the alternative assumption that job risks vary ex ante by education level. This assumption is motivated by the findings in Section 4.2, which show that lower-education groups are slower to adjust their perceptions of separation risk, despite facing larger fluctuations in those risks. In contrast, it is the middle-education group whose beliefs about job finding are the most sluggish in responding to real-time changes. We quantify the role of both misperceived risks and overall precautionary saving motives for each group. We calibrate the discount factor of low- and middle-education groups to target a quarterly MPC of 0.34, the MPC reported by Fuster et al. (2021) for individuals with less than a bachelor's degree. The discount factor of the high education group is calibrated to target a quarterly MPC of 0.27, the MPC reported by Fuster

[17] Also, Broer et al. (2021b) argues that job separations shape the short-term response, while job finding drives longer-term dynamics.

et al. (2021) for bachelor's degree holders and above.

Two key findings emerge. First, as expected, the low-education group exhibits the largest ex post consumption response during recessions, reflecting the interaction between the higher volatility of their realized job transitions and their higher MPC. For instance, at the trough of the Great Recession, low-education workers' total consumption stemming solely from ex-post impacts was as large as a 2-percentage-point shortfall relative to its steady state, whereas the high-education workers had a shortfall of consumption of only about 0.5 percentage points.

Second, compared to the high-education group, the low-education group shows a much smaller precautionary response overall, driven by their muted sensitivity in updating beliefs. This pattern is evidenced in Figure 12 by a much less noticeable red bar with the low-education group versus the middle and high education groups. It is also indicated by a much wider gap between their subjective and objective responses, and a smaller gap between their subjective and ex post responses. Due to the underreactive perceived risks, low-education groups exhibit the largest degree of under-insurance during the recessions.

Our group-specific analysis has an aggregate implication. When the workers most exposed to cyclical job risks are also the least responsive in updating their beliefs and engaging in self-insurance, the result is a sharper drop in consumption at the onset of unemployment shocks. Such interaction of risk exposure and under-insurance due to sticky risk perceptions creates a potential amplification mechanism for aggregate consumption to unexpected income shocks—not through its overall cyclicality, but through the uneven distribution of responses across groups. While heterogeneous risk exposure does not inherently amplify the aggregate impact of job risks, it can do so when exposure is positively correlated with under-insurance.[18] Our findings suggest this condition holds empirically, as those facing more cyclical risks appear especially prone to underreacting to changes in job risk.

5.5 A case study of the COVID recession

Our baseline simulations are based on the pre-2020 period. In this section, we focus specifically on the COVID-19 recession, which stands out in two key ways: it was highly unexpected ex ante and unusually short-lived ex post. These differences are central to assessing the relative roles of expectations versus realizations in driving consumption fluctuations.[19]

Figure 13 shows model-implied consumption responses to ex ante perceptions (red bar), ex

[18]A similar mechanism is discussed in Patterson (2023) where workers with high cyclical income exposure also tend to have high MPCs. The positive correlation between income exposure to the business cycle and MPCs creates an amplification mechanism.

[19]While the duration of the shock may have been uncertain—e.g., the number of waves in the U.S.—the probability of a permanent shock was very low.

post realizations (blue bar), and their combined effects (black line), abstracting from shocks outside January-November 2020. While March 2020 marked a sharp and unexpected rise in job separation rates—a defining moment of the COVID shock—the figure reveals that ex ante perceptions also exerted a significant impact on the consumption drop at the recession's onset. In April 2020, the aggregate consumption drop due to the heightened fear of not being able to find a job was about 1.2 percentage points. This drop was largely driven by the sharp decline in perceived job-finding probabilities in the SCE. As expected, ex post realizations played an equally important role during the initial stages of the COVID crisis and a more important one during the recovery afterwards. The respective patterns with job-finding and separations are plotted in Figure 14.

Figure 13 also shows consumption fluctuations under two counterfactuals: objective expectations (machine forecasts) and perfect foresight. Unlike in previous recessions, the COVID episode reveals a notable gap between the objective (orange) and perfect foresight (green) lines, highlighting the difficulty of anticipating COVID dynamics using only pre-existing information and without knowledge of policy responses. As of April 2020, machine forecasts projected a sharp, persistent drop in job-finding rates, leading to a steeper decline in consumption and a slower recovery, and reflecting the historical persistence of the series of objective job risk.[20]

In contrast, under perfect foresight, where ex ante risks equal ex post realizations, the model implies a much faster recovery following the initial consumption drop. The gap between these two scenarios mirrors the predictive wedge shown in Figure 3 between ex ante expectations and actual outcomes.

The contrast between the two scenarios underscores the importance of making a distinction between rational ex ante risk forecasts (b) and realized outcomes (c). In incomplete market macroeconomic models, it is common to equate ex ante risks with ex post realizations of job flows. While this simplification may be innocuous in normal times—or even during past recessions—it leads to markedly different consumption dynamics in an unprecedented crisis like COVID, where the gap between ex ante risks and ex post outcomes is particularly pronounced.

Our COVID exercise also underscores that assumptions about perceived unemployment risks play a key role in shaping aggregate consumption dynamics due to fluctuations in unemployment risks. Although it is rather plausible that the sharp but short-lived deterioration in labor market conditions in COVID episodes contributed to the observed drop in consumption, it is implausible that such ex post developments were fully anticipated ex ante and were perceived as unemployment risks. Assuming they were would imply unrealistically large precautionary responses. Moreover, even if one could define correct perceptions based on prevailing macro

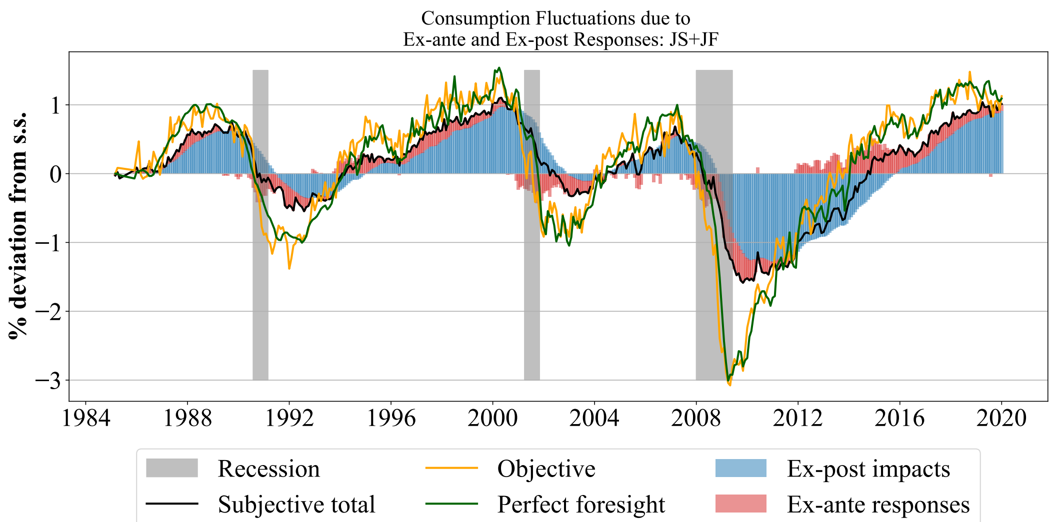
[20]One could argue that machine forecasts are inadequate here, as they cannot incorporate expectations of government intervention. Still, this exercise is informative, since even the best forecasts cannot fully capture unprecedented shocks.

conditions, it is unlikely that these could serve as the benchmark guiding actual self-insurance behaviors, which were much attenuated due to belief stickiness.

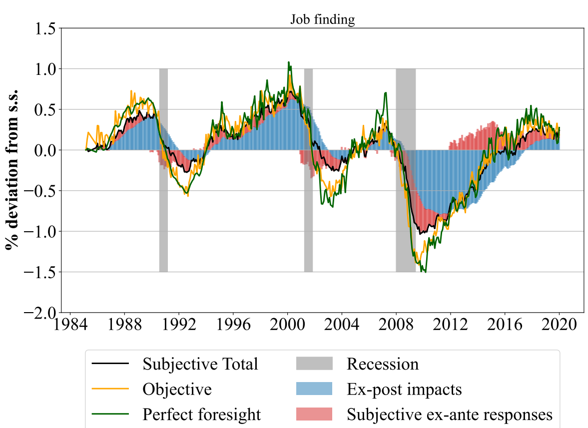
6 Conclusion

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 that 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. This belief stickiness limits the ex ante channel in driving consumption response and the degree of self-insurance, resulting in a larger impact of 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 countercyclical job risks. We show the quantitative importance of aggregate and distributional consumption drops due to precautionary savings, misperceived risks, and unexpected income shock response.

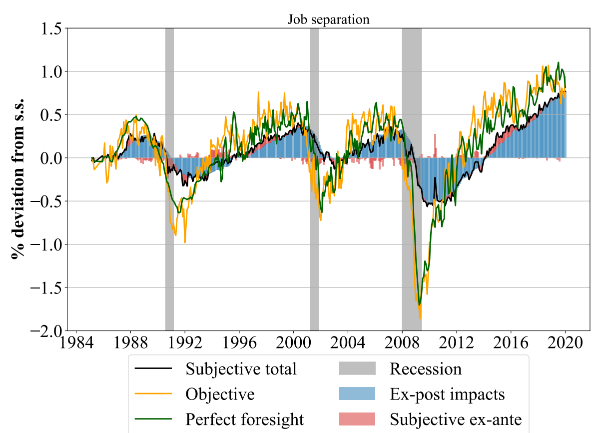
Figure 11: Consumption fluctuations due to unemployment risks



(a) JF

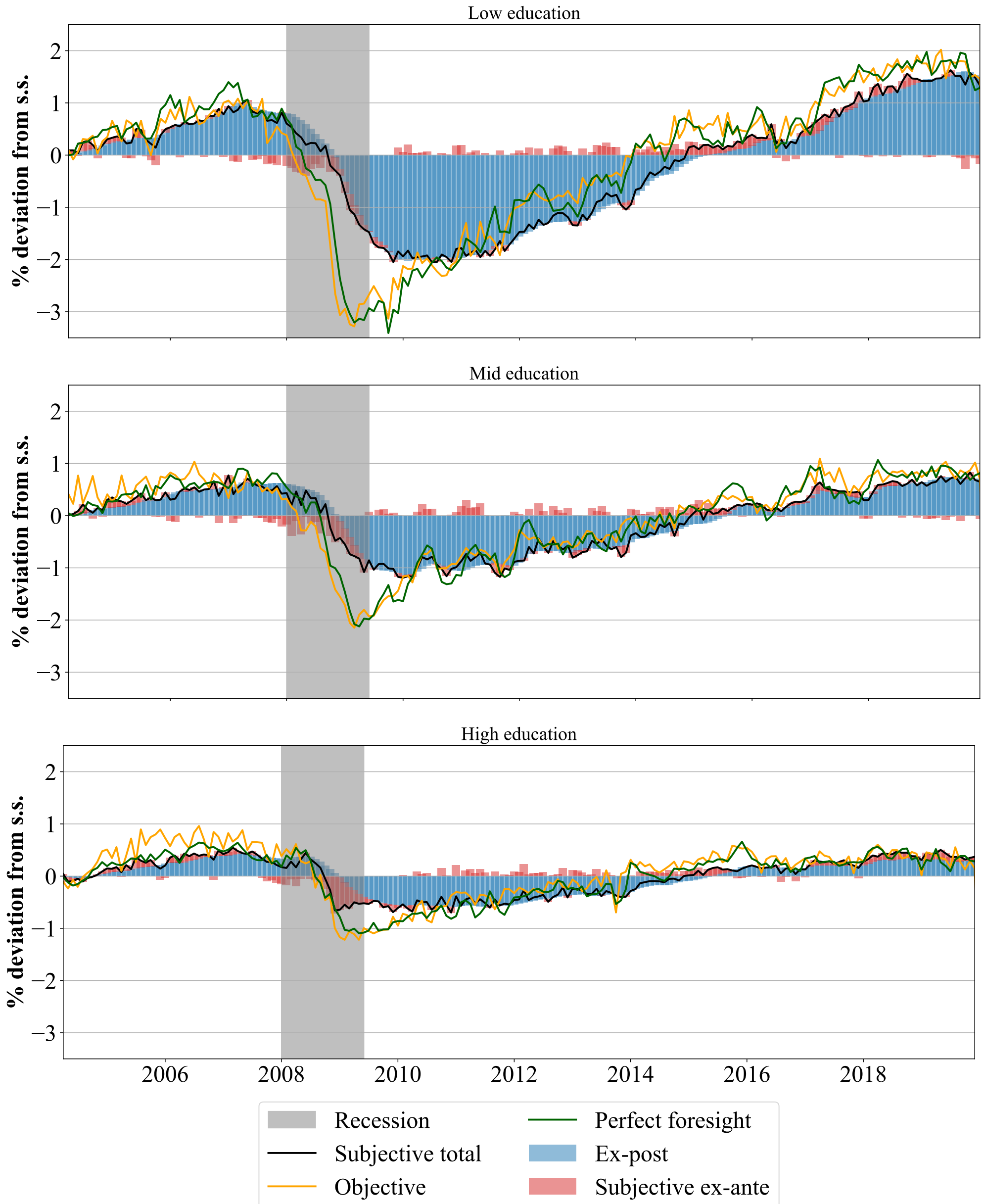


(b) JS



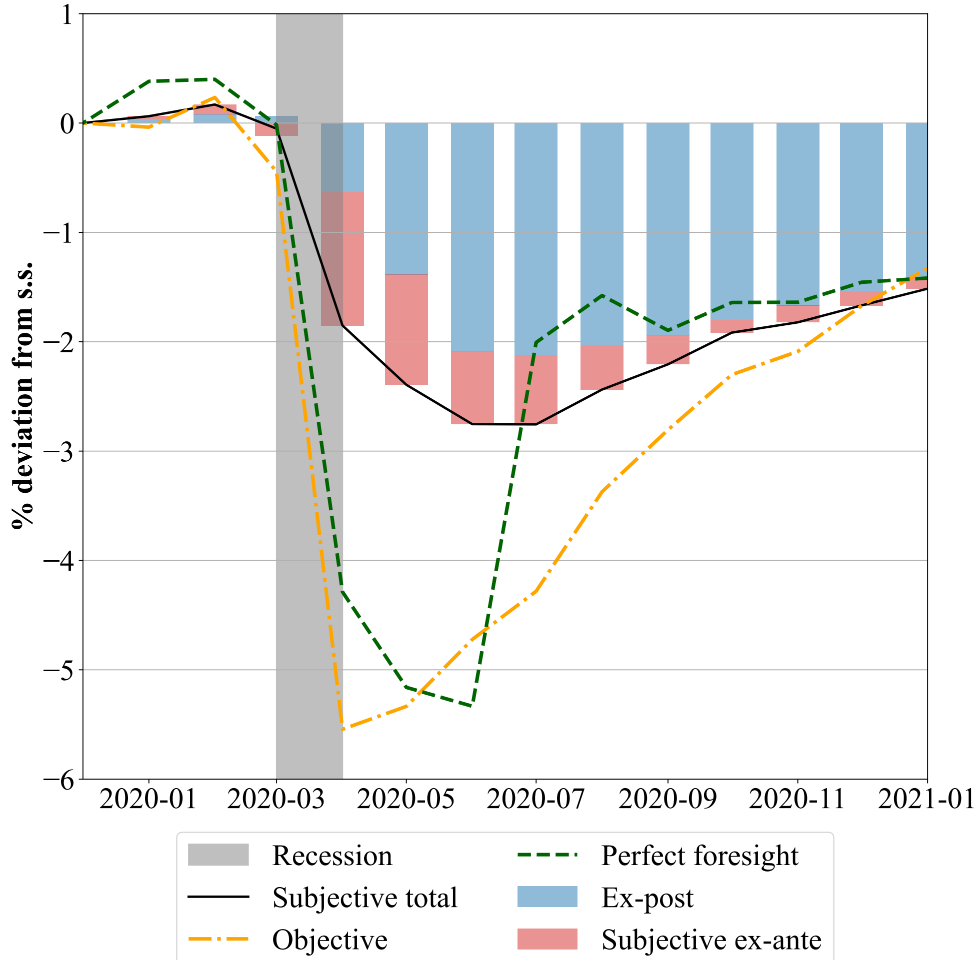
Note: The figure compares the partial-equilibrium aggregate consumption deviations from the model's steady state, simulated under various scenarios. The baseline simulation (black line) combines the impacts of ex-ante response to perceived job risk (the red bar) and the ex-post impacts of shocks to the realized job transition rates (the blue bar). In addition, it plots the consumption paths under two alternative scenarios where either agents' perceived risks match the ex-ante objective risks (orange line) or agents' perceived risks exactly reflect the shocks to the realized job flow rates (green line).

Figure 12: Consumption fluctuations due to unemployment risks by education



Note: The figure compares, for each education group, their partial-equilibrium aggregate consumption deviations from the model's steady state, simulated under different assumptions about the perceived risks, as explained in Figure 11.

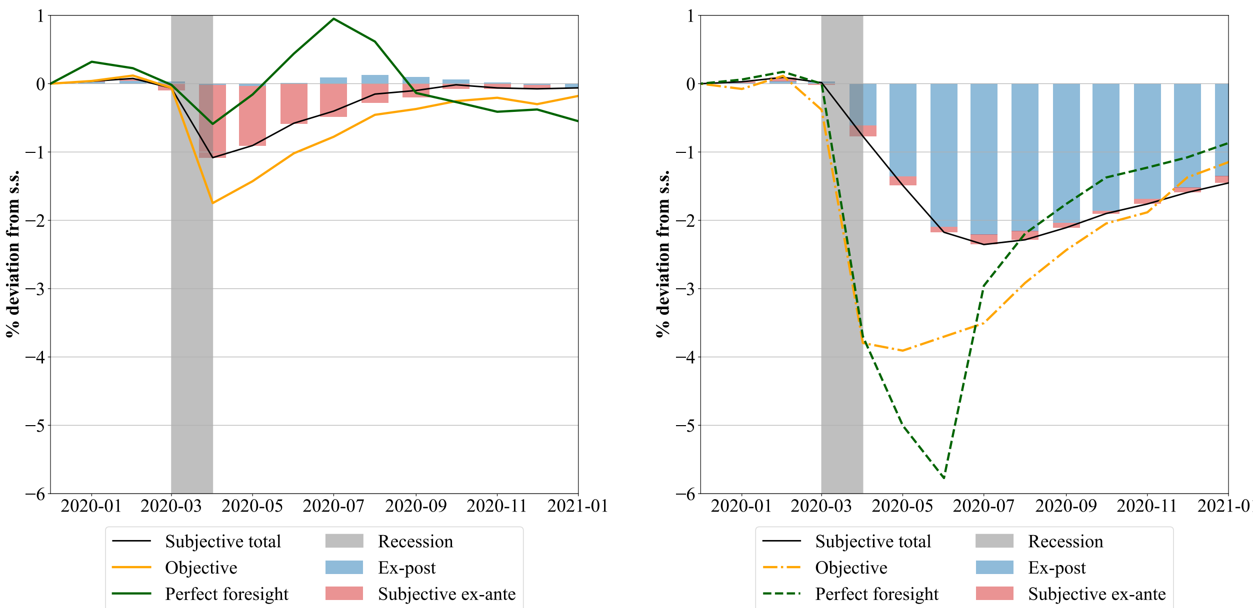
Figure 13: Consumption fluctuations due to unemployment risks during COVID



Note: The figure reproduces the model experiments for the COVID recession as done in Figure 11 for the pre-2020 sample. It assumes that no shocks to risks and perceptions occurred before January 2020.

Figure 14: Consumption fluctuations due to unemployment risks during COVID

(a) JF (b) JS



Note: The figure breaks down the model simulation results for the COVID recession in Figure 13 into job-finding and job-separation components. Panel (a) shows the job-finding rate, and panel (b) shows the job-separation.

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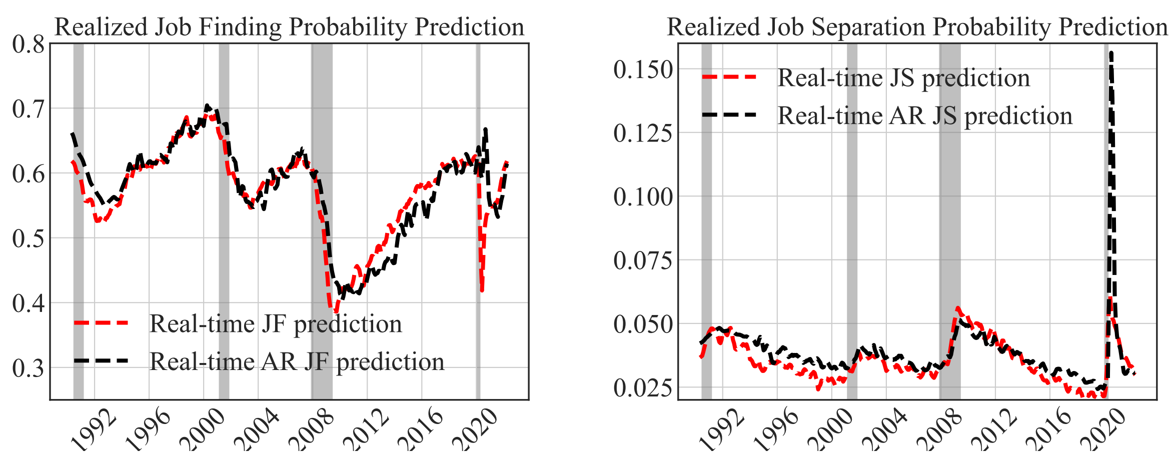
A Additional Empirical Results

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

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

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



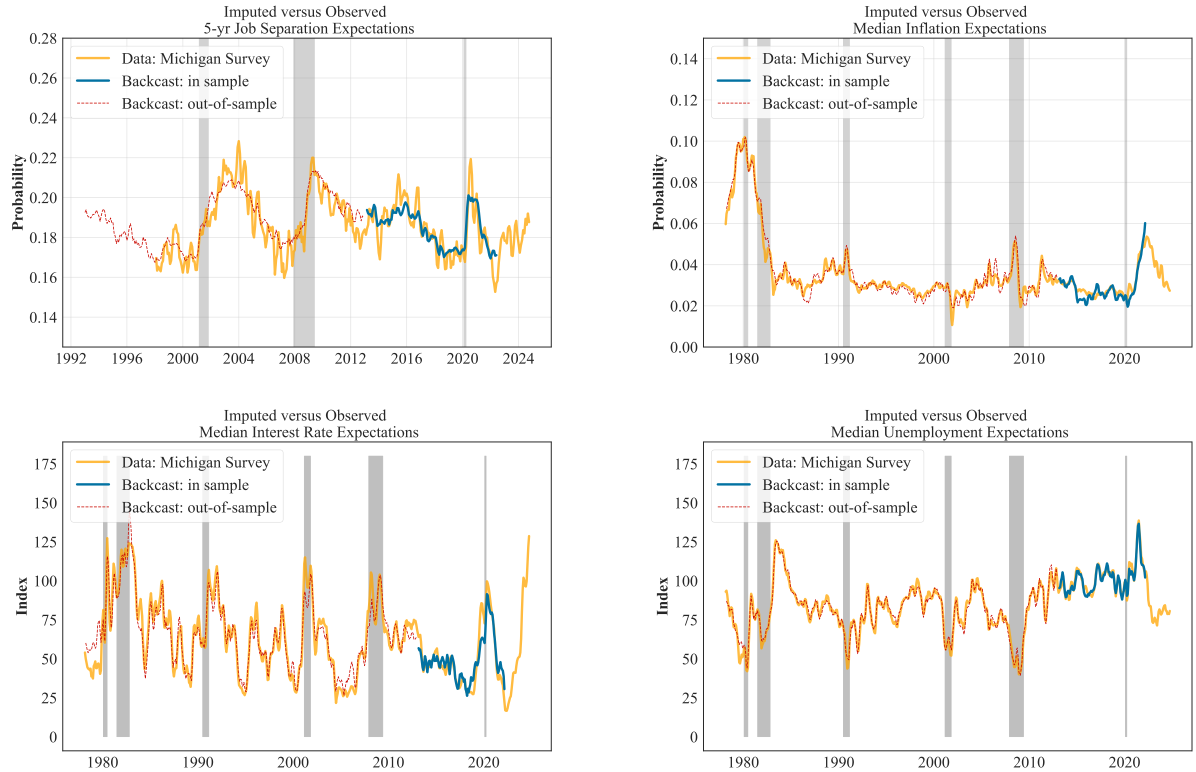
Note: Multi-variate LASSO real-time forecasts versus one from AR(1) model.

A.2 Additional results with imputation of perceived job risks

A.2.1 Cross-validation of the imputing methodology

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

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



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

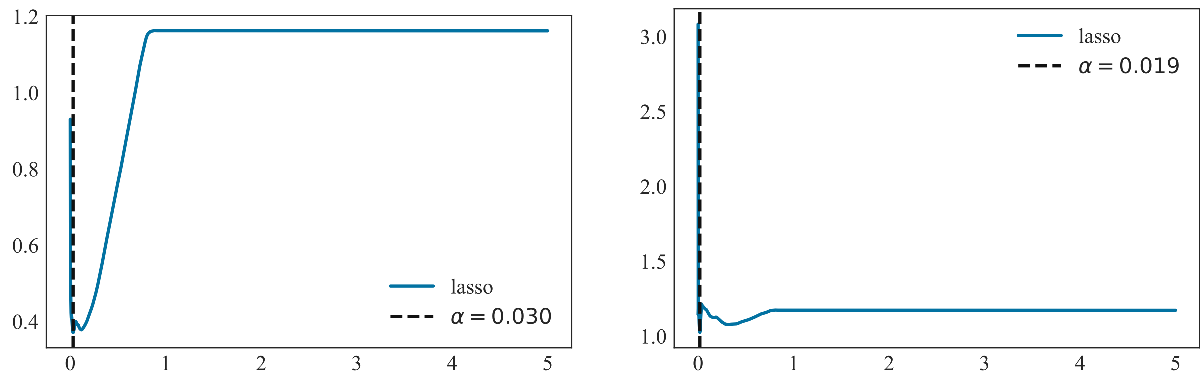
A.2.2 Hyper-parameter tuning of the LASSO model using cross-validation

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

A.2.3 Inclusion of the pandemic era

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

Figure A.3: Model selection using cross-validation



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

A.2.4 Selected covariates of perceived risks

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

A.2.5 Imputed beliefs by education group

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

A.3 Additional evidence for belief distortions over business cycles

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

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

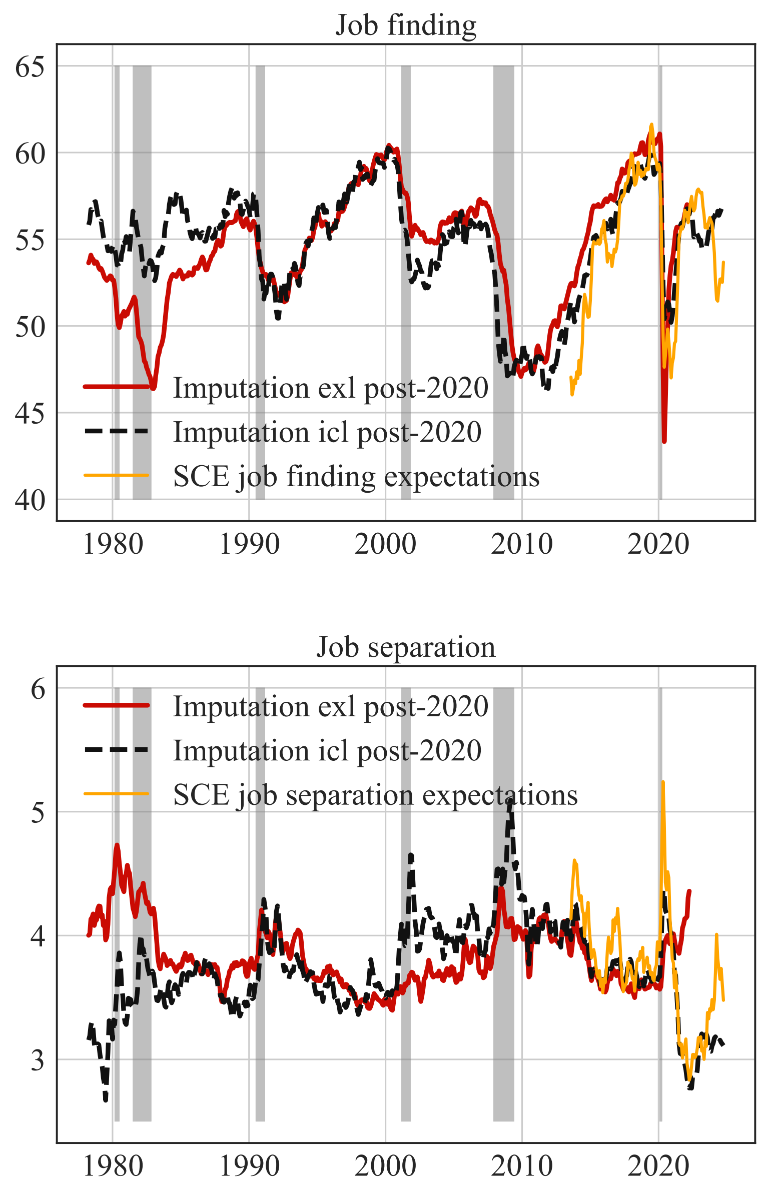
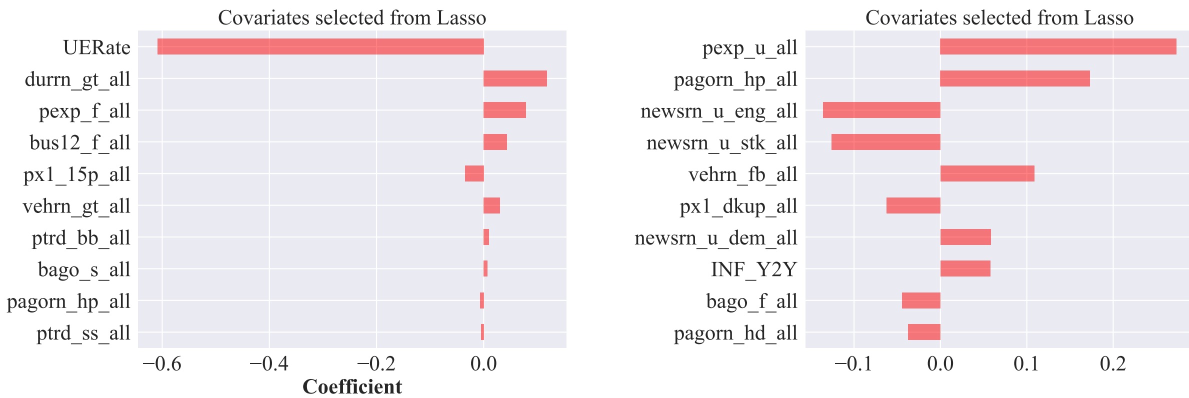


Figure A.5: Selected variables of LASSO model of perceived job risks



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

A.4 Additional regression results

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

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

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

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

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

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

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

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

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

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

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

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

Table A.5: Regression results of realized on perceived job finding probability: In sample

	$\widetilde{JF}$	$\widetilde{JF}^{p25}$	$\widetilde{JF}^{p50}$	$\widetilde{JF}^{p75}$	$\widetilde{JF}^{LEdu}$	$\widetilde{JF}^{MEdu}$	$\widetilde{JF}^{HEdu}$
$\widehat{JF}$	0.798***	2.628***	1.164***	0.387***	0.820***	0.730***	0.623***
	(0.213)	(0.677)	(0.343)	(0.078)	(0.265)	(0.071)	(0.099)
Const	1.200	-9.944**	-0.980	3.769***	0.053	0.116***	0.193***
	(1.280)	(4.069)	(2.058)	(0.469)	(0.148)	(0.040)	(0.057)
Adj. R^2	0.632	0.634	0.542	0.514	0.248	0.603	0.346
N	107	107	107	107	106	106	106

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

Table A.6: Regression results of realized on perceived job separation probability: In sample

	$\widetilde{JS}$	$\widetilde{JS}^{p25}$	$\widetilde{JS}^{p50}$	$\widetilde{JS}^{p75}$	$\widetilde{JS}^{LEdu}$	$\widetilde{JS}^{MEdu}$	$\widetilde{JS}^{HEdu}$
$\widehat{JS}$	0.140**	0.609***	0.336***	0.061	0.250***	0.239***	0.220***
	(0.067)	(0.111)	(0.130)	(0.143)	(0.062)	(0.042)	(0.055)
Const	1.114***	-1.907***	0.122	1.400***	0.882***	0.988***	1.062***
	(0.062)	(0.103)	(0.118)	(0.133)	(0.117)	(0.062)	(0.045)
Adj. R^2	0.091	0.299	0.101	-0.004	0.119	0.300	0.276
N	107	107	107	107	106	106	106

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

Table A.7: Regression results of realized on perceived job finding probability: In sample (with lags)

	$\widetilde{JF}$	$\widetilde{JF}^{p25}$	$\widetilde{JF}^{p50}$	$\widetilde{JF}^{p75}$	$\widetilde{JF}^{LEdu}$	$\widetilde{JF}^{MEdu}$	$\widetilde{JF}^{HEdu}$
$\widehat{JF}$	0.601***	2.009***	0.862***	0.313***	0.362	0.619***	0.497**
	(0.108)	(0.335)	(0.187)	(0.035)	(0.384)	(0.131)	(0.206)
$\widehat{JF}_{t-3}$	0.369***	1.097***	0.610***	0.124**	0.438	0.159	0.149
	(0.129)	(0.412)	(0.179)	(0.049)	(0.322)	(0.123)	(0.213)
Const	0.166	-12.809***	-2.826**	3.465***	0.068	0.087**	0.180***
	(0.877)	(2.932)	(1.330)	(0.373)	(0.147)	(0.044)	(0.069)
Adj. R^2	0.740	0.717	0.644	0.542	0.201	0.591	0.306
N	104	104	104	104	103	103	103

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

Table A.8: Regression results of realized on perceived job separation probability: In sample (with lags)

	$\widetilde{JS}$	$\widetilde{JS}^{p25}$	$\widetilde{JS}^{p50}$	$\widetilde{JS}^{p75}$	$\widetilde{JS}^{LEdu}$	$\widetilde{JS}^{MEdu}$	$\widetilde{JS}^{HEdu}$
$\widehat{JS}$	0.286***	0.743***	0.460***	0.388***	0.257***	0.225***	0.179***
	(0.043)	(0.118)	(0.074)	(0.075)	(0.056)	(0.036)	(0.058)
$\widehat{JS}_{t-3}$	-0.196***	-0.195	-0.203	-0.439***	-0.023	0.018	0.071
	(0.066)	(0.161)	(0.143)	(0.132)	(0.041)	(0.030)	(0.054)
Const	1.168***	-1.847***	0.199	1.520***	0.906***	0.980***	1.037***
	(0.057)	(0.112)	(0.132)	(0.130)	(0.132)	(0.071)	(0.042)
Adj. R^2	0.160	0.309	0.096	0.098	0.109	0.293	0.287
N	104	104	104	104	103	103	103

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

B Additional Model Results

B.1 Details of the baseline experiments

The model experiments in Figure 11 are based on directly estimated shocks to JF/JS, $\widetilde{JF}/\widetilde{JS}$ and JF^*/JS^*. To obtain such shocks, we estimate, respectively, a monthly AR(1) model of each one of these sequences in the sample period up to the 2020 M1. The predicted residuals are the estimated shocks to realized rates, beliefs, and rational job risk, which are plotted in Figure A.9.

Figure A.10 complements Figure 12 by showing the education-specific consumption aggregation fluctuations due to job-separation and job-finding risks, separately.

B.2 Alternative experiments at quarterly frequency

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

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

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

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

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

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

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

where θ_{it} is iid mean one lognormal with standard deviation σ_θ. γ is the replacement ratio of an unemployment insurance, which is set to be 0.5. Our benchmark model does not consider the expiration of unemployment insurance as in Kekre (2023).[21]

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

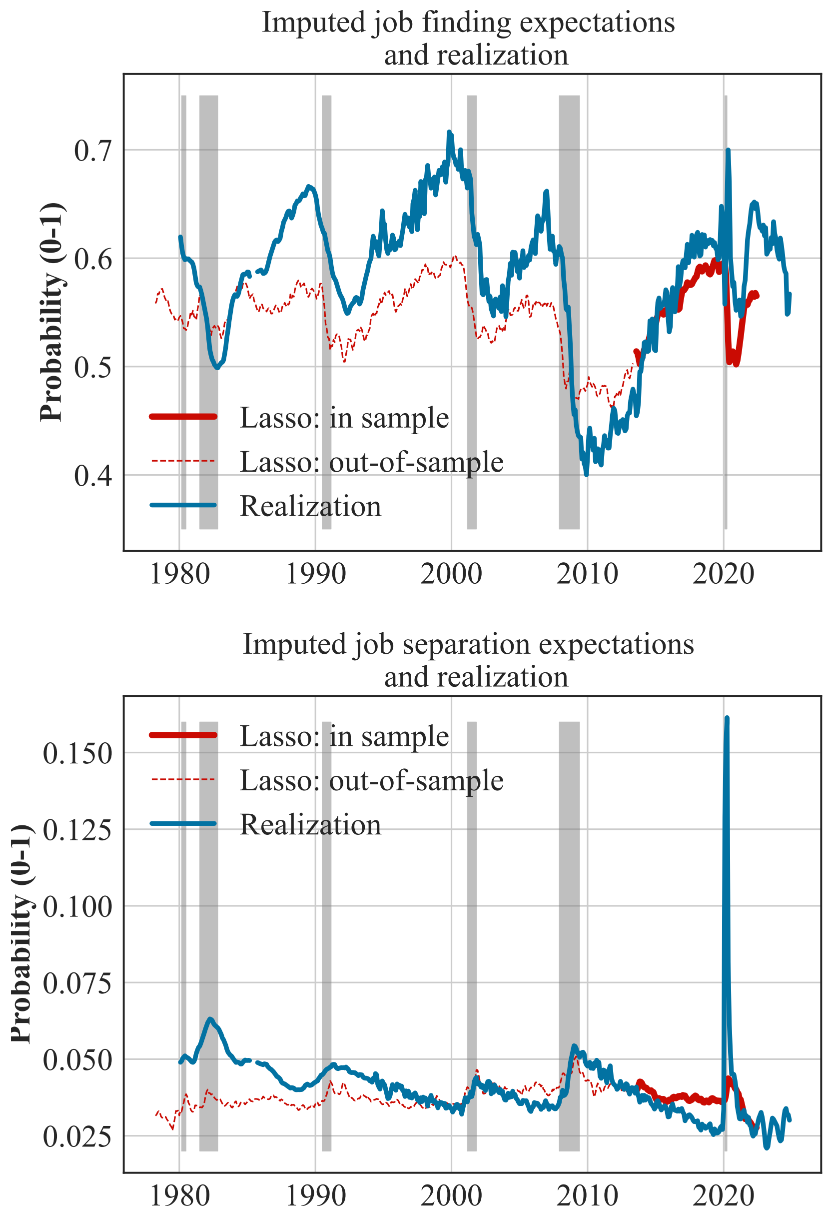
$$\begin{aligned} p(n_{i,t+1} = e | n_{i,t} = u) &= JF_t \\ p(n_{i,t+1} = u | n_{i,t} = e) &= JS_t(1 - JF_t) \end{aligned}$$

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

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

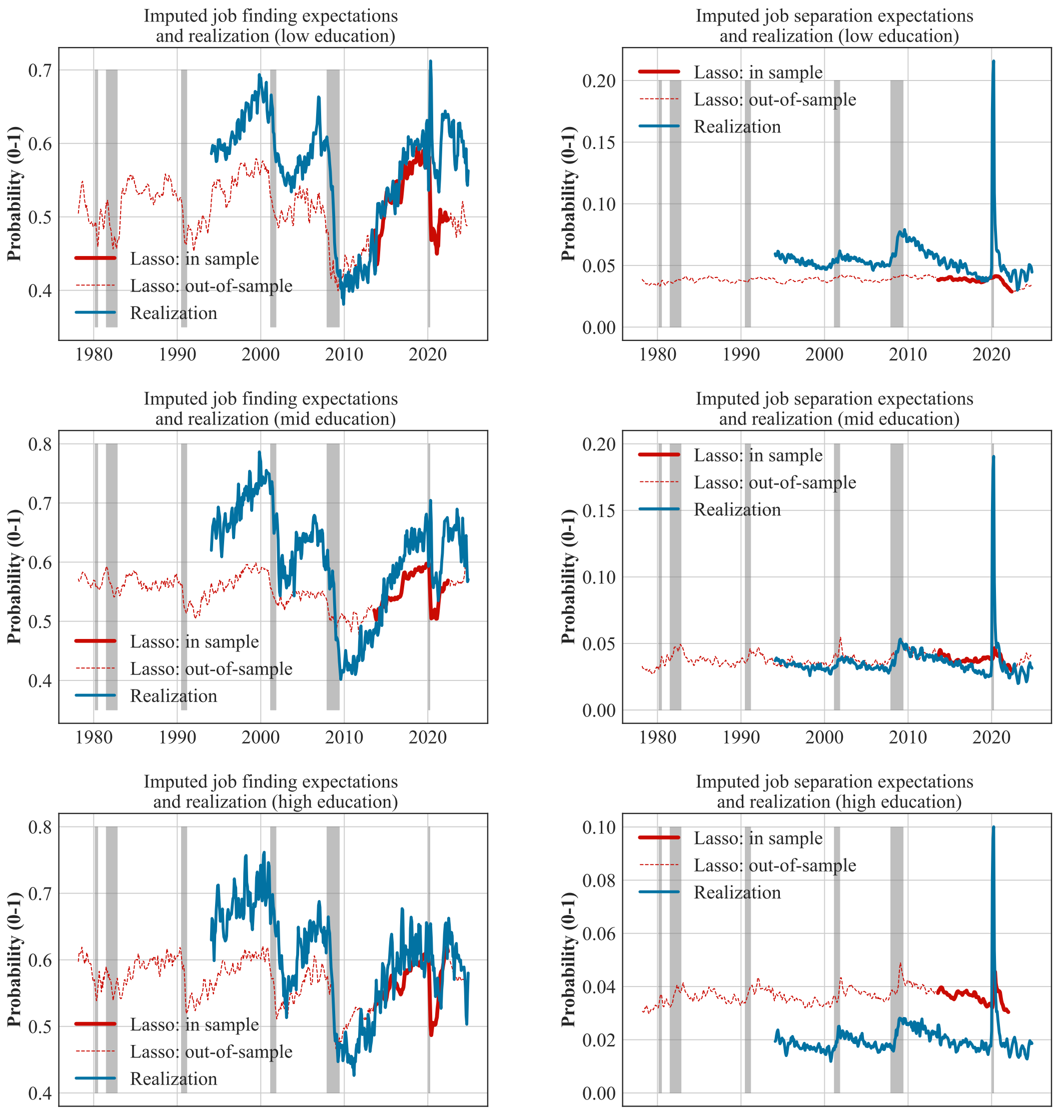
[21] Kekre (2023) estimates the income ratios during unemployment relative to pre-displacement with and without unemployment insurance to be 0.76 and 0.55, respectively.

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



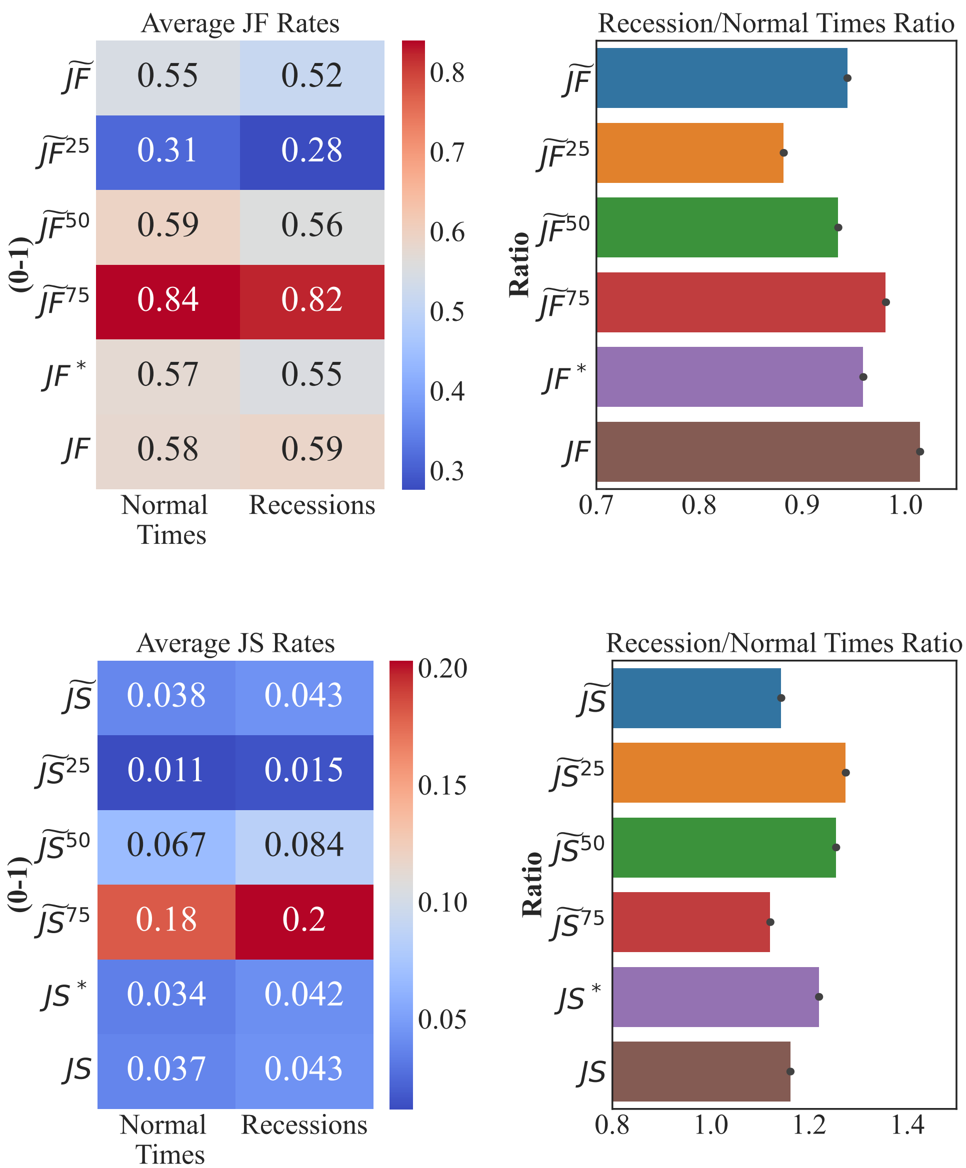
Note: Imputed perceived risks in the sample (2013-2022) and out of the sample (1980-2013) compared to realized job flow rates.

Figure A.7: Imputed beliefs by education



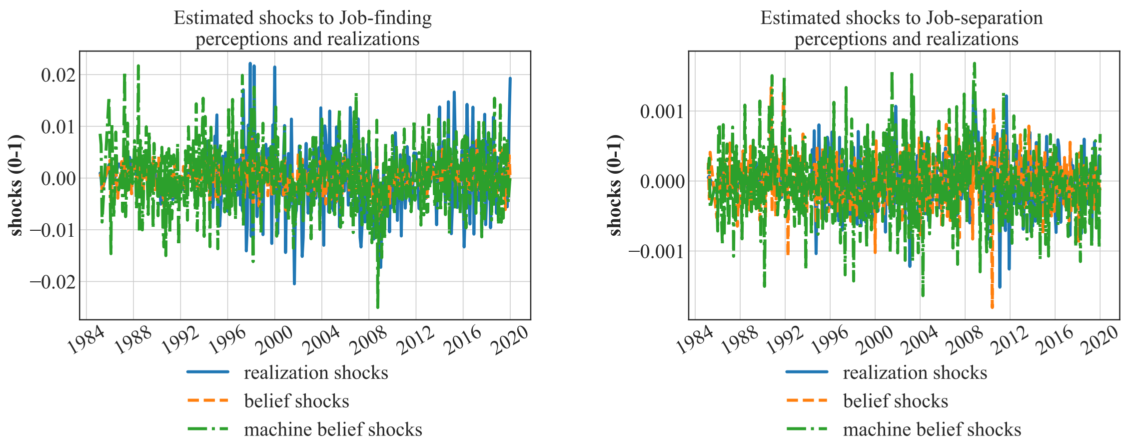
Note: These figures plot the imputed perceived job-separation and job-finding rates by low, middle and high educations, respectively, using the same methodology and the education-specific expectations in the MSC.

Figure A.8: Business cycle patterns of risks and perceptions: Normal times versus recessions



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

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

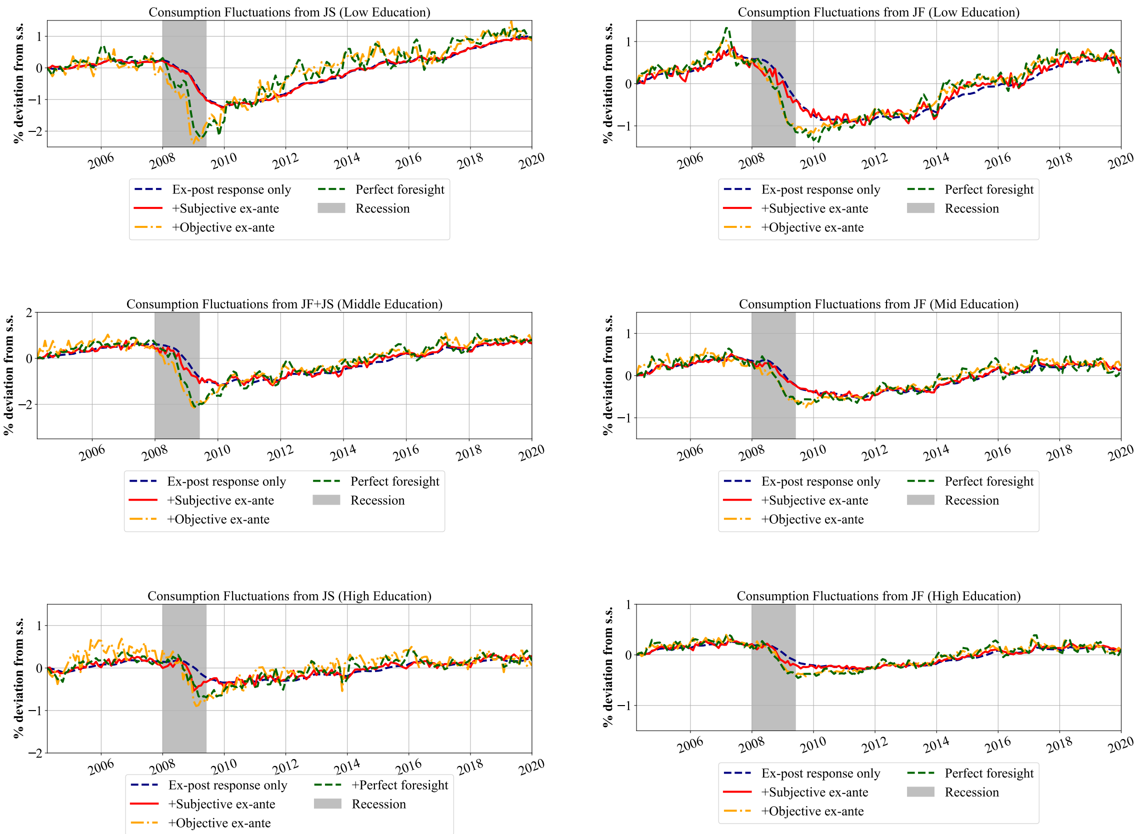


Note: The figure plots the estimated shocks used for the experiments in Figure 11, based on an estimation of a monthly AR(1) model on demeaned $JS_t \& JF_t$, $\widetilde{JS}_t \& \widetilde{JF}_t$, and $JS^*_t \& JF^*_t$. They are defined in Equation 30. The sample period is between 1984 and 2020.

Table A.9: Household calibration in model at quarterly frequency

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

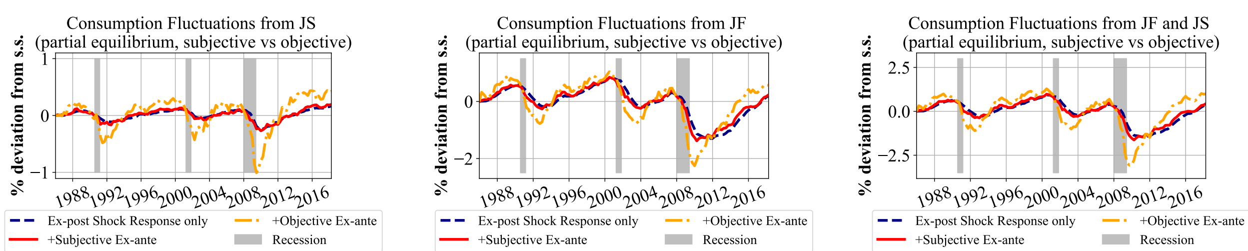
Figure A.10: Consumption fluctuations due to JS and JF risks: By education



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

Figure A.11: **Quarterly** consumption fluctuations due to unemployment risks

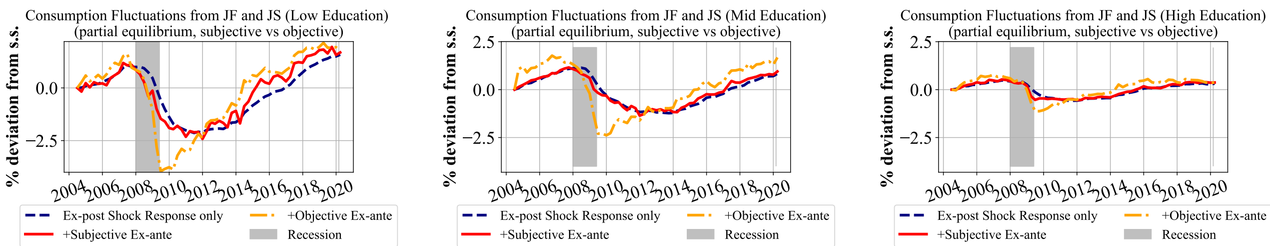
Job separation | Job finding | Combined



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

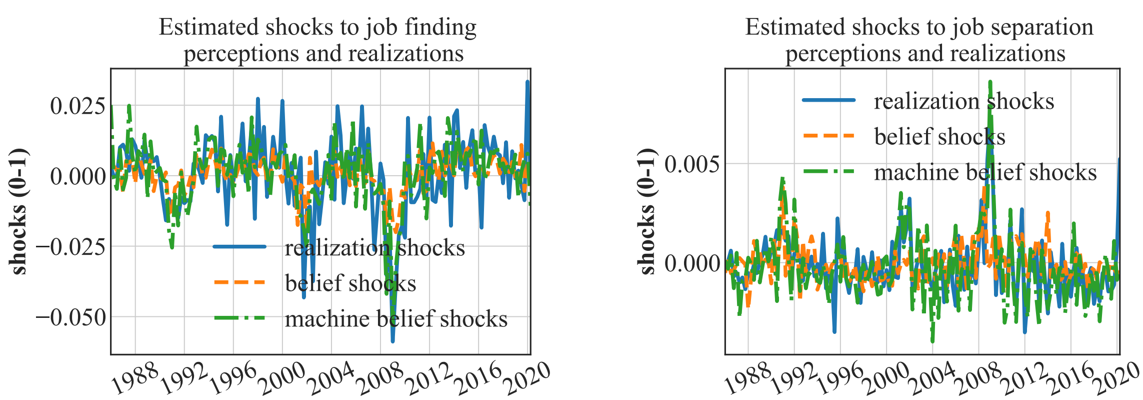
Figure A.12: **Quarterly** consumption fluctuations due to unemployment risks: By education

Low education | Middle education | High education



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

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



Note: The figure plots the estimated shocks used for the alternative experiments with the quarterly model, based on an estimation of a quarterly AR(1) model on demand $JS_t\&JF_t$, $\widetilde{JS}_t\&\widetilde{JF}_t$, and $JS^*_t\&JF^*_t$. They are defined in Equation 30. The sample period is between 1984 and 2020.