Perceived Unemployment Risks over the Business Cycle*

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Abstract

This paper studies how households perceive unemployment risks and how those perceptions shape aggregate consumption dynamics over the business cycle. We backcast perceived job-finding and separation risks to 1978 and construct a real-time objective benchmark. We find that these perceptions predict subsequent labor market flows but adjust sluggishly to changes in objective unemployment risks. Embedding these series into a heterogeneous-agent consumption-savings model reveals that belief stickiness dampens ex ante consumption drops due to precautionary savings yet amplifies ex post consumption drops due to income losses. We also discuss heterogeneity in these perceptions and its implications on aggregate consumption.

Keywords: Expectations, Unemployment Risks, Incomplete Markets, Consumption, Business Cycles, Machine Learning

JEL Codes: D84, E21, E71

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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 channels.[1] The first is an *ex ante* precautionary channel, driven by expectations: heightened fears of unemployment induce households to save and reduce consumption, thereby depressing aggregate demand. The second is an *ex post* income channel: realized job losses directly reduce household income and consumption. The ex ante channel affects everyone exposed to unemployment risks, while the ex post channel applies only to those who actually lose their jobs.

These two channels are typically disciplined by the observed worker flows between employment and unemployment. Yet, realized separation rates do not necessarily capture the true ex ante risk of job loss that shapes workers' precautionary behavior, but can be outcomes of unforeseen macroeconomic shocks. For instance, workers in 2019 did not anticipate the COVID-19 pandemic, and their perceived risk of job loss for 2020 was far lower than the separations that ultimately occurred.

Moreover, households' perceived risk of job loss need not coincide with the actual real-time job-losing risk implied by prevailing macroeconomic conditions. A large literature documents systematic deviations between household expectations and full-information rational expectations (FIRE). This raise a natural question: do households accurately perceive the unemployment risks? 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 to (c) realized outcomes, and calculates the forecast errors to detect deviations from FIRE. By additionally incorporating (b), we identify the gap between subjective perceptions of unemployment risk and their ex ante rational benchmark. This extends prior studies, which document biases in labor market expectations based on comparisons with ex post outcomes (Stephens, 2004; Spinnewijn, 2015; Mueller et al., 2021; Balleer et al., 2021).

Our measure of perceived unemployment risk (a) is constructed from responses to questions on labor market expectations in the Survey of Consumer Expectations (SCE), produced by

[1] Bayer et al. (2019); Haan et al. (2018); Broer et al. (2021b); Graves (2020) show that countercyclical unemployment risk is an important driver of aggregate fluctuations. McKay and Reis (2021); Boone et al. (2021); Kekre (2023) study the stabilizing role of unemployment insurance and its distributional consequences.

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. We externally validate this imputation strategy by showing that backcasted versions of several benchmark series, produced with the same procedure, closely match their observed counterparts. This resulting historical series enables us to analyze multiple business cycles and to assess the role of precautionary behavior over a much longer horizon.

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

Two main findings emerge from comparing these measures. First, the comparison of (a) perceived unemployment risk with (c) realized job transition rates shows that households' ex ante subjective beliefs, especially about job-finding probabilities, are strong predictors of actual labor market transitions. This 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 of (a) with (b) reveals a systematic gap between subjective beliefs and machine-learning-based forecasts: perceptions adjust sluggishly to changes in real-time unemployment risk. While the algorithmic forecasts accurately predict job transitions over a three-month horizon—except during abrupt crises such as the onset of COVID—average subjective expectations underreact and fail to incorporate available predictive signals, indicating a deviation from FIRE.

In addition to showing the underreactive patterns of perceived unemployment risks relative to their real-time rational benchmark, the second contribution of the paper is to quantify the degree of consumption fluctuations due to fluctuations of such perceptions. In particular, We incorporate our measures of perceived and objective unemployment risk, together with observed job transition rates, into a heterogeneous-agent model with idiosyncratic unemployment risks, where job-finding and separation govern 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 ex-ante precautionary channels in responses to perceived risks versus ex-post income losses due to actual changes in unemployment transitions. We simulate the path of aggregate consumption under three scenarios, all of which use (c) realized job transition rates to determine actual income losses, but differ in how households perceive unemployment risks. In the first, perceptions follow our empirical measure of (a) perceived unemployment risk. In the second, perceptions are aligned with our measure of (b) objective unemployment risk. In the third, perceptions track (c) realized transition rates one-for-one. The first scenario provides a factual decomposition of consumption fluctuations into precautionary versus income-driven components, while the latter two offer counterfactual quantifications under ex ante rational or ex post correct perceptions.

Our simulations of aggregate consumption from 1986 onward show that the precautionary channel is sharp and substantial when workers are assumed to hold rational (objective) perceptions of unemployment risk. By contrast, when we use workers' empirical perceptions—which systematically underreact to macroeconomic dynamics—the strength of the precautionary channel is significantly attenuated. Underreaction leads households to under-insure, resulting in a smaller initial drop in consumption during recessions, but also a more sluggish recovery, as there is less precautionary saving to draw down. These results indicate that the impact of fluctuations in unemployment risks on aggregate consumption depends critically on how households perceive such risks. While ex ante precautionary responses would have been an important driver of aggregate consumption fluctuations under FIRE, such force is effectively muted due to underreactive perceptions of unemployment risks over business cycles.

Lastly, we emphasize the critical interplay between job-risk heterogeneity and belief distortions. Low-education workers, who are disproportionately exposed to cyclical unemployment risk, also hold the stickiest beliefs. As a result, they are the most under-insured when unemployment shocks materialize, amplifying the ex post impact of such shocks over the business cycle. This pattern suggests that fluctuations in labor market risks leave uneven imprints across households, not only because of differences in their exposure to aggregate shocks, but also because of heterogeneity in their ability to self-insure given their subjective perceptions of such risks. The underinsurance of those most exposed to business cycle fluctuations echoes Patterson (2023), who finds that workers with highly cyclical incomes also have the highest MPCs. Such a correlation amplifies business cycle fluctuations. Particularly sticky beliefs among these high-risk workers may contribute to this amplification mechanism.

Related Literature. This paper contributes to empirical work on expectations about aggregate labor market conditions (Carroll, 2003; Tortorice, 2012; Kuchler and Zafar, 2019). We adopt the flow approach to unemployment, which has become standard in modern macro-labor analysis. Our paper builds on the empirical evidence of biases in job-finding expectations documented by Mueller et al. (2021), who also use data from the SCE. In contrast to their focus on individual-level job-finding expectations, we study job-finding and separation expectations at the macro level over the business cycle. They show that individuals' expectations underreact to changes in unemployment durations, while we document that individuals' expectations also underreact to cyclical shifts in underlying true transition probabilities.

A related strand of work compares perceived unemployment risks with realized transitions, as surveyed by Mueller and Spinnewijn (2023). This literature has produced divergent evidence of both over-optimism and over-pessimism in job expectations. For instance, Arni (2013), Spinnewijn (2015), Conlon et al. (2018), and Mueller et al. (2021) find that workers tend to overstate their job-finding probabilities, with biases especially pronounced for longer unemployment durations. Conlon et al. (2018) attribute this bias to over-optimism about both offer arrival rates and wage offers. Balleer et al. (2021) explores the macroeconomic consequences of the over-optimism bias in an incomplete-market model. On the separation side, Stephens (2004) and subsequent work (Dickerson and Green, 2012; Balleer et al., 2023) document upward biases in job-loss perceptions. At the same time, Dickerson and Green (2012); Hendren (2017); Pettinicchi and Vellekoop (2019); Hartmann and Leth-Petersen (2024) show that workers' perceived risks nonetheless predict actual unemployment outcomes reasonably well, indicating they have advance knowledge about their employment prospects. Our paper extends this literature in two ways. First, we focus on the cyclical dynamics of job-risk perceptions relative to realizations, rather than on level differences. Second, because realized transitions need not be identical to the ex ante true risks, we construct a proxy for such an objective benchmark.

Our work relates to a broader literature following Dominitz and Manski (1997) and Dominitz (2001) on income expectations and subjective income risks. Recent contributions include Wang (2023); Caplin et al. (2023); Rozsypal and Schlafmann (2023); Koşar and Van der Klaauw (2025). A common theme in this research is that survey-based expectations often diverge systematically from model-implied counterparts, yet remain highly predictive of household decisions.

We also contribute to a growing literature that incorporates subjective unemployment risk perceptions into otherwise standard heterogeneous-agent macroeconomic models with uninsured unemployment risks (Pappa et al., 2023). The closest study to ours is Bardóczy and Guerreiro (2023), who also use expectations data to quantify the precautionary saving channel. Our key distinction is to rely on household expectations of labor market transitions from the SCE, rather than forecasts of the unemployment rate from the Survey of Professional Forecasters (SPF). Since households themselves are the ones making consumption-smoothing decisions, we argue that their expectations are a more relevant input for modeling precautionary behavior. Furthermore, to assess the role of imperfect expectations in consumption, we move beyond ex post forecast errors by comparing subjective beliefs not only to realized outcomes but also to objective ex ante benchmarks.

A parallel literature incorporates informational frictions or belief distortions into search-and-matching models to address the unemployment volatility puzzle (Morales-Jiménez, 2022; Menzio et al., 2022; Rodrıguez, 2023; Mitra, 2024; Lee, 2025). In contrast, we explore the implications of perceived unemployment risks for consumption-saving decisions and aggregate demand fluctuations. Our findings of the heterogeneity in labor market expectations also connect 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 workers' belief rigidity does not often decrease with the cyclical exposure of their unemployment risks—suggests that mechanisms beyond optimal information acquisition may drive such stickiness.

Finally, we build on the literature that uses real-time forecasting to approximate ex ante risks. Our approach is closely related to Bianchi et al. (2022), who propose using machine-efficient forecasts as a rational benchmark rather than relying on a specified data-generating process. We adapt this framework to the labor market context, treating such forecasts as proxies for true ex ante unemployment risks. This approach relates to Jurado et al. (2015) and Rossi and Sekhposyan (2015), who distinguish between ex ante risks and ex post realizations in measuring macroeconomic risks.

Roadmap. The rest of the paper is organized as follows. Section 2 measures perceptions of job-finding and separation rates in the survey of consumer expectations. Section 3 constructs an objective benchmark for unemployment risks using real-time machine-learning forecasts and backcasts job-finding and separation perceptions to the late 1970s. Section 4 benchmarks perceptions against these real-time risks, provides evidence for under-reaction and information rigidity, and characterizes business-cycle comovements of perceived, objective, and realized unemployment risks. Section 5 embeds these series in a heterogeneous-agent consumption-saving model and quantifies their impacts on aggregate consumption. Section 6 turns to heterogeneity of perceived unemployment risks and Section 7 concludes.

2 Perceived Unemployment Risks

2.1 Data

The data on perceived unemployment 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 transition rates are calculated using data from the Current Population Survey (CPS), in which households are surveyed for four consecutive months, rotated out for the next eight months, and then surveyed again for another four months before leaving the sample permanently. This short panel dimension allows us to track workers' movement between employment and unemployment (e.g., Fujita and Ramey, 2009). 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.[2]

Time Aggregation. The perceived transition probabilities are reported at horizons that differ from the realized flow rates. For comparability, we convert all rates into a three-month horizon using the following procedure. Let p_1, p_2, and p_3 denote the monthly flow rates for three consecutive months. The time-aggregated three-month transition probability is then $1-(1-p_1)(1-p_2)(1-p_3)$. For job-separation probabilities reported at a one-year horizon, we first convert them into continuous-time Poisson rates and then re-express them at a three-month horizon.

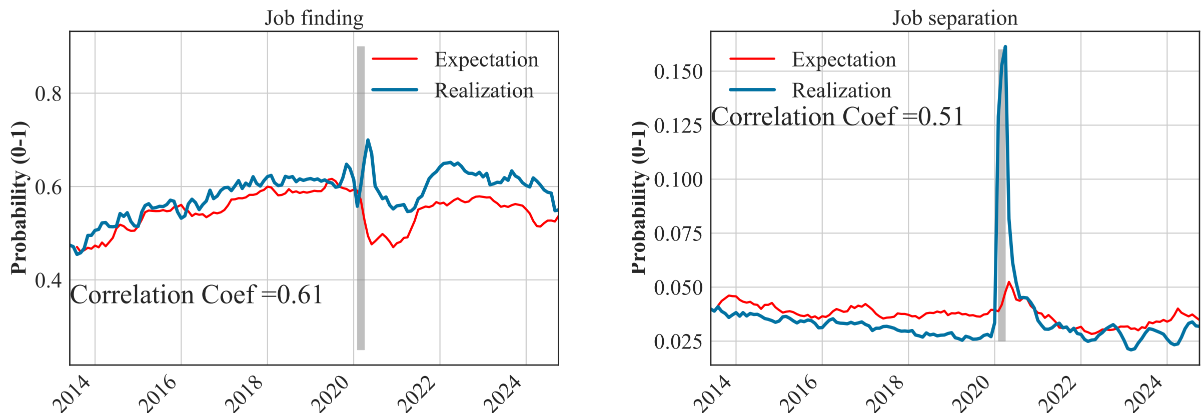
2.2 Perceived risks versus realized flows

Figure 1 compares perceived transition probabilities with realized transition probabilities over the sample period since 2013. Perceptions track realizations reasonably well at the aggregate level, as reflected both in the similarity in the figure and in the high correlation coefficients

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

between the two series. Specifically, the correlation between the perceived three-month-ahead job-finding rate and its realized counterpart is 0.61, while the correlation between the perceived separation rate and its realized counterpart is 0.51.

Figure 1: Perceived versus realized worker flow rates



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

The correlation between perceived risks and realized flow rates would have been even higher absent the COVID pandemic crisis, which generated the largest deviations of perceived from subsequent realizations. At the onset of the pandemic, the perceived job-finding rate fell sharply, yet the actual job-finding rate increased initially. Similarly, perceived separation risk spiked at the onset of the crisis, but by far less than the surge in actual separations. These deviations reflect the unanticipated nature of the COVID shock. However, the dynamics of perceived risks and corresponding realizations moved in tandem again within two months of the outbreak. The unusual labor market dynamics during the COVID crisis were unprecedented even for professional economists, and remain a subject of ongoing research. Therefore, it is noteworthy that average perceptions of unemployment risks still retained some predictive power for realized flows, despite the crisis.

The correlation between ex ante perceived unemployment risks and ex post realizations, while positive, is far from perfect, indicating a deviation from perfect foresight. This is consistent with growing evidence that households' macroeconomic expectations, especially regarding inflation and unemployment rates, tend to contain systematic forecast errors. By construction, realized flow rates inevitably incorporate aggregate shocks that were unforeseen ex ante. Nevertheless, average perceived unemployment risks capture predictable variation in subsequent labor market flows. This suggests that these measured beliefs contain meaningful variations that reflect the underlying state of the economy.

2.3 Forecast errors of perceived unemployment risks

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

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

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

To test the informational efficiency of perceived unemployment risks, we estimate a regression of forecast errors on their own lag term with an intercept:

$$\mathrm{FE}^{JF}_{t,t+3} = \alpha + \beta \mathrm{FE}^{JF}_{t-3,t} + \gamma X_{t-3} + \epsilon_t \tag{1}$$

where X_{t-3} denotes the information set available at time $t-3$. The null hypothesis under FIRE is that agents fully react to new shocks to the underlying variable. A significantly positive estimate of β indicates that forecast errors are predictable from past forecast errors. That past errors persist into subsequent forecasts in the same direction reflects the presence of information rigidity. This approach is standard in the literature on expectation formation (see, e.g., Coibion and Gorodnichenko, 2015; Fuhrer, 2018; Coibion et al., 2018).

The estimation results for forecast errors in job-finding and separation perceptions are reported in Table 1. They strongly reject the null hypothesis of full efficiency ($H_0 : \beta = 0$). For job finding, the coefficient from the 3-month-apart auto-regression of average forecast errors is 0.256. Education-specific estimates range from 0.183 for the high-education group to 0.535 for the low-education group. For separation, although the autocorrelation of average forecast errors is not statistically significant, the education-specific estimates are all significantly positive, ranging from 0.20 for the low-education group to 0.55 for the high-education group.

These positive and significant autocorrelations of non-overlapping forecast errors indicate the presence of information rigidity in perceptions of unemployment risks. In particular, they imply that forecast errors made three months earlier persist into current forecast errors. The fact that these estimates are well below one points to only a moderate degree of information rigidity. This is plausible as the underlying shocks to job finding and separation are persistent.[3]

[3] Coibion and Gorodnichenko (2012) show that in models such as sticky expectations and noisy information, the autocorrelation of forecast errors equals the product of the degree of information rigidity and the persistence of the forecasted variable.

Table 1: Forecast error regressions

Panel A: Forecast error of job-finding rate				
	All	Low Edu	Mid Edu	High Edu
Lag forecast error	0.256***	0.545***	0.272***	0.183**
	(0.087)	(0.076)	(0.084)	(0.088)
Constant	-0.027***	-0.027***	-0.038***	-0.024***
	(0.004)	(0.007)	(0.005)	(0.004)
Observations	121	124	124	124
R^2	0.068	0.295	0.079	0.034
Panel B: Forecast error of separation rate				
	All	Low Edu	Mid Edu	High Edu
Lag forecast error	0.131	0.202**	0.267***	0.554***
	(0.091)	(0.089)	(0.088)	(0.075)
Constant	0.003*	0.076***	0.079***	0.051***
	(0.002)	(0.009)	(0.010)	(0.009)
Observations	121	124	124	124
R^2	0.017	0.040	0.070	0.308

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Notes: The table reports the auto-regression results of average and various education groups' respective average forecast errors of expectations of job-finding and separation rate with their respective 3-month-lagged values, as defined in Equation 1.

3 Objective Unemployment Risks

3.1 Real-time machine-learning forecast

In the previous section, we directly compare ex ante perceived risks with ex post realization of transitions. We reject the perfect foresight assumption, as ex ante perceived risks systematically differ from realized flow rates. However, such differences cannot be interpreted as deviations from the rational expectations benchmark—even if perceived risks are fully rational ex ante conditional on real-time economic conditions, unanticipated shocks could still induce a gap between ex ante perceptions and ex post realizations. We therefore require a proxy for true ex ante unemployment risks to characterize the deviations of perceived unemployment risks from rational expectations.

Following Bianchi et al. (2022), we construct such a proxy using machine-learning-based real-time forecasts of labor market transition rates. Specifically, for each month t in our sample, we use a LASSO model to select the set of predictors that makes the best in-sample prediction of realized flow rates over a 10-year rolling window up to t, as defined in the following equation:

$$\begin{aligned} JF_{t,t+3} &= \beta_0^t + \sum_{i=1}^{p} \beta_i^t X_{t,i} + \epsilon_t, \\ \text{subject to} \quad & \sum_{i=1}^{p} |\beta_i^t| \leq \lambda. \end{aligned} \tag{2}$$

Because this procedure is implemented in real time, the estimated coefficients are time-specific: the forecasting model at t is estimated solely on information available up to t. Next, we generate a 3-month-ahead out-of-sample forecast, $\widehat{\text{JF}}^*_{t+3|t}$, using the optimally chosen coefficient estimates, β^{t*}, obtained through k-fold cross-validation:

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

About 600 time series are considered as candidate predictors of flow rates, including both real-time macroeconomic indicators and forward-looking expectations of households and professional forecasters. Specifically, the following categories 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").[4]

- 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

[4]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).

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 not make such an assumption, instead recognizing their potential as part of the broader real-time information set.

In principle, any real-time variable that could have entered agents' information sets at t is admissible. While we cannot exhaustively capture all series, the broad coverage of our dataset provides a reasonable proxy for the full information environment. An important input for real-time forecasting is individuals perceived risk of unemployment. Research shows that people often have superior insight into their own job prospects, which economists might otherwise classify as unexpected shocks (Hendren, 2017). By incorporating average perceived risks, we leverage this informational advantage. If household expectations reliably predict future job transitionsas demonstrated earlierthe machine-learning algorithm will identify them as valuable predictors.

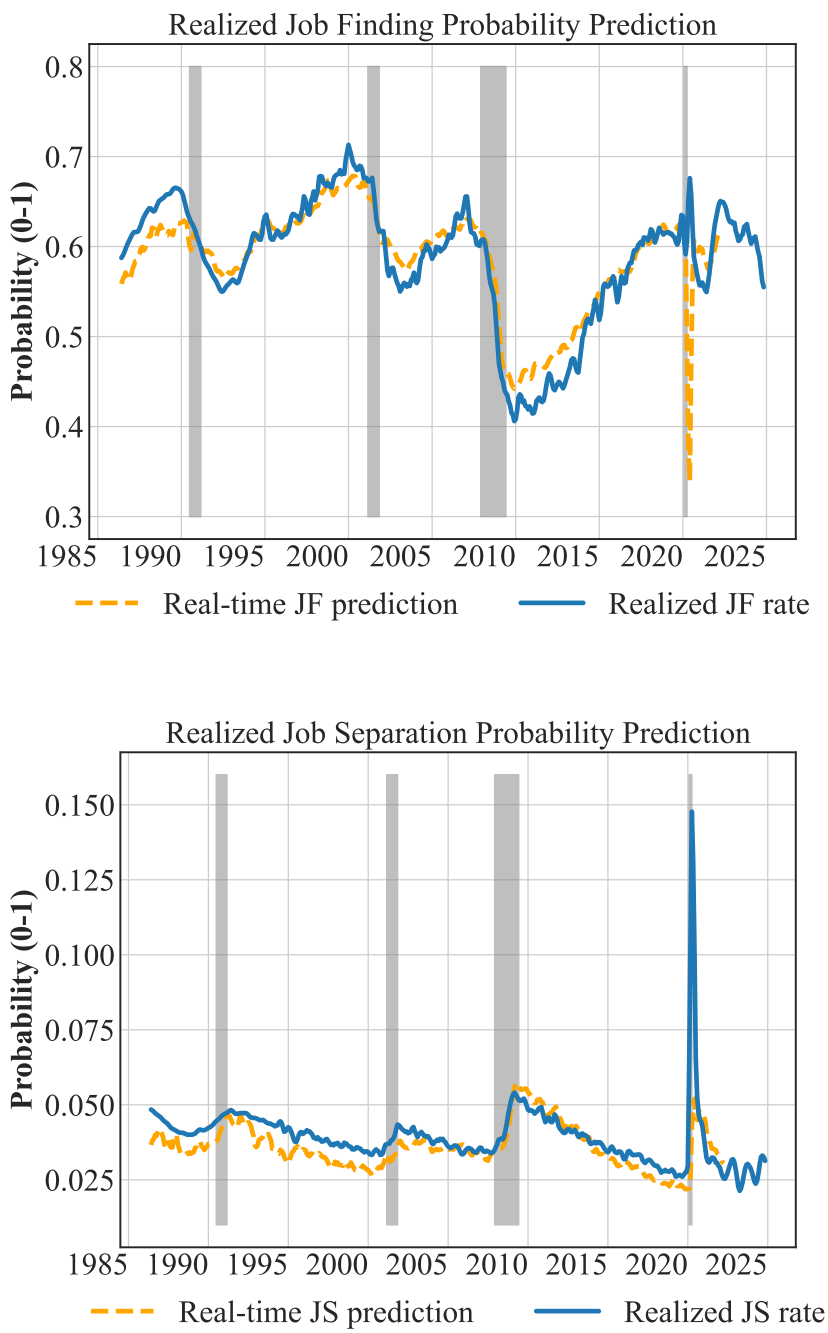
However, direct measures of perceived unemployment risk are only available in the SCE since 2013. To address this limitation, we directly use all available MSC household expectations series, assuming these are correlated with perceived unemployment risks. This assumption also underpins our imputation strategy in Section 3.2.

Real-time unemployment risks. Figure 2 plots the real-time machine-efficient forecasts of transition rates against the realized transition rates. Each point on the blue line corresponds to a forecast generated using only information available up to that time, based on a selected set of predictors with the optimally chosen penalty to prevent overfitting. Overall, the machine-efficient forecasts track subsequent labor market movements closely, with the notable exception of major recessions, most prominently the COVID-19 crisis in the first quarter of 2020.

These results suggest that near-horizon labor market flows are highly predictable when forecasts are conditioned on the full set of real-time information, particularly during normal times. In sudden crisis episodes such as the COVID pandemic outbreak, even the 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 quickly adapt and and provide accurate predictions of subsequent dynamics in worker flows.

Figure 3 highlights the importance of using real-time forecasts without relying on hindsight. For most of the sample, the machine-efficient real-time forecasts of job-finding and separation rates exhibit non-zero forecast errors, indicating even rational ex ante unemployment risks could not have perfectly anticipated subsequent realizations of labor market flows. By contrast, one-shot retrospective machine-learning forecasts, constructed based on the entire sample period,

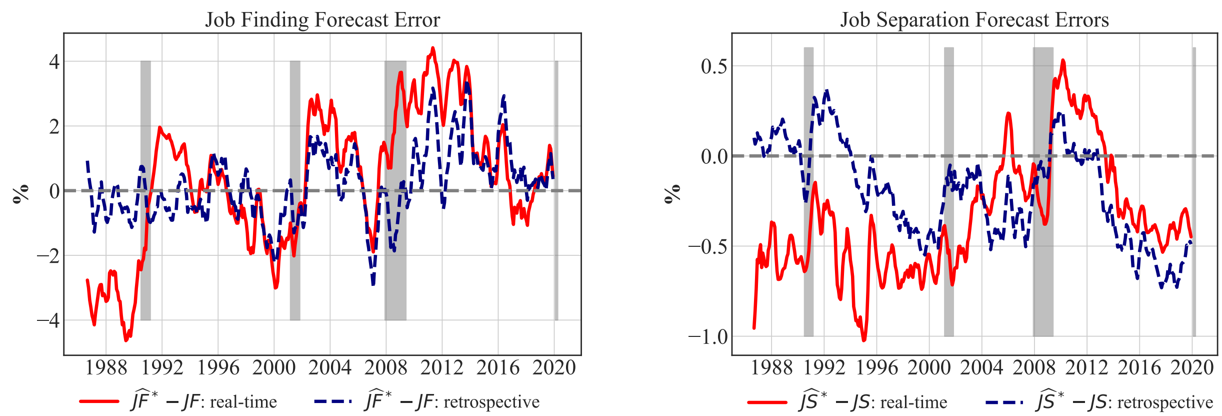
Figure 2: Machine prediction of worker flow rates



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

yield forecast errors that average to zero, due to overfitting to future realizations rather than genuine predictive content. This suggests that, relative to a well-informed benchmark of ex ante risks, unexpected shocks to realized unemployment risks inevitably occur.

Figure 3: Forecast errors of real-time vs. retrospective unemployment 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 worker flows? One of the predictors most frequently selected in the real-time forecasting exercises is the unemployment rate. A higher contemporaneous unemployment rate predicts a higher separation rate and a lower job-finding rate. This is not surprising, as the unemployment rate captures the overall state of the labor market and strongly correlates with the subsequent transition rates.

In addition, many forward-looking expectation variables in the MSC also consistently predict future labor market outcomes. This suggests that households' expectations contain meaningful forward-looking information on labor market risks. It is worth noting that such predictability should not be interpreted as causal. Rather, we view it as evidence that households incorporate into their expectations about their future employment prospects the same information that is relevant for forecasting macroeconomic outcomes.

Three categories of household expectations commonly appear in the LASSO model selections. The first set of variables directly relates to the self-reported exposure to labor market news. 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, particularly the durable goods purchase intentions. Several papers (Carroll and Dunn, 1997; Harmenberg and Öberg, 2021) have empirically established a negative relationship between labor market 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 unemployment 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 labor market transition rates. This pattern confirms the finding by Leduc and Liu (2016) that is also based on the uncertainty question elicited in the MSC.

3.2 Backcasting perceptions

Directly observed measures of perceived unemployment risks have been available in the SCE only since 2013. Meanwhile, the MSC has collected a wide range of expectation measures for a much longer time span, with some series extending back to the 1960s. Under the assumption that the correlations across different expectations are stable over time, we exploit the estimated correlation between perceived unemployment risks in the SCE and other expectations in the MSC during the overlapping sample period to impute historical values of perceived unemployment risks back for earlier decades.[5] To do so, we implement a LASSO model that selects, from a broad set of contemporaneous variables, those most predictive of measured perceived unemployment risks, as specified below:

$$\begin{aligned} \widetilde{\mathrm{JF}}_{t+3|t} &= \gamma_0 + \sum_{i=1}^{p} \gamma_i X_{t,i} + \epsilon_t, \\ \text{subject to} \quad & \sum_{i=1}^{p} |\gamma_i| \leq \lambda. \end{aligned} \tag{4}$$

where $\widetilde{JF}_t$ denotes the average 3-month job-finding expectations in 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 macroeconomic aggregates. We include the latter in addition to expectational variables because, in theory, agents may have incorporated real-time realizations into their information sets when forming expectations. As before, we rely on cross-validation to de-

[5] We reject the null hypothesis of a structural break using the test of Andrews (1993).

termine the optimal degree of regularization in the LASSO model, and obtain the corresponding coefficient estimates for the selected predictors, which we denote by γ_i^* for $i = 1, 2, ..., p$.

We externally validate our imputation methodology by exploiting the fact that expectations about 1-year-ahead inflation and 5-year separation probabilities have been measured in the MSC for a much longer period. Figure A.1 in the Appendix suggests that imputations based solely on 2013–2022 in-sample data can generate out-of-sample backcasts of these expectations that almost mimic the observed data, with correlations ranging from 80% to 99%.

What are the most important covariates of perceived unemployment risks? The LASSO procedure highlights numerous expectation variables from the MSC, including durable purchases, news heard about economic conditions, recent experiences, and future expectations of personal finances. Figure A.3 in the Appendix reports the top predictors of perceived job-finding and separation rates, respectively. The signs of these correlations all have sensible and intuitive interpretations.

In addition to expectations, real-time macroeconomic realizations are also important covariates of perceived unemployment risks. In particular, the recent unemployment rate stands out as the most important variable that co-moves with the contemporaneous perceived separation rate. Inflation and inflation expectations are also noteworthy. Higher recent inflation realizations are associated with elevated perceived separation risk. Meanwhile, higher inflation expectations, as measured by the share of those who expect higher inflation above 15%, are associated with lower job-finding perceptions. The positive association of inflation (and inflation expectations) with unemployment risks is consistent with the finding by Hou and Wang (2024).

Figure 4 plots the in-sample and out-of-sample fits from the optimal LASSO model. A key advantage of LASSO models is its ability to penalize in-sample over-fitting, as reflected in the difference between the in-sample predictions of the beliefs and the actual beliefs. We prefer this approach over conventional linear models such as OLS, given our primary objective of accurate out-of-sample prediction. The backcasted series of perceived unemployment risks before 2013 exhibits reasonable cyclical movements. During each of the five recessions since the 1980s, the imputed job-finding perceptions dropped significantly compared to normal times, and the separation perceptions significantly increased.

Using the imputed beliefs, we corroborate the results from Section 2.2 based on directly observed beliefs that job-finding perceptions predict realized job-finding rates quite well, whereas the separation expectations are much less predictive of realized separation rates. Specifically, the correlations of the imputed beliefs with their realizations three months later are 0.81 for job-finding and 0.16 for separation rates.

Our benchmark imputations use the 2013–2022 period, which witnessed drastic movements in the labor markets. In Appendix A.1.2, we test the sensitivity of our results to excluding the Covid era. We show that the belief imputations based only on the pre-COVID sample would have implied a much steeper drop in job-finding perceptions than the perceptions measured in the SCE during this period, and the imputed separation perceptions would have been overly optimistic compared to the actual perceptions. Because our ultimate goal here is to generate the most reliable backcast of beliefs for earlier periods in which no direct measure of such beliefs exists, we decided to retain the full sample for training the LASSO model.

4 Perceived, Objective, and Realized Unemployment Risks

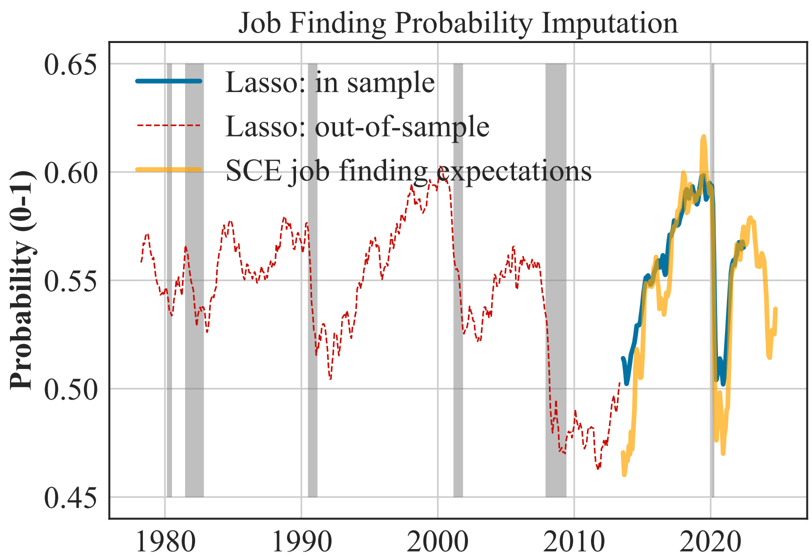
With the proxied objective unemployment risk from the real-time machine-learning forecasts, denoted $\widehat{JF}^*$ and $\widehat{JS}^*$, we can now directly estimate the degree of belief distortion, namely the extent to which perceived unemployment risks $\widetilde{JF}$ and $\widetilde{JS}$ deviate from rational ex ante unemployment risks. In particular, we regress $\widetilde{JF}$ and $\widetilde{JS}$ on their respective machine-efficient forecasts, $\widehat{JF}^*$ and $\widehat{JS}^*$. Both sides of the equation are in logs so that the coefficients can be interpreted as elasticities of beliefs with respect to real-time risk. A coefficient of unity corresponds to perceptions fully reacting to real-time rational risk, i.e., no under- or overreaction.

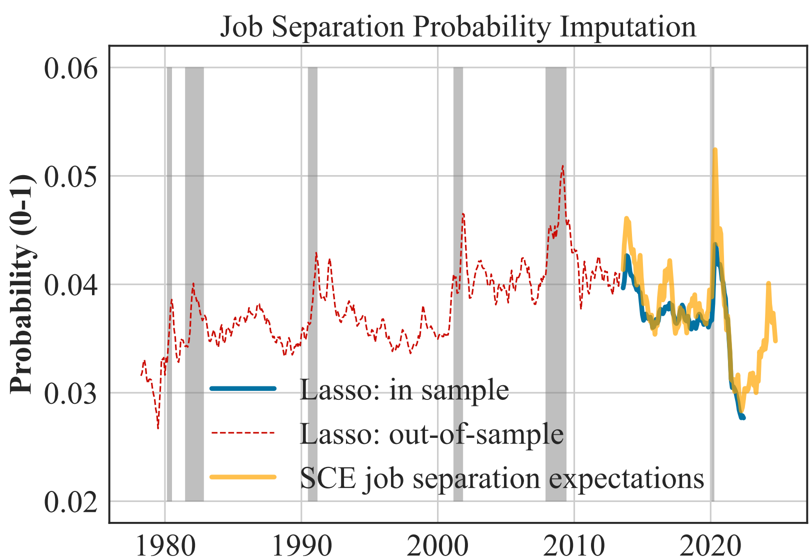
Our estimation results in Table 2 suggest that although both job-finding and job-separation perceptions co-move with real-time risks, the estimated sensitivities–well below one–reveal systematic underreaction. As shown in Column (1) of Table 2, a one-percentage-point increase in real-time job-finding raises the average perceived job-finding rate by about 0.46 percentage points. In contrast, Column (2) shows a much weaker response of separation perceptions: the coefficient on $\widehat{JS}^*_{t+3|t}$ is 0.235, implying that a one-percentage-point increase in the machine forecast raises the perceived separation rate by only about 0.2 percentage points. The imputation procedure does not drive this underreaction. Using only post-2013 SCE data without imputed beliefs (Columns (5)–(6)) yields similar patterns, with even lower sensitivity for job-finding perceptions (0.34) and a slightly higher estimate for separation perceptions (0.24). Figure 5 plots the perceived risks against real-time machine-efficient risk forecasts, in addition to ex-post realized transition rates, which visually illustrate such patterns.

Information rigidity in the form of Sticky Expectations. As an extension, we add the 3-month lagged perceived risks $\widetilde{JF}_{t|t-3}$ and $\widetilde{JS}_{t|t-3}$ to the regressions of (1) and (2), respectively. This specification allows us to test whether the observed underreaction in perceived unemployment risks follow a recursive pattern of the Sticky Expectations model, as represented in Equation 5.[6] Following Mankiw and Reis (2002), Carroll (2003), and Coibion and Gorod-

[6]Several studies have estimated the updating rate λ to be significantly below one, based on survey expectations of inflation, unemployment, and other macroeconomic variables; see, for example, Mankiw and Reis (2002),

Figure 4: Backcasted perceptions of unemployment risks





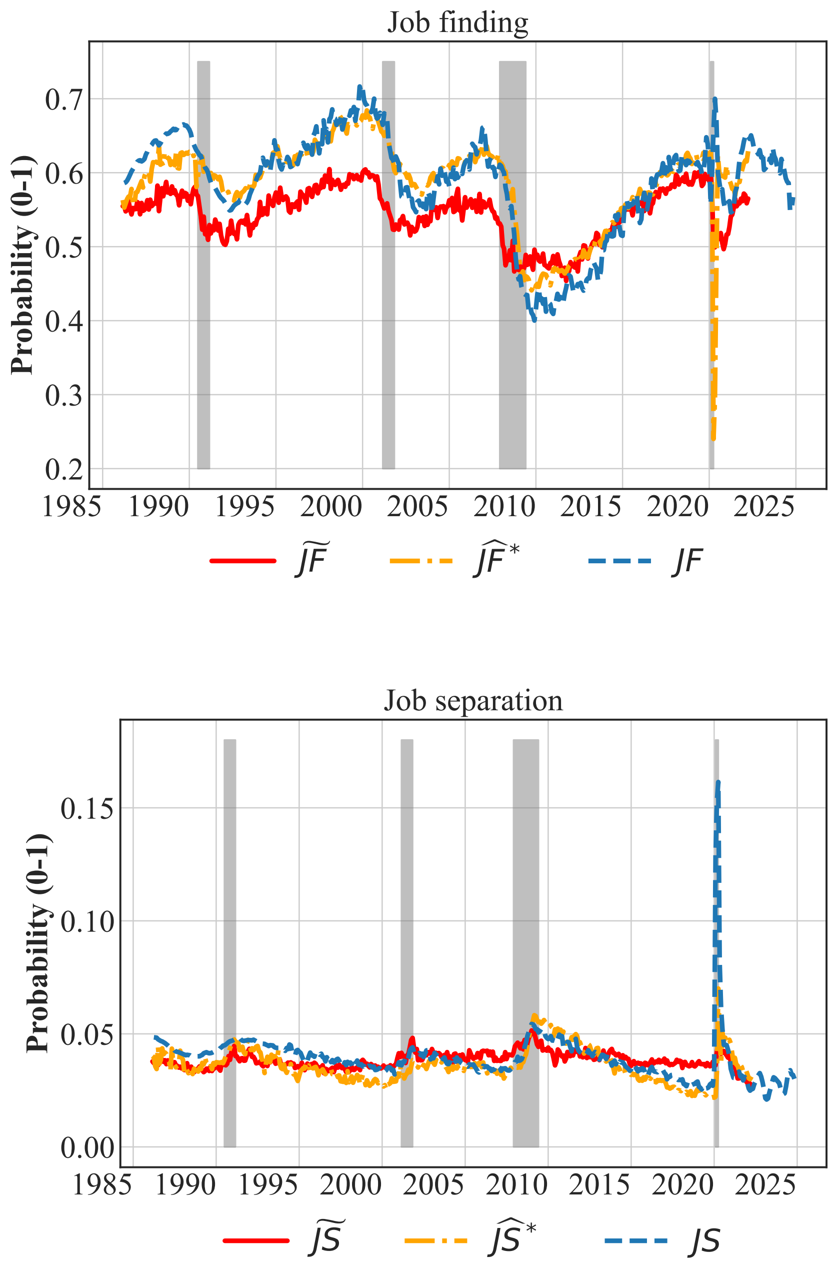
Notes: The two charts plot backcasted perceived unemployment risks that are predicted using the selected LASSO model based on in-sample cross-validation.

Table 2: Regression of perceived job-finding and separation probability on real-time forecasts

	Baseline				Only SCE			
	$\widetilde{JF}$	$\widetilde{JS}$	$\widetilde{JF}$	$\widetilde{JS}$	$\widetilde{JF}$	$\widetilde{JS}$	$\widetilde{JF}$	$\widetilde{JS}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{JF}^*$	0.457***		0.144***		0.340**		0.244***	
	(0.027)		(0.029)		(0.142)		(0.015)	
$\widetilde{JF}_{t-3}$			0.748***				0.696***	
			(0.046)				(0.060)	
$\widehat{JS}^*$		0.235***		0.057**		0.163**		0.060
		(0.022)		(0.031)		(0.075)		(0.090)
$\widetilde{JS}_{t-3}$				0.780***				0.630***
				(0.022)				(0.166)
Const	2.138***	1.042***	0.903***	0.220***	3.947***	1.083***	0.355	0.394**
	(0.079)	(0.040)	(0.176)	(0.075)	(0.855)	(0.073)	(0.345)	(0.168)
Adj. R^2	0.601	0.263	0.878	0.670	0.278	0.092	0.786	0.380
N	434	434	431	431	107	107	104	104

Notes: Column (1) and (2) report the regression results of $\log\left(\widetilde{JF}_{t+3|t}\right) = \alpha_{JF} + \beta_{JF}\log\left(\widehat{JF}^*_{t+3|t}\right) + \epsilon_t$, and $\log\left(\widetilde{JS}_{t+3|t}\right) = \alpha_{JS} + \beta_{JS}\log\left(\widehat{JS}^*_{t+3|t}\right) + \epsilon_t$, respectively. Columns (3) and (4) additionally control for the 3-month lagged belief $\log\left(\widehat{JF}^*_{t|t-3}\right)$ or $\log\left(\widehat{JS}^*_{t|t-3}\right)$*, respectively. Column (5)-(8) repeat column (1)-(4) with only in-sample data since 2013.**, and *** represent significance of the coefficient at the 10%, 5%, and 1% levels.

Figure 5: Survey perceived unemployment risks vs. machine-efficient forecasts



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

nichenko (2015), the Sticky Expectation model assumes that a fraction λ of agents updates their beliefs fully and rationally each period, while the remaining $1-\lambda$ continue to rely on outdated beliefs due to infrequent updating. This yields the prediction that the 3-month-ahead perceptions of risks at t are equal to the weighted average of the rational expectations at t and the lagged six-month-ahead beliefs. We can use machine forecasts $\widehat{JF}^*_{t+3|t}$ to directly proxy for the former variable. Although the latter is not directly observed in the data, it is correlated with the lagged 3-month-ahead perceptions, $\widetilde{JF}_{t|t-3}$ and $\widetilde{JS}_{t|t-3}$. Controlling for the lagged perceptions pick up the effects of the second term in the equation. Therefore, the coefficient of the machine forecast can be read off as an estimate of λ in the model.

$$\widetilde{JF}_{t+3|t} = \lambda JF^*_{t+3|t} + (1-\lambda)\widetilde{JF}_{t+3|t-3} \tag{5}$$

The estimates are reported in columns (3) and (4) for the full sample period with backcasted perceptions and columns (7) and (8) for the SEC sample without backcasted perceptions in Table 2. In line with the canonical SE framework, the coefficients of 3-month lag perceptions are all statistically significant and positive. In all eight specifications, controlling for lagged beliefs lowers the estimates of the sensitivity of perceptions with respect to machine forecasts. This suggests that current perceived risks underreact to real-time changes in risks while are dependent on past beliefs about job risks.

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

With the three measures (a) perceived risks ($\widetilde{JF}, \widetilde{JS}$), (b) objective risks ($\widehat{JF}^*, \widehat{JS}^*$), and (c) realization of job flow rates (JF, JS), we have established two main findings. First, we reject perfect foresight, in that household and even ex ante rational and fully informed forecasts of risks do not fully predict ex post realizations, as evidenced by the gap between (a) subjective perceptions and (c) realizations. Second, perceived unemployment risks deviate from their objective ex ante counterparts, partially due to information rigidity.

In this section, we summarize the dynamic patterns of (a), (b), and (c) across the past four business cycles in our sample, which are central to understanding consumption fluctuations through these channels. We consider two metrics. The first is the unconditional standard deviation of each series. The second is the peak-to-trough ratio within each recession, which provides an intuitive measure of cyclical change.

Carroll (2003), and Coibion and Gorodnichenko (2012). An alternative micro-foundation of such information rigidity is noisy information models, in which agents learn about the true state of the economy through noisy public and private signals. Like SE, these models generate serially correlated forecast errors, but they do not yield the exact prediction as Equation 5.

Over the 1990–2024 period, which spans four recessions and substantial cyclical swings in unemployment risks, the unconditional standard deviation of realized job-finding rates is about 7.2 percentage points. Most of these variations are reflected in real-time job-finding probabilities, with a standard deviation of about 6.9 percentage points. In contrast, perceived job-finding rates fluctuate much less, with a standard deviation of only 4 percentage points. For separation, the unconditional standard deviations for perceptions, objective forecasts, and realizations are 0.2, 0.8, and 0.7 percentage points, respectively. Both job-finding and separation perceptions are markedly less volatile than the realized unemployment risks and the objective risks.

Such rankings of the relative volatility of perceptions and realizations are also apparent in Table 3, which reports the peak and trough rates in each of the four recessions in the sample period. From the onset to the end of a typical recession, the real-time job-finding rate drops by 27%, whereas the perceived job-finding rate decreases by only 10%. Separation perceptions are even more sluggish than job-finding perceptions. On average, perceived separation risk rises by just 11% over a recession, as opposed to a 49% increase in the real-time separation risk forecast and a 52% increase in realized separation rates. The overall pattern is robust to excluding the pandemic.

Table 3: Business cycle patterns of unemployment risks and perceptions

(a) Peak-to-trough ratio of JF

	1990	2001	2007	2020	Mean
$\widetilde{JF}$	$\frac{0.57}{0.52} = 1.10$	$\frac{0.56}{0.53} = 1.06$	$\frac{0.53}{0.48} = 1.10$	$\frac{0.60}{0.50} = 1.20$	1.11
JF^*	$\frac{0.59}{0.6} = 0.98$	$\frac{0.65}{0.60} = 1.08$	$\frac{0.61}{0.46} = 1.33$	$\frac{0.63}{0.30} = 2.1$	1.37
JF	$\frac{0.64}{0.60} = 1.07$	$\frac{0.68}{0.62} = 1.10$	$\frac{0.59}{0.44} = 1.34$	$\frac{0.65}{0.56} = 1.16$	1.17

(b) Peak-to-trough ratio of JS

	1990	2001	2007	2020	Mean
$\widetilde{JS}$	$\frac{0.036}{0.040} = 0.90$	$\frac{0.042}{0.044} = 0.95$	$\frac{0.042}{0.047} = 0.89$	$\frac{0.036}{0.043} = 0.84$	0.90
JS^*	$\frac{0.037}{0.047} = 0.79$	$\frac{0.032}{0.039} = 0.82$	$\frac{0.036}{0.055} = 0.61$	$\frac{0.022}{0.048} = 0.46$	0.67
JS	$\frac{0.044}{0.047} = 0.94$	$\frac{0.034}{0.042} = 0.81$	$\frac{0.034}{0.051} = 0.67$	$\frac{0.026}{0.13} = 0.20$	0.66

Notes: The top table reports the perceived job-finding rate, real-time forecast of job-finding rate, and realized job-finding rate at the beginning and the last month of each one of the four recessions, and the peak-to-trough ratios of these rates. The bottom table reports the corresponding statistics for the separation rate.

These average patterns mask substantial heterogeneity in unemployment risks and perceptions. Figure 3 plots the movements of perceptions over the business cycle across different percentiles of the perceived-risk distribution. For job finding, while the average worker's perceived job-finding rate drops by 15% from the peak to the trough of a recession, roughly comparable to the realized job finding, the low job-finding rate worker at the 25th percentile perceives a much steeper drop of about 25%, compared with a drop of only 10% for workers at the 75th percentile. For separation, although the average worker's separation perceptions increase by only 15% in recessions, the median worker's perceptions increased by more than twice as much, roughly 35%. These results highlight that recessions affect workers unevenly through unemployment risk channels. Heterogeneity in perceptions reveals the uneven footprints of business cycle fluctuations. Heterogeneity in risk exposures implies different degrees of ex ante precautionary saving behaviors and their consequent ex post shock responses, a topic to which we turn now.

5 Quantifying Aggregate Consumption Responses

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 labor market transition rates into a standard heterogeneous-agent model with persistent unemployment. 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, rather than 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 an incomplete-market model of consumption and saving. The economy consists of a continuum of perpetual youth that dies at rate D. Each household is subject to 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 Problem. Each period t, a household's state variables include asset holding a_{it}, productivity ψ_{it}, employment status $n_{it} \in \{e, u\}$, and perceptions about job-finding and separation rates $\mathbf{p}_t = (p_t^{ue}, p_t^{eu})$. The household solves the following dynamic programming problem:

$$V_t(a_{it}, \psi_{it}, n_{it}; \mathbf{p}_t) = \max_{c_{it}, a_{it+1}} u(c_{it}) + \beta(1-D)\mathbb{E}_t\big[V_{t+1}(a_{it+1}, \psi_{it+1}, n_{it+1}; \mathbf{p}_{t+1})\big]$$

subject to the constraints:

$$a_{it+1} = (1+r)a_{it} + y_{it} - c_{it}$$
$$a_{it+1} \geq 0$$

where c_{it} is consumption, and r is the net return on the risk-free asset.

Income Process. Labor income y_{it} is given by the product of a persistent productivity component ψ_{it}, and an employment-state-dependent income factor ζ_{it}:

$$y_{it} = \psi_{it} \cdot \zeta_{it}$$

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

$$\log \psi_{it} = \rho_\psi \log \psi_{it-1} + \eta_{it}, \quad \eta_{it} \sim \mathcal{N}(0, \sigma_\psi^2)$$

The employment-state-dependent income component ζ_{it} is:

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

where θ_{it} is an temporary productivity component that follows an i.i.d. lognormal shock with mean one and standard deviation σ_θ, and χ represents the unemployment insurance (UI) replacement rate.

Employment status evolves according to a Markov process:

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

Belief Dynamics. Workers form subjective beliefs about these transition rates, $\mathbf{p}_t = (p_t^{ue}, p_t^{eu})$, where p_t^{ue} is workers' perceived job-finding rate and p_t^{eu} perceived separation rate. Both follow an AR(1) process.

Calibration. Table 4 reports the calibrated parameters of the model. The unemployment insurance replacement rate is set at 50%. Given the paper's focus on business cycle fluctuations in perceived unemployment risks, we assume that the perceived unemployment 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).[7] Such MPC also indirectly disciplines the sensitivity of consumption to 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 4: Calibration for the baseline monthly model

Description	Parameter	Value	Source / Target
CRRA coefficient	γ	2	Standard
Real interest rate	r	$1.05^{1/12}-1$	5% annual real rate
Probability of Death	D	0.002	Carroll et al. (2017)
UI replacement rate	χ	0.5	50% replacement rate
Persistence of productivity	ρ_ψ	0.997	Kekre (2023)
Std. dev. of productivity shocks	σ_ψ	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

Notes: This table reports the calibrated parameters of the model.

5.2 Ex ante/ex post decomposition of aggregate consumption responses

We start by characterizing the aggregate consumption response to changes in unemployment risks and shocks. For a given increase in the job-finding and separation probability, whether realized or perceived, households with different levels of liquid wealth adjust their consumption differently. ex ante responses differ due to different intensities of precautionary responses. ex post responses differ due to heterogeneous MPCs resulting from different wealth levels. Aggregate consumption effects summarize these heterogeneous individual 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. Take a rise in separation risks as an example. Using the consumption Jacobians, the black line in Figure 6 plots the total consumption response to an increase in the separation probability at horizon $t+h$, with $h=10$, when it is both perceived since period 0 and realized

[7] Specifically, 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.

10 months later. It 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 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.

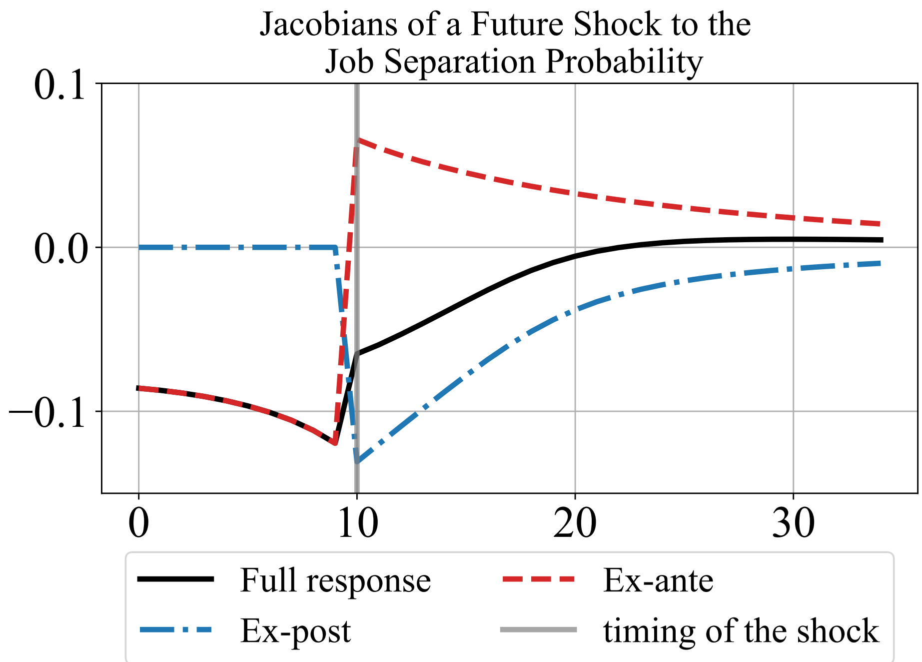
The ex ante Jacobian (the red line) captures workers' precautionary behavior before the shock at $t = 10$. That is their self-insurance response to a perceived increase in separation risk that ultimately does not materialize. Because this risk hypothetically affects all workers, it leads to heterogeneous 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 separation risks. This channel only affects those who lose their job unexpectedly. Combining the ex ante and ex post Jacobians yields the total Jacobian corresponding to the black line in Figure 6. Notice that the actual consumption drops 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.

The strength of ex-ante and ex-post channels depends on the economy's steady-state distribution of liquid wealth, which in turn is shaped by household preferences. For instance, a lower discount factor β, or greater impatience, leads households to hold less wealth and display higher MPCs, amplifying their immediate consumption drop after a job loss. The effect of β on ex-ante responses is more nuanced. Greater patience makes households more forward-looking and responsive to future income changes, but it also raises their steady-state savings. As more households move out of liquidity constraints, their precautionary motives weaken. The magnitude and dynamics of ex-ante responses reflect the balance between these opposing forces. Appendix A.11 shows the Jacobian decomposition from Figure 6 under alternative β values and further discusses the robustness of our baseline results.

Although we use $h = 10$ as an example, the decomposition logic holds for any horizon. Appendix Figure A.7 plots the decomposition for other horizons. Consider a special case of $h = 0$. That is, the shock to the separation probability immediately occurs. In this case, the ex ante Jacobian is flat, as there are no ex ante responses and the entire consumption impact comes from ex post effects. More generally, the size of the ex ante effect decreases with the horizon h, while the ex post effect does not. The nearer the perceived future feared risk, the larger the consumption drops to build buffers.

Figure 6: Consumption Jacobian with respect to a 10-period-ahead shock to the separation rate



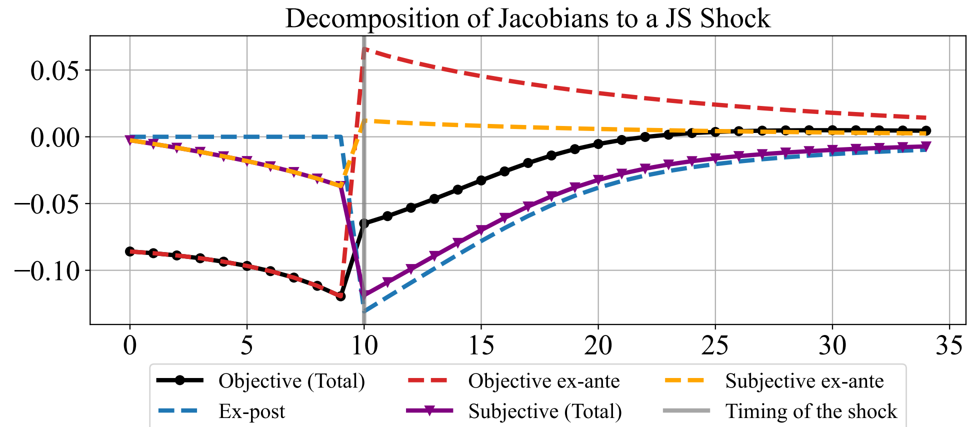
Notes: This figure plots the total and decomposed Jacobians of the aggregate consumption with respect to a shock to job-separation probability at $t+10$. The Jacobian is defined as in Auclert et al. (2021).

We next illustrate how a wedge between perceived unemployment risks and subsequent realizations alters the ex ante and ex post consumption responses to a separation shock. Figure 7 shows that underreactive beliefs—as documented in survey expectations about both job-finding and separation rates—dampen the precautionary channel while amplifying the income-loss channel associated with unemployment. The figure includes two additional consumption responses under sticky belief updating.[8] The purple line plots the subjective consumption response to an increase in the separation rate 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 involves a transformation of the baseline Jacobians under perfect foresight. Two key features emerge. First, the ex ante component of the response is significantly muted relative to the full-update benchmark (red line). Second, under sticky beliefs, the consumption drop at $t = 10$ and thereafter is substantially larger, reflecting weaker self-insurance. This under-insurance mechanism, due to underreactive perceptions, plays a central role in the model results we present next. Rather than focusing on the

[8]Although Figure 7 presents the subjective Jacobian decomposition to illustrate the under-insurance mechanisms arising from sticky beliefs about unemployment risks, the model experiments in the following section rely directly on the empirically estimated patterns of $\widetilde{JF}_t$ and $\widetilde{JS}_t$.

specific sticky expectations formulation, however, we proceed with a more general approach to modeling subjective perceptions.

Figure 7: Subjective consumption Jacobians with sticky expectations



Notes: 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.

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

Combining the ex ante and ex post Jacobians constructed above with the empirical perceptions, realizations, and objective risk proxies, we simulate the path of aggregate consumption deviations from the steady state implied by each series. Our baseline analysis spans 1988–2020. We model each series as an AR(1) process, allowing both persistence and shock realizations to differ across them. This flexible specification captures the joint dynamics of perceived and realized unemployment risks in a manner that directly matches the data, without imposing a specific model of expectation formation.

$$\textbf{Realizations: } JF_t = \rho_{JF} JF_{t-1} + \varepsilon_{JF,t}, \quad JS_t = \rho_{JS} JS_{t-1} + \varepsilon_{JS,t} \tag{6}$$

$$\textbf{Perceptions: } \widetilde{JF}_t = \rho_{\widetilde{JF}} \widetilde{JF}_{t-1} + \varepsilon_{\widetilde{JF},t}, \quad \widetilde{JS}_t = \rho_{\widetilde{JS}} \widetilde{JS}_{t-1} + \varepsilon_{\widetilde{JS},t} \tag{7}$$

$$\textbf{Objective risks: } \widehat{JF}^*_t = \rho_{\widehat{JF}^*} \widehat{JF}^*_{t-1} + \varepsilon_{\widehat{JF}^*,t}, \quad \widehat{JS}^*_t = \rho_{\widehat{JS}^*} \widehat{JS}^*_{t-1} + \varepsilon_{\widehat{JS}^*,t} \tag{8}$$

By estimating each equation, we recover the corresponding sequence of shocks that replicate the observed time series, as shown in Figure A.8 in the Appendix. Although our specification separates the dynamics of perceived risks and realized flow rates, the empirically filtered shocks to the two series are correlated over a common horizon. This imperfect correlation reflects the presence of both shared and independent components in 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.

$$\{\hat{\varepsilon}_{JF,t}, \quad \hat{\varepsilon}_{JS,t}, \quad \hat{\varepsilon}_{\widetilde{JF},t}, \quad \hat{\varepsilon}_{\widetilde{JS},t}, \quad \hat{\varepsilon}_{\widehat{JF}^*,t}, \quad \hat{\varepsilon}_{\widehat{JS}^*,t}\} \quad \text{for } t = 1, \ldots, T. \tag{9}$$

The separation of ex ante and ex post Jacobians allows us to flexibly discipline each channel in the model with their corresponding empirical series. In particular, by combining the ex post Jacobian with the estimated realization shocks $\{\hat{\varepsilon}_{JF,t}, \hat{\varepsilon}_{JS,t}\}$, we can simulate solely the ex post consumption fluctuations. This scenario corresponds to a hypothetical world in which workers perceive no changes in the job-finding and separation risks ex ante, and only a fraction of them, determined by the size of the estimated shock, unexpectedly experience realized changes in job-finding and separation rates.

Similarly, by combining the ex ante Jacobian defined above with the estimated shocks to perceptions $\{\hat{\varepsilon}_{\widetilde{JF},t}, \hat{\varepsilon}_{\widetilde{JS},t}\}$, objective risks $\{\hat{\varepsilon}_{\widehat{JF}^*,t}, \hat{\varepsilon}_{\widehat{JS}^*,t}\}$, or realizations $\{\hat{\varepsilon}_{JF,t}, \hat{\varepsilon}_{JS,t}\}$, we produce ex ante consumption fluctuations under alternative assumptions. While the magnitude of the ex post channel is invariant to expectations, the quantification of the ex ante channel depends critically on which expectation is used. Adding the respective ex ante impact and the common ex post one yields the overall consumption dynamics under different assumptions about expectations.

We start with the baseline quantification under subjective perceptions of unemployment risks, assuming that workers' expectations follow the survey-based measures of job-finding and separation perceptions and they act upon these beliefs. This baseline experiment can be viewed as a factual decomposition because it directly incorporates empirical perceptions of unemployment risks to quantify ex ante impacts. The red bars, blue bars, and the black line in Figure 8 represent the ex ante, ex post, and total consumption dynamics, respectively.

Figure 8 shows that, although ex post impacts are the dominant driver of consumption fluctuations, ex ante responses to changes in perceived risks also make a non-negligible contribution, as indicated by the red bars. This finding confirms the importance of perceived unemployment risks in shaping aggregate consumption dynamics, even when such perceptions adjust sluggishly. Put differently, it is not only the realizations of unemployment shocks but also the fear of unemployment that influences aggregate consumption dynamics over the business cycle. Moreover, ex ante impacts often lead ex post impacts, consistent with our earlier finding that perceived unemployment risks partially predict subsequent labor market outcomes. The 2008 Great Recession illustrates this pattern vividly: 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 negative.

Counterfactual experiments. As a comparison with the baseline simulation, we conduct two counterfactual exercises based on alternative assumptions about how risks are perceived. The first (orange line in Figure 8) assumes that workers' expectations follow our constructed measure of rational expectations, $\widehat{JF}^*_t$ and $\widehat{JS}^*_t$, effectively equating the perceived risks to (b) objective risks under the FIRE assumption. The second (green line in Figure 8) assumes "perfect foresight," meaning that their perceived risks move one-for-one with realized shocks to the transition probabilities, effectively equating the perceived risks to (c) ex post realizations.[9]

(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 rational benchmark. Throughout the sample, consumption fluctuations implied by subjective perceptions are attenuated relative to those implied by objective risks. Objective risks dictated sharper consumption responses at the onset of each recession than subjective perceptions. This gap arises because of the underreactive nature of the perceived risks relative to their rational benchmark. As unemployment risk rises more slowly in workers' minds than it actually does, those who eventually lose jobs have to experience a larger consumption adjustment at the shock's realization. Underreactive perceptions therefore translate to substantial under-insurance, and the smaller stock of precautionary wealth in turn contributes to the slow recovery later.[10]

This wedge is quantitatively important. For instance, 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 objective risks, given the persistently weak labor market during that time. In contrast, the negative consumption gap implied by the perceived unemployment risks during this period was 1.5 percentage points. One might conclude that collective underreaction of perceived risks stabilize aggregate consumption by preventing an even deeper drop. Yet this "stabilization" came at the cost of slower recoveries and disproportionate welfare losses for the under-insured households that bore the brunt of unemployment shocks, as such households have a smaller stock of precautionary wealth.

[9]Here "perfect foresight" specifically refers to the shocks to ex ante risk perceptions matching those to 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.

[10]To address the concern that this pattern may be driven by our use of the imputed beliefs, Figure A.12 presents model simulations based solely on post-2013 perceived unemployment risks directly measured in the SCE. The pattern persists.

(b) versus (c). Comparing the two counterfactuals highlights the distinction between ex ante unemployment risks and ex post realizations of unemployment risks. The model-implied responses under these assumptions are close to each other. This similarity is consistent with the earlier finding that machine forecasts predict most of the subsequent labor market flows in past recessions, although the COVID crisis was a major exception. The small gap suggests that the common practice in this literature of equating unemployment risks to realized job flow rates is largely 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.

Job-finding versus separation. Additional insights arise when we separately assess the role of job-finding and separation risks, as shown in the bottom panels in Figure 8. First, when considering separation alone, the stickiness of beliefs generate almost no ex ante precautionary saving response during recessions, as indicated by the nearly invisible red bars in the right bottom figure in Figure 8. Consequently, total consumption responses based on subjective perceptions closely mirror the ex post impact and fall short of the response implied by objective risk.

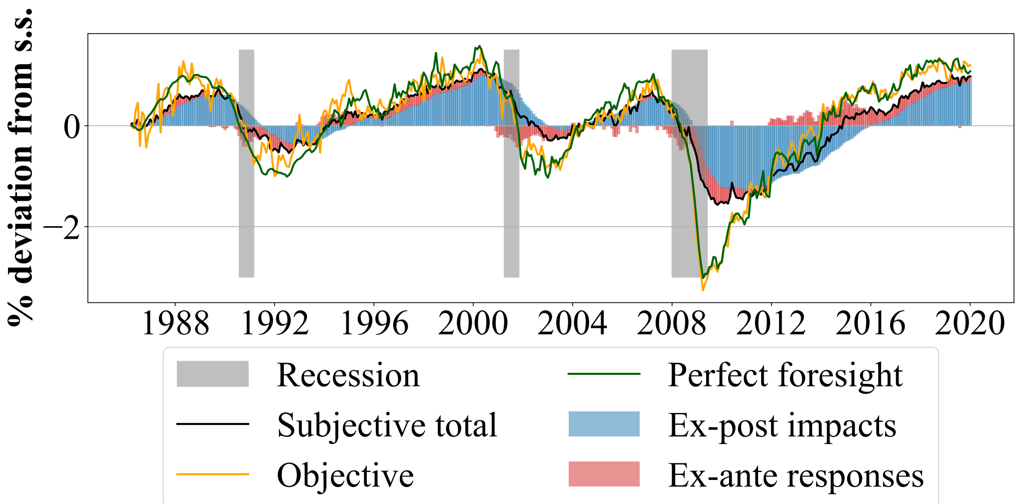
Second, in the case of job-finding risk, precautionary saving plays a non-trivial role in driving consumption. However, because job-finding perceptions adjust only partially to the true underlying risk, there remains a large gap between simulations using objective risk or perfect foresight versus subjective expectations.

Third, the combined impact of job-finding and separation—shown in the top panel of Figure 8—is driven largely by the job-finding channel. This pattern reflects three main factors. First, beliefs about job-finding rates are more responsive than those about separation rates, amplifying the precautionary saving motive. Second, fluctuations in the job-finding rate account for a larger share of unemployment dynamics over the business cycle (Shimer, 2012; Fujita and Ramey, 2009; Elsby et al., 2009). Lastly, note that job-finding risk matters not only for the unemployed but also for the employed, since employed workers face the risk of job loss followed by difficulty in re-employment.

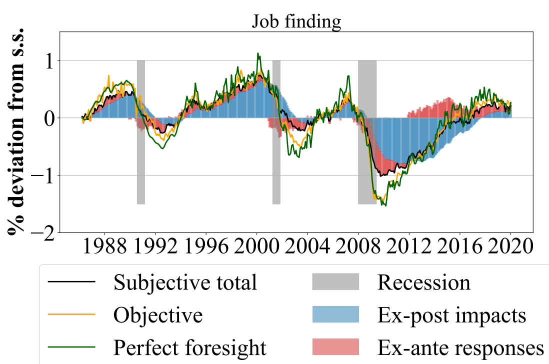
Discussion. We conclude this section with a note on the broader macroeconomic implications of imperfect perceptions of unemployment risks. Our analysis has been partial-equilibrium in nature, focusing on the direct consumption responses to such risks. Nevertheless, insights from Angeletos and Huo (2021) and Angeletos and Lian (2023) suggest how these findings may extend to general equilibrium (GE) environments considered in a class of macroeconomic models that feature market incompleteness, labor market frictions, and nominal rigidities. These

Figure 8: Consumption fluctuations due to unemployment risks

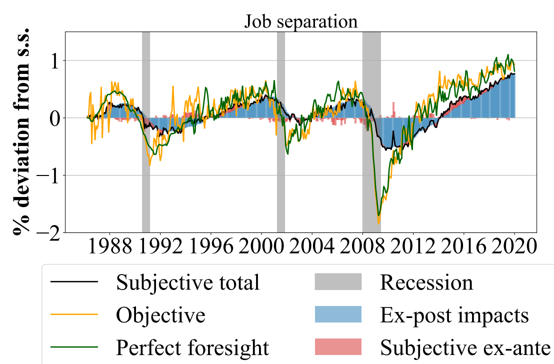
(a) JF+JS



(b) JF



(c) JS



Notes: 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 unemployment 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).

papers show that when expectations are subject to frictions—such as incomplete information or bounded rationality—the GE propagation of shocks tends to be dampened if individual responses display strategic complementarities. Underreactive expectations attenuate the initial adjustment of agents, and because individual responses reinforce one another, the muted reaction of each agent reduces the amplification mechanism present in the frictionless benchmark. In our context, the partial equilibrium consumption response feeds back positively into others' consumption via the Keynesian demand multiplier effect under nominal rigidity. Hence, weaker self-insurance responses imply a dampening of aggregate demand fluctuations in GE. This mechanism also helps rationalize why concerns about equilibrium indeterminacy with countercylical unemployment risks (Ravn and Sterk, 2021) or self-fulfilling downward spiral (Haan et al., 2018) may be less empirically relevant.

5.4 Case study of the COVID recession

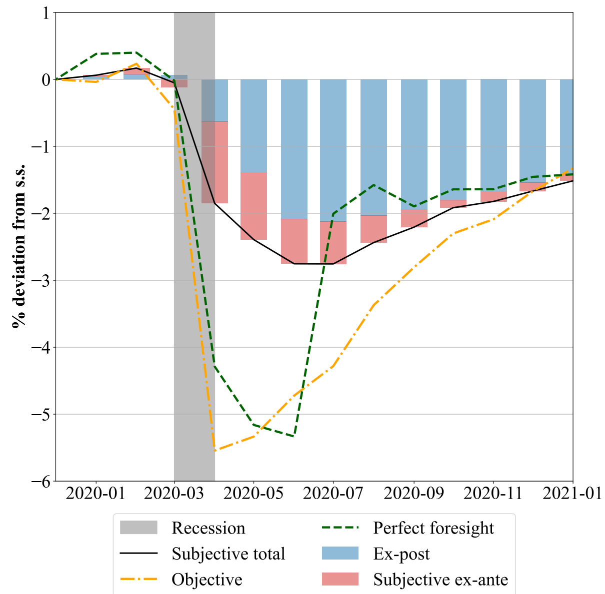
Our baseline simulations are based on the pre-2020 period. In this section, we turn to the COVID-19 recession, which stands out in two respects: it was highly unexpected ex ante and unusually short-lived ex post. These features are central for assessing the relative roles of expectations versus realizations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

Figure 9 presents model-implied consumption responses to ex ante perceptions (red bar), ex post realizations (blue bar), and their combined effects (black line), abstracting from shocks outside January–November 2020. March 2020 brought a sharp and unexpected rise in separations—a salient feature of the COVID shock—but the figure reveals that ex ante perceptions also contributed significantly to the consumption drop at the onset. In April 2020, the aggregate consumption drop due to heightened fears 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 at the onset of the crisis and an n even larger role during the subsequent recovery. The corresponding patterns for job-finding and separations are plotted in Figure 9b and 9c, respectively.

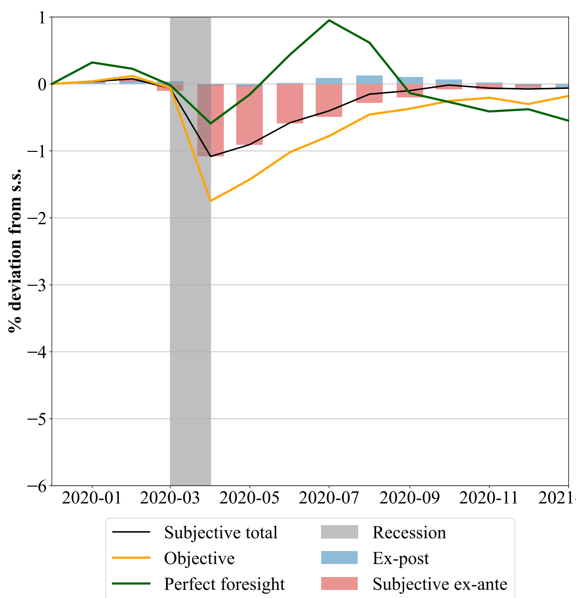
Figure 9 also shows consumption fluctuations under two counterfactuals: objective expectations (machine forecasts) and perfect foresight. Unlike in previous recessions, the COVID episode reveals a notable gap between the objective (orange) and perfect foresight (green) lines, highlighting the difficulty of anticipating COVID dynamics based solely on pre-existing information 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 unemployment risk.

Figure 9: Consumption fluctuations due to unemployment risks during COVID

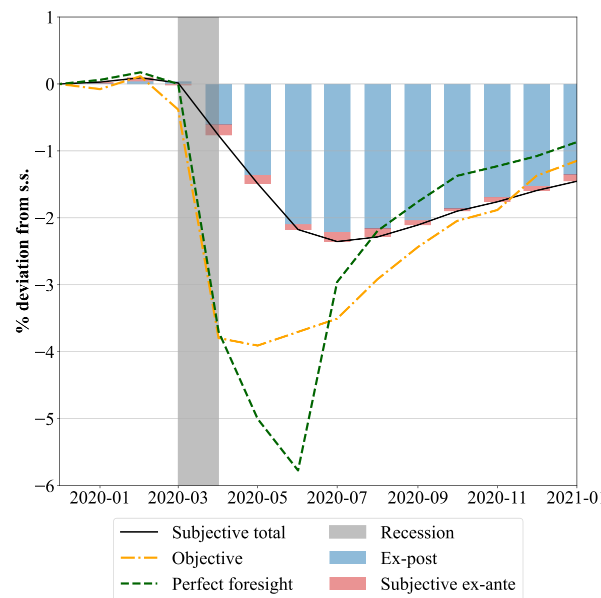
(a) Overall



(b) Job-finding



(c) Separation



Notes: The figure reproduces the model experiments for the COVID recession as done in Figure 8 for the pre-2020 sample. It assumes that no shocks to risks and perceptions occurred before January 2020. Panel (b) and (c) break down the model simulation results for the COVID recession in Figure 9 into job-finding and job-separation components.

By 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 in Figure 2 between ex ante expectations and actual outcomes.

This contrast between the two scenarios underscores the importance of distinguishing rational ex ante risk forecasts (b) from realized outcomes (c). In incomplete-market models, it is common to equate ex ante risks with ex post realizations of worker flows. While such 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 unusually large.

The COVID exercise further highlights that assumptions about perceived unemployment risks play an important role in shaping aggregate consumption dynamics due to fluctuations in unemployment risks. Although the sharp but short-lived deterioration in labor market conditions contributed to the consumption drop, it is implausible that ex post developments were fully anticipated ex ante and perceived as unemployment risks. Treating them as such would imply unrealistically large precautionary responses. Moreover, even if one could define correct perceptions based on prevailing macro conditions, it is unlikely that these could serve as the benchmark guiding actual self-insurance behaviors, which were much attenuated due to belief stickiness.

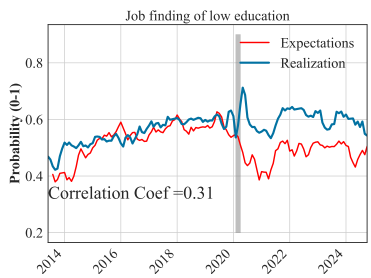
6 Heterogeneity

6.1 Heterogeneity across education groups

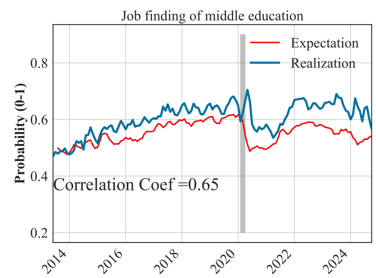
The results presented above are based on averages across all households in the survey. A natural question is whether perceptions and realizations align similarly within demographic groups. Prior work highlights the importance of heterogeneity in unemployment risks in driving aggregate labor market dynamics (Hall and Kudlyak, 2019; Ahn and Hamilton, 2020; Gregory et al., 2021; Patterson, 2023). Perceptions of labor market risks are also heterogeneous, as shown by Mueller et al. (2021) and Wang (2023). Motivated by this evidence, we report perceptions and realizations separately for high school or less, some college, and bachelor's degree and above (low-, middle-, and high-education groups from now on) in Figure 10. The figure shows that, within each education group, perceived risks track realized flows closely, with correlations comparable to those at the aggregate level. At the same time, substantial heterogeneity emerges in the realized rates themselves, both in levels and in volatility. Low-education workers face higher separation rates and lower job-finding rates than high-education workers. By contrast, perceived risks differ less across education groups, especially for separation rates. At the onset of the pandemic, low-education workers appear to particularly under-forecast their separation risk, while their realized separations rose much more sharply than for the other two groups. In addition, while low-education workers were more pessimistic about their job-finding prospects, realized job-finding dynamics were similar across groups. These patterns underscore the importance of considering heterogeneity not only in the risks households face but also in how they perceive those risks.

Figure 10: Perceived versus realized worker flow rates by education

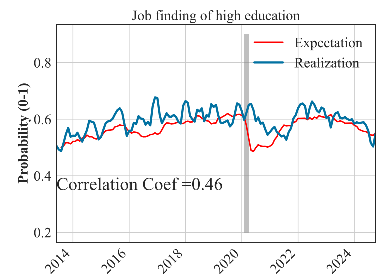
(a) JF of low education



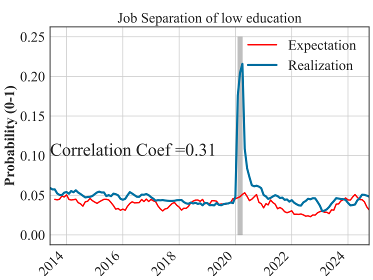
(b) JF of middle education



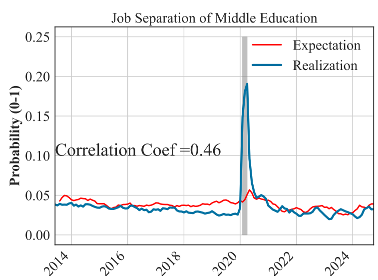
(c) JF of high education



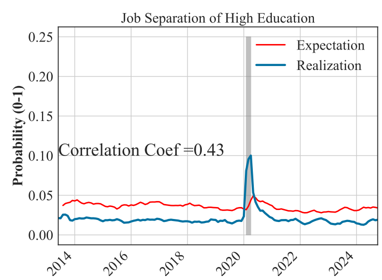
(d) JS of low education



(e) JS of middle education



(f) JS of high education



Notes: This figure plots the 3-month-ahead unemployment 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.

Is there heterogeneity in belief distortions, in addition to heterogeneity in the unemployment risks faced by workers? If those most exposed cyclical unemployment risks systematically under-perceive such movements—and therefore under-insure themselves—aggregate consumption fluctuations are amplified by the heterogeneous footprints of uninsured unemployment risks. We explore this question by exploiting the fact that we can construct group-specific risk forecasts for each education group, i.e., $\widehat{JF}^{HighEdu*}$, $\widehat{JF}^{MidEdu*}$, $\widehat{JF}^{LowEdu*}$, which account for the heterogeneity in unemployment risk exposures across education groups.

The estimates are reported below in Table 5. For the job-finding rate, the middle-education group is the most rigid relative to their real-time risks, compared to low- and high-education groups. For the separation rate, however, the low-education group displays the strongest underreaction, indicating the highest degree of information rigidity. These patterns are consistent with Figure 10: low-education workers underestimate spikes in separation rates and respond more strongly to declines in job-finding rates at the onset of the pandemic, compared to the high-education group.[11] Across education groups, beliefs exhibit rigidity, with the coefficients always below 60 percent.[12]

Table 5: Regression results of perceived risks on real-time forecasts by education group

	Job finding perceptions			Separation perceptions		
	$\widetilde{JF}^{EduLow}$	$\widetilde{JF}^{EduMid}$	$\widetilde{JF}^{EduHigh}$	$\widetilde{JS}^{EduLow}$	$\widetilde{JS}^{EduMid}$	$\widetilde{JS}^{EduHigh}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{JF}^{*Edu}$	0.556***	0.271***	0.449***			
	(0.048)	(0.023)	(0.044)			
$\widehat{JS}^{*Edu}$				0.159***	0.283***	0.215***
				(0.052)	(0.077)	(0.062)
Const	1.700***	2.888***	2.192***	1.087***	0.981***	1.143***
	(0.190)	(0.092)	(0.177)	(0.080)	(0.099)	(0.047)
Adj. R^2	0.542	0.560	0.510	0.306	0.368	0.334
N	278	278	278	278	278	278

Notes: Column (1)-(3) report the regression results of $\log\left(\widetilde{JF}^{\text{Edu}}_{t+3|t}\right) = \alpha^{\text{Edu}} + \beta^{\text{Edu}} \log\left(\widehat{JF}^{*\text{Edu}}_{t+3|t}\right) + \epsilon_t \quad \forall \quad \text{Edu} \in \{\text{LowEdu}, \text{MidEdu}, \text{HighEdu}\}$, respectively. Columns (4)-(6) report the analogous regression results for job separation (JS). *, **, and *** represent significance of the coefficient at the 10%, 5%, and 1% levels.

6.2 Quantitative results with heterogeneity across education groups

Figure 11 simulates consumption fluctuations for each education group separately, allowing unemployment risks to vary by education. We quantify the role of both misperceived risks and precautionary saving motives for each education group. We calibrate the discount factor of

[11] Assuming a strong correlation between education and liquid wealth, Broer et al. (2021a) predict a U-shaped pattern, with poor and rich households having the strongest incentives to know the current state of the world. Our results are consistent with this prediction for job-finding risks, but contradict it for separation risks. In fact, workers without a high school degree have the weakest reaction in beliefs to changes in realized separation rates, despite facing the largest welfare losses from suboptimal precautionary savings.

[12] Appendix A.2 examines the role of heterogeneity by studying the patterns of different percentiles of the perceived unemployment risks.

low- and middle-education groups to target a quarterly MPC of 0.34, as 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, as reported by Fuster et al. (2021) for bachelor's degree holders and above.

Two key findings emerge. First, as expected, the low-education group exhibits the largest ex post consumption response during recessions, reflecting the interaction between the greater 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 fell by as much as 2 percentage points relative to its steady state, whereas high-education workers experienced a shortfall of consumption of only about 0.5 percentage points.

Second, compared to the high-education group, the low-education group displays a much smaller precautionary response overall, driven by their muted sensitivity in updating beliefs. This pattern is evident in Figure 11: the red bar is far less pronounced for the low-education group than for the middle- and high-education groups. It is also reflected in a much wider gap between their subjective and objective responses, and a smaller gap between their subjective and ex post responses. Because of these underreactive perceived risks, the low-education group exhibits the largest degree of under-insurance during recessions.

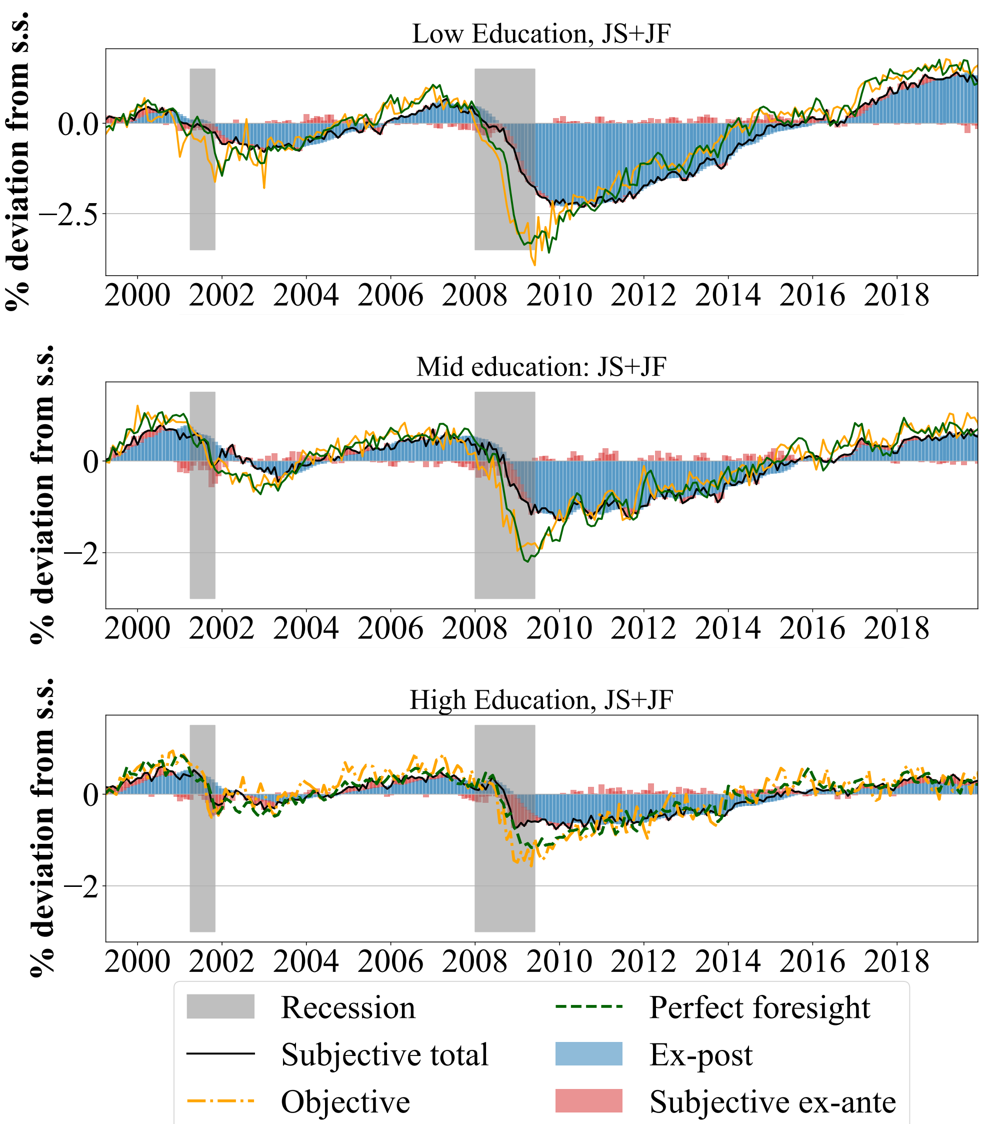
Our group-specific analysis has an aggregate implication. When the workers most exposed to cyclical unemployment risks are also the least responsive in updating their beliefs and engaging in self-insurance, the result is a sharper drop in consumption at the onset of unemployment shocks. This interaction of risk exposure and under-insurance due to sticky risk perceptions generates a potential amplification mechanism for aggregate consumption in response to unexpected income shocks—not through aggregate cyclicality per se, but through the uneven distribution of responses across groups. While heterogeneous risk exposure does not inherently amplify the aggregate impact of unemployment risks, it can do so when exposure is positively correlated with under-insurance.[13] Our findings suggest that this condition holds empirically, as those facing more cyclical risks appear to be especially prone to underreacting to changes in unemployment risk.

7 Conclusion

More employed workers lose jobs and fewer unemployed workers find jobs in recessions than in normal times. Do people anticipate these changes? This paper asks whether business cycle

[13] 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 and MPCs creates an amplification mechanism.

Figure 11: Consumption fluctuations due to unemployment risks by education



Notes: 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 8.

fluctuations in unemployment risks are perceived by heterogeneous households, both on average and across groups differentially exposed to unemployment risks. The answer to this question determines the size of the consumption declines in recessions and whether consumption declines are driven mainly by heightened ex ante precautionary behavior or by unexpected ex post shocks.

This paper finds that average perceptions of unemployment risks, especially those regarding separations, adjust only sluggishly to evolving labor market conditions. This belief stickiness dampens the role of the ex ante channel in driving consumption responses and limits self-insurance, thereby amplifying the impact of ex post shocks. Job-finding perceptions are slightly less rigid, inducing sizable precautionary saving responses. Furthermore, we show that the imprints of aggregate labor market fluctuations and their consumption impacts are heterogeneous across households, critically depending on how such risks are perceived. We contribute to the large body of literature incorporating unemployment risks as a channel of aggregate consumption fluctuations by empirically quantifying the importance of both aggregate and distributional consumption declines arising from precautionary savings, misperceived risks, and unexpected income losses.

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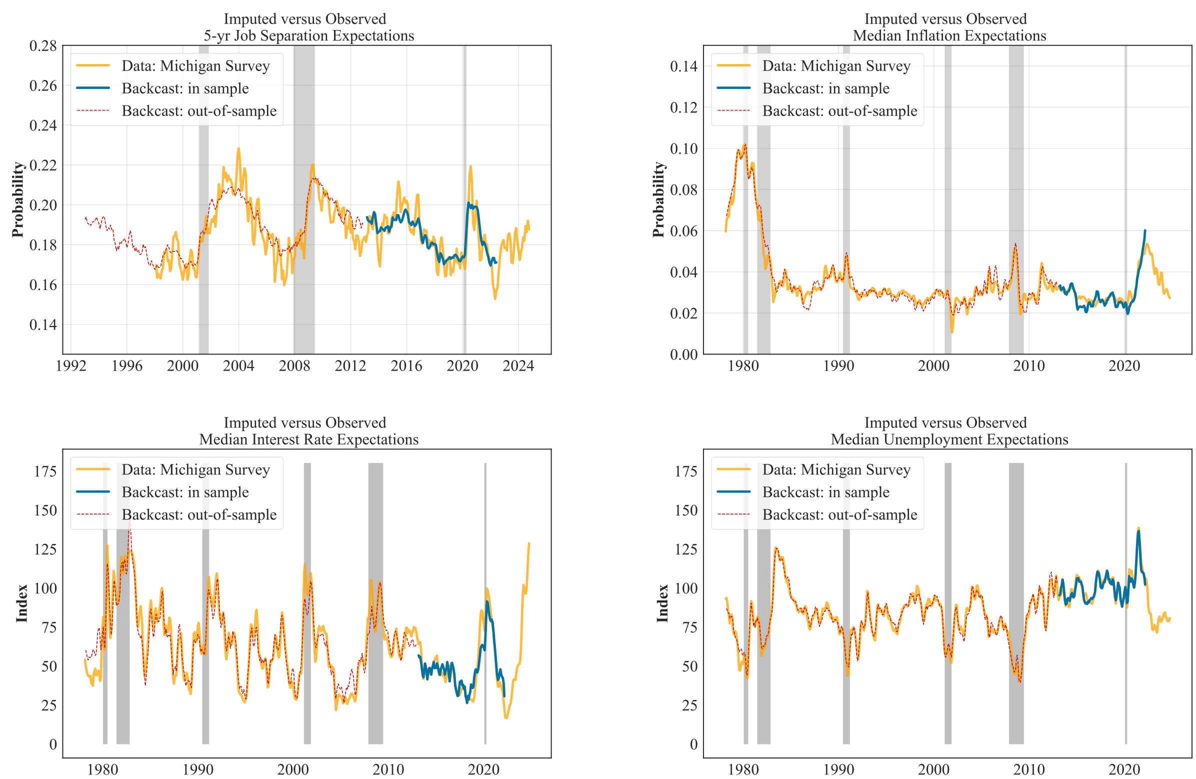
A Additional Empirical Results

A.1 Additional results with imputation of perceived unemployment risks

A.1.1 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.1 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-imputing methods.

Figure A.1: Imputed beliefs versus observed expectations in the MSC



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

A.1.2 Inclusion of the pandemic era

Figure A.2 compares the imputed unemployment 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.

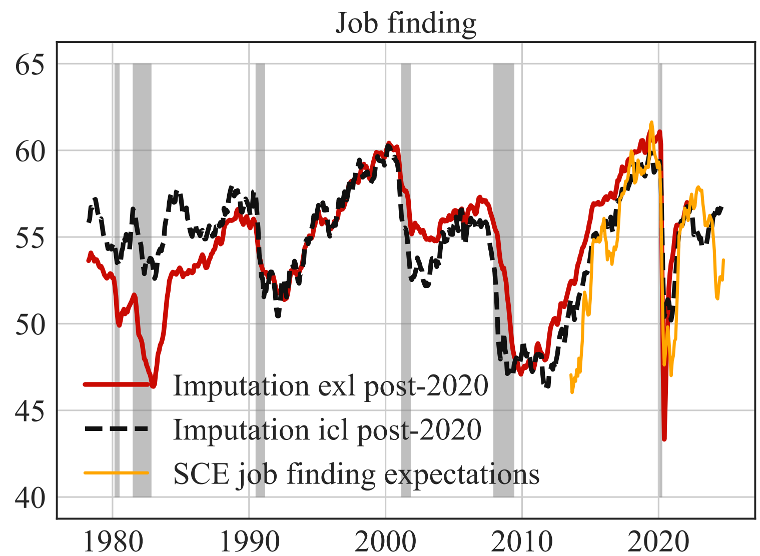
A.1.3 Selected covariates of perceived risks

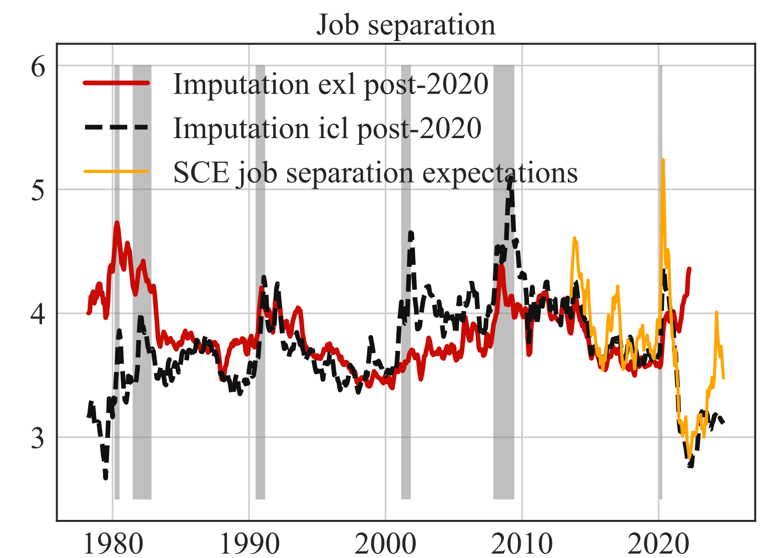
Figure A.3 reports the 10 most important variables selected from the LASSO model of imputation of perceived unemployment risks, ranked by the absolute value of their estimated coefficients associated with the normalized value of each variable.

A.1.4 Imputed beliefs by education group

Figure A.5 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.

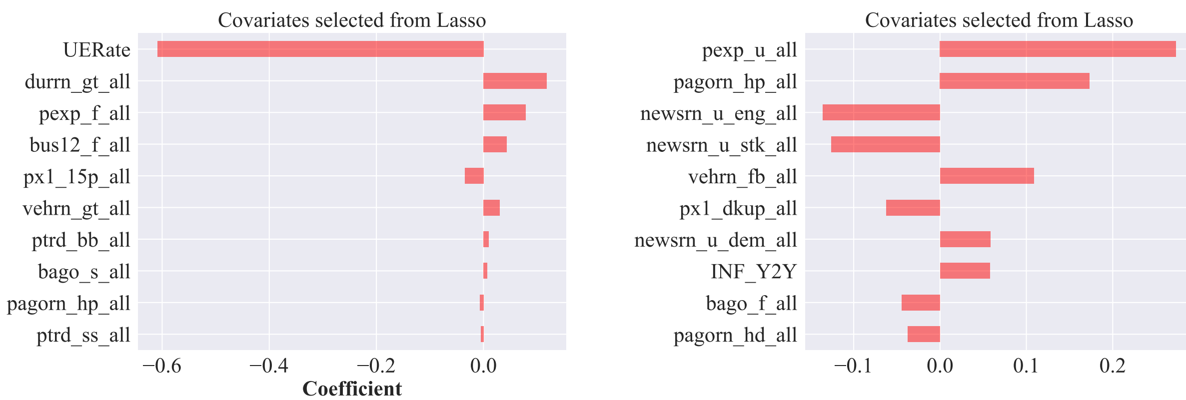
Figure A.2: Imputing beliefs including or excluding Covid era





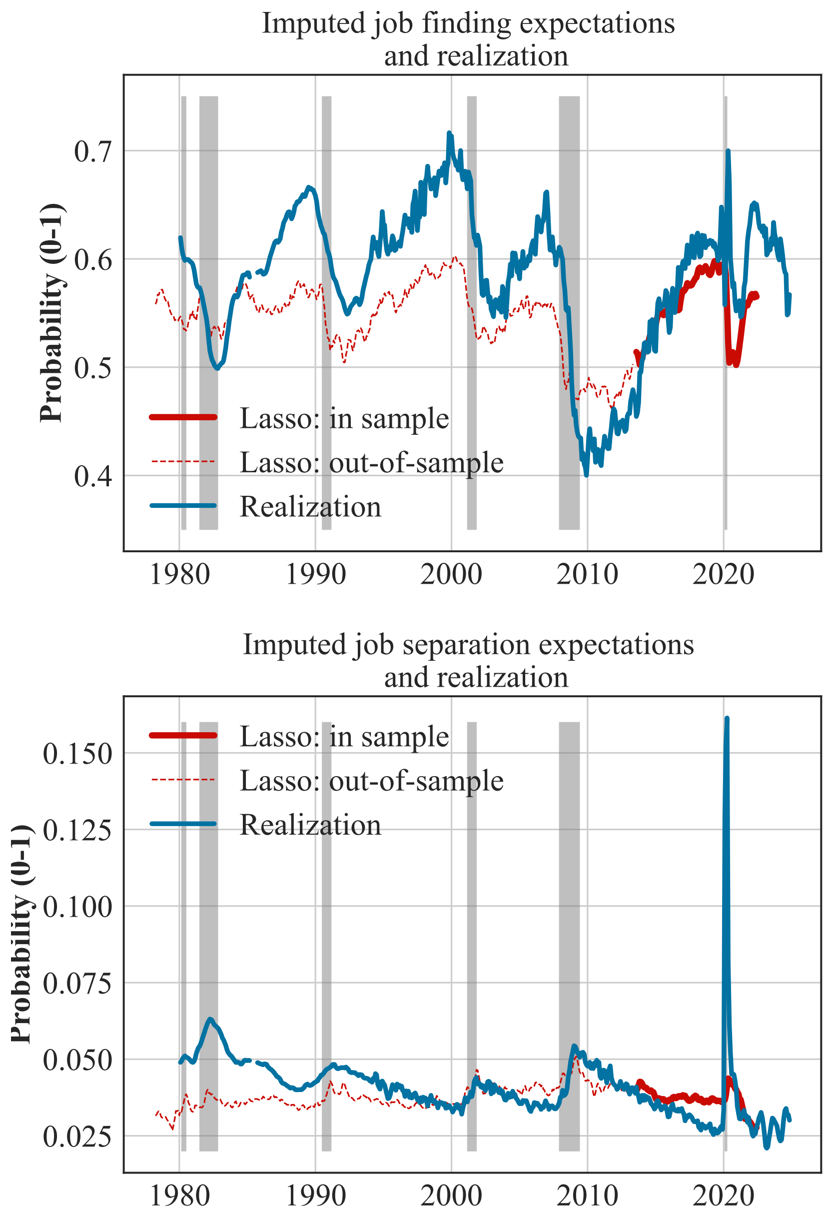
Notes: These figures compare the imputed perceived job finding and separation risks based on samples either including or excluding the sample period after 2020 January.

Figure A.3: Selected variables of LASSO model of perceived unemployment risks



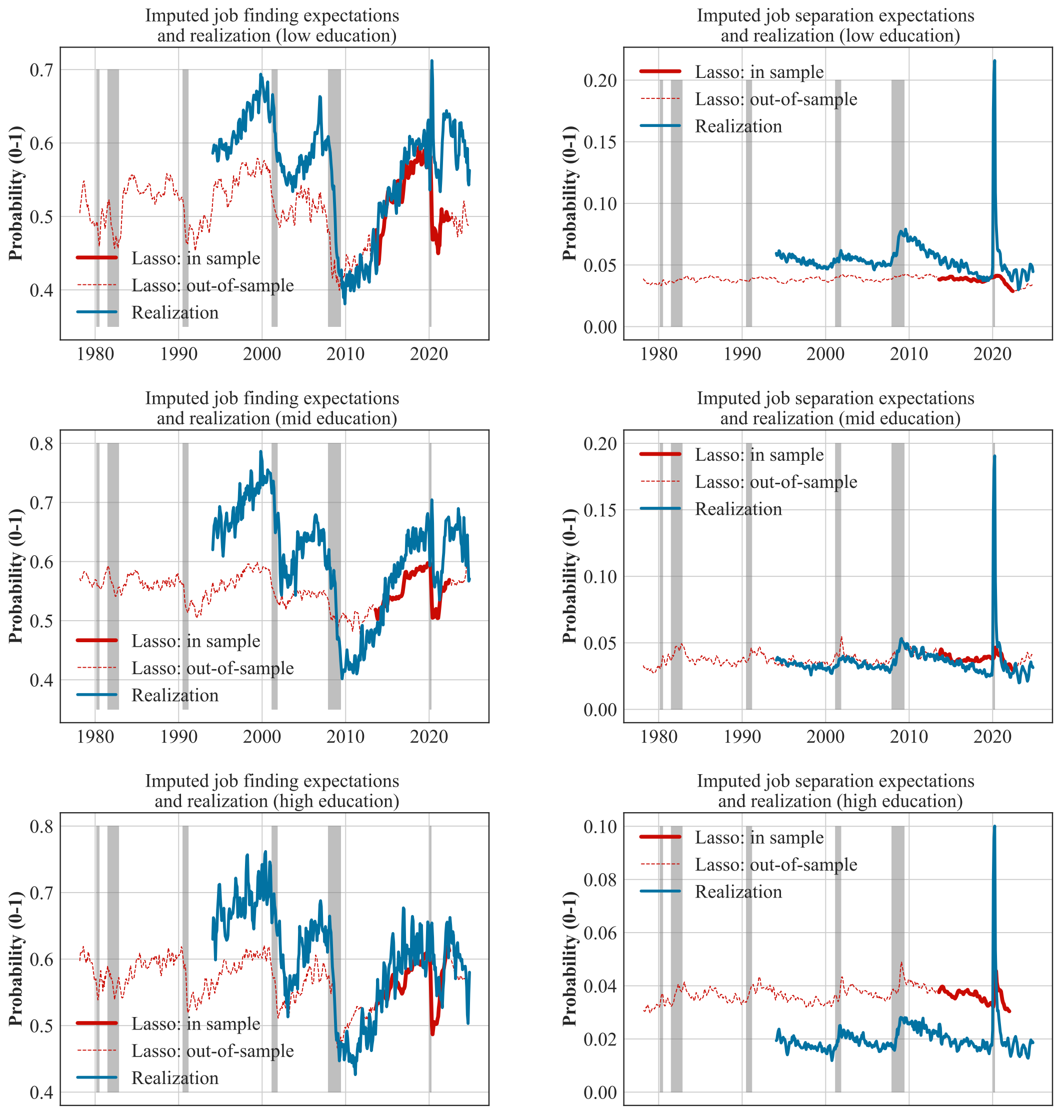
Notes: selected variables ranked by the absolute value of their estimated coefficients in the LASSO imputation model for perceived job finding (left) and job separation (right). The in-sample is between 2013-2020. UERate: real-time unemployment rate. Durrn_gt_all: good time to buy durables. Pexp_f_all: 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.

Figure A.4: Imputed job-finding rate and realizations



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

Figure A.5: Imputed beliefs by education



Notes: 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.

A.2 Heterogeneity across percentiles of perceived unemployment risks

Section 6 assumes that the unemployment risks workers face differ across education, one observable dimension. In this section, we examine the role of heterogeneity more generally along potentially unobservable dimensions by studying the patterns of different percentiles of the perceived unemployment risks. In particular, instead of focusing on the mean perceived unemployment risks as reported in Table 2, we regress the q-th percentile of perceived job-finding and separation risks $\widetilde{JF}^q$ and $\widetilde{JS}^q$ for $q = \{25, 50, 75\}$ on the aggregate real-time risk measure. This allows us to investigate whose expectations are most responsive to changes in aggregate labor market conditions. The estimated sensitivities are reported in Table A.1 below.

Table A.1: Regression results of perceived risks at different percentiles on real-time forecasts

	Job finding perceptions			Separation perceptions		
	$\widetilde{JF}^{p25}$	$\widetilde{JF}^{p50}$	$\widetilde{JF}^{p75}$	$\widetilde{JS}^{p25}$	$\widetilde{JS}^{p50}$	$\widetilde{JS}^{p75}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{JF}^*$	0.684***	0.709***	0.313***			
	(0.075)	(0.071)	(0.264)			
$\widehat{JS}^*$				0.170***	1.630***	1.591***
				(0.015)	(0.175)	(0.035)
Const	-0.088***	0.179***	0.654***	0.005***	0.009	0.126***
	(0.045)	(0.042)	(0.020)	(0.001)	(0.006)	(0.009)
Adj. R^2	0.638	0.602	0.273	0.510	0.602	0.273
N	434	434	434	434	434	434

Notes: Column (1)–(3) reports the regression results of $\widetilde{JF}^q_{t+3|t} = \alpha^q + \beta^q \widehat{JF}^*_{t+3|t} + \epsilon_t \quad \forall q \in \{25, 50, 75\}$, respectively, where q represent the percentile of the risk beliefs. Columns (4)–(6) report the results with the same specifications for job separation (JS). *, **, and *** represent significance of the coefficient at the 10%, 5%, and 1% levels.

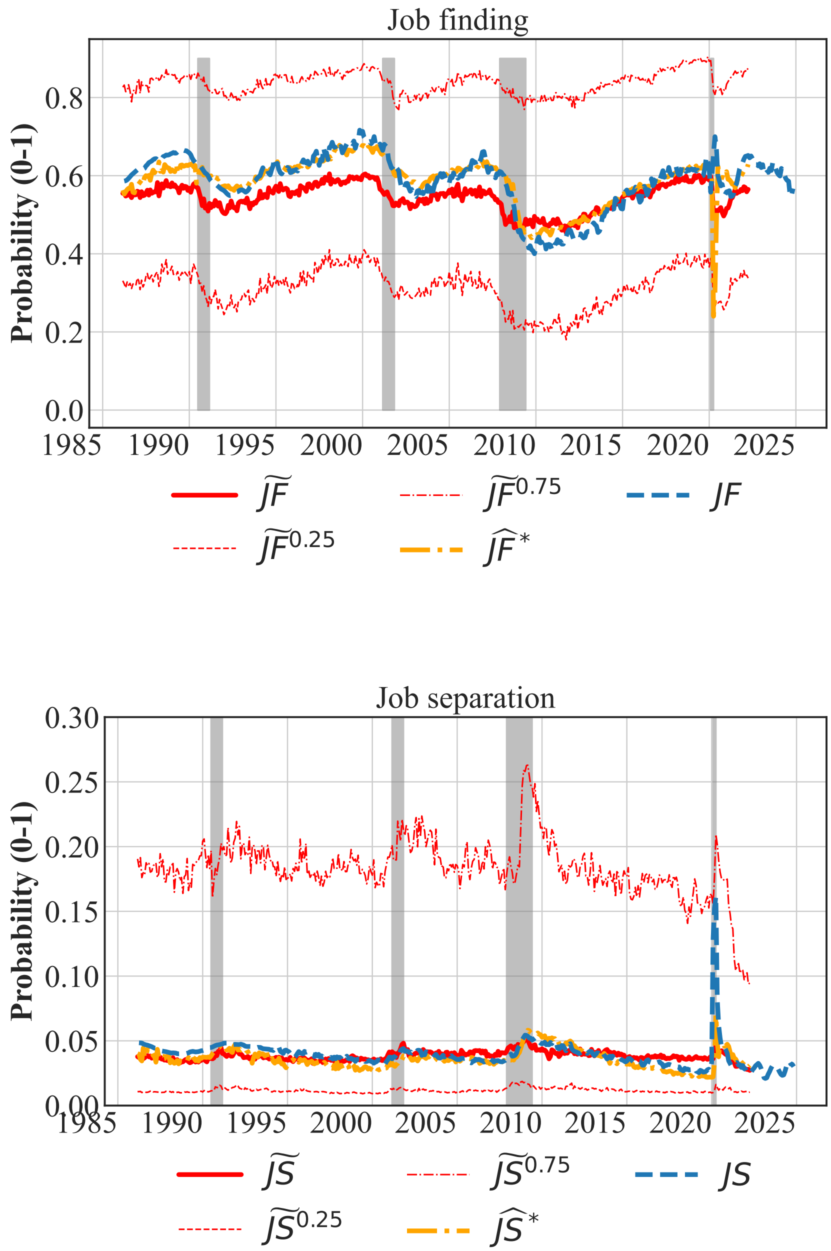
Job-finding perceptions at the 25th percentile respond the most to the aggregate real-time job-finding rates, as implied by the coefficient estimates of 0.684 for this group. Workers with medium job finding risk perceptions exhibit similar sensitivity with the size of 0.709. In contrast, perceptions of workers at the 75th percentile comove much less, with only a sensitivity of 0.313. Put simply, workers who believe they face poor job-finding prospects are the ones whose perceptions adjust most to current labor market conditions. An elasticity greater than one indicates that their beliefs move by more than one-to-one to changes in aggregate job-finding rates.

For separation perceptions, it is the median- and high-risk workers whose beliefs respond the most strongly to the aggregate real-time separation rate. The estimated sensitivities range from 0.170 for the 25th percentile to 1.63 for the 50th percentile and 1.59 for the 75th percentile. The beliefs of those who report higher separation perceptions exhibit stronger belief sensitivity than those who report lower separation perceptions.

Although in theory, the heterogeneous sensitivities of perceptions may be due to heterogeneous patterns of their subjective expectations, they intuitively reflect the uneven risk exposures of different workers. Workers who perceive themselves to face high unemployment risk (high separation and low job-finding risk perceptions) exhibit the greatest responsiveness to aggregate conditions. Business cycles, therefore, are not merely changes in aggregate unemployment risks; there are also shifts in the marginal workers who bear the brunt of risks. For example, during recessions, the marginal worker facing separation risks shifts downward from the top 10th percentile of perceived-risk distribution toward the median. The sensitivity of perceptions thus helps reveal who these marginal workers are.

Figure A.6 further demonstrates that perceived risks at different percentiles exhibit heterogeneous volatilities. The perceived risks of those low job-finding and high separation perceptions exhibit larger fluctuations than those who report lower perceived risks.

Figure A.6: Survey perceived unemployment risks versus machine-efficient risk forecasts by distribution



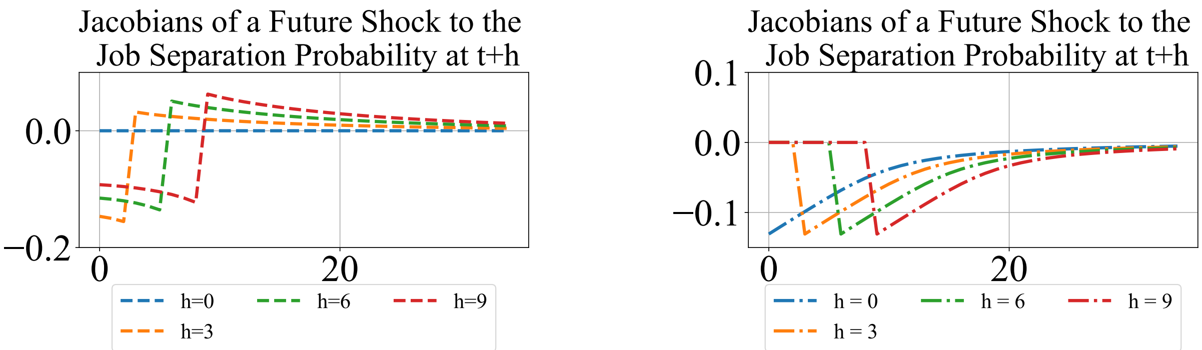
Notes: The figures plot the average and heterogeneous perceived unemployment risks at different quantiles, real-time unemployment risks, and realized transition rates.

B Additional Model Results

B.1 Consumption Jacobians at different horizons

Figure A.7 plots the ex-ante and ex-post Jacobians at different future horizons.

Figure A.7: Consumption fluctuations due to unemployment risks in different horizons



(a) Ex-ante

(b) Ex-post

Notes: This figure plots the ex-ante and ex-post Jacobians as in Figure 6 in response to a future shock to the probability of job separation at t+h for different values of h.

B.2 Details of the baseline experiments

The model experiments in Figure 8 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 unemployment risk, which are plotted in Figure A.8.

Figure A.9 complements Figure 11 by showing the education-specific consumption aggregation fluctuations due to job-separation and job-finding risks, separately.

B.3 Robustness with the model results

In this section, we present the model results under alternative calibrations of preference parameters to those in the baseline results, as in Figure 8.

Time discount factor. We redo the model simulation under two alternative values of the

Figure A.8: Shocks to realized job transitions, perceptions, and rational forecasts

Notes: The figure plots the estimated shocks' 3-month moving average values used for the experiments in Figure 8, 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 9. The sample period is between 1984 and 2020.

monthly discount factor: $\beta^{high} = 0.99$ and $\beta^{low} = 0.97$, displayed in Figure A.10a and A.10b, respectively.

The differences ultimately stem from different elasticities in aggregate consumption with respect to ex-ante unemployment risks and ex-post realizations, as summarized in the following Jacobians in Figure A.11.

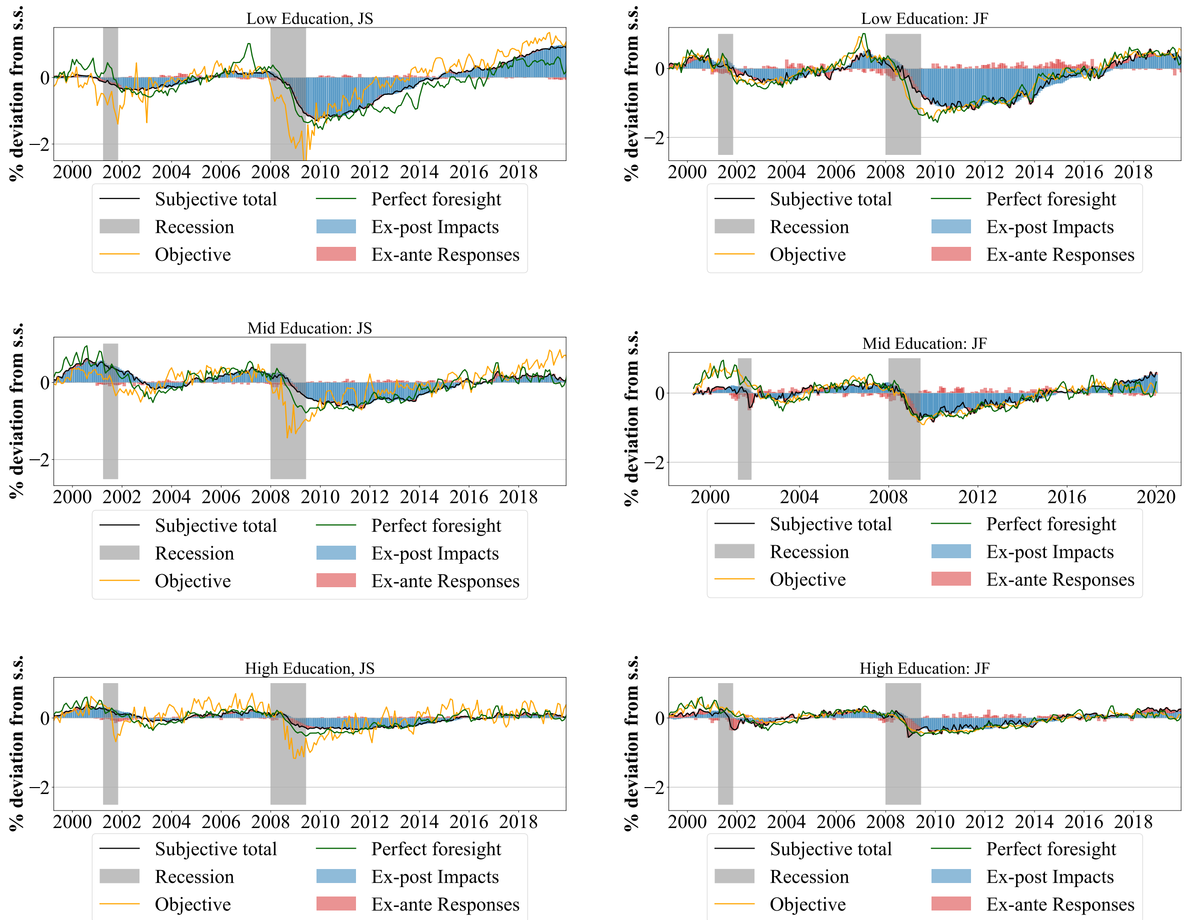
Backcast versus observed beliefs. Figure A.12 shows the model experiments only using the observed perceived risks in SCE since 2013, instead of those imputed, as reported in the main text of the paper.

B.4 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.

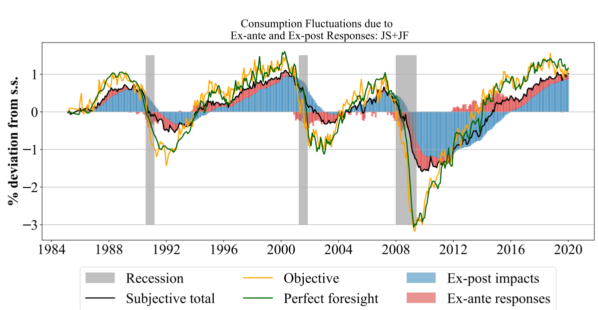
The employment status $n_{i,t}$ transitions between two states following a 2-state Markov process. Unlike the monthly model in the baseline, the employment-to-unemployment transition probability is the product of the separation JS_t rate and 1 minus job-finding rate $1 - JF_t$, so that workers who loss their jobs are allowed to search and possibly find a job during the same

Figure A.9: Consumption fluctuations due to JS and JF risks: by education

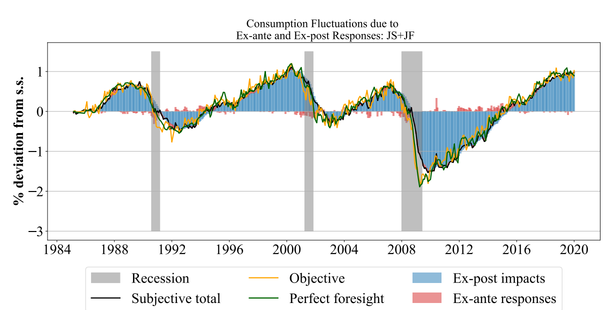


Notes: The figure compares for each education group their partial-equilibrium aggregate consumption deviations from the model's steady state by simulations based on empirically estimated shocks to perceived unemployment risk (subjective) and the real-time forecast risk (objective), in addition to the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

Figure A.10: Consumption fluctuations due to unemployment risks under different β values



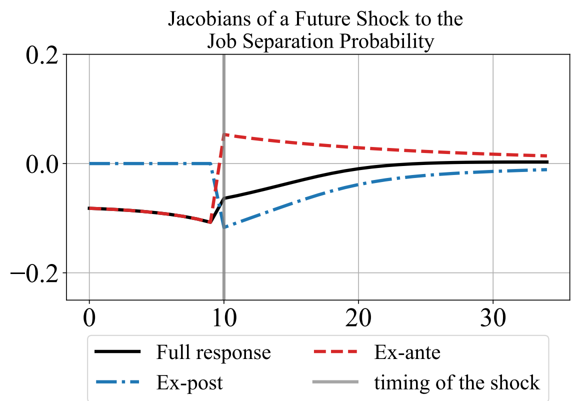
(a) $\beta = 0.99$



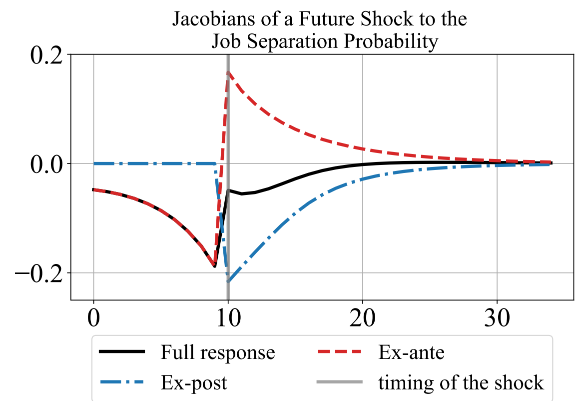
(b) $\beta = 0.97$

Notes: This figure plots the model simulation results as those in Figure 8 under alternative discount factor values $\beta = 0.99$ and $\beta = 0.97$, respectively.

Figure A.11: Consumption Jacobian with respect to an anticipated 10-period-ahead shock to the job separation probability: under different β



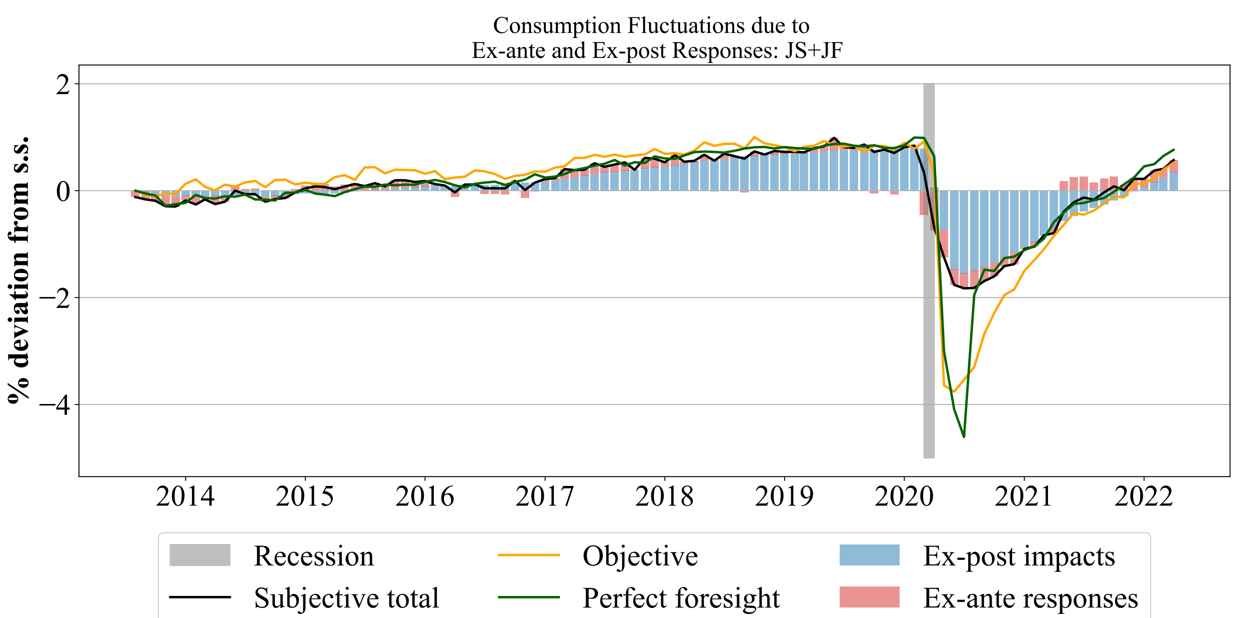
(a) $\beta = 0.99$



(b) $\beta = 0.97$

Notes: This figure plots the Jacobians as in Figure 6 under alternative discount factor values $\beta = 0.99$ and $\beta = 0.97$, respectively.

Figure A.12: Model simulation with only observed perceived risks in SCE



Notes: This figure plots the model simulation results as those in Figure 8 with directly observed job-finding and separation expectations from SCE since 2013, instead of those imputed.

Table A.2: Calibration in model at quarterly frequency

Description	Parameter	Value	Source/Target
CRRA	γ	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	χ	0.5	50% replacement rate
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	unemployment rate 5%
Discount Factor	β	0.964	Quarterly MPC 0.21

quarter.

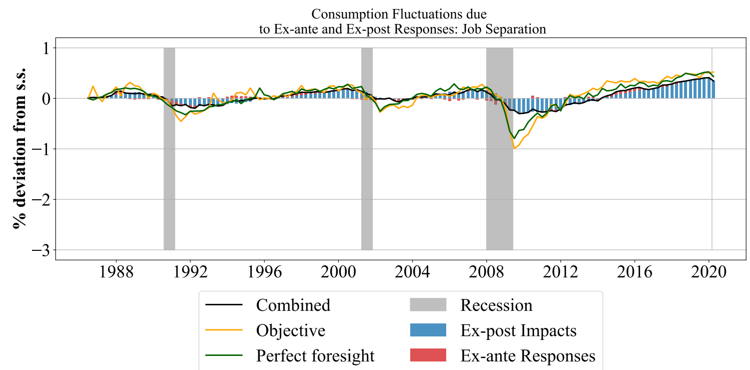
$$\begin{aligned} p(n_{i,t+1} = e | n_{i,t} = u) &= JF_t \\ p(n_{i,t+1} = u | n_{i,t} = e) &= JS_t(1 - JF_t) \end{aligned}$$

We again target a quarterly MPC of 0.21 as in the monthly baseline. This yields a quarterly discount factor $\beta = 0.964$. Other values of parameter calibration for the quarterly version of the model are described in the table below:

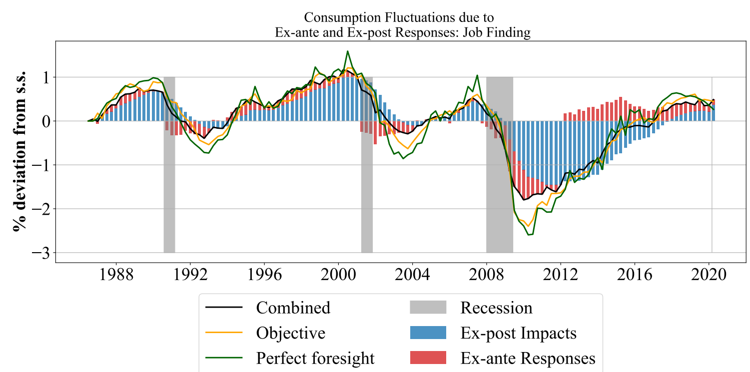
Figure A.13 and Figure A.14 plot the model results for the aggregate consumption and education-specific consumption impacts. Figure A.15 plots the underlying shocks used for the experiments.

Figure A.13: Quarterly consumption fluctuations due to unemployment risks

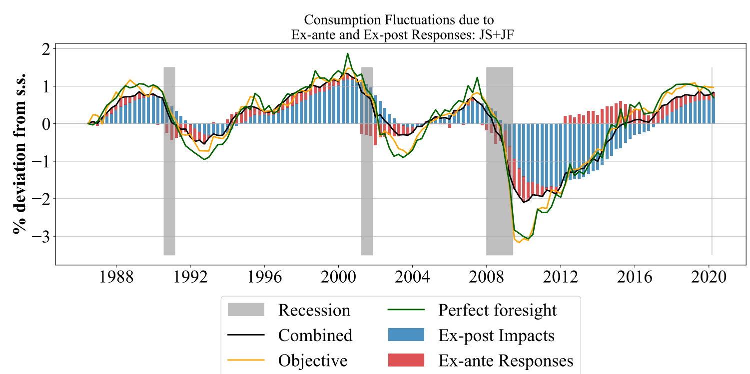
Job separation



Job finding



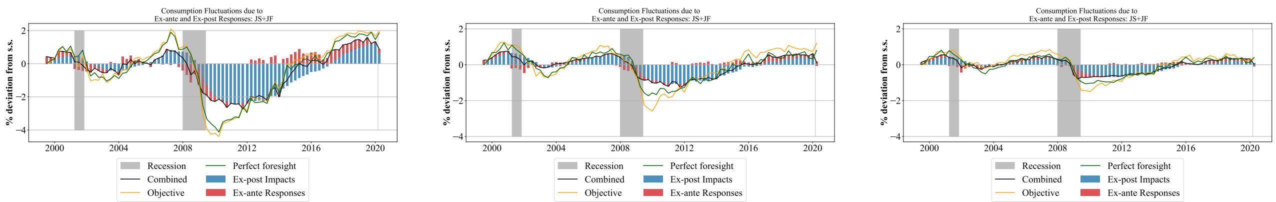
Job finding +Job Separation



Notes: 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 unemployment 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). The results are from a quarterly variation of the baseline model set at the monthly frequency as shown in Figure 8.

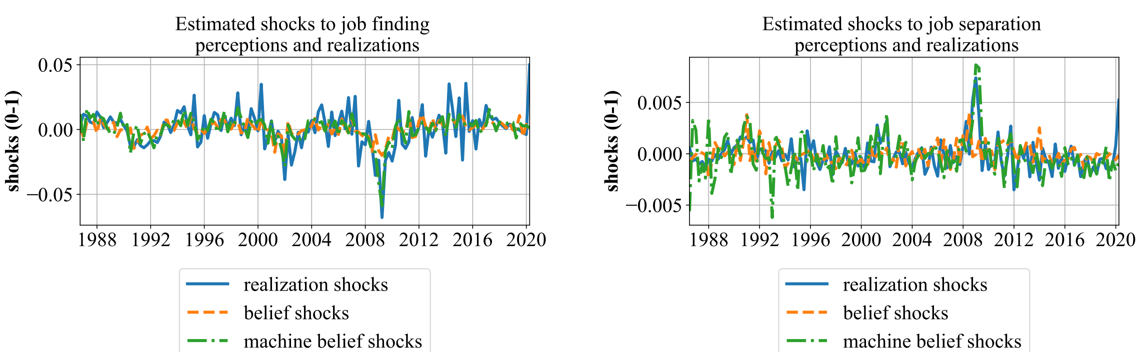
Figure A.14: Quarterly consumption fluctuations due to unemployment risks: by education

Low education | Middle education | High education



Notes: The figure compares, for each education group, 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 unemployment 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). The results are from a quarterly variation of the baseline model set at the monthly frequency as shown in Figure 11.

Figure A.15: Quarterly shocks to realized job transitions, perceptions, and rational forecasts



Notes: 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 9. The sample period is between 1984 and 2020.