

INTERNATIONAL MONETARY FUND

Shocks to Inflation Expectations

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WP/22/72

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**2022
APR**



WORKING PAPER

IMF Working Paper
Research Department

Shocks to Inflation Expectations
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Authorized for distribution by Malhar Mabar
April 2022

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ABSTRACT: The consensus among central bankers is that higher inflation expectations can drive up inflation today, requiring tighter policy. We assess this by devising a novel method for identifying shocks to inflation expectations, estimating a semi-structural VAR where an expectation shock is identified as that which causes measured expectations to diverge from rationality. Using data for the United States, we find that a positive inflation expectations shock is deflationary and contractionary: inflation, output, and interest rates all fall. These results are inconsistent with the standard New Keynesian model, which predicts inflation and interest rate hikes. We discuss possible resolutions to this new puzzle.

JEL Classification Numbers:	D84, E31, E32, E52
Keywords:	Inflation, Sentiments, Expectations, Monetary Policy
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WORKING PAPERS

Shocks to Inflation Expectations

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1 Introduction

“The 1970s saw two periods in which there were large increases in energy and food prices, raising headline inflation for a time. [...] One likely contributing factor was that the public had come to generally expect higher inflation—one reason why we now monitor inflation expectations so carefully.”

Jerome Powell, August 27, 2021¹

Central bankers take great interest in inflation expectations. The concern – as illustrated by the quote above – seems to be that expectations of inflation tomorrow can in their own right drive inflation today, necessitating higher interest rates and lower output to stabilize prices. In the worst case, inflation expectations might become “de-anchored”, a perilous situation where only the most aggressive and painful corrective action can bring inflation and expectations back into line.

The conceptual underpinning for policymakers’ worries is typically based on the New Keynesian Phillips Curve. In its simplest form, this says that inflation today is a function of expectations of inflation tomorrow and the output gap:

$$\pi_t = \beta\pi_t^{e,1} + \kappa\hat{y}_t \tag{1}$$

where π_t is current inflation, \hat{y}_t is the output gap and $\pi_t^{e,1}$ denotes expectations of one-period-ahead inflation. Thus, a shock to expected future inflation (i.e. an exogenous increase in $\pi_t^{e,1}$) worsens the trade-off between inflation and output. All else equal, either inflation must be higher or output must be lower, a natural worry for central bankers. This paper aims to evaluate this worry, addressing four questions.

First: what do we mean by shocks to inflation expectations? We define them as exogenous departures from rational expectations, and refer to them as “inflation sentiments”.²

¹Speech at Jackson Hole, <https://www.federalreserve.gov/newsevents/speech/powell20210827a.htm>

²A note on terminology. We use “inflation expectations” as a general term used for more casual dis-

These are potentially important for business cycles but their macroeconomic impact is not well understood. A large literature shows that measured inflation expectations are broadly inconsistent with full information and rational expectations.³ And theory predicts that changes to inflation sentiments should have large macroeconomic effects. As we demonstrate, a standard New Keynesian model features a expectations multiplier larger than one – inflation responds more than one-for-one to a positive sentiment shock. Yet there is, as far as we know, no work cleanly identifying and measuring the macroeconomic impact of these shocks. This paper aims to fill that gap.⁴

Second: how can we measure shocks to inflation expectations? We derive a novel strategy for identifying sentiment shocks and quantifying their macroeconomic effects. We estimate a vector autoregression (VAR) which includes both inflation and measured inflation expectations. We then identify the inflation sentiment from the variation in the data where forecasted inflation departs from the conditional expectation of inflation. Because a VAR is a machine for estimating conditional expectations, we use the reduced-form impulse responses themselves as the cross-equation identifying restrictions to isolate the inflation sentiment shocks. This is a semi-structural VAR, identifying one shock: the inflation sentiment.

This method is unique in its ability to isolate sentiment shocks from other forces that affect expectations. This includes *news shocks* – information about the about future fundam-

cussions, say of economic intuition or broad policy debates. We reserve the term “inflation sentiments” for narrower, more technical usage, meaning specifically the difference between economic agents’ inflation expectations and the mathematical conditional expectation of inflation of i.e. $\pi_t^{e,1} - \mathbb{E}_t \pi_{t+1}$.

³Examples include: upward bias in firms’ and households’ inflation forecasts (Candia et al., 2021), variation in the bias by income level (Bruine de Bruin et al., 2010); for households and by industry for firms (Savignac et al., 2021); large disagreement in forecasts (Mankiw et al., 2003); large uncertainty about future inflation (Binder, 2017); poor understanding of recent inflation (Jonung, 1981); and underreaction to relevant news (Coibion and Gorodnichenko, 2015a). Weber et al. (2021) survey the literature and argue that “the precise mechanisms through which inflation expectations affect decisions... remain ambiguous.”

⁴There is also a long, mostly theoretical literature on the impact of rational but non-fundamental inflation shocks, often termed “sunspots”, including Kydland and Prescott (1977), Clarida et al. (2000), Benhabib et al. (2001b), and Benhabib et al. (2001a). Our focus on the non-rational component of inflation expectations shocks is a complement to rather than a substitute for this analysis.

mentals⁵ – and *noise shocks*⁶ – the errors in noisy signals about fundamentals.⁷ To prove this point, we simulate a standard New Keynesian model with noise and news shocks, as well as shocks to inflation sentiments, productivity, and preferences. Running our method on the simulated data validates our approach, as it recovers the sentiment shocks, even in small samples. Although we only use this method to identify inflation sentiments, it has broader applications, such as identifying as shocks to expected future GDP growth.

Third: what are the macroeconomic consequences of shocks to inflation expectations? We document that sentiment shocks are important drivers of business cycles, but have macroeconomic impacts that are inconsistent with the standard New Keynesian framework. Using data from the United States since the early 1980s, we identify shocks to household inflation forecasts, which we estimate drive only 7%-15% of inflation volatility (depending on the measure) but almost a quarter of volatility in interest rates and more than a third for production. Next, we show that the response of the macroeconomy to a structural shock to inflation sentiments is deflationary: inflation falls and, despite monetary policy loosening, output declines. We also show that these results hold no matter whether we use household, market, or professional forecasters' expectations.⁸ This is a puzzle because the New Keynesian model has an expectations multiplier larger than one. In contrast, our estimated multiplier is negative.

Fourth: how can this puzzle be resolved? Although we do not offer a complete answer, we provide some evidence that this puzzle is not necessarily inconsistent with the New Keynesian framework. If monetary policy responds less aggressively to inflation than in the

⁵Papers such as Cochrane (1994), Beaudry and Portier (2006), and Beaudry and Lucke (2010) estimate VARs that imply news plays a large role in the business cycle. Beaudry and Portier (2014) survey the evidence.

⁶For mixed evidence on the importance of noise shocks, see for example Barsky and Sims (2012), Blanchard et al. (2013), Forni et al. (2017a), Forni et al. (2017b), Chahrour and Jurado (2018), Gazzani (2020), or Chahrour and Jurado (2021).

⁷More generally, our sentiment shock is orthogonal to any other shock to which agents respond with rational expectations. This includes sunspots that produce rationally self-fulfilling equilibria (Clarida et al., 2000) and errors due to learning from small sample data (Milani, 2017). The latter case we explicitly address in Section 4.4.

⁸One exception is when we use the Federal Reserve's own inflation forecasts as a measure of expectations. There, the impulse responses look similar to policy shock: interest rates rise, inflation and output fall. These results *can* be rationalized by the canonical New Keynesian model; the expectation error by a central banker causes a policy mistake.

canonical model, then there exist equilibria where responses to inflation sentiment shocks can be deflationary, in line with our evidence. In such cases, other forces – for example, fiscal policy – must play the preeminent role in determining inflation.

Our empirical work contributes to a growing empirical literature that attempts to identify sentiments in aggregate time series. Two strands are most closely related. First, Levchenko and Pandalai-Nayar (2020) use a structural VAR to jointly identify TFP surprises, news about future TFP (following Barsky and Sims (2011)) and shocks that affect expectations, which they label the sentiment. Their identification assumption is that the sentiment is orthogonal to the TFP and news shocks, and otherwise maximizes forecast errors. They find that the sentiment shock is expansionary and drives a majority of short-run business cycle fluctuations. A drawback of their identification is that sentiments cannot necessarily be distinguished from forces that move expectations orthogonal to TFP and news, such as discount factor shocks. Our method allows for such identification. Second, Chahrour and Jurado (2021) use a non-causal VAR to identify changes to TFP forecasts that are orthogonal to productivity at all horizons, and show that these “expectational disturbances” explain a large share of business cycle volatility. Shocks identified this way may include sentiments, but also noise shocks to which agents respond with rational expectations. Again, our identification approach can separately identify sentiments from noise or other shocks. Finally, a broader empirical literature studies “sentiments”, although typically they are not cleanly identified as deviations from rational expectations. Work in this literature mainly focuses on shocks to expectations about future TFP or GDP.⁹ To the best of our knowledge, we are the first to explicitly identify non-rational shocks to inflation expectations.¹⁰

⁹Other strategies abound. Some papers estimate sentiments as shocks to measured consumer confidence, including Barsky and Sims (2012) and Fève and Guay (2019); these approaches typically find little role for their identified shocks to contribute to business cycles. Clements and Galvão (2021) use GDP data revisions to isolate expectation shocks. Lagerborg et al. (2020) use mass shooting fatalities to instrument for sentiments. More generally, Angeletos et al. (2020) show that the main shock driving business cycles is nearly orthogonal to productivity.

¹⁰A larger literature documents that the full information rational expectations (FIRE) hypothesis fails for inflation forecasts in general. Coibion and Gorodnichenko (2012) and Coibion and Gorodnichenko (2015a)

Our work also connects to a long literature on the macroeconomic effects of inflation expectations. This has typically focused on evaluating the empirical properties of expectations in the New Keynesian Phillips Curve (NKPC). In contrast, we identify *structural* shocks to expectations and characterize their general macroeconomic effects. One strand of this literature focuses on the relative importance of past versus future expected inflation in determining prices. See, for example, Galí and Gertler (1999), Rudd and Whelan (2005), and Rudd and Whelan (2006). In another strand, Roberts (1997) and Adam and Padula (2011) show that the empirical New Keynesian Phillips Curve (NKPC) more closely matches the theoretical curve when surveyed forecasts are used rather than rational expectations. Nunes (2010) and Fuhrer (2012) include both surveyed forecasts and estimates of rational expectations into the NKPC, but come to different conclusions about whether contemporaneous inflation is more sensitive to the former or the latter.¹¹

2 Motivating Model

This short section aims to articulate more formally the default view of how inflation expectations affect the macroeconomy. This allows us to be more precise about how inflation sentiments interact with standard theory, and establishes a baseline against which to compare our empirical analysis in the next section.

Specifically, we modify the canonical three-equation New Keynesian model¹² to include an explicit shock to inflation expectations. We briefly show that this generates macroeconomic responses which coincide with the central bankers’ narrative in the introduction: inflation rises, monetary policy tightens, and output falls or rises depending on the policy response.

document that consensus SPF inflation forecasts underreact to news, while Bordalo et al. (2020) estimate that individual forecasters overreact.

¹¹Additionally, Brissimis and Magginas (2008) demonstrate that the NKPC fits the Great Moderation period well when using surveyed expectations, a conclusion confirmed for the Great Recession by Coibion and Gorodnichenko (2015b). Coibion et al. (2018) discuss further advantages of empirical expectations, with special attention paid to the NKPC. For a general survey of expectations in the NKPC, see Mavroeidis et al. (2014).

¹²See Galí (2008) for a textbook description.

The canonical three-equation New Keynesian model is given by:

$$\begin{aligned}
 \text{New Keynesian Phillips curve:} & \quad \pi_t = \beta\pi_t^{e,1} + \kappa y_t \\
 \text{Fisher equation:} & \quad i_t = \mathbb{E}_t[\gamma(y_{t+1} - y_t)] + \pi_t^{e,1} \\
 \text{Taylor rule:} & \quad i_t = \phi_y y_t + \phi_\pi \pi_t
 \end{aligned}$$

where π_t is inflation, $\pi_t^{e,1}$ is inflation expectations, y_t is the output gap, i_t is the nominal interest rate, and $\mathbb{E}_t[\cdot]$ denotes the mathematical conditional expectation operator.¹³

When expectations are rational, this framework is unable to model the situation we want to think about. For example, imagine that the central bank is committed to delivering a certain inflation path. But for some reason economic agents doubt the central bank’s commitment to their policy goal, and expect inflation higher than what the policymaker will deliver. By definition, such beliefs cannot be rational. The conditional expectation of inflation *is* the path that the policymaker will deliver. If agents think something different, then they *must* be departing from rationality.

We thus modify the canonical model to allow expected inflation to depart from the rational expectation:

$$\pi_t^{e,1} = \mathbb{E}_t[\pi_{t+1}] + \zeta_t \tag{2}$$

where ζ_t is exogenous and stochastic. To distinguish it from $\pi_t^{e,1}$, we refer to ζ_t as the *inflation sentiment*. The sentiment may be autocorrelated, and we refer to the (mean-zero, white noise) innovations to the sentiment as the *sentiment shock*.

Expected inflation still has a rational component, so policymakers can still affect expectations today by communicating future policies – this will affect the $\mathbb{E}_t[\pi_{t+1}]$ part of expectations. Shocks to real fundamentals will affect the rational component too, as usual. And because ζ_t is mean-zero, expectations are still rational on average. But now fundamentals and policies do not *entirely* drive expectations; there is scope for inflation expectations

¹³We impose rationality on expected future output for simplicity. No one seems to be unduly concerned about “de-anchored output expectations”.

to move in ways outside of the the control of policymakers. Thus, we think, we capture a concern that policymakers have when they talk about the importance of inflation expectations.

The canonical model has clear predictions about the effects of such a sentiment shock: a positive sentiment shock should increase inflation and interest rates, and in most cases will cause real output to contract. To see why, consider the simplest case where the sentiment ζ_t is i.i.d. Then the model becomes:

$$\pi_t = \beta\zeta_t + \kappa y_t \quad \text{[AS]} \quad (3)$$

$$\phi_\pi \pi_t = -(\phi_y + \gamma)y_t + \zeta_t \quad \text{[AD]} \quad (4)$$

These two equations are referred to as the New Keynesian “aggregate supply” and “aggregate demand” curves (Eggertsson and Krugman, 2012), due to their resemblance to the traditional Keynesian relationships.

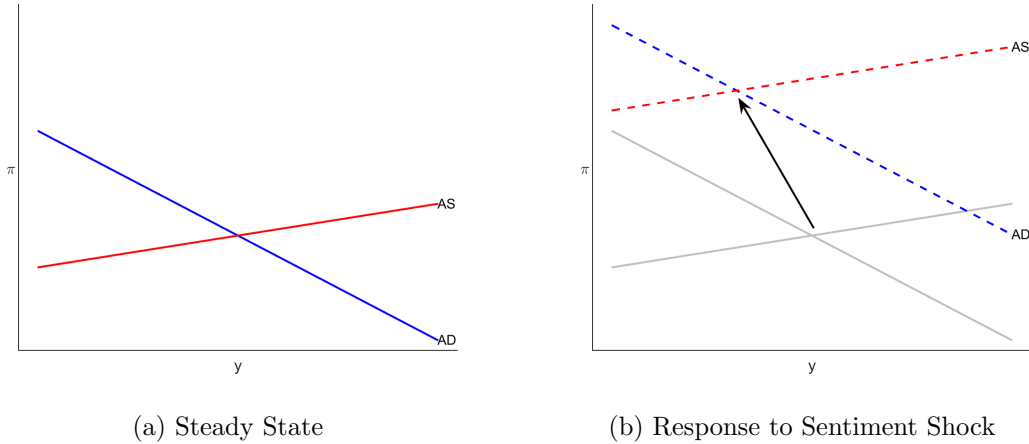


Figure 1: New Keynesian Aggregate Supply and Demand after a Sentiment Shock

Figure 1 plots how the AS and AD curves respond to a sentiment shock. The AS (Phillips) curve shifts upwards because sticky-price firms expect higher prices in the future, so they would choose higher prices today, at every level of the output gap. Absent any change in the AD curve, this shift alone would create inflation and lower output. This

is because the AD curve is downward-sloping, which is due entirely to the central bank's policy response: when inflation rises, the central bank raises interest rates and pushes down on output.

However, the sentiment shock also shifts the AD curve upwards because it impacts the Fisher equation. By raising household expectations of future inflation, the shock lowers the effective real interest rate, increasing contemporaneous consumption and hence output. This AD shift ameliorates the decline in output, but further increases inflation.

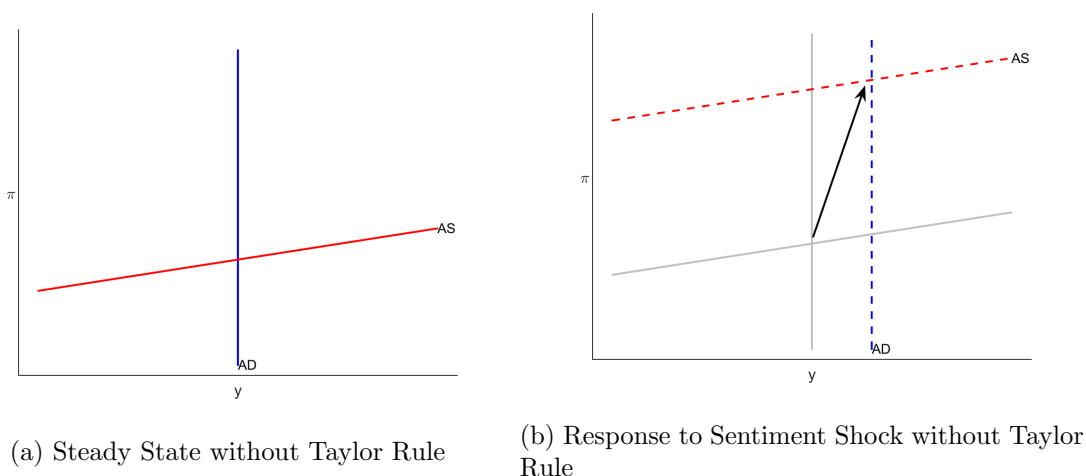


Figure 2: New Keynesian Sentiment Shock without a Policy Response

It should be clear from the above that the baseline model predicts higher inflation, but output is potentially ambiguous. Can the AD shift dominate, raising output? And how will interest rates respond?

To answer these questions it is helpful to think about the special case where the central bank does not respond to inflation, $\phi_\pi = 0$. Then the AD curve is vertical, as shown in Figure 2. Without the central bank's policy response, inflation increases by more, because the AS curve rises along a vertical AD curve. On top of this, the AS curve shifts to the right; agents expect high inflation, so real real rates are low, boosting consumption and output, even though nominal rates rise (as the Taylor rule still puts weight on the output gap). So overall, the shock has positive real and nominal effects: inflation, output, and the

interest rate all rise. When $\phi_\pi > 0$, the outcome is slightly different. With a flatter AD curve, output can fall. Indeed, in most standard calibrations, this effect dominates and the shock causes a recession.

In sum: the baseline New Keynesian model with a standard Taylor rule makes strong predictions for the effect of a positive shock to inflation expectations. Inflation rises regardless of the policy regime. And although the central bank faces a trade-off between controlling inflation and creating a recession, nominal rates increase unambiguously. The net effect on output depends on the strength of the policy response, but is negative for standard parameter values.

3 Identifying Shocks to Inflation Expectations

Having defined what we mean by shocks to inflation expectations, we now detail a method to measure them. Our method exploits two facts. First, that inflation expectation shocks are departures from the mathematical conditional expectation of future inflation. Second, that a reduced-form VAR is a machine for estimating conditional expectations. We thus estimate a VAR which includes both inflation and a measure of inflation expectations, using the reduced-form coefficients to estimate the rational component of the response of expectations to shocks. We use this to inform an identifying restriction which can recover the non-rational movement in inflation expectations, i.e. sentiment shocks.

3.1 Basic VAR Structure

Consider the following vector autoregression (VAR). π_t denotes inflation in period t , f_t^h denotes the period t forecast of inflation over the following h periods (e.g. inflation over the next year) and y_t denotes a $n \times 1$ vector of other macroeconomic time series.¹⁴ The VAR

¹⁴We use the term “forecast” to mean an empirical time series, distinct from the more general concept of an expectation. A forecast is a real world measure of expectations.

is given by

$$\begin{pmatrix} f_t^h \\ \pi_t \\ y_t \end{pmatrix} = B \begin{pmatrix} f_{t-1}^h \\ \pi_{t-1} \\ y_{t-1} \end{pmatrix} + A\varepsilon_t \quad (5)$$

where $\varepsilon_t \sim N(0, I)$ is an i.i.d. $(n+2) \times 1$ vector of shocks. We consider forecasts h periods ahead which is what appears in the data, typically reporting some agents' expected inflation over the next year. This is different from the inflation expectation in equation (2), which was a one-period object. While the basic idea is the same, we have to carefully relate the two when moving to the dynamic New Keynesian model in Section 5.

The structural shocks are related to the VAR's reduced form "innovations" u_t by

$$u_t = A\varepsilon_t$$

We subdivide $\varepsilon_t = \begin{pmatrix} \varepsilon_t^S \\ \varepsilon_t^F \end{pmatrix}$ into $n+1$ "fundamental" shocks ε_t^F that determine inflation, output, etc. consistent with rational expectations, and one "sentiment" shock ε_t^S that independently affects expectations.

Standard VAR estimation identifies B and the autocovariance matrix of forecast errors Σ , which satisfies

$$\Sigma = AA'$$

Σ is symmetric, so it has $(n+2)(n+3)/2$ unique entries; we need at least $(n+2)(n+1)/2$ independent restrictions in order to identify the $(n+2)^2$ entries in A . When A is identified, the structural shocks ε_t may be recovered from the innovations u_t .

3.2 Identifying Assumption

The identifying assumption is that *the sentiment shock ε_t^S is the only one that causes contemporaneous forecasts to deviate from rational expectations*. The fundamental shocks may only affect contemporaneous inflation forecasts f_t^h through their average effects on future

inflation.

The effect of the reduced form innovation u_t on inflation k periods into the future is the standard impulse response function (IRF) $\phi_\pi(k)$:

$$\phi_\pi(k) = e_\pi B^k$$

where e_π is the standard basis vector identifying the π entry in the data vector. The total inflation over horizon h is the sum of inflation in each of the next h periods, so the effect of a reduced form shock on horizon h inflation is:

$$\phi_\pi^h = \sum_{k=1}^h e_\pi B^k \quad (6)$$

which we denote by ϕ_π^h , a row vector that captures how each reduced form shock affects inflation over the h period horizon. The rational expectation of horizon h inflation (denoted by π_{t+h}^h) after a reduced form shock u_t is

$$\mathbb{E}[\pi_{t+h}^h | u_t] = \phi_\pi^h u_t$$

The innovation depends on structural shocks by $u_t = A\varepsilon_t$, so the rational expectation conditional on a structural shock is

$$\mathbb{E}[\pi_{t+h}^h | \varepsilon_t] = \phi_\pi^h A \varepsilon_t$$

Partition the matrix A along similar dimensions as the shock vector $\varepsilon_t = \begin{pmatrix} \varepsilon_t^S \\ \varepsilon_t^F \end{pmatrix}$:

$$A = \begin{pmatrix} A_f^S & A_f^F \\ A_c^S & A_c^F \end{pmatrix}$$

where the scalar A_f^S is the contemporaneous effect of the sentiment shock on forecasts, and

the row vector A_f^F is the effect of the fundamental shocks. The blocks A_c^S and A_c^F are the corresponding effects on the remaining contemporaneous variables.

The identifying assumption implies that the effects of fundamental shocks on contemporaneous forecasts is equal to their effects on the rational expectation, i.e.

$$\phi_\pi^h \begin{pmatrix} A_f^F \\ A_c^F \end{pmatrix} = A_f^F$$

which can be inverted to find the effect of fundamental shocks on forecasts:

$$(1 - \phi_{\pi,f}^h)^{-1} \phi_{\pi,c}^h A_c^F = A_f^F \quad (7)$$

where $\phi_{\pi,f}^h$ denote the first entry in ϕ_π^h and let $\phi_{\pi,c}^h$ denotes the remaining entries. Equation (7) is our identifying restriction. It says that any fundamental shock causes the inflation forecast f_t^h to move by exactly the amount that the price level will change in the next h periods. That is, the forecast responds rationally. Any variation which departs from this is loaded onto the sentiment shock.

The implied restrictions for the matrix A are:

$$A = \begin{pmatrix} * & (1 - \phi_{\pi,f}^h)^{-1} \phi_{\pi,c}^h A_c^F \\ * & A_c^F \end{pmatrix} \quad (8)$$

where $*$ denotes unrestricted entries, of which there are $n + 2$ in the first column. This unrestricted column is the contemporaneous impact of the inflation sentiment shock.

In general, the block A_c^F is not identified. An arbitrary assumption must be made to select a A_c^F block. In our implementation, we let it be lower triangular so that the fundamental shocks have a causal ordering (as in Christiano et al. (1999) among many others). This does not affect the sentiment shock ε_t^S ; every valid choice of A_c^F is just a unitary transformation of the fundamental shocks alone and yields the same sentiment shocks.

In Section 5.2 we test our method for identifying inflation sentiments by applying it to data simulated from a model with several extra shocks which might be though difficult to distinguish from sentiments. We find that the method consistently identifies the sentiment shock, and is accurate even in realistically small samples.

3.3 Implementation

Implementing the identification procedure is straightforward:

1. Estimate the VAR in reduced form:

$$\begin{pmatrix} f_t \\ \pi_t \\ y_t \end{pmatrix} = B \begin{pmatrix} f_{t-1} \\ \pi_{t-1} \\ y_{t-1} \end{pmatrix} + u_t$$

to recover coefficient matrix B and series of reduced form innovations u_t .

2. Calculate Σ as the variance matrix corresponding to u_t
3. Construct vector ϕ_π^h for the appropriate horizon by equation (6)
4. Calculate A using the restrictions from ϕ_π^h and equation (8) (this calculation is typically nonlinear, depending on the assumptions used to identify A_c^F)
5. Invert to recover the shock vector by

$$\varepsilon_t = A^{-1}u_t$$

4 Estimated inflation sentiments

In this section estimate the vector autoregression articulated in the preceding section using US data, outlining our baseline results.

4.1 Data

Our baseline specification includes six variables. Five of these are utterly standard, following the choices by Coibion (2012), who selects a monthly analog to the standard set by Christiano et al. (1999): inflation is the log change in the CPI, a commodity price index is included from the PPI, the industrial production index and unemployment rate measure economic activity, and the nominal interest rate is the Federal Funds Rate (FFR). Given that our results may depend on the specification of our empirical approach, it is important that we convince the reader that our statistical model is not somehow mis-specified. We tackle this issue in details in Section 4.5 where we run an extensive model selection exercise. But for now we offer convention as a defence. By sticking so closely to the most commonly-used set of variables, we leave ourselves no room to manipulate our results through the choice of specification.

The one novel variable in our VAR is expectations, for which we use the median 12-month-ahead inflation forecast from the Michigan Survey of Consumers. This measure has two advantages: it is collected monthly, and it represents expectations of ordinary households rather than professional forecasters. We prefer monthly data because the higher resolution should give us a better chance of identifying a sentiment shock, although, we also run specifications with quarterly data. Together, our baseline sample runs from 1982:M1 - 2021:M12.

We also consider three alternative measures of inflation forecasts. The expectations of the median household may not correspond to those of firms setting prices, or policymakers setting interest rates, so other measurements may yield interesting insights. To measure the expectations of the market, we use the Cleveland Fed's 12-month-ahead inflation forecasts, which are published monthly. To get a sense of the views of (potentially!) more informed economic observers, and to comport with the standard in the literature,¹⁵ we also run our VAR with consensus forecasts from the Survey of Professional Forecasters (SPF). This data

¹⁵e.g. Coibion and Gorodnichenko (2012), Coibion and Gorodnichenko (2015a), and Lagerborg et al. (2020) among many others. Coibion et al. (2018) include further examples in their survey of the literature.

is quarterly, so we use the direct quarterly analogues of the other series, with one exception – substituting quarterly GDP for industrial production (as too is standard). Finally, we use the Federal Reserve’s Greenbook inflation forecasts as a measure of policymakers’ expectations. These are released at frequencies lower than monthly but higher than quarterly. So we take the last available observation in each quarter, on the grounds that it is (as close as possible to) fully-informed by all the data available that quarter.

For use in the VAR we deseasonalize and stationarize the data by removing common monthly (or, for quarterly data, quarterly) components and a linear time trend. More generally, in our choice of data and specification, we aim to be as unoriginal as possible in our baseline estimation. Model mis-specification is a potential challenge to our findings and our first line of defence is that we are adhering strictly to convention. So although our statistical approach could be misguided, we are at least in good company.

4.2 Baseline Results

Figure 3 shows the impulse responses to a one-standard-deviation structural inflation sentiment shock for our baseline monthly model. We use an Akaike information criterion to choose lag length, which selects a three-lag specification.

On impact, expected inflation rises by around 25 basis points. Inflation itself increases on impact by more than 40 basis points at an annualized rate. But this is not statistically significant and after the first period the impulse remains persistently below zero. After 3 months, the impact on the price level is zero and thereafter consistently negative. So overall, the impact is deflationary. The inflation impulse is itself useful in trying to understanding the expectations response, as it permits a decomposition of the change in inflation expectation into its rational and sentimental parts. The rational component of one-year-ahead inflation expectations in period t is the cumulative sum of monthly inflation over periods $t+1$ to $t+12$. So we can compute the impulse for this component simply as the appropriate forward-looking sum of inflation. This, shown in the top-middle panel, declines by about 10 basis points on impact and reflects the medium term response of inflation – average

monthly annualized inflation declines by close to 0.1 percent over periods 1 to 12. With the rational component in hand, we can subtract it from the inflation expectations impulse to recover the sentiment.¹⁶ This is shown in the upper right panel. Characterizing the size and dynamics of this object is a valuable result in its own right. We find such shocks to be moderately large – typically in the order of around 40 basis points – and of limited persistence – decaying almost to zero within a year.

How can the rational expectation of future inflation go down if we identify a shock orthogonal to it? Here, having a conceptual framework in mind, such as the model in the previous section, is useful. If an exogenous shock to inflation expectations has macroeconomic effects, one should expect it to affect future inflation. And if it affects future inflation, the rational component of expectations must respond. So one should expect a response of the rational part of inflation expectations. To understand this from a purely statistical perspective, recall that we identify here the variation which causes inflation forecasts to depart from their rational expectation. This is a restriction on the difference between measured expectations and their rational component, not on the rational component itself.

More generally, the dynamic effects of the shock to the inflation sentiment are at odds with the predictions of the standard New Keynesian model. Although inflation rises on impact, it remains low for almost a year. Although the decline in real activity (as measured by industrial production) is consistent with the canonical framework, the response of monetary policy is most certainly not. Interest rates decline by around 15 to 20 basis points. Although this is relatively small the effect is very persistent, lasting almost two years before becoming statistically insignificant. This persistence is matched and even exceeded by that of real activity, which remains well below its starting level for several years.

Although the impulse responses can measure the size of the sentiment shock in a literal sense, this does not tell us whether this shock is actually big in a macroeconomic sense. It could be that these shocks are swamped by the impact of other, fundamental shocks.

¹⁶In the notation of equation (2) we are performing the decomposition $\pi_t^{e,12} = \mathbb{E}_t \sum_{j=1}^{12} \pi_{t+j} + \zeta_t^{12}$, where ζ_t^{12} is the sentiment component for one-year-ahead inflation. In the next section, we clarify how to extend the conceptual framework of the New Keynesian model to account for this.

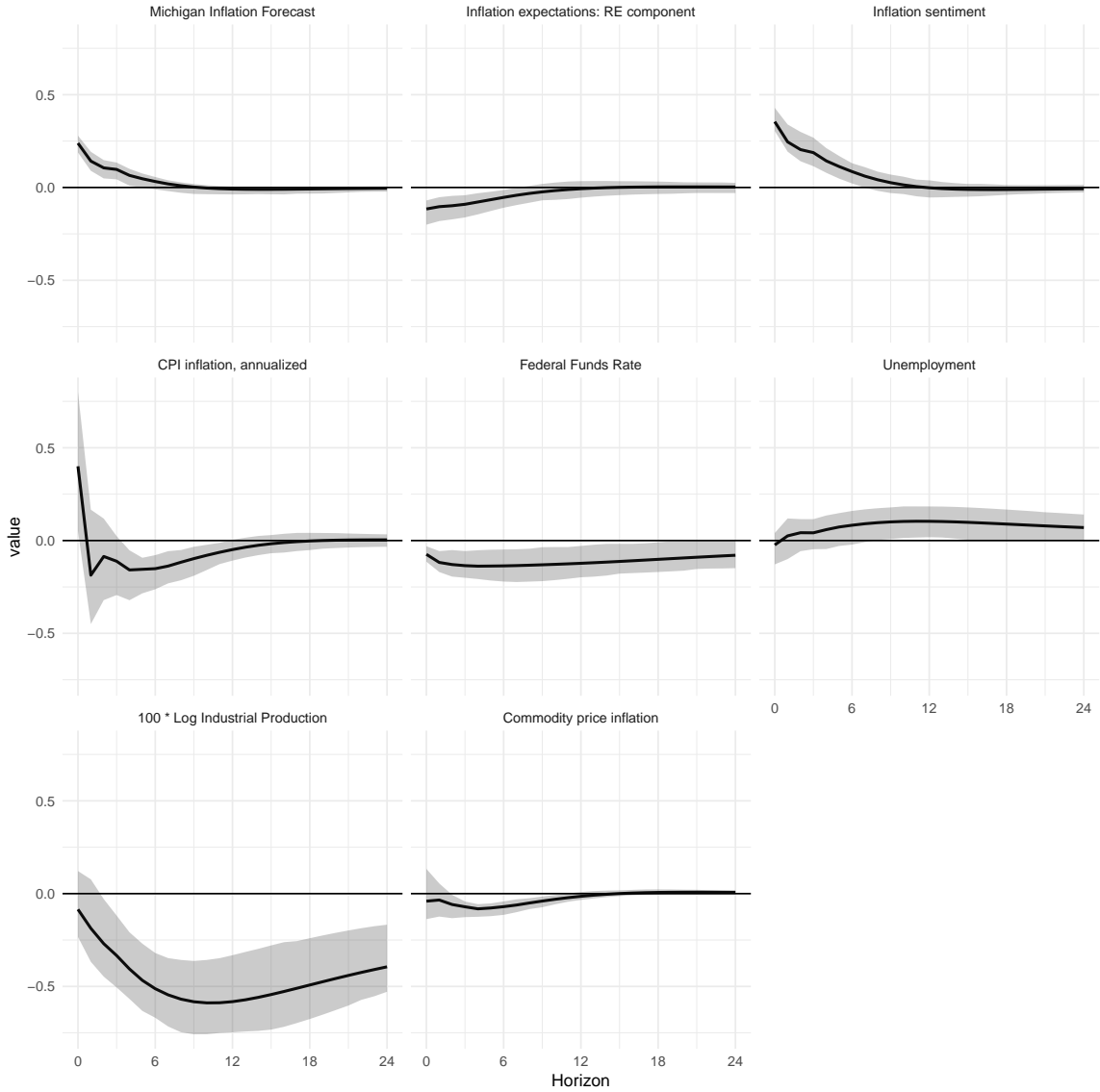


Figure 3: Impulse Responses to a Sentiment Shock

Structural impulse responses to a one standard deviation sentiment shock, baseline model. Shaded ranges show a 90 percent confidence interval, computed from bootstrap with 500 replications.

To address this, we compute the variance decomposition of the structural VAR, which attributes the variation in each variable into that due to the non-fundamental and other (fundamental) shocks.¹⁷

Figure 4 presents this decomposition, adding together the impact of the fundamental shocks into one object. It shows that inflation sentiment shocks are responsible for a relatively large share of the variation of inflation expectations at short horizons but less at longer ones. This presumably reflects the fact that the direct (via ζ_t) and indirect (via $\mathbb{E}_t\pi_{t+1}$) effects of the sentiment shock on expected inflation offset, limiting their overall effects. In the long run, around 80 percent of the variation in inflation expectations is due to fundamental factors. Similar long-run effects hold true for most other variables, with inflation sentiments driving between around 10 and 20 percent of the variation. For industrial production, however, sentiment shocks seem to be of significant and growing importance at long horizons, consistent with the large and delayed response of industrial production to sentiment shocks. Overall, the results in Figure 4 suggest that sentiment shocks may be an important driver of real macroeconomic fluctuations.

In Figure 5 we plot the time series for the estimated sentiment. The light gray line is the time series estimated from the baseline model, while the dark line a 12-month moving average. Sentiments are largest during the financial crisis, when household inflation expectations remained persistently high. Estimated sentiments are also high at the end of 2021; after a year of resurgent inflation, households expect even more.

4.3 Alternative Measures of Inflation Expectations

We now turn to the results from repeating our analysis with alternate measures of inflation expectations. This serves a dual purpose, both acting as a check on the broader validity of our results, but also allowing an investigation of how different types of agents' inflation expectations might have different macroeconomic consequences. In particular, we estimate three further VARs. The first uses a monthly measure of market expectations, calculated

¹⁷See Hamilton (2020) for details.

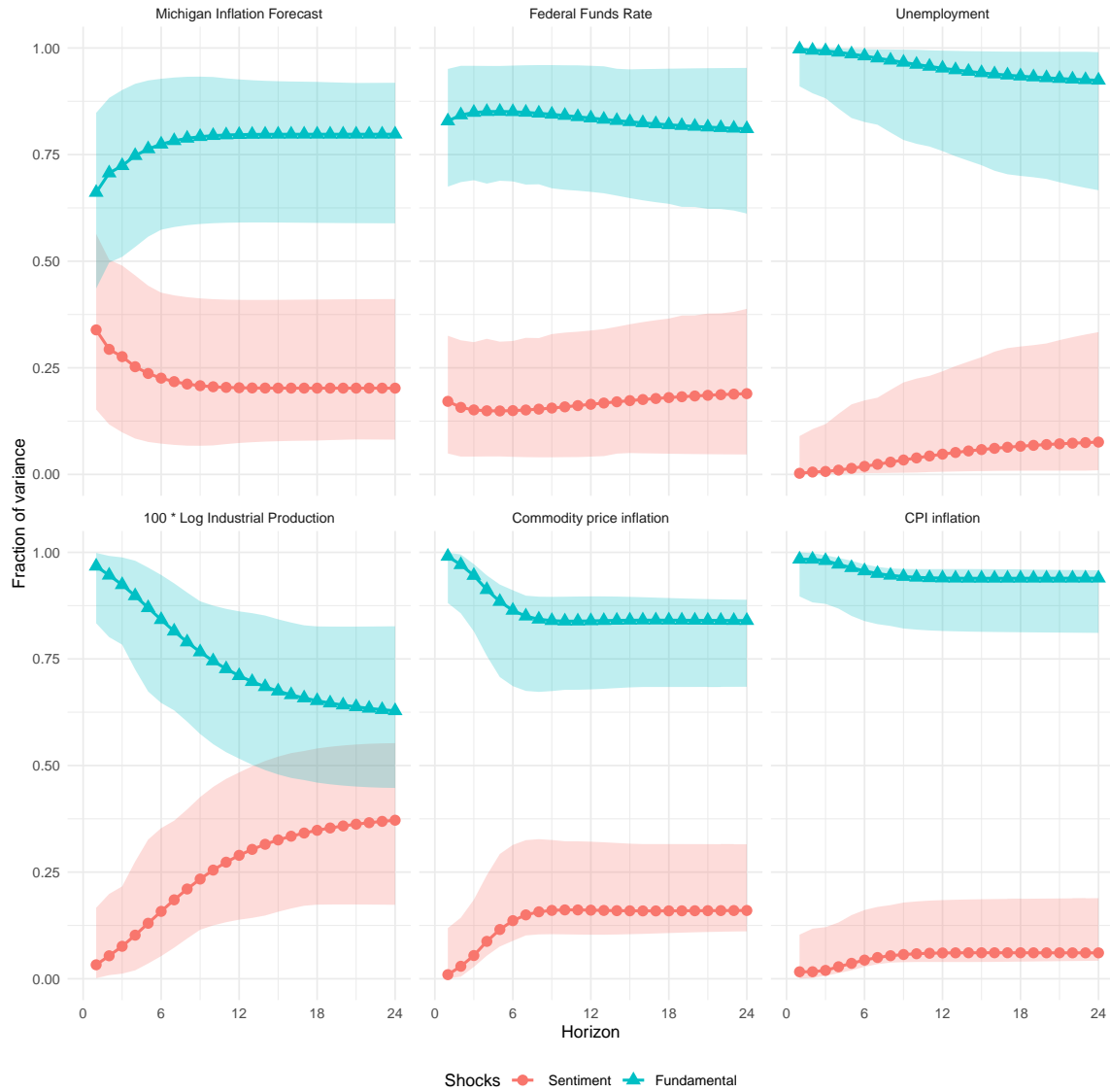


Figure 4: Variance Decomposition

The variance decomposition for each horizon in the baseline model. Shaded ranges show a 90 percent confidence interval, computed from bootstrap with 500 replications.

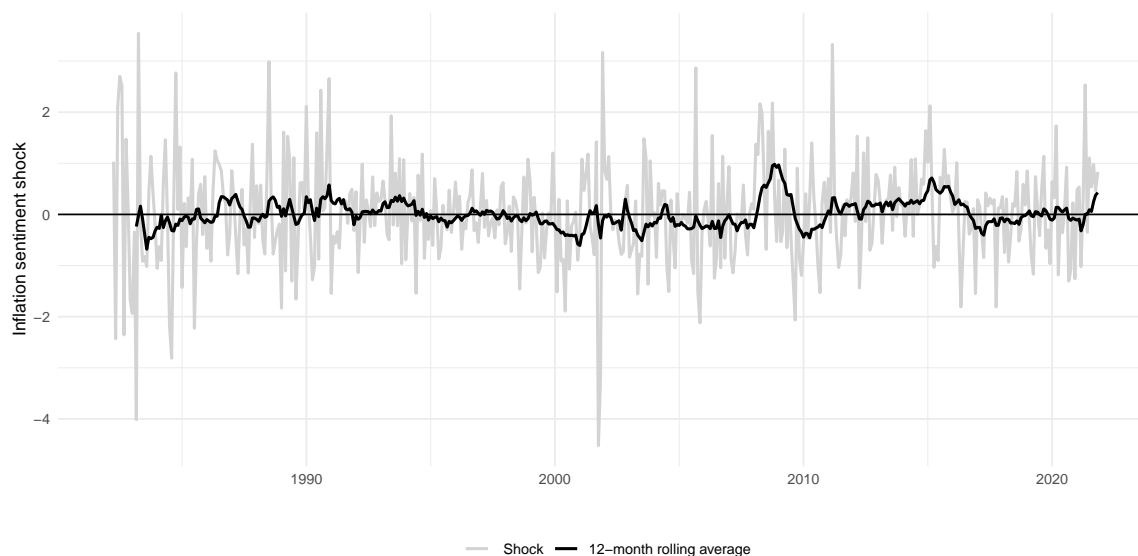


Figure 5: Inflation Sentiment Time Series

by the Federal Reserve Bank of Cleveland using bond prices, derivatives, and surveys. The second uses a quarterly measure of economists' expectations: the Survey of Professional Forecasters' (SPF) average. The third uses the central bank's own expectation, as reported in the Fed's Greenbook forecasts.

We report the results from all three exercises in Figure 6, in addition to our baseline VAR. For simplicity, we do not report here the responses for unemployment and commodity price inflation (although we do include them in the VAR) as their inclusion is principally a matter of model fit, rather than a test of economic theory.

The most notable feature of Figure 6 is that a one-standard-deviation inflation sentiment shock is almost identical on impact across the alternative measures. This not an artifact of our method. If the behavior of different inflation expectations series were sufficiently varied they *could have* produced inflation sentiment shocks of differing sizes – we do not force them to be similarly-sized. Moreover, the time profile of households', professional forecasters' and the central bank's departures from rationality are near-identical. The Cleveland Fed's market-based measure is less persistent. This difference could reflect the unforgiving nature of markets, which punish traders who make misguided forecasts much more obviously than

households, professional forecasters, or Federal Reserve Board members.

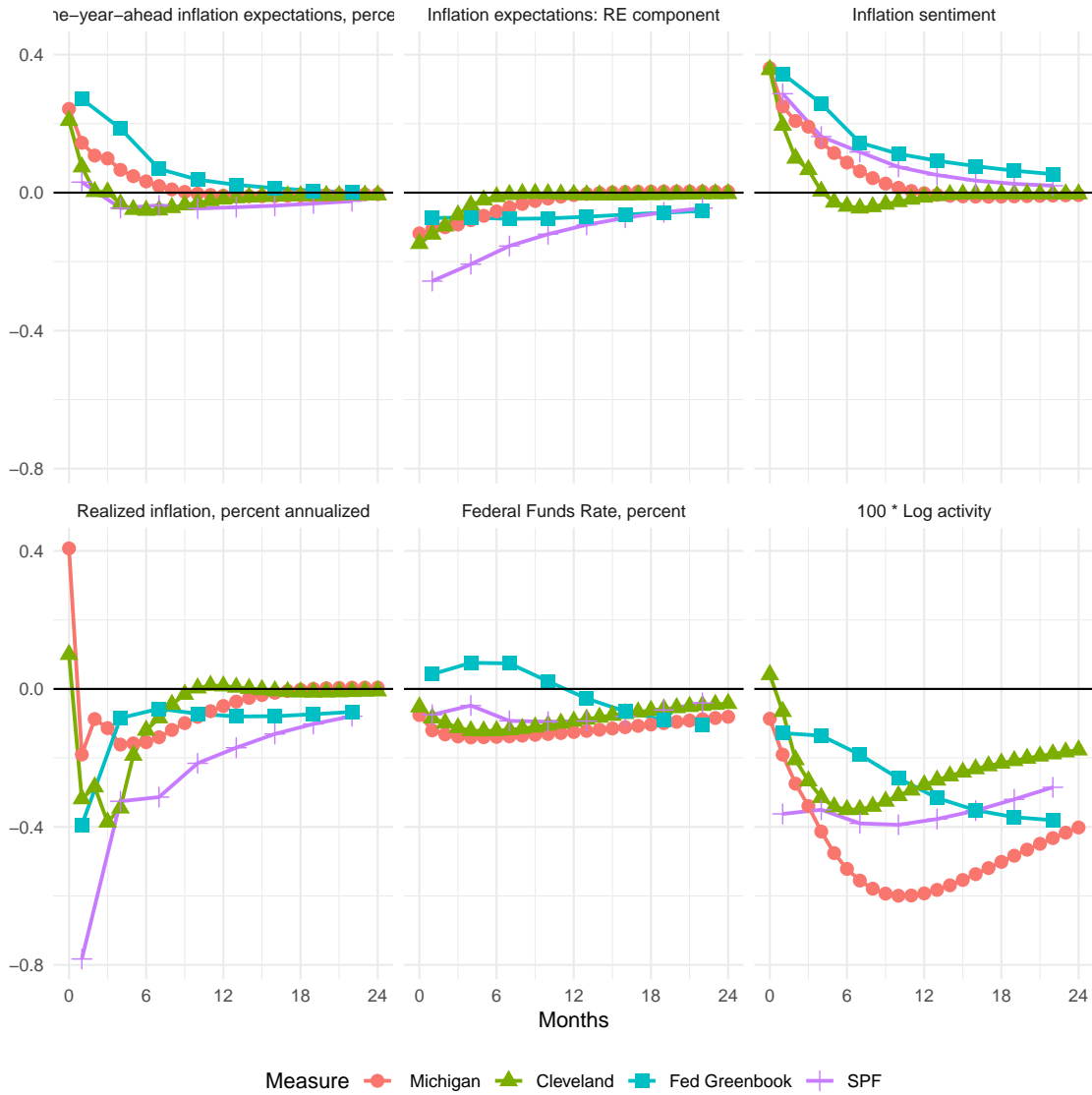


Figure 6: Impulse Responses to a Sentiment Shock for Alternative Forecast Measures

All sentiment shocks are associated with deflation and recession, in line with our baseline findings. The two monthly measures also feature remarkably similar short-term inflation dynamics, with a positive but statistically insignificant response on impact. Given this agreement, though, we interpret this as a consequence of the timing of the monthly data. Lags in pricing behavior and survey design mean that the overall deflationary effect of a

sentiment might not show up immediately in prices. For example, the Michigan survey is conducted throughout the relevant month. And so shocks to expectations of inflation in the second half of the month cannot possibly affect prices set (and surveyed by the BLS) in the first half of the month. As such, we prefer to look through the first period response of both responses and instead characterize them as broadly deflationary, consistent with the quarterly-frequency models.

Interest rates likewise agree with our baseline model, falling in all cases except one: a shock to the Federal Reserve Board’s inflation sentiment is followed instead by higher interest rates. Given our motivating model in Section 2, it is a puzzle that sentiments generally cause deflation and monetary easing. In contrast, the response to the Fed’s sentiment is not puzzling at all: it looks just like a policy shock. If the Fed expects inflation, it acts as if it expects inflation. It raises rates to combat an inflation which never materializes. Instead, the economy experiences deflation and recession, consistent with the standard response to policy tightening. Appendix A demonstrates this unsurprising response to a Fed forecasting error in the canonical New Keynesian model.

The alternative expectation measures are also all responsible for sizeable shares of macroeconomic volatility, but with different effects on different time series. Table 1 reports our estimated the variance decomposition for each measure. These are the contributions to long-run variance, so the “Michigan” column reports exactly the right-most shares of the baseline results in Figure 4. In all cases, sentiment shocks drive 10% or more of the variance in real activity, which is measured as industrial production for the monthly series (Michigan, Cleveland) and real GDP for the quarterly series (SPF, Greenbook). However, the effects on the noninal series are more heterogeneous. The SPF and Greenbook sentiment shocks contribute to little of the long-run variance in interest rates. And in contrast to our baseline results, large shares of the realized inflation variance are due to Cleveland and SPF sentiment shocks.

In summary, the puzzle we document is robust to how inflation expectations are measured. Alternate measures of inflation expectations produce very similar sentiment shocks,

	Michigan	Cleveland	SPF	Fed Greenbook
100 * Log activity	0.363 (0.169, 0.512)	0.111 (0.022, 0.257)	20412.583 (0.461, 0.786)	0.265 (0.076, 0.691)
Federal Funds Rate	0.205 (0.032, 0.405)	0.105 (0.007, 0.276)	14715.964 (0.078, 0.747)	0.030 (0.046, 0.427)
Realized inflation	0.056 (0.035, 0.176)	0.154 (0.086, 0.248)	11048.476 (0.532, 0.833)	0.072 (0.090, 0.596)
Year-ahead inf. exp.	0.187 (0.084, 0.389)	0.106 (0.061, 0.213)	1107.642 (0.209, 0.721)	0.111 (0.035, 0.384)

Table 1: Long Run Variance Shares Attributed to the Sentiment Shock, for each Forecast Measure

Bootstrapped 90 percent confidence interval in parentheses

and macroeconomic responses which are broadly in line with our baseline results. No specification reproduces the predictions of the canonical New Keynesian model from Section 2, and only the Fed’s sentiments seem to be rationalized by controlling which agents receive a sentiment shock (Appendix A).

4.4 Identification without the Benefit of Hindsight

One assumption of our baseline approach is that agents form rational expectations using the true statistical model: the rational expectation that we use to identify the sentiment is the conditional forecast (equation (6)) estimated from the entire sample. However, even rational agents might form different expectations if older data do not imply the same dynamics as we estimate. Our baseline approach is a fine approximation if learning is fast, but if learning is slow, a rational agent will form expectations differently in 1992 than in 2022. Some research suggests that slow learning may be responsible for many of the observed puzzles in expectations data (Farmer et al., 2021), or produce rational shocks that resemble sentiments Milani (2017). In this section, we test if our results are robust to this concern.

To account for learning, we independently run our entire estimation at every time period τ , beginning in 1992 when 10 years of data are available. This way, we identify the sentiment in every period, using the rational expectation formed from data available at that date. The

structure of the VAR (5) becomes

$$\begin{pmatrix} f_t^h \\ \pi_t \\ y_t \end{pmatrix} = B_\tau \begin{pmatrix} f_{t-1}^h \\ \pi_{t-1} \\ y_{t-1} \end{pmatrix} + A_\tau \varepsilon_t \quad t \leq \tau \quad (9)$$

At every period τ we calculate the reduced form shock u_τ from the τ -period VAR (9), identify the coefficient matrix A_τ , and calculate the shock vector by $\varepsilon_\tau = A_\tau^{-1}u_\tau$. Then, we calculate the average responses to our identified shocks ε_τ to estimate a *learning-robust* result.

The learning-robust estimates are qualitatively similar to our baseline results. Figure 7 plots the first column of the time-varying A_τ . This is the contemporaneous effect of a sentiment shock on each time series, estimated using data available in the given period. For each series, the blue dashed line is the average value over the sample period: our learning-robust estimate of the instantaneous impact of a sentiment shock. The dotted line is the value at the end point: our baseline result which uses information from the entire sample to identify the shock at each point in time. These two lines are broadly similar with one main exception: the learning-robust result suggests a stronger contraction in real activity. In response to a sentiment shock, industrial production falls by more than our baseline result, and unemployment rises on impact instead of only rising over time.

Figure 7 also demonstrates that our results are robust to exclusion of the zero-lower-bound (ZLB) period. The plotted value in any particular period gives our baseline estimate excluding any data after that time. Thus any value from before 2009 excludes the ZLB period in the United States. For example, estimates using data up to 2008 all have the same sign as our baseline results. Moreover, like the learning-robust estimates, excluding the ZLB period implies larger contemporaneous declines in real activity after a sentiment shock. In particular, truncating the sample before the ZLB period implies that positive sentiment shocks increase inflation on impact, consistent with our other estimated effects on real activity.

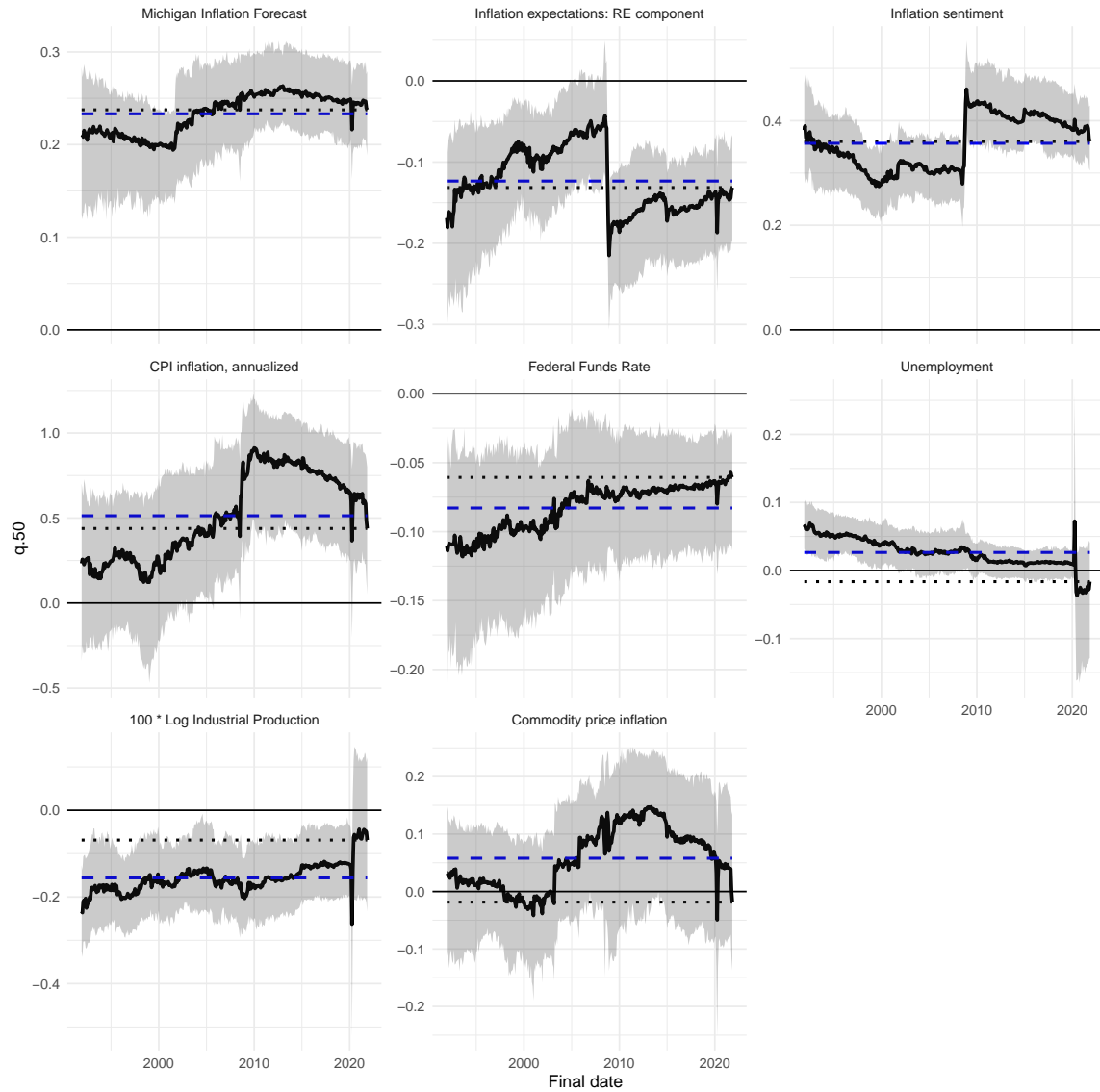


Figure 7: Time Varying Estimation of Sentiment Shock Effects

Each subplot is an entry in the A_τ coefficient matrix, estimated using data up to the specified year. Shaded ranges show a 90 percent confidence interval, computed from bootstrap with 500 replications. The black dotted lines are the full-sample estimates and the blue dashed lines are the averages across the rolling estimates.

4.5 Model Selection

A reasonable objection to our analysis is that we might be using a mis-specified statistical model. If our model is mis-specified then our claim to identify inflation sentiments is not valid. In Section 4.1 we sidestepped this issue with an appeal to convention, including just the variables most commonly used in other VARs. Here, we return to this issue, conducting an extensive model selection exercise.

We allow for the potential inclusion of 26 other monthly macroeconomic times series in our VAR, shown in Table 2. These plausibly capture other sources of macroeconomic variation which might be missing from our baseline framework. Since the number of parameters grows with the square of the number of variables, simply including all these variables in the VAR is likely to replace one problem with others, trading mis-specification for over-fitting and imprecision. We thus adopt two methods which aim to include as much of the useful variation in the additional data while avoiding these problems: a factor-augmented VAR (FAVAR) and a machine learning approach.

The factor-augmented VAR, popularized by Bernanke et al. (2005), aims to extract the most important dimensions of variation in a set of possible covariates by transforming them into their principal components. A small number of the most informative principal components are then included in the VAR. Specifically, we extend the specification in equation (5) to:

$$\begin{pmatrix} f_t^h \\ \pi_t \\ y_t \\ F_t \end{pmatrix} = B \begin{pmatrix} f_{t-1}^h \\ \pi_{t-1} \\ y_{t-1} \\ F_t \end{pmatrix} + A\varepsilon_t \quad (10)$$

Where y_t includes only the federal funds rate and log industrial production, and F_t includes the first N principal components of the remaining series in Table 2. In practice, we use the first 4, 8, and 12 principal components, as they cover 50, 75, and 90 percent of the variance in the data respectively.

Figure 8 shows the impulse responses for the baseline and factor-augmented VARs. The

main findings from our baseline model hold true. The identified sentiment is almost exactly the same. And despite a positive response of prices in the first period (where timing issues might be driving things) the overall effect of the shock is deflationary: cumulative inflation in the 12 months after the shock falls in all versions, and by as much as 20 basis points in the largest factor-augmented cases. Real activity, as measured by industrial production also falls, and monetary policy loosens, albeit by less than in the baseline. Figure 9 shows the 90 percent confidence intervals for period 0 responses for these experiments, which look generally similar to our baseline results.

The advantage of factor methods is that they are transparent and well-understood¹⁸. One downside is that it is not obvious what is the right number of factors to use. More factors improve the fit but also increases the likelihood of over-fitting. The temptation to emphasize the particular factor model which aligns with one’s priors is strong. Machine learning methods can offer a better solution.

Group	Variables	Transformation
Prices	<i>Consumer Prince Index, Commodity Price Index</i>	Growth rate
Interest rates	<i>Federal Funds Rate</i> , 3-month, 1-, 2-, 5-, 10-, 20-, and 30-year US Treasury rates	None
Financial	USD vs. GBP, JPY, and CAD exchange rates, Real oil price, Willis 5000 Index	Log
Money & Credit	M2, Currency in Circulation, Bank credit, Chicago Fed financial conditions leverage index	Log (excl. leverage)
Real Activity	<i>Industrial Production</i> , New housing starts, Vehicle sales	Log
Labor Markets	<i>Unemployment rate</i> , Employment, Average hours	Log (excl. unemp.)
Fiscal	Real government surplus ratio	Unit variance

Table 2: Variables Available for FAVAR and Machine Learning Model Selection

Items in italics are those used in the baseline specification. All specifications also include the Michigan Consumer Survey mean inflation expectation.

Machine learning methods for selecting VAR models allow out-of-sample forecast performance to select the appropriate statistical model. We apply four methods proposed by Nicholson et al. (2017) and Nicholson et al. (2020), each of which imposes a penalty for VAR

¹⁸Stock and Watson (2005) discuss estimation and identification in FAVAR models. Stock and Watson (2011) survey the literature more broadly.

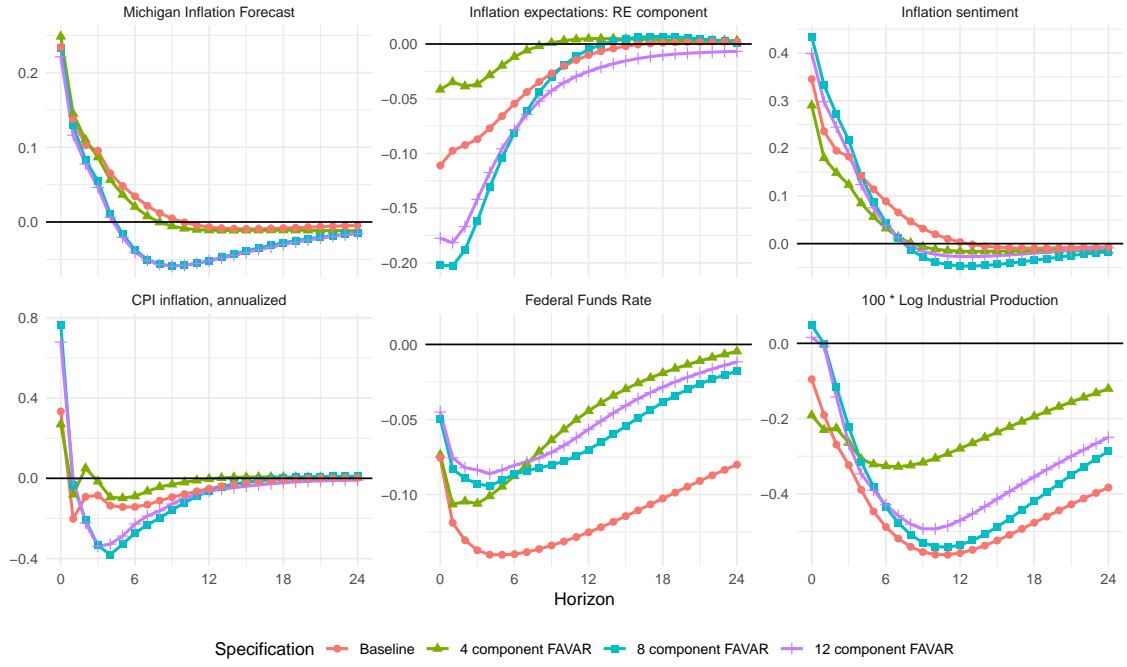


Figure 8: Factor-Augmented VAR Impulse responses.

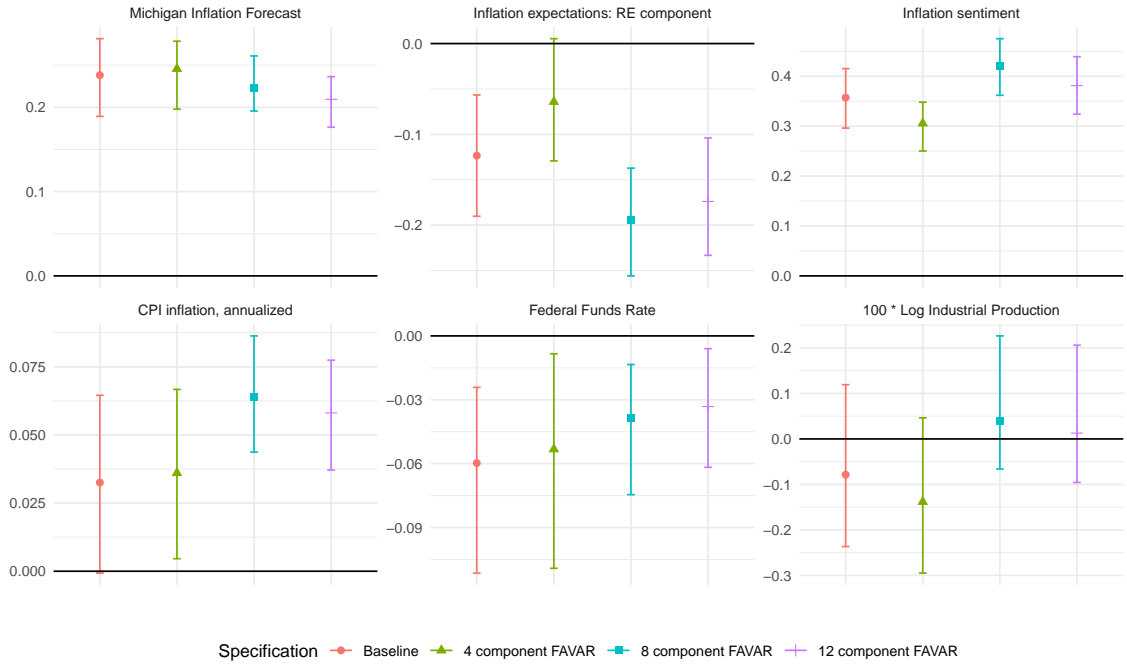


Figure 9: Sentiment Shock on Impact in Factor-Augmented VARs

Vertical bars show 90 percent confidence interval computed from 500 bootstrap replications.

coefficients different from zero. The first is a basic least absolute shrinkage and selection operator (LASSO) where the penalty is linear in the absolute value. The second is an elastic net regularization approach, which applies a linear combination of the LASSO and ridge (i.e. quadratic) penalties. The third, is a component-wise hierarchical VAR (HVARC), restricting candidate models to those where each row of the VAR lag matrix has non-zero coefficients up to a row-specific maximum lag. The fourth is a tapered LASSO, which downweights longer lags. In all cases the penalty functions depend on tuning parameters. These are selected by rolling cross-validation on the middle third of the sample. The final third of the the data is reserved for model evaluation, as measured by the out-of-sample mean square forecast errors.

Figure 10 shows the impulse responses from the four machine learning methods. As with the FAVAR approach, they are qualitatively very similar to our baseline estimates. Overall, the shock is well-identified as broadly deflationary in the the price level declines in the 12 months after the shock. Real activity declines, although perhaps not as soon or as far as in our baseline. The one area where the machine learning models differ from our baseline is in the policy response, which appears to be much smaller.

The benefit of a machine learning approach is that one can more easily evaluate the models themselves. Unlike with the FAVAR approach, where one hopes that one has “enough” factors, cross-validation means that within a given category of model one is likely picking a near-optimal specification. And by reserving a portion of the data for out-of-sample evaluation, different categories of models can be compared. Table 3 conducts such a comparison for the four machine learning models and two benchmarks – the simple average for each variable, and the AIC baseline we use above. In all cases, the machine learning methods have superior out-of-sample performance, with the tapered-lag LASSO the best. That said, the AIC baseline still performs remarkably well, with the best machine learning model offering only a 1.6 percent improvement in forecast accuracy relative to the naïve unconditional average.¹⁹

¹⁹ $(7.97 - 6.46)/91.39 \approx 1.6$ percent.

Overall, the model selection broadly validates our measurement of the inflation sentiment and our characterization of its macroeconomic impact as deflationary (average inflation falls) and contractionary (real activity declines). One aspect of our results that the model selection exercise does not completely confirm is the response of monetary policy, which is much more muted in all the alternative models.

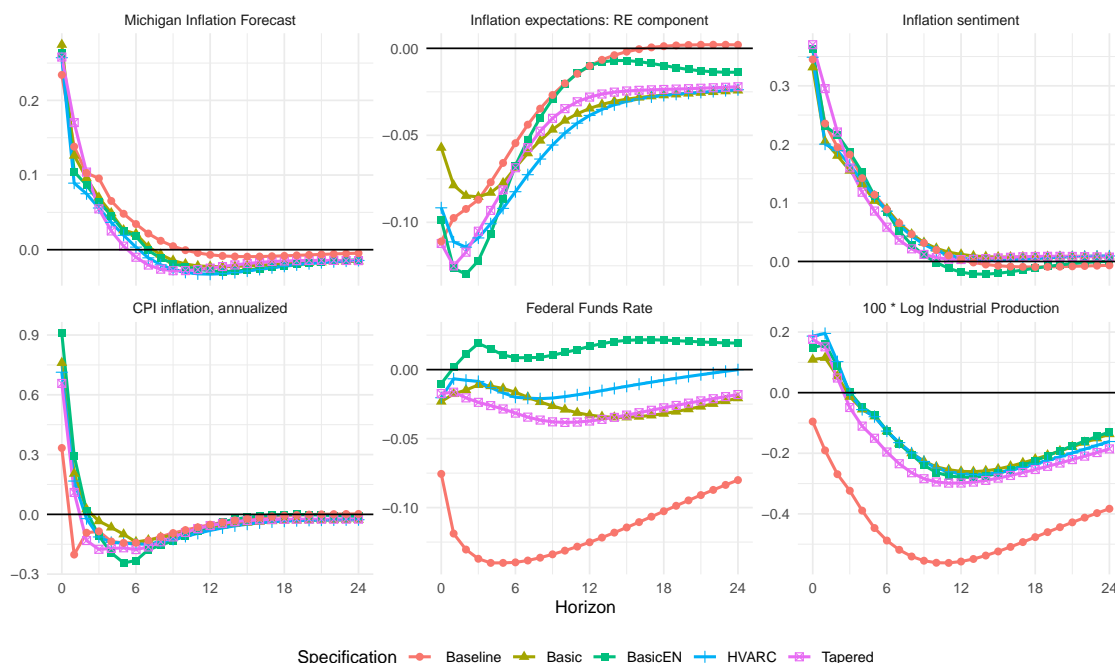


Figure 10: Model selection by Machine learning

“Basic”: VAR coefficients selected by LASSO; “BasicEN”: LASSO, but with an elastic net loss function; “HVARC”: Component-wise lag-length; “Tapered”: Lag-weighted LASSO

	Avg.	AIC	Basic	BasicEN	HVARC	Tapered
Frac. active coefficients			0.28	0.85	0.99	0.99
Mean MSFE	91.39	7.97	7.03	7.46	7.01	6.46
MSFE st dev	7.26	2.92	2.66	2.73	2.67	2.42

Table 3: Machine Learning Forecast Evaluation

“Basic”: VAR coefficients selected by LASSO; “BasicEN”: LASSO, but with an elastic net loss function; “HVARC”: Component-wise lag-length; “Tapered”: Lag-weighted LASSO

5 Interpreting the Evidence

In this section we seek to better understand our results by comparing them to a full dynamic New Keynesian model. To address two questions, we extend the standard conceptual framework beyond the simple motivating model in Section 2, adding dynamics and a bevy of additional shocks.

First: how puzzling are our findings compared to a New Keynesian DSGE model? But even with extra bells and whistles, the canonical New Keynesian model is still fundamentally at odds with our VAR results: a positive sentiment shock still causes inflation to rise, inducing a contractionary response by the central bank and a recession. The richer model reinforces the puzzle.

Second: does our estimation strategy reliably identify the effects of sentiment shocks? We show that it does. To do so, we estimate the structural VAR on simulated data, showing that it consistently recovers the true sentiment shocks even in the presence of confounding news, noise, discount factor shocks, and policy shocks, even on samples of similar length to ours. This is an important validation of our method: it shows that if inflation expectation shocks did generate macroeconomic fluctuations in line with the standard New Keynesian model, we would estimate impulse responses to sentiment shocks consistent with it.

5.1 A Dynamic New Keynesian model

We modify the canonical New Keynesian model by introducing additional shocks and information structure. The additional structural shocks are standard. We include stochastic terms for productivity a_t , interest rate deviations x_t , and discount factor z_t . The standard three equations (the New Keynesian Phillips Curve, the Euler equation, and the Taylor rule) become

$$\pi_t = \beta\pi_t^{e,1} + \kappa(y_t - \psi a_t)$$

$$0 = \mathbb{E}_t[\gamma(y_t - y_{t+1})] + i_t - \pi_t^{e,1} + z_t$$

$$i_t = \phi_y y_t + \phi_\pi \pi_t + x_t$$

where z_t is a stochastic deviation of the discount factor, and x_t is the central bank's stochastic deviation from the interest rate rule. Inflation expectations are determined as in Section 2:

$$\pi_t^{e,1} = \mathbb{E}_t[\pi_{t+1}] + \zeta_t$$

where $\mathbb{E}_t[\cdot]$ is the rational expectations operator.

We have to make some assumption about how agents form forecasts at different horizons. If we had data on forecasts at every monthly horizon, we could do this empirically. But absent such evidence, we assume that a sentiment shock has the same effect on period t and $t+1$ forecasts of the inflation rate in any month $t+j$. This is equivalent to demanding that the law of iterated expectations holds for agents when they make forecasts, i.e. they correctly assess the impacts of the sentiment on their future forecasts. That is:

$$\pi_t^{e,12} = \mathbb{E}_t\left[\sum_{j=0}^{11} \pi_{t+j}^{e,1}\right] \quad (11)$$

We assume our exogenous stochastic terms are governed by AR(1) processes:

$$\zeta_t = \theta_\zeta \zeta_{t-1} + \varepsilon_t^\zeta$$

$$a_t = \theta_a a_{t-1} + \varepsilon_t^a$$

$$x_t = \theta_x x_{t-1} + \varepsilon_t^x$$

$$z_t = \theta_z z_{t-1} + \varepsilon_t^z$$

We also endow agents with additional information. They receive news about future productivity shocks, but the news is inexact. At time t , agents observe a noisy signal v_t of future productivity shocks:

$$v_t = \varepsilon_{t+1}^a + \nu_t$$

where ν_t is an i.i.d. noise shock. The news signal allows some future inflation to be anticipated. For example, if agents learn that TFP will rise, they expect that future output and inflation will increase. Thus the news signal v_t affects forecasts today. However, because the signal v_t is in the information set of agents at time t news shocks affect the *rational* part of inflation expectations.

These additional features present a stringent test of our identification strategy, showing that it can resolve concerns raised elsewhere. The discount factor shock addresses the issue discussed in Levchenko and Pandalai-Nayar (2020): current methods have difficulties separating the effects of sentiments from other unobserved factors that move expectations, such as shocks to preferences. And we include the news signal in order to demonstrate that our sentiment is also independently identified from other shocks to agents' information sets. VAR studies such as Barsky and Sims (2011) or Chahrour and Jurado (2021) identify news or noise by disciplining how expectations respond to structural shocks. Although our method is similar in spirit, it identifies something quite different: a sentiment shock. Thus, it is important to show that our approach is also not confounded by news or noise.

Parameter	Interpretation	Value
β	Discount factor	0.997
γ	Risk aversion	1
κ	Phillips Curve elasticity	0.2
ψ	Output gap elasticity	0.2
ϕ_π	Policy response to inflation	1.5
ϕ_y	Policy response to output	0.1
θ_ζ	Sentiment autocorrelation	0.77
θ_a	TFP autocorrelation	0.98
θ_x	Interest rate deviation autocorrelation	0.49
θ_z	Discount factor autocorrelation	0.56
σ_ζ	Sentiment shock standard deviation	0.29
σ_a	TFP shock standard deviation	0.26
σ_ν	Noise shock standard deviation	0.26
σ_x	Interest rate shock standard deviation	0.14
σ_z	Discount factor shock standard deviation	0.14

Table 4: Standard Monthly Calibration

We assign a standard calibration to the economy, following Galí (2008). Table 4 reports

our parameter values. To calibrate the time series for the shock processes, we adopt the monthly analogs to the quarterly MLE estimates from Smets and Wouters (2007). Additionally, we set the noise variance σ_v^2 to be half of the productivity shock variance σ_a^2 , so that only half of the productivity shock process is predictable. The addition of sentiment shocks introduces two parameters about which the literature is quiet. First, we set the sentiment autocorrelation $\theta_\zeta = 0.77$ to reproduce the monthly persistence of the inflation sentiment that we estimated in Section 4.2. Second, we conservatively set the standard deviation of the sentiment shock to $\sigma_\zeta = 0.29$ to explain 15% of output volatility, a lower bound of what we estimate is due to the sentiment.

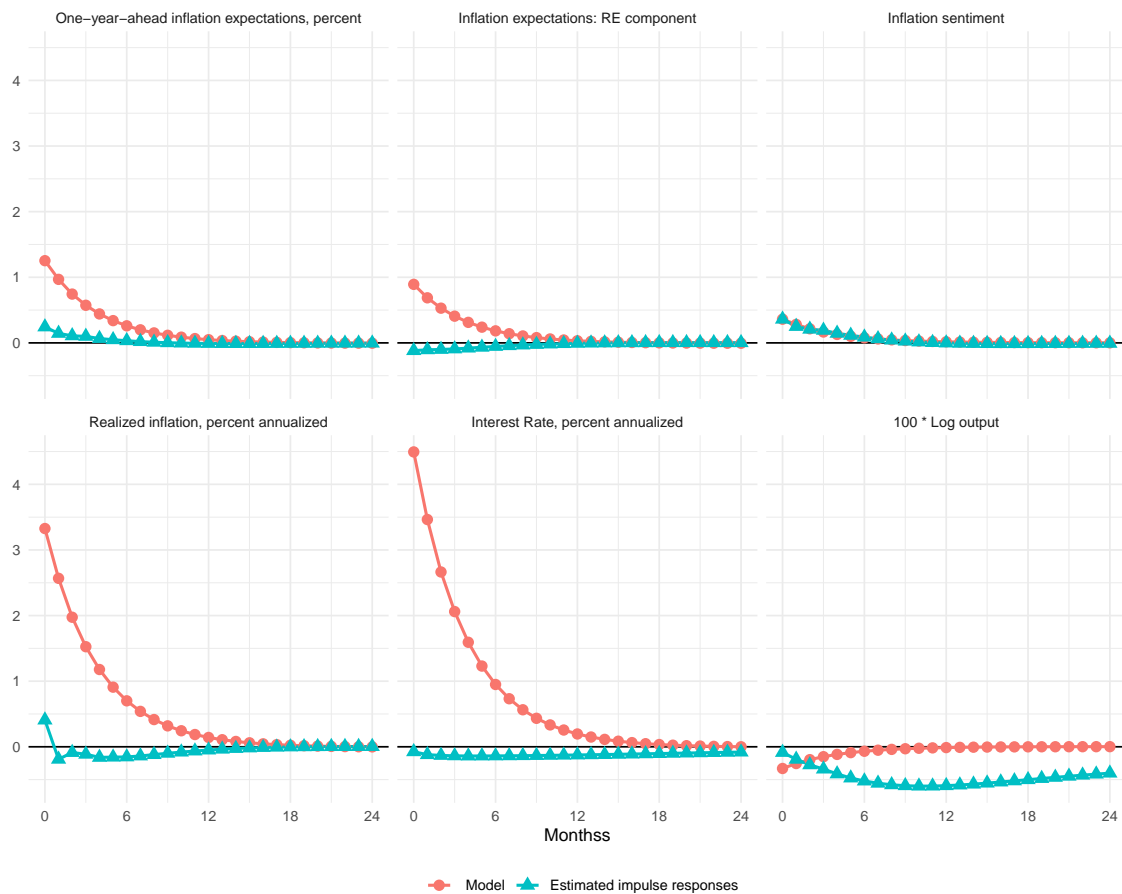


Figure 11: Inflation Sentiment Shock: Dynamic New Keynesian Model versus Baseline VAR Estimates

Figure 11 plots the dynamic effects of an inflation sentiment shock in the dynamic New

Keynesian model. For ease of comparison with our estimated shocks, the sentiment shock scaled to equal one standard deviation of those estimated in the baseline results (around 0.35 percentage points, top right panel). The intuition for the model responses (pink circles) resembles that of the static model in Section 2, but the dynamics are driven by the Calvo pricing friction – that only a fixed fraction of firms can reset their prices each period. Initially, inflation expectations rise due to the sentiment. Because prices are sticky, firms that can change their prices today will increase them, as they want to avoid their prices being too low tomorrow. Thus, inflation happens today. This is the direct impact of the sentiment shock. But there is also an indirect impact, acting through rational expectations. Inflation today means that, some firms’ prices will be higher tomorrow. Consumers will thus substitute away from these firms’ products, increasing demand for those that cannot increase prices today. Of these firms, some will be able to reset prices tomorrow. And with higher demand, they will raise their prices, creating inflation tomorrow. But firms today anticipate this – except for the sentiment, their expectations are rational. So they respond by further raising prices today.²⁰ We term this indirect impact is the “rational expectations multiplier” for inflation sentiments. It is quantitatively rather large. Even though the central bank raises real rates, realized inflation over the next 12 months (the top middle panel) increases by around one percentage point, producing an indirect impact around two times the size of the direct one. Indeed, this is why interest rates have to rise so much – higher inflation erodes the real interest rate. If this is the framework that central bankers have in mind when talking about inflation expectations, then they are right to be concerned about them as an source of inflationary shocks.

However, these dynamics are clearly at odds with the estimated results from Section 4.2, also shown in Figure 11 (blue triangles). For the same sentiment shock, the estimated responses are generally smaller in magnitude and of different sign for inflation (except the first period) and interest rates. In particular, the measured inflation expectations multiplier – which is large and positive in the model – is much smaller and negative. The ratio of

²⁰Forecasted inflation in this figure is for the following year, given by equation 11, as it was in our empirical analysis. This is why the rational component does not track the inflation impulse response exactly.

realized one-year inflation to the one-year-ahead inflation sentiment shock is around -0.3 versus 2 in the model.

5.2 Validating our Identification

We now use the extended New Keynesian model developed in the preceding section to form two tests our identification strategy.

The first test is a long-sample test, meant to uncover whether our method is at least asymptotically valid. We simulate the model for 100,000 periods and estimate shocks to inflation sentiments using the semi-structural identification procedure in Section 3, applied to a VAR featuring inflation, output, interest rate and year-ahead inflation expectations. The green triangles in Figure 3 plot our estimates from the large sample. The red circles plots the true impulse responses to the sentiment shock, just as in Figure 11. These coincide almost exactly. This says that given enough data, we can precisely identify the effects of sentiment shocks from preferences, news, noise, and other structural shocks in the model.

Although our method is asymptotically valid, it could be that our empirical results are a fluke, due to statistical noise in a short sample. To assess this possibility we repeatedly simulate 39 year samples, mimicking the data in our baseline regressions. The blue squares in Figure 12 plot the median estimated impulse response function from these smaller simulations, while the gray shaded area is the bootstrapped 90 percent confidence interval. Broadly speaking, the median is very close to the true shock and its impact – perhaps with a small amount of attenuation bias, but qualitatively the results are very similar. Moreover, the confidence intervals at least on impact are tight enough to convincingly reject the possibility that our results – disinflation, lower interest rates, and a hump-shaped output loss – could be generated by a dynamic New Keynesian model of this sort.

Together these exercises represent the acid test of our identification strategy. If something was wrong with our approach, it would recover counterfactual impulse responses. That it doesn't, even in the presence of other potentially confounding shocks, says that our method is valid.

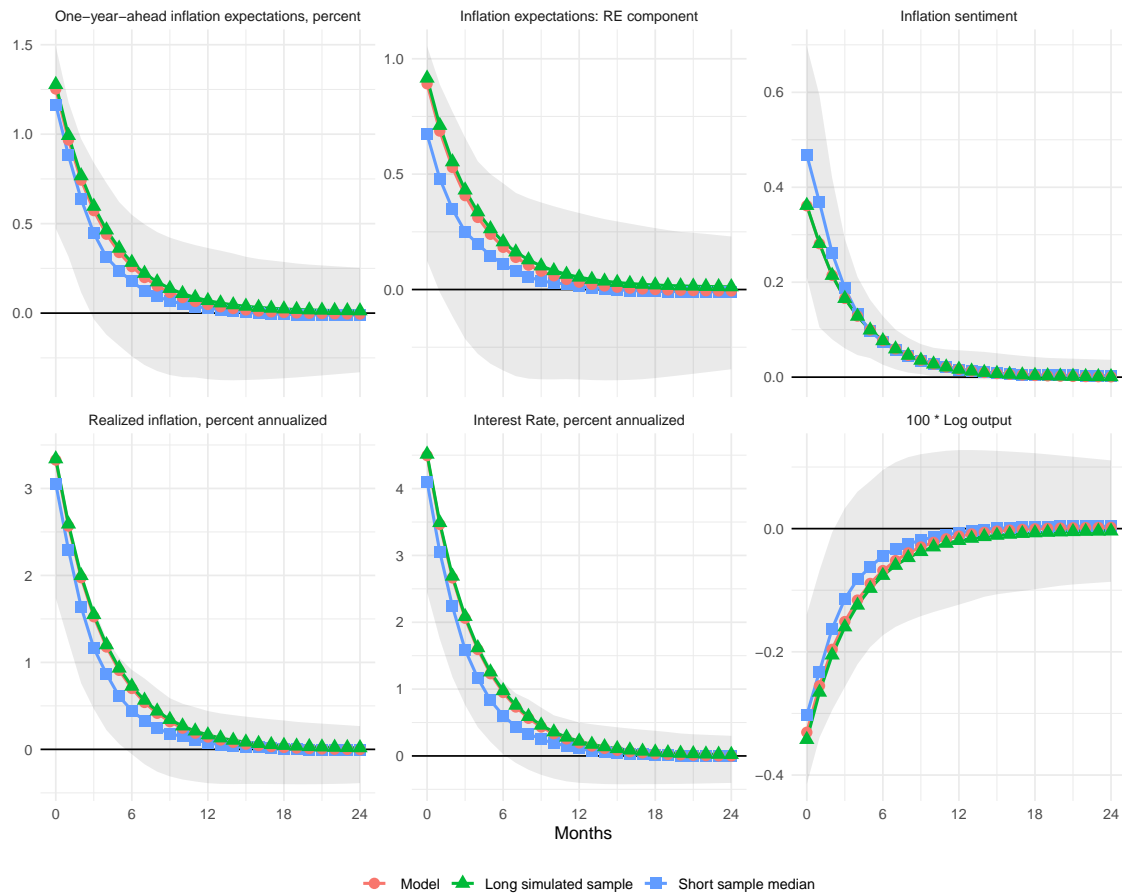


Figure 12: Validation Exercise: Structural Impulse Responses to a Sentiment Shock

The “long simulated sample” shows the point estimates of the structural VAR decomposition using a single sample of 100,000 points. The shaded range shows the 90 percent confidence interval from 500 shorter simulations, each of 39 years, as in Figure 6. “Short sample median” is the median across these 500 simulations.

6 Partial Resolution of the Puzzle

Our identification reliably recovers the sentiment, and our estimates are clearly inconsistent with the canonical New Keynesian model. Should we reject the model entirely? Not so fast. Deflation, recession, and monetary tightening may not be the canonical predictions, but they are not necessarily inconsistent with the underlying machinery of the New Keynesian model.

A sentiment shock necessarily created inflation in the static model of Section 2, because the New Keynesian Phillips curve shifted left along the downward-sloping aggregate demand curve. But the aggregate demand curve need not be downward-sloping in a dynamic model. It is for the standard calibration considered in Table 4, but some alternative parameter values can flip the sign. Thus, one way to rationalize our result that sentiments cause deflation and recession is to consider a dynamic model with a modified Taylor rule.

A sentiment shock can be deflationary if monetary policy is sufficiently passive, so that inflation no longer raises the real interest rate. To see why, consider an equilibrium of the canonical model where inflation and output are both AR(1):

$$\mathbb{E}_t[y_{t+1}] = \theta_y y_t \quad \mathbb{E}_t[\pi_{t+1}] = \theta_\pi \pi_t$$

This relationship holds exactly for versions of the New Keynesian model with a single AR(1) exogenous state. In a more general model, it is still a useful approximation for demonstrating our point. With this assumption, the two variable AS-AD system from Section 2 becomes:

$$(1 - \beta\theta_\pi)\pi_t = \beta\zeta_t + \kappa y_t \quad [\text{AS}]$$

$$(\phi_\pi - \theta_\pi)\pi_t = (\gamma(\theta_y - 1) - \phi_y)y_t + \zeta_t \quad [\text{AD}]$$

Despite our persistence assumption, the AS curve remains upward-sloping. However, the AD curve may change sign entirely. Specifically, if $\theta_\pi > \phi_\pi$ – that is, if monetary policy response to inflation is less than the persistence of inflation itself – then the AD curve slopes upward and sentiment shocks shift it downward. Figure 13 plots this response to the

sentiment shock. The AS curve shifts left as always, but now moves the economy down the upward-sloping AD curve. The AD curve shifts down, compounding the effects: deflation and recession.

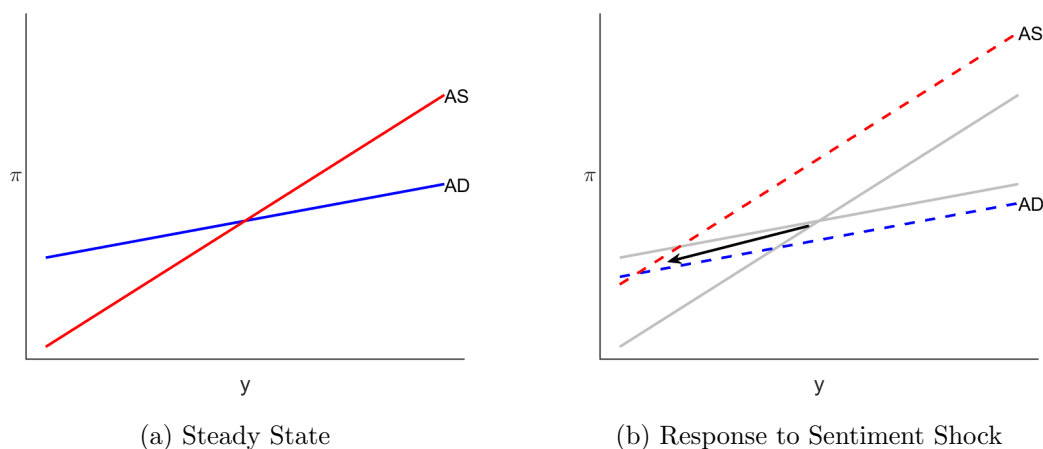


Figure 13: New Keynesian Sentiment Shock with Persistence and Passive Monetary Policy

How can passive monetary policy produce this deflationary response? The $\theta_\pi > \phi_\pi$ condition says that monetary policy is sufficiently passive that inflation today increase raises future inflation by more than the central bank raises nominal interest rates. Thus, inflation must lower the average real interest rate.²¹

Why do we say this resolution of the empirical puzzle is only partial? Usually the Taylor principle, which imposes that $\phi_\pi > 1$, determines equilibrium in the New Keynesian model. But if $\theta_\pi > \phi_\pi$ and inflation expectations are stable then $\phi_\pi < 1$ and the Taylor principle is violated. If relaxing the principle is required to explain the data, then it raises additional questions about how equilibrium is determined. If the central bank responds less aggressively than the Taylor principle demands, multiple equilibria are possible. But some of these equilibria resemble our empirical results.

In order to find alternative equilibria, we relax the Taylor principle by setting $\phi_\pi = 0.2$: the central bank still raises interest rates to combat inflation, but does so less than

²¹Of course, this condition alone is not sufficient to ensure that sentiments produce the observed results; monetary policy must make the AD curve upward-sloping, but not so steeply that its slope exceeds that of the AS curve, in which case other results are possible. And relaxing the Taylor principle of $\phi_\pi > 1$ is not as straightforward as this simplified system suggest.

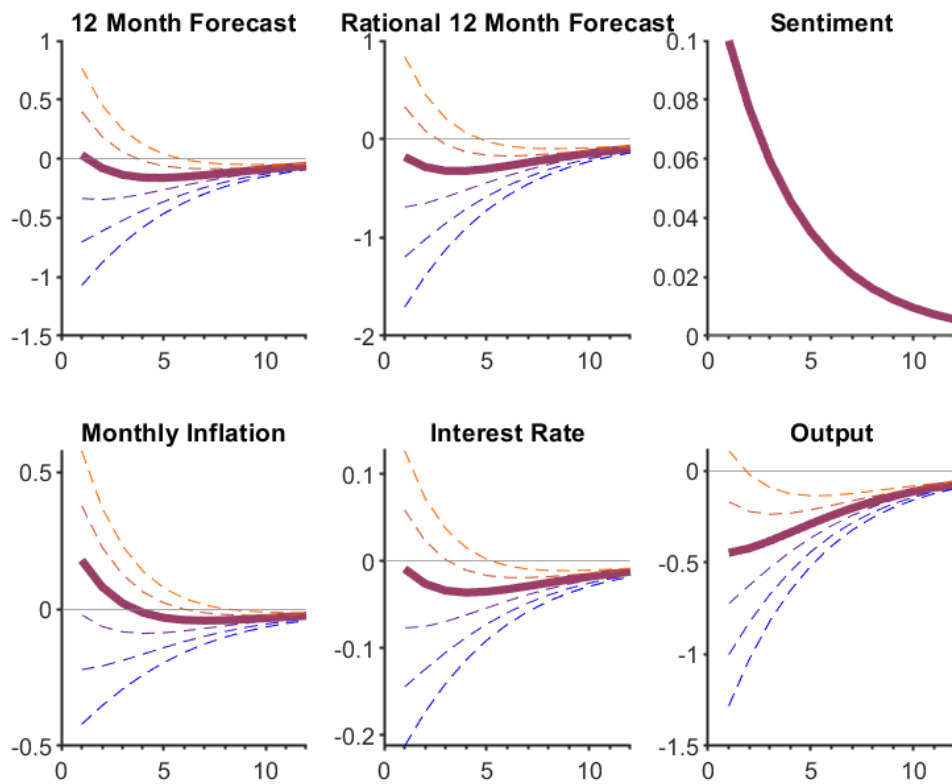


Figure 14: Sentiment Shocks in the New Keynesian Model with Multiple Equilibria

one-for-one. Figure 14 plots multiple equilibria in the dynamic New Keynesian model with this modification. The same shade in each plot corresponds to the same equilibrium. We highlight in bold a particular equilibrium that qualitatively resembles our empirical estimates. Inflation jumps up before quickly becoming prolonged deflation. Forecasts of annual inflation immediately rise, but this is driven by the sentiment, because 12-month-ahead inflation is negative. Output falls on impact, and remains below trend. The central bank lowers interest rates in response to both the recession and the deflation.

The macroeconomy is probably not flush with multiplicity, so why is it interesting that one of many equilibria resemble our estimates? Why would the world experience this equilibrium versus any other? There may be other mechanisms outside the three-equation New Keynesian model that selects the equilibrium. One possibility is fiscal policy; Cochrane (2017) argues that for any initial inflation response (i.e. any particular equilibrium in Figure 14), there exists some fiscal policy that rationalizes it,²² and suggests that perhaps empirical dynamics be used to discipline equilibrium selection. Our findings can help do so.

7 Conclusion

We developed a novel method to identify sentiment shocks from a structural VAR with aggregate data and empirical forecasts. When applied to inflation forecasts, we find a puzzle: a positive shock to inflation expectations are contractionary, deflationary, and induce monetary loosening. This is inconsistent with the canonical New Keynesian model, in which such shocks are inflationary, and only cause a recession if the following policy tightening is sufficiently aggressive. We offer a partial and tentative resolution to this puzzle – highlighting that the role of fiscal policy might be important in interpreting our results. Our findings suggest two avenues for additional work.

First: what explains the puzzle? Why are inflation sentiments deflationary? Does it matter who receives the sentiment? We see similar responses to household, market, and

²²Many possibilities abound for selecting equilibrium without the Taylor Principle, although not all criteria may select the realistic equilibrium that we identify. Such possibilities include bounded rationality (Gabaix (2020), Angeletos and Lian (2021)) and one-period-ahead price setting (Gali (1999), Cochrane (2014)).

professional forecaster sentiments. But what about firms?

Second: our method for identifying sentiments is robust, and can apply to expectations of quantities other than inflation. Do sentiments of future GDP have the effects that a long information frictions literature predicts? What of sentiments for other variables with measured expectations, such as interest and exchange rates, income, wages, and so forth?

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A Whose Sentiment?

What if different actors in the economy form expectations differently? In this section we vary who receives the sentiment in the static New Keynesian model, and consider how it affects the predictions of the canonical theory.

We consider shocks to three different forecasts: those of firms, households, and the central bank. We denote the inflation forecasts of each of these sectors by $\pi_{f,t}^{e,1}$, $\pi_{hh,t}^{e,1}$, and $\pi_{cb,t}^{e,1}$ respectively. In order to allow sentiments to affect the central bank directly, we modify their Taylor rule to depend on expected inflation. Together with the Fisher equation and New Keynesian Phillips Curve, the 3 equation model becomes:

$$\begin{aligned}
 \text{New Keynesian Phillips curve:} & \quad \pi_t = \beta\pi_{f,t}^{e,1} + \kappa y_t \\
 \text{Fisher equation:} & \quad i_t = \mathbb{E}_t[\gamma(y_{t+1} - y_t)] + \pi_{hh,t}^{e,1} \\
 \text{Modified Taylor rule:} & \quad i_t = \phi_y y_t + \phi_\pi \pi_t + \phi_e \pi_{cb,t}^{e,1}
 \end{aligned}$$

The firms' inflation forecast $\pi_{f,t}^{e,1}$ enters the New Keynesian Phillips curve, which characterizes the optimal price setting decision by sticky price firms. The households' inflation forecast $\pi_{hh,t}^{e,1}$ enters the Fisher equation, which describes their optimal consumption-savings decision. Finally, the central bank's inflation forecast $\pi_{cb,t}^{e,1}$ appears in the new Taylor rule.

As before, the dynamic New Keynesian model reduces to a two-equation static model when sentiments are i.i.d. If we allow firms, households, and central banks to receive different sentiment shocks, the static New Keynesian equations become:

$$\begin{aligned}
 \pi_t &= \beta\zeta_{f,t} + \kappa y_t & \text{[AS]} \\
 \phi_\pi \pi_t &= -(\phi_y + \gamma)y_t + \zeta_{hh,t} - \phi_e \zeta_{cb,t} & \text{[AD]}
 \end{aligned}$$

where $\zeta_{f,t}$, $\zeta_{hh,t}$, and $\zeta_{cb,t}$ denote sentiment shocks to firms, households, and the central bank respectively.

Figure 15 plots the response of the macroeconomy to each type of sentiment. When

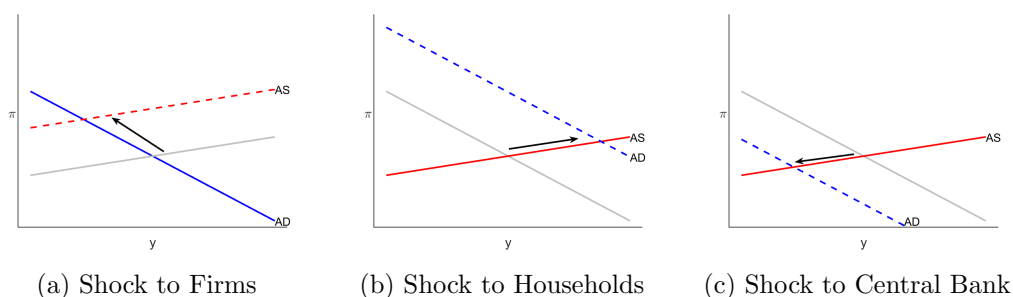


Figure 15: New Keynesian Response to Different Sentiment Shocks

firms' sentiments $\zeta_{f,t}$ increase (panel (a)), they set prices higher ceteris paribus, shifting the New Keynesian Phillips (AS) curve up. This raises inflation, which prompts policy to tighten, increasing the real interest rate and contracting output. When households' sentiments $\zeta_{hh,t}$ increase (panel (b)), they expect higher inflation, perceive real interest rates to decline, and increase consumption. This moves the economy up along the Phillips curve, increasing real output and contemporaneous inflation, despite the central bank's response of raising rates to combat the inflation. When the central bank's sentiment $\zeta_{cb,t}$ increase (panel (c)), it preemptively raises interest rates ($\phi_e > 0$), reducing current inflation and creating a recession.

Crucially, all three sentiments result in monetary policy tightening. If households or firms receive a sentiment shock, inflation increases and the central bank raises interest rates. If the central bank receives a sentiment shock, it mistakenly raises rates, creating deflation. There is no way that a sentiment shock in this static model can result in a decrease in interest rates. Furthermore, the only way that sentiments can result in deflation is if they overwhelmingly affect the central bank. How do these predictions compare to the data? Only the sentiment shocks to the Fed's forecasts are consistent with these effects.



PUBLICATIONS

Shocks to Inflation Expectations
Working Paper No. **WP/2022/072**