Disturbed Household Beliefs and Their Lasting Impact on Consumption*

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Abstract

In this study, I leverage the comovement in households' expectations to identify shocks that shift the entire system of their beliefs about the economy – sentiment shocks. The estimated shock series is correlated with consumer sentiment measures, and distinct from standard macroeconomic disturbances found in the literature. My empirical analysis shows that sentiment shocks have large and long-lived impacts on household consumption, with the response of durable good spending being especially strong. Sentiment shocks can account for over 30% of the volatility in durable consumption and around 20% in non-durables at horizon of one to two years. I augment an otherwise standard New Keynesian model with sentiment shocks that trigger a deviation of expectations from the rational benchmark. I present an analytical result to show that the proposed version of the model can generate output fluctuations of either sign in response to a positive sentiment shock. The estimated parameters suggest that sentiment disturbances have non-negligible effects on the dynamics of macroeconomic variables. Based on these parameter estimates, my quantitative results imply that the equilibrium effects of sentiment shocks on aggregate output and inflation are primarily driven by expectations of future interest rate changes. The latter reflects the anticipated monetary policy reaction to expected fluctuations in output arising from sentiment disturbances.

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1 Introduction

Economic expectations of ordinary agents such as households have been shown to comove in response to the arrival of unanticipated information. Given that households' beliefs have been found to deviate from the full information, rational expectations framework – the prevailing view in modern macroeconomics,[1] a body of research aims to identify variable-specific exogenous shocks to households' forecasts. However, papers in this literature do not account for the documented comovement in their beliefs: households jointly revise all economic expectations when exogenous shocks hit.

In this paper, I exploit the comovement in households' expectations and allow for the type of shocks that lead households to revise the entire system of their economic beliefs. I refer to this kind of shocks as "sentiment shocks" since households have been found to adjust their expectations in the direction consistent with the change in sentiments. Sentiments here should be understood as reflecting "animal spirits" (Keynes, 1936). The latter correspond to psychological and emotional biases which guide the behavior and ultimately influence economic decisions of individuals.

In the first step, I identify sentiment shocks and estimate the dynamic responses to these disturbances. In doing so, I leverage survey data collected by the Michigan Survey of Consumers (MSC), which provide information on households' economic beliefs across a range of topics over a long time span. Using Structural Vector Autoregression (SVAR), I propose to identify sentiment shocks by exploiting the empirically documented comovement in households' expectations and their consumption responses triggered by changes in the perceived economic outlook.

I investigate the dynamic responses to sentiment shocks and find that these disturbances have a lasting negative influence on subjective probability of real income gains

[1]For example, inflation expectations are an important determinant of economic behavior of firms and households, thus much research has focused on this type of expectations. A prominent feature of households' and firms' inflation forecasts is that they are biased upward. D'Acunto et al. (2023) show that households' inflation expectations are systematically higher than those of financial participants. Candia et al. (2023) provide further evidence that households' expectations of inflation exceed those of professional forecasters and deviate significantly from those of firms. In turn, inflation forecasts formed by firms are also subject to a positive bias and vary across different industries, as shown by Savignac et al. (2021).

and possibly other dimensions of expectations. Since households' beliefs remain depressed for a long time, I document a persistent negative effect on both non-durable and durable consumption, with the response of durables being especially strong. Specifically, as inflation forecast rises by almost 0.1 percentage point (pp), durable consumption falls by more than 1% on impact and stays below its steady state level by 0.9% across most remaining horizons. The empirical literature has documented that households actively rely on their beliefs in making economic choices, and I present evidence that sentiment shocks shifting the entire system of households' beliefs, have pronounced and long-lived consequences for aggregate consumption. Lagerborg et al. (2023) estimate statistically significant effects of their sentiment shocks on non-durable consumption, but they focus on one sentiment measure at a time disregarding the correlation embedded in households' expectations.

I further evaluate the contribution of sentiment shocks to variance of macroeconomic time series and document that sentiment disturbances explain around 35% of fluctuations in durable consumption within a one year horizon, indicating that durable spending is highly dependent on consumer beliefs. Likewise, sentiment shocks are responsible for around 20% of variation in consumption of non-durable goods between one and six years after the impact. My empirical findings are consistent with predictions of the model developed by Bhandari et al. (2025), in which pessimistic beliefs lead households to expect lower consumption, and these downward expectations translate into a large and lasting fall in consumer spending.

Although real activity indicators hardly move immediately after sentiment shock realizes, a pronounced decline in consumption paves the way for the gradual onset of a recession. This dynamic pattern is consistent with an observation that contribution of sentiment shocks to unemployment variation is higher at longer horizons: for example, they account for slightly more than 5% at horizon of one month, but this figure increases to over 15% three years following the impact. Furthermore, I observe the monetary authority cut interest rates with a significant lag in response to unfavorable developments in the economy, which suggests that estimated sentiment shocks are distinct from standard monetary policy shocks.

Having estimated a time series of sentiment shocks, I present evidence that they are not exclusively associated with recessionary episodes or periods of elevated uncertainty, which supports the interpretation of these shocks as reflecting shifts in psychological and emotional biases unrelated to economic fundamentals. I also report calculated correlations between a sentiment shock series and other standard shock measures available in the literature. Results show that correlations are all close to zero and never statistically significant at the 5% confidence level.

Furthermore, I calculate the correlation between estimated sentiment shocks and a variety of sentiment indices that capture distinct dimensions of consumer beliefs, and find statistically significant relationships for all pairs. This exercise supports the idea that sentiment shocks reshape the entire system of beliefs formed by households since sentiment disturbances lead them to revise both perceptions of current economic conditions and their expectations.

My baseline results point to an increase in consumer prices even though I do not impose such a restriction. This observation suggests that firms may also be influenced by sentiment shocks, which could affect their optimal choices. This view finds support in the literature. For example, Coibion et al. (2020a) present empirical evidence that Italian firms with higher inflation forecasts tend to increase prices and reduce their labor force; more importantly, same firms report that they expect deterioration of economic conditions both at the company and national levels.

In light of the previous observation, I extend the results to investigate if SVAR model favors positive inflation dynamics. Allowing for a positive response generates a persistent increase in inflation, with the peak more than two times higher than in the baseline model, which lends support to the idea that firms may likewise experience sentiment shocks. Under these conditions, an expected drop in demand may lead firms to believe that they will face liquidity constraints in later periods. This belief can possibly rationalize their choice to raise prices immediately after sentiment shocks hit, as in the model proposed by Gilchrist et al. (2017).[2]

To identify specific dimensions of consumer beliefs and understand their relationship with sentiment shocks, I exploit a broader set of questions from the MSC questionnaire. I include multiple quantitative responses elicited over time in a factor model,

[2]This paper does not explicitly consider sentiment shocks, but instead analyzes the effects of contemporaneous demand shocks.

which helps collapse them into a few main common factors.

This analysis uncovers several key dimensions of consumer beliefs and provides a meaningful interpretation of corresponding factors that shape economic perceptions and forecasts of households. I find that the first factor captures beliefs about the personal financial situation and expectations of overall economic conditions in the U.S. Households' perceptions of current business conditions and projections of unemployment dynamics are represented by the second factor. The MSC elicits respondents' attitude toward the purchase of expensive consumer goods and houses, and the model isolates these beliefs into a separate factor. The last factor summarizes households' opinions about the change in business conditions in a year from now.

The sign of estimated factor loadings suggests that the factors represent distinct dimensions of consumer sentiments. I calculate the correlation between sentiment shocks and the period-by-period change in each extracted factor. This exercise shows that the correlation is negative and strongest for those factors that reflect the expectation aspect of households' sentiments. The statistically significant correlation for all the factors confirms that identified sentiment shocks indeed capture fluctuations in sentiments.

To demonstrate that sentiment shocks trigger a response of households' sentiments, I extend the information set of SVAR by including the factor representing forward-looking beliefs. Hence, using the same baseline restrictions, I identify sentiment shocks in this factor-augmented SVAR model without dictating the sign of the factor response. I compare it with a separate SVAR specification, in which I extract sentiment shocks directly from the factor series and leave inflation forecasts unrestricted in their response to these factor-based shocks, keeping all remaining restrictions from the baseline. This approach addresses the potential concern that using only two series – inflation expectations and probability of income gains, to identify sentiment shocks may be insufficient to accurately capture movements in households' sentiments.

The estimation results provide evidence that sentiment shocks identified from inflation expectations can be interpreted as disturbances to consumer sentiments. This conclusion is justified by two observations. Firstly, the factor responses across both SVAR specifications exhibit a lasting decline (deterioration in sentiments) and are comparable in magnitude. Secondly, the model with shocks extracted from the factor shows that inflation beliefs rise, and the path of probability series is almost identical to that in the other specification. The finding that inflation expectations increase in response to deterioration in sentiments, lends support to a similar restriction included in the baseline identification scheme.

Finally, I provide a formal treatment of sentiment shocks within a modified New Keynesian model, which serves as a tractable setting for the evaluation of their effects. I extend an otherwise standard framework by allowing the perceptions and expectations of economic agents to respond to sentiment disturbances in a manner consistent with the empirical evidence on sentiment-driven beliefs. Since households and firms act on their expectations, sentiment shocks are allowed to affect the economic outcomes in the model.

Using the closed form solution of the simplified model, I show how the general equilibrium effect of sentiment shocks is determined by the coefficients representing the partial equilibrium effect on aggregate output and inflation. Furthermore, I derive analytical results demonstrating that, depending on parameter values, a positive sentiment shock can produce responses of either sign in output, inflation or the short-term interest rate.

The estimation of model parameters suggests that sentiment disturbances are highly persistent, resulting in long-lived effects on output and inflation. Impulse responses reveal that a positive sentiment shock, reflecting an improvement in sentiments, generates a contraction in output. Using the decomposition of the total effect into separate expectation channels within the simplified model, I find that a negative response of output is primarily driven by expectations of higher future interest rates. The latter reflects households' belief that the central bank will react to higher anticipated output arising from positive sentiment disturbances.

Related Literature. This paper connects to a strand of macroeconomic literature that empirically explores the role of shocks to expectations in a range of contexts. One of the early contributions belongs to Leduc et al. (2007) who quantify the role of shocks to inflation expectations in VAR in the high inflation setting of the 1970s in the U.S. Clark and Davig (2011) also augment a standard VAR with inflation forecasts and distinguish between shocks to short- and long-term inflation expectations. While these papers estimate innovations to explain time-varying volatility of realized inflation or long-run inflation expectations, I focus on multiple time series of economic expectations to show that household consumption represents the main propagation channel of a single sentiment shock.

Closely related is the work by Adams and Barrett (2024) who identify shocks to households' inflation forecasts, to which they refer as "inflation sentiments". Their central findings show that estimated disturbances to expectations of inflation lead to deflationary effects and contraction of the economy. In their empirical analysis, they assume that there exist shocks which specifically hit rational inflation expectations. In this paper, I draw on compelling evidence that households jointly update their beliefs in response to changes in the economic environment (Andre et al., 2022; Coibion et al., 2023), and, in contrast to Adams and Barrett (2024), show that a single shock generates fluctuations in the entire system of consumer perceptions and expectations regarding the economy. Furthermore, my results suggest that durable consumption is particularly sensitive to perturbations in household beliefs.[3]

Ascari et al. (2023) are also interested in assessing the contribution of shocks to short-run inflation expectations to aggregate fluctuations and base their empirical approach on sign restrictions implied by their DSGE model. They find that positive shocks cause higher inflation and a decline in the economy's output. The measure of inflation expectations employed in their empirical analysis comes from the Survey of professional forecasters, however, their forecasts have been shown to be largely consistent with theory and therefore frequently used as a rational benchmark. Relative to Ascari et al. (2023), this paper contributes further by focusing on expectations of households – agents who are less informed and whose behavior is prone to deviations from rationality, thus this approach allows for more precise identification of unanticipated movements in beliefs.

[3]I also find that a decline in both durable and non-durable consumption leads to gradual rise in unemployment and a fall in IP. Thus, sentiment shocks can be considered as an additional source of aggregate business cycle fluctuations, which connects this paper to a broad line of research that identifies an array of other structural shocks affecting the economy. In particular, papers in this literature measure the effects of monetary policy (Romer and Romer, 2004; Christiano et al., 2005; Gertler and Karadi, 2015) and fiscal policy shocks (Mountford and Uhlig, 2009; Romer and Romer, 2010), productivity shocks (Kydland and Prescott, 1982; Galí, 1999), technological news disturbances (Beaudry and Portier, 2006; Barsky and Sims, 2011), uncertainty shocks (Bloom, 2009).

The analysis in Werning (2022) is related to this paper, as he studies the effect of higher inflation expectations on contemporaneous inflation allowing for arbitrary, including non-rational, expectations. He considers a range of firm price setting models and shows that the passthrough effect can be close to zero or exceed one depending on a given model. However, Werning (2022) takes a partial equilibrium approach, so this paper complements his contribution by taking into account general equilibrium effects on output and prices.

This study contributes to the empirical literature that analyzes how fluctuations in sentiments and, more broadly, confidence are associated with business cycles. Barsky and Sims (2012) examine the meaning of innovations to consumer confidence by comparing data-based impulse responses with those obtained from the model, and conclude that estimated confidence shocks are likely to reflect the news received by consumers about future productivity. To identify shocks to confidence, Fève and Guay (2019) implement an identification strategy based on restrictions at various horizons, and find that their shocks do not contribute meaningfully to variation in quantities and prices. Lagerborg et al. (2023) adopt a different identification approach: authors use mass shootings as an instrument, and their findings show that innovations to consumer expectation index have noticeable effects on the real activity, labor market and result in a short-lived response of prices. The non-technology business cycle shock estimated by Levchenko and Pandalai-Nayar (2020) and labeled as "sentiment shock", is shown to explain much of short-run fluctuations in the U.S. and be responsible for a significant share of volatility in macroeconomic aggregates of Canada. In this paper, I exploit the comovement of households' current perceptions and future expectations of economic conditions, and rely on relatively weak identifying restrictions to demonstrate that estimated sentiment shocks are highly relevant for consumption dynamics.

In a related stream of research, a number of papers suggest alternative treatments of pessimistic beliefs within formal models. Angeletos and La'O (2013) associate extrinsic shocks with frictions in coordination and communication that perturb agents' beliefs and have non-trivial implications for the aggregate economy. Angeletos et al. (2018) introduce shocks to higher-order beliefs in a variety of models and interpret them as variation in confidence about the short-run economic outlook. They show that these disturbances can generate comovement in output, consumption and investment. A theory of subjective beliefs is proposed by Bhandari et al. (2025), who demonstrate that greater pessimism raises unemployment and inflation forecasts, which in turn produces contractionary outcomes. Maxted (2024) extends a macro-finance model to incorporate diagnostic expectations (Bordalo et al., 2018), and shows that their interaction with financial frictions gives rise to boom-bust investment cycles. Relative to this literature, I explore a variant of boundedly rational expectations under full information in a New Keynesian framework and establish that, depending on parameter values, sentiment shocks may lead to either an economic expansion or a downturn.

Finally, my empirical findings on the high responsiveness of household consumption to belief fluctuations indirectly link this paper to a body of literature that investigates whether changes in expectations induced by newly available information about future productivity, may be an important determinant of cyclical fluctuations. In a seminal article, Beaudry and Portier (2006) argue that a shock series based on stock prices reflects anticipated changes in future TFP growth. Blanchard et al. (2013) include both news and noise shocks in their model and reach a different conclusion that noisy information about future productivity fundamentals accounts for a large share of volatility in output and consumption. Chahrour and Jurado (2022) use an identification condition based on recoverability and apply it to separately identify technological surprises and disturbances in expectations of future technology. They present empirical evidence that the latter explain much of cyclical fluctuations in GDP. In this study, I show that, holding economic fundamentals fixed at all horizons, shifts in households' and firms' expectations are partly driven by variation in sentiments that are unrelated to productivity.

The remainder of the paper is organized as follows. Section 2 provides a definition of the sentiment shock and formalizes this concept. Section 3 describes an econometric framework and identifying restrictions. I discuss the empirical relevance of sentiment shocks in section 4 and consider extensions of the baseline results in section 5. I develop a formal model with sentiment shocks and present quantitative implications in sections 6 and 7, respectively. Finally, section 8 concludes.

2 Defining Sentiment Shocks

Before proceeding with identification, I specify what I mean by "sentiment shocks". Section 2.1 discusses several features of households' and firms' beliefs, and in section 2.2, I provide the definition of sentiment shocks.

2.1 Characteristics of Beliefs

Modern macroeconomic models feature expectations of economic fundamentals, and researchers commonly impose the assumption of full information and rational expectations (FIRE) framework. However, empirical literature recently has shown that measured agents' expectations do not satisfy the FIRE assumption. Economic studies largely focused on inflation expectations and found some striking features of the latter. In particular, D'Acunto et al. (2023) document that households' inflation expectations persistently exceed those of financial market participants and professional forecasters, and Candia et al. (2023) present similar findings that inflation expectations of firms often diverge from what professional forecasters believe. If one considers financial market participants and professional forecasters as agents who are most sophisticated and informed about the economy, their expectations can serve as a proxy for the rational benchmark. It implies that expectations of inflation held by households and firms systematically deviate from the rational counterpart.

Other researchers study multiple dimensions of the belief system jointly. In a recent paper, Kamdar and Ray (2025) conduct a component analysis of all consumer beliefs based on two different surveys, and find that they are mostly driven by just several factors, which resemble sentiments. For example, if households forecast higher inflation, they revise unemployment expectations upward and expect a worsening of their personal financial situation in the future. These observations on a range of households' expectations can all be linked to a decline in consumer sentiment.

2.2 Discussion of Sentiment Shocks

I assign a leading role to sentiments as the driver of beliefs. Within this paper, sentiments should be understood in the context of "animal spirits", the term that was coined by Keynes (1936). In this setting, animal spirits refer to psychological traits and emotions that guide the behavior and ultimately influence economic decisions of agents. Since the objective of professional forecasters is to make precise economic forecasts, they must be relying only on the available economic data and are unlikely to take personal sentiments into account. Households and firms, on the other hand, do not face these constraints and are free to form beliefs in the way they deem reasonable, possibly resting upon their subjective feelings. Therefore, variation in sentiments gives rise to excessive pessimism or optimism about the economic outlook, which translates to an update of their beliefs.

Psychological frictions and emotional biases are difficult to predict, so it becomes natural to interpret a deviation of households' or firms' perceptions and expectations from rationality as a sentiment shock. Although inflation forecasts gained the main interest among researchers, some surveys elicited agents' expectations of other variables. The findings of papers studying the response of a variety of expectations to exogenous shocks or information provision justify a general conclusion that households and firms tend to jointly form expectations of economic outcomes (Andre et al., 2022; Coibion et al., 2023; Candia et al., 2023). It implies that an improvement or a decline in households' and firms' sentiments will trigger a revision of all economic expectations, which is consistent with the findings of Kamdar and Ray (2025).

Since sentiments are likely driven by people's instincts and emotions, it motivates the following definition of sentiment shock:

Definition 2.1. *Sentiment shocks* are unpredictable disturbances to the economic beliefs of households and firms that reflect fluctuations in sentiments in the sense of "animal spirits" and are orthogonal to

1. changes in economic fundamentals such as TFP, output, inflation, financial conditions, and

2. changes in monetary and fiscal policy.

I adopt the definition above to identify sentiment shocks from consumer beliefs.

3 Econometric Approach and Identifying Restrictions

This section focuses on an econometric approach to identification of sentiment shocks. I proceed in several steps: I present a SVAR model in section 3.1, additional identifying restrictions are discussed in section 3.2, while section 3.3 provides information on data and details on a SVAR specification.

3.1 Model and Identification

Consider a SVAR model of the form

$$y_t^\top A_0 = \sum_{l=1}^{p} y_{t-l}^\top A_l + c^\top + \varepsilon_t^\top, \tag{1}$$

where y_t is an $n \times 1$ vector of endogenous macroeconomic variables at time t (think, for example, of GDP, inflation and interest rate), A_l is matrix of parameters at lag l ($1 \leq l \leq p$), p is the lag length, A_0 determines contemporaneous relationships of variables contained in y_t and is assumed invertible, and c is an $n \times 1$ vector of constants. An $n \times 1$ vector ε_t represents structural shocks such that j-th entry in ε_t is a structural shock corresponding to j-th variable in y_t (for example, cost-push shock enters an equation for inflation). Assume also that in the cross-section, structural shocks are uncorrelated with one another and each have unit variance: $\varepsilon_t \sim (0, I_n)$ for any t.

Let me define $A_+^\top \equiv (A_1^\top, \ldots, A_p^\top, c)$ of dimensions $n \times m$, where $m = np + 1$, and $x_t^\top \equiv (y_{t-1}^\top, \ldots, y_{t-p}^\top, 1)$, then the structural relationship (1) can be compactly written as

$$y_t^\top A_0 = x_t^\top A_+ + \varepsilon_t^\top. \tag{2}$$

By right-multiplying (2) by A_0^{-1}, I obtain the reduced-form VAR

$$y_t^\top = x_t^\top B + u_t^\top, \tag{3}$$

where $B \equiv A_+A_0^{-1}$ and $u_t^\intercal \equiv \varepsilon_t^\intercal A_0^{-1}$ is an $1 \times n$ vector of reduced-form shocks. Recalling that structural shocks in ε_t are uncorrelated with one another and have unit variance each, a covariance matrix of reduced-form shocks is

$$\mathbb{E}(u_t u_t^\intercal) = (A_0 A_0^\intercal)^{-1} \equiv \Sigma. \tag{4}$$

However, the number of restrictions on A_0 given by condition (4) is not sufficient to determine A_0 uniquely. Thus, to identify structural shocks and its dynamic propagation in the economy, researchers typically impose additional restrictions on A_0. For example, Sims (1980) proposed a recursive (Cholesky) ordering of shocks, in which case $(A_0^\intercal)^{-1}$ is the unique lower triangular matrix in the Cholesky decomposition of Σ. However, this approach imposes a fixed structure that determines which variables contemporaneously respond to structural shocks and which do not. With application to sentiment shock, it is not clear a priori which variables should not move in response to a shock.

There are other types of restrictions that a researcher may want to impose on SVAR parameters. They include restrictions based on contribution of shock to variance of variables at specific horizons (Barsky and Sims, 2011) and narrative restrictions that make structural shock align with the established narrative associated with certain historical episodes (Antolín-Díaz and Rubio-Ramírez, 2018; Ludvigson et al., 2021). Since the literature does not offer a clear perspective of sentiment shocks, while theoretical papers are silent about the contribution of these shocks to business cycles, the aforementioned approaches are not suitable for the exercise of interest.

This motivates me to consider a combination of sign and zero restrictions to identify sentiment shocks in SVAR, which I discuss in detail in section 3.2. To implement this idea, I rely on the theory and Bayesian numerical methods developed by Arias et al. (2018), which respect both zero and sign restrictions in SVAR. Further details on the identification problem, reduced-form and structural parameterization, and implementation of numerical methods are provided in Appendix section B.

3.2 Discussion of Identifying Restrictions

In the SVAR framework, sentiment shocks are identified as structural disturbances to households' economic forecasts. Since all the expectations of households and firms about the economy move after new information arrives or agents are hit by a shock, as found in empirical and experimental studies[4], any economic expectation should work. This paper relies on inflation expectations of households to identify sentiment shocks for several reasons. Firstly, among multiple variables, households are most likely to think first about expected inflation when confronted with adverse shock because inflation naturally erodes real value of their assets and they may observe price fluctuations on a regular basis. Secondly, the literature documents that households are the agents whose expectations exhibit the largest deviation from those of professional forecasters taken as a rational benchmark[5], so using households' forecasts maximizes the chance of identifying sentiment shocks. The last reason pertains to data availability: surveys most often elicit expectations about inflation, and collecting forecasts from households is practically easier while surveys aimed at firms are typically conducted for a limited number of times in a specific year and do not satisfy the consistency requirement.

Without loss of generality, assume that inflation expectations are ordered first in y_t. To identify sentiment shocks, I need to identify only the first column of $(A_0^\top)^{-1}$ which represents the responses of endogenous variables to a sentiment shock on impact. In doing so, I impose a combination of zero and sign restrictions on responses of select variables at different horizons consistent with theory, which I refer to as the "baseline identification".

Firstly, I identify sentiment shocks from the inflation forecast series and impose a normalization restriction that a positive sentiment shock raises inflation expectations. Denote the impulse response function of a variable x to a structural shock s at horizon h as $\mathrm{IRF}(x, s, h)$, then an identifying restriction 1 is

$$\mathrm{IRF}(\text{inflation expectations}_t, \varepsilon_{1t}, h) > 0, \ h = 0. \tag{5}$$

[4] See, for example, Andre et al. (2022), Coibion et al. (2022), Candia et al. (2023), and Coibion et al. (2023).

[5] D'Acunto et al. (2023) and Coibion et al. (2020b) show that households' expectations of inflation are persistently above those of professional forecasters beginning with 2000.

I impose additional sign restrictions to help distinguish sentiment shocks from other structural shocks. In doing so, I rely on the findings of research on macroeconomic expectations which documents that both households and firms jointly form their expectations across multiple dimensions. Therefore, a realization of a sentiment shock should lead agents to revise inflation forecasts as well as expectations of other relevant economic outcomes. The proposition that a single sentiment shock drives economic expectations of agents is consistent with findings of Kamdar and Ray (2025), which suggest that households' economic beliefs follow a one dimensional structure.[6] Specifically, they draw on micro level data from MSC and New York Fed's Survey of Consumer Expectations and show that a single component is responsible for at least 75% of variation over time in consumers' beliefs. An increase in the component is associated with more optimistic economic outlook (better business conditions, higher income, improved finances), thus the component looks like a measure of households' sentiments.

A clear manifestation of the sentiment-like component jointly shaping households' beliefs emerges in the comparison of their inflation and unemployment expectations. Kamdar and Ray (2025) demonstrate that households, who anticipate unemployment to increase, tend to believe in higher inflation in the future, and vice versa, and that this pattern is stable over time. Other papers also find a similar relationship between expected inflation and unemployment for U.S. households (Binder, 2020; Andre et al., 2022). Candia et al. (2024) document a sharp increase in inflation forecasts of U.S. firms following an inflation surge in 2021, similarly to households, and although they do not provide expectations of real outcomes, U.S. firms are also likely to associate a bad economic situation with higher inflation, as was shown for Italian firms (Coibion et al., 2020a).

To sharpen identification of sentiment shocks proposed in this paper, I include one more belief-based series and sign its response in the way consistent with the aforementioned evidence. The MSC mostly asks for categorical responses, but there are also several questions which solicit a numerical answer from respondents (besides inflation forecasts). To augment the information set of SVAR with non-price expectations, I include the probability of real income gains which is a subjective estimate of house-

[6]More extensive empirical findings are documented in an earlier version of the paper, see Kamdar (2019).

holds. I specifically consider real income gains because the MSC question explicitly asks each respondent to compare expected income growth with expected inflation rate. Consistent with the empirical evidence on consumer beliefs, an unfavorable sentiment shock raises inflation expectations and reduces the chance of real income gains, hence an identifying restriction 2 is given by

$$\text{IRF}(\text{probability of real income gains}_t, \varepsilon_{1t}, h) < 0, \; h = 0. \tag{6}$$

Note that sentiment shocks are identified from expected inflation, so a positive shock raises households' inflation forecasts and is unfavorable. Thus, a positive sentiment shock creates a more pessimistic outlook and prompts a decline in probability of real income gains, which explains a negative sign in the restriction (6).

In order to align with households' beliefs about personal finances and aggregate business conditions, I sign the change in consumption when sentiment shock hits. The theory identifies several channels through which changes in inflation expectations may influence consumption decisions. One mechanism suggests that higher expected inflation lowers the perceived real interest rate, thereby encouraging households to spend more. However, higher inflation forecast erodes the real value of nominal assets and future income, so an alternative channel posits that households reduce current consumption due to negative wealth and income effects. Furthermore, households associate higher future inflation with a bad economic situation (Kamdar and Ray, 2025), which may force them to cut down on current spending.

The two channels described above act to move consumption in opposite directions, thus it is not clear based on theory how households' consumption responds to shifts in inflation beliefs. Empirical studies also present mixed evidence on this matter. Based on the MSC data, Bachmann et al. (2015) do not find significant relationship between respondents' inflation expectations and their readiness to spend on durables, except for those whose forecast was close to realized inflation. Burke and Ozdagli (2023) find that for specific household types, durable consumption increases as expectations of inflation rise, but there is no relationship for spending on non-durables. Other papers attempt to evaluate causal effects of changes in inflation expectations on consumption. D'Acunto et al. (2022) exploit an announcement of the value-added tax increase, which raised inflation forecasts, and document a higher readiness to spend on durables among consumers. At the same time, drawing on results from an experiment, Coibion et al. (2022) find that households holding higher inflation beliefs increase non-durable spending, but reduce purchases of durable goods.

Rather than relying on ambiguous theory predictions and inconclusive empirical findings, I draw on the fact that households associate higher expected inflation with a decline in their personal financial situation. As consumers anticipate a deterioration of financial conditions, they reduce spending on both durable and non-durable goods.[7] This mechanism finds support in the literature: for example, Christelis et al. (2015) find that during the Great Recession, U.S. households expecting more persistent wealth losses cut their consumption to a greater extent. Accordingly, I impose identifying restrictions 3 and 4 in the form

$$\mathrm{IRF}(\text{nondurable consumption}_t, \varepsilon_{1t}, h) < 0,\ h = 0, \tag{7}$$

$$\mathrm{IRF}(\text{durable consumption}_t, \varepsilon_{1t}, h) < 0,\ h = 0. \tag{8}$$

I now turn to a discussion of zero identifying restrictions. To begin with, I restrict the response of inflation expectations to zero at specific horizons, which is meant to capture the attempts of monetary authority to bring elevated expectations back to target using verbal communication. It has become a common practice for central banks to develop communication strategies that provide the general public with the reasoning behind their policy choices and signal the expected path of monetary policy, for example, the forward guidance of future short-term interest rates[8].

Managing inflation expectations has also been considered an essential part of the communication policy: if central bank observes a rise in inflation expectations, it may refer to it as a reason to tighten its policy such that economic agents expect higher interest rates in the future and revise their inflation expectations down to their regular

[7]Nevertheless, I verify the validity of these identifying restrictions on consumption responses in Appendix section C.1 in which I identify sentiment shocks leaving consumption responses unrestricted. In this case, the data suggest that sentiment shocks cause a decline in both durable and non-durable consumption.

[8]For a discussion of the effectiveness of forward guidance by the Federal Reserve, see Campbell et al. (2012).

level. In this sense, central bank strives to "anchor" inflation expectations of the general public. A successful policy of expectation management enables it to take full control of the real interest perceived by economic agents and hence communicate forward guidance more effectively. In the case of an unfavorable sentiment shock, it unexpectedly raises households' inflation expectations and causes deviations from the Federal Reserve's target[9], which creates a possibility of de-anchored expectations. I assume that central bank takes action using communication tools to restore the anchored state. Therefore, an identifying restriction 5 is

$$\text{IRF}(\text{inflation expectations}_t, \varepsilon_{1t}, h) = 0,\ h \in [H_1, H_2], \tag{9}$$

where ε_{1t} is sentiment shock which takes the first entry in a vector of structural shocks ε_t in (2). Condition (9) states that following realization of the shock, central bank exploits proper communication policy to make sure that inflation expectations of households and firms are re-anchored by horizon H_1. Since there is no guarantee that expectations will be tied to the anchor forever, restriction (9) holds only up to some finite horizon H_2.

To be able to implement this restriction, I need to specify the horizons H_1 and H_2. The Federal Reserve does not explicitly announce the time frame over which it aims to re-anchor inflation expectations. Instead, I base the value of H_1 on the most recent episode following the pandemic when there was a world-wide increase in expected inflation including in the U.S. According to the Michigan Survey of Consumers, median one-year-ahead inflation expectations of households stood at historical levels in March 2021 (3.1%) before jumping to 4.6% two months later. They did not come close to 3% until June 2023 (3.3%), and although there was another spike in November 2023 (4.5%), inflation forecasts continued to hover around 3% afterwards.

These readings imply that households' inflation expectations remained de-anchored for a long time: it took them more than two years to return to levels observed before take-off.[10] Assuming that expectations return swiftly to steady state one year after the shock may distort the degree of persistence of inflation forecasts, thus I rely on the

[9]This paper studies the U.S. economy, so I focus on the Federal Reserve.

[10]Firms' inflation forecasts also de-anchored following the pandemic, see Candia et al. (2024) who document key stylized facts.

empirical pattern and assume that the Federal Reserve is able to re-anchor inflation expectations two years after realization of sentiment shock. Given monthly frequency of data, this corresponds to $H_1 = 24$.

Specifying horizon H_2 determines how long the Fed can keep expectations of households anchored. Since economic agents may face multiple shocks over time, it is difficult to isolate the contribution of monetary policy to stability of expectations over time. In an experiment, there are more opportunities to control the environment, so my choice of H_2 is guided by Coibion et al. (2022). Their experimental findings suggest that inflation expectations of households treated with the monetary policy communication are indistinguishable from those in the control group six months after information provision. They find a statistically significant difference in expectations between the groups three months after treatment, but this effect fades by six months. I average these monthly horizons to determine the duration of inflation expectation anchoring, which rounds to five months, and set $H_2 = 28$. From an empirical perspective, the ability of the Fed to keep inflation expectations in line with its target for five consecutive months is a reasonable minimum estimate. Moreover, Skaperdas (2025) empirically shows that households' expectations of inflation tend to move only in response to large inflation surprises which are unlikely to materialize during such a short period of five months.

Additionally, I restrict consumer prices to not respond for certain time after sentiment shock hits. The restriction is motivated by the following. Inflation expectations are a relevant factor for firms' economic choices, and they take those expectations into account when setting prices (Coibion et al., 2020a). Sentiment shock identified from households' inflation expectations leads their forecasts to deviate from the initial level, but firms cannot easily observe these changes in households' beliefs. Instead, it may take time for firms to recognize that consumers hold higher expectations of inflation, and their pricing policy will be adjusted accordingly with a lag. This restriction also helps distinguish sentiment shocks from cost-push shocks, which typically trigger an immediate response of inflation.

Moreover, an additional empirical observation provides motivation for restricting this response to zero. Imagine that firms happen to observe households' inflation expectations rise and are ready to change prices within the same period when shock arrives, but nominal price rigidity may prevent them from doing so.[11] If one thinks of price stickiness in Calvo (1983) fashion, a common modeling choice in macro models, there will be a fraction of firms being able to reset the price and immediately respond to an increase in households' inflation expectations, thus inflation is unlikely to be zero. This notwithstanding, it should have minor effects on an aggregate price level since other firms keep their prices unchanged, so assuming no response in consumer prices offers a reasonable approximation. Formally, firms do not change prices faced by households, for H_3 periods after a realization of sentiment shock, thus an identifying restriction 6 is summarized as

$$\text{IRF}(\text{consumer prices}_t, \varepsilon_{1t}, h) = 0, \;\; h \in [0, H_3]. \tag{10}$$

I impose a minimal restriction on prices and set $H_3 = 0$, which implies that prices are unresponsive to sentiment shock only on impact. The data will inform how prices will evolve at further horizons. In Appendix section C.2, I also consider the identification with no restrictions on inflation, which allows the price response to be flexible.

Table 1 summarizes all the restrictions imposed to identify sentiment shocks, which constitutes the baseline identification.

Identifying Restriction	Variable	Type of Restriction	Horizons
1	Inflation expectations	Positive	On impact
2	Probability of income gains	Negative	On impact
3	Non-durable consumption	Negative	On impact
4	Durable consumption	Negative	On impact
5	Inflation expectations	Zero	[24, 28]
6	Consumer prices	Zero	On impact

Table 1: Baseline identification scheme.

Notes: Summary of identifying restrictions for sentiment shocks in SVAR. Details are provided in the text.

[11] For a survey of empirical evidence of price rigidity and approaches to incorporating it in macro models, see (Nakamura and Steinsson, 2013).

3.3 Data, VAR Specification, and Implementation

The survey data come from the Michigan Survey of Consumers (MSC) conducted by the Survey Research Center at the University of Michigan. The MSC interviews around 1000 households each month yielding a sample representative at the national level (except Alaska and Hawaii). It elicits a variety of responses, mostly categorical, about current and expected personal finances, overall business conditions, attitudes toward buying large durable items, vehicles and houses as well as anticipated changes in inflation, unemployment and interest rates.

The MSC allows for quantitative responses in select questions. For example, the questionnaire asks "By what percent do you expect prices to go up, on the average, during the next 12 months?", and I use the answer to this question as a measure of households' inflation expectations. Additionally, this paper relies on numerical responses to the question "What do you think the chances are that your (family) income will increase by more than the rate of inflation in the next five years or so?", which is a subjective estimate of probability of real income gains.

Besides survey data, I employ time series data at the monthly frequency, and follow the monetary policy literature (Coibion, 2012; Gertler and Karadi, 2015; Ramey, 2016) to select the following macro variables: industrial production (in logs), CPI inflation rate, unemployment and shadow rate (Wu and Xia, 2016). The baseline SVAR identification includes inflation rates since central banks tend to target inflation rather than price level.[12] The set of variables is augmented by real durable and non-durable consumption entering VAR in logs. Detailed description of the data and corresponding sources are provided in Appendix section A.1.

Baseline specification of SVAR model considers a sample period from January 1998 to December 2024. I estimate the VAR given in (3) with $p = 12$ lags. I implement Bayesian numerical algorithms of Arias et al. (2018) to generate at least 5,000 effective parameter draws.

Since the sample period covers the COVID-19 episode, when macro variables exhibited highly volatile behavior not observed at least in the past 50 years, I employ

[12] In Appendix section C.4, I check robustness of the results and estimate a VAR specification with CPI price index instead.

Pandemic Priors suggested by Cascaldi-Garcia (2025) as a flexible way to account for this unusual dynamics. The parameter that determines how much signal should be taken from the abnormal observations, is optimally selected by maximizing the marginal likelihood under the normal-inverse-Wishart prior, as proposed by Cascaldi-Garcia (2025).

4 Empirical Relevance of Sentiment Shocks

This section assesses the empirical properties of estimated sentiment shocks. I recover a historical time series of sentiment disturbances, evaluate the dynamic response of the economy to these shocks and quantify their contribution to the volatility of select macroeconomic variables.

4.1 History of Sentiment Shocks

Given the SVAR parameter draws, I recover a historical path of sentiment shocks, which helps assess whether their realizations coincide with specific events in the past. Specifically, for each draw, I estimate a series of sentiment shocks over the period from January 1999 to December 2024, which yields a shock distribution at each month. I calculate the posterior median for each month along with 90% posterior bands.[13]

Figure 1 plots a median path of sentiment shocks, and red dashed horizontal lines represent $\pm$ one standard deviation computed from the median path. The SVAR identification suggests that a positive sentiment shock depresses sentiments, so positive realizations are considered unfavorable for consumers and the economy.

For interpretation, one may recall that any structural shock in the SVAR is a linear combination of forecast errors, thus sentiment shocks do not have clear measurement units. However, I can compare the magnitude of shocks with its standard deviation over time. The autocorrelation of sentiment shocks is -0.08, indicating low persistence over time. Combined with frequently observed large shock realizations, this suggests that the estimated series displays pronounced volatility.

Figure 1 indicates that sentiment shocks do not follow a predictable pattern linked to the state of the business cycle. Although some large positive sentiment shocks oc-

[13] The time series mean of the median path of sentiment shocks is -0.0014.

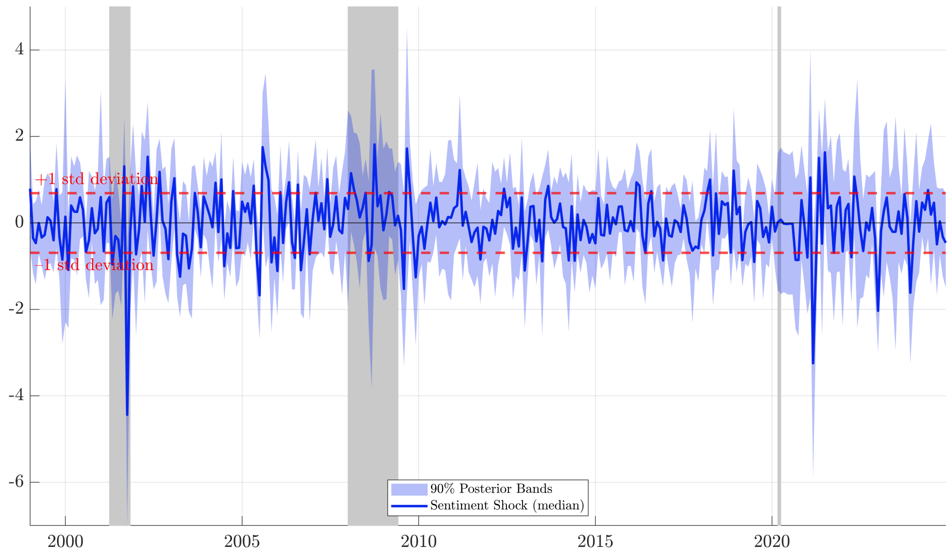

Figure 1: Historical path of sentiment shocks.

Notes: Figure displays the median path of sentiment shocks and 90% posterior bands. Red dashed horizontal lines represent ± one standard deviation around the time series mean. See text for details. Estimation of sentiment shocks is performed with the baseline identification, all identifying restrictions are summarized in Table 1. Sample period: from January 1998 to December 2024. A time series of shocks starts from January 1999 because of the VAR lag length set at 12. Grey shaded areas denote NBER recessions.

curred during recessionary episodes (for example, February and October 2008), others emerged in August 2005 and July 2021 – periods of economic expansion. A similar conclusion holds for negative sentiment shocks. For example, large negative realizations are estimated for March 2001 amid the economic recovery from the Covid-19-related slowdown, yet shocks of the same sign were also recorded during the 2001 recession.

Since sentiment shocks influence potentially all aspects of households' expectations, they are likely to affect various measures of sentiments. Establishing the close relationship of these shocks of interest with other sentiment indicators provides further support to the interpretation of shocks as exogenous disturbances to a single factor governing consumer beliefs. However, a realization of a sentiment shock today shifts the *level* of current forecasts relative to yesterday, thus a proper approach requires that a shock at

Variable	Correlation	Variable	Correlation
Index of Consumer Sentiment	-0.367***	Δ News EPU	0.062
Current finances	-0.284***	Δ Three-component EPU	0.053
Expected finances	-0.243***	JK Monetary policy shock	-0.049
Business conditions, 12 months ahead	-0.330***	JK CBI shock	0.012
Business conditions, 5 years ahead	-0.292***	J Monetary policy shock	0.015
Current buying conditions	-0.208***	J Odyssean FG shock	-0.029
Current sentiment index	-0.283***	J LSAP shock	-0.097*
Expected sentiment index	-0.353***	J Delphic shock	0.032
News sentiment index	-0.108*	S Monetary policy shock	-0.020
Recession indicator	0.025	S FG shock	-0.034
Δ Macro uncertainty, 1m ahead	0.042	S LSAP shock	0.026
Δ Macro uncertainty, 3m ahead	0.044	Oil supply news shock	0.067
Δ Macro uncertainty, 12m ahead	0.055	Gov-t spending news shock	0.084

Table 2: Correlation between sentiment shocks and other sentiment indices, macro variables, and shock measures.

Notes: Table shows the correlation between sentiment shocks and multiple sentiment indices along with its components (MSC), News sentiment index (Shapiro et al., 2022), U.S. recession indicator (NBER), macro uncertainty measures (Jurado et al., 2015), Economic Policy Uncertainty (EPU) indices (Baker et al., 2016), and shocks: JK is Jarociński and Karadi (2020), J is Jarociński (2024), S is Swanson (2021), oil supply news shocks are constructed by Känzig (2021), government spending news shocks are built by Ramey and Zubairy (2018). In the case of sentiment indices (from the MSC and Shapiro et al. (2022)), the correlation is calculated with the first difference of these indices.
Stars denote statistical significance: *** – <1%, ** – <5%, * – <10%.

time t be compared with a change in a sentiment measure between $t-1$ and t.

To this end, I calculate correlation of estimated sentiment shocks with the first difference of a variety of indicators, Table 2 presents the results. The MSC constructs their main Index of Consumer Sentiment (ICS) from five separate components which, in turn, can be aggregated into two indices: one reflects beliefs about current economic conditions and the second one measures expectations regarding the economy's future prospects. Correlations of sentiment shocks with all these sentiment indices from the MSC and their components are negative and statistically significant at 1% confidence level.

A notable observation is that although sentiment shocks are identified from the expectation variable (inflation forecasts), statistical significance is confirmed for correlations with indices measuring households' attitude to *current* economic conditions. Therefore, sentiment shocks affect both current economic perceptions and forecasts about future developments. The correlations are not strong, but one should take into account that a sentiment shock is only an exogenous perturbation, and consumer sentiments may react to other endogenous variables. Thus, obtaining the correlation of at least 0.2 (in absolute value) is a noteworthy finding. I also consider the News sentiment index developed by Shapiro et al. (2022): the correlation is weaker, but significant at 10% level.

To further investigate the relationship between sentiment shocks and economic states, I calculate correlation of shocks with a U.S. recession indicator (NBER), first differences in measures of macroeconomic uncertainty 1, 3 and 12 months ahead (Jurado et al., 2015) and economic policy uncertainty indices (Baker et al., 2016). Table 2 corroborates conclusions derived from a historical time series of sentiment shocks: estimated correlations are indistinguishable from zero.

There might be a concern that the identification procedure captures a standard shock as a sentiment shock. I verify this by assessing correlation of sentiment shocks with other common disturbances estimated in the literature.[14] Table 2 shows that the correlation is close to zero for all except Jarociński (2024) LSAP shock, but since statistical significance is only at 10% confidence level, this correlation may be spurious.

4.2 Dynamic Propagation

Before looking at real macro variables, it is interesting to see if identified sentiment shock produces only a temporary or persistent shift in households' beliefs. Figure 2 presents impulse responses to one standard deviation sentiment shock employing baseline identification (restrictions are summarized in Table 1), and plots posterior median response along with 68% and 90% posterior bands. Inflation expectations (top left panel) rise on impact of sentiment shock by almost 0.1pp and converge to steady state relatively quickly, which could be the result of imposed zero restrictions to reflect effective monetary policy communication.

[14]Monetary shocks estimated by Swanson (2021) and Jarociński (2024) are available at FOMC frequency. I convert these series to monthly frequency following the approach of Gertler and Karadi (2015). Firstly, for a given day, I cumulate all the shocks over the last 30 days (dates with no FOMC meetings have shocks equal to zero). Secondly, I average the cumulated daily values over the days of a given month, which provides a shock estimate for that month.

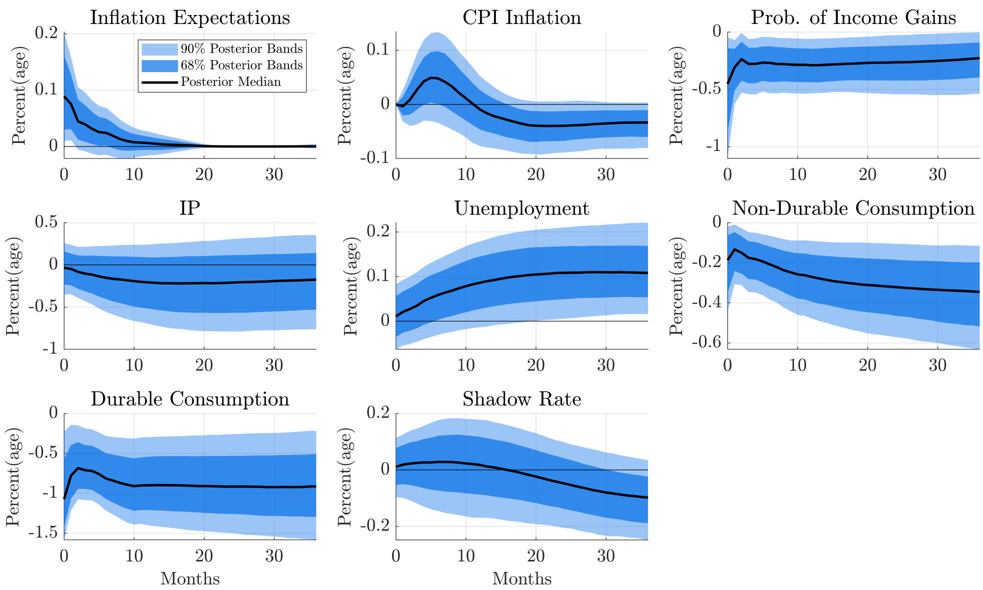

Figure 2: Impulse responses to sentiment shock.

Notes: Baseline identification, all identifying restrictions are summarized in Table 1. Positive sentiment shock raises inflation expectations. Sample period: from January 1998 to December 2024. Black line depicts posterior median response, shaded areas denote 68% and 90% posterior bands.

However, the response of the probability of real income gains exhibits a high degree of persistence (top right panel): although a decline is largest on impact, more than 95% of distribution of the responses remain negative 24 months after the shock. This implies that households' forecasts, once perturbed, could stay affected for a prolonged period and are slow to revert to normal. Additionally, the results suggest that sentiment shock identified from one expectations series likely moves all other consumer beliefs jointly and can serve as the single factor documented in Kamdar and Ray (2025).

Interestingly, although inflation is restricted from responding only on impact, an increase is observed shortly after sentiment shock occurs. To provide more precise quantitative evaluation, I report in Table 3 probability of the event that the response of a variable remains positive or negative for at least a specified share of the horizons considered. It shows that inflation rises at least in six periods over horizons [1, 12] in over 75% of all the draws. Accelerating inflation may suggest that firms react by raising

Variable	Sign	Horizons	Probability over		
			50% of horizons	75% of horizons	100% of horizons
Inflation Expectations	Positive	[0, 12]	86.77	72.32	54.93
CPI Inflation	Positive	[1, 12]	76.57	58.87	20.81
IP	Negative	[0, 24]	74.59	68.29	52.28
Unemployment	Positive	[0, 24]	92.75	85.34	57.48
Shadow Rate	Positive	[0, 24]	55.25	40.98	21.96
Prob. of Income Gains	Negative	[0, 24]	98.35	97.01	91.79
Non-Durable Consumption	Negative	[0, 24]	99.67	99.33	95.24
Durable Consumption	Negative	[0, 24]	99.13	98.70	97.01

Table 3: Calculated probability of signed response.

Notes: Shows probability that the response of a variable is positive or negative for a given minimum share of the horizons considered. Probability is calculated as a percentage of all SVAR parameter draws that satisfy criteria. Baseline identification, all restrictions are summarized in Table 1. Sample period: from January 1998 to December 2024.

prices because they either become aware of elevated consumer inflation expectations or experience sentiment shock directly. I investigate this possibility in SVAR with the modified identification in section 5.1.

Responses of consumption confirm that households act on their beliefs. While this link has been causally established in the experimental literature, the evidence of those studies points only to short-lived, if any, effects of exogenous movements in expectations of inflation on consumer spending. Figure 2 demonstrates that sentiment shock induces a lasting impact on consumption. Specifically, durable consumption falls by 1% on impact, and the negative effect persists for all 36 subsequent months following the arrival of sentiment shock (consumption remains below its steady state level by 0.9% across most horizons). A similar pattern holds for consumption of non-durables: an initial fall by almost 0.2% is followed by a further decline to 0.35% by horizon 36. Table 3 confirms sustained adverse effects of sentiment shock: there is over a 95% probability that both durable and non-durable consumption decline in each of the 24 consecutive periods. The depressed state of consumption can be attributed to households' belief that future real income is likely to decrease, as can be inferred from the response of probability of real income gains. These empirical patterns are line with predictions of a business cycle model with subjective beliefs proposed by Bhandari et al. (2025), in which higher pessimism triggers a pronounced and persistent drop in real consumption.

A sustained drop in consumption exerts lagged effects on measures of real activity.

As Figure 2 shows, unemployment does not respond contemporaneously to sentiment shock, but starts to rise gradually. It reaches a peak of roughly 0.1pp above the steady state 20 months after the shock and remains at that level thereafter. As a narrower measure of economic activity, IP exhibits a more subdued response: its largest contraction is 0.2%, but this is sizable relative to an initial change in inflation expectations (0.1pp). Although the posterior bands are wide, one should note that responses in the Bayesian setting are stochastic objects and correlated between horizons, so it is worth exploring responses jointly. Accordingly, Table 3 suggests that IP contracts in at least 13 months over the two year horizon with almost 75% probability. Note that the observed decline in economic activity is in line with disinflation emerging from horizon 20 onward, as shown in Figure 2. Evolution of these two real activity indicators justify that what I identify as sentiment shock is different from supply shock because unexpected changes in supply lead to an immediate response of both inflation and IP while in the case of sentiment shock, inflation does not move on impact, and IP adjusts only slowly.

The dynamics of the shadow rate (see Figure 2) further indicate that the identified shock is distinct from standard monetary policy shocks. The rate initially displays some upward movement, but the magnitude is very small. Instead, it can be interpreted as a brief tightening reaction of monetary authority to elevated inflation expectations. As the economy enters a downturn in the following periods, the Fed adopts an accommodating policy and cuts the interest rate.

To summarize, these findings show that sentiment shock can trigger prolonged shifts in households' beliefs and generate persistent contractionary effects that last for as long as three years. The mechanism seems to operate through a reduction of consumer spending resulting from a deterioration of households' expectations about the future state of the economy. Sentiment shock raises inflation forecasts only temporarily, but households believe that a contraction of their real income will persist for an extended period. Durable goods are high-cost items that households are willing to purchase only if they are confident that their future income will be sufficient to cover this large expenditure. Given households' reliance on stable future income to justify such a large expenditure, it is therefore unsurprising that durable spending falls markedly by 1% on impact of sentiment shock. Lower expectations of future real income likely have negative effects on all components of consumption, including non-durable.

Firms are likely to alter their behavior because they might learn that consumers expect higher inflation in the future, or experience sentiment shock directly similarly to households. Consequently, this provides firms with an incentive to raise prices, which can be seen in top middle panel in Figure 2. Higher inflation can contribute to negative effects of sentiment shock on consumption.

As the downturn initially triggered by a pronounced decrease in aggregate consumer demand progresses, a subsequent fall in households' income exerts additional downward pressure on their spending (which is reflected in Figure 2 by the depressed response of durable goods consumption and persistent downward trend in non-durable consumption). As aggregate demand declines, firms respond by reducing their labor force, leading to a gradual increase in unemployment.

Based on the potential one-dimensional structure of households' beliefs, it can be argued that sentiment shock is likely to change not only inflation forecasts, but also expectations of nominal interest rates, thus expected real interest rates may move as well. Unfortunately, the MSC does not report quantitative beliefs of interest rates, which precludes drawing conclusions about forecasts of real interest rates. However, I can rely on the insights from the study conducted by Coibion et al. (2023) who generated an exogenous variation in households' expectations of real interest rates in the experimental context. They find that the willingness to purchase durable goods is lower among households who anticipate higher real market rates, and there is no evidence of the effects on non-durable consumption.

Durable goods are expensive big ticket items, and not all households have the means to purchase them without taking a loan, so high sensitivity of spending on durables to real interest rates is consistent with findings of Coibion et al. (2023). My earlier findings show that sentiment shock has negative and long-lasting effects on durable consumption (see Figure 2). One way to reconcile this result with documented findings from Coibion et al. (2023) is to assume that households expect nominal interest rates to increase by more than inflation, which translates to an expected rise in real rates. This resembles the Taylor principle: central bank raises the nominal interest rate by more than one-to-one in response to higher inflation. Dräger et al. (2016) find that around 50% of

Variable	Horizon				
	1 month	6 months	1 year	3 years	6 years
Inflation Expectations	8.54 (0.10, 44.64)	6.85 (0.38, 31.86)	6.14 (0.51, 27.37)	4.89 (0.44, 22.27)	4.79 (0.59, 20.93)
CPI Inflation	0.00 (0.00, 0.00)	0.69 (0.06, 4.49)	1.05 (0.13, 6.40)	2.65 (0.45, 9.22)	3.82 (0.82, 13.12)
IP	5.08 (0.05, 35.62)	5.14 (0.27, 38.06)	5.44 (0.29, 41.56)	5.95 (0.32, 44.11)	6.94 (0.51, 39.87)
Unemployment	5.80 (0.05, 37.73)	7.36 (0.54, 44.44)	10.44 (0.84, 49.83)	17.68 (1.59, 56.84)	16.27 (1.91, 45.86)
Shadow Rate	4.38 (0.03, 34.89)	4.17 (0.16, 31.06)	3.93 (0.16, 28.75)	6.31 (0.68, 26.51)	10.23 (1.35, 32.23)
Prob. of Income Gains	9.00 (0.09, 52.96)	12.38 (0.93, 52.85)	14.60 (1.26, 51.99)	16.60 (1.61, 47.95)	13.41 (1.48, 41.78)
Non-Durable Consumption	8.93 (0.09, 50.89)	13.59 (1.15, 54.78)	18.12 (2.38, 56.33)	21.68 (3.13, 53.81)	18.63 (2.57, 48.95)
Durable Consumption	35.04 (1.59, 74.87)	34.22 (2.70, 71.76)	35.12 (4.26, 68.83)	31.02 (4.06, 64.21)	24.80 (2.98, 58.62)

Table 4: Forecast error variance decomposition. Sentiment shocks.

Notes: Table presents the posterior median share of the variance of variables explained by sentiment shocks (in percent). 90% posterior bands are reported in parentheses. Baseline identification, all identifying restrictions are summarized in Table 1. Sample period: from January 1998 to December 2024.

households form expectations in a manner aligned with the Taylor rule, so consumers may indeed forecast higher real interest rates in response to sentiment shock. Other empirical evidence available for households (Carvalho and Nechio, 2014; Dräger and Lamla, 2015) lends additional support to this view.

4.3 Explanatory Power

I assess the contribution of sentiment shocks to fluctuations in macroeconomic variables in the VAR by conducting a Forecast error variance decomposition (FEVD). Table 4 reports the posterior median contribution of sentiment shocks (in percent) to the volatility of variables at specific horizons and 90% posterior bands in parentheses. According to the median values, sentiment shocks contribute almost 9% to the variance of inflation expectations in the short run, and their contribution declines at further horizons. The share of inflation variance explained by sentiment shocks is small at short horizons, and rises to over 3% in the medium term.

Sentiment shocks are likely to drive households' beliefs jointly, including subjective probability of real income gains. Table 4 shows that their contribution to fluctuations in this probability series is close to 17% at 3 years, which is greater than for inflation expectations.

The results indicate that sentiment shocks are an important driver of durable consumption. In the short run, their contribution to variation in durable good spending exceeds one-third and remains around 25% six years after the shock. This finding suggests that durable consumption is highly sensitive to households' beliefs, with sentiment shocks playing a prominent role. The contribution of these shocks to the variance of non-durable consumption is smaller, but still considerable: it stands at 10–15% at short horizons and climbs to more than 20% over 3 years upon impact.

We saw from Figure 2 that the response of IP is muted, and the estimates from Table 4 are aligned with that finding: sentiment shocks explain only 6–7% of fluctuations in IP at long horizons. In contrast, sentiment shocks account for about 17% of unemployment volatility over the 3 and 6 year horizons and less than 10% of it in the short run. Recall that unemployment gradually increases in response to an unfavorable sentiment shock (see Figure 2), which is consistent with its estimated FEVD.

To sum up, sentiment shocks generate temporary fluctuations in inflation expectations, but contribute more substantially to the variation in the perceived probability of income gains beyond six months. They explain a notable share of the variance of durable consumption at most horizons, and represent an important driver of non-durable goods spending at medium-term horizons. Because the real activity measures respond sluggishly to sentiment shocks, their contribution to unemployment fluctuations becomes meaningful over the medium run. These results suggest that sentiment shocks may generate a deep consumption-led business cycle.

5 Extensions of Empirical Results

In this section, I consider extensions of the baseline SVAR model and provide additional empirical evidence in favor of sentiment shocks.

5.1 Firms Experiencing Sentiment Shocks

In the baseline identification, I employ inflation expectations of households to identify sentimental movements in their beliefs. Prices were restricted not to respond on impact because changes in households' beliefs are not immediately observable by other agents, so firms may respond to higher inflation forecasts of households by adjusting prices only with a delay.

This identification restriction assumes that firms do not experience sentiment shocks in the same way as households, however, there remains a possibility that they do. Indeed, firms are hierarchical structures in which individual managers make pricing and production decisions potentially relying on sentiments that shape economic expectations. Savignac et al. (2021) provide the empirical evidence that inflation expected by managers in French firms depend on the position they hold. Therefore, price setting behavior may respond differently to fluctuations in managers' sentiments depending on the level at which firms make decisions.

The empirical literature documents that firms use their inflation beliefs when making business decisions. Coibion et al. (2018) find that across firms in New Zealand, lower inflation expectations lead them to cut investment and employment. Based on the survey data from Italian firms, findings of Coibion et al. (2020a) show that firms, whose inflation beliefs are exogenously increased, tend to raise prices and reduce employment several quarters following the information intervention. Crucially, they project other beliefs of firms on their inflation forecasts and document that higher expected inflation leads them to expect the worsening situation in the economy and deterioration of within-company business conditions.

This finding aligns with the way sentiment-driven households' beliefs adjust to shocks. If indeed firms are exposed to sentiment shock, they may be willing to increase prices with the upward revision of their inflation forecast. As was already noted earlier, Figure 2 points to a possible uptick of inflation shortly after impact. To validate this hypothesis, I modify the baseline identification in the following way: I remove the zero restriction on prices (10) and impose a sign restriction such that on impact prices rise

Identifying Restriction	Variable	Type of Restriction	Horizons
1	Inflation expectations	Positive	On impact
2	Probability of income gains	Negative	On impact
3	Non-durable consumption	Negative	On impact
4	Durable consumption	Negative	On impact
5	Inflation expectations	Zero	[24, 28]
6	Consumer prices	Positive	On impact

Table 5: Alternative identification scheme.

Notes: Summary of alternative identifying restrictions for sentiment shocks in SVAR. Details are provided in the text.

in response to positive sentiment shock:

$$\text{IRF}(\text{consumer prices}_t, \varepsilon_{1t}, h) > 0, \ h = 0. \tag{11}$$

All restrictions considered in the alternative identification are summarized in Table 5.

Given alternative restrictions, Figure 3 plots posterior median impulse responses (in black) along with 68% and 90% posterior bands (in blue). Allowing prices to rise results in a more sizable increase in inflation: it reaches the peak of around 0.05pp under baseline identification while its highest level is over 0.1pp when alternative restrictions are implemented (more than two times higher). Inflation jumps by 0.1pp immediately after the shock and continues to move upward for several periods, thus data speak in favor of a positive response of inflation.[15]

This can be verified further from Table 6 which reports the probability that a given variable responds positively or negatively in at least a certain proportion of horizons considered. It shows that with almost 90% probability a positive inflation response is observed in at least 10 periods over horizons 0–12, and inflation always remains above its steady state value over the same horizons in 60% of all parameter draws.

To compare two SVAR models explicitly, I fix a horizon and examine the responses of variables across all parameter draws in each framework. I set horizon considered to

[15] I evaluate the validity of the restriction that inflation rises in response to unfavorable sentiment shocks, in Appendix section C.2. In doing so, I leave the inflation response unrestricted, and estimation results lend support to an assumption that inflation is likely to increase.

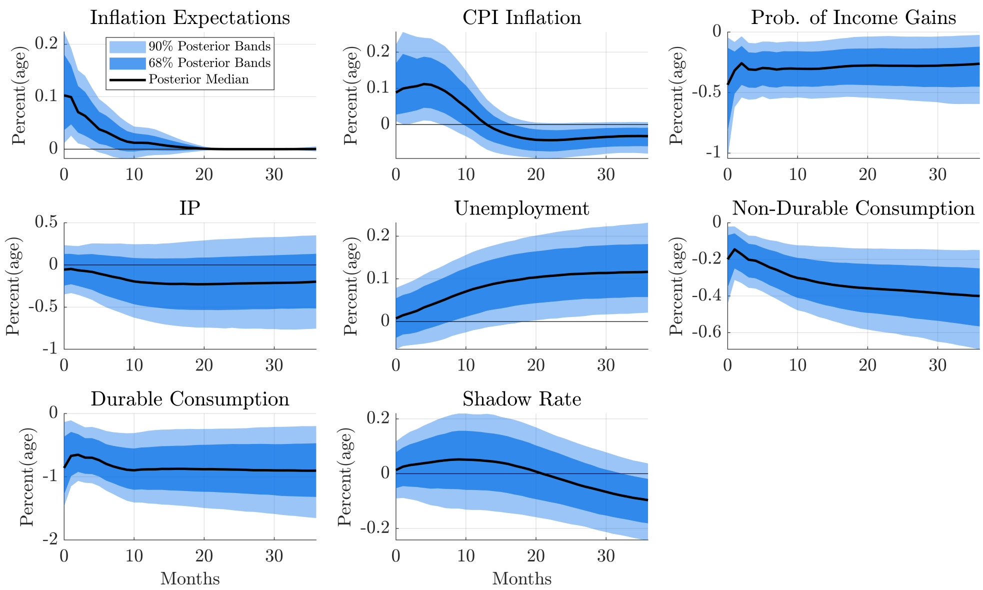

Figure 3: Impulse responses to sentiment shock. Inflation rises on impact.

Notes: Alternative identification, all identifying restrictions are summarized in Table 5. Positive sentiment shock raises inflation expectations. Sample period: from January 1998 to December 2024. Black line depicts posterior median response, shaded areas denote 68% and 90% posterior bands.

6, which is close to the period in which inflation peaks in both models. Figure 4 plots histograms of responses to positive sentiment shock, normalized to probability density function, for each SVAR estimated with baseline or alternative identification. From top middle panel depicting inflation responses it can be clearly seen that the mass of distribution in model in which prices rise on impact, shifts to the right, and the median is also higher. Although the sign restriction was implemented only on impact, the data lend support to this model.

Other macro quantities included in VAR model respond to sentiment shock in the manner similar to that observed under baseline identification. Inflation expectations rise on impact and gradually converge to its steady state while the probability of income gains exhibits long-lasting negative effects. Unemployment peaks at 0.1pp and the drop in durable consumption amounts to 0.9%, just as in the baseline identification. A slightly different trajectory is estimated for non-durable consumption. Since firms

Variable	Sign	Horizons	Probability over		
			50% of horizons	75% of horizons	100% of horizons
Inflation Expectations	Positive	[0, 12]	92.15	81.09	67.89
CPI Inflation	Positive	[0, 12]	95.08	86.38	60.07
IP	Negative	[0, 24]	75.78	66.92	52.27
Unemployment	Positive	[0, 24]	90.84	79.40	53.40
Shadow Rate	Positive	[0, 24]	65.88	52.36	28.76
Prob. of Income Gains	Negative	[0, 24]	98.98	97.46	93.83
Non-Durable Consumption	Negative	[0, 24]	99.77	99.64	97.46
Durable Consumption	Negative	[0, 24]	99.08	98.58	96.58

Table 6: Calculated probability of signed response. Inflation rises on impact.

Notes: Shows probability that the response of a variable is positive or negative for a given minimum share of the horizons considered. Probability is calculated as a percentage of all SVAR parameter draws that satisfy criteria. Alternative identification, see Table 5 for all restrictions. Sample period: from January 1998 to December 2024.

charge higher prices, which is manifested in elevated inflation, a larger fall in non-durable spending follows. The latter is partly reflected in Table 6: the chance that consumption of non-durable goods declines across all the horizons 0–24, becomes higher compared to Table 3. This finding is consistent with Figure 4 which demonstrates that the distribution of responses of non-durable consumption is more heavily concentrated on negative values.

Estimation of SVAR model with a positive sign restriction on inflation reinforces the economy's reaction observed in the baseline identification. The occurrence of positive sentiment shock changes beliefs of both households and firms in a way that they anticipate worsening financial and business conditions ahead (lower real income and earnings) and form elevated inflation expectations. Since future demand is likely to shrink, firms may believe that they will find themselves liquidity-constrained in subsequent periods, which explains why they choose to raise prices in the short-run, as in a model of Gilchrist et al. (2017).

Driven by unfavorable economic prospects, households instantly respond to sentiment shock by cutting down purchases of both non-durable and durable goods, with the effect on the latter being substantially larger. Higher prices and falling real income of households may act as contributing factors to a considerable and long-lasting decline in consumption. As aggregate demand remains weak, firms cut existing jobs, which causes unemployment to rise steadily. A slowdown in the economy is consistent with

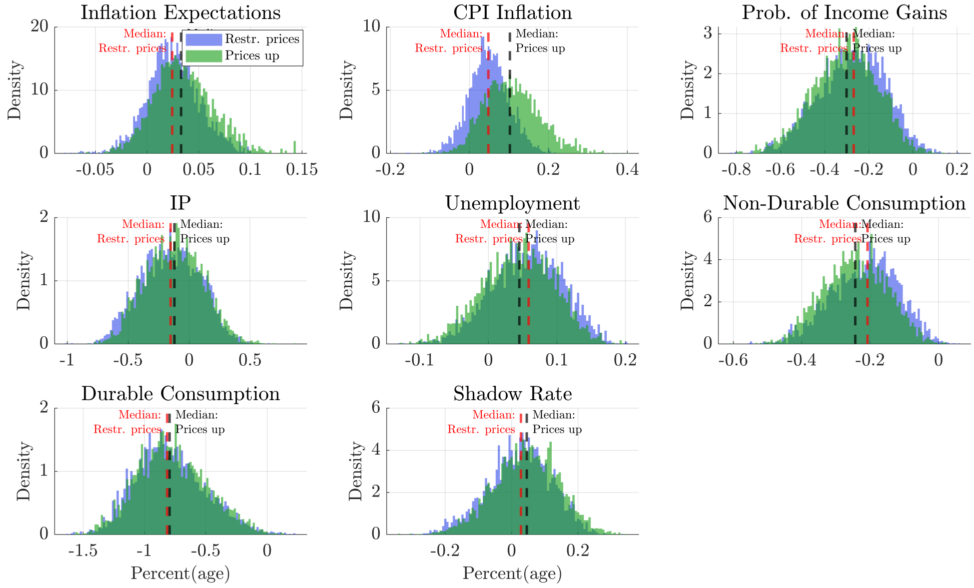

Figure 4: Histograms of responses to sentiment shock at horizon 6 across two SVARs.

Notes: Plots responses of variables to sentiment shock in SVAR models across all parameter draws. Histograms are normalized to a probability density function. Two models considered: one where prices are restricted not to respond on impact (in blue), and the other where prices increase on impact (in green). All restrictions are summarized in Tables 1 and 5, respectively. Positive sentiment shock raises inflation expectations. Sample period: from January 1998 to December 2024. Vertical dashed lines denote posterior median responses in each model.

disinflation depicted in Figure 3 at later horizons.

5.2 Factor Structure of Consumer Beliefs

In the analysis based on SVAR, I rely on two series – inflation expectations and probability of real income gains – to identify exogenous shifts in sentiments, which I refer to as sentiment shocks. There might be a concern that exploiting only two series may not be sufficient to isolate movements in households' sentiments because consumer beliefs may be characterized along multiple dimensions.

This motivates me to examine a broader measure of households' perceptions over time by taking into account a larger number of questions asked by the MSC. I use a factor model as a tool of dimension reduction, which enables me to collapse multiple responses into a few factors and evaluate the key forces driving households' perceptions and forecasts. See Appendix section D for a description of the factor model.

I include quantitative time series whenever possible, but since the MSC elicits mostly qualitative responses, for this type of questions, I calculate the percentage of respondents who chose a particular option, and use this series in the factor model. Appendix section A.2 provides further details on which MSC questions are included and how quantitative time series are computed for the factor analysis. The total number of MSC questions from which I derive quantitative responses, is 19.

Ideally, I would like to obtain a model in which each variable has a high loading, in absolute terms, only on one common factor. Achieving this would allow for a cleaner interpretation of the common factors. Accordingly, given that there exist multiple alternative models with rotated loadings and factors that fit the data equally well, I search for the rotation that provides the cleanest interpretation of the estimated factors. A common criterion is the varimax rotation whereby one seeks to maximize a sample variance of the standardized loadings summed across the estimated factors, the details are presented in Appendix section D.1. I estimate the unknown parameters by maximum likelihood, and opt to extract four common factors because it permits an economically meaningful interpretation of each.

With the rotation described above, it is instructive to examine estimated factor loadings presented in Table 7. For ease of comparison, I highlight in bold the loadings greater than 0.5 in absolute value. The model suggests a reasonable interpretation of factors. Most questions that heavily load on the first factor, describe (both current and expected) personal finances of households, their expectations about business conditions in the future and house selling attitudes. The second factor may be interpreted as one representing households' perceptions of current business conditions and forecast of changes in unemployment. Expected business conditions in the next year load positively on the second factor, which may suggest that consumers form expectations about the economy's prospects drawing on current developments as well. The third factor highlights households' attitudes toward buying large, expensive goods and houses, while the only variable with a sizable loading on the fourth factor reflects the expected change in

MSC Question	Factors 1	2	3	4
Current Financial Situation Compared with a Year Ago, Better	**0.85**	0.35	0.22	-0.12
Expected Change in Financial Situation in a Year, Better	**0.86**	0.12	0.24	0.19
Expected Household Income Change During Next Year	**0.84**	-0.07	-0.00	-0.23
Expected Change in Real Household Income During Next Year, Up	**0.90**	0.14	0.11	0.07
Probability of Losing a Job During Next 5 Years	-0.30	-0.19	0.26	0.39
Probability of Adequate Retirement Income	0.25	0.02	**-0.56**	0.33
Change in Likelihood of Comfortable Retirement, Up	**0.90**	0.21	-0.08	-0.07
News Heard of Recent Changes in Business Conditions, Relative	0.13	**0.86**	0.29	0.02
Current Business Conditions Compared with a Year Ago, Better	0.27	**0.90**	0.18	-0.23
Expected Change in Business Conditions in a Year, Better	0.14	0.01	-0.00	**0.96**
Business Conditions Expected During Next Year, Good	**0.65**	**0.56**	0.41	0.02
Business Conditions Expected During Next 5 Years, Good	**0.69**	0.35	0.45	0.08
Expected Change in Unemployment During Next Year, More	-0.14	**-0.88**	-0.01	-0.13
Expected Change in Interest Rates During Next Year, Up	0.27	0.41	-0.11	-0.28
Opinions About Government's Economic Policy, Good	**0.75**	0.16	0.03	0.11
Buying Conditions for Large Household Goods, Good	0.42	0.37	**0.77**	-0.14
Buying Conditions for Vehicles, Good	0.20	0.11	**0.94**	0.20
Buying Conditions for Houses, Good	0.02	0.11	**0.91**	0.18
Selling Conditions for Houses, Good	**0.79**	0.30	-0.26	-0.04

Table 7: Estimated factor loadings.

Notes: Table presents estimated factor loadings $\hat{\Lambda}$ from a factor model $X = \mu + \Lambda f + \eta$ estimated by maximum likelihood with 4 factors. Criterion is "varimax" rotation. See text and Appendix section D for details. Loadings greater than 0.5 in absolute value are highlighted in bold.

business conditions. This last factor may look similar to the first one, however, this expectation series is concerned about the *change* in aggregate business conditions between today and a year from now while other comparable questions elicit opinions about the *level* of economic conditions continuously over a specific time horizon. As a result, the model favors treating the series about the change as a distinct factor.

The results suggest that households' beliefs are organized around several dimensions: expectations about a personal financial situation and aggregate economic conditions, perceptions about a current economic situation, and consumer attitudes toward purchasing large items. Almost all loadings highlighted in Table 7 have the expected sign, which implies that the factors represent distinct dimensions of consumer sentiments.

To understand how well the factor model performs to explain time series of survey data, I calculate communality for each variable $k = 1, \ldots, 19$ as $h_k^2 \equiv \sum_{j=1}^{m} \hat{\Lambda}_{kj}^2$, where $m = 4$ is total number of common factors, and present estimates in Table 8. The communality for a given variable may be interpreted as the fraction of variation in that variable explained by the factor model. The larger the communality is, the better is the model performance for that variable. To aid visual interpretation, I highlight in bold the values greater than 0.6.

The communality estimates provide evidence that the factor model does a good job for the majority of variables. There are only a few exceptions (three out of 19), which also correspond to variables with relatively low estimated factor loadings (see Table 7).

Since I employ series of inflation forecasts and probability of real income gains to identify sentiment shocks, it would be interesting to calculate correlation of shocks with each dimension of households' sentiments. When shock occurs, it changes the level of a variable, so I assess correlation of sentiment shocks estimated from two SVAR models, with first difference of each factor. Factors are predicted by the weighted least squares (Bartlett) method.

Estimated correlations are presented in Table 9. It shows that correlation with first difference of each factor is negative: when sentiment shock arrives, sentiments deteriorate, and a factor declines, which corroborates the interpretation of factors as sentiment measures. The highest negative correlation is recorded with first difference of factor 1

MSC Question	Communality
Current Financial Situation Compared with a Year Ago, Better	**0.91**
Expected Change in Financial Situation in a Year, Better	**0.84**
Expected Household Income Change During Next Year	**0.76**
Expected Change in Real Household Income During Next Year, Up	**0.85**
Probability of Losing a Job During Next 5 Years	0.35
Probability of Adequate Retirement Income	0.49
Change in Likelihood of Comfortable Retirement, Up	**0.86**
News Heard of Recent Changes in Business Conditions, Relative	**0.84**
Current Business Conditions Compared with a Year Ago, Better	**0.97**
Expected Change in Business Conditions in a Year, Better	**0.95**
Business Conditions Expected During Next Year, Good	**0.91**
Business Conditions Expected During Next 5 Years, Good	**0.82**
Expected Change in Unemployment During Next Year, More	**0.80**
Expected Change in Interest Rates During Next Year, Up	0.33
Opinions About Government's Economic Policy, Good	**0.61**
Buying Conditions for Large Household Goods, Good	**0.92**
Buying Conditions for Vehicles, Good	**0.98**
Buying Conditions for Houses, Good	**0.87**
Selling Conditions for Houses, Good	**0.77**

Table 8: Communality for each variable included in factor model.

Notes: Table reports communality for each variable k (MSC question) calculated as $h_k^2 \equiv \sum_{j=1}^{m} \hat{\Lambda}_{kj}^2$ where $m = 4$ is the number of common factors. $\hat{\Lambda}_{kj}$ is (k, j) entry of estimated matrix of factor loadings in a factor model $X = \mu + \Lambda f + \eta$ estimated by maximum likelihood with 4 factors. Criterion is "varimax" rotation. See text and Appendix section D for details. Communalities greater than 0.6 are highlighted in bold.

Variable	Correlation (1)	(2)
Factor 1	-0.10*	-0.08
Δ Factor 1	-0.32***	-0.32***
Factor 2	-0.03	-0.05
Δ Factor 2	-0.20***	-0.20***
Factor 3	-0.01	-0.04
Δ Factor 3	-0.11*	-0.14**
Factor 4	-0.11**	-0.11*
Δ Factor 4	-0.25***	-0.26***

Table 9: Correlation of sentiment shocks with factors.

Notes: Sentiment shock estimates are obtained from SVAR models: (1) with baseline identification (see section 4.2), (2) with alternative identification (see section 5.1). Factors are estimated from a factor model $X = \mu + \Lambda f + \eta$, see text for details.
Stars denote statistical significance: *** – <1%, ** – <5%, * – <10%.

in line with interpretation that factor 1 reflects consumer expectations of economic outcomes. Correlation with changes in factor 4 is second highest, which is consistent with this factor capturing expected changes in business environment. Weaker correlation of sentiment shocks is observed with first difference of factors 2 and 3, which summarize, correspondingly, perceptions of current business conditions and buying attitudes. Note that this pattern holds for both SVAR models, with very similar correlation estimates.

The findings above suggest that sentiment shocks explain around one third of variation in period-by-period changes in economic and financial expectations. Moreover, shocks also account for about 20% of shifts in households' perceptions of current developments in business conditions. It is noteworthy that around 10% of fluctuations in consumer attitudes toward the purchase of big-ticket items can also be attributed to sentiment shocks.

5.3 Augmenting VAR With a Factor

As was noted in the previous section, there is a concern that using only inflation expectations and probability series in SVAR may be insufficient to identify sentiment shocks accurately. The reason is that the belief system held by households at the time of decision making is likely to be larger than that consisting of only two series mentioned above. Therefore, a limited information set in VAR may lead to biased estimates of the object of interest, in particular, IRFs, and may result in sentiment shocks that do not capture shifts in the entire system of economic beliefs. Furthermore, the factors are estimated based on all the available quantitative information from the survey, so identifying sentiment shocks directly from factors may be a preferred option.

Identifying Restriction	Variable	Type of Restriction	Horizons
1	Factor 1	Positive	On impact
2	Probability of income gains	Positive	On impact
3	Non-durable consumption	Positive	On impact
4	Durable consumption	Positive	On impact
5	Inflation expectations	Zero	[24, 28]
6	Consumer prices	Zero	On impact

Table 10: Identification of sentiment shocks from factor 1.

Notes: Summary of identifying restrictions for sentiment shocks in SVAR which are extracted from factor 1 (see section 5.2). Details are provided in the text.

To address these concerns, I perform two exercises. Firstly, I augment a list of macro variables (see section 3.3) with the first factor estimated in the previous section so as to enlarge the information set. Motivation for including this specific factor comes from its strongest correlation with estimated sentiment shocks (see Table 9). I impose baseline identifying restrictions (see Table 1) and leave the sign of the factor response unrestricted to let data entirely determine its evolution.

Secondly, I consider one more specification of SVAR in which sentiment shocks are identified directly from the first factor. In this exercise, I do not impose a sign restriction on the response of inflation expectations in order to verify whether factor-based sentiment shocks lead to shifts in inflation forecasts. I keep other zero and sign restrictions. Note that since an increase in the factor is associated with improved sentiments, sign restrictions on probability of income gains, non-durable and durable consumption are implemented with an opposite sign. All restrictions for this specification are presented in Table 10.

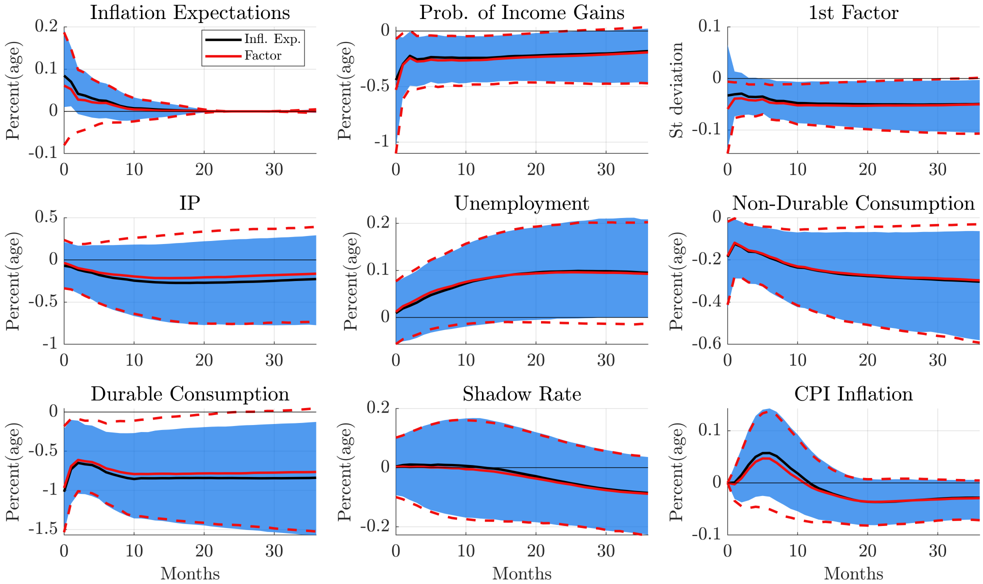

Figure 5: Impulse responses to sentiment shocks identified from either inflation expectations or factor.

Notes: Two SVAR models are augmented with factor 1. In the first model (black solid lines and blue shaded areas), sentiment shock is identified from inflation expectations; in the second model (red solid and dashed lines), sentiment shock is identified from factor 1. All identifying restrictions are summarized in Tables 1 and 10, respectively. Sign of responses from the second model is flipped for ease of comparison. Sample period: from January 1998 to December 2024. Black and red solid lines depict posterior median responses, blue shaded areas and red dashed lines denote 90% posterior bands.

I plot impulse responses from two SVAR specifications jointly in Figure 5. The factor may turn negative throughout the sample, so instead of taking log, I normalize it with respect to its standard deviation. Since a positive sentiment shock extracted from factor results in improvement of sentiments, I flip the sign of responses from this SVAR specification to facilitate comparison with the other model.

It is worth highlighting how close posterior median responses are across both models. On impact, the magnitude of decline in factor is slightly larger in SVAR with factor-based sentiment shocks, but subsequently both models yield almost identical dynamics. Specification with sentiment shocks identified from inflation expectation series shows that the first factor remains subdued at almost all horizons. Wide posterior bands of its response in the beginning may be explained by not imposing a sign restriction. Nevertheless, the negative median response of the factor immediately after impact of shock and a decline thereafter confirms that sentiment shocks extracted from inflation expectations, indeed capture fluctuations in households' sentiments.

Although inflation forecasts were unrestricted in SVAR with factor-based sentiment shocks, it indicates that expected inflation increases, and the response closely aligns with that obtained in the other specification. This finding validates a restriction employed in this paper that inflation expectations rise as sentiments deteriorate. Responses of other macro variables, including non-durable and durable consumption, inflation, are comparable across both SVAR specifications.

Overall, I find that sentiment shocks identified from inflation beliefs, indeed reflect disturbances to households' sentiments, and generate dynamic responses similar to those in the alternative SVAR model in which shocks are extracted from the factor series.

6 An Equilibrium Model with Sentimental Beliefs

In this section, I develop a model in which economic agents shape their perceptions and expectations subject to sentiment shocks, which leads to a deviation of their forecasts from the rational benchmark. Beyond sentiment shocks, I consider productivity and monetary policy shocks which serve as shifters of aggregate supply and demand, respectively. Because a rational agent should not take sentiment shocks into account when forming expectations about future outcomes, I call expectations "rational" if they are based only on standard productivity and monetary policy shocks, and call them "sentimental" if agents rely on both standard and sentiment shocks to form their economic perceptions.

The framework is based on the small-scale New Keynesian model (Galí, 2008); the ingredients are standard except that agents experience sentiment shocks, which gives rise to sentimental expectations. To formally make a distinction between rational and sentimental expectations, suppose at time t an agent forecasts a realization of a random variable ξ at time $t+1$. If an agent is rational, his expectations are based on the history of standard shocks, so rational expectations of a random variable ξ are given by

$$\mathbb{E}_t\xi_{t+1} \equiv \mathbb{E}(\xi_{t+1}|\mathcal{F}_t),$$

where $\mathcal{F}_t$ is a sigma-algebra generated by past and current innovations to standard macroeconomic shocks up to period t:

$$\mathcal{F}_t = \sigma\left(\varepsilon_s^a, \varepsilon_s^v \mid s \leq t\right),$$

and $\varepsilon_t^a, \varepsilon_t^v$ are innovations to, respectively, productivity and monetary policy shocks.

An agent with sentimental beliefs additionally observes the entire history of sentiment shocks, thus a sentimental forecast of a random variable ξ is defined as

$$\hat{\mathbb{E}}_t\xi_{t+1} \equiv \mathbb{E}(\xi_{t+1}|\mathcal{G}_t),$$

where $\mathcal{G}_t$ is a sigma-algebra generated by standard as well as sentiment shocks up to period t:

$$\mathcal{G}_t = \sigma\left(\varepsilon_s^a, \varepsilon_s^v, \varepsilon_s^\zeta \,\middle|\, s \leq t\right),$$

and ε_t^ζ is an innovation to sentiment shocks.

6.1 Economic Environment

Time is discrete $t = 0, 1, 2, \ldots$ and corresponds to quarterly frequency. The model is inhabited by a representative household, a continuum of firms which are identical ex post, and a monetary authority. I assume that all individual agents (households and firms) are subject to sentiment shocks, in line with empirical evidence discussed in sections 3.2 and 5.1, thus their expectations are sentimental.

Consider a representative household who consumes final good C_t, supplies labor L_t, and may save by investing into risk-free one-period government bond. The optimization problem is to maximize a discounted flow of utilities subject to budget constraint

$$\max_{\{C_{t+s},L_{t+s},B_{t+s}\}} \hat{\mathbb{E}}_t \sum_{s=1}^{\infty} \beta^s \left[\frac{C_{t+s}^{1-\gamma_c}}{1-\gamma_c} - \chi \frac{L_{t+s}^{1+\gamma_L}}{1+\gamma_L} \right]$$
$$\text{subject to} \tag{12}$$
$$C_t + B_t = W_t L_t + \frac{R_{t-1}}{\Pi_t} B_{t-1} + \int_0^1 profit_{jt} \, \mathrm{d}j,$$

where B_t denotes savings into government bond, R_{t-1} is nominal risk-free interest rate set by the monetary authority, $\Pi_t \equiv P_t/P_{t-1}$ is gross inflation between periods $t-1$ and t, and $profit_{jt}$ is net profit from firm j owned by household. Let $\mu_{c,t}$ denote the Lagrange multiplier attached to a budget constraint. Note that $\hat{\mathbb{E}}_t$ in the objective function (12) denotes an operator representing sentimental expectations.

I consider a log-linearized version of the model. Appendix section E.1 contains detailed derivations of optimality conditions from household problem. Household optimization leads to an optimality condition

$$\hat{c}_t = \sum_{s=0}^{\infty} \beta^s \left[(1-\beta) \hat{\mathbb{E}}_t \hat{y}_{t+s} - \frac{\beta}{\gamma_c} \hat{\mathbb{E}}_t \left(\hat{r}_{t+s} - \pi_{t+s+1} \right) \right], \tag{13}$$

where lowercase letters with hats denote log-deviation of a variable from its steady state. This condition shows that current output (equal to current spending of household) depends on sentimental expectations of the entire paths for aggregate output, short-term nominal interest rate and inflation. If households anticipate higher output, they also forecast that income will increase, which stimulates their spending and, therefore, current output. Similarly, higher anticipated real interest rate discourages current spending, so output today declines. I will discuss how sentimental expectations are formed, after I present the supply side of the economy.

Each intermediate firm is indexed by $j \in [0,1]$ and hires labor in the competitive market at real wage W_t taken by each firm as given to produce an intermediate good j with the technology identical across firms:

$$y_{jt} = A_t L_{jt}^{1-\alpha},$$

where A_t is common aggregate productivity that follows AR(1) in logs. Each period, a random fraction $1-\theta$ of the entire firm population are allowed to reset their price, as in Calvo (1983). The problem of firm j that is given an opportunity to reset its price is to maximize a flow of expected profits

$$\begin{aligned}
&\max_{P_{jt}^*} \hat{\mathbb{E}}_t \sum_{s=0}^{\infty} \theta^s \Lambda_{t,t+s} \frac{P_t}{P_{t+s}} \left(P_{jt}^* \, y_{t+s|t} - TC_{t+s}(y_{t+s|t}) \, P_{t+s} \right) \\
&\qquad\qquad \text{subject to} \\
&Y_{t+s|t} = \left(\frac{P_{jt}^*}{P_{t+s}} \right)^{-\varepsilon} Y_{t+s}
\end{aligned} \tag{14}$$

where $\Lambda_{t,t+s} \equiv \beta^s \mu_{c,t+s}/\mu_{c,t}$ is a stochastic discount factor, $TC_{t+s}(y_{t+s|t})$ is real total cost of producing $y_{t+s|t}$, and P_t is aggregate price level. Similar to household, all firms share sentimental expectations $\hat{\mathbb{E}}_t$.

Appendix section E.2 contains detailed derivations of optimality conditions from firm problem. The log-linearized version of firm j's optimality condition is

$$p_{jt}^* - p_{t-1} = (1-\beta\theta) \sum_{s=0}^{\infty} (\beta\theta)^s \left(\psi_y \hat{\mathbb{E}}_t \hat{y}_{t+s} - \psi_a \hat{\mathbb{E}}_t a_{t+s} \right) + \sum_{s=0}^{\infty} (\beta\theta)^s \hat{\mathbb{E}}_t \pi_{t+s}. \tag{15}$$

It shows that price inflation of firm j is determined by sentimental expectations of the entire paths for aggregate output, productivity and inflation. Expectations of higher aggregate output (which implies higher income in the economy) or higher inflation encourage a given firm j to increase a reset price, and anticipation of higher productivity leads it to lower the price.

Lastly, there is a monetary authority that controls a short-term nominal interest rate following a Taylor-type rule (Taylor, 1993). Monetary authority smooths the interest rate path by placing weight ρ_r on the previous period's interest rate. In a log-linearized form, the Taylor-type rule is given by

$$\hat{r}_t = \rho_r \hat{r}_{t-1} + (1-\rho_r)\left(\phi_\pi \pi_t + \phi_y \hat{y}_t \right) + v_t^R, \tag{16}$$

where a monetary policy shock v_t^R follows an AR(1).

6.2 Linking Sentiment Shocks with Sentimental Beliefs

Sentimental expectations are incorporated into the model in a stylized way to align with empirical facts. The literature on expectations and the evidence presented in section 4.2 suggest that economic beliefs react jointly to exogenous disturbances. In contrast to other papers that assume the existence of distinct shocks to expectations of each variable, I introduce a single sentiment shock ζ_t that affects all beliefs simultaneously with the convention that positive shocks are associated with an improvement in sentiments.[16] I do not aim to explain a persistent bias in households' or firms' expectations relative to professional forecasters[17]. Instead, I assume that sentimental expectations are on average rational, but a realization of a sentiment shock results in their deviation from the rational part. Another feature evident from correlations of estimated sentiment shocks with other variables (see Tables 2 and 9) is that households adjust not only their expectations of future outcomes, but also perceptions of current economic conditions.

I assume that households and firms observe sentiment shocks. In line with empirical facts, sentimental perceptions and forecasts at horizon $s \geq 0$ are defined by

$$\hat{\mathbb{E}}_t x_{t+s} = \mathbb{E}_t x_{t+s} + D_x \hat{\mathbb{E}}_t \zeta_{t+s},$$

where $\mathbb{E}_t$ is the rational expectation operator and the parameter D_x controls how strongly and in what direction the perceptions and expectations of a given variable respond to sentiment shocks. There may be a certain degree of persistence in the evolution of sentiment shocks, thus they are assumed to follow an AR(1) with the persistence parameter ρ_ζ and standard deviation of the innovation term σ_ζ.

[16]It is important to note the difference in sign conventions between the VAR analysis and the model. The empirical VAR approach identifies sentiment shocks from inflation expectations; hence, a positive shock corresponds to a deterioration in sentiments. In the model, I adopt the opposite convention to align with the intuitive interpretation that positive shocks are favorable and therefore improve sentiments.

[17]See, for example, the work of Bhandari et al. (2025) who propose an explanation of the wedge in households' forecasts.

Given this structure, sentimental forecasts can be written as

$$\hat{\mathbb{E}}_t x_{t+s} = \mathbb{E}_t x_{t+s} + D_x \rho_\zeta^s \, \zeta_t, \tag{17}$$

where the operator $\hat{\mathbb{E}}_t$ applied to ζ_t is removed because a current sentiment shock is observed by agents. This definition suggests that households and firms form a sentimental forecast/perception by taking a rational forecast / current observation of a given quantity and combining it with a sentiment shock. The parameter D_x determines how strongly sentimental beliefs deviate from the rational benchmark in response to a sentiment shock. Given $\rho_\zeta \in [0, 1)$, the effect of sentiment shocks on agents' beliefs weakens with horizon s.

In the New Keynesian model, sentimental expectations of aggregate output, inflation and productivity are defined according to (17), that is

$$\hat{\mathbb{E}}_t \hat{y}_{t+s} = \mathbb{E}_t \hat{y}_{t+s} + D_y \rho_\zeta^s \, \zeta_t, \tag{18}$$

$$\hat{\mathbb{E}}_t \pi_{t+s} = \mathbb{E}_t \pi_{t+s} + D_\pi \rho_\zeta^s \, \zeta_t, \tag{19}$$

and

$$\hat{\mathbb{E}}_t a_{t+s} = \mathbb{E}_t a_{t+s} + D_a \rho_\zeta^s \, \zeta_t. \tag{20}$$

Beliefs about the short-term interest rate are defined in a similar spirit. I assume households recognize that the central bank sets the interest rate according to the monetary policy rule. Specifically, when forecasting the future policy rate, households are aware that the monetary authority will set the interest rate depending on future inflation and output, but they form their forecasts using sentimental beliefs. This assumption is in line with the evidence documented by Dräger et al. (2016) that around half of U.S. households form expectations consistent with the Taylor rule – the share similar to that of professional forecasters. Therefore, sentimental expectations of the short-term interest rate at horizon $s \geq 0$ are given by

$$\hat{\mathbb{E}}_t \hat{r}_{t+s} = \mathbb{E}_t \hat{r}_{t+s} + D_r \rho_r^s \zeta_t + (\phi_\pi D_\pi + \phi_y D_y)(1 - \rho_r) \sum_{k=1}^{s} \rho_r^{s-k} \rho_\zeta^k \, \zeta_t. \tag{21}$$

Similarly to sentimental beliefs of aggregate output, inflation and productivity defined above, sentimental forecasts of the interest rate comprise a rational component and a component that is governed by sentiment shocks. Derivation of (21) is shown in Appendix section E.3.

Note that the last two terms in (21) depend on the parameter D_r, which controls how strongly perception of the current interest rate deviates from its true value, as well as parameters of the monetary policy rule and sentiment-related parameters D_π, D_y. To remain consistent with the empirical evidence on the comovement of beliefs driven by sentiments (see, for example, Kamdar and Ray (2025) and section 5.2), I impose the following sign restrictions: $D_y > 0, D_a > 0, D_\pi < 0, D_r < 0$. In other words, a positive sentiment shock improves agents' sentiments, and they expect higher aggregate income and productivity, but lower inflation and interest rate.

Given the definition of sentimental beliefs, I substitute them into the equilibrium conditions (13) and (15), and rewrite those in a recursive form. Derivations are provided in Appendix section E.4. The aggregate demand equation is given by

$$\hat{y}_t = \mathbb{E}_t \hat{y}_{t+1} - \frac{1}{\gamma_c}\left(\hat{r}_t - \mathbb{E}_t \pi_{t+1}\right) + \varphi \zeta_t, \tag{22}$$

where

$$\begin{aligned}\varphi = &\underbrace{\frac{1-\beta}{\beta}\frac{D_y}{1-\beta\rho_\zeta}}_{\mathrm{I}} - \frac{1}{\gamma_c}\left(\underbrace{\frac{D_r}{1-\beta\rho_r}}_{\mathrm{II}} + \underbrace{\frac{\beta\rho_\zeta(\phi_\pi D_\pi + \phi_y D_y)(1-\rho_r)}{(1-\beta\rho_r)(1-\beta\rho_\zeta)}}_{\mathrm{III}}\right) \\ &+ \frac{1}{\gamma_c}\underbrace{\frac{\rho_\zeta D_\pi}{1-\beta\rho_\zeta}}_{\mathrm{IV}}.\end{aligned} \tag{23}$$

Notice that with no sentiment shocks in the model ($D_y = D_r = D_\pi = 0$), the last term drops out, and the demand equation reduces to a fully rational version. The parameter φ represents the partial equilibrium effect of a sentiment shock on aggregate output, holding all other variables and rational forecasts fixed.

The parameter can be decomposed into distinct components that capture how sentiment shocks distort variable-specific beliefs relative to the rational expectation benchmark. The expression for φ presented in (23) includes four components. Component I reflects expectations of the entire trajectory of aggregate output induced by sentiment shocks, while Component IV corresponds to sentiment-driven expectations of future inflation. Component II captures the households' perception of the current interest rate. Since households are aware of the Taylor rule, Component III represents expectations of future interest rates set by the central bank that households believe responds to sentiment-driven fluctuations in future inflation and output.

The Phillips curve augmented with sentiment shocks is derived in Appendix section E.5 and takes the form

$$\pi_t = \kappa_y \hat{y}_t - \kappa_a a_t + \beta \mathbb{E}_t \pi_{t+1} + \psi \zeta_t, \tag{24}$$

where

$$\psi = \underbrace{\frac{(1-\beta\theta)(1-\theta)\psi_y D_y}{\theta(1-\beta\theta\rho_\zeta)}}_{\text{I}} - \underbrace{\frac{(1-\beta\theta)(1-\theta)\psi_a D_a}{\theta(1-\beta\theta\rho_\zeta)}}_{\text{II}} + \underbrace{\frac{(1-\theta)D_\pi}{\theta(1-\beta\theta\rho_\zeta)}}_{\text{III}}. \tag{25}$$

Similar to the aggregate demand equation, the Phillips curve equation contains a rational benchmark as a special case with $D_y = D_a = D_\pi = 0$, which implies $\psi = 0$. The parameter ψ captures the partial equilibrium effect of a sentiment shock on inflation, holding every other variable and rational expectations fixed.

The expression for ψ specified in (25) shows that there are three parts that reflect sentimental components of beliefs. Because firms take into account the entire path of future aggregate output, productivity and inflation, sentiment shocks jointly shift all of these dimensions of their forecasts. Accordingly, Component I reflects contemporaneous perceptions of output and its expectations at all future horizons, as shaped by sentiment shocks, and similar productivity and inflation beliefs are encapsulated in Components II and III, respectively.

6.3 Analytical Framework

Before looking at quantitative results, it is useful to build intuition about how sentiment shocks affect the economy. To do so, I consider a simplified model without interest rate smoothing ($\rho_r = 0$), which enables me to obtain the solution in a closed form. With no dependence on last period's endogenous variables, the solution is static and linear in three exogenous shocks

$$
\begin{aligned}
\hat{y}_t &= M_a a_t + M_v v_t^R + M_\zeta \zeta_t, \\
\pi_t &= Q_a a_t + Q_v v_t^R + Q_\zeta \zeta_t, \\
\hat{r}_t &= U_a a_t + U_v v_t^R + U_\zeta \zeta_t.
\end{aligned}
$$

I find the solution by method of undetermined coefficients. Plugging these expressions into equilibrium conditions (13), (15) and the monetary policy rule (16), and matching states yields the solution. Since sentiment shock is the primary source of interest, I only present the corresponding coefficients:

$$
M_\zeta = \frac{-\frac{\phi_\pi}{\gamma_c}\psi + \varphi}{1 + \frac{\phi_\pi}{\gamma_c}\kappa_y + \frac{\phi_y}{\gamma_c}}, \tag{26}
$$

$$
Q_\zeta = \frac{\psi\left(1 + \frac{\phi_y}{\gamma_c}\right) + \kappa_y \varphi}{1 + \frac{\phi_\pi}{\gamma_c}\kappa_y + \frac{\phi_y}{\gamma_c}}, \tag{27}
$$

$$
U_\zeta = \frac{\phi_\pi \psi + \varphi\left(\phi_\pi \kappa_y + \phi_y\right)}{1 + \frac{\phi_\pi}{\gamma_c}\kappa_y + \frac{\phi_y}{\gamma_c}}. \tag{28}
$$

All standard parameters in the expressions above are positive, and parameters φ, ψ represent the partial equilibrium effect of sentiment shocks on, respectively, aggregate output and inflation holding all other variables and rational expectations fixed. Expressions above show that all coefficients $M_\zeta, Q_\zeta, U_\zeta$ increase in both φ and ψ except that M_ζ decreases in ψ.

Intuition for these relationships is as follows. Suppose φ increases and consider a positive realization of sentiment shock. In response to improved sentiments, households spend more, and output increases due to a direct effect. Higher aggregate output in the economy encourages firms to set higher prices, which leads to an inflation rise. Both higher output and higher inflation provide an incentive for monetary authority to raise interest rate, and output still increases in the end although by less than an initial impulse.

Now, suppose ψ increases under the same scenario when positive sentiment shock occurs. The direct effect implies that firms would be willing to cut prices by less in response to improved sentiments. With a higher level of prices, monetary authority tends to raise interest rate, which negatively affects consumer spending. As a result, output in the economy increases by less, and prices end up being higher in response to same-sized positive sentiment shock.

In general, given sign restrictions $D_y > 0, D_a > 0, D_\pi < 0$ and $D_r < 0$, the sign of coefficients φ and ψ, and therefore $M_\zeta, Q_\zeta, U_\zeta$ is unknown. However, I present analytical results below and show that under certain conditions, it is possible to obtain any sign of a given coefficient from M_ζ, Q_ζ and U_ζ. Therefore, this model can produce either sign of the response of macro variables to sentiment shocks depending on parameter values.

Let me focus on M_ζ which governs how aggregate output contemporaneously reacts to sentiment shocks. Proposition 6.1 below shows that under certain parametric restrictions, for any given $D_r < 0$, $D_a > 0$ and $D_\pi < 0$, one can find a value $D_y > 0$ at which M_ζ may be either positive, negative, or zero, that is, an output response on impact may take any sign. I can establish a similar result with the roles of D_π and D_y switched if an alternative condition on parameters is imposed.

Proposition 6.1. *Consider the case $\rho_r = 0$. If $\beta\phi_\pi > 1$ and $\frac{1-\beta}{\beta} < \frac{\beta}{\gamma_c}\rho_\zeta\phi_y$, then for given $D_r < 0, D_a > 0$ and $D_\pi < 0$, there exists a threshold value $\bar{D}_y > 0$ such that we have $M_\zeta < (>)\ 0$ for $D_y > (<) \bar{D}_y$ and $M_\zeta = 0$ for $D_y = \bar{D}_y$.*

Alternatively, if the following additional condition is satisfied

$$
\begin{aligned}
&-\frac{D_r}{\gamma_c} + \frac{\phi_\pi(1-\beta\theta)(1-\theta)\psi_a}{\gamma_c\theta(1-\beta\theta\rho_\zeta)} D_a < \\
&-\frac{1}{1-\beta\rho_\zeta}\left(\frac{1-\beta}{\beta} - \frac{\beta\rho_\zeta\phi_y}{\gamma_c}\right) D_y + \frac{\phi_\pi(1-\beta\theta)(1-\theta)\psi_y}{\gamma_c\theta(1-\beta\theta\rho_\zeta)} D_y,
\end{aligned}
$$

then for given $D_r < 0, D_a > 0$ and $D_y > 0$, there exists a threshold value $\bar{D}_\pi < 0$ such that we have $M_\zeta > (<)\ 0$ for $D_\pi < (>)\ \bar{D}_\pi$ and $M_\zeta = 0$ for $D_\pi = \bar{D}_\pi$.

Proof. Proof is given in Appendix section F. □

I present a slightly different result summarized in Proposition 6.2, for Q_ζ which governs an on impact response of inflation to sentiment shocks. Under relatively weak parametric conditions, I show that it is possible to make inflation increase or fall in response to sentiment shocks by varying either D_y or D_π. The latter determine the degree of sensitivity of agents' beliefs about output and inflation to sentiment shocks.

Proposition 6.2. *Consider the case $\rho_r = 0$. As long as*

$$\frac{\kappa_y}{1-\beta\rho_\zeta}\left(\frac{\beta\rho_\zeta\phi_y}{\gamma_c} - \frac{1-\beta}{\beta}\right) \neq \left(1+\frac{\phi_y}{\gamma_c}\right)\frac{(1-\beta\theta)(1-\theta)\psi_y}{\theta(1-\beta\theta\rho_\zeta)},$$

then for given $D_\pi < 0$ and $D_y \equiv \bar{D}_y > 0$, there exist values $D_r < 0, D_a > 0$ such that the sign of Q_ζ can be made either positive or negative by choosing $D_y \gtrless \bar{D}_y$. Otherwise, we cannot alter the sign of Q_ζ by varying D_y.

Alternatively, as long as

$$\frac{\kappa_y\rho_\zeta}{\gamma_c(1-\beta\rho_\zeta)}(\beta\phi_\pi - 1) \neq \left(1+\frac{\phi_y}{\gamma_c}\right)\frac{(1-\theta)}{\theta(1-\beta\theta\rho_\zeta)},$$

then for given $D_y > 0$ and $D_\pi \equiv \bar{D}_\pi < 0$, there exist values $D_r < 0, D_a > 0$ such that the sign of Q_ζ can be made either positive or negative by choosing $D_\pi \gtrless \bar{D}_\pi$. Otherwise, we cannot alter the sign of Q_ζ by varying D_π.

Proof. Proof is given in Appendix section F. □

I present a similar result for the coefficient U_ζ which determines a contemporaneous response of the interest rate to sentiment shocks. Proposition 6.3 shows that under relatively weak parametric restrictions, the coefficient U_ζ can be made positive or negative by varying either D_y or D_π. In other words, under specific parameterization, the interest rate may increase or decline as a result of sentiment shocks.

Proposition 6.3. *Consider the case $\rho_r = 0$. As long as*

$$\frac{\phi_\pi\kappa_y + \phi_y}{1-\beta\rho_\zeta}\left(\frac{\beta\rho_\zeta\phi_y}{\gamma_c} - \frac{1-\beta}{\beta}\right) \neq \phi_\pi\frac{(1-\beta\theta)(1-\theta)\psi_y}{\theta(1-\beta\theta\rho_\zeta)},$$

then for given $D_\pi < 0$ and $D_y \equiv \bar{D}_y > 0$, there exist values $D_r < 0, D_a > 0$ such that the sign of U_ζ can be made either positive or negative by choosing $D_y \gtrless \bar{D}_y$. Otherwise, we cannot alter the sign of U_ζ by varying D_y.

Alternatively, as long as

$$(\phi_\pi \kappa_y + \phi_y)\frac{\rho_\zeta}{\gamma_c(1-\beta\rho_\zeta)}(\beta\phi_\pi - 1) \neq \phi_\pi \frac{(1-\theta)}{\theta(1-\beta\theta\rho_\zeta)},$$

then for given $D_y > 0$ and $D_\pi \equiv \bar{D}_\pi < 0$, there exist values $D_r < 0, D_a > 0$ such that the sign of U_ζ can be made either positive or negative by choosing $D_\pi \gtrless \bar{D}_\pi$. Otherwise, we cannot alter the sign of U_ζ by varying D_π.

Proof. Proof is given in Appendix section F. □

7 Quantitative Implications of Model with Sentimental Beliefs

I present quantitative implications for the model with sentimental beliefs from section 6. First, I estimate parameters in two versions of the model. Next, I present impulse responses to sentiment shocks in comparison with those to fundamental disturbances. Finally, I decompose the partial and general equilibrium effects of sentiment shocks into separate expectation effects.

7.1 Parameter Estimation and Targeted Moments

The model features several new parameters that characterize the response of expectations to sentiment shocks. Since it is a small-scale model, I choose to follow a limited information estimation approach and employ a Simulated method of moments (SMM) (Duffie and Singleton, 1993) to estimate sentiment-related parameters and the parameters governing stochastic processes of fundamental shocks.

The essence of SMM is to find the parameter values that minimize the weighted distance between empirical moments and the moments implied by model-simulated data. I use the optimal weight matrix defined by the inverse of heteroscedasticity and autocorrelation consistent covariance matrix of moments (Newey and West, 1987).

Before estimation, I fix some standard parameters at the values commonly found in the literature, and set the interest rate smoothing parameter at the estimate provided

Parameter	Description	Value
β	Discount factor	0.995
γ_c	Elasticity of intertemporal substitution	1
γ_L	Inverse Frisch elasticity of labor supply	1
α	Elasticity of output to labor	0.33
θ	Probability of keeping price unchanged	0.75
ε	Elasticity of substitution between varieties	6
ϕ_π	Taylor rule coefficient on inflation	1.5
ϕ_y	Taylor rule coefficient on output	0.1
ρ_r	Interest rate smoothing	0.65
σ_ζ	Standard deviation of sentiment shocks	1

Table 11: Fixed model parameters.

Notes: Table presents parameters that are fixed at values commonly found in the literature, and the value of parameter ρ_r is the estimate provided by Carvalho et al. (2021).

by Carvalho et al. (2021). I normalize the standard deviation of sentiment shocks $\sigma_\zeta = 1$ since their effects on a given variable x are multiplicative with the parameter D_x, and the standard deviation cannot be separately identified. Table 11 presents values for the fixed parameters.

In estimating the parameters, I target a set of second order moments and the on-impact impulse response of inflation expectations to sentiment shocks. In addition to using inflation forecasts for moment calculation, I include an expected change in real household income in the next year and associate real income with output in the model. I obtain this time series from the directional responses to the corresponding MSC question following the approach of Bhandari et al. (2025) based on the method of Carlson and Parkin (1975) and Mankiw et al. (2004), the details are provided in Appendix section A.4.

To highlight the contribution of sentiment shocks, I consider a fully rational version of the model in which I turn off sentiment shocks, and reestimate the parameters of stochastic processes of fundamental shocks by SMM. I use the same set of targeted moments except for the impulse response of inflation expectations.

I present the estimated parameters in Table 12. The results show that sentiment-related parameter estimates are statistically different from zero, and sentiment shocks

Parameter	σ_a	σ_v	ρ_a	ρ_v	D_y	D_π	D_a	D_r	ρ_ζ
SE Model	0.0074 (0.0004)	0.0006 (0.0005)	0.8065 (0.0053)	0.3104 (0.0310)	0.0119 (0.0016)	-0.0003 (0.0000)	0.0118 (0.0016)	-0.0195 (0.0007)	0.9901 (0.0021)
RE Model	0.0045 (0.0000)	0.0046 (0.0000)	0.8997 (0.0000)	0.0000 (0.0008)					

Table 12: Parameter estimates in two versions of the model.

Notes: Table presents parameter estimates from the sentimental model (SE) and the purely rational model (RE). Parameters are estimated by a Simulated Method of Moments. Standard errors are in parentheses.

Moments:	$corr(\Delta y_t, \Delta y_{t-1})$	$corr(\mathbb{E}_t\pi_{t+1}, \mathbb{E}_{t-1}\pi_t)$	$corr(r_t, r_{t-1})$	$corr(\mathbb{E}_t\pi_{t+1}, \mathbb{E}_t\Delta y_{t+1})$
Data	-0.101	0.757	0.956	-0.370
SE Model	-0.081	0.771	0.990	-0.246
RE Model	-0.223	0.817	0.588	-0.372
Moments:	$corr(\mathbb{E}_t\pi_{t+1}, \Delta y_t)$	$corr(\mathbb{E}_t\pi_{t+1}, \pi_t)$	$corr(\mathbb{E}_t\pi_{t+1}, r_t)$	$std(\Delta y_t)$
Data	-0.064	0.693	0.281	0.011
SE Model	-0.038	0.707	0.406	0.008
RE Model	0.129	0.976	-0.024	0.010
Moments:	$std(r_t)/std(\pi_t)$	$std(\mathbb{E}_t\pi_{t+1})/std(\pi_t)$	$IRF_0(\mathbb{E}_t\pi_{t+1}), \%$	
Data	2.290	0.461	-0.017	
SE Model	2.296	0.394	-0.017	
RE Model	2.028	0.762		

Table 13: Data-based moments and simulated moments in two versions of the model.

Notes: Table reports data-based moments, and simulated moments in the sentimental model (SE) and the purely rational model (RE). Model-implied moments are averaged across simulated samples using estimated parameter values.

play a non-negligible role in driving macroeconomic fluctuations. The shock persistence is estimated close to one, suggesting that sentiment disturbances generate prolonged effects on the economy, consistent with the empirical evidence presented in section 4.2. The fully rational model attributes no persistence to monetary policy disturbances, but once sentiment shocks are introduced, the estimated persistence becomes positive and statistically significant.

I simulate both versions of the model evaluated at the respective parameter estimates and report average model-implied moments along with empirical counterparts in Table 13. The framework incorporating sentiment shocks is able to match most moments closely, whereas the performance of the purely rational model is notably worse in this regard.

7.2 Impulse Responses

I compute impulse responses of three model variables to each shock, with the initial impulse given by one standard deviation. I choose the sign of responses to fundamental shocks such that output declines and plot them in Figure 6.

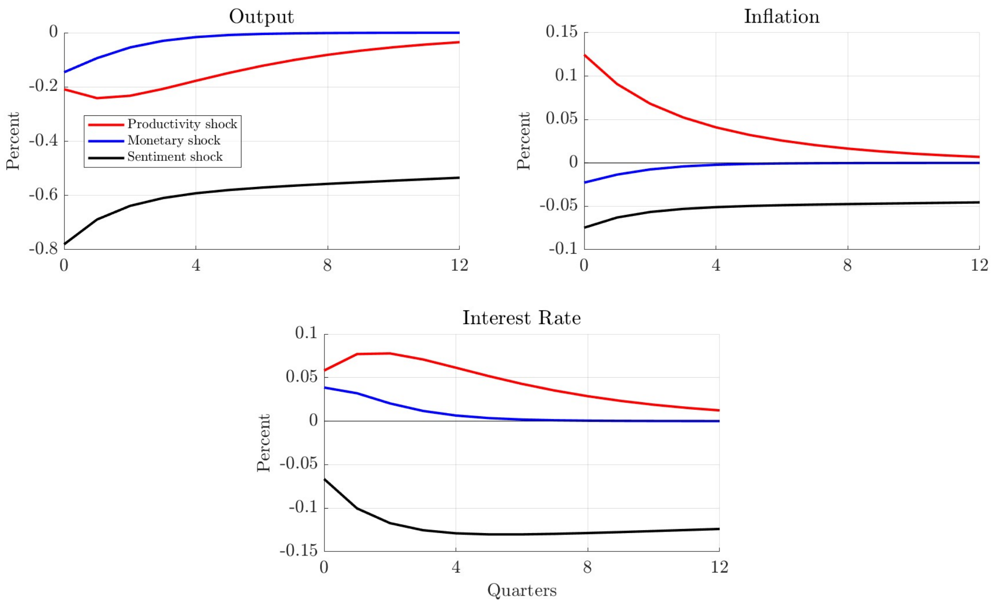

Figure 6: Model-implied impulse responses to each shock.

Notes: Figure presents impulse responses of three model variables to a positive sentiment shock and two fundamental shocks: monetary policy and productivity. The initial impulse is given by one standard deviation. The sign of responses to fundamental shocks is chosen such that output declines.

I find that a positive sentiment shock leads to a decline in prices (inflation decreases), and has large, negative effects on output. The long-lived response of the latter variable matches highly persistent empirical responses of consumption quantities in the VAR, which can be attributed to a high estimate of the sentiment persistence. Since both output and inflation fall on impact, the central bank responds by cutting interest rates, and the downward path persists at further horizons due to interest rate smoothing.

Recall that a positive sentiment shock corresponds to an improvement in sentiments, thus both inflation expectations and realized inflation decline, in line with VAR-based empirical findings. In contrast, the model generates a contraction in output under conditions of improved sentiments.

To understand what drives these responses, I decompose the partial equilibrium effect of a sentiment shock on output and inflation, captured by coefficients φ and ψ, respectively, into distinct sentimental expectation effects. The expression for φ given in (23) suggests that the partial equilibrium effect of sentiment shocks on output can be decomposed into expectations of the entire trajectories of aggregate output, inflation and the interest rate. Since households in the model recognize that the central bank follows a Taylor rule, their interest rate expectations incorporate both the perception of the current policy rate and forecasts of future rates determined by the central bank's response to anticipated fluctuations in output and inflation. Similarly, an expression for ψ presented in (25) suggests a decomposition of the partial equilibrium effect on inflation into expectations of the entire future paths of aggregate output, productivity and inflation.

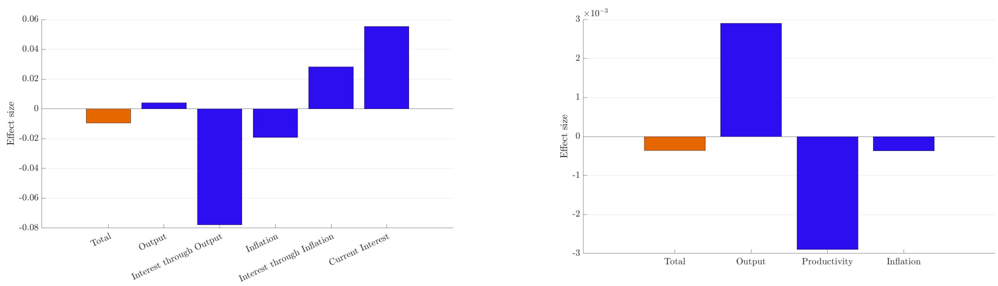

Figure 7: Decomposition of partial equilibrium effects of sentiment shocks on output and inflation.

Notes: Left panel presents a decomposition for output, right panel - for inflation. Partial equilibrium effects of sentiment shocks on output and inflation in the model with sentimental beliefs are given by expressions (23) and (25), respectively. See text for details.

I plot this decomposition for output and inflation in Figure 7. It shows that the negative partial equilibrium effect on output is primarily driven by expectations of higher future interest rates which reflect the central bank's anticipated response to higher expected output. Forecasts of lower future inflation determine the negative partial equilibrium effect on inflation: although expectations of the full paths of output and productivity give rise to large effects, they cancel each other out.

Since the model is solved numerically, analytical expressions for the responses of model variables to a sentiment shock are not available. However, I can consider a special case without interest rate smoothing ($\rho_r = 0$) and use the solution in closed form obtained in section 6.3. On impact responses of macro variables to a sentiment shock are given by (26)-(28), which, in turn, are the functions of φ and ψ. The analytical solution enables me to perform a similar decomposition of the general equilibrium effect of a sentiment shock on aggregate output, inflation and the interest rate.

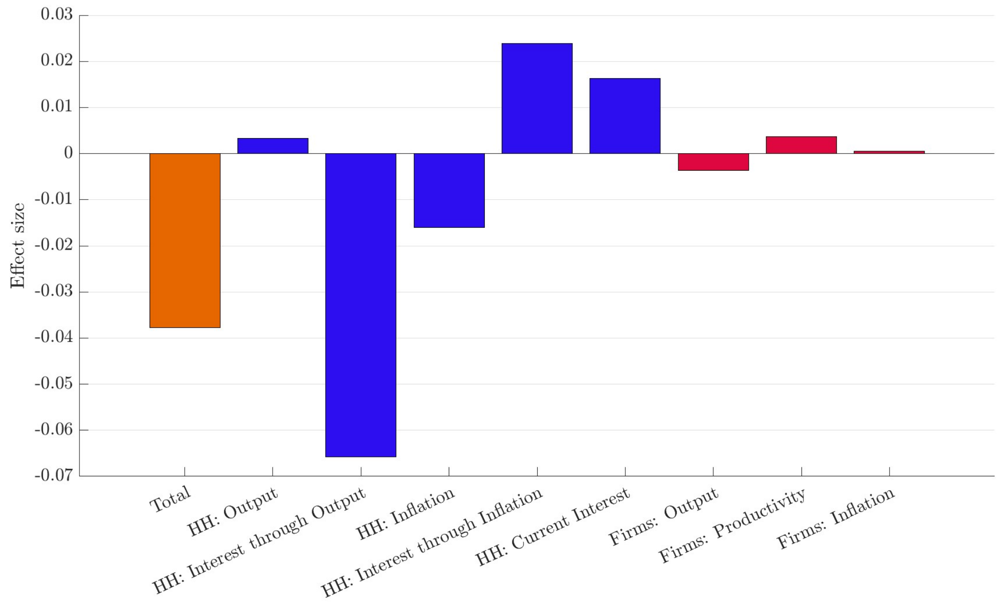

Figure 8: Decomposition of general equilibrium effect of sentiment shocks on output.

Notes: Model without interest rate smoothing. General equilibrium effect of sentiment shocks on output is given by expression (26). See text for details.

I present the decomposition for output in Figure 8 and find that the general equilibrium effect on output in this version of the model is also mainly shaped by household's forecasts of higher interest rates resulting from the central bank's response to anticipated increases in future output. Some effects, for example, operating through expectations of future inflation and the current perception of interest rates, largely offset each other.

In Appendix section G, I plot the decomposition of the general equilibrium effect on inflation and the interest rate. I make a similar conclusion that the magnitude and sign of these effects are mainly explained by higher anticipated interest rates.

8 Conclusions

This paper leverages the comovement in households' expectations and proposes the idea that there exists a type of shocks that lead households to revise the entire system of their economic beliefs. I refer to this kind of shocks as "sentiment shocks", while sentiments should be understood as reflecting "animal spirits" that correspond to psychological and emotional biases.

I use survey data from the Michigan Survey of Consumers and propose to identify these shocks in SVAR by exploiting the empirically documented comovement of households' beliefs and their consumption responses triggered by shifts in the perceived economic outlook.

Examining the dynamic propagation of sentiment shocks, I find that these disturbances exert prolonged effects on consumer perceptions and expectations of current and future economic conditions. As a result, I document a persistent negative impact on both non-durable and durable consumption, with the effect on durable spending being especially pronounced. These results are robust to alternative identifying restrictions, different sample periods, and additional VAR exercises. Sentiment shocks account for a sizable proportion of fluctuations in both durable and non-durable consumption, and are distinct from standard macroeconomic shocks available in the literature.

I augment a standard New Keynesian model by introducing sentiment shocks that generate deviations of agents' perceptions and expectations from their rational counterparts. Estimation of parameters in the extended framework indicates a non-trivial contribution of sentiment shocks to cyclical dynamics. I find that the effects of sentiment disturbances on model variables are primarily driven by households' expectations of future interest rate movements arising from the central bank's response to anticipated variations in output.

Appendices

A Data and Sources

A.1 Data Used in VAR

1. The following time series were retrieved from FRED Database (2025):

- Industrial production, monthly, Total Index, FRED ID: INDPRO. Transformation: $100 \times \ln(\cdot)$.
- Consumer Price Index for All Urban Consumers: All Items in U.S. City Average, monthly, Percent Change from Year Ago, FRED ID: CPIAUCSL.
- Unemployment Rate, monthly, Percent, FRED ID: UNRATE.
- Real personal consumption expenditures: Durable goods, monthly, chain-type quantity index, FRED ID: DDURRA3M086SBEA. Transformation: $100 \times \ln(\cdot)$.
- Real personal consumption expenditures: Nondurable goods, monthly, chain-type quantity index, FRED ID: DNDGRA3M086SBEA. Transformation: $100 \times \ln(\cdot)$.
- Consumer Price Index for All Urban Consumers: All Items in U.S. City Average, monthly, Index (1982–1984=100), FRED ID: CPIAUCSL. Transformation: $100 \times \ln(\cdot)$.

2. The following time series were retrieved from Surveys of Consumers (2025):

- Inflation expectations: Table 32: Expected Change in Prices During the Next Year, monthly, Median, Percent.
- Probability of real income gains: Table 16: Probability of Real Income Gains During the Next 5 Years, monthly, Mean, Percent.
- Proportion of respondents who expect their real income to go up: Table 14: Expected Change in Real Household Income During Next Year, Percentage of

respondents reporting ‘Income Up More’ relative to the total of ‘Income Up More’, ‘Income Up Same’ and ‘Prices Up More’ responses

A.2 Data Used in Factor Model

1. The following time series were constructed from Surveys of Consumers (2025):

- Table 6: Current Financial Situation Compared with a Year Ago, Percentage of respondents reporting ‘Better’ relative to the total of ‘Better’, ‘Same’ and ‘Worse’ responses

- Table 8: Expected Change in Financial Situation in a Year, Percentage of respondents reporting ‘Better Off’ relative to the total of ‘Better Off’, ‘Same’ and ‘Worse’ responses

- Table 13: Expected Household Income Change During the Next Year, Median, Percent

- Table 14: Expected Change in Real Household Income During Next Year, Percentage of respondents reporting ‘Income Up More’ relative to the total of ‘Income Up More’, ‘Income Up Same’ and ‘Prices Up More’ responses

- Table 17: Probability of Losing a Job During the Next 5 Years, Mean, Percent

- Table 18: Probability of Adequate Retirement Income, Mean, Percent

- Table 19: Change in Likelihood of Comfortable Retirement, Percentage of respondents reporting ‘Gone Up’ relative to the total of ‘Gone Up’, ‘Stay the Same’ and ‘Gone Down’ responses

- Table 23: News Heard of Recent Changes in Business Conditions, Relative Index: number of respondents who heard favorable news minus number of respondents who heard unfavorable news plus 100

- Table 25: Current Business Conditions Compared with a Year Ago, Percentage of respondents reporting ‘Better Now’ relative to the total of ‘Better Now’, ‘Same’ and ‘Worse Now’ responses

- Table 26: Expected Change in Business Conditions in a Year, Percentage of respondents reporting 'Better' relative to the total of 'Better', 'Same' and 'Worse' responses
- Table 28: Business Conditions Expected During the Next Year, Percentage of respondents reporting 'Good Times' relative to the total of 'Good Times', 'Uncertain' and 'Bad Times' responses
- Table 29: Business Conditions Expected During the Next 5 Years, Percentage of respondents reporting 'Good Times' relative to the total of 'Good Times', 'Uncertain' and 'Bad Times' responses
- Table 30: Expected Change in Unemployment During the Next Year, Percentage of respondents reporting 'More' relative to the total of 'More', 'Same' and 'Less' responses
- Table 31: Expected Change in Interest Rates During the Next Year, Percentage of respondents reporting 'Go Up' relative to the total of 'Go Up', 'Stay the Same' and 'Go Down' responses
- Table 34: Opinions About the Government's Economic Policy, Percentage of respondents reporting 'Good Job' relative to the total of 'Good Job', 'Fair Job' and 'Poor Job' responses
- Table 35: Buying Conditions for Large Household Goods, Percentage of respondents reporting 'Good time to buy' relative to the total of 'Good time to buy', 'Uncertain/Depends' and 'Bad time to buy' responses
- Table 37: Buying Conditions for Vehicles, Percentage of respondents reporting 'Good time to buy' relative to the total of 'Good time to buy', 'Uncertain' and 'Bad time to buy' responses
- Table 41: Buying Conditions for Houses, Percentage of respondents reporting 'Good time to buy' relative to the total of 'Good time to buy', 'Uncertain/Depends' and 'Bad time to buy' responses

- Table 43: Selling Conditions for Houses, Percentage of respondents reporting 'Good time to sell' relative to the total of 'Good time to sell', 'Uncertain/Depends' and 'Bad time to sell' responses

A.3 Data Used in Estimation of Model Parameters

1. The following time series were retrieved from FRED Database (2025):

- Real Gross Domestic Product, quarterly, Billions of Chained 2017 Dollars, Seasonally Adjusted Annual Rate, FRED ID: GDPC1.
- Population Level, quarterly (average across corresponding months), Thousands of Persons, FRED ID: CNP16OV.
- Log-change in GDP per capita = $\Delta \ln(GDPC1/(4 \times CNP16OV))$.
- Gross Domestic Product: Implicit Price Deflator, quarterly, Index 2017=100, FRED ID: GDPDEF.
- Inflation = $\ln(GDPDEF_t) - \ln(GDPDEF_{t-1})$.
- Federal Funds Effective Rate, quarterly, Percent, FRED ID: FEDFUNDS.
- Interest rate = $\ln(1 + FEDFUNDS/400)$.

2. The following time series were retrieved from Surveys of Consumers (2025):

- Inflation Expectations, Table 32: Expected Change in Prices During the Next Year, quarterly, Median, Percent. Transformation: divided by 400.
- Expected change in real household income, quarterly, Mean, Percent. Transformation: divided by 400. Obtained from qualitative data following the method of Bhandari et al. (2025), Carlson and Parkin (1975), and Mankiw et al. (2004), see Appendix section A.4 for details. Based on proportions reported in Table 14: Expected Change in Real Household Income During Next Year.

A.4 Quantitative Expectations from Categorical Data

The MSC only elicits qualitative responses (up, same, or down) to a question concerning an expected change in real household income. To recover a quantitative time series, I follow the approach of Bhandari et al. (2025) based on the method of Carlson and Parkin (1975) and Mankiw et al. (2004). I assume that in each period t, there exists a continuous cross-sectional distribution of expected changes in real income given by a Normal distribution $\mathcal{N}(\mu_t, \sigma_t^2)$ where both mean and standard deviation are time-varying. I also assume there is a time-invariant threshold value a such that households whose income expectations exceed a (lie below $-a$) report it as "expected income up" ("expected income down"), whereas the responses of income expectations that lie within an interval $[-a, a]$ are recorded as "same expected income".

Let me denote the time t proportion of responses "up", "same" and "down" as q_t^u, q_t^s, q_t^d, correspondingly. The assumptions stated above imply that

$$q_t^d = \Phi\left(\frac{-a-\mu_t}{\sigma_t}\right), \quad q_t^u = 1 - \Phi\left(\frac{a-\mu_t}{\sigma_t}\right),$$

where $\Phi(\cdot)$ denotes a cdf of the standard Normal distribution. Isolating the mean and standard deviation yields

$$\sigma_t = \frac{2a}{\Phi^{-1}(1-q_t^u) - \Phi^{-1}(q_t^d)},$$

$$\mu_t = a - \sigma_t \Phi^{-1}(1-q_t^u).$$

It remains to pin down an unknown a. I select the value of a such that the time series average of the cross-sectional standard deviations σ_t divided by the time series average of the cross-sectional dispersion of the forecast[18] for real personal consumption expenditure obtained from Survey of Professional Forecasters (2025), is equal to a similar ratio for inflation expectations. Given the value of a, I obtain a time series of expected mean

[18]For CPI inflation, I use the difference between the 75th and the 25th percentiles of the forecasts for the inflation level as a dispersion measure; for real personal consumption expenditure, I use the difference between the 75th and 25th percentiles of the projections for Q/Q growth as a dispersion measure. The forecast horizon is four quarters ahead for both variables.

changes in real household income (in percent).

B Imposing Both Zero and Sign Restrictions in SVAR

B.1 Identification Problem

The reduced-form parameters B of the VAR model in (3) are identified. Thus, given a sample of realized data $\{y_t\}_{t=1}^T$, one can obtain the estimates of reduced-form shocks $\{\hat{u}_t\}_{t=1}^T$ and the covariance matrix $\hat{\Sigma}$. In empirical macroeconomics, researchers are typically interested in dynamic responses of variables to a given structural shock. A SVAR model in (3) implies that an on-impact response of endogenous variables in y_t to each structural shock in ε_t is given by $(A_0^\intercal)^{-1}$, thus it depends on the matrix A_0. The subsequent evolution of $\{y_t\}$ follows endogenous dynamics in (3) governed by reduced-form parameters B.

However, one may not easily find the unique matrix A_0 given estimates of (B, Σ). More precisely, two sets of structural parameters (A_0, A_+) and $(\bar{A}_0, \bar{A}_+)$ are observationally equivalent if and only if the distribution of the stochastic process y_t is the same (Rothenberg, 1971). For VAR model considered here, it implies that the same set of reduced-form parameters (B, Σ) may be associated with multiple sets of structural parameters (A_0, A_+).

To demonstrate this explicitly for a Gaussian VAR model, suppose we found one set of structural parameters (A_0, A_+) that satisfies a VAR model (3) and condition (4). Take some $n \times n$ orthogonal matrix Q and define $\bar{A}_0 = A_0 Q$, $\bar{A}_+ = A_+ Q$. This new set of structural parameters fits a VAR model equally well:

$$\bar{A}_+ \bar{A}_0^{-1} = A_+ Q Q^{-1} A_0^{-1} = A_+ A_0^{-1} = B,$$

and

$$\mathbb{E}(u_t u_t^\intercal) = (\bar{A}_0 \bar{A}_0^\intercal)^{-1} = (A_0 \underbrace{Q Q^\intercal}_{=I_n} A_0^\intercal)^{-1} = \Sigma.$$

Since any orthogonal matrix Q will work, there are infinitely many sets of structural parameters that correspond to reduced-form parameters (B, Σ).

B.2 Distribution over Reduced-Form and Structural Parameters

We saw in the discussion above that a given set of reduced-form parameters (B, Σ) may be associated with multiple sets of structural parameters (A_0, A_+). If we restrict VAR models to be Gaussian, then (A_0, A_+) and $(\bar{A}_0, \bar{A}_+)$ are observationally equivalent if and only if $\bar{A}_0 = A_0 Q$ and $\bar{A}_+ = A_+ Q$ for some matrix Q from the set of all $n \times n$ orthogonal matrices. Recall that both sets of structural parameters give the same reduced-form parameters (B, Σ). Given this, the reduced-form parameterization can be extended to include some orthogonal matrix Q, which will allow to directly embed zero restrictions and select the draws that satisfy sign restrictions. SVAR model (2) can be rewritten in the orthogonal reduced-form parameterization

$$y_t^\top = x_t^\top B + \varepsilon_t^\top Q^\top h(\Sigma), \tag{A.1}$$

where matrix $h(\Sigma)$ is some differentiable decomposition of the covariance matrix Σ such that $h(\Sigma)^\top h(\Sigma)$. I take $h(\Sigma)$ to be the Cholesky decomposition.

Drawing from the orthogonal reduced-form parameterization is easier, but I am interested in drawing structural parameters. Arias et al. (2018) define a mapping from (A_0, A_+) to (B, Σ, Q) by

$$f_h(A_0, A_+) = (\underbrace{A_+ A_0^{-1}}_{B}, \underbrace{(A_0 A_0^\top)^{-1}}_{\Sigma}, \underbrace{h((A_0 A_0^\top)^{-1}) A_0}_{Q}).$$

The inverse mapping also exists and can be explicitly stated as

$$f_h^{-1}(B, \Sigma, Q) = (\underbrace{h(\Sigma)^{-1} Q}_{A_0}, \underbrace{B h(\Sigma)^{-1} Q}_{A_+}).$$

This enables one to transform reduced-form parameters and an orthogonal matrix to structural parameters and then verify if the desired restrictions are satisfied.

The methods of Arias et al. (2018) are implemented using a Bayesian approach. Authors argue that they are most efficient when the priors distribution belongs to a family of conjugate distributions. The priors should be determined for both reduced-form parameters (B, Σ) and the space of orthogonal matrices. In this regard, reduced-form parameters are assumed to follow the normal-inverse-Wishart (NIW) distribution, and I select a uniform distribution over the space of orthogonal matrices conditional on reduced-form parameters following the reasoning advanced by Arias et al. (2018). The joint distribution is referred to as the uniform-normal-inverse-Wishart (UNIW).

In this case, authors show that if one independently draws (B, Σ, Q) from the UNIW distribution over the orthogonal reduced-form parameters and transforms them into structural parameters (A_0, A_+), we actually obtain independent draws of structural parameters (A_0, A_+) from normal-generalized-normal (NGN) distribution over the structural parameterization. Since we can easily draw from the NIW distribution, and know the explicit mapping from reduced-form to structural parameters given by the function f_h^{-1}, this result makes it possible to obtain draws of structural parameters that satisfy all the zero and sign restrictions of interest.

B.3 Numerical Algorithm

The following algorithm from Arias et al. (2018) enables one to draw independently from the distribution over the structural parameterization conditional on zero restrictions where z_j zero restrictions are imposed on jth structural shock. $F(A_0, A_+)$ denotes $r \times n$ matrix representing IRFs, and Z_j is $z_j \times r$ matrix that defines z_j zero restrictions on jth structural shock.

1. Draw (B, Σ) from NIW distribution.
2. For each $j = 1, \ldots, n$, draw $\boldsymbol{x}_j \in \mathbb{R}^{n+1-j-z_j}$ independently from standard Normal distribution and define $\boldsymbol{w}_j = \boldsymbol{x}_j / \|\boldsymbol{x}_j\|$.
3. Define $Q = [\boldsymbol{q}_1, \boldsymbol{q}_2, \ldots, \boldsymbol{q}_n]$ recursively by $\boldsymbol{q}_j = K_j \boldsymbol{w}_j$ such that columns of differentiable almost everywhere matrix K_j form an orthonormal basis for the null space of the $(j - 1 + z_j) \times n$ matrix

$$M_j = \left[\boldsymbol{q}_1 \; \ldots \; \boldsymbol{q}_{j-1} \; \left(Z_j F \left[f_h^{-1}(B, \Sigma, I_n) \right] \right)^\intercal \right]^\intercal .$$

4. Set $(A_0, A_+) = f_h^{-1}(B, \Sigma, Q)$.

5. Repeat steps 1–4 until the required number of draws is obtained.

Arias et al. (2018) note that the distribution over structural parameters given zero restrictions implied by the algorithm above is different from the NGN distribution over structural parameters given zero restrictions. They develop a method to compute numerically the density of the distribution from the algorithm above, which can be used as a proposal distribution in the importance sampler to draw independently from the distribution of interest (NGN) over structural parameters (A_0, A_+) conditional on zero restrictions.

The algorithm based on the theory and implementation of Arias et al. (2018) that allows to obtain independent draws from NGN distribution over structural parameters given both zero and sign restrictions, is provided below.

1. Use the algorithm outlined above to obtain a draw (A_0, A_+).

2. If (A_0, A_+) satisfy the sign restrictions, set its importance weight to

$$\frac{NGN(A_0, A_+)}{NIW\,(f_h(A_0, A_+))\, v_{(g \circ f_h)|\mathcal{Z}}(A_0, A_+)} \propto \frac{|\det(A_0)|^{-(2n+m+1)}}{v_{(g \circ f_h)|\mathcal{Z}}(A_0, A_+)},$$

   where $\mathcal{Z}$ denotes the set of structural parameters that satisfy zero restrictions, $v_{(g \circ f_h)|\mathcal{Z}}(\cdot)$ is the volume element and g is auxiliary function (see Arias et al. (2018) for details). If (A_0, A_+) do not satisfy the sign restrictions, set importance weight to zero.

3. Repeat steps 1–2 until the required number of draws is obtained.

4. Resample with replacement using the importance weights.

C Robustness Exercises and Extensions

In section 4, I found that a positive sentiment shock leads to a persistent decline in both durable and non-durable consumption, a gradual increase in unemployment and effects on inflation under two identification schemes. These results may be dependent on a particular specification of the VAR, so I perform a series of robustness checks in this section to verify that conclusions continue to qualitatively hold true. I consider different samples (extending a baseline one to start in 1978 or excluding a period of the COVID-19 pandemic), an alternative measure of consumer price inflation and removing zero restrictions on the response of inflation expectations in identification.

C.1 Unrestricted Responses of Consumption

The baseline identifying restrictions dictate that both durable and non-durable consumption fall on impact of adverse sentiment shocks. My findings further show that following an on-impact decline in consumption, sentiment shocks cause large negative effects on these quantities that persist for at least three years. One may argue that a fall in consumption may be a direct result of the restrictions imposed in the beginning.

Here, I demonstrate that even without these restrictions, I still find that both consumption categories display prolonged negative responses to unfavorable sentiment shocks. To do so, I remove sign restrictions on consumption from the baseline identification while keeping the remaining zero and sign restrictions (Table 1 lists all baseline restrictions), estimate VAR following the same steps as before and identify sentiment shocks.

I plot the resulting impulse responses in Figure A.1. The bottom left panel clearly indicates that the distribution of durable consumption responses is heavily skewed toward negative values across all the horizons considered, including on impact. The position of the median response provides evidence of this: it lies closer to the left tail of the distribution and stabilizes around -0.7% from horizon 10 onward. Although some probability mass of the response distribution is located in the positive domain, this fact is a natural consequence of set identification when no sign restrictions are imposed on consumption, since with non-zero probability some rotation matrices might generate a positive response. Nevertheless, this SVAR specification favors a fall in durable consumption as a result of weakened beliefs.

Estimation of this SVAR version also shows that non-durable spending tends to decline steadily over time, as can be inferred from the middle right panel of Figure

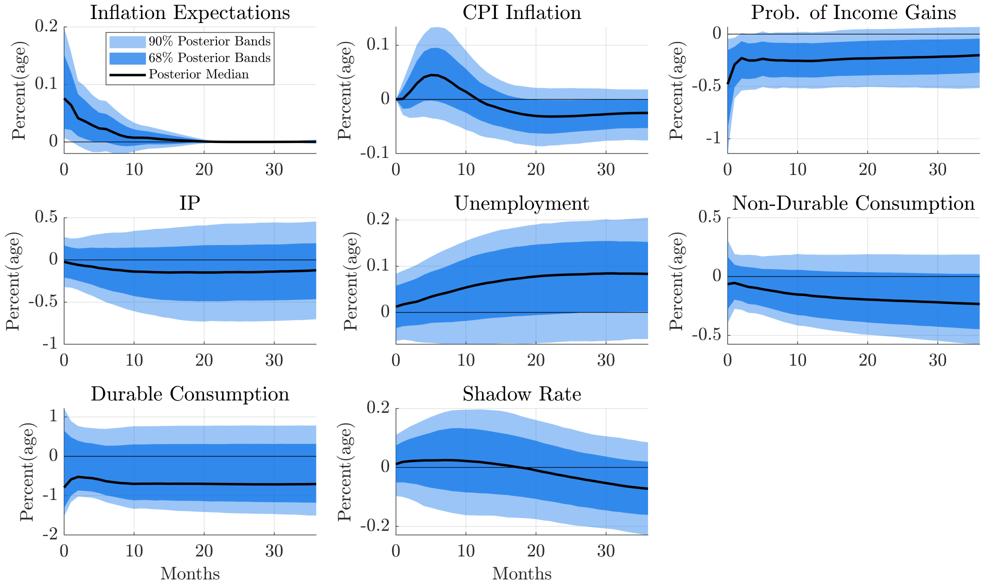

Figure A.1: Impulse responses to sentiment shock. Consumption responses are unrestricted.

Notes: I remove sign restrictions on consumption responses and keep all remaining zero and sign restrictions. All identifying restrictions originally imposed in the baseline version, are summarized in Table 1. Positive sentiment shock raises inflation expectations. Sample period: from January 1998 to December 2024. Black line depicts posterior median response, shaded areas denote 68% and 90% posterior bands.

A.1. Responses of non-durable consumption can take both positive and negative sign on impact, but the posterior median is estimated negative. This downward pattern continues further, and by horizon 30, around 80% of probability mass is concentrated on negative responses.

Comparison of the response distribution across two SVAR specifications one year after the shock supports the conclusion that consumption evolution is not driven by on impact sign restrictions. In Figure A.2, I plot histograms of responses for the baseline SVAR version and the other one with no sign restrictions on consumption, and normalize them to a probability density function. The bottom left panel depicts responses of durable good spending and shows that for the model with unrestricted consumption, a main part of the probability mass lies on the negative semi-axis. The modes of both

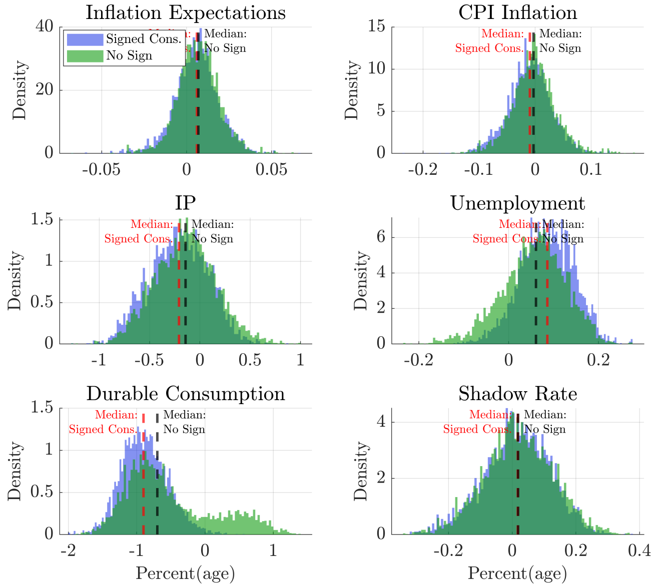

Figure A.2: Histograms of responses to sentiment shock at horizon 12 across two SVARs.

Notes: Plots responses of variables to sentiment shock in SVAR models across all parameter draws. Histograms are normalized to a probability density function. Two models considered: the baseline where both durable and non-durable consumption contract on impact (in blue), and the other where no such sign restrictions are imposed. All restrictions for the baseline SVAR are summarized in Table 1. Positive sentiment shock raises inflation expectations. Sample period: from January 1998 to December 2024. Vertical dashed lines denote posterior median responses in each model.

distributions are almost identical, while the medians are positioned very close to each other. The middle right panel implies similar conclusions for responses of non-durable consumption.

Thus, even if both durable and non-durable consumption are left unrestricted, I do find evidence that deterioration of beliefs induced by sentiment shocks translates into a reduction in households' spending on goods of both categories.

C.2 Unrestricted Response of Inflation

The main text employs identifying restrictions which require that the response of CPI inflation be either zero or positive on impact. Zero restrictions may result in biased estimates of impulse responses if they do not happen to hold in the true data generating process. Imposing a specific sign (positive in this case) may also lead to misleading conclusions in case the opposite sign is true, and the identified set of impulse responses will characterize the effects of shocks different from those of interest. This concern is valid for identification of sentiment shocks since an increase or decrease in inflation may be consequential for the direction of response and the subsequent evolution of consumption.

I present evidence that inflation indeed tends to accelerate in the short run and ends up being below the steady state at longer horizons. Specifically, I leave the response of inflation completely unrestricted and keep other restrictions from the baseline identification (see Table 1).

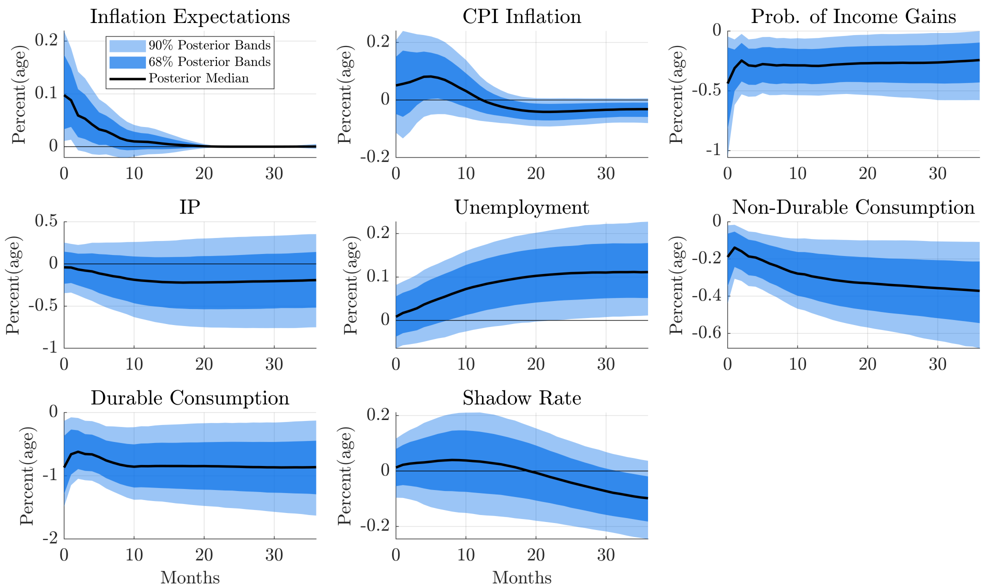

Figure A.3: Impulse responses to sentiment shock. Inflation response is unrestricted.

Notes: I remove any restrictions on inflation response and keep all remaining zero and sign restrictions. All identifying restrictions originally imposed in the baseline version, are summarized in Table 1. Positive sentiment shock raises inflation expectations. Sample period: from January 1998 to December 2024. Black line depicts posterior median response, shaded areas denote 68% and 90% posterior bands.

I report estimated impulse responses under the less restrictive identification scheme in Figure A.3. The top center panel illustrates that inflation follows an upward trend for around five months since the shock impact before reversing and remaining below the steady state. The distributions of short-run responses are located primarily on positive values at horizons 0–10, as suggested by probabilities presented in Table A.1. It is worthwhile to note that the patterns of durable and non-durable consumption responses remain unchanged relative to the baseline identification results, and the estimated magnitudes of decline are very similar. Thus, a restriction of an increase in inflation on impact of sentiment shock appears to be valid.

C.3 Excluding a COVID Period

The baseline sample ends in December 2024 and overlaps with the COVID period characterized by volatile dynamics. Both inflation expectations and realized inflation in U.S. hit record high levels during this time, and measures of consumer confidence showed a persistent decline. Sentiment shocks which occurred during this episode, may play a meaningful role in estimating large effects on consumption and, as a result, on the broader economy.

I show that excluding the COVID episode from analysis qualitatively does not change conclusions. Specifically, the sample starts in January 1998 and stops in December 2019 just before COVID began to spread, and I use this shortened sample to estimate the same VAR specification as in the main text.

Figure A.4 plots impulse responses to adverse sentiment shocks identified with baseline restrictions. Consumer beliefs jointly respond to sentiment shock: as inflation expectations rise, probability of income gains remains below its steady state level at almost all horizons following an initial drop.

More pessimistic outlook generates a deep contraction in durable consumption, as we saw in section 4.2. The peak decline is estimated to be lower using a sample that excludes COVID: 0.9% as compared to over 1% with an original sample. There are also differences in the response path. Main text results show that from horizon 10 and on, durable consumption stays at a persistently depressed level. Meanwhile, estimation based on a short sample suggests that consumption of durable goods exhibits modest upward dynamics after stabilizing at a lower level over horizons 10–30.

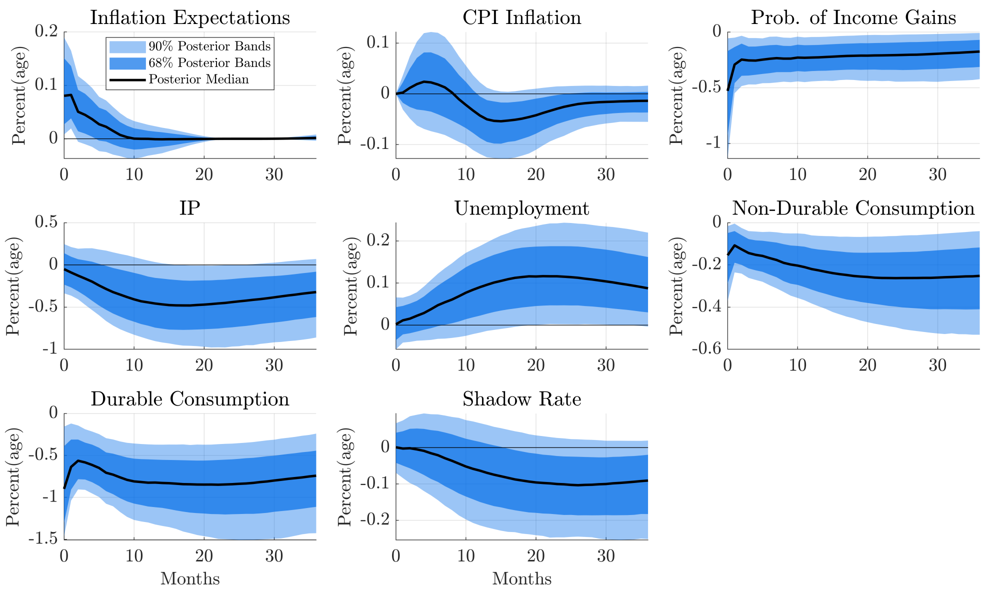

Figure A.4: Impulse responses to sentiment shock. Sample excludes the COVID episode.

Notes: Sample period: from January 1998 to December 2019. Baseline identification, all identifying restrictions are summarized in Table 1. Positive sentiment shock raises inflation expectations. Black line depicts posterior median response, shaded areas denote 68% and 90% posterior bands.

Deteriorating households' beliefs also lead to a fall in non-durable consumption in line with results from section 4.2. Its evolution in short run looks very similar, and differences arise in subsequent periods. Using an original sample produces a lasting decline in household spending on non-durables that intensifies over time. However, when the COVID episode data are not included in VAR, I estimate a smaller magnitude of contraction in non-durable consumption (a little over 0.25% versus almost 0.35%) and record an upward trend at longer horizons. Despite these quantitative differences, I find that the COVID event does not appear to play a primary role in generating pronounced negative effects of sentiment shocks on consumption.

A notable decline in consumption results in recessionary developments in the economy. The shape of the unemployment response and a peak increase are closely aligned across both VAR specifications based on different samples. Nevertheless, I find that when the COVID period is excluded, IP falls by a much larger magnitude: its peak decline is estimated at over 0.45% in contrast to just above 0.2%. This result can be attributed to two things: a rapid recovery of IP that began in the second half of 2020, and the use of Pandemic priors in VAR, which absorbs unusually volatile dynamics during the early COVID months, including a sharp contraction in IP.

A historic rise in inflation in 2021-2022 not covered by a shorter sample can explain a more moderate upward movement in CPI inflation, as evidenced in the top center panel of Figure A.4. At subsequent horizons, it decreases, and the response turns negative, which is consistent with the main text findings. When estimation is based on a shorter sample, the Fed starts cutting interest rates sooner, which may indicate its reaction to a sharper contraction in IP.

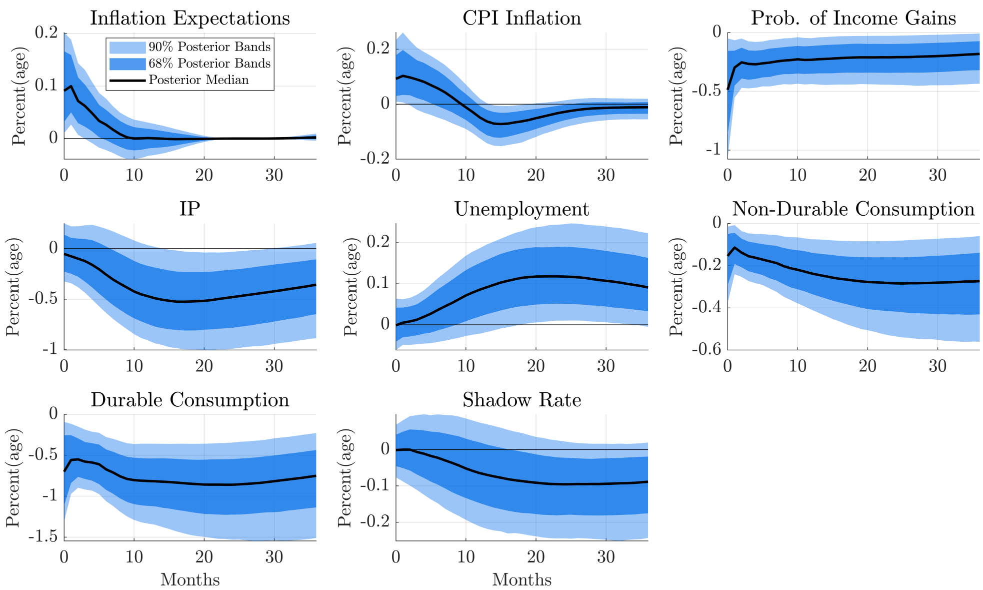

Figure A.5: Impulse responses to sentiment shock. Sample excludes the COVID episode. Inflation rises on impact.

Notes: Sample period: from January 1998 to December 2019. Alternative identification, all identifying restrictions are summarized in Table 5. Positive sentiment shock raises inflation expectations. Black line depicts posterior median response, shaded areas denote 68% and 90% posterior bands.

I also explore the consequences of employing a shorter sample when the identification scheme restricts inflation to rise on impact, the impulses responses are displayed in

Figure A.5. Similar to the full sample results, the specification with the COVID period excluded also favors acceleration of inflation following a sentiment shock realization with comparable peak values of around 0.1pp, although the persistence of this short-term positive effect appears to be lower. The inflation response turns negative afterwards, and the peak decline in inflation is close to 0.07pp, which is by 0.03pp bigger than that under the full sample estimation.

I find similar differences in consumption paths across the samples when a positive inflation response is imposed. Both durable and non-durable consumer spending fall to a lesser extent, and signs of rebound emerge 30 months after the shock. In line with results discussed above using the baseline identification, IP appears to respond more strongly to adverse sentiment shocks when COVID data are not accounted for: the fall at its peak amounts to more than 0.5% compared with just over 0.2%.

Taken together, estimated effects of sentiment shocks suggest that both consumption types and real activity measures begin converging back to their steady state levels sooner, and I reveal some differences in the magnitude of impulse responses. Despite this, the comparison across two main identification schemes demonstrates that the key conclusions continue to hold even if a turbulent COVID episode is excluded from the analysis.

C.4 Alternative Measures for Prices

The baseline VAR specification includes CPI inflation among the variables and characterizes whether sentiment shocks generate an acceleration of inflation or disinflation. In the latter case, a price level may either increase at a more moderate pace or decrease. To explore this, I include a CPI in *log-level* instead of CPI inflation and reestimate the baseline VAR specification.

Figure A.6 plots impulse responses for this specification using baseline identifying restrictions presented in Table 1. In contrast to the baseline VAR (see Figure 2), I do not find a price increase shortly after the impact of a sentiment shock, instead prices remain mostly unchanged over horizons 1–10. The subsequent evolution, however, is consistent with one implied by the baseline results: I observe a downward trend in the price level which stays below the steady state by 0.08% three years after a shock occurs.

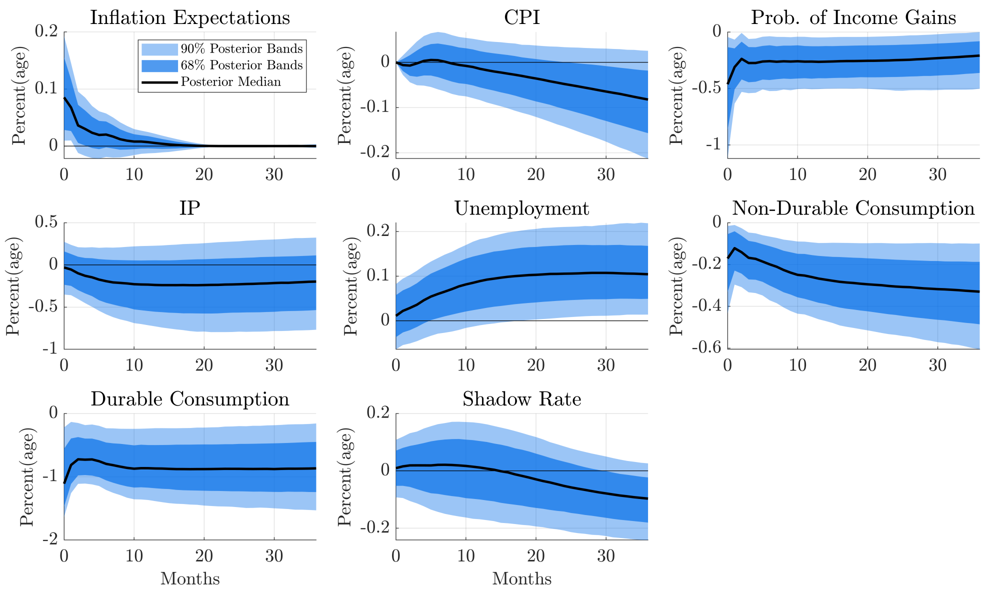

Figure A.6: Impulse responses to sentiment shock. CPI level.

Notes: Specification with CPI included in *log-level*. Baseline identification, all identifying restrictions are summarized in Table 1. Positive sentiment shock raises inflation expectations. Sample period: from January 1998 to December 2024. Black line depicts posterior median response, shaded areas denote 68% and 90% posterior bands.

Households' beliefs and real activity indicators react to a sentiment shock in a similar manner in both VAR specifications. The results with CPI included in levels point to a lasting and sizable decline in durable consumption, and suggest that non-durable spending keeps falling as time elapses since the impact. An observation of the price decrease is well aligned with these contractionary movements, and confirms that a slowdown is primarily driven by the demand side factors.

C.5 Extended Sample

An original sample starts in January 1998 and thus avoids the high inflation period of 1970s. This choice may be considered advantageous because inclusion of this period is likely to play a meaningful role in estimation of effects of sentiment shocks. I examine this question by focusing on the sample that starts in January 1982 and ends in December 2024. The choice of the starting point is motivated by an observation that inflation declines after reaching historically high levels and remains below 9% in all other periods.

Since probability of real income gains used in main text estimation, is not available from January 1982, I instead include the percentage of respondents who expect their income to increase more than prices will go up. I impose a similar sign restriction on this variable: the percentage of respondents falls in response to positive sentiment shocks that raise inflation expectations.

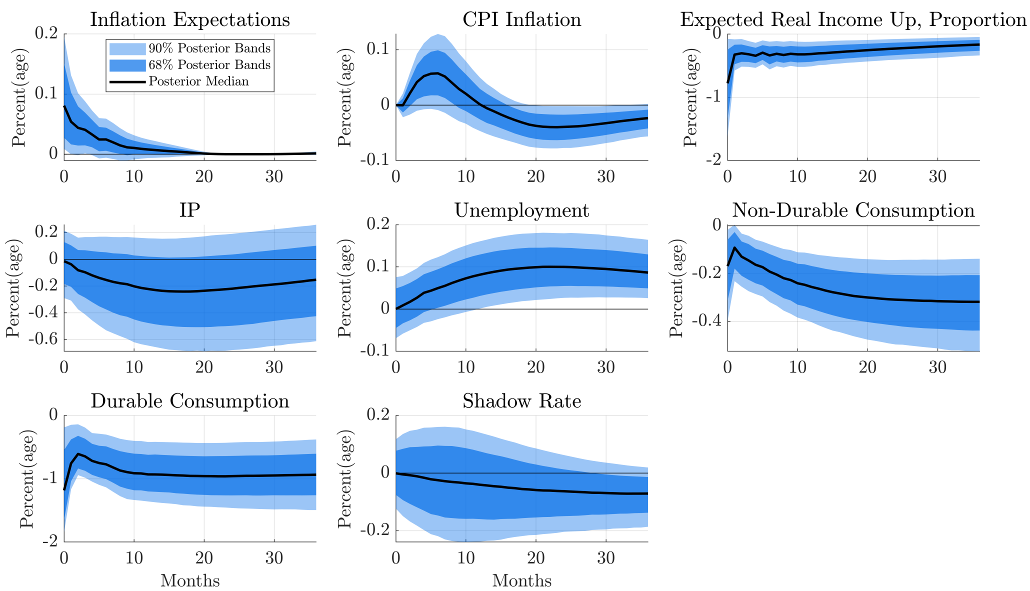

Figure A.7: Impulse responses to sentiment shock. Extended sample starts in January 1982.

Notes: Probability of real income gains is replaced with the percentage of respondents who expect their income to increase more than prices will go up. Identifying restrictions are based on Baseline identification (see Table 1). Positive sentiment shock raises inflation expectations. Sample period: from January 1982 to December 2024. Black line depicts posterior median response, shaded areas denote 68% and 90% posterior bands.

I implement baseline identifying restrictions and present the results in Figure A.7, which shows that the percentage of respondents who expect their real income to increase, falls on impact by almost 0.8pp and remains subdued at all subsequent horizons. A similar persistent response was observed for probability of real income gains in the sample starting in January 1998 (see Figure 2), so both series help sharpen identification of sentiment shocks.

More pessimistic beliefs have immediate effects on consumer spending. As was the case with results from the main text, durable consumption reacts most strongly. It drops by almost 1.2% on impact of sentiment shock - the fall is a bit larger relative to a shorter sample, after some upward correction declines again and persists in a depressed state (over 0.95% below trend as compared to 0.9% based on a shorter sample).

Non-durable spending also demonstrates contractionary dynamics, which resembles the baseline results. Its initial decline is a little bit over 0.15%, but is amplified at further horizons and reaches the magnitude of over 0.3%, which comes close to almost 0.35% under the baseline sample period. Thus, I find that consumption responses to sentiment shocks follow similar trajectories and exhibit comparable magnitudes of decline when extending the sample.

Sentiment shocks elicit a strong reaction of both consumption quantities, which generates a business cycle. Similar to the baseline results, we observe a gradual weakening of real activity, as reflected in downward movement in IP and an increase in unemployment. I find that probability distributions of IP and unemployment responses are more concentrated around corresponding medians, whose estimates are found similar across original and extended samples. Therefore, the model implies greater precision in estimating contractionary effects of sentiment shocks. It is also worthwhile to note that data indicate a short-lived increase in inflation followed by disinflation at later horizons in accordance with baseline findings.

Since Figure A.7 indicates that price inflation accelerates following positive sentiment shocks, I let inflation rise on impact (alternative identifying restrictions). From Figure A.8 which plots the responses, we observe an on-impact decline by 0.65pp in the percentage of households who report that their real income will rise. At later horizons, the response remains below the initial level. Qualitatively, it looks similar to the trajectory of probability of real income gains in the original sample depicted in Figure 3, although the response of probability appears to be more persistent. Expected inflation increases on impact and gradually returns to the steady state level, in line with results

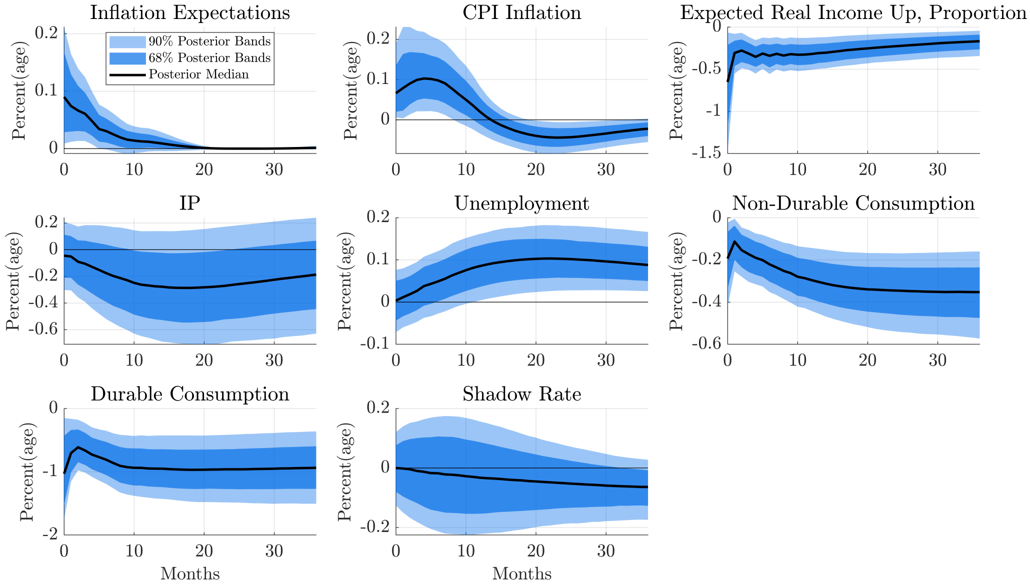

Figure A.8: Impulse responses to sentiment shock. Inflation rises on impact. Extended sample starts in January 1982.

Notes: Probability of real income gains is replaced with the percentage of respondents who expect their income to increase more than prices will go up. Identifying restrictions are based on alternative identification (see Table 5). Positive sentiment shock raises inflation expectations. Sample period: from January 1982 to December 2024. Black line depicts posterior median response, shaded areas denote 68% and 90% posterior bands.

obtained from the original sample.

Depressed economic beliefs lead to long-lived negative effects on consumer spending in both categories. The shape of durable consumption response is qualitatively similar across both specifications based on different sample periods, but it is worth highlighting quantitative differences. Specifically, in the case of an extended sample, durable consumption falls by more than 1% on impact and exhibits a persistent decline of around 0.95% starting from horizon 10 and on, as compared to, respectively, 0.85% and almost 0.9% from the baseline sample results.

Overall, non-durable consumption follows a downward path in response to sentiment shocks: the on-impact effect of -0.2% is comparable across both samples, but the rate of decline at subsequent months is slower when considering a longer period. As a result, the consumption response reaches the trough of -0.35%, in contrast to the estimate of -0.4% implied by the original sample.

The patterns of inflation and unemployment responses are comparable across two specifications based on different samples. However, I find some quantitative differences in the path of IP. With an extended sample, I observe a more pronounced decline of almost 0.3% in IP around horizon 15, and it starts to converge back to a baseline level thereafter.

Despite the fact that some of the estimated effects differ quantitatively, my findings based on the extended sample that starts in January 1982, still show that sentiment shocks jointly move economic beliefs, which in turn has immediate and lasting effects on both durable and non-durable consumption.

C.6 Unrestricted Response of Inflation Expectations

My identifying restrictions postulate that monetary authorities successfully manage inflation expectations and can re-anchor them at the target after sentiment shocks distort forecasts of expected inflation. I explore the role of these assumptions by identifying sentiment shocks with no zero restrictions imposed on the response of inflation expectations. At the same time, I keep the remaining identifying restrictions in SVAR.

Figure A.9 plots the results of estimating this SVAR specification. Inflation forecasts tend to converge to a steady state level faster, but stay close to the path estimated with a full list of restrictions. The negative response of probability of real income gains is more pronounced in the very short run, but it reverses at longer horizons and lies slightly above the trajectory implied by the baseline.

Overall, the shape of durable consumption response is comparable to that obtained with the baseline identification: it drops on impact, displays some upward dynamics for the next several periods, nevertheless, the decline persists from horizon 10 and on. I find that removing zero restrictions on inflation expectations has some quantitative implications for durable spending. In particular, its largest fall of around 0.75% occurs on impact, and at most of the remaining horizons, durable consumption remains persistently below its steady state, within the range of -0.7% and -0.65%. Analogous figures from the baseline estimation are, correspondingly, more than 1% and approxi-

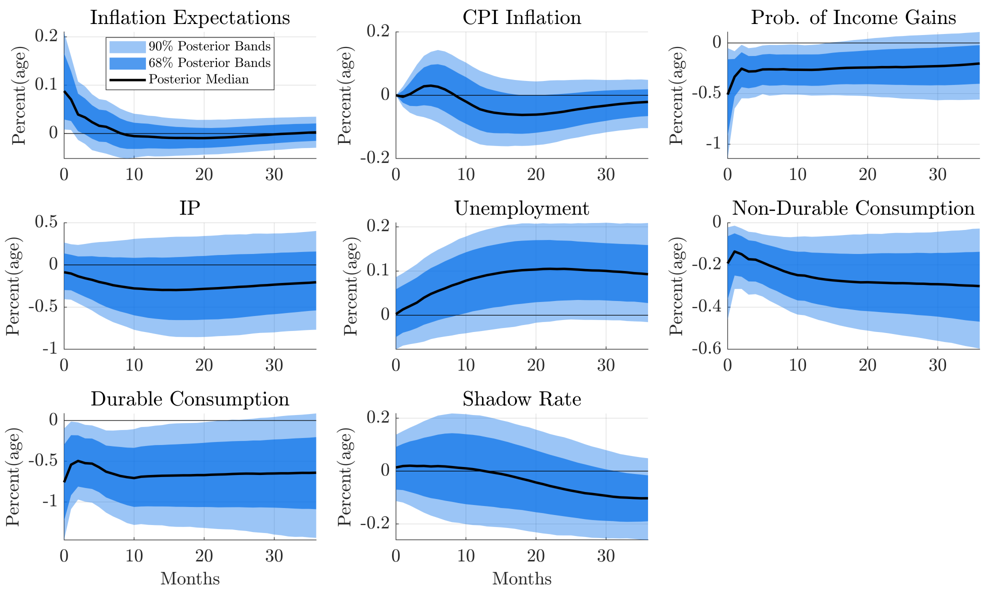

Figure A.9: Impulse responses to sentiment shock. No zero restrictions on inflation expectations response.

Notes: I do not impose zero restrictions on inflation expectations response and keep all remaining identifying restrictions coming from baseline identification. Original identifying restrictions are summarized in Table 1. Positive sentiment shock raises inflation expectations. Sample period: from January 1998 to December 2024. Black line depicts posterior median response, shaded areas denote 68% and 90% posterior bands.

mately -0.9%. These differences may stem from the faster improvement of households' beliefs with no active management of expectations by central bank. This is evidenced by the observation that inflation forecasts in Figure A.9 turn negative, in other words, households expect that inflation will be lower than what they thought before sentiment shocks hit.

I document quantitative differences for non-durable consumption, but to a lesser extent. The magnitude of an initial fall is similar, and non-durable spending gradually contracts over time. The downward adjustment, however, occurs at a more moderate rate, resulting in a decline of 0.3% relative to slightly less than 0.35% under the baseline.

The effects on other real activity measures are mostly similar. Unemployment gradually rises in the beginning, reaches a peak of the same magnitude, but starts falling earlier. A SVAR version with no restrictions imposed on inflation beliefs implies a deeper contraction in IP.

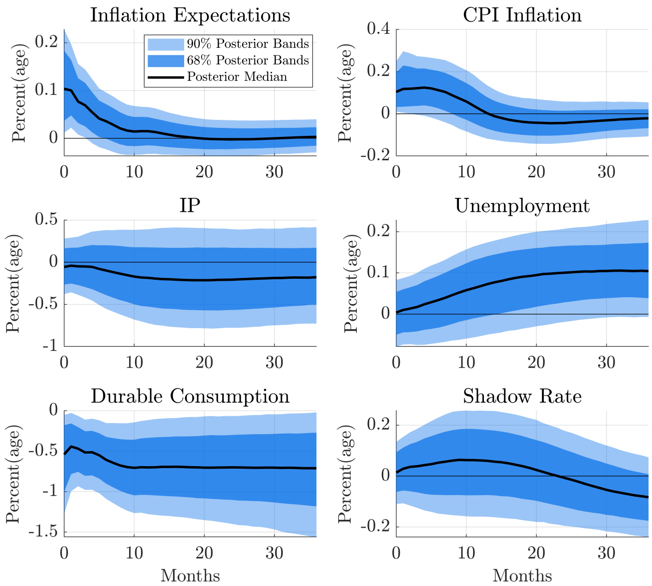

Figure A.10: Impulse responses to sentiment shock. Inflation rises on impact. No zero restrictions on inflation expectations response.

Notes: I do not impose zero restrictions on inflation expectations response and keep all remaining identifying restrictions coming from alternative identification. Original identifying restrictions are summarized in Table 5. Positive sentiment shock raises inflation expectations. Sample period: from January 1998 to December 2024. Black line depicts posterior median response, shaded areas denote 68% and 90% posterior bands.

Next, I assess the role of restrictions on inflation expectations in an alternative identification scheme which assumes an increase in inflation on impact of adverse sentiment shocks, and plot the results in Figure A.10. I find that consumer beliefs regarding expected inflation and real income gains, respond almost identically to the case with zero restrictions imposed on inflation forecasts.

Durable consumption is the variable that exhibits smaller fluctuations, although the overall response pattern remains unchanged. Specifically, spending on durables drops by almost 0.55% on impact (compared to slightly more than 0.85% under the assumption that central bank can effectively re-anchor inflation expectations), continues to decline further until horizon 10, after which it stabilizes at 0.7% below its steady state value (compared to approximately 0.9%).

Implementing an alternative identification scheme with no restrictions on expected inflation does not result in meaningful differences in median responses of other macroeconomic variables. Thus, the main impact of lifting these identifying restrictions is concentrated in the path of durable consumption. Nevertheless, even under these estimates, the relative effect is substantial: a 0.1pp rise in inflation beliefs generates a fall of 0.7% in durable consumption.

D Factor Model

Suppose that we have p traits observed at each point in time. For now, let me omit the time subscript. Collect all those traits together in $p \times 1$ vector

$$X = \begin{pmatrix} x_1 \\ \vdots \\ x_p \end{pmatrix}.$$

Vector X is a random object, and we assume that its moments up to second order exist. Denote the population mean of traits by vector

$$\mu = \begin{pmatrix} \mu_1 \\ \vdots \\ \mu_p \end{pmatrix}$$

Denote unobserved common factor by f_j, and assume there are in total m factors. A $m \times 1$ vector of all factors collected together is denoted by

$$f = \begin{pmatrix} f_1 \\ \vdots \\ f_m \end{pmatrix}.$$

We assume that each observable trait is linearly related to all m factors, which yields, in matrix notation,

$$X = \mu + \Lambda f + \eta, \tag{A.2}$$

where Λ is $p \times m$ matrix of coefficients, called matrix of factor loadings, where element Λ_{kj} shows how factor j affects trait k. The last term η of dimensions $p \times 1$ denotes specific factors. Standard assumptions are imposed:

1. common factors have zero mean and unit variance
2. specific factors have zero mean, but unrestricted variance: $\mathrm{Var}(\eta_k) = \psi_k, \quad k = 1, \ldots, p$
3. common factors are uncorrelated with one another: $\mathrm{cov}(f_l, f_j) = 0, \quad l \neq j$
4. specific factors are uncorrelated with one another: $\mathrm{cov}(\eta_k, \eta_r) = 0, \quad k \neq r$
5. common and specific factors are uncorrelated with one another: $\mathrm{cov}(\eta_k, f_j) = 0, \quad \forall k,\ j$

These assumptions imply that the covariance matrix of traits Ω can be expressed in terms of model parameters as

$$\Omega = \Lambda \Lambda^\mathsf{T} + \Psi,$$

$\Psi = \mathbb{E}(\eta\, \eta^\mathsf{T})$ is a diagonal covariance matrix of specific factors η.

The factor model is estimated by maximum likelihood method assuming that specific factors follow a multivariate Normal distribution. Our assumptions imply that a vector of traits is also normally distributed with mean vector μ and covariance matrix $\Omega = \Lambda\Lambda^\mathsf{T} + \Psi$. Parameters to be estimated are μ, Λ, Ψ. Denote traits observed at time t by

$$X_t = \begin{pmatrix} x_{1t} \\ \vdots \\ x_{pt} \end{pmatrix},$$

and assume that traits are sampled independently. Estimates of unknown parameters μ, Λ, Ψ are obtained by maximizing the log-likelihood of the sample $\{X_t\}_{t=1}^{T}$:

$$l(\mu, \Lambda, \Psi) = -\frac{Tp}{2} \ln 2\pi - \frac{T}{2} \ln |\Lambda\Lambda^\mathsf{T} + \Psi| - \frac{1}{2} \sum_{t=1}^{T} (X_t - \mu)^\mathsf{T} (\Lambda\Lambda^\mathsf{T} + \Psi)^{-1} (X_t - \mu).$$

Numerical algorithm is employed to arrive at optimal parameter estimates $\hat{\mu}, \hat{\Lambda}, \hat{\Psi}$.

D.1 Varimax Rotation

Let Q denote some $m \times m$ orthogonal matrix. A factor model in (A.2) is not unique because it is observationally equivalent to a rotated factor model

$$X = \mu + \Lambda^* f^* + \eta,$$

where $\Lambda^* = \Lambda Q$ and $f^* = Q^\mathsf{T} f$ for the same data vector X. Since there are infinitely many orthogonal matrices Q, there exist infinitely many equivalent models of the type (A.2) that fit the data equally well.

The varimax rotation enables me to find the orthogonal matrix Q that leads to the easiest possible interpretation of the estimated factors. The procedure is defined as follows. Firstly, it requires to standardize the factor loadings by the corresponding communality:

$$\tilde{\Lambda}^*_{kj} = \hat{\Lambda}^*_{kj} / \hat{h}_k,$$

where the communality of the trait k is given by

$$\hat{h}_k = \left(\sum_{j=1}^{m} \hat{\Lambda}^2_{kj} \right)^{1/2}.$$

Secondly, the varimax criterion searches for the rotation that maximizes the sample variances of the standardized loadings summed over all m common factors, which is

$$\sum_{j=1}^{m}\left(\frac{1}{p}\sum_{k=1}^{p}\left(\tilde{\Lambda}_{kj}^{*}\right)^{4}-\frac{1}{p^{2}}\left[\sum_{k=1}^{p}\left(\tilde{\Lambda}_{kj}^{*}\right)^{2}\right]^{2}\right).$$

E Derivations in Model with Sentimental Beliefs

E.1 Household's Problem

There is a unit mass of identical households indexed by $h \in [0,1]$. Each derives utility from consumption and disutility from supplying labor. Household h maximizes a discounted flow of utilities subject to budget constraint

$$\begin{gathered}\max_{\{C_{h,t+s},L_{h,t+s},B_{h,t+s}\}} \hat{\mathbb{E}}_t \sum_{s=1}^{\infty}\beta^s\left[\frac{C_{h,t+s}^{1-\gamma_c}}{1-\gamma_c}-\chi\frac{L_{h,t+s}^{1+\gamma_L}}{1+\gamma_L}\right] \\ \text{subject to} \\ C_{h,t}+B_{h,t}=W_tL_{h,t}+\frac{R_{t-1}}{\Pi_t}B_{h,t-1}+\int_0^1 profit_{jt}\,\mathrm{d}j.\end{gathered} \tag{A.3}$$

Notations for letters follow the main text. It is assumed that the labor union bargains with firms on behalf of the households, thus the wage rate does not depend on h. I also assume that total hours worked and the shares in firms' profits are equally distributed among the households.

Let the Lagrange multiplier attached to budget constraint at time $t+s$ be $\beta^s\Lambda_{h,t+s}$, then Lagrangian is given by

$$\begin{aligned}\mathcal{L}=\hat{\mathbb{E}}_t\sum_{s=1}^{\infty}\beta^s&\left[\frac{C_{h,t+s}^{1-\gamma_c}}{1-\gamma_c}-\chi\frac{L_{h,t+s}^{1+\gamma_L}}{1+\gamma_L}+\right.\\ \Lambda_{h,t+s}&\left.\left(W_{t+s}L_{h,t+s}+\frac{R_{t+s-1}}{\Pi_{t+s}}B_{h,t+s-1}+\int_0^1 profit_{j,t+s}\,\mathrm{d}j-C_{h,t+s}-B_{h,t+s}\right)\right].\end{aligned}$$

FOCs are

$$
\begin{aligned}
C_{h,t+s}^{-\gamma_c} &= \Lambda_{h,t+s} \\
\chi L_{h,t+s}^{\gamma_L} &= W_{t+s}\Lambda_{h,t+s} \\
\Lambda_{h,t+s} &= \beta R_{t+s}\hat{\mathbb{E}}_{t+s}\left(\frac{\Lambda_{h,t+s+1}}{\Pi_{t+s+1}}\right).
\end{aligned}
$$

Let $s = 0$. I consider a log-linearized version of the model. In log-linear form, the last condition from FOCs in combination with the first one $\hat{\lambda}_{ht} = -\gamma_c \hat{c}_{ht}$ gives

$$
-\gamma_c \hat{c}_{ht} = \hat{r}_t + \hat{\mathbb{E}}_t\left(-\gamma_c \hat{c}_{h,t+1} - \pi_{t+1}\right),
$$

where lowercase letters with hat ($\hat{}$) denote log-linear deviation of variable from the steady state. Rearrange this last optimality condition as

$$
\hat{\mathbb{E}}_t(\hat{c}_{h,t+1}) = \hat{c}_{ht} + \frac{1}{\gamma_c}\left(\hat{r}_t - \hat{\mathbb{E}}_t \pi_{t+1}\right).
$$

Iterating it forward yields

$$
\hat{\mathbb{E}}_t(\hat{c}_{h,t+s}) = \hat{c}_{ht} + \frac{1}{\gamma_c}\hat{\mathbb{E}}_t \sum_{k=0}^{s-1}\left(\hat{r}_{t+k} - \pi_{t+k+1}\right), \quad s \geq 1. \tag{A.4}
$$

Plug the expression for firm j's profits into budget constraint, and using the labor market equilibrium condition, budget constraint may be written as

$$
B_{ht} + C_{ht} = \frac{R_{t-1}}{\Pi_t} B_{h,t-1} + Y_t,
$$

where $Y_t = \int_0^1 y_{jt}\, \mathrm{d}j$ is aggregate output. Log-linearize (but linearize with respect to B_{ht}) this version of budget constraint to obtain

$$
\hat{b}_{ht} + \bar{Y}\hat{c}_{ht} = \frac{1}{\beta}\hat{b}_{h,t-1} + \bar{Y}\hat{y}_t,
$$

where in the steady state, $\bar{Y} = \bar{C}$, $\bar{R} = \frac{\bar{\Pi}}{\beta}$; $\hat{b}_{ht} = B_{ht} - \bar{B}$ and $\bar{B} = 0$ since government bonds are in zero net supply. Iterating log-linearized budget constraint forward gives

$$\bar{Y}\, \hat{\mathbb{E}}_t \sum_{s=0}^{\infty} \beta^{s+1} \left(\hat{c}_{h,t+s} - \hat{y}_{t+s}\right) = \hat{b}_{h,t-1}.$$

Split the sum into consumption series and output series, and then use (A.4) to substitute away expected consumption. These steps yield

$$\hat{b}_{h,t-1} = -\bar{Y} \sum_{s=0}^{\infty} \beta^{s+1} \hat{\mathbb{E}}_t \hat{y}_{t+s} + \bar{Y} \frac{\beta \hat{c}_{ht}}{1-\beta} + \frac{\bar{Y}}{\gamma_c} \frac{\beta^2}{1-\beta} \sum_{s=0}^{\infty} \beta^s \hat{\mathbb{E}}_t \left(\hat{r}_{t+s} - \pi_{t+s+1}\right).$$

Isolate current consumption:

$$\hat{c}_{ht} = \frac{1-\beta}{\beta} \frac{\hat{b}_{h,t-1}}{\bar{Y}} + \sum_{s=0}^{\infty} \beta^s \left[(1-\beta) \hat{\mathbb{E}}_t \hat{y}_{t+s} - \frac{\beta}{\gamma_c} \hat{\mathbb{E}}_t \left(\hat{r}_{t+s} - \pi_{t+s+1}\right) \right].$$

Given that all households are identical, and $\int_0^1 \hat{b}_{h,t-1}\, \mathrm{d}h = 0$, we obtain

$$\hat{c}_t = \sum_{s=0}^{\infty} \beta^s \left[(1-\beta) \hat{\mathbb{E}}_t \hat{y}_{t+s} - \frac{\beta}{\gamma_c} \hat{\mathbb{E}}_t \left(\hat{r}_{t+s} - \pi_{t+s+1}\right) \right],$$

which is (13).

E.2 Firm's Problem

There is a continuum of intermediate firms of unit mass that are indexed by $j \in [0,1]$. They hire labor in the competitive market at real wage W_t and produce intermediate good j using the technology

$$y_{jt} = A_t L_{jt}^{1-\alpha},$$

where A_t is common aggregate productivity. Each firm is subject to Calvo-type price frictions (Calvo, 1983). Firm j solves an optimization problem

$$\begin{aligned}
&\max_{P_{jt}^*} \hat{\mathbb{E}}_t \sum_{s=0}^{\infty} \theta^s \Lambda_{t,t+s} \frac{P_t}{P_{t+s}} \left(P_{jt}^* \, y_{t+s|t} - TC_{t+s}(y_{t+s|t}) \, P_{t+s} \right) \\
&\qquad \text{subject to} \\
&Y_{t+s|t} = \left(\frac{P_{jt}^*}{P_{t+s}} \right)^{-\varepsilon} Y_{t+s}
\end{aligned} \tag{A.5}$$

where $TC_{t+s}(y_{t+s|t})$ is real total cost of producing $y_{t+s|t}$. After plugging a constraint into the objective, one obtains FOCs

$$\hat{\mathbb{E}}_t \sum_{s=0}^{\infty} \theta^s \Lambda_{t,t+s} \frac{P_t}{P_{t+s}} \left((1-\varepsilon) Y_{t+s|t} + \varepsilon MC_{t+s}(Y_{t+s|t}) P_{t+s} \frac{(P_{jt}^*)^{-\varepsilon-1}}{(P_{t+s})^{-\varepsilon}} Y_{t+s} \right) = 0.$$

Multiplying both sides by $\frac{P_{jt}^*}{P_{t-1}}$ and rearranging, we have

$$\hat{\mathbb{E}}_t \sum_{s=0}^{\infty} \theta^s \Lambda_{t,t+s} \frac{P_t}{P_{t+s}} \left(\frac{P_{jt}^*}{P_{t-1}} - \frac{\varepsilon}{\varepsilon - 1} MC_{t+s}(Y_{t+s|t}) \frac{P_{t+s}}{P_{t-1}} \right) Y_{t+s|t} = 0.$$

Log-linearization around a steady state gives

$$\hat{\mathbb{E}}_t \sum_{s=0}^{\infty} (\beta\theta)^s \left(p_{jt}^* - p_{t-1} - \widehat{mc}_{t+s|t} - p_{t+s} + p_{t-1} \right) = 0,$$

and after isolating $p_{jt}^* - p_{t-1}$,

$$p_{jt}^* - p_{t-1} = (1-\beta\theta) \, \hat{\mathbb{E}}_t \sum_{s=0}^{\infty} (\beta\theta)^s \left(\widehat{mc}_{t+s|t} + p_{t+s} - p_{t-1} \right). \tag{A.6}$$

Real marginal cost for an individual firm j is $\widehat{mc}_{t+s|t} = \hat{w}_{t+s} - \frac{1}{1-\alpha} a_{t+s} + \frac{\alpha}{1-\alpha} \hat{y}_{t+s|t}$. Combining this with real marginal cost average for the entire economy $\widehat{mc}_{t+s} = \hat{w}_{t+s} -$

$\frac{1}{1-\alpha}a_{t+s} + \frac{\alpha}{1-\alpha}\hat{y}_{t+s}$ and firm's demand function yields

$$\widehat{mc}_{t+s|t} = \widehat{mc}_{t+s} - \frac{\alpha\varepsilon}{1-\alpha}(p^*_{jt} - p_{t+s}).$$

Using this relationship in (A.6) and rearranging the terms, we obtain

$$p^*_{jt} - p_{t-1} = (1-\beta\theta)\,\hat{\mathbb{E}}_t \sum_{s=0}^{\infty} (\beta\theta)^s \left(M\widehat{mc}_{t+s} + p_{t+s} - p_{t-1}\right), \tag{A.7}$$

where $M = \frac{1-\alpha}{1-\alpha+\alpha\varepsilon}$.

Note that $p_{t+s} - p_{t-1} = \sum_{k=0}^{s} \pi_{t+k}$, where $\pi_t \equiv \ln(P_t/P_{t-1})$, and

$$\sum_{s=0}^{\infty} (\beta\theta)^s \sum_{k=0}^{s} \pi_{t+k} = \frac{1}{1-\beta\theta} \sum_{s=0}^{\infty} (\beta\theta)^s \pi_{t+s}.$$

Using this in (A.7) enables one to rewrite it as

$$p^*_{jt} - p_{t-1} = (1-\beta\theta)\,\hat{\mathbb{E}}_t \sum_{s=0}^{\infty} (\beta\theta)^s M\widehat{mc}_{t+s} + \hat{\mathbb{E}}_t \sum_{s=0}^{\infty} (\beta\theta)^s \pi_{t+s}. \tag{A.8}$$

Finally, we can express $\widehat{mc}_t$ in terms of $\hat{y}_t$ and a_t by combining $\widehat{mc}_t = \hat{w}_t - \frac{1}{1-\alpha}a_t + \frac{\alpha}{1-\alpha}\hat{y}_t$, aggregated FOCs from household's problem with respect to labor $\gamma_L\hat{l}_t = \hat{w}_t - \gamma_c\hat{y}_t$ and production function $\hat{y}_t = a_t + (1-\alpha)\hat{l}_t$, which leads to $\widehat{mc}_t = \left(\gamma_c + \frac{\gamma_L+\alpha}{1-\alpha}\right)\hat{y}_t - \frac{1+\gamma_L}{1-\alpha}a_t$. Plugging this relationship in (A.8) results in the final equation that determines an optimal reset price for firm j as a function of sentimental expectations:

$$p^*_{jt} - p_{t-1} = (1-\beta\theta) \sum_{s=0}^{\infty} (\beta\theta)^s \left[\psi_y \hat{\mathbb{E}}_t \hat{y}_{t+s} - \psi_a \hat{\mathbb{E}}_t a_{t+s}\right] + \sum_{s=0}^{\infty} (\beta\theta)^s \hat{\mathbb{E}}_t \pi_{t+s}, \tag{A.9}$$

where

$$\psi_y = M\left(\gamma_c + \frac{\gamma_L+\alpha}{1-\alpha}\right),$$

$$\psi_a = M\frac{1+\gamma_L}{1-\alpha}.$$

E.3 Sentimental Expectations of Interest Rate

Monetary policy rule is given by

$$\hat{r}_t = \rho_r \hat{r}_{t-1} + (1-\rho_r)\left(\phi_\pi \pi_t + \phi_y \hat{y}_t\right) + v_t^R.$$

Households are aware that interest rates are set according to this rule, and monetary policy shocks follow an AR(1) process. Sentimental forecast of interest rates at time $t+1$ is

$$\begin{aligned}
&\hat{\mathbb{E}}_t \hat{r}_{t+1} = \hat{\mathbb{E}}_t\left[\rho_r \hat{r}_t + (1-\rho_r)\left(\phi_\pi \pi_{t+1} + \phi_y \hat{y}_{t+1}\right) + v_{t+1}^R\right] = \\
&\rho_r\left(\hat{r}_t + D_r\zeta_t\right) + (1-\rho_r)\left(\phi_\pi\left(\mathbb{E}_t \pi_{t+1} + D_\pi \rho_\zeta \zeta_t\right) + \phi_y\left(\mathbb{E}_t \hat{y}_{t+1} + D_y \rho_\zeta \zeta_t\right)\right) + \rho_v v_t^R = \\
&\mathbb{E}_t \hat{r}_{t+1} + \rho_r D_r \zeta_t + (1-\rho_r)\left(\phi_\pi D_\pi + \phi_y D_y\right)\rho_\zeta \zeta_t,
\end{aligned}$$

where

$$\mathbb{E}_t \hat{r}_{t+1} = \rho_r \hat{r}_t + \left(\phi_\pi \mathbb{E}_t \pi_{t+1} + \phi_y \mathbb{E}_t \hat{y}_{t+1}\right) + \rho_v v_t^R$$

is rational forecast.

Guess that sentimental forecast at horizon $s \geq 0$ is given by the formula

$$\hat{\mathbb{E}}_t \hat{r}_{t+s} = \mathbb{E}_t \hat{r}_{t+s} + \rho_r^s D_r \zeta_t + (\phi_\pi D_\pi + \phi_y D_y)(1-\rho_r)\sum_{k=1}^{s} \rho_r^{s-k} \rho_\zeta^k \zeta_t. \tag{A.10}$$

I prove it by induction. It trivially gives the expression at $s=0$ with the convention that $\sum_{k=1}^{s} f_s = 0$ if $s=0$. Suppose that the guess is true at some horizon s. At horizon

$s+1$, sentimental forecast is

$$
\begin{aligned}
&\hat{\mathbb{E}}_t \hat{r}_{t+s+1} = \hat{\mathbb{E}}_t \left[\rho_r \hat{r}_{t+s} + (1-\rho_r)\left(\phi_\pi \pi_{t+s+1} + \phi_y \hat{y}_{t+s+1}\right) + v^R_{t+s+1}\right] \\
&= \mathbb{E}_t \hat{r}_{t+s+1} + \rho_r^{s+1} D_r \zeta_t + \rho_r (\phi_\pi D_\pi + \phi_y D_y)(1-\rho_r) \sum_{k=1}^{s} \rho_r^{s-k} \rho_\zeta^k \zeta_t + \\
&(1-\rho_r)\left(\phi_\pi D_\pi \rho_\zeta^{s+1} \zeta_t + \phi_y D_y \rho_\zeta^{s+1} \zeta_t\right) \\
&= \mathbb{E}_t \hat{r}_{t+s+1} + \rho_r^{s+1} D_r \zeta_t + (\phi_\pi D_\pi + \phi_y D_y)(1-\rho_r) \sum_{k=1}^{s} \rho_r^{s+1-k} \rho_\zeta^k \zeta_t + \\
&(1-\rho_r)\left(\phi_\pi D_\pi + \phi_y D_y\right) \rho_\zeta^{s+1} \zeta_t \\
&= \mathbb{E}_t \hat{r}_{t+s+1} + \rho_r^{s+1} D_r \zeta_t + (\phi_\pi D_\pi + \phi_y D_y)(1-\rho_r) \sum_{k=1}^{s+1} \rho_r^{s+1-k} \rho_\zeta^k \zeta_t,
\end{aligned}
$$

where I used the guess (A.10) and definition of sentimental expectations in (18)-(20). The last line is exactly the guess (A.10) at horizon $s+1$, thus the proof is complete.

E.4 Aggregate Demand Equation

Since there is a representative household in the economy, aggregate version of household optimality condition (13) is

$$
\hat{y}_t = \sum_{s=0}^{\infty} \beta^s \left[(1-\beta)\hat{\mathbb{E}}_t \hat{y}_{t+s} - \frac{\beta}{\gamma_c}\left(\hat{\mathbb{E}}_t \hat{r}_{t+s} - \hat{\mathbb{E}}_t \pi_{t+s+1}\right)\right].
$$

Using the expressions for sentimental expectations in (18), (21) and (19), we obtain

$$
\begin{aligned}
&\hat{y}_t = (1-\beta) \sum_{s=0}^{\infty} \beta^s \left[\mathbb{E}_t \hat{y}_{t+s} + D_y \rho_\zeta^s \zeta_t\right] \\
&- \frac{\beta}{\gamma_c} \sum_{s=0}^{\infty} \beta^s \left[\mathbb{E}_t \hat{r}_{t+s} + D_r \rho_r^s \zeta_t + (\phi_\pi D_\pi + \phi_y D_y)(1-\rho_r) \sum_{k=1}^{s} \rho_r^{s-k} \rho_\zeta^k \, \zeta_t\right] \\
&+ \frac{\beta}{\gamma_c} \sum_{s=0}^{\infty} \beta^s \left[\mathbb{E}_t \pi_{t+s+1} + D_\pi \rho_\zeta^{s+1} \zeta_t\right].
\end{aligned}
$$

Separate rational expectations from sentiment shocks to get

$$
\begin{aligned}
\hat{y}_t &= (1-\beta)\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\hat{y}_{t+s} - \frac{\beta}{\gamma_c}\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\hat{r}_{t+s} + \frac{\beta}{\gamma_c}\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\pi_{t+s+1} \\
&+ (1-\beta)\frac{D_y}{1-\beta\rho_\zeta}\zeta_t - \frac{\beta}{\gamma_c}\frac{D_r}{1-\beta\rho_r}\zeta_t \\
&- \frac{\beta}{\gamma_c}(\phi_\pi D_\pi + \phi_y D_y)(1-\rho_r)\sum_{s=0}^{\infty}\beta^s\sum_{k=1}^{s}\rho_r^{s-k}\rho_\zeta^k\,\zeta_t + \frac{\beta}{\gamma_c}\frac{D_\pi\rho_\zeta}{1-\beta\rho_\zeta}\zeta_t \\
&= (1-\beta)\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\hat{y}_{t+s} - \frac{\beta}{\gamma_c}\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\hat{r}_{t+s} + \frac{\beta}{\gamma_c}\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\pi_{t+s+1} \\
&+ (1-\beta)\frac{D_y}{1-\beta\rho_\zeta}\zeta_t - \frac{\beta}{\gamma_c}\frac{D_r}{1-\beta\rho_r}\zeta_t \\
&- \frac{\beta}{\gamma_c}(\phi_\pi D_\pi + \phi_y D_y)(1-\rho_r)\frac{\beta\rho_\zeta}{(1-\beta\rho_r)(1-\beta\rho_\zeta)}\zeta_t + \frac{\beta}{\gamma_c}\frac{\rho_\zeta D_\pi}{1-\beta\rho_\zeta}\zeta_t.
\end{aligned}
$$

We may compactly write it by defining

$$
\begin{aligned}
\Upsilon \equiv\ & (1-\beta)\frac{D_y}{1-\beta\rho_\zeta} - \frac{\beta}{\gamma_c}\frac{D_r}{1-\beta\rho_r} \\
& - \frac{\beta}{\gamma_c}(\phi_\pi D_\pi + \phi_y D_y)(1-\rho_r)\frac{\beta\rho_\zeta}{(1-\beta\rho_r)(1-\beta\rho_\zeta)} + \frac{\beta}{\gamma_c}\frac{\rho_\zeta D_\pi}{1-\beta\rho_\zeta},
\end{aligned}
$$

and then

$$
\begin{aligned}
\hat{y}_t =\ & (1-\beta)\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\hat{y}_{t+s} - \frac{\beta}{\gamma_c}\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\hat{r}_{t+s} \\
& + \frac{\beta}{\gamma_c}\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\pi_{t+s+1} + \Upsilon\zeta_t.
\end{aligned}
$$

Next, I rewrite the condition above in a recursive form:

$$
\begin{aligned}
\hat{y}_t =\ & (1-\beta)\hat{y}_t - \frac{\beta}{\gamma_c}\hat{r}_t + \frac{\beta}{\gamma_c}\mathbb{E}_t\pi_{t+1} + (1-\beta)\sum_{s=1}^{\infty}\beta^s\mathbb{E}_t\hat{y}_{t+s} \\
& - \frac{\beta}{\gamma_c}\sum_{s=1}^{\infty}\beta^s\mathbb{E}_t\hat{r}_{t+s} + \frac{\beta}{\gamma_c}\sum_{s=1}^{\infty}\beta^s\mathbb{E}_t\pi_{t+s+1} + \Upsilon\zeta_t.
\end{aligned}
\tag{A.11}
$$

I can make index s start from 0 in sums, which will give a term with expected output. Note that since rational expectation operator $\mathbb{E}_t$ contains information only on fundamental shocks, we have $\mathbb{E}_t\zeta_{t+1} = 0$. Thus, I transform (A.11) into

$$\begin{aligned}\hat{y}_t &= (1-\beta)\hat{y}_t - \frac{\beta}{\gamma_c}\hat{r}_t + \frac{\beta}{\gamma_c}\mathbb{E}_t\pi_{t+1} + (1-\beta)\beta\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\hat{y}_{t+1+s} \\ &- \frac{\beta}{\gamma_c}\beta\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\hat{r}_{t+1+s} + \frac{\beta}{\gamma_c}\beta\sum_{s=0}^{\infty}\beta^s\mathbb{E}_t\pi_{t+s+2} + \beta\Upsilon\mathbb{E}_t\zeta_{t+1} + \Upsilon\zeta_t - \beta\Upsilon\underbrace{\mathbb{E}_t\zeta_{t+1}}_{=0} \\ &= (1-\beta)\hat{y}_t - \frac{\beta}{\gamma_c}\hat{r}_t + \frac{\beta}{\gamma_c}\mathbb{E}_t\pi_{t+1} + \beta\mathbb{E}_t\hat{y}_{t+1} + \Upsilon\zeta_t.\end{aligned}$$

Isolating $\hat{y}_t$ yields

$$\hat{y}_t = -\frac{1}{\gamma_c}\hat{r}_t + \frac{1}{\gamma_c}\mathbb{E}_t\pi_{t+1} + \mathbb{E}_t\hat{y}_{t+1} + \varphi\zeta_t,$$

where

$$\begin{aligned}\varphi = &\frac{1-\beta}{\beta}\frac{D_y}{1-\beta\rho_\zeta} - \frac{1}{\gamma_c}\frac{D_r}{1-\beta\rho_r} \\ &- \frac{1}{\gamma_c}\frac{\beta\rho_\zeta(\phi_\pi D_\pi + \phi_y D_y)(1-\rho_r)}{(1-\beta\rho_r)(1-\beta\rho_\zeta)} + \frac{1}{\gamma_c}\frac{\rho_\zeta D_\pi}{1-\beta\rho_\zeta}.\end{aligned}$$

Thus, it gives (22).

E.5 Phillips Curve

Using the definition of sentimental expectations in (18), (19) and (20), we can isolate the terms containing rational expectations from the terms which depend on sentiment shocks:

$$\begin{aligned}p^*_{jt} - p_{t-1} = (1-\beta\theta)\ &\sum_{s=0}^{\infty}(\beta\theta)^s\left[\psi_y\mathbb{E}_t\hat{y}_{t+s} - \psi_a\mathbb{E}_t a_{t+s}\right] + \sum_{s=0}^{\infty}(\beta\theta)^s\mathbb{E}_t\pi_{t+s} \\ + \frac{(1-\beta\theta)\psi_y D_y}{1-\beta\theta\rho_\zeta}\zeta_t &- \frac{(1-\beta\theta)\psi_a D_a}{1-\beta\theta\rho_\zeta}\zeta_t + \frac{D_\pi}{1-\beta\theta\rho_\zeta}\zeta_t.\end{aligned}$$

Introduce notation

$$\nu \equiv \frac{(1-\beta\theta)\psi_y D_y}{1-\beta\theta\rho_\zeta} - \frac{(1-\beta\theta)\psi_a D_a}{1-\beta\theta\rho_\zeta} + \frac{D_\pi}{1-\beta\theta\rho_\zeta}.$$

Since the mass of firms resetting the price each period is $1-\theta$, inflation is given by $\pi = (1-\theta)\int_0^1 (p^*_{jt} - p_{t-1})\,\mathrm{d}j$. Aggregating optimal price setting condition above across all firms leads to

$$\pi_t = (1-\beta\theta)(1-\theta)\sum_{s=0}^{\infty}(\beta\theta)^s\left[\psi_y \mathbb{E}_t \hat{y}_{t+s} - \psi_a \mathbb{E}_t a_{t+s}\right] + (1-\theta)\sum_{s=0}^{\infty}(\beta\theta)^s \mathbb{E}_t \pi_{t+s} + (1-\theta)\nu\zeta_t.$$

We can rewrite the relationship above in a recursive form

$$\begin{aligned}
\pi_t &= (1-\beta\theta)(1-\theta)\left(\psi_y \hat{y}_t - \psi_a a_t\right) + (1-\theta)\pi_t \\
&\quad + (1-\beta\theta)(1-\theta)\beta\theta\sum_{s=0}^{\infty}(\beta\theta)^s\left[\psi_y \mathbb{E}_t \hat{y}_{t+1+s} - \psi_a \mathbb{E}_t a_{t+1+s}\right] + (1-\theta)\beta\theta\sum_{s=0}^{\infty}(\beta\theta)^s \mathbb{E}_t \pi_{t+1+s} \\
&\quad + \beta\theta(1-\theta)\nu\mathbb{E}_t\zeta_{t+1} + (1-\theta)\nu\zeta_t - \beta\theta(1-\theta)\nu\underbrace{\mathbb{E}_t\zeta_{t+1}}_{=0} \\
&= (1-\beta\theta)(1-\theta)\left(\psi_y \hat{y}_t - \psi_a a_t\right) + (1-\theta)\pi_t + \beta\theta\mathbb{E}_t\pi_{t+1} + (1-\theta)\nu\zeta_t.
\end{aligned}$$

Finally, combining similar terms for inflation together and isolating it on the left-hand side gives us the Phillips curve in (24):

$$\pi_t = \kappa_y \hat{y}_t - \kappa_a a_t + \beta\mathbb{E}_t\pi_{t+1} + \psi\zeta_t,$$

where

$$\kappa_y = \frac{(1-\theta)(1-\beta\theta)}{\theta}\psi_y,$$
$$\kappa_a = \frac{(1-\theta)(1-\beta\theta)}{\theta}\psi_a,$$

and

$$\psi = \frac{(1-\theta)(1-\beta\theta)\psi_y D_y}{\theta(1-\beta\theta\rho_\zeta)} - \frac{(1-\theta)(1-\beta\theta)\psi_a D_a}{\theta(1-\beta\theta\rho_\zeta)} + \frac{(1-\theta)D_\pi}{\theta(1-\beta\theta\rho_\zeta)}.$$

F Proofs of Propositions

Proof of Proposition 6.1. Denominator in expression for M_ζ given in (26) is positive since all parameters $\gamma_c, \phi_\pi, \phi_y, \kappa_y > 0$, so the sign of M_ζ is determined by $-\frac{\phi_\pi}{\gamma_c}\psi + \varphi$.

Pick any value $D_r < 0, D_a > 0$. Plugging expressions for φ (23) and ψ (25) into $-\frac{\phi_\pi}{\gamma_c}\psi + \varphi$, grouping similar terms together and setting it to zero yields

$$
\begin{aligned}
&-\frac{\phi_\pi}{\gamma_c}\psi + \varphi = \frac{1}{1-\beta\rho_\zeta}\left(\frac{1-\beta}{\beta} - \frac{\beta\rho_\zeta\phi_y}{\gamma_c}\right)D_y - \frac{\phi_\pi(1-\beta\theta)(1-\theta)\psi_y}{\gamma_c\theta(1-\beta\theta\rho_\zeta)}D_y \\
&+ \frac{\rho_\zeta}{\gamma_c(1-\beta\rho_\zeta)}(1-\beta\phi_\pi)D_\pi - \frac{\phi_\pi(1-\theta)}{\gamma_c\theta(1-\beta\theta\rho_\zeta)}D_\pi \\
&- \frac{D_r}{\gamma_c} + \frac{\phi_\pi(1-\beta\theta)(1-\theta)\psi_a}{\gamma_c\theta(1-\beta\theta\rho_\zeta)}D_a = 0.
\end{aligned}
$$

Note that following our assumptions, both coefficients for D_y are negative, both coefficients for D_π are negative, and last two terms are positive since $D_r < 0,\ D_a > 0$. Collecting all coefficients together for each parameter D_y and D_π, we obtain

$$
-\frac{\phi_\pi}{\gamma_c}\psi + \varphi = \eta_y D_y + \eta_\pi D_\pi + \eta_0 = 0,
$$

where $\eta_y < 0, \eta_\pi < 0, \eta_0 > 0$. Isolating D_y gives

$$
D_y = -\frac{\eta_\pi}{\eta_y}D_\pi - \frac{\eta_0}{\eta_y} \equiv \bar{D}_y > 0.
$$

Therefore, for any given $D_\pi < 0$, there exists $\bar{D}_y > 0$ such that $M_\zeta = 0$. If $D_y > (<)\ \bar{D}_y$, we have $M_\zeta < (>)\ 0$.

Alternatively, we can isolate D_π to get

$$
D_\pi = -\frac{\eta_y}{\eta_\pi}D_y - \frac{\eta_0}{\eta_\pi} \equiv \bar{D}_\pi.
$$

However, a threshold value $\bar{D}_\pi$ is not always negative because $-\frac{\eta_0}{\eta_\pi} > 0$. Thus, for any given $D_y > 0$, if $\eta_0 < -\eta_y D_y$, there exists $\bar{D}_\pi < 0$ such that $M_\zeta = 0$. If $D_\pi < (>)\ \bar{D}_\pi$, we have $M_\zeta > (<)\ 0$. □

Proof of Proposition 6.2. Expression for Q_ζ is given in (27). Since $\gamma_c, \phi_\pi, \phi_y, \kappa_y > 0$, denominator is always positive, and the sign of Q_ζ is determined by $(1+\frac{\phi_y}{\gamma_c})\psi + \kappa_y\varphi$.

Fix any values of $D_y > 0, D_\pi < 0$ and denote them by $\bar{D}_y, \bar{D}_\pi$. Substitute expressions for φ and ψ (given in (23) and (25), respectively) into $(1+\frac{\phi_y}{\gamma_c})\psi + \kappa_y\varphi$ to obtain

$$\begin{aligned}
&\left(1+\frac{\phi_y}{\gamma_c}\right)\psi + \kappa_y\varphi = \\
&\frac{\kappa_y}{1-\beta\rho_\zeta}\left(\frac{1-\beta}{\beta} - \frac{\beta\rho_\zeta\phi_y}{\gamma_c}\right)\bar{D}_y + \left(1+\frac{\phi_y}{\gamma_c}\right)\frac{(1-\beta\theta)(1-\theta)\psi_y}{\theta(1-\beta\theta\rho_\zeta)}\bar{D}_y \\
&+ \frac{\kappa_y\rho_\zeta}{\gamma_c(1-\beta\rho_\zeta)}(1-\beta\phi_\pi)\bar{D}_\pi + \left(1+\frac{\phi_y}{\gamma_c}\right)\frac{(1-\theta)}{\theta(1-\beta\theta\rho_\zeta)}\bar{D}_\pi \\
&- \frac{\kappa_y}{\gamma_c}D_r - \left(1+\frac{\phi_y}{\gamma_c}\right)\frac{(1-\beta\theta)(1-\theta)\psi_a}{\theta(1-\beta\theta\rho_\zeta)}D_a.
\end{aligned}$$

Collecting all similar terms together, given some $D_r < 0, D_a > 0$, one can rewrite the above expression more compactly as

$$\left(1+\frac{\phi_y}{\gamma_c}\right)\psi + \kappa_y\varphi = \omega_y\bar{D}_y + \omega_\pi\bar{D}_\pi + \omega_r D_r + \omega_a D_a,$$

where $\omega_r < 0,\ \omega_a < 0$, but signs of ω_y and ω_π are generally undetermined.

Note that the expression $\left(1+\frac{\phi_y}{\gamma_c}\right)\psi + \kappa_y\varphi$ may take any sign. However, it is always possible to find some D_r, D_a such that the expression is exactly zero. Suppose that it is positive: $\omega_y\bar{D}_y + \omega_\pi\bar{D}_\pi + \omega_r D_r + \omega_a D_a > 0$. Since it linearly decreases in D_a, and $D_a > 0$, there exists a value of D_a such that $\omega_y\bar{D}_y + \omega_\pi\bar{D}_\pi + \omega_r D_r + \omega_a D_a = 0$.

Similarly, suppose the expression is negative. Since it linearly decreases in D_r, and $D_r < 0$, there exists D_r such that $\omega_y\bar{D}_y + \omega_\pi\bar{D}_\pi + \omega_r D_r + \omega_a D_a = 0$. Therefore, it is indeed possible to find such values of D_r, D_a to make the expression zero. Denote them by $\bar{D}_r$ and $\bar{D}_a$.

Finally, given $\bar{D}_y, \bar{D}_\pi, \bar{D}_r, \bar{D}_a$ defined at earlier steps, one can obtain any sign of $\left(1+\frac{\phi_y}{\gamma_c}\right)\psi + \kappa_y\varphi$, and therefore, Q_ζ by considering $D_y > (<)\ \bar{D}_y$, but exact ranges depend on sign of ω_y. Suppose $\omega_y > 0$, then if $D_y > (<)\ \bar{D}_y$, we obtain $Q_\zeta > (<)\ 0$. If $\omega_y < 0$, then if $D_y > (<)\ \bar{D}_y$, we obtain $Q_\zeta < (>)\ 0$. In the case of $\omega_y = 0$, Q_ζ is invariant to changes in D_y.

In a similar manner, for given $\bar{D}_y, \bar{D}_\pi, \bar{D}_r, \bar{D}_a$, suppose $\omega_\pi > 0$. If $D_\pi > (<)\ \bar{D}_\pi$, we obtain $Q_\zeta > (<)\ 0$. In the other case when $\omega_\pi < 0$: if $D_\pi > (<)\ \bar{D}_\pi$, we conclude that $Q_\zeta < (>)\ 0$. In the case of $\omega_\pi = 0$, Q_ζ is invariant to changes in D_π. $\square$

Proof of Proposition 6.3. U_ζ is given by (28). We are interested in the sign of this expression, and since $\gamma_c, \phi_\pi, \phi_y, \kappa_y > 0$, the denominator $1 + \frac{\phi_\pi}{\gamma_c}\kappa_y + \frac{\phi_y}{\gamma_c} > 0$, the sign of U_ζ is determined by $\phi_\pi\psi + (\phi_\pi\kappa_y + \phi_y)\varphi$.

Pick any values of $D_y > 0, D_\pi < 0$ and denote them by $\bar{D}_y, \bar{D}_\pi$. Plugging the expressions for φ and ψ under condition $\rho_r = 0$ given in (23) and (25), into $\phi_\pi\psi + (\phi_\pi\kappa_y + \phi_y)\varphi$ yields

$$
\begin{aligned}
&\phi_\pi\psi + (\phi_\pi\kappa_y + \phi_y)\varphi = \\
&\phi_\pi \frac{(1-\beta\theta)(1-\theta)\psi_y}{\theta(1-\beta\theta\rho_\zeta)}\bar{D}_y + \frac{\phi_\pi\kappa_y + \phi_y}{1-\beta\rho_\zeta}\left(\frac{1-\beta}{\beta} - \frac{\beta\rho_\zeta\phi_y}{\gamma_c}\right)\bar{D}_y \\
&+ \phi_\pi \frac{(1-\theta)}{\theta(1-\beta\theta\rho_\zeta)}\bar{D}_\pi + (\phi_\pi\kappa_y + \phi_y)\frac{\rho_\zeta}{\gamma_c(1-\beta\rho_\zeta)}(1-\beta\phi_\pi)\bar{D}_\pi \\
&- \frac{\phi_\pi\kappa_y + \phi_y}{\gamma_c}D_r - \phi_\pi \frac{(1-\beta\theta)(1-\theta)\psi_a}{\theta(1-\beta\theta\rho_\zeta)}D_a.
\end{aligned}
$$

Denote coefficients for each D parameter by ω with corresponding subscript, then we can write

$$
\phi_\pi\psi + (\phi_\pi\kappa_y + \phi_y)\varphi = \omega_y\bar{D}_y + \omega_\pi\bar{D}_\pi + \omega_a D_a + \omega_r D_r,
$$

where only $\omega_a < 0, \omega_r < 0$ have definitive sign.

In general, expression $\phi_\pi\psi + (\phi_\pi\kappa_y + \phi_y)\varphi$ may assume any sign, but by varying either D_r or D_a, one can make it exactly zero. Suppose it is positive: $\phi_\pi\psi + (\phi_\pi\kappa_y + \phi_y)\varphi > 0$. Leveraging the fact that $\omega_a < 0$, $D_a > 0$ and the expression of interest is linear in D_a, there exists some D_a such that $\omega_y\bar{D}_y + \omega_\pi\bar{D}_\pi + \omega_a D_a + \omega_r D_r = 0$.

In the other case ($\phi_\pi\psi + (\phi_\pi\kappa_y + \phi_y)\varphi < 0$), we can make use of the fact that this expression linearly decreases in D_r, which implies that there exists some D_r that delivers $\omega_y\bar{D}_y + \omega_\pi\bar{D}_\pi + \omega_a D_a + \omega_r D_r = 0$. Indeed, we can choose some values of D_a or D_r which make the expression zero. Let me denote these values by $\bar{D}_a$ and $\bar{D}_r$.

Given parameter values $\bar{D}_y, \bar{D}_\pi, \bar{D}_r, \bar{D}_a$ defined earlier, we can obtain any sign of $\phi_\pi\psi + (\phi_\pi\kappa_y + \phi_y)\varphi$, and therefore, U_ζ by varying D_y. Specific ranges depend on the sign of ω_y. Suppose $\omega_y > 0$, then if $D_y > (<)\ \bar{D}_y$, we conclude that $U_\zeta > (<)\ 0$. In case $\omega_y < 0$, if $D_y > (<)\ \bar{D}_y$, we find that $U_\zeta < (>)\ 0$. In the case of $\omega_y = 0$, U_ζ is invariant to changes in D_y.

Similarly, we can establish this result for D_π. Given parameter values $\bar{D}_y, \bar{D}_\pi, \bar{D}_r, \bar{D}_a$, suppose $\omega_\pi > 0$, then if $D_\pi > (<)\ \bar{D}_\pi$, we conclude that $U_\zeta > (<)\ 0$. Assuming that $\omega_\pi < 0$, we find that if $D_\pi > (<)\ \bar{D}_\pi$, the above considerations imply $U_\zeta < (>)\ 0$. In the case of $\omega_\pi = 0$, U_ζ is invariant to changes in D_π. □

G Additional Figures and Tables

Variable	Sign	Horizons	Probability over		
			50% of horizons	75% of horizons	100% of horizons
Inflation Expectations	Positive	[0, 12]	87.88	75.50	60.15
CPI Inflation	Positive	[0, 10]	81.78	74.10	55.50
IP	Negative	[0, 24]	75.01	67.05	50.58
Unemployment	Positive	[0, 24]	91.22	80.97	54.99
Shadow Rate	Positive	[0, 24]	60.90	47.02	25.94
Prob. of Real Gains	Negative	[0, 24]	98.52	96.81	92.17
Non-Durable Consumption	Negative	[0, 24]	99.28	98.82	96.11
Durable Consumption	Negative	[0, 24]	98.54	97.80	94.67

Table A.1: Calculated probability of signed response. Response of CPI inflation is unrestricted.

Notes: Shows probability that the response of a variable is positive or negative for a given minimum share of the horizons considered. Probability is calculated as a percentage of all SVAR parameter draws that satisfy criteria. Identification leaves the inflation response unrestricted, see Appendix section C.2 for details. Sample period: from January 1998 to December 2024.

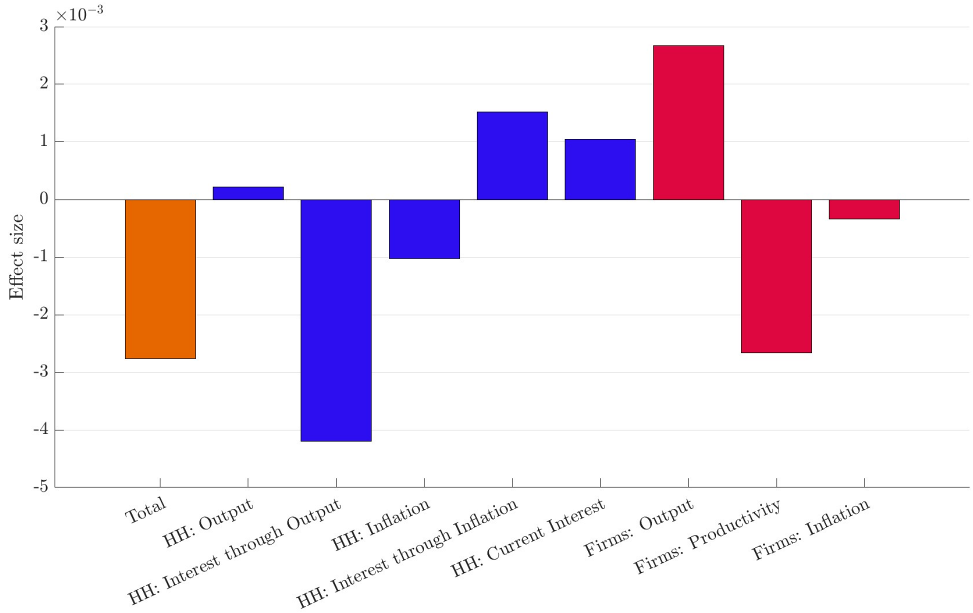

Figure A.11: Decomposition of general equilibrium effect of sentiment shocks on inflation.

Notes: Model without interest rate smoothing. General equilibrium effect of sentiment shocks on inflation is given by expression (27). See main text for details.

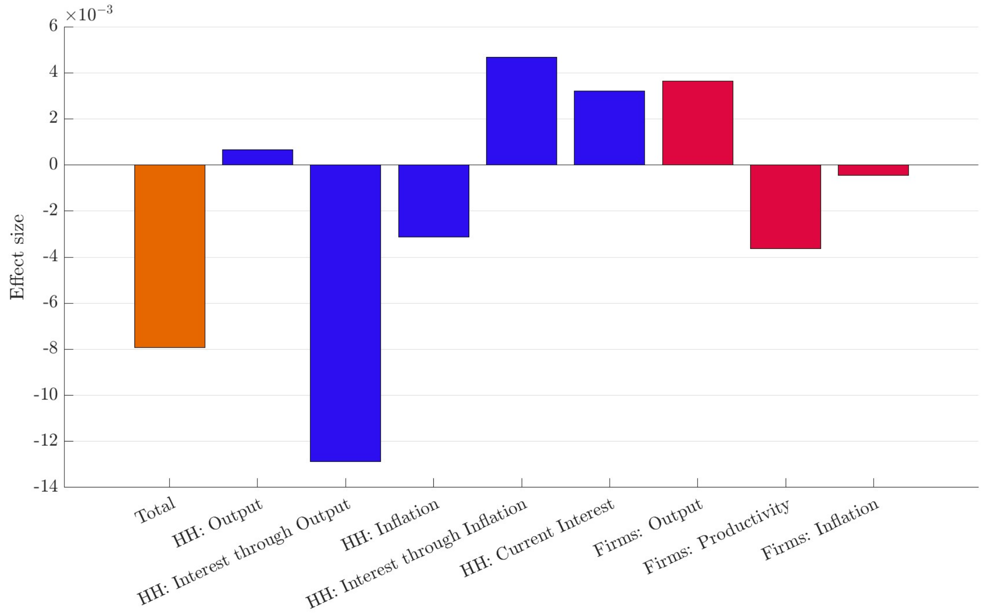

Figure A.12: Decomposition of general equilibrium effect of sentiment shocks on interest rate.

Notes: Model without interest rate smoothing. General equilibrium effect of sentiment shocks on the interest rate is given by expression (28). See main text for details.

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