

Unexpected Expectations

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Monetary policy announcements move interest rates and reveal information about the economy. Using the Michigan Survey of Consumers, Consensus Economics, and the Survey of Professional Forecasters, we show that contractionary monetary policy surprises raise near-term beliefs about real activity even as agents anticipate higher interest rates. Inflation beliefs also rise among households and professional forecasters, while the response in Consensus Economics is weaker. We rationalize these facts in a New Keynesian model in which households and firms observe noisy signals about monetary and non-monetary fundamentals. We estimate the model by matching quarterly macroeconomic and belief responses to the same monetary surprise. In the estimated model, a contractionary surprise lowers activity and prices but raises output forecasts, because it bundles the policy innovation with the systematic response of policy to demand and inflationary pressure. Removing this information restores the conventional response: a pure monetary tightening lowers activity and prices and leads to downward revisions of output and inflation forecasts. A VAR identification that imposes these belief responses selects a shorter tightening that is more disinflationary per unit of tightening, as the model predicts.

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JEL Classifications: E31, E32, E52, E70.

1. Introduction

An interest-rate surprise is not necessarily a monetary policy shock. A policy announcement changes the stance of policy, but it may also reveal the central bank’s assessment of current and future economic conditions. When the central bank and private agents do not share the same information set, the observed surprise combines an exogenous policy disturbance with news about the fundamentals to which policy responds. The two components have different implications. A pure tightening depresses activity and inflation. Favorable news revealed by the same announcement can instead improve the outlook. Recovering the causal effect of monetary policy therefore requires knowing not only how market prices move around an announcement, but also what private agents learn from it.

This distinction creates a basic tension in the empirical evidence. High-frequency interest-rate innovations are widely used to identify monetary policy because they isolate movements that were not anticipated immediately before an announcement. Yet an unanticipated movement need not be uninformative about the economy. In influential evidence, contractionary announcement surprises raise private forecasts of output growth, a response that is difficult to reconcile with a conventional monetary tightening ([Nakamura and Steinsson 2018](#)). The increase may reflect information held by the central bank, private agents’ response to public news released before the meeting, or a mixture of policy and information shocks ([Romer and Romer 2000](#); [Jarociński and Karadi 2020](#); [Bauer and Swanson 2023](#)). Each interpretation has different consequences for identification and for the transmission mechanism.

This paper studies the tension through the beliefs of the agents whose decisions transmit monetary policy. We ask three questions. First, is the improvement in the outlook confined to financial-market forecasts, or does it appear across households and professional forecasters? Second, can a quantitative equilibrium model account simultaneously for optimistic belief revisions and contractionary macroeconomic outcomes following the same surprise? Third, can the response of beliefs help distinguish a pure monetary disturbance from the information bundled with an observed policy announcement?

Our first contribution is to provide systematic evidence on the response of beliefs across populations, survey designs, and monetary policy instruments. We combine three U.S. surveys. The Michigan Survey of Consumers (MSC) measures households’ views about business conditions, prices, and interest rates. Consensus Economics (CE) provides monthly forecasts from financial and research economists. The Survey of Professional Forecasters (SPF) supplies quarterly forecasts from professional macroeconomic forecasters. These sources differ in respondents’ expertise, incentives, question format, forecast horizon,

and frequency. Common results across them are therefore unlikely to be an artifact of a particular survey design.

For every population, we estimate a Bayesian proxy VAR separately for each belief measure and each of six prominent monetary policy instruments. The instruments span narrative innovations, high-frequency surprises, decompositions of policy and information shocks, and measures that purge the Federal Reserve's response to public news. We do not presume that any one instrument perfectly resolves the identification problem. Instead, the cross-instrument comparison asks which features of belief adjustment survive substantially different identifying assumptions.

One fact is remarkably stable. Following a contractionary surprise, near-term beliefs about real activity improve even though expected short-term interest rates rise. Consumer sentiment increases under all six instruments. CE economists revise real GDP growth upward in most specifications. SPF forecasts of GDP growth increase on impact under five of the six instruments, and the response is close to zero under the narrative measure of [Romer and Romer \(2004\)](#). The result is not driven by respondents failing to recognize a tightening: each group anticipates higher interest rates. Nor is it confined to households with limited incentives to collect macroeconomic information. It is present among professional forecasters whose business is to interpret incoming policy and macroeconomic news.

Inflation expectations provide a useful contrast. They rise among households and SPF forecasters, but are close to zero or decline in CE. This heterogeneity argues against describing the information content of announcements as a single scalar signal that shifts every dimension of the outlook in the same direction. It also makes the real-activity result more informative. Across surveys, respondents disagree about the inflationary content of the announcement while agreeing that near-term activity news is favorable. In all three populations, the unconventional response is concentrated on impact and fades rapidly. The evidence is therefore about short-run inference from an announcement, not a permanent revision in perceived potential output or long-run inflation.

The cross-instrument robustness does not imply that existing monetary policy instruments are invalid. A shock series can remove a particular source of contamination and still be correlated with the way private agents update beliefs at short horizons. For example, controlling for the Federal Reserve's response to public data does not eliminate information that agents infer from the policy decision itself. Likewise, separating high-frequency interest-rate and stock-price comovement need not remove every signal relevant for survey respondents. Our results instead establish that forecast revisions are an additional observable with which to assess what an identified surprise contains.

Our second contribution is to provide a quantitative equilibrium account of the joint response of beliefs and outcomes. We introduce dispersed information into an otherwise standard New Keynesian economy. Households and firms receive noisy private signals about monetary, demand, technology, and cost-push disturbances. The central bank observes the aggregate state and sets the interest rate according to a Taylor rule. Consequently, the policy rate is both an instrument and a signal. An unexpected increase can reflect an exogenous monetary disturbance, but it can also reveal that the central bank is responding systematically to stronger demand or other fundamentals.

The structure is designed around the empirical object rather than around persistence alone. Distinct household and firm information sets allow beliefs to affect aggregate demand and price setting through the margins on which those decisions are made. Multiple latent disturbances make inference from the interest rate nondegenerate: if all unexpected rate movements came from a single monetary shock, the model could not generate the belief puzzle. Higher-order uncertainty then propagates signal extraction through two interacting strategic-complementarity blocks. This mechanism creates endogenous persistence without adding mechanical lags to the IS or Phillips curves, and it delivers the pure-shock counterfactual needed for identification.

We discipline the model with a demanding minimum-distance exercise. All empirical targets correspond to the [Jarociński and Karadi \(2020\)](#) instrument and all model dynamics are quarterly. The macroeconomic block consists of the responses of an industrial-production gap, the price level, and the three-month Treasury bill rate from a macro-only proxy VAR. The belief block consists of SPF revisions for real GDP growth, CPI inflation, and the Treasury bill rate. We match the first four quarterly responses of each variable, expressed per percentage point of the impact increase in the policy rate, and estimate the persistence and relative volatility of four disturbances together with the precision of households' and firms' signals. All moments receive equal weight, so that the precisely estimated belief responses do not leave the transmission of policy to output and prices undisciplined.

Keeping the macroeconomic and belief blocks in separate VARs is deliberate. Survey series differ in frequency, sample coverage, target definition, and measurement error. Adding one survey at a time to the aggregate VAR would make the macroeconomic target move with the belief measure being studied. The macro-only VAR instead supplies a common transmission benchmark, while the survey VAR measures how a particular population updates. Because both blocks use the same external instrument, this separation changes the information set of the estimating equations without changing the underlying monetary surprise.

The estimated model accounts for the main features of the evidence, although not for all of their magnitudes. It reproduces the gradual decline in the price level and the path of the policy rate over the first year, and it generates a persistent contraction in the industrial-production gap, albeit a smaller one than in the data. In the belief block, a contractionary surprise raises output forecasts and expected interest rates on impact, as in the SPF, but by less. The model predicts a downward revision of inflation forecasts; inflation is also the belief response that varies most across surveys.

The estimates also identify where incomplete information matters. Households, whose expectations define the pre-announcement benchmark for the surprise, learn little about the monetary disturbance. Professional forecasters, whose revisions we map to firms' expectations, observe monetary and demand conditions almost perfectly. The observed surprise therefore combines the policy innovation with demand and cost-push conditions that households had not incorporated, and forecasters revise their outlook in response to these conditions. The upward revision of output forecasts reflects the systematic response of policy to news that forecasters process, rather than their uncertainty about the nature of the policy innovation.

We next use the model to separate the observed surprise from a pure monetary policy shock. Because a structural innovation and an observed surprise are different random variables, we compare them in two ways: for the same impact on the policy rate, and for shocks of one standard deviation. A pure tightening lowers the output gap and the price level and leads to downward revisions of output and inflation forecasts. The optimism observed after the announcement is therefore not an expansionary effect of tighter policy; it is the response to information bundled with the rate decision. This information has two further consequences. It makes the observed surprise a more persistent tightening, because part of the rate increase is the systematic response of policy to demand and to persistent cost-push pressure. And it carries inflationary news, so that per unit of tightening a pure shock lowers prices more than the observed surprise.

Our third contribution takes this implication back to the data. We augment a narrative sign-restriction VAR with restrictions on the response of output and inflation forecasts. The baseline identification leaves beliefs unrestricted and recovers the same combination seen in the survey evidence: output and prices fall while forecast revisions rise. Requiring near-term beliefs to decline, as they do after the model's pure tightening, selects a beliefs-adjusted shock with conventional belief responses and contractionary macroeconomic effects. Relative to the baseline, the beliefs-adjusted shock implies a shorter tightening and, per unit of tightening, a larger decline in prices, as the model predicts. Beliefs are therefore useful not only as outcomes to be explained, but also as identifying information

about the composition of a policy surprise.

Taken together, the results connect three objects that are often studied separately: announcement surprises, survey expectations, and macroeconomic transmission. The survey evidence reveals what agents infer. The model maps that inference into spending and pricing decisions. The final VAR uses the model's counterfactual prediction to refine empirical identification. This sequence also clarifies the scope of our conclusion. We do not argue that every contractionary surprise is dominated by good news, or that central bank information always attenuates monetary transmission. We show that the short-run response of beliefs contains information that is quantitatively important for distinguishing the policy action from the state-contingent news conveyed with it.

Related Literature. Our paper contributes first to the literature on central bank information and monetary policy identification. [Romer and Romer \(2000\)](#) show that Federal Reserve decisions reveal information not contained in commercial forecasts, while [Nakamura and Steinsson \(2018\)](#) use high-frequency movements in real rates and forecasts to document an information effect around FOMC announcements. [Jarociński and Karadi \(2020\)](#) exploit the joint response of interest rates and stock prices to separate policy and information shocks, and [Miranda-Agrippino and Ricco \(2021\)](#) purge policy innovations of predictable central bank responses. [Bauer and Swanson \(2023\)](#) emphasize private agents' response to public news before the announcement as an alternative explanation. We complement these approaches by observing revisions directly across three populations and by showing that the short-horizon real-activity response survives across instruments built to address different forms of contamination.

Second, we contribute to the literature that uses surveys to study expectation formation. Predictable forecast errors and sluggish revisions provide extensive evidence against full-information rational expectations ([Coibion and Gorodnichenko 2012, 2015](#)). Sticky-information and noisy-information models explain such behavior through infrequent updating or imperfect signals ([Mankiw and Reis 2002](#); [Sims 2003](#); [Woodford 2003](#); [Maćkowiak and Wiederholt 2009](#)). Our exercise differs in conditioning on monetary policy announcements and in requiring one estimated equilibrium model to account jointly for forecast revisions and aggregate impulse responses. The distinction between household and firm information sets also allows the same informational friction to operate through aggregate demand and price setting rather than treating survey expectations as an external wedge.

Third, the paper relates to work on higher-order beliefs and endogenous persistence. When agents act on private information, aggregate expectations need not satisfy the

representative-agent law of iterated expectations, and strategic interaction can amplify sluggish learning (Nimark 2008; Angeletos and Huo 2018, 2021). We embed this logic in a quantitative New Keynesian model with two decision-making groups and estimate the information structure from event-time responses. The resulting model is rich enough to distinguish the observed surprise from the underlying monetary innovation while remaining sufficiently tractable to derive both objects in closed form.

Finally, our beliefs-adjusted identification exercise is related to sign and narrative approaches that discipline monetary shocks with qualitative economic restrictions (Uhlig 2005; Antolín-Díaz and Rubio-Ramírez 2018a). We add restrictions on survey revisions motivated by an estimated model rather than impose additional signs on the conventional macroeconomic variables. This lets beliefs select among observationally admissible rotations and provides a direct bridge between expectation formation and structural identification.

Roadmap. Section 2 presents the survey evidence. Section 3 develops the dispersed-information New Keynesian model. Section 4 estimates the model, evaluates its fit, and reports the pure-shock counterfactual. Section 5 constructs the beliefs-adjusted monetary policy shock series. A final section concludes. Derivations, additional empirical results, and the exact macroeconomic targets used in estimation appear in the Appendix.

2. Empirical Puzzles on Expectations

We begin from the standard monetary benchmark. In the canonical New Keynesian model, a contractionary monetary policy shock raises the nominal interest rate above the systematic component of the policy rule. With sticky prices, the real interest rate rises and aggregate demand contracts. Output and inflation fall.

Full-information rational expectations (FIRE) extend these predictions to beliefs. If agents observe the shock and know the structure of the economy, they revise output and inflation forecasts downward and the nominal-rate forecast upward. The signs of realized outcomes and forecasts should therefore be aligned.

We confront this implication with evidence from three populations of U.S. forecasters. The MSC captures household beliefs at monthly frequency, CE surveys financial and research economists each month, and the SPF provides quarterly forecasts from professional forecasters. We estimate a Bayesian proxy-VAR separately for each belief measure and each of six monetary policy instruments. The common departure from FIRE is on the real side: contractionary surprises improve beliefs about near-term activity while raising

expected interest rates. The inflation response varies across surveys, a distinction we preserve throughout the analysis.

2.1. Data on Beliefs

We construct belief measures from three surveys that differ in population coverage, question format, and frequency. Our primary evidence uses MSC and CE at monthly frequency; SPF provides a quarterly cross-check. For CE and SPF, which collect quantitative point forecasts at specific target dates, we define the average forecast revision as

$$(1) \quad FR_t(x_{t+h}) = F_t x_{t+h} - F_{t-1} x_{t+h},$$

where $F_t x_{t+h}$ is the cross-sectional mean forecast formed at date t for variable x at horizon h . The revision measures the change in average beliefs about the same future outcome across two consecutive survey rounds. Two features of the MSC prevent applying the same construction. First, the MSC does not collect point forecasts: most questions yield qualitative responses or balance scores rather than numerical estimates. Second, the MSC asks about conditions “over the next twelve months,” a rolling horizon; consecutive surveys therefore target different end periods, violating the fixed-target condition embedded in FR_t .

The Michigan Survey of Consumers is conducted monthly by the University of Michigan on a rotating panel of approximately 900-1000 U.S. households, with data available since the 1940s. We use three measures. The Index of Consumer Sentiment (ICS) aggregates responses to five questions about personal finances and aggregate business conditions, providing a composite indicator of perceived economic well-being. The mean expected inflation rate comes from the question “By about what percent do you expect prices in general to go up or come down during the next 12 months?” Because the question does not specify a price index, respondents may have in mind any combination of CPI, gasoline, food, or other prices; direct quantitative comparison with professional forecasters’ CPI or GDP deflator forecasts is therefore not appropriate, and we treat this measure as qualitative evidence on inflation expectations. The balance score for expected interest rates is the percentage of respondents expecting rates for borrowing money to go up minus the percentage expecting them to go down, plus 100, so that higher values indicate that more households expect higher rates.

The Consensus Economics survey is conducted monthly by an international survey organization based in London. It polls approximately 700–1000 economists from financial institutions, consulting firms, research centers, and universities. Respondents provide

forecasts of approximately 20 macroeconomic variables anchored to specific calendar years rather than fixed horizons ahead. The CE data therefore require a rolling-horizon interpolation to form a consistent one-year-ahead revision, detailed in Section 2.2. We use forecast revisions for real GDP growth, CPI inflation, and the three-month Treasury bill rate.

The Survey of Professional Forecasters has been conducted quarterly since 1968Q4, first by the American Statistical Association and the National Bureau of Economic Research, and since 1990Q1 by the Federal Reserve Bank of Philadelphia. Each quarter, forecasters are surveyed on the day the Bureau of Economic Analysis releases its advance GDP estimate for the prior quarter. We use forecast revisions for real GDP growth, CPI inflation, and the three-month Treasury bill rate, enabling direct comparison with CE at a lower frequency.

2.2. Estimation

To study the macroeconomic effects of monetary policy shocks on both aggregate variables and economic agents' beliefs, we estimate a Bayesian vector autoregression (VAR) following the approach in [Miranda-Agrippino and Ricco \(2021\)](#). The reduced-form VAR is given by

$$(2) \quad \mathbf{x}_t = \mathbf{c} + \sum_{k=1}^p \beta_k \mathbf{x}_{t-k} + \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \Sigma_u),$$

where $\mathbf{x}_t$ denotes the vector of endogenous variables at time t , $\mathbf{c}$ is a vector of intercepts, p is the lag length, and $\mathbf{u}_t$ is a Gaussian white-noise innovation with covariance matrix Σ_u . The vector $\mathbf{x}_t$ includes the one-year Treasury rate as the policy indicator,¹ the unemployment rate, the consumer price index, the excess bond premium (EBP) of [Gilchrist and Zakrajšek \(2012\)](#), and one measure of beliefs. We include each belief measure separately, using a rolling measure of forecast revisions

$$(3) \quad \text{FR}_t^{(12)} = \frac{h}{12} \text{FR}_t^{(h)} + \frac{12-h}{12} \text{FR}_t^{(12+h)}$$

for the CE survey data following [Dovern et al. \(2012\)](#), also adopted by [Miranda-Agrippino and Ricco \(2021\)](#), because CE forecasts are anchored to calendar years rather than a fixed horizon ahead. We use the standard revision with fixed horizon for SPF and the corresponding indices from the MSC. The sample spans from 1978M1 to 2019M6 for MSC, from 1989M11 for the CE beliefs, and from 1990Q4 to 2019Q1 for SPF. The VAR includes nine

¹We follow [Gertler and Karadi \(2015\)](#) and use the one-year nominal rate to account for the zero lower bound episode.

lags and estimation is conducted using Bayesian techniques with standard macroeconomic priors.

Identification of monetary policy shocks is central to our analysis. Reduced-form innovations to interest rates may reflect endogenous policy responses, anticipatory movements, central bank information effects, or a “Fed response to news” channel. To isolate exogenous monetary policy surprises, we employ external instruments in the spirit of [Stock and Watson \(2012\)](#) and [Mertens and Ravn \(2013\)](#). Let $\varepsilon_t^{\text{mp}}$ denote the structural monetary policy shock and z_t an external instrument. The instrument must satisfy two moment conditions:

- (4) Relevance: $\mathbb{E}[z_t \varepsilon_t^{\text{mp}}] \neq 0$,
- (5) Exogeneity: $\mathbb{E}[z_t \varepsilon_t^j] = 0$ for all $j \neq \text{mp}$.

The first condition requires the instrument to be correlated with the monetary policy shock. The second requires orthogonality with all other structural disturbances. Operationally, we regress the reduced-form innovation of the policy rate on the instrument to recover the structural monetary shock and use it to construct impulse responses.

We consider six instruments widely used in the literature. [Romer and Romer \(2004\)](#) construct narrative shocks using internal Federal Reserve documents to identify policy intentions while purging endogenous and anticipatory components, effectively assuming the Federal Reserve possesses superior information. [Gertler and Karadi \(2015\)](#) employ high-frequency surprises around FOMC announcements, interpreting narrow-window interest rate changes as exogenous policy innovations. [Jarociński and Karadi \(2020\)](#) decompose high-frequency surprises by exploiting the joint movement of interest rates and stock prices to separate monetary policy shocks from central bank information shocks. [Miranda-Agrippino and Ricco \(2021\)](#) further refine high-frequency instruments by accounting explicitly for information rigidities. [Bauer and Swanson \(2023\)](#) introduce the “Fed response to news” channel, emphasizing that monetary surprises may reflect systematic responses to publicly available information. Finally, [Aruoba and Drechsel \(2025\)](#) develop a narrative-based approach using natural language processing techniques to infer the Federal Reserve’s information set and extract policy shocks from textual communication.

To ensure that our results are not driven by the fact that some CE forecasts precede the FOMC decisions and therefore have not yet incorporated the new monetary shock, we exclude instruments associated with FOMC decisions that occur after the survey. This guarantees that the shock precedes the survey response, retaining 144 instrument observations (40.33% of the original sample). We apply an analogous restriction to the SPF:

within each quarter, we cumulate the monthly instruments that fall before the survey date and discard those that follow. We cannot implement this timing strategy for the MSC, as individual survey response dates are not available. Nonetheless, since the survey is conducted throughout the entire month, a fraction of respondents react on impact to the monetary shocks.

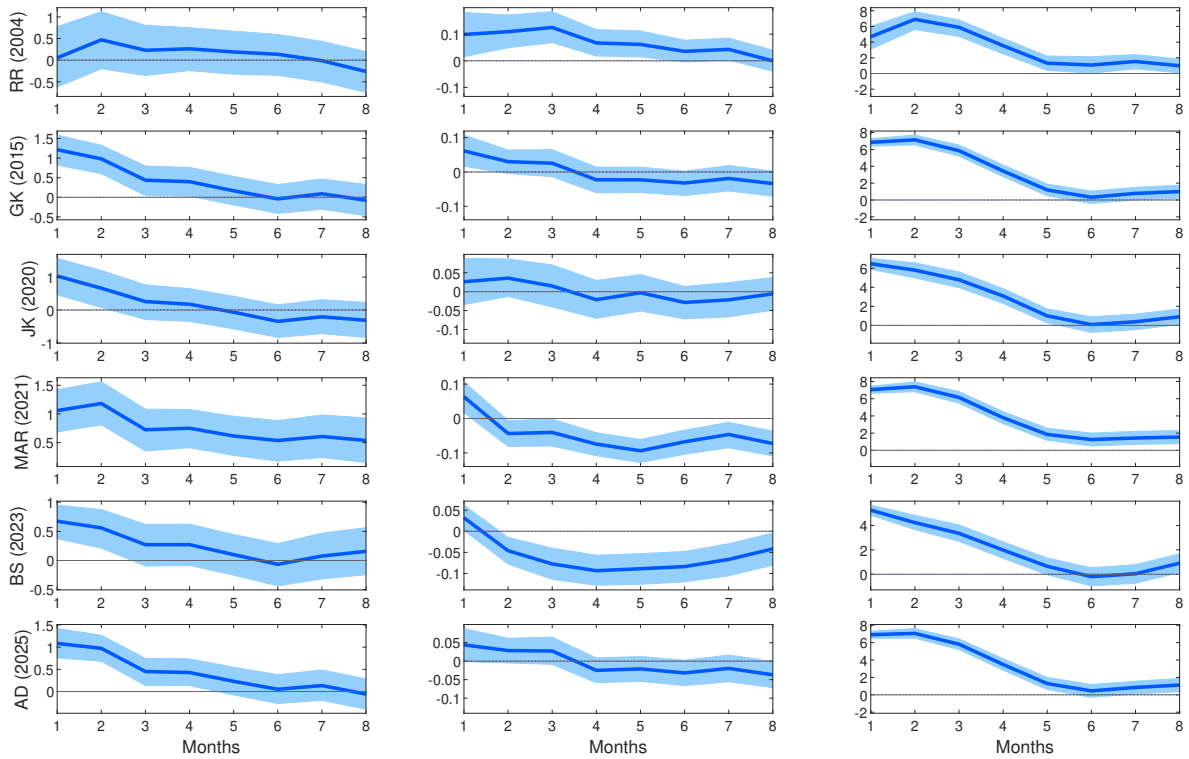
2.3. Results

Each figure below displays impulse responses of belief measures to a contractionary one-standard-deviation monetary policy shock. The six rows correspond to the six instruments: [Romer and Romer \(2004\)](#), [Gertler and Karadi \(2015\)](#), [Jarociński and Karadi \(2020\)](#), [Miranda-Agrippino and Ricco \(2021\)](#), [Bauer and Swanson \(2023\)](#), and [Aruoba and Drechsel \(2025\)](#). Shaded bands are 68 percent posterior coverage intervals. The three columns in each figure report responses of expected real activity, expected inflation, and expected short-term interest rates. We impose the timing restriction for CE and SPF throughout; results without this restriction appear in Appendix A (Figures A5 for CE) and are qualitatively unchanged.

2.3.1. Michigan Survey of Consumers

Figure 1 reports results for household beliefs. Three findings stand out. First, the Index of Consumer Sentiment rises on impact under all six instruments. This response is robust to the choice of identification scheme, spanning narrative measures that exploit internal Fed documents ([Romer and Romer 2004](#)) and high-frequency measures that use intraday interest rate movements ([Gertler and Karadi 2015](#)). Households become more optimistic about economic conditions precisely when monetary policy tightens, the opposite of the FIRE prediction. Second, mean expected inflation rises on impact in most specifications. This evidence must be interpreted with care: the MSC inflation question does not specify a price index, so the response reflects households’ subjective notion of “prices in general” rather than a precisely defined deflator. Nevertheless, the direction is consistently positive, and the absence of a negative response is itself informative. Third, the balance score for expected interest rate changes moves in the correct direction—households anticipate higher rates—confirming that respondents process the rate signal but do not infer a deteriorating outlook from it.

The responses are significant at the impact horizon and fade over the following three to five months. The transitory nature of the puzzle is an important feature: it is not that households are permanently optimistic, but rather that their beliefs spike upward on impact and then revert. Appendix Figure A2 shows that the unemployment balance score, the



A. Consumer Sentiment

B. Inflation Expectations

C. Interest Rate Expectations

Note: Each row corresponds to a different monetary policy instrument. RR (2004): [Romer and Romer \(2004\)](#); GK (2015): [Gertler and Karadi \(2015\)](#); JK (2020): [Jarociński and Karadi \(2020\)](#); MAR (2021): [Miranda-Agrippino and Ricco \(2021\)](#); BS (2023): [Bauer and Swanson \(2023\)](#); AD (2025): [Aruoba and Drechsel \(2025\)](#). Horizontal axis: months after the shock. Shaded areas are 68% posterior coverage bands. Consumer Sentiment is the Index of Consumer Sentiment. Inflation expectations are the mean expected annual price change. Interest rate expectations are the balance score for expected rate changes.

FIGURE 1. Impulse Responses to a Monetary Policy Shock: Michigan Survey of Consumers

percentage of households expecting more unemployment minus the percentage expecting less, plus 100, falls on impact under four of the six instruments, so that fewer households expect unemployment to rise.

2.3.2. Consensus Economics

Figure 2 reports the CE evidence from financial and research economists, a population that monitors macroeconomic data closely and has strong incentives to form accurate forecasts. The results parallel those from the MSC. Real GDP growth forecast revisions are positive on impact across most identification schemes, ranging from approximately 0.02 to 0.06 percentage points. Although smaller in magnitude than the SPF responses discussed below,

the direction is consistent and holds even under the narrative instrument of [Romer and Romer \(2004\)](#). The CPI inflation response is centered near zero or slightly negative on impact, in contrast to the MSC and SPF results. This divergence across surveys is informative: CE respondents forecast CPI specifically and may be more attuned to the disinflationary effects of tighter policy on this particular price index, yet they still revise GDP upward. The response of three-month Treasury bill expectations is positive on impact, approximately 0.05 percentage points, confirming that financial economists correctly internalize the rate increase. These patterns are robust to the timing restriction: Appendix Figure [A5](#) reports results from a sample without the restriction, and the output and rate responses are qualitatively unchanged. CPI revisions turn somewhat more negative without the restriction, consistent with the possibility that survey observations collected before the FOMC decision contain partial information about the upcoming announcement.

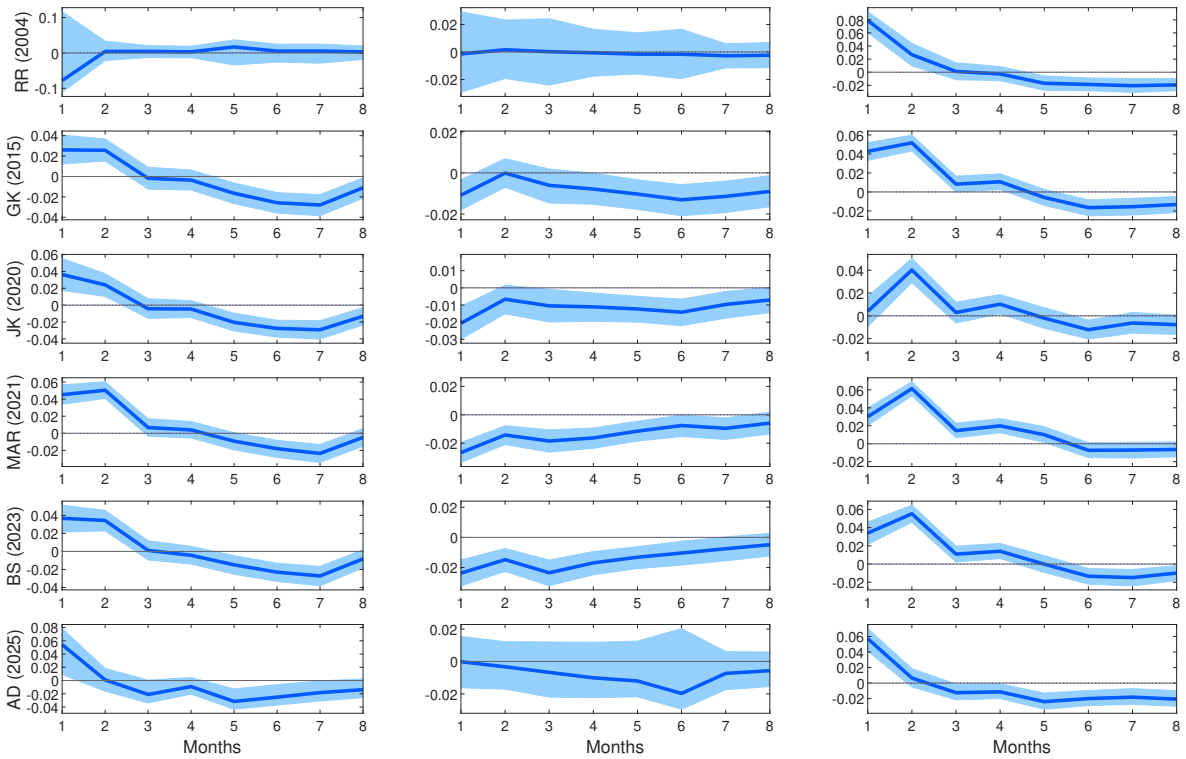
2.3.3. Survey of Professional Forecasters

Figure [3](#) reports quarterly evidence from the SPF. Real GDP growth forecast revisions are positive on impact under five of the six instruments, ranging from 0.10 to 0.20 percentage points; under the narrative instrument of [Romer and Romer \(2004\)](#), the impact response is close to zero. CPI inflation revisions are also positive on impact, approximately 0.10 percentage points in most specifications. The three-month Treasury bill forecast rises by roughly 0.20 percentage points on impact, reflecting that SPF forecasters correctly anticipate the policy rate increase. Three aspects of these results deserve emphasis.

First, the magnitude of the GDP revision is notable given the quarterly frequency. If a single contractionary announcement shifted CE forecasters' monthly GDP revisions by 0.02–0.06 percentage points, and a typical quarter contains two to three FOMC meetings, accumulating these revisions yields quarterly responses broadly consistent with the SPF results. The two surveys therefore paint a coherent quantitative picture despite their different frequencies.

Second, SPF respondents are among the most informed and incentivized forecasters: they are professional macroeconomists who release their projections publicly. The belief puzzle is not confined to less sophisticated agents. It appears among exactly those individuals who, in theory, should process monetary policy signals most accurately.

Third, as with MSC and CE, the responses are concentrated at the impact horizon. GDP and CPI revisions lose statistical significance after one to two quarters. The transience of the puzzle rules out interpretations based on a permanent shift in the perceived state of the economy and is instead consistent with a short-lived informational component in monetary policy announcements that agents extract on impact and then revise away as



A. Real GDP Growth

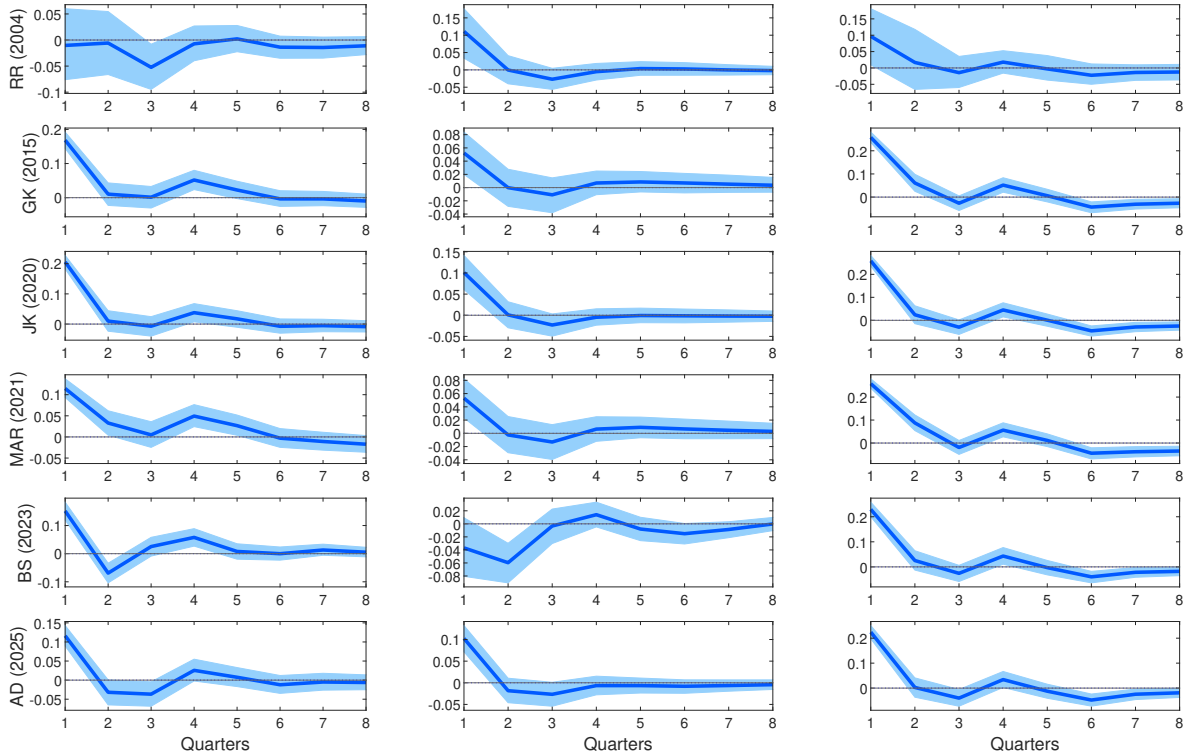
B. CPI Inflation

C. 3-Month T-Bill Rate

Note: Sample restricted to months in which the FOMC decision precedes the survey date. Each row corresponds to a different instrument. RR (2004): [Romer and Romer \(2004\)](#); GK (2015): [Gertler and Karadi \(2015\)](#); JK (2020): [Jarociński and Karadi \(2020\)](#); MAR (2021): [Miranda-Agrippino and Ricco \(2021\)](#); BS (2023): [Bauer and Swanson \(2023\)](#); AD (2025): [Aruoba and Drechsel \(2025\)](#). Horizontal axis: months. Shaded areas are 68% posterior coverage bands.

FIGURE 2. Impulse Responses to a Monetary Policy Shock: Consensus Economics

subsequent data arrive.



A. Real GDP Growth

B. CPI Inflation

C. 3-Month T-Bill Rate

Note: Each row corresponds to a different instrument. RR (2004): [Romer and Romer \(2004\)](#); GK (2015): [Gertler and Karadi \(2015\)](#); JK (2020): [Jarociński and Karadi \(2020\)](#); MAR (2021): [Miranda-Agrippino and Ricco \(2021\)](#); BS (2023): [Bauer and Swanson \(2023\)](#); AD (2025): [Aruoba and Drechsel \(2025\)](#). Horizontal axis: quarters. Shaded areas are 68% posterior coverage bands. Sample restricted to include only shocks falling before the survey date within each quarter.

FIGURE 3. Impulse Responses to a Monetary Policy Shock: Survey of Professional Forecasters

2.4. Summary of Empirical Findings

The impulse responses reveal a systematic departure from the FIRE benchmark, but not a uniform one across variables. The robust fact is the response of expected activity: contractionary monetary policy surprises improve the near-term outlook across households, financial economists, and professional forecasters, even as expected short-term rates rise. Inflation beliefs increase in the MSC and SPF but are close to zero or negative in CE. The real-activity result survives across identification strategies ranging from narrative measures ([Romer and Romer 2004](#)) to high-frequency instruments designed to separate policy and information components ([Jarociński and Karadi 2020](#); [Miranda-Agrippino and](#)

[Ricco 2021](#)).

The natural interpretation is that announcements reveal information about the state of the economy that is absent from private priors. If the central bank's information set differs from that of private agents, an unexpected rate increase can reveal favorable fundamentals even when the policy innovation itself is contractionary. [Jarociński and Karadi \(2020\)](#) show that mixing these components distorts inference about monetary transmission. In our data, the increase in output forecasts need not mean that agents regard tighter policy as expansionary; it can instead reflect good news inferred from the central bank's systematic response. The heterogeneous inflation evidence cautions against treating the information component as a single one-dimensional signal.

A second disciplining fact is that the unusual belief response is short-lived. Revisions are largest on impact and generally return toward zero within a few months or quarters. This profile is consistent with agents extracting a signal from the announcement and subsequently incorporating macroeconomic releases that reduce uncertainty. The next section formalizes this mechanism in an equilibrium model in which private signals are noisy and the policy rate is informative about several latent disturbances.

3. Theoretical Framework

Section 2 established that contractionary monetary policy surprises can improve the near-term outlook even as agents anticipate higher rates. We now develop an equilibrium model in which this combination arises because the policy rate is both an instrument and a signal. The purpose of the model is not to make monetary tightening expansionary. It is to explain how a contractionary policy disturbance and favorable revisions in private beliefs can coexist in the response to an observed announcement.

3.1. Motivation Behind the Theoretical Model

The empirical evidence places four requirements on the theoretical framework. First, the object observed in the data is a policy surprise rather than a labeled structural shock. The model must therefore allow the same unexpected rate increase to contain both an exogenous monetary disturbance and information about the systematic policy response. A full-information model cannot meet this requirement: once all fundamentals are observed, agents know why the rate moved and no signal-extraction problem remains.

Second, beliefs must affect the decisions that determine aggregate outcomes. We distinguish households from firms because expectations enter the two central New Keynesian

margins differently. Households' beliefs about real rates and income determine spending, whereas firms' beliefs about marginal costs, demand, and other prices determine price setting. Group-specific signal precision lets the model confront belief heterogeneity without disconnecting forecasts from behavior.

Third, agents must be uncertain about more than the monetary disturbance. We include monetary, demand, technology, and markup shocks so that an observed rate movement has competing structural interpretations. This is essential for the mechanism. A higher rate attributed to an exogenous monetary innovation is bad news for activity; a higher rate attributed to stronger demand can be good news even though the policy response itself is contractionary. Estimation determines which ambiguity matters quantitatively rather than assigning the information effect to a residual news shock.

Fourth, the framework must propagate beliefs through general equilibrium and deliver a pure-shock counterfactual. Noisy private signals generate higher-order uncertainty: agents care not only about fundamentals, but also about how others perceive them. The resulting spending–income and pricing interactions create endogenous persistence, as in [Angeletos and Huo \(2018\)](#) and [Angeletos and Huo \(2021\)](#). At the same time, the linear solution lets us remove the nonmonetary news from the observed surprise and trace the structural monetary innovation. These features make the model both disciplined by the six empirical impulse responses and useful for the identification exercise in [Section 5](#).

We implement these requirements by adding dispersed information to an otherwise standard New Keynesian economy. Households and firms observe noisy private signals about the four aggregate disturbances. The central bank observes the aggregate state and sets the policy rate according to a Taylor rule. Private agents therefore cannot perfectly distinguish an exogenous policy innovation from the endogenous response of policy to fundamentals. An unexpected increase in the rate changes their posterior beliefs about both, affecting aggregate demand through household spending and inflation through firms' price setting.

3.2. Households

There is a unit continuum of ex ante identical households, indexed by $i \in \mathcal{I}_c = [0, 1]$. Household i chooses consumption, labor, and bond holdings to maximize $\mathbb{E}_{i0} \sum_{t=0}^{\infty} \beta^t U(C_{it}, N_{it}; Z_t)$, where Z_t is a common preference shifter and $U(C, N; Z) = [C^{1-\sigma}/(1-\sigma) - N^{1+\varphi}/(1+\varphi)] Z$. The parameter $1/\sigma$ is the intertemporal elasticity of substitution and φ is the inverse Frisch elasticity. Households are identical in preferences and endowments but can choose differently because their private signals, and hence their posterior beliefs, differ.

Households' Problem. The household consumption index is $C_{it} = \left(\int_{\mathcal{J}_f} C_{ijt}^{(\epsilon_t-1)/\epsilon_t} dj \right)^{\epsilon_t/(\epsilon_t-1)}$, where C_{ijt} is household i 's consumption of variety $j \in \mathcal{J}_f = [0, 1]$ and ϵ_t is the elasticity of substitution across varieties. Cost minimization yields

$$(6) \quad C_{ijt} = \left(P_{jt}/P_t \right)^{-\epsilon_t} C_{it}$$

where the aggregate price index is defined as $P_t \equiv \left(\int_{\mathcal{J}_f} P_{jt}^{1-\epsilon_t} dj \right)^{\frac{1}{1-\epsilon_t}}$. Using the above conditions, one can show that $\int_{\mathcal{J}_f} P_{jt} C_{ijt} dj = P_t C_{it}$.

In real terms, households choose consumption, labor, and savings subject to

$$(7) \quad C_{it} + B_{it} = R_{t-1} B_{i,t-1} + W_{it}^r N_{it} + D_{it},$$

where B_{it} denotes savings (or bond purchases) by household i , R_{t-1} denotes the gross real return on savings, W_{it}^r denotes the real wage at time t , and D_{it} denotes dividends received from the profits produced by firms.

The optimality conditions from the household problem satisfy $C_{it}^{-\sigma} = \beta \mathbb{E}_{it} \left(R_t Z_{t+1} / Z_t C_{i,t+1}^{-\sigma} \right)$ and $C_{it}^\sigma N_{it}^\varphi = \mathbb{E}_{it} W_t^r$.

Auxiliary Shocks. If individual wages and dividends revealed the aggregate state without noise, households could reconstruct other agents' information from equilibrium outcomes, undoing the intended information friction. Following [Angeletos and Huo \(2018\)](#), we therefore overlay each household's observed labor and dividend income with high-variance idiosyncratic auxiliary shocks, and impose the analogous structure on firms. Private realizations then remain noisy signals of aggregate conditions.

Let W_t and D_t denote, respectively, the average real wage and the average real dividend from firms' profits. The real wage and the dividend received by consumer i at time t are given by, respectively, $W_{it} = \zeta_{it}^W W_t$ and $D_{it} = \zeta_{it}^D D_t$, where $\{\zeta_{it}^W, \zeta_{it}^D\}$ are i.i.d. across i and t . The auxiliary shocks enter only at the individual level and average out in the aggregate, and do not affect equilibrium dynamics.

3.3. Firms

Each variety is produced by a monopolistically competitive firm $j \in \mathcal{J}_f = [0, 1]$ using labor, $Y_{jt} = A_t N_{jt}$. Common technology follows the log-AR(1) process

$$(8) \quad a_t = \rho_a a_{t-1} + \varepsilon_t^a$$

where $0 \leq \rho_a < 1$ and the innovation satisfies $\varepsilon_t^a \sim \mathcal{N}(0, \sigma_a^2)$.

Price-Setting. Nominal price rigidities take the form of a Calvo price-setting friction. In every period, each firm can reset its price with probability $1 - \theta$, independent of the time of the last price change. A measure $1 - \theta$ of firms can reset their prices in a given period, and the average duration of a price is given by $1/(1 - \theta)$.

A firm that reoptimizes in period t chooses P_{jt}^* to maximize the expected discounted profits generated while that price remains effective. Formally,

$$P_{jt}^* = \arg \max_{P_{jt}} \sum_{k=0}^{\infty} \theta^k \mathbb{E}_{jt} \left\{ \Lambda_{t,t+k}/P_{t+k} \left[P_{jt} Y_{j,t+k|t} - \mathcal{C}_{t+k}(Y_{j,t+k|t}) \right] \right\},$$

subject to the demand schedule in (6). Here $\Lambda_{t,t+k} \equiv \beta^k (C_{t+k}/C_t)^{-\sigma}$ is the stochastic discount factor, $\mathcal{C}_t(\cdot)$ is nominal cost, and $Y_{j,t+k|t}$ is output at $t + k$ for a firm that last reset its price at t . The first-order condition is

$$(9) \quad \sum_{k=0}^{\infty} \theta^k \mathbb{E}_{jt} \left[\Lambda_{t,t+k} Y_{j,t+k|t} / P_{t+k} \left(P_{jt} - \mathcal{M}_t \Psi_{j,t+k|t} \right) \right] = 0,$$

where $\mathcal{M}_t = \varepsilon_t/(\varepsilon_t - 1)$ denotes the time-varying markup, $\Psi_{j,t+k|t} \equiv \mathcal{C}'_{t+k}(Y_{j,t+k|t}) = W_{jt}^n$ denotes the nominal marginal cost for firm j , and W_{jt}^n is the nominal wage faced by firm j .

Auxiliary Shocks. Equivalently to the consumer side, we make use of the auxiliary shock $W_{jt}^n = \zeta_{jt}^F W_t^n$ with ζ_{jt}^F i.i.d. across j and t .

3.4. Monetary Policy

Monetary policy is conducted following a Taylor rule of the form

$$(10) \quad i_t = \phi_\pi \pi_t + \phi_y \tilde{y}_t + v_t$$

where π_t denotes the inflation rate, $\tilde{y}_t$ denotes the output gap, and the monetary policy shock v_t follows the AR(1) process

$$(11) \quad v_t = \rho_v v_{t-1} + \varepsilon_t^v$$

where $0 \leq \rho_v < 1$ and $\varepsilon_t^v \sim \mathcal{N}(0, \sigma_v^2)$.

3.5. Information Structure

Households and firms do not observe the four aggregate disturbances directly. Their information sets consist of the histories of their private signals.²

Each period, agent l in group g receives one Gaussian signal about each disturbance:

$$(12) \quad x_{lgt}^v = v_t + u_{lgt}^v, \quad u_{lgt}^v \sim \mathcal{N}(0, \sigma_{gv}^2),$$

$$(13) \quad x_{lgt}^z = z_t + u_{lgt}^z, \quad u_{lgt}^z \sim \mathcal{N}(0, \sigma_{gz}^2),$$

$$(14) \quad x_{lgt}^a = a_t + u_{lgt}^a, \quad u_{lgt}^a \sim \mathcal{N}(0, \sigma_{ga}^2),$$

$$(15) \quad x_{lgt}^\mu = \mu_t + u_{lgt}^\mu, \quad u_{lgt}^\mu \sim \mathcal{N}(0, \sigma_{g\mu}^2),$$

where $g \in \{c, f\}$ indexes households and firms and $n \in \{v, z, a, \mu\}$ indexes the monetary, demand, technology, and markup disturbances. The standard deviation σ_{gn} governs the precision of group g 's signal about disturbance n . Allowing it to vary across groups and shocks is the model's source of information heterogeneity.

3.6. Equilibrium Dynamics

The model is solved in its log-linearized version around a steady state with zero inflation. We relegate the detailed derivation to Appendix C, and sketch here the main steps.

DEFINITION 1. *Given an initial price level P_{-1} , a general equilibrium is a path for prices $\{P_t, W_t, \pi_t, R_t, i_t\}_{t=0}^\infty$, aggregates $\{Y_t, C_t, B_t, D_t\}_{t=0}^\infty$, and individual allocation rules $\{C_{it}, P_{jt}\}_{t=0, \forall i, j}^\infty$ such that consumers and firms optimize, taking their information sets as given; monetary policy follows (10); and the goods, labor, and bond markets clear.*

DIS curve. The optimal intratemporal labor supply condition can be log-linearized to

$$(16) \quad \mathbb{E}_{it} w_t^r = \sigma c_{it} + \varphi n_{it},$$

where a lower case variable denotes the logarithm deviation of the capital letter variable from steady-state, $x_t = \log X_t - \log X$, and the intertemporal Euler condition can be log-linearized to

$$(17) \quad c_{it} = -1/\sigma \mathbb{E}_{it} r_t + (1 - \rho_z)/\sigma \mathbb{E}_{it} z_t + \mathbb{E}_{it} c_{it+1},$$

²The idiosyncratic components of the auxiliary shocks introduced in Sections 3.2–3.3 are assumed to have large variance relative to their aggregate components.

where we define the ex-post real interest rate as the difference between the nominal interest rate and one-period-ahead inflation, $r_t = i_t - \pi_{t+1}$, and $z_t \equiv \log Z_t$ follows an exogenous AR(1) process

$$(18) \quad z_t = \rho_z z_{t-1} + \varepsilon_t^z,$$

where $0 \leq \rho_z < 1$ and $\varepsilon_t^z \sim \mathcal{N}(0, \sigma_z^2)$. The individual household DIS curve is then

$$(19) \quad c_{it} = -\beta/\sigma \mathbb{E}_{it} r_t + \beta(1 - \rho_z)/\sigma \mathbb{E}_{it} z_t - \beta\psi(1 - \rho_a) \mathbb{E}_{it} a_t + (1 - \beta) \mathbb{E}_{it} c_t + \beta \mathbb{E}_{it} c_{i,t+1},$$

with $c_t = \int c_{it} di$ and $\psi \equiv (1 + \varphi)/[\sigma(1 - \alpha) + \varphi + \alpha]$.³ Iterating forward and aggregating across households, the aggregate DIS curve can be written as

$$(20) \quad \tilde{y}_t = -\frac{\beta}{\sigma} \sum_{k=0}^{\infty} \beta^k \bar{\mathbb{E}}_t^c r_{t+k} + \frac{\beta(1 - \rho_z)}{\sigma} \sum_{k=0}^{\infty} \beta^k \bar{\mathbb{E}}_t^c z_{t+k} - \beta\psi(1 - \rho_a) \sum_{k=0}^{\infty} \beta^k \bar{\mathbb{E}}_t^c a_{t+k} + (1 - \beta) \sum_{k=0}^{\infty} \beta^k \bar{\mathbb{E}}_t^c \tilde{y}_{t+k}$$

where $\tilde{y}_t = \tilde{c}_t$ denotes the output gap, and $\bar{\mathbb{E}}_t^c(\cdot) = \int_0^1 \mathbb{E}_{it}(\cdot) di$ denotes the cross-sectional average forecast across households.⁴ As in the textbook NK model, the demand curve (20) can be summarized as a single equation; however, under incomplete information, it cannot be collapsed into a first-order stochastic difference equation since the hierarchy of beliefs prevents the law of iterated expectations (LIE) from holding at the aggregate level.

Phillips curve. Following Angeletos and Huo (2018) and Angeletos and Huo (2021), we simplify the model by assuming that firms observe aggregate prices through period $t - 1$ but do not extract information from them.⁵ This allows us to write the Phillips curve in inflation terms.

Combining the firms' pricing condition and the goods market clearing, the (log-linearized) firm-level Phillips curve is given by

$$(21) \quad \pi_{jt} = \theta \lambda \mathbb{E}_{jt} \mu_t + \kappa \theta \mathbb{E}_{jt} \tilde{y}_t + (1 - \theta) \mathbb{E}_{jt} \pi_t + \beta \theta \mathbb{E}_{jt} \pi_{j,t+1}$$

where $\pi_t = \int \pi_{jt} dj$, $\lambda = (1 - \theta)(1 - \beta\theta)(1 - \alpha)/[\theta(1 - \alpha + \alpha\epsilon)]$, $\kappa = \lambda [\sigma + (\varphi + \alpha)/(1 - \alpha)]$, and

³The model derivation is relegated to Appendix C.

⁴We show in appendix C that the expected natural real interest rate is given by $\mathbb{E}_{it} r_t^n = -\sigma\psi(1 - \rho_a) \mathbb{E}_{it} a_t$.

⁵An alternative formulation lets firms remain uncertain about the history of the aggregate price level, p^{t-1} .

μ_t is a markup shock, which follows an exogenous AR(1) process

$$(22) \quad \mu_t = \rho_\mu \mu_{t-1} + \varepsilon_t^\mu$$

where $0 \leq \rho_\mu < 1$ and $\varepsilon_t^\mu \sim \mathcal{N}(0, \sigma_\mu^2)$.⁶ Iterating forward and aggregating across firms, the aggregate Phillips curve can be written as

$$(23) \quad \pi_t = \lambda \theta \sum_{k=0}^{\infty} (\beta \theta)^k \bar{\mathbb{E}}_t^f \mu_{t+k} + \kappa \theta \sum_{k=0}^{\infty} (\beta \theta)^k \bar{\mathbb{E}}_t^f \tilde{y}_{t+k} + (1 - \theta) \sum_{k=0}^{\infty} (\beta \theta)^k \bar{\mathbb{E}}_t^f \pi_{t+k}$$

where $\bar{\mathbb{E}}_t^f(\cdot) = \int_0^1 \mathbb{E}_{jt}(\cdot) dj$ is the cross-sectional average forecast across firms.

Equilibrium Dynamics. The economy is described by two interacting dynamic beauty contests: the spending–income feedback in households’ decisions, summarized by (19), and strategic complementarity in firms’ price setting, summarized by (21).

The equilibrium dynamics must satisfy the individual-level optimal policy functions (19) and (21). Expectations must be consistent with the Taylor rule (10), the exogenous shock processes, and the signals in (12)–(15). Proposition 1 characterizes the resulting fixed point.

PROPOSITION 1. *In equilibrium, the aggregate outcome obeys the following law of motion*

$$(24) \quad c_t = \sum_{n=\{v,z,a,\mu\}} \sum_{j=1}^2 \frac{\psi_{1jn}}{\rho_n} \sum_{k=0}^{\infty} \left(\rho_n^{k+1} - \vartheta_{jn}^{k+1} \right) \varepsilon_{t-k}^n$$

$$(25) \quad \pi_t = \sum_{n=\{v,z,a,\mu\}} \sum_{j=1}^2 \frac{\psi_{2jn}}{\rho_n} \sum_{k=0}^{\infty} \left(\rho_n^{k+1} - \vartheta_{jn}^{k+1} \right) \varepsilon_{t-k}^n$$

where the coefficients ψ_{kjn} and the stable roots ϑ_{jn} are functions of the calibrated parameters, the persistence and variance of disturbance n , and the two groups’ signal precision. Appendix B gives the complete mapping while allowing $\sigma_{cn} \neq \sigma_{fn}$.

PROOF. See Appendix B. □

The representation separates fundamental persistence, ρ_n , from the endogenous roots ϑ_{jn} generated by dispersed information and strategic interaction. Each impulse response is a weighted difference between these decay rates. As signals become uninformative, the endogenous roots approach the persistence of the underlying state: aggregate responses

⁶The model derivation is relegated to Appendix C.

become more delayed and persistent. As signal noise vanishes, the endogenous roots converge toward zero and this additional source of persistence disappears. The model can therefore match sluggish aggregate dynamics and sharp forecast revisions without imposing ad hoc lagged output or inflation terms.

4. Estimation and Results

The empirical object in Section 2 is a monetary policy surprise: an innovation in the policy rate relative to agents' pre-announcement information. In the model, this object differs from the structural monetary policy shock. Using households' average expectation to measure the forecast error, the surprise can be written as

$$(26) \quad \text{mps}_t^c = i_t - \bar{\mathbb{E}}_t^c i_t = \phi_\pi \left(\pi_t - \bar{\mathbb{E}}_t^c \pi_t \right) + \phi_y \left(\tilde{y}_t - \bar{\mathbb{E}}_t^c \tilde{y}_t \right) + v_t - \bar{\mathbb{E}}_{t-1}^c v_t.$$

Here $\bar{\mathbb{E}}_t^c$ denotes households' average expectation conditional on the information available immediately before the policy announcement in quarter t . Applied to the Taylor rule (10), it evaluates the systematic component of policy at households' period- t nowcasts of inflation and the output gap, $\bar{\mathbb{E}}_t^c \pi_t$ and $\bar{\mathbb{E}}_t^c \tilde{y}_t$, and the policy disturbance at its forecast from the previous quarter, $\bar{\mathbb{E}}_{t-1}^c v_t = \rho_v \bar{\mathbb{E}}_{t-1}^c v_{t-1}$.

This timing reflects how monetary announcements are embedded in the flow of information within a quarter. Because the model is specified at quarterly frequency, a policy decision takes place well inside the period over which inflation and output are measured. By the time of the announcement, agents have observed a substantial part of the quarter's data releases, such as monthly price indices, indicators of real activity, and survey evidence, and they form nowcasts of current macroeconomic conditions accordingly. Dating their expectations of inflation and the output gap at $t - 1$ would discard this within-quarter information and attribute to the announcement news that private agents had already incorporated. The policy disturbance is different in nature: it is the component of the decision that the announcement itself reveals, so its relevant benchmark is the forecast formed before the quarter began. Both operators therefore apply a common principle, namely that each component of the policy rate is compared with the best forecast available just before the announcement, to objects that become observable at different moments. The same principle underlies the high-frequency instruments used in Section 2, which measure surprises against market expectations that already incorporate all macroeconomic releases preceding the announcement.

We measure the surprise with households' expectations because, in the model, house-

holds are the agents whose decisions are governed by the expected path of the policy rate. The policy rate affects the economy only through households' intertemporal choices: their Euler equation (17) and the aggregate demand curve (20) depend on expected real interest rates, and households are the agents who hold nominal bonds in (7). Firms' pricing decisions in (21), by contrast, depend on expected markups, output, and inflation, but not on the nominal rate. Households are therefore the model counterpart of the investors whose expectations are embedded in the interest-rate futures used to measure high-frequency surprises. The mapping is functional rather than literal: the model has no separate financial sector, and the expectations that define the surprise are those of the agents for whom the policy rate is a payoff-relevant price. Survey forecasts of activity and inflation are informative instead about the beliefs that enter price setting, which is why we map the SPF revisions to firms' expectations below.

The first two terms capture news about the endogenous state embedded in the systematic policy response; only the last term isolates news about the monetary disturbance. Under full information the distinction collapses. With noisy information, an observed tightening can also reveal the conditions to which policy responds systematically, such as strong demand or persistent inflationary pressure, even when the structural policy innovation is contractionary. Proposition A1 in Appendix B derives the responses of aggregate outcomes and forecast revisions to mps_t^c .

4.1. Minimum-Distance Estimation

We estimate the model at quarterly frequency and require every target to correspond to the same shock. The macroeconomic targets are the responses to the [Jarociński and Karadi \(2020\)](#) monetary policy instrument from a monthly proxy VAR containing an industrial-production gap, the CPI, and the three-month Treasury bill rate. We aggregate the monthly posterior impulse responses to quarterly frequency; the output gap and interest rate remain in levels, while CPI inflation responses are cumulated to obtain the price-level response. The belief targets are the output-growth, CPI-inflation, and Treasury-bill forecast revisions from the quarterly SPF VAR reported in Figure 3, again using the [Jarociński and Karadi \(2020\)](#) instrument and the three-lag quarterly specification.

We intentionally obtain the two blocks from separate systems. The macro-only VAR supplies a single benchmark for aggregate transmission that is invariant to the survey series used to measure beliefs. This matters because MSC, CE, and SPF differ in frequency, sample period, target definition, and measurement error. If a survey variable were appended to the macro VAR in each exercise, the estimated responses of activity, prices, and interest rates would change mechanically with the chosen survey and could no longer serve as

common targets. The SPF VAR is instead used for the object it measures directly: how professional forecasts are revised. The separation does not splice together responses to different shocks. Both systems use the same [Jarociński and Karadi \(2020\)](#) instrument, so they identify the same monetary surprise under different estimating information sets. Appendix Figure A1 reports the exact macroeconomic responses entering the criterion.

All responses are expressed per percentage point of the impact increase in the policy rate, both in the data, draw by draw, and in the model. This normalization changes the scale relative to Section 2, where responses refer to a one-standard-deviation shock: the median impact response of the Treasury-bill rate to a one-standard-deviation [Jarociński and Karadi \(2020\)](#) surprise is between 0.23 and 0.27 percentage points in the SPF VARs and 0.09 percentage points in the macroeconomic VAR, so the targets are about four and eleven times, respectively, the corresponding responses to a one-standard-deviation surprise. The criterion includes the first four quarterly responses of each of the six variables. Since the impact response of the policy rate equals one by construction, this yields 23 moments. Figure 4 reports responses up to eight quarters; the last four quarters are not targeted and therefore provide a check on the propagation implied by the estimates. We map the SPF moments to firms' average expectations, the belief block that enters price setting in the model. The standard New Keynesian parameters are calibrated at quarterly frequency. We estimate the four shock persistences, the innovation standard deviations of the demand, technology, and cost-push disturbances, and the eight signal-noise standard deviations. All standard deviations are expressed relative to that of the monetary innovation, σ_v , which we normalize to one. The normalization is without loss of generality: the targeted responses are invariant to a common rescaling of all innovation and noise standard deviations.⁷

The criterion is the sum of squared deviations between the empirical median responses and the model responses. We weight all moments equally rather than by the inverse of their posterior variances, for two reasons. First, the belief responses are estimated much more precisely than the macroeconomic responses: within the estimation window, the average half-width of the 68 percent bands is 0.13 percentage points for the forecast revisions and 0.63 for the macroeconomic variables. Inverse-variance weights would assign 95 percent of the total weight to the twelve belief moments, and the transmission of policy to output and prices, which is the object of the counterfactual analysis below, would be left essentially undisciplined. Second, the two blocks are estimated in separate systems with different samples, frequencies, and specifications, so differences in the width of their bands reflect differences in the estimation environment as well as in the information

⁷Persistences are parameterized with a logistic transformation so that $0 < \rho_n < 1$, and all standard deviations are parameterized in logs to impose positivity.

content of the moments. Equal weights treat a deviation of one percentage point as equally costly for every variable. We restrict the parameter space to configurations in which a pure monetary innovation raises the nominal policy rate on impact; the restriction does not bind at the estimate. Because the criterion is nonconvex, we evaluate it at 10,000 quasi-random starting values and run local optimizations from the 100 best. The model has 15 estimated parameters and 8 overidentifying restrictions.

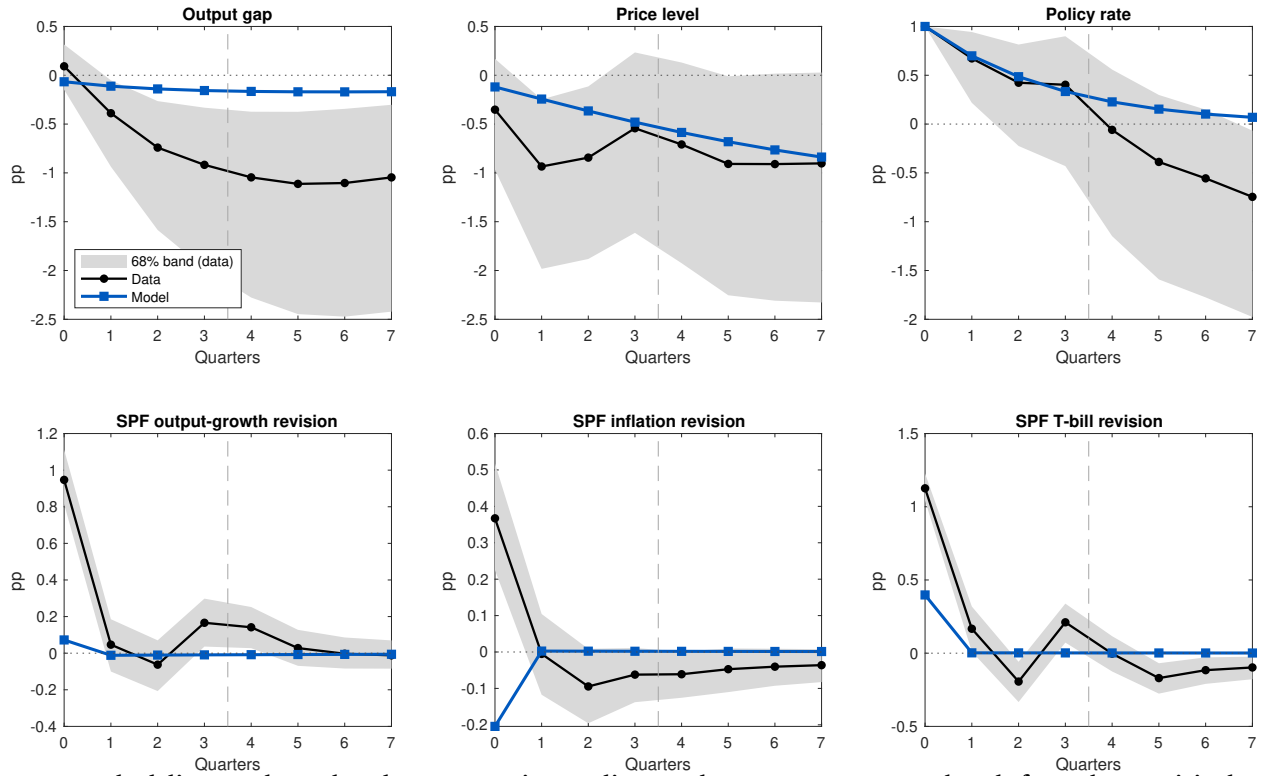
4.2. Model Fit and Estimated Information Frictions

Figure 4 compares the empirical targets with the model-implied responses. The top row contains the macroeconomic block and the bottom row the SPF forecast revisions. The model reproduces the gradual decline in the price level, also beyond the four quarters used in estimation, and the path of the policy rate within the estimation window, although it does not generate the subsequent decline of the rate below its steady-state level. It produces a persistent but small contraction in the industrial-production gap: the trough is 0.17 percentage points, compared with 1.1 percentage points in the data. In the belief block, the model matches the sign of the impact revisions of output and Treasury-bill forecasts, but not their magnitude; the output revision is 0.07 percentage points, against 0.95 in the data. The model generates a downward impact revision of inflation forecasts, whereas the SPF revision is positive. Inflation beliefs are, however, the least uniform belief response documented in Section 2: they rise in the MSC and the SPF but not in CE, and the impact response of CE inflation revisions in Section 5 is not distinguishable from zero.

Relative to empirical uncertainty, the macroeconomic block is fitted closely. Over the eight quarters shown in Figure 4, the ratio of the root mean squared fitting error to the average 68 percent half-width is 0.94 for output, 0.34 for the price level, and 0.61 for the interest rate. For the three forecast revisions, the ratios lie between 2.6 and 2.8, because their empirical bands are narrow and the model understates the size of the impact revisions.

Table 1 reports the estimates. The monetary disturbance has a quarterly persistence of 0.86, and the demand disturbance one of 0.62. The cost-push process is estimated at the upper bound of its persistence, and technology innovations are negligible relative to the other disturbances; we do not attach a structural interpretation to either block. Because the targeted responses are invariant to a common rescaling of all standard deviations, only relative magnitudes are informative.

The central estimates concern the distribution of information across the two groups. Households, whose expectations define the pre-announcement benchmark in equation (26), learn little about the monetary disturbance: the standard deviation of their



Note: Black lines and gray bands are posterior medians and 68 percent coverage bands from the empirical VARs. Blue lines are the model-implied responses at the point estimates. All responses are expressed per percentage point of the impact increase in the policy rate. Since a one-standard-deviation [Jarociński and Karadi \(2020\)](#) surprise raises the Treasury-bill rate by about 0.23 to 0.27 percentage points on impact in the SPF VARs, the belief responses in this figure are roughly four times those in the corresponding row of Figure 3, which refer to a one-standard-deviation shock. The vertical dashed line marks the last quarter included in the estimation criterion. The macroeconomic targets use the [Jarociński and Karadi \(2020\)](#) instrument in the industrial-production-gap proxy VAR; belief targets use the same instrument in the SPF VAR. CPI inflation is cumulated to a price-level response. Horizontal axes measure quarters after the surprise.

FIGURE 4. Empirical and Model-Implied Responses to a Contractionary Monetary Policy Surprise

signal noise is fourteen times that of the monetary innovation, so their expectation of the disturbance moves by only 2 percent of an innovation on impact. Firms, whose expectations are mapped to the SPF, observe the monetary and demand disturbances almost perfectly. Households also observe demand with error. Their demand signal is precise relative to the size of demand innovations, but the remaining error is of the same order of magnitude as a monetary innovation. As a result, the observed surprise combines the policy innovation with demand and cost-push conditions that households had not incorporated, while professional forecasters, who observe these conditions, revise their outlook accordingly. In the estimated model, the upward revision of output forecasts after a contractionary surprise therefore reflects the systematic response of policy to news that

forecasters process, as in [Bauer and Swanson \(2023\)](#), rather than forecasters' uncertainty about the nature of the policy innovation.

4.3. Counterfactual: The Pure Monetary Policy Shock

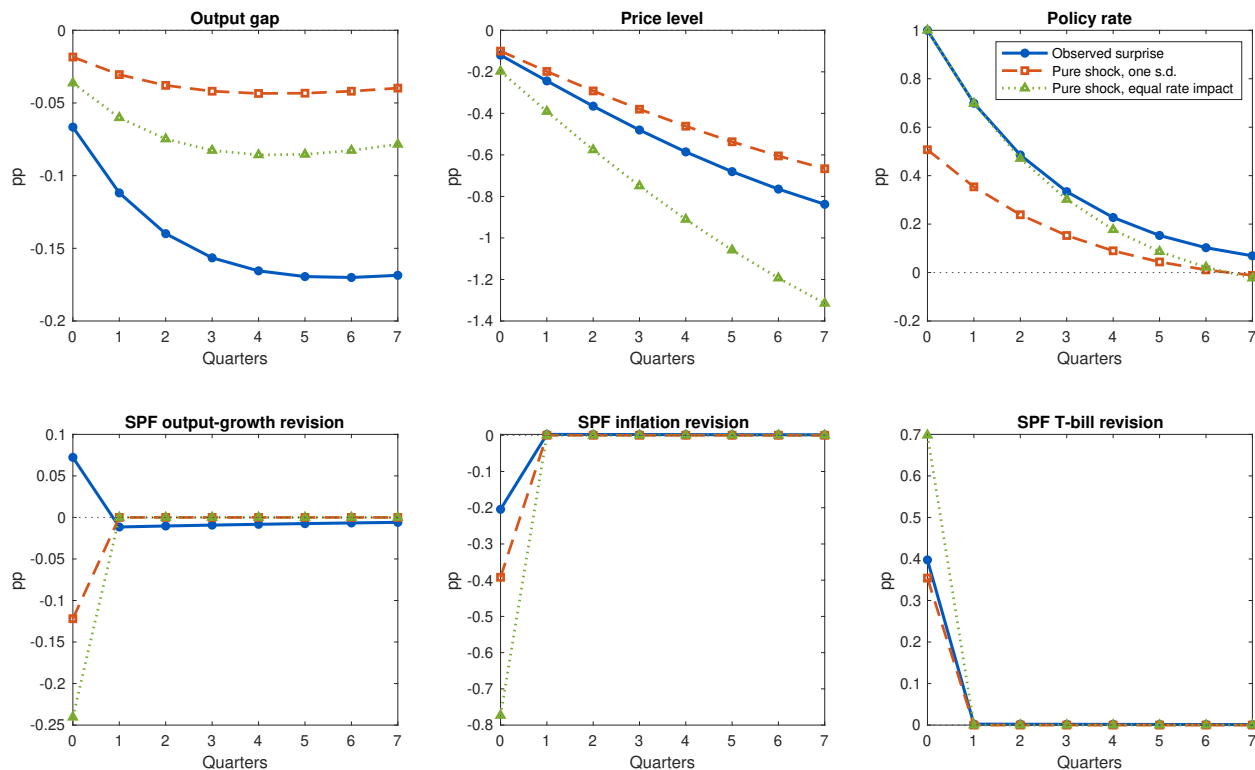
The fitted response in Figure 4 concerns the contaminated surprise in equation (26). We now shut down the nonmonetary components of that surprise and trace the response to the structural innovation ε_t^v . Corollary A1 in Appendix B provides the closed-form responses. Because an observed surprise and a structural innovation are different random variables, comparing their magnitudes requires a normalization.

Figure 5 reports two. The equal-impact normalization rescales the pure shock so that its impact effect on the interest rate equals that of the observed surprise, one percentage point. It is the model counterpart of the normalization used in Section 5. The one-standard-deviation normalization compares a one-standard-deviation monetary innovation with a one-standard-deviation surprise, using the factor $\phi_v = \sqrt{\mathbb{V}(\text{mps}_t^c)}/\sigma_v$. Because part of the variation in observed surprises is not monetary, the pure shock raises the interest rate by only 0.51 percentage points on impact under this normalization.

The counterfactual delivers three results. First, a pure tightening has conventional effects. Under both normalizations it lowers the output gap and the price level and leads to downward revisions of output and inflation forecasts. Under the equal-impact normalization, the impact revisions are -0.24 and -0.77 percentage points, compared with 0.07 and -0.20 after the observed surprise. The upward revision of output forecasts after a contractionary surprise is therefore not a property of the monetary disturbance but of the information that accompanies it.

Second, this information makes the observed surprise a more persistent tightening. The nonmonetary components of the surprise reflect the systematic response of policy to demand and to persistent cost-push pressure. They account for 30 percent of the impact effect of the surprise on the policy rate, for the entire rate response from quarter six onward, and for about 40 percent of the cumulative rate response over two years. The policy rate is correspondingly less persistent after a pure shock: under the equal-impact normalization, it stands 0.18 percentage points above its steady-state level after four quarters, compared with 0.23 after the surprise, and it falls below steady state in quarter seven.

Third, relative to the policy innovation it accompanies, the information lowers activity and raises prices. For a given impact on the policy rate, the pure shock lowers the output gap by at most 0.09 percentage points, about half the trough after the surprise. Relative to the cumulative increase in the policy rate over two years, the pure shock lowers the price level 1.8 times as much as the surprise, because it carries no inflationary news.



Note: Blue lines report responses to the observed (contaminated) monetary policy surprise, normalized to raise the policy rate by one percentage point on impact. Orange dashed lines report the pure monetary policy shock under the one-standard-deviation normalization. Green dotted lines report the pure shock under the equal-impact normalization. Inflation responses are cumulated to obtain the price level. Horizontal axes measure quarters after the shock.

FIGURE 5. Contaminated Monetary Policy Surprise and Pure Monetary Policy Shock

Since the two rate paths are similar in the model, the equal-impact normalization also implies a larger decline in the price level after the pure shock: 1.31 percentage points in quarter seven, against 0.84. Under the one-standard-deviation normalization, the pure shock delivers 45 percent of the cumulative tightening of the surprise, and both output and the price level respond less to the pure shock than to the surprise.

The beliefs-adjusted identification in Section 5 provides an empirical counterpart to these patterns. Imposing belief responses consistent with a pure tightening selects a shorter tightening than the baseline identification, with smaller responses of output and prices for the same impact on the federal funds rate and a larger decline in prices per unit of cumulative tightening. In the model, too, removing the information shortens the tightening, weakens the output contraction, and raises the disinflation per unit of tightening, while the response of prices is smaller when the cumulative tightening is smaller, as under the one-standard-deviation normalization. The two exercises rely on different measures of activity, prices, and beliefs, and the shortening of the tightening is

more pronounced in the VAR, so the correspondence is qualitative.

The counterfactual provides the restriction used in the next section. Once a monetary innovation is purged of the information bundled with the announcement, near-term output and inflation forecasts are revised downward. We use this implication to augment a standard narrative sign-restriction VAR and construct a beliefs-adjusted monetary policy shock series.

5. Beliefs-Adjusted Monetary Policy Shocks

The model-based counterfactual separates the observed rate surprise from the underlying monetary innovation. We now use the same distinction as an empirical identifying restriction. The exercise asks whether requiring beliefs to respond as they do after a pure tightening changes the shocks and macroeconomic responses recovered from a conventional sign-restriction VAR.

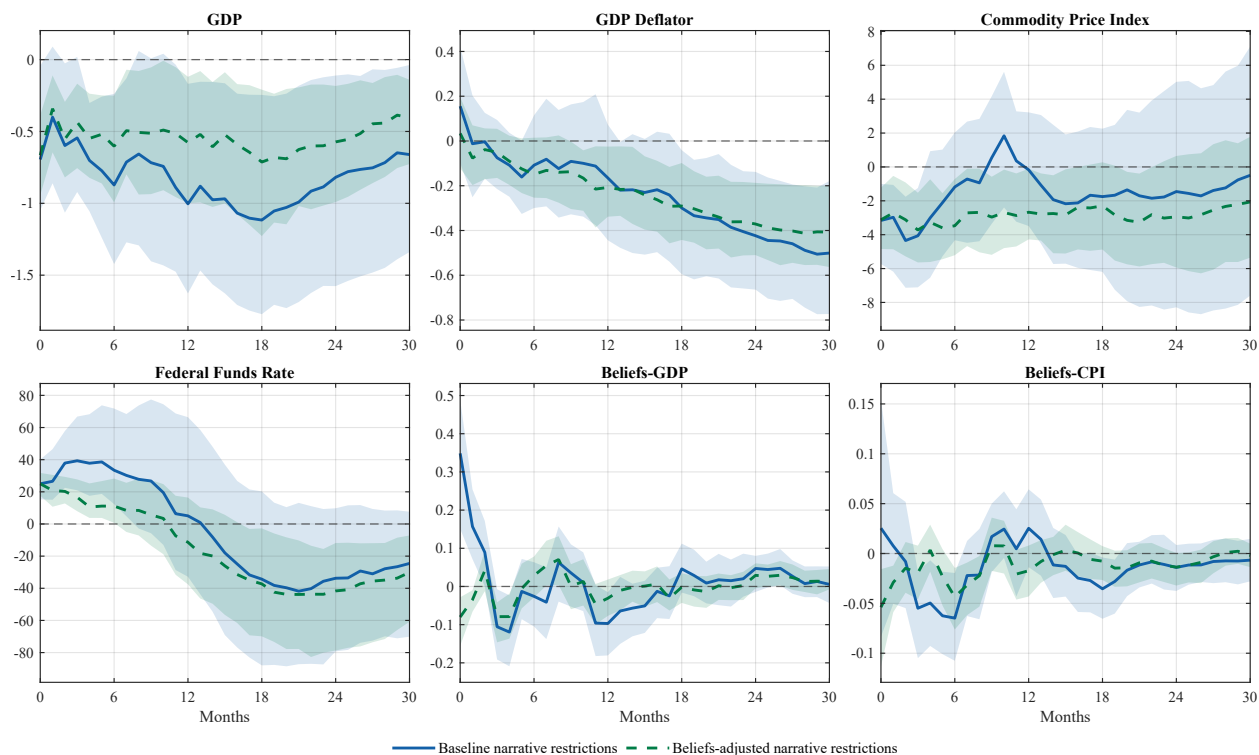
We estimate a six-variable monthly Bayesian VAR containing real GDP, the GDP deflator, a commodity price index, the federal funds rate, and CE forecast revisions for GDP growth and CPI inflation. The final two variables are the GDP-belief and inflation-belief measures introduced in Section 2.1. The sample runs from April 1990 to November 2007. The VAR includes twelve lags and a constant, the reduced-form prior is flat, and rotations are drawn until 30,000 satisfy the sign restrictions. After the narrative restriction and importance resampling, the baseline and beliefs-adjusted posteriors retain 1,934 and 395 draws, respectively. The baseline identification combines the sign and narrative restrictions in Uhlig (2005) and Antolín-Díaz and Rubio-Ramírez (2018b).

ASSUMPTION 1 (sign). A contractionary monetary policy shock raises the federal funds rate for six months and lowers the commodity price index for one month.

*ASSUMPTION 2 (narrative). The shock is positive in February 1994 and is the main driver of the unexpected increase in the federal funds rate in that month.*⁸

The baseline deliberately leaves output, the GDP deflator, and both belief measures unrestricted. The solid lines in Figure 6 report the resulting responses, normalized to raise the federal funds rate by 25 basis points on impact. The macroeconomic responses have the expected signs: real GDP and the GDP deflator decline after the tightening. The belief measures do not. The GDP forecast revision rises on impact, and the inflation revision is small and positive, reproducing within a single system the tension documented in Section 2.

⁸The CE data begin in 1989, so we do not impose narrative restrictions on earlier episodes.



Note: Solid blue lines report posterior medians under the baseline sign and narrative restrictions; dashed green lines add the restriction that GDP and inflation forecast revisions decline on impact and one month later. Both identifications are normalized to raise the federal funds rate by 25 basis points on impact. Shaded areas are 68 percent posterior coverage bands. The federal funds rate is expressed in basis points and all other variables in percentage points. Horizontal axes measure months after the shock.

FIGURE 6. Dynamic Responses to a Monetary Policy Shock: Baseline and Beliefs-Adjusted Identifications

Because no sign is imposed on either belief variable, this response is an outcome of the baseline identification rather than a mechanical consequence of the restrictions.

We next add the identifying implication of the pure-shock counterfactual:

ASSUMPTION 3 (beliefs). *A contractionary monetary policy shock lowers GDP and inflation forecast revisions during the first two months.*

This restriction does not assert that forecasts must remain depressed at every horizon. It only rules out the short-run optimism that the model attributes to information contamination. The two-month window is deliberately short relative to the quarterly model response and mirrors the impact nature of the empirical puzzle.

The dashed lines in Figure 6 report the beliefs-adjusted responses. By construction, both forecast revisions decline at short horizons. The restriction also changes the unrestricted macroeconomic responses while preserving their conventional signs: real GDP and the GDP deflator fall after the tightening. Relative to the baseline, the beliefs-adjusted shock

implies a considerably shorter tightening. The federal funds rate returns to zero after about eleven months rather than fourteen, and its cumulative increase over the first year is slightly more than a third of that in the baseline. For the same impact on the policy rate, output falls by less at all horizons and the GDP deflator falls by less beyond the first year; relative to the cumulative increase in the federal funds rate over the first year, the cumulative decline in the GDP deflator over the same period is about four times as large as in the baseline. Both features mirror the counterfactual in Figure 5, in which the information bundled with the surprise is associated with a more persistent policy response and with inflationary news. The differences in the responses of output and prices lie essentially within the 68 percent bands, whereas the paths of the federal funds rate differ significantly between the second and the seventh month.

Table 2 provides a simple historical check. It compares the standardized beliefs-adjusted series with five prominent monetary policy shock measures in four episodes emphasized by Antolín-Díaz and Rubio-Ramírez (2018b). The beliefs-adjusted series is positive in February 1994 and negative in October 1998, April 2001, and November 2002, matching the narrative signs and the Jarociński and Karadi (2020) series in all four cases. The sign in February 1994 is imposed by the narrative restriction; the other three are not. Over the full sample, the correlation of the beliefs-adjusted shocks with the six external measures is low, as is common across families of monetary policy shocks, but it is higher than for the baseline shocks for four of the six measures and unchanged for the other two (Appendix Table A4). Restricting beliefs therefore moves the identified shocks toward external measures of monetary policy.

This historical agreement is a useful validation, but the central contribution of the exercise is structural. The survey restrictions select shocks whose effects on beliefs are consistent with the pure-shock counterfactual in Figure 5 and whose macroeconomic effects remain contractionary under the same impact normalization. In that sense, the empirical identification uses the model to connect survey evidence with the measurement of monetary policy shocks.

6. Conclusion

Monetary policy announcements affect the economy through both policy and information. Survey forecasts make the distinction visible. Across households, financial economists, and professional forecasters, contractionary surprises improve the near-term outlook for real activity even as expected interest rates rise. Inflation beliefs respond less uniformly, increasing in the MSC and SPF but not in CE. The common feature is a short-lived dis-

connect between the expected real outlook and the conventional effect of a monetary tightening.

A New Keynesian model with dispersed information reproduces this disconnect without making monetary policy expansionary. In the estimated model, households learn little about the monetary disturbance, while professional forecasters observe the conditions to which policy responds. An observed surprise therefore bundles the policy innovation with the systematic response of policy to demand and to persistent inflationary pressure, and forecasters revise their outlook accordingly. Once this information is removed, a pure tightening lowers output and prices and leads to downward forecast revisions. The information also makes the observed tightening more persistent and offsets part of its disinflationary effect.

The beliefs-adjusted VAR turns this theoretical implication into an identification restriction. Requiring output and inflation forecasts to decline after a pure tightening selects shocks with conventional belief responses and contractionary effects on activity and prices. As in the model, the resulting tightening is shorter, and its disinflationary effect per unit of tightening is larger. More broadly, the results show that beliefs are not merely an outcome of monetary policy. They provide information about what an observed policy surprise contains and can therefore help distinguish the stance of policy from the news conveyed by the central bank.

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Parameter	Description	Value	Source
<i>Calibrated New Keynesian parameters</i>			
σ	Inverse intertemporal elasticity	1.000	Galí (2015)
β	Discount factor	0.990	Galí (2015)
φ	Inverse Frisch elasticity	5.000	Galí (2015)
$1 - \alpha$	Labor share	0.750	Galí (2015)
ϵ	Elasticity across varieties	9.000	Galí (2015)
$1 - \theta$	Calvo reset probability	0.250	Galí (2015)
ϕ_π	Inflation coefficient, Taylor rule	1.500	Galí (2015)
ϕ_y	Output-gap coefficient, Taylor rule	0.125	Galí (2015)
<i>Shock processes</i>			
ρ_v	Monetary-shock persistence	0.857	Estimated
ρ_z	Demand-shock persistence	0.622	Estimated
ρ_a	Technology-shock persistence	0.383	Estimated
ρ_μ	Cost-push-shock persistence	0.999 [†]	Estimated
σ_v	Monetary innovation s.d.	1	Normalization
σ_z	Demand innovation s.d.	757	Estimated
σ_a	Technology innovation s.d.	0.003	Estimated
σ_μ	Cost-push innovation s.d.	12.1	Estimated
<i>Signal-noise standard deviations</i>			
σ_{1v}	Monetary signal, households	14.0	Estimated
σ_{1z}	Demand signal, households	1.06	Estimated
σ_{1a}	Technology signal, households	0.422	Estimated
$\sigma_{1\mu}$	Cost-push signal, households	30.0	Estimated
σ_{2v}	Monetary signal, firms	0.001 [†]	Estimated
σ_{2z}	Demand signal, firms	0.081	Estimated
σ_{2a}	Technology signal, firms	0.082	Estimated
$\sigma_{2\mu}$	Cost-push signal, firms	110	Estimated

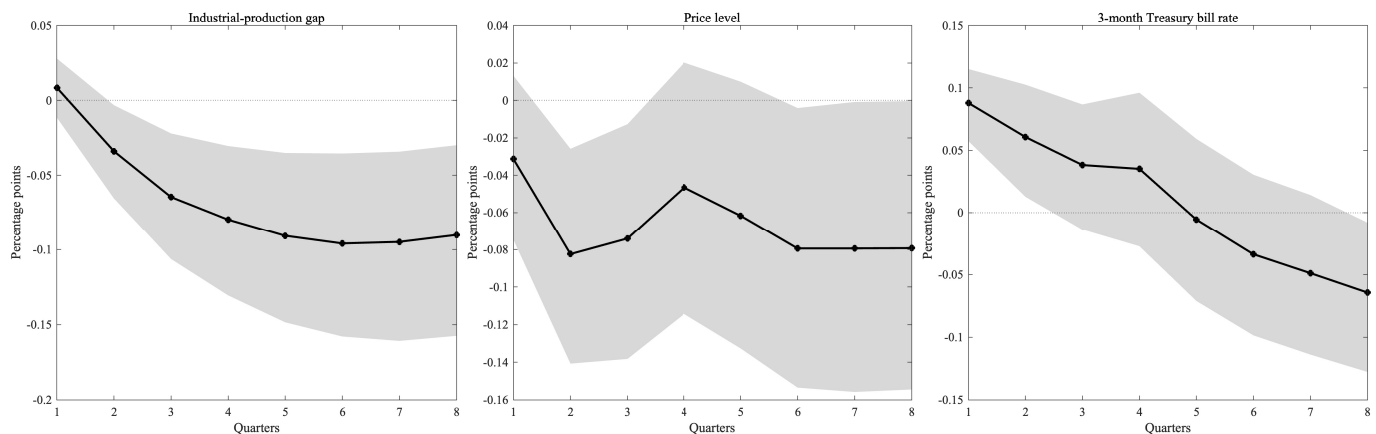
Note: All parameters are quarterly. Innovation and signal parameters are standard deviations, expressed relative to the standard deviation of the monetary innovation, $\sigma_v = 1$. A dagger indicates an estimate at the boundary of the admissible parameter region.

TABLE 1. Calibrated and Estimated Parameters

Date	GMS (2025)	MAR (2021)	JK (2020)	AD (2023)	GK (2015)	RR (2004)
February 1994	1.78	-0.33	1.93	0.74	0.26	1.80
October 1998	-2.54	-4.55	-3.77	-0.02	-1.21	-0.04
April 2001	-1.37	-6.58	-6.64	-0.02	-3.98	-0.04
November 2002	-0.69	-0.88	-0.22	-3.10	-1.20	-0.04

Note: Entries are standardized to have mean zero and standard deviation one. *GMS* denotes the beliefs-adjusted series, computed as the month-by-month posterior median of the shock draws, each standardized over the sample; the remaining columns report the measures described in Section 2.2.

TABLE 2. Monetary Policy Shocks in Selected Episodes



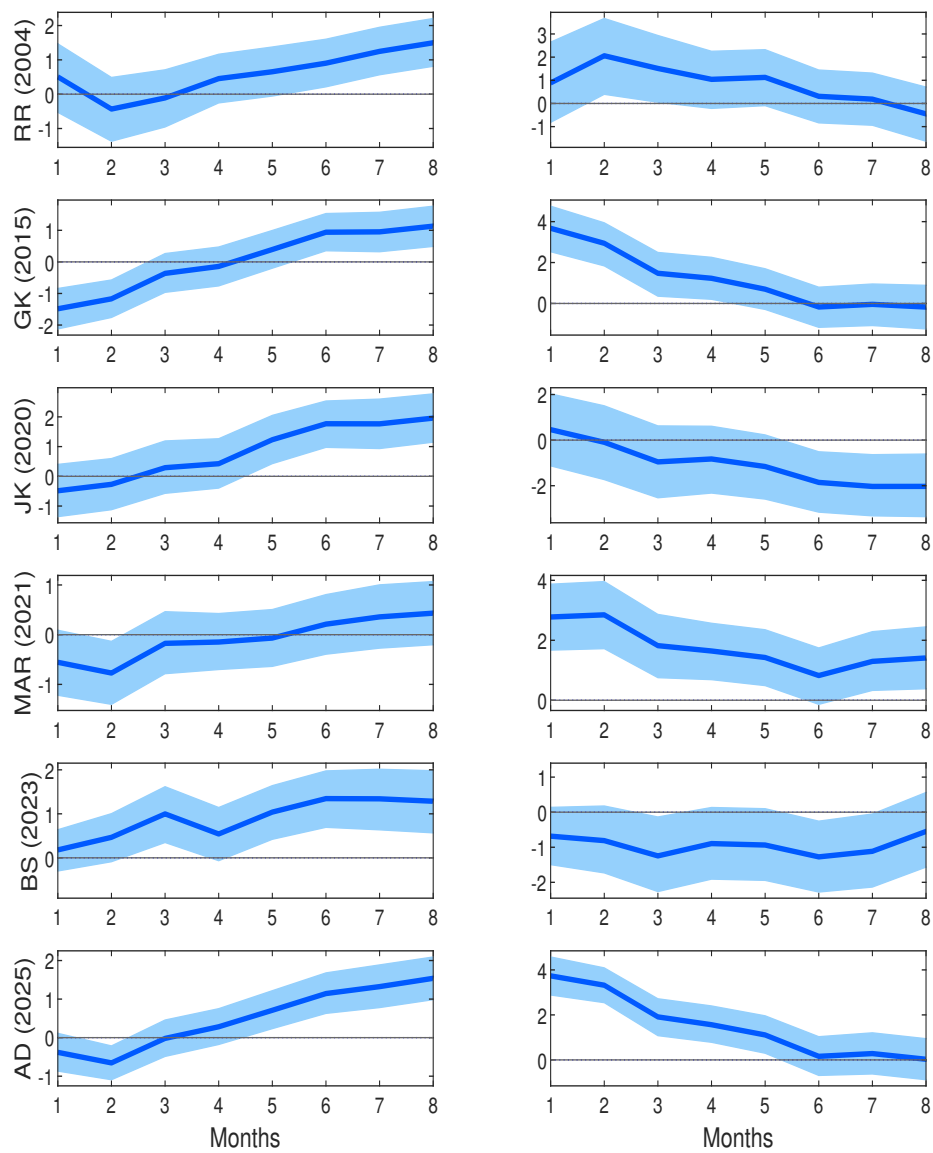
Note: The black lines and gray bands report posterior medians and 68 percent coverage intervals. The responses use the [Jarociński and Karadi \(2020\)](#) instrument in the macro-only monthly proxy VAR and are aggregated to quarterly means. CPI responses are cumulated to obtain the price level. The VAR contains no belief measure. Horizontal axes measure quarters after the surprise; vertical axes measure percentage points.

FIGURE A1. Macroeconomic Responses Used in the Model Estimation

Appendix A. Empirical Appendix

A.1. Macroeconomic Targets Used in Model Estimation

Figure A1 reports the macroeconomic impulse responses matched in Section 4. They come from the macro-only monthly proxy VAR and use the [Jarociński and Karadi \(2020\)](#) instrument. Posterior draws are aggregated to quarterly means, and monthly CPI responses are cumulated before aggregation so that the target is the price level. No survey or forecast-revision variable enters this VAR. The belief targets are estimated separately in the SPF systems reported in Figure 3; using the same external instrument in both blocks preserves a common shock while preventing survey-specific sampling and measurement from changing the aggregate benchmark.

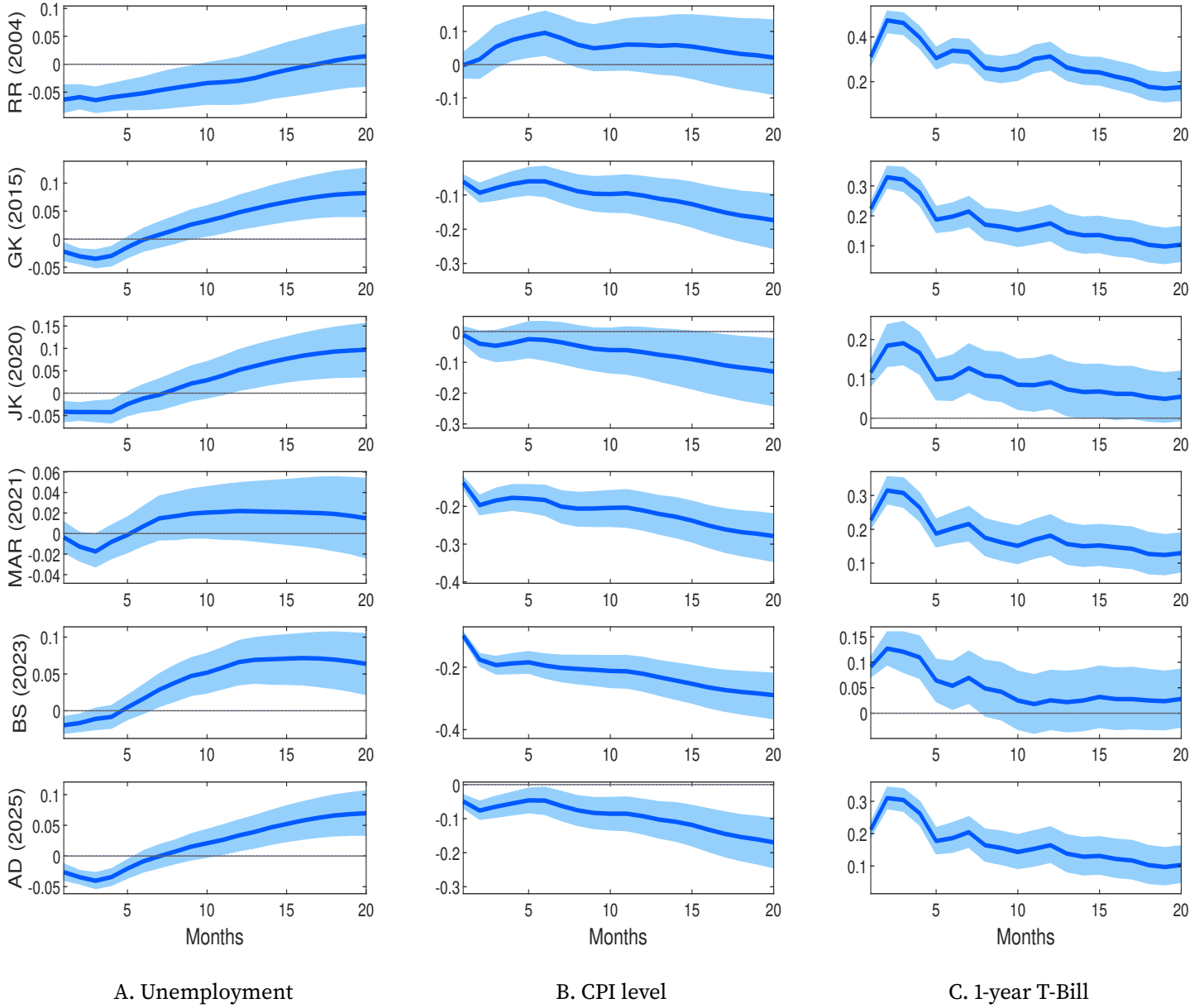


A. Unemployment

B. 1 Year Business Expectations

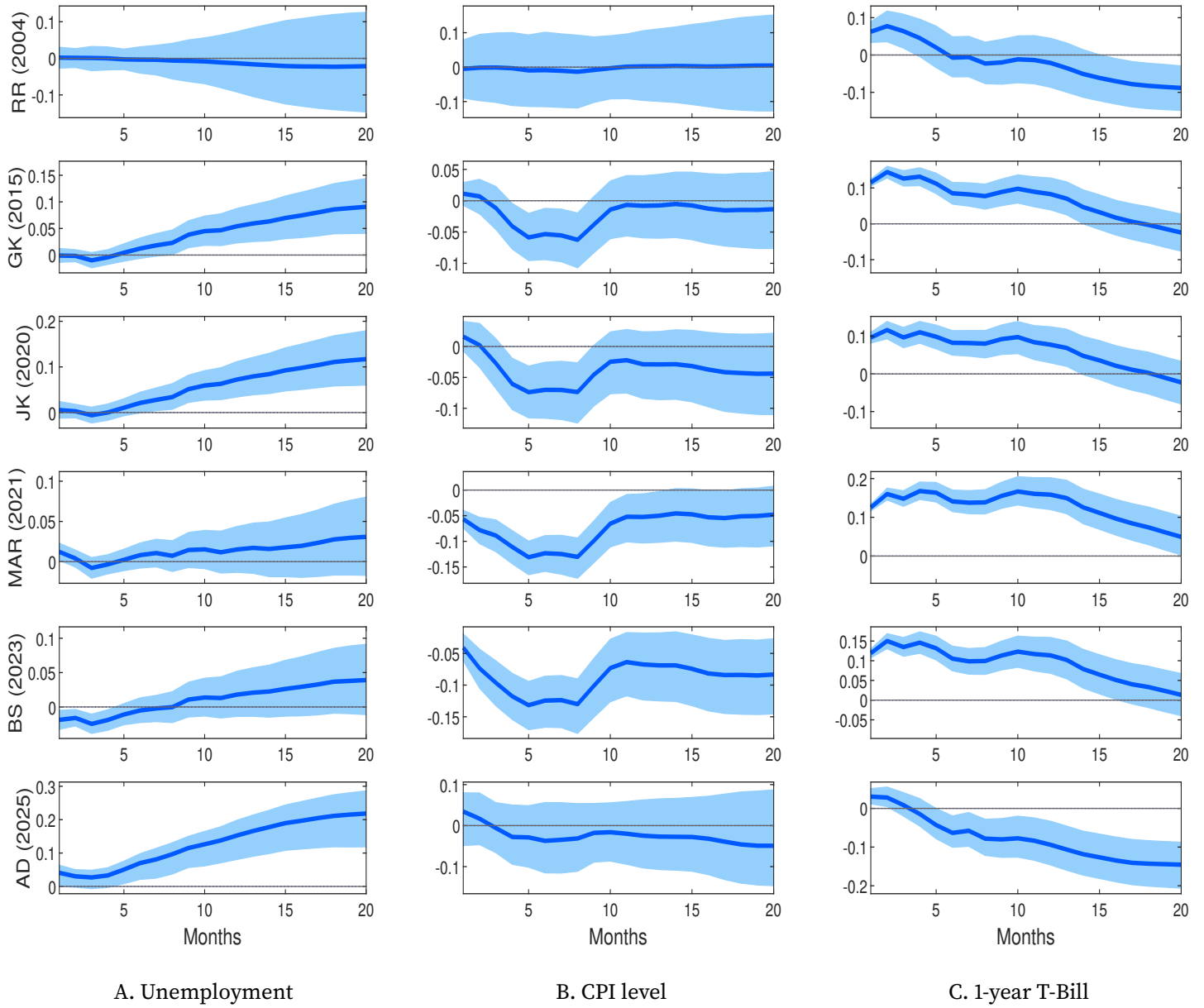
Note: RR (2004): [Romer and Romer \(2004\)](#); GK (2015): [Gertler and Karadi \(2015\)](#); JK (2020): [Jarociński and Karadi \(2020\)](#); MAR (2021): [Miranda-Agrippino and Ricco \(2021\)](#); BS (2023): [Bauer and Swanson \(2023\)](#); AD (2025): [Aruoba and Drechsel \(2025\)](#). The horizontal axis displays the time which is measured in months. Vertical axis values refer to deviations from steady state in percentage points. Shaded areas are 68 percent posterior coverage bands.

FIGURE A2. Dynamic Responses to a Monetary Policy Shock: Other Beliefs from the MSC



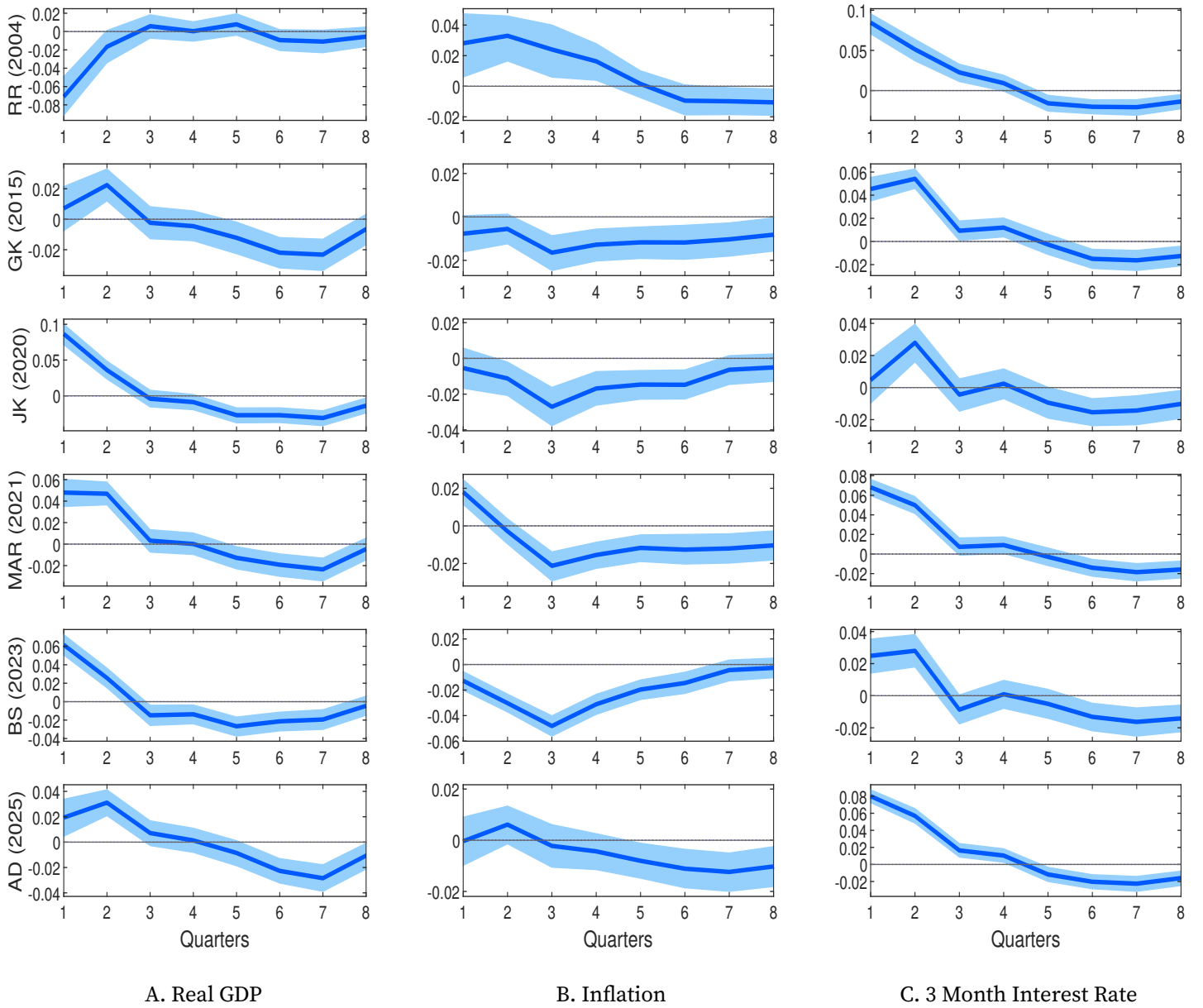
Note: RR (2004): [Romer and Romer \(2004\)](#); GK (2015): [Gertler and Karadi \(2015\)](#); JK (2020): [Jarociński and Karadi \(2020\)](#); MAR (2021): [Miranda-Agrippino and Ricco \(2021\)](#); BS (2023): [Bauer and Swanson \(2023\)](#); AD (2025): [Aruoba and Drechsel \(2025\)](#). The horizontal axis displays the time which is measured in months. Vertical axis values refer to deviations from steady state in percentage points. Shaded areas are 68 percent posterior coverage bands.

FIGURE A3. Dynamic Responses to a Monetary Policy Shock: Macroeconomic variables with MSC beliefs



Note: RR (2004): [Romer and Romer \(2004\)](#); GK (2015): [Gertler and Karadi \(2015\)](#); JK (2020): [Jarociński and Karadi \(2020\)](#); MAR (2021): [Miranda-Agrippino and Ricco \(2021\)](#); BS (2023): [Bauer and Swanson \(2023\)](#); AD (2025): [Aruoba and Drechsel \(2025\)](#). The horizontal axis displays the time which is measured in months. Vertical axis values refer to deviations from steady state in percentage points. Shaded areas are 68 percent posterior coverage bands.

FIGURE A4. Dynamic Responses to a Monetary Policy Shock: Macroeconomic variables with CE beliefs

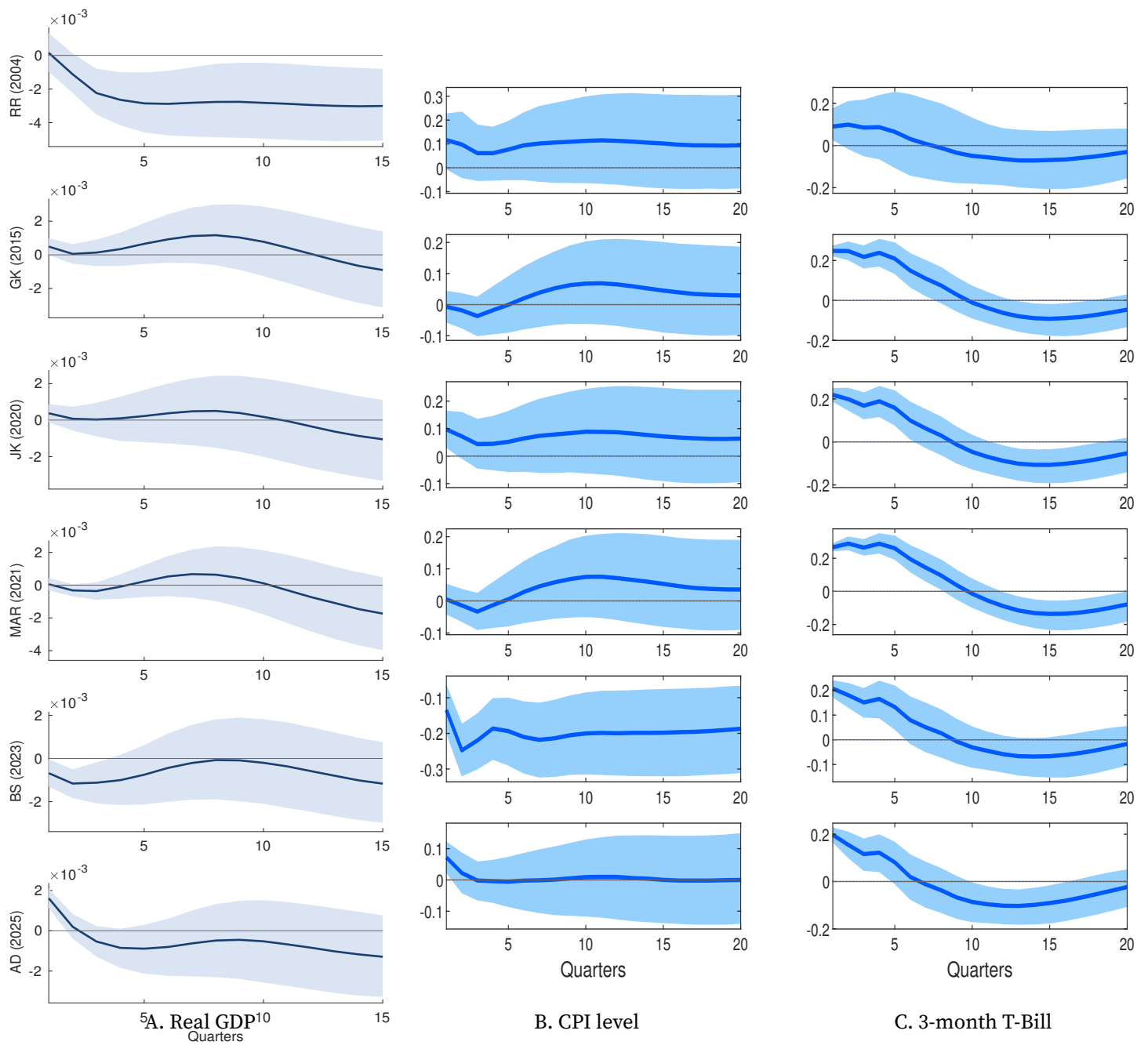


Note: RR (2004): [Romer and Romer \(2004\)](#); GK (2015): [Gertler and Karadi \(2015\)](#); JK (2020): [Jarociński and Karadi \(2020\)](#); MAR (2021): [Miranda-Agrippino and Ricco \(2021\)](#); BS (2023): [Bauer and Swanson \(2023\)](#); AD (2025): [Aruoba and Drechsel \(2025\)](#). The horizontal axis displays the time which is measured in months. Vertical axis values refer to deviations from steady state in percentage points. Shaded areas are 68 percent posterior coverage bands.

FIGURE A5. Dynamic Responses to a Monetary Policy Shock: Monthly Beliefs from CE without timing

F-STATISTIC	
RR(2004)	0.0032
GK(2015)	19.4185
JK(2020)	8.1489
MAR(2021)	19.9034
BS(2023)	13.0233
AD(2025)	0.1631

TABLE A1. Relevance of instruments with timing restriction in CE VAR



Note: RR (2004): [Romer and Romer \(2004\)](#); GK (2015): [Gertler and Karadi \(2015\)](#); JK (2020): [Jarociński and Karadi \(2020\)](#); MAR (2021): [Miranda-Agrippino and Ricco \(2021\)](#); BS (2023): [Bauer and Swanson \(2023\)](#); AD (2025): [Aruoba and Drechsel \(2025\)](#). The horizontal axis measures quarters. Vertical axis values refer to deviations from steady state in percentage points. Shaded areas are 68 percent posterior coverage bands.

FIGURE A6. Dynamic Responses to a Monetary Policy Shock: Macroeconomic variables with SPF beliefs

F-STATISTIC	
RR(2004)	7.6
GK(2015)	17.64
JK(2020)	1.47
MAR(2021)	8.06
BS(2023)	0.75
AD(2025)	18.9

TABLE A2. Relevance of instruments with MSC VAR

F-STATISTIC	
RR(2004)	3.3
GK(2015)	21.9
JK(2020)	11.23
MAR(2021)	25.04
BS(2023)	3.01
AD(2025)	18.68

TABLE A3. Relevance of instruments with SPF VAR

A.2. Correlation of the Identified Shocks with External Measures

Table A4 reports the correlation between the monthly shocks identified in Section 5 and the six external measures described in Section 2.2, over the 200 months from April 1991 to November 2007 for which the VAR delivers shocks. Correlations are computed draw by draw on the retained posterior draws.

	RR (2004)	GK (2015)	JK (2020)	MAR (2021)	BS (2023)	AD (2023)	Average
Baseline	0.01	0.08	0.12	0.11	0.10	0.07	0.08
	[-0.06, 0.10]	[0.01, 0.17]	[0.06, 0.17]	[0.03, 0.17]	[0.04, 0.16]	[-0.01, 0.18]	[0.03, 0.14]
Beliefs-adjusted	0.10	0.20	0.12	0.17	0.11	0.17	0.15
	[0.05, 0.15]	[0.13, 0.26]	[0.07, 0.16]	[0.13, 0.23]	[0.07, 0.16]	[0.10, 0.24]	[0.11, 0.19]

Note: Posterior medians and, in brackets, 16th and 84th percentiles across the 1,934 baseline and 395 beliefs-adjusted retained draws. Each shock draw is standardized over the sample. External measures enter as published, without the survey timing restriction.

TABLE A4. Correlation of Identified Shocks with External Measures

Appendix B. Proofs of Propositions in the Main Text

Proof of Proposition 1. The best response of agent l in group g is specified as follows

$$(A.1) \quad a_{lgt} = \varphi_{gv}\mathbb{E}_{lgt}v_t + \varphi_{gz}\mathbb{E}_{lgt}z_t + \varphi_{ga}\mathbb{E}_{lgt}a_t + \varphi_{g\mu}\mathbb{E}_{lgt}\mu_t + \beta_g\mathbb{E}_{lgt}a_{igt+1} + \sum_{j=1}^2 \gamma_{gj}\mathbb{E}_{lgt}a_{jt} + \sum_{j=1}^2 \alpha_{gj}\mathbb{E}_{lgt}a_{jt+1}$$

where a_{-gt} is the aggregate action of the other group at time t . Let $\mathbf{a}_t = (a_{gt})$ be a column vector collecting the aggregate actions of all groups (e.g., the vector of aggregate consumption and aggregate inflation), let $\boldsymbol{\varphi} = (\varphi_{gn})$ be a column vector containing the value of $\{\varphi_{gn}\}_n$ across groups, let $\boldsymbol{\beta} = \text{diag}(\beta_g)$ be a 2×2 diagonal matrix of discount factors, with off-diagonal elements equal to 0, let $\boldsymbol{\gamma}$ be a 2×2 matrix collecting the (contemporaneous) interaction parameters γ_{gj} , let $\boldsymbol{\alpha} = (\alpha_{gk})$ be a 2×2 matrix collecting the (future) interaction parameters α_{gj} , and finally let $\boldsymbol{\delta} \equiv \boldsymbol{\beta} + \boldsymbol{\alpha}$,

$$\mathbf{a}_t = \begin{bmatrix} a_{1t} \\ a_{2t} \end{bmatrix}, \quad \boldsymbol{\varphi} = \begin{bmatrix} \varphi_{1v} & \varphi_{1z} & \varphi_{1a} & \varphi_{1\mu} \\ \varphi_{2v} & \varphi_{2z} & \varphi_{2a} & \varphi_{2\mu} \end{bmatrix}, \quad \boldsymbol{\beta} = \begin{bmatrix} \beta_1 & 0 \\ 0 & \beta_2 \end{bmatrix}, \quad \boldsymbol{\gamma} = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}, \quad \boldsymbol{\alpha} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}$$

We now solve the expectation terms in (A.1). The shock processes and the private signals in (12)–(15) admit the following state-space representation:

$$(A.2) \quad \begin{aligned} \mathbf{Z}_t &= \mathbf{F}\mathbf{Z}_{t-1} + \boldsymbol{\Phi}\mathbf{S}_{lgt} \\ \mathbf{X}_{lgt} &= \mathbf{H}\mathbf{Z}_t + \boldsymbol{\Psi}_g\mathbf{S}_{lgt} \end{aligned}$$

$$\text{with } \mathbf{Z}_t = \begin{bmatrix} v_t & z_t & a_t & \mu_t \end{bmatrix}^\top, \mathbf{S}_{lgt} = \begin{bmatrix} \varepsilon_t^v & \varepsilon_t^z & \varepsilon_t^a & \varepsilon_t^\mu & u_{it}^v & u_{it}^z & u_{it}^a & u_{it}^\mu \end{bmatrix}^\top, \mathbf{H} = \mathbf{I}_4, \mathbf{F} = \begin{bmatrix} \rho_v & 0 & 0 & 0 \\ 0 & \rho_z & 0 & 0 \\ 0 & 0 & \rho_a & 0 \\ 0 & 0 & 0 & \rho_\mu \end{bmatrix}, \text{ and}$$

$$\boldsymbol{\Phi} = \begin{bmatrix} \tau_v^{-1/2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \tau_z^{-1/2} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \tau_a^{-1/2} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \tau_\mu^{-1/2} & 0 & 0 & 0 & 0 \end{bmatrix}, \quad \boldsymbol{\Psi}_g = \begin{bmatrix} 0 & 0 & 0 & 0 & \tau_{gv}^{-1/2} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \tau_{gz}^{-1/2} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \tau_{ga}^{-1/2} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \tau_{g\mu}^{-1/2} \end{bmatrix}.$$

The signal system can be written as

$$(A.3) \quad \mathbf{X}_{lgt} = \begin{bmatrix} \frac{\tau_v^{-1/2}}{1-\rho_v L} & 0 & 0 & 0 & \tau_{gv}^{-1/2} & 0 & 0 & 0 \\ 0 & \frac{\tau_z^{-1/2}}{1-\rho_z L} & 0 & 0 & 0 & \tau_{gz}^{-1/2} & 0 & 0 \\ 0 & 0 & \frac{\tau_a^{-1/2}}{1-\rho_a L} & 0 & 0 & 0 & \tau_{ga}^{-1/2} & 0 \\ 0 & 0 & 0 & \frac{\tau_\mu^{-1/2}}{1-\rho_\mu L} & 0 & 0 & 0 & \tau_{g\mu}^{-1/2} \end{bmatrix} \mathbf{S}_{lgt} = \mathbf{M}_g(L)\mathbf{S}_{lgt}, \quad \mathbf{S}_{lgt} \sim \mathcal{N}(0, \mathbf{I})$$

The Wold theorem states that there exists another representation of the signal process (A.3), $\mathbf{X}_{lgt} =$

$\mathbf{B}_g(L)\mathbf{w}_{lgt}$, such that $\mathbf{B}_g(L)$ is invertible and $\mathbf{w}_{lgt} \sim (0, \mathbf{V}_g)$ is white noise. Hence, we can write the following equivalence

$$(A.4) \quad \mathbf{X}_{lgt} = \mathbf{M}_g(L)\mathbf{S}_{lgt} = \mathbf{B}_g(L)\mathbf{w}_{lgt}$$

In the Wold representation of $\mathbf{X}_{lgt}$, observing $\{\mathbf{X}_{lgt}\}$ is equivalent to observing $\{\mathbf{w}_{lgt}\}$, and $\{\mathbf{X}_{lg}^t\}$ and $\{\mathbf{w}_{lg}^t\}$ contain the same information. Furthermore, note that the Wold representation has the property that, using the equivalence (A.4), both processes share the autocovariance generating function, $\rho_{xx,g}(L) = \mathbf{M}_g(L)\mathbf{M}_g^\top(L^{-1}) = \mathbf{B}_g(L)\mathbf{V}_g\mathbf{B}_g^\top(L^{-1})$. Computing this last term,

$$\begin{aligned} \mathbf{M}_g(L)\mathbf{M}_g^\top(L^{-1}) &= \begin{bmatrix} \tau_{gv}^{-1} + \frac{\tau_v^{-1}L}{(L-\rho_v)(1-\rho_vL)} & 0 & 0 & 0 \\ 0 & \tau_{gz}^{-1} + \frac{\tau_z^{-1}L}{(L-\rho_z)(1-\rho_zL)} & 0 & 0 \\ 0 & 0 & \tau_{ga}^{-1} + \frac{\tau_a^{-1}L}{(L-\rho_a)(1-\rho_aL)} & 0 \\ 0 & 0 & 0 & \tau_{g\mu}^{-1} + \frac{\tau_\mu^{-1}L}{(L-\rho_\mu)(1-\rho_\mu L)} \end{bmatrix} \\ &= \begin{bmatrix} \frac{1-\lambda_{gv}L}{1-\rho_vL} \frac{\rho_v}{\lambda_{gv}\tau_{gv}} \frac{L-\lambda_{gv}}{L-\rho_v} & 0 & 0 & 0 \\ 0 & \frac{1-\lambda_{gz}L}{1-\rho_zL} \frac{\rho_z}{\lambda_{gz}\tau_{gz}} \frac{L-\lambda_{gz}}{L-\rho_z} & 0 & 0 \\ 0 & 0 & \frac{1-\lambda_{ga}L}{1-\rho_aL} \frac{\rho_a}{\lambda_{ga}\tau_{ga}} \frac{L-\lambda_{ga}}{L-\rho_a} & 0 \\ 0 & 0 & 0 & \frac{1-\lambda_{g\mu}L}{1-\rho_\mu L} \frac{\rho_\mu}{\lambda_{g\mu}\tau_{g\mu}} \frac{L-\lambda_{g\mu}}{L-\rho_\mu} \end{bmatrix} \end{aligned}$$

where, in the second equality, we have used the result that λ_{gn} , for $n \in \{r, z, a, \mu\}$, are the four inside roots of the determinant of $\mathbf{M}_g(L)\mathbf{M}_g^\top(L^{-1})$, $L^2 - \left(\frac{1}{\rho_n} + \rho_n + \frac{\tau_{gn}}{\rho_n\tau_n}\right)L + 1$, satisfying $(\rho_n - \lambda_{gn})(1 - \rho_n\lambda_{gn}) = \lambda_{gn}\frac{\tau_{gv}}{\tau_v}$. We can easily identify the unknown matrices,

$$\begin{aligned} \mathbf{B}_g(L) &= \begin{bmatrix} \frac{1-\lambda_{gv}L}{1-\rho_vL} & 0 & 0 & 0 \\ 0 & \frac{1-\lambda_{gz}L}{1-\rho_zL} & 0 & 0 \\ 0 & 0 & \frac{1-\lambda_{ga}L}{1-\rho_aL} & 0 \\ 0 & 0 & 0 & \frac{1-\lambda_{g\mu}L}{1-\rho_\mu L} \end{bmatrix}, \quad \mathbf{V}_g = \begin{bmatrix} \frac{\rho_v}{\lambda_{gv}\tau_{gv}} & 0 & 0 & 0 \\ 0 & \frac{\rho_z}{\lambda_{gz}\tau_{gz}} & 0 & 0 \\ 0 & 0 & \frac{\rho_a}{\lambda_{ga}\tau_{ga}} & 0 \\ 0 & 0 & 0 & \frac{\rho_\mu}{\lambda_{g\mu}\tau_{g\mu}} \end{bmatrix}, \\ \mathbf{B}_g^\top(L^{-1}) &= \begin{bmatrix} \frac{L-\lambda_{gv}}{L-\rho_v} & 0 & 0 & 0 \\ 0 & \frac{L-\lambda_{gz}}{L-\rho_z} & 0 & 0 \\ 0 & 0 & \frac{L-\lambda_{ga}}{L-\rho_a} & 0 \\ 0 & 0 & 0 & \frac{L-\lambda_{g\mu}}{L-\rho_\mu} \end{bmatrix}. \end{aligned}$$

Let us now move to the forecast of variables. Consider a variable $f_t = A(L)\mathbf{S}_{lgt}$. Applying the Wiener-Hopf prediction filter, we can obtain the forecast as

$$\mathbb{E}_{lgt}f_t = \left[A(L)\mathbf{M}_g^\top(L^{-1})\mathbf{B}_g(L^{-1})^{-1} \right]_+ \mathbf{V}_g^{-1}\mathbf{B}_g(L)^{-1}\mathbf{X}_{lgt},$$

where $[\cdot]_+$ denotes the annihilator operator. Recall from condition (19) that we are interested in obtaining $\mathbb{E}_{lgt}v_t$, $\mathbb{E}_{lgt}z_t$, $\mathbb{E}_{lgt}a_t$, $\mathbb{E}_{lgt}\mu_t$, $\mathbb{E}_{lgt}a_{jt}$, $\mathbb{E}_{lgt}a_{j,t+1}$, and $\mathbb{E}_{lgt}a_{lg,t+1}$. we need to find the $A(z)$ polynomial for each

of the forecasted variables. we start from the exogenous monetary policy shock, which can be written as $v_t = \begin{bmatrix} \frac{\tau_v^{-1/2}}{1-\rho_v L} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \mathbf{S}_{lgt} = A_v(L) \mathbf{S}_{lgt}$. Similarly, $A_z(L) = \begin{bmatrix} 0 & \frac{\tau_z^{-1/2}}{1-\rho_z L} & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$, $A_a(L) = \begin{bmatrix} 0 & 0 & \frac{\tau_a^{-1/2}}{1-\rho_a L} & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$ and $A_\mu(L) = \begin{bmatrix} 0 & 0 & 0 & \frac{\tau_\mu^{-1/2}}{1-\rho_\mu L} & 0 & 0 & 0 & 0 \end{bmatrix}$. Let us now move to the endogenous variables. In this case, we need to guess (and verify) that each agent i 's policy function takes the form $a_{lgt} = h_{gv}(L)x_{lgt}^\nu + h_{gz}(L)x_{lgt}^z + h_{ga}(L)x_{lgt}^a + h_{g\mu}(L)x_{lgt}^\mu$.⁹ Aggregate action can then be expressed as

$$\begin{aligned} a_{gt} &= \int_0^1 a_{lgt} dl \in g = \int_0^1 [h_{gv}(L)x_{lgt}^\nu + h_{gz}(L)x_{lgt}^z + h_{ga}(L)x_{lgt}^a + h_{g\mu}(L)x_{lgt}^\mu] dl \\ &= h_{gv}(L) \frac{\tau_v^{-1/2}}{1-\rho_v L} \varepsilon_t^\nu + h_{gz}(L) \frac{\tau_z^{-1/2}}{1-\rho_z L} \varepsilon_t^z + h_{ga}(L) \frac{\tau_a^{-1/2}}{1-\rho_a L} \varepsilon_t^a + h_{g\mu}(L) \frac{\tau_\mu^{-1/2}}{1-\rho_\mu L} \varepsilon_t^a \\ &= \begin{bmatrix} h_{gv}(L) \frac{\tau_v^{-1/2}}{1-\rho_v L} & h_{gz}(L) \frac{\tau_z^{-1/2}}{1-\rho_z L} & h_{ga}(L) \frac{\tau_a^{-1/2}}{1-\rho_a L} & h_{g\mu}(L) \frac{\tau_\mu^{-1/2}}{1-\rho_\mu L} & 0 & 0 & 0 & 0 \end{bmatrix} \mathbf{S}_{lgt} = A_{ag0}(L) \mathbf{S}_{lgt} \\ a_{g,t+1} &= \begin{bmatrix} h_{gv}(L) \frac{\tau_v^{-1/2}}{L(1-\rho_v L)} & h_{gz}(L) \frac{\tau_z^{-1/2}}{L(1-\rho_z L)} & h_{ga}(L) \frac{\tau_a^{-1/2}}{L(1-\rho_a L)} & h_{g\mu}(L) \frac{\tau_\mu^{-1/2}}{L(1-\rho_\mu L)} & 0 & 0 & 0 & 0 \end{bmatrix} \mathbf{S}_{lgt} = A_{ag1}(L) \mathbf{S}_{lgt}. \end{aligned}$$

Finally,

$$\begin{aligned} a_{lgt,t+1} &= \frac{1}{L} \begin{bmatrix} h_{rg}(L) & h_{zg}(L) & h_{ag}(L) & h_{\mu g}(L) \end{bmatrix} \mathbf{X}_t = \frac{1}{L} \begin{bmatrix} h_{rg}(L) & h_{zg}(L) & h_{ag}(L) & h_{\mu g}(L) \end{bmatrix} \mathbf{M}_g(L) \mathbf{S}_{lgt} \\ &= \begin{bmatrix} \frac{h_{rg}(L)}{L} \frac{\tau_v^{-1/2}}{1-\rho_v L} & \frac{h_{zg}(L)}{L} \frac{\tau_z^{-1/2}}{1-\rho_z L} & \frac{h_{ga}(L)}{L} \frac{\tau_a^{-1/2}}{1-\rho_a L} & \frac{h_{g\mu}(L)}{L} \frac{\tau_\mu^{-1/2}}{1-\rho_\mu L} & \frac{h_{gv}(L)}{L} \tau_{gv}^{-1/2} & \frac{h_{gz}(L)}{L} \tau_{gz}^{-1/2} & \frac{h_{ga}(L)}{L} \tau_{ga}^{-1/2} & \frac{h_{g\mu}(L)}{L} \tau_{g\mu}^{-1/2} \end{bmatrix} \mathbf{S}_{lgt} \\ &= A_{gi}(L) \mathbf{S}_{lgt}. \end{aligned}$$

We are now armed with the necessary objects to obtain the five different forecasts. Lets start with exogenous variables,

$$\begin{aligned} \mathbb{E}_{lgt} v_t &= \left[A_v(L) \mathbf{M}_g^T(L^{-1}) \mathbf{B}_g(L^{-1})^{-1} \right]_+ \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt} = \left[\frac{L}{\tau_v(1-\rho_v L)(L-\lambda_{gv})} \quad 0 \quad 0 \quad 0 \right]_+ \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt} \\ &= \left[\left[\frac{\phi_v(L)}{L-\lambda_{gv}} \right]_+ \quad 0 \quad 0 \quad 0 \right] \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt}, \quad \phi_v(z) = \frac{L}{\tau_v(1-\rho_v L)} \\ &= \left[\frac{\phi_v(L)-\phi_v(\lambda_{gv})}{L-\lambda_{gv}} \quad 0 \quad 0 \quad 0 \right] \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt} = \left[\frac{1}{\tau_v(1-\rho_v L)(1-\rho_v \lambda_{gv})} \quad 0 \quad 0 \quad 0 \right] \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt} \\ &= \left[\frac{\lambda_{gv} \tau_{gv}}{\rho_v \tau_v(1-\rho_v \lambda_{gv})} \frac{1}{1-\lambda_{gv} L} \quad 0 \quad 0 \quad 0 \right] \mathbf{X}_{lgt} = \frac{\lambda_{gv} \tau_{gv}}{\rho_v \tau_v(1-\rho_v \lambda_{gv})} \frac{1}{1-\lambda_{gv} L} x_{lgt}^\nu = \left(1 - \frac{\lambda_{gv}}{\rho_v} \right) \frac{1}{1-\lambda_{gv} L} x_{lgt}^\nu \\ (A.5) \quad &= G_{gv}(L) x_{lgt}^\nu. \end{aligned}$$

In the same manner, we can obtain

$$(A.6) \quad \mathbb{E}_{lgt} z_t = \left(1 - \frac{\lambda_{gz}}{\rho_z} \right) \frac{1}{1-\lambda_{gz} L} x_{lgt}^z = G_{gz}(L) x_{lgt}^z$$

$$(A.7) \quad \mathbb{E}_{lgt} a_t = \left(1 - \frac{\lambda_{ga}}{\rho_a} \right) \frac{1}{1-\lambda_{ga} L} x_{lgt}^a = G_{ga}(L) x_{lgt}^a$$

$$(A.8) \quad \mathbb{E}_{lgt} \mu_t = \left(1 - \frac{\lambda_{g\mu}}{\rho_\mu} \right) \frac{1}{1-\lambda_{g\mu} L} x_{lgt}^\mu = G_{g\mu}(L) x_{lgt}^\mu.$$

⁹In this framework agents only observe signals, and the policy function can only depend on current and past signals.

Looking now at the endogenous variables,

$$\begin{aligned}
\mathbb{E}_{lgt} a_{kt} &= \left[A_{ak0}(L) \mathbf{M}_g^T(L^{-1}) \mathbf{B}_g(L^{-1})^{-1} \right]_+ \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt} \\
&= \left[\frac{Lh_{kv}(L)}{\tau_v(1-\rho_v L)(L-\lambda_{gv})} \quad \frac{Lh_{kz}(L)}{\tau_z(1-\rho_z L)(L-\lambda_{gz})} \quad \frac{Lh_{ka}(L)}{\tau_a(1-\rho_a L)(L-\lambda_{ga})} \quad \frac{Lh_{k\mu}(L)}{\tau_\mu(1-\rho_\mu L)(L-\lambda_{g\mu})} \right]_+ \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt} \\
&= \left[\left[\frac{\phi_{ak0v}(L)}{L-\lambda_{gv}} \right]_+ \quad \left[\frac{\phi_{ak0z}(L)}{L-\lambda_{gz}} \right]_+ \quad \left[\frac{\phi_{ak0a}(L)}{L-\lambda_{ga}} \right]_+ \quad \left[\frac{\phi_{ak0\mu}(L)}{L-\lambda_{g\mu}} \right]_+ \right] \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt}, \quad \phi_{ak0n}(z) = \frac{Lh_{kn}(L)}{\tau_n(1-\rho_n L)} \\
&= \left[\frac{\phi_{ak0v}(L) - \phi_{ak0v}(\lambda_{gv})}{L-\lambda_{gv}} \quad \frac{\phi_{ak0z}(L) - \phi_{ak0z}(\lambda_{gz})}{L-\lambda_{gz}} \quad \frac{\phi_{ak0a}(L) - \phi_{ak0a}(\lambda_{ga})}{L-\lambda_{ga}} \quad \frac{\phi_{ak0\mu}(L) - \phi_{ak0\mu}(\lambda_{g\mu})}{L-\lambda_{g\mu}} \right] \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt} \\
&= \left[\frac{Lh_{kv}(L) - \lambda_{gv} h_{kv}(\lambda_{gv})}{\tau_v(1-\rho_v L)(L-\lambda_{gv})} \frac{1-\rho_v L}{1-\rho_v \lambda_{gv}} \quad \frac{Lh_{kz}(L) - \lambda_{gz} h_{kz}(\lambda_{gz})}{\tau_z(1-\rho_z L)(L-\lambda_{gz})} \frac{1-\rho_z L}{1-\rho_z \lambda_{gz}} \quad \frac{Lh_{ka}(L) - \lambda_{ga} h_{ka}(\lambda_{ga})}{\tau_a(1-\rho_a L)(L-\lambda_{ga})} \frac{1-\rho_a L}{1-\rho_a \lambda_{ga}} \quad \frac{Lh_{k\mu}(L) - \lambda_{g\mu} h_{k\mu}(\lambda_{g\mu})}{\tau_\mu(1-\rho_\mu L)(L-\lambda_{g\mu})} \frac{1-\rho_\mu L}{1-\rho_\mu \lambda_{g\mu}} \right] \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt} \\
&= \left[\frac{\lambda_{gv} \tau_{gv} \left[\frac{Lh_{kv}(L) - \lambda_{gv} h_{kv}(\lambda_{gv})}{\tau_v(1-\rho_v L)(L-\lambda_{gv})} \frac{1-\rho_v L}{1-\rho_v \lambda_{gv}} \right]}{\rho_v \tau_v (1-\lambda_{gv} L)(L-\lambda_{gv})} \quad \frac{\lambda_{gz} \tau_{gz} \left[\frac{Lh_{kz}(L) - \lambda_{gz} h_{kz}(\lambda_{gz})}{\tau_z(1-\rho_z L)(L-\lambda_{gz})} \frac{1-\rho_z L}{1-\rho_z \lambda_{gz}} \right]}{\rho_z \tau_z (1-\lambda_{gz} L)(L-\lambda_{gz})} \quad \frac{\lambda_{ga} \tau_{ga} \left[\frac{Lh_{ka}(L) - \lambda_{ga} h_{ka}(\lambda_{ga})}{\tau_a(1-\rho_a L)(L-\lambda_{ga})} \frac{1-\rho_a L}{1-\rho_a \lambda_{ga}} \right]}{\rho_a \tau_a (1-\lambda_{ga} L)(L-\lambda_{ga})} \quad \frac{\lambda_{g\mu} \tau_{g\mu} \left[\frac{Lh_{k\mu}(L) - \lambda_{g\mu} h_{k\mu}(\lambda_{g\mu})}{\tau_\mu(1-\rho_\mu L)(L-\lambda_{g\mu})} \frac{1-\rho_\mu L}{1-\rho_\mu \lambda_{g\mu}} \right]}{\rho_\mu \tau_\mu (1-\lambda_{g\mu} L)(L-\lambda_{g\mu})} \right] \mathbf{X}_{lgt} \\
&= \sum_{n \in \{v, z, a, \mu\}} \frac{\lambda_{gn} \tau_{gn} \left[\frac{Lh_{kn}(L) - \lambda_{gn} h_{kn}(\lambda_{gn})}{1-\rho_n \lambda_{gn}} \right]}{\rho_n \tau_n} \frac{1}{(1-\lambda_{gn} L)(L-\lambda_{gn})} x_{lgt}^n \\
&= \sum_{n \in \{v, z, a, \mu\}} \left(1 - \frac{\lambda_{gn}}{\rho_n} \right) \left[Lh_{kn}(L)(1-\rho_n \lambda_{gn}) - \lambda_{gn} h_{kn}(\lambda_{gn})(1-\rho_n L) \right] \frac{1}{(1-\lambda_{gn} L)(L-\lambda_{gn})} x_{lgt}^n \\
(A.9) \quad &= \sum_{n \in \{r, z, a, \mu\}} G_{0gkn}(L) x_{lgt}^n \\
\mathbb{E}_{lgt} a_{k,t+1} &= \sum_{n \in \{v, z, a, \mu\}} \left(1 - \frac{\lambda_{gn}}{\rho_n} \right) \left[h_{kn}(L)(1-\rho_n \lambda_{gn}) - h_{kn}(\lambda_{gn})(1-\rho_n L) \right] \frac{1}{(1-\lambda_{gn} L)(L-\lambda_{gn})} x_{lgt}^n \\
(A.10) \quad &= \sum_{n \in \{r, z, a, \mu\}} G_{1gkn}(L) x_{lgt}^n \\
\mathbb{E}_{lgt} a_{l,t+1} &= \left[A_{gli}(L) \mathbf{M}_g^T(L^{-1}) \mathbf{B}_g(L^{-1})^{-1} \right]_+ \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt} \\
&= \left[\frac{h_{gv}(L)}{L-\lambda_{gv}} \left(\frac{1}{\tau_v(1-\rho_v L)} + \frac{L-\rho_v}{L\tau_v} \right) \quad \frac{h_{gz}(L)}{L-\lambda_{gz}} \left(\frac{1}{\tau_z(1-\rho_z L)} + \frac{L-\rho_z}{L\tau_z} \right) \quad \frac{h_{ga}(L)}{L-\lambda_{ga}} \left(\frac{1}{\tau_a(1-\rho_a L)} + \frac{L-\rho_a}{L\tau_a} \right) \quad \frac{h_{g\mu}(L)}{L-\lambda_{g\mu}} \left(\frac{1}{\tau_\mu(1-\rho_\mu L)} + \frac{L-\rho_\mu}{L\tau_\mu} \right) \right]_+ \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt} \\
&= \left[\left[\frac{\phi_{igv1}(L)}{L-\lambda_{gv}} \right]_+ + \left[\frac{\phi_{igv2}(L)}{L-\lambda_{gv}} \right]_+ \quad \left[\frac{\phi_{igz1}(L)}{L-\lambda_{gz}} \right]_+ + \left[\frac{\phi_{igz2}(L)}{L-\lambda_{gz}} \right]_+ \quad \left[\frac{\phi_{iga1}(L)}{L-\lambda_{ga}} \right]_+ + \left[\frac{\phi_{iga2}(L)}{L-\lambda_{ga}} \right]_+ \quad \left[\frac{\phi_{ig\mu1}(L)}{L-\lambda_{g\mu}} \right]_+ + \left[\frac{\phi_{ig\mu2}(L)}{L-\lambda_{g\mu}} \right]_+ \right] \mathbf{V}_g^{-1} \mathbf{B}_g(L)^{-1} \mathbf{X}_{lgt} \\
&= \sum_{n \in \{v, z, a, \mu\}} \left(\frac{h_{gn}(L)}{L-\lambda_{gn}} \left(\left(1 - \frac{\lambda_{gn}}{\rho_n} \right) \frac{1-\rho_n \lambda_{gn}}{1-\rho_n L} + \frac{\lambda_{gn}(L-\rho_n)}{\rho_n L} \right) - \frac{h_{gn}(0)}{L} \right) \frac{1-\rho_n L}{1-\lambda_{gn} L} x_{it}^n \\
(A.11) \quad &= \sum_{n \in \{r, z, a, \mu\}} G_{ign}(L) x_{lgt}^n
\end{aligned}$$

where $\phi_{ign1}(L) = \frac{h_{gn}(L)}{\tau_n(1-\rho_n L)}$ and $\phi_{ign2}(L) = \frac{h_{gn}(L)(L-\rho_n)}{\tau_{gn}}$. Inserting our obtained expressions into (A.1), and removing the x_{lgt}^n terms, and rearranging terms on the LHS and RHS

$$\begin{aligned}
&h_{gn}(L) \left\{ 1 - \beta_g \left[\left(1 - \frac{\lambda_{gn}}{\rho_n} \right) \frac{1-\rho_n \lambda_{gn}}{1-\rho_n L} + \frac{\lambda_{gn}(L-\rho_n)}{\rho_n L} \right] \frac{1-\rho_n L}{(1-\lambda_{gn} L)(L-\lambda_{gn})} \right\} \\
&- \sum_{k=1}^2 h_{kn}(L) \frac{(\rho_n - \lambda_{gn})(1-\rho_n \lambda_{gn})}{\rho_n} \frac{\gamma_{gk} z + \alpha_{gk}}{(1-\lambda_{gn} L)(L-\lambda_{gn})} \\
&= \varphi_{gn} \left(1 - \frac{\lambda_{gn}}{\rho_n} \right) \frac{1}{1-\lambda_{gn} L} - \beta_g \frac{1-\rho_n L}{L(1-\lambda_{gn} L)} h_{gn}(0) - \sum_{k=1}^2 h_{kn}(\lambda_{gn}) \left(1 - \frac{\lambda_{gn}}{\rho_n} \right) \frac{\gamma_{gk} \lambda_{gn} + \alpha_{gk}}{(1-\lambda_{gn} L)(L-\lambda_{gn})} (1-\rho_n L)
\end{aligned}$$

Multiplying both sides by $L(L - \lambda_{gn})(1 - \lambda_{gn}L)$,

$$\begin{aligned} & h_{gn}(L) [L(L - \lambda_{gn})(1 - \lambda_{gn}L) - \beta_g(L - \lambda_{gn})(1 - \lambda_{gn}L)] - \sum_{k=1}^2 h_{kn}(L) \left(1 - \frac{\lambda_{gn}}{\rho_n}\right) (1 - \rho_n \lambda_{gn})L(\gamma_{gk}L + \alpha_{gk}) \\ &= \varphi_{gn} \left(1 - \frac{\lambda_{gn}}{\rho_n}\right) L(L - \lambda_{gn}) - \beta_g(1 - \rho_n L)(L - \lambda_{gn})h_{gn}(0) - \sum_{k=1}^2 h_{kn}(\lambda_{gn}) \left(1 - \frac{\lambda_{gn}}{\rho_n}\right) (\gamma_{gk}\lambda_{gn} + \alpha_{gk})L(1 - \rho_n L) \end{aligned}$$

We can write the above system of equations in terms of $\mathbf{h}(L)$ in matrix form

$$(A.12) \quad \mathbf{C}_n(L)\mathbf{h}_n(L) = \mathbf{d}_n(L)$$

where

$$\mathbf{C}_n(L) \equiv \text{diag} \{ \lambda_{gn} \} \left[(\beta - IL) \text{diag} \left\{ \left(L - \frac{1}{\rho_n} \right) (L - \rho_n) \right\} - (\beta - IL)L \text{diag} \left\{ \frac{\tau_{gn}}{\rho_n \tau_n} \right\} - L \text{diag} \left\{ \frac{\tau_{gn}}{\rho_n \tau_n} \right\} (L\gamma + \alpha) \right]$$

That is, we can write $\mathbf{C}_n(L) = \begin{bmatrix} C_{n11}(L) & C_{n12}(L) \\ C_{n21}(L) & C_{n22}(L) \end{bmatrix}$, where

$$\begin{aligned} C_{n11}(L) &= \lambda_{1n} \left[(\beta_1 - L) \left(L - \frac{1}{\rho_n} \right) (L - \rho_n) + \frac{\tau_{1n}}{\rho_n \tau_n} L [L(1 - \gamma_{11}) - \delta_{11}] \right], & C_{n12}(L) &= -\lambda_{1n} L \frac{\tau_{1n}}{\rho_n \tau_n} (L\gamma_{12} + \delta_{12}) \\ C_{n22}(L) &= \lambda_{2n} \left[(\beta_2 - L) \left(L - \frac{1}{\rho_n} \right) (L - \rho_n) + \frac{\tau_{2n}}{\rho_n \tau_n} L [L(1 - \gamma_{22}) - \delta_{22}] \right], & C_{n21}(L) &= -\lambda_{2n} L \frac{\tau_{2n}}{\rho_n \tau_n} (L\gamma_{21} + \delta_{21}) \end{aligned}$$

We can also write $\mathbf{d}_n(z) = \begin{bmatrix} d_{1n}[L; h_{1n}(\cdot)] \\ d_{2n}[L; h_{2n}(\cdot)] \end{bmatrix}$, where

$$d_{gn}(L) = \varphi_{gn} \left(1 - \frac{\lambda_{gn}}{\rho_n}\right) L(L - \lambda_{gn}) - \beta_g(1 - \rho_n L)(L - \lambda_{gn})h_{gn}(0) - \sum_{k=1}^2 h_{kn}(\lambda_{gn}) \left(1 - \frac{\lambda_{gn}}{\rho_n}\right) (\gamma_{gk}\lambda_{gn} + \alpha_{gk})L(1 - \rho_n L)$$

From (A.12), the solution to the policy function is given by $\mathbf{h}_n(L) = \mathbf{C}_n(L)^{-1} \mathbf{d}_n(L) = \frac{\text{adj } \mathbf{C}_n(L)}{\det \mathbf{C}_n(L)} \mathbf{d}_n(L)$. Hence, we need to obtain $\det \mathbf{C}_n(L)$. Note that the degree of $\det \mathbf{C}_n(L)$ is a polynomial of degree 6 on L . Denote the inside roots of $\det \mathbf{C}_n(L)$ as $\{\zeta_{1n}, \zeta_{2n}, \zeta_{3n}, \zeta_{4n}\}$, and the outside roots as $\{\vartheta_{1n}^{-1}, \vartheta_{2n}^{-1}\}$. Because agents cannot use future signals, the inside roots have to be removed. Note that the number of free constants in $\mathbf{d}_n(L)$ is 4: $\{h_{gn}(0)\}$ and $\{\tilde{h}_n(\lambda_{gn}) = \sum_{k=1}^2 h_{kn}(\lambda_{gn}) \left(1 - \frac{\lambda_{gn}}{\rho_n}\right) (\gamma_{gk}\lambda_{gn} + \alpha_{gk})\}$ for each $g \in \{1, 2\}$. With a unique solution, it has to be the case that the number of outside roots is 2. By Cramer's rule, $h_{gn}(L)$ is given by

$$h_{1n}(L) = \frac{\det \begin{bmatrix} d_{1n}(L) & C_{n12}(L) \\ d_{2n}(L) & C_{n22}(L) \end{bmatrix}}{\det \mathbf{C}_n(L)}, \quad h_{2n}(L) = \frac{\det \begin{bmatrix} C_{n11}(L) & d_{1n}(L) \\ C_{n21}(L) & d_{2n}(L) \end{bmatrix}}{\det \mathbf{C}_n(L)}$$

which are the policy function for groups 1 (consumers) and 2 (firms). The degree of the numerator is 5, as the highest degree of $d_{gn}(L)$ is 1 degree less than that of $\mathbf{C}_n(L)$. By choosing the appropriate constants

$\{h_{1n}(0), \tilde{h}_n(\lambda_{1n}), h_{2n}(0), \tilde{h}_n(\lambda_{2n})\}$, the 4 inside roots will be removed. Therefore, the 4 constants are solutions to the following system of linear equations

$$\det \begin{bmatrix} d_{1n}(\zeta_{sn}) & C_{n12}(\zeta_{sn}) \\ d_{2n}(\zeta_{sn}) & C_{n22}(\zeta_{sn}) \end{bmatrix} = 0, \quad \text{for } \{\zeta_{sn}\}_{s=1}^4$$

After removing the inside roots in the denominator, the degree of the numerator is 1 and the degree of the denominator is 2. The above determinants can be written as a system of 4 equations and 4 unknowns (our free constants). Once we have set the appropriate free constants the policy functions will be $h_{gn}(L) = \frac{\tilde{\psi}_{gn,1} + \tilde{\psi}_{gn,2}L}{(1-\vartheta_1L)(1-\vartheta_2L)}$, and hence we have

$$a_{gnt} = h_{gn}(L)n_t = \frac{\tilde{\psi}_{gn1} + \tilde{\psi}_{gn2}L}{(1-\vartheta_1L)(1-\vartheta_2L)}n_t = \sum_{j=1}^2 \psi_{gnj} \left(1 - \frac{\vartheta_{jn}}{\rho_n}\right) \frac{1}{1-\vartheta_{jn}L} n_t = \sum_{j=1}^2 \psi_{gnj} \tilde{\vartheta}_{jnt}$$

We can write

$$\mathbf{a}_{nt} = \begin{bmatrix} a_{1nt} \\ a_{2nt} \end{bmatrix} = \Psi_n \tilde{\vartheta}_t = \begin{bmatrix} \psi_{11,n} & \psi_{12,n} \\ \psi_{21,n} & \psi_{22,n} \end{bmatrix} \begin{bmatrix} \tilde{\vartheta}_{1nt} \\ \tilde{\vartheta}_{2nt} \end{bmatrix} = \begin{bmatrix} \psi_{11,n} \tilde{\vartheta}_{1nt} + \psi_{12,n} \tilde{\vartheta}_{2nt} \\ \psi_{21,n} \tilde{\vartheta}_{1nt} + \psi_{22,n} \tilde{\vartheta}_{2nt} \end{bmatrix}$$

Notice that we can write $\tilde{\vartheta}_{gnt}(1 - \vartheta_{gn}L) = \left(1 - \frac{\vartheta_{gn}}{\rho_n}\right) n_t \implies \tilde{\vartheta}_{gnt} = \vartheta_{gn} \tilde{\vartheta}_{gn,t-1} + \left(1 - \frac{\vartheta_{gn}}{\rho_n}\right) n_t$, which we can write as a system as $\tilde{\vartheta}_{nt} = \Lambda_n \tilde{\vartheta}_{n,t-1} + \Gamma_n n_t$, where $\Lambda_n = \begin{bmatrix} \vartheta_{1n} & 0 \\ 0 & \vartheta_{2n} \end{bmatrix}$, $\Gamma_n = \begin{bmatrix} 1 - \frac{\vartheta_{1n}}{\rho_n} \\ 1 - \frac{\vartheta_{2n}}{\rho_n} \end{bmatrix}$. Hence, we can write $\mathbf{a}_{nt} = Q_n \tilde{\vartheta}_{nt} = \Psi_n (\Lambda_n \tilde{\vartheta}_{n,t-1} + \Gamma_n n_t) = \Psi_n \Lambda_n \tilde{\vartheta}_{n,t-1} + \Psi_n \Gamma_n n_t = \Psi_n \Lambda_n \Psi_n^{-1} \mathbf{a}_{n,t-1} + \Psi_n \Gamma_n n_t = A_n \mathbf{a}_{n,t-1} + B_n n_t$. Finally, $\mathbf{a}_t = \sum_n \mathbf{a}_{nt}$. $\square$

PROPOSITION A1. Let mps_t^c denote the monetary policy surprise in (26), measured with households' expectations, and let $k \in \{c, f\}$ index the group whose forecast revisions are considered. Define

$$\mathbb{V}(mps_t^c) = \sum_n \left(\frac{\gamma_n^2}{1 - \lambda_{cn}^2} + 2 \sum_{j=1}^2 \frac{\gamma_n \gamma_{jn}}{1 - \lambda_{cn} \vartheta_{jn}} + \sum_{j=1}^2 \frac{\gamma_{jn}^2}{1 - \vartheta_{jn}^2} + 2 \frac{\gamma_{1n} \gamma_{2n}}{1 - \vartheta_{1n} \vartheta_{2n}} \right) \sigma_n^2.$$

(i) The reaction of group- k forecast revisions to the “uncleaned” monetary policy surprise is given by the OLS coefficients

$$\begin{aligned} \beta_{FR,ky}^h &= \frac{\mathbb{C} \left[\bar{\mathbb{E}}_{t+h}^k \tilde{y}_{t+1+h} - \bar{\mathbb{E}}_{t-1+h}^k \tilde{y}_{t+1+h}, mps_t^c \right]}{\mathbb{V}(mps_t^c)} = \frac{\sum_n \zeta_{kyn} \lambda_{kn}^h \left(\frac{\gamma_n}{1 - \lambda_{kn} \lambda_{cn}} + \sum_{j=1}^2 \frac{\gamma_{jn}}{1 - \lambda_{kn} \vartheta_{jn}} \right) \sigma_n^2}{\mathbb{V}(mps_t^c)} \\ \beta_{FR,k\pi}^h &= \frac{\mathbb{C} \left[\bar{\mathbb{E}}_{t+h}^k \pi_{t+1+h} - \bar{\mathbb{E}}_{t-1+h}^k \pi_{t+1+h}, mps_t^c \right]}{\mathbb{V}(mps_t^c)} = \frac{\sum_n \zeta_{k\pi n} \lambda_{kn}^h \left(\frac{\gamma_n}{1 - \lambda_{kn} \lambda_{cn}} + \sum_{j=1}^2 \frac{\gamma_{jn}}{1 - \lambda_{kn} \vartheta_{jn}} \right) \sigma_n^2}{\mathbb{V}(mps_t^c)} \\ \beta_{FR,ki}^h &= \frac{\mathbb{C} \left[\bar{\mathbb{E}}_{t+h}^k i_{t+1+h} - \bar{\mathbb{E}}_{t-1+h}^k i_{t+1+h}, mps_t^c \right]}{\mathbb{V}(mps_t^c)} = \phi_\pi \beta_{FR,k\pi}^h + \phi_y \beta_{FR,ky}^h + \frac{(\rho_v - \lambda_{kv}) \lambda_{kv}^h \left(\frac{\gamma_v}{1 - \lambda_{kv} \lambda_{cv}} + \sum_{j=1}^2 \frac{\gamma_{jv}}{1 - \lambda_{kv} \vartheta_{jv}} \right) \sigma_v^2}{\mathbb{V}(mps_t^c)} \end{aligned}$$

where, for $g \in \{y, \pi\}$, $\zeta_{kgn} = \left(1 - \frac{\lambda_{kn}}{\rho_n}\right) \sum_{j=1}^2 \psi_{gnj} \left[\rho_n - \frac{(1-\rho_n\lambda_{kn})\vartheta_{jn}^2}{\rho_n(1-\vartheta_{jn}\lambda_{kn})} \right]$, $\gamma_{gn} = \sum_{j=1}^2 \frac{\lambda_{cn}^2 \psi_{gnj} (\rho_n - \vartheta_{jn})(1-\rho_n\vartheta_{jn})}{\rho_n^2(1-\lambda_{cn}\vartheta_{jn})(\lambda_{cn}-\vartheta_{jn})}$ and $\gamma_{gjn} = -\frac{\lambda_{cn}\vartheta_{jn}\psi_{gnj}(\rho_n-\vartheta_{jn})(1-\rho_n\vartheta_{jn})}{\rho_n^2(1-\lambda_{cn}\vartheta_{jn})(\lambda_{cn}-\vartheta_{jn})}$, $\gamma_v = \phi_\pi \gamma_{\pi v} + \phi_y \gamma_{yv} + 1$, $\gamma_n = \phi_\pi \gamma_{\pi n} + \phi_y \gamma_{yn}$ for $n \neq v$, and $\gamma_{jn} = \phi_\pi \gamma_{\pi jn} + \phi_y \gamma_{yjn}$. In the estimation, SPF revisions correspond to firms, $k = f$.

(ii) The reaction of aggregate macro variables to the “uncleaned” monetary policy surprise is given by the OLS coefficients

$$\begin{aligned} \beta_{\text{IRF},y}^h &= \frac{\mathbb{C}[\tilde{y}_{t+h}, \text{mps}_t^c]}{\mathbb{V}(\text{mps}_t^c)} = \frac{\sum_n \left\{ \left[\frac{\gamma_n}{1-\rho_n\lambda_{cn}} + \sum_{j=1}^2 \frac{\gamma_{jn}}{1-\rho_n\vartheta_{jn}} \right] \rho_n^h \beta_{yn} + \sum_{j=1}^2 \left[\frac{\gamma_n}{1-\lambda_{cn}\vartheta_{jn}} + \frac{\gamma_{1n}}{1-\vartheta_{1n}\vartheta_{jn}} + \frac{\gamma_{2n}}{1-\vartheta_{2n}\vartheta_{jn}} \right] \vartheta_{jn}^h \beta_{yjn} \right\} \sigma_n^2}{\mathbb{V}(\text{mps}_t^c)} \\ \beta_{\text{IRF},\pi}^h &= \frac{\mathbb{C}[\pi_{t+h}, \text{mps}_t^c]}{\mathbb{V}(\text{mps}_t^c)} = \frac{\sum_n \left\{ \left[\frac{\gamma_n}{1-\rho_n\lambda_{cn}} + \sum_{j=1}^2 \frac{\gamma_{jn}}{1-\rho_n\vartheta_{jn}} \right] \rho_n^h \beta_{\pi n} + \sum_{j=1}^2 \left[\frac{\gamma_n}{1-\lambda_{cn}\vartheta_{jn}} + \frac{\gamma_{1n}}{1-\vartheta_{1n}\vartheta_{jn}} + \frac{\gamma_{2n}}{1-\vartheta_{2n}\vartheta_{jn}} \right] \vartheta_{jn}^h \beta_{\pi jn} \right\} \sigma_n^2}{\mathbb{V}(\text{mps}_t^c)} \\ \beta_{\text{IRF},i}^h &= \frac{\mathbb{C}[i_{t+h}, \text{mps}_t^c]}{\mathbb{V}(\text{mps}_t^c)} = \phi_\pi \beta_{\text{IRF},\pi}^h + \phi_y \beta_{\text{IRF},y}^h + \frac{\left(\frac{\gamma_v}{1-\rho_v\lambda_{cv}} + \sum_{j=1}^2 \frac{\gamma_{jv}}{1-\rho_v\vartheta_{jv}} \right) \rho_v^h \sigma_v^2}{\mathbb{V}(\text{mps}_t^c)} \end{aligned}$$

where $\beta_{gn} = \sum_{j=1}^2 \psi_{gnj}$ and $\beta_{gjn} = -\frac{\psi_{gnj}\vartheta_{jn}}{\rho_n}$ for $g \in \{y, \pi\}$ and $j \in \{1, 2\}$.

PROOF. We first characterize the forecast revisions. By Proposition 1, each aggregate outcome can be written as

$$a_{jt} = \sum_n \left[\beta_{jn} \sum_{m=0}^{\infty} \rho_n^m \varepsilon_{t-m}^n + \sum_{s=1}^2 \beta_{jsn} \sum_{m=0}^{\infty} \vartheta_{sn}^m \varepsilon_{t-m}^n \right], \quad \beta_{jn} = \sum_{s=1}^2 \psi_{jns}, \quad \beta_{jsn} = -\frac{\psi_{jns}\vartheta_{sn}}{\rho_n},$$

that is, as a combination of terms of the form $\sum_{m=0}^{\infty} \omega^m \varepsilon_{t-m}^n$ with $\omega \in \{\rho_n, \vartheta_{1n}, \vartheta_{2n}\}$. Because ε_{t+1}^n cannot be forecast at t or $t-1$, the revision of the forecast of $\sum_m \omega^m \varepsilon_{t+1-m}^n$ between $t-1$ and t equals

$$\omega \left[\mathbb{E}_t^g \sum_{m=0}^{\infty} \omega^m \varepsilon_{t-m}^n - \omega \mathbb{E}_{t-1}^g \sum_{m=0}^{\infty} \omega^m \varepsilon_{t-1-m}^n \right] = \omega \sum_{m=0}^{\infty} \omega^m \left(\mathbb{E}_t^g \varepsilon_{t-m}^n - \mathbb{E}_{t-1}^g \varepsilon_{t-m}^n \right).$$

The term in parentheses is the update of beliefs about a past innovation. For agent l in group g , the only new information about disturbance n in period t is the innovation in her signal, $x_{lgt}^n - \mathbb{E}_{l,g,t-1} x_{lgt}^n$. Its covariance with ε_{t-m}^n is $\lambda_{gn}^m \sigma_n^2$: the signal noise is independent of the fundamental innovations, and the forecast error $n_t - \mathbb{E}_{l,g,t-1} n_t$ loads λ_{gn}^m on ε_{t-m}^n (see the derivation of $v_t - \mathbb{E}_{t-1}^k v_t$ below). By the projection theorem,

$$\mathbb{E}_{lgt} \varepsilon_{t-m}^n - \mathbb{E}_{l,g,t-1} \varepsilon_{t-m}^n = \frac{\lambda_{gn}^m \sigma_n^2}{\mathbb{V}(x_{lgt}^n - \mathbb{E}_{l,g,t-1} x_{lgt}^n)} \left(x_{lgt}^n - \mathbb{E}_{l,g,t-1} x_{lgt}^n \right).$$

Averaging across agents, the signal innovations aggregate to $n_t - \mathbb{E}_{t-1}^g n_t = \sum_{m=0}^{\infty} \lambda_{gn}^m \varepsilon_{t-m}^n$. Summing over m ,

$$\mathbb{E}_t^g \sum_{m=0}^{\infty} \omega^m \varepsilon_{t-m}^n - \omega \mathbb{E}_{t-1}^g \sum_{m=0}^{\infty} \omega^m \varepsilon_{t-1-m}^n = \frac{\sigma_n^2}{\mathbb{V}(x_{lgt}^n - \mathbb{E}_{l,g,t-1} x_{lgt}^n)} \frac{1}{1 - \omega \lambda_{gn}} \sum_{m=0}^{\infty} \lambda_{gn}^m \varepsilon_{t-m}^n.$$

The constant follows from the case $\omega = \rho_n$, in which the left-hand side is $\bar{\mathbb{E}}_t^g n_t - \rho_n \bar{\mathbb{E}}_{t-1}^g n_{t-1} = (1 - \lambda_{gn}/\rho_n) \sum_m \lambda_{gn}^m \varepsilon_{t-m}^n$ by (A.5). Hence $\sigma_n^2/\mathbb{V}(\cdot) = (1 - \lambda_{gn}/\rho_n) (1 - \rho_n \lambda_{gn})$, and collecting terms,

$$(A.13) \quad \bar{\mathbb{E}}_{t+h}^g a_{j,t+1+h} - \bar{\mathbb{E}}_{t-1+h}^g a_{j,t+1+h} = \sum_n \zeta_{gjn} \sum_{m=0}^{\infty} \lambda_{gn}^m \varepsilon_{t+h-m}^n$$

where

$$\zeta_{gjn} = \left(1 - \frac{\lambda_{gn}}{\rho_n}\right) (1 - \rho_n \lambda_{gn}) \left[\frac{\beta_{jn} \rho_n}{1 - \rho_n \lambda_{gn}} + \sum_{s=1}^2 \frac{\beta_{jsn} \vartheta_{sn}}{1 - \vartheta_{sn} \lambda_{gn}} \right] = \left(1 - \frac{\lambda_{gn}}{\rho_n}\right) \sum_{s=1}^2 \psi_{jns} \left[\rho_n - \frac{(1 - \rho_n \lambda_{gn}) \vartheta_{sn}^2}{\rho_n (1 - \vartheta_{sn} \lambda_{gn})} \right].$$

For the policy disturbance itself ($\beta_{jv} = 1$ and $\beta_{jsv} = 0$), this gives $\zeta = \rho_v - \lambda_{gv}$, the loading used below for policy-rate revisions. The monetary policy surprise in (26) is measured with households' average expectations,

$$\text{mps}_t^c = i_t - \bar{\mathbb{E}}_t^c i_t = \phi_\pi (\pi_t - \bar{\mathbb{E}}_t^c \pi_t) + \phi_y (\tilde{y}_t - \bar{\mathbb{E}}_t^c \tilde{y}_t) + v_t - \bar{\mathbb{E}}_{t-1}^c v_t,$$

while the forecast revisions are those of a group $k \in \{c, f\}$. To express the surprise in terms of the fundamental innovations, we first derive the forecast errors of a generic group k .

We know aggregate endogenous variables evolve according to

$$\begin{aligned} a_{kt} &= \sum_n \sum_{j=1}^2 \left(1 - \frac{\vartheta_{jn}}{\rho_n}\right) \psi_{kjn} \frac{1}{(1 - \vartheta_{jn} L)(1 - \rho_n L)} \varepsilon_t^n = \sum_n \frac{\psi_{kjn}}{\rho_n} \sum_{s=0}^{\infty} \left(\rho_n^{s+1} - \vartheta_{jn}^{s+1}\right) \varepsilon_{t-s}^n \\ &= \sum_n \left[\beta_{kn} \sum_{l=0}^{\infty} \rho_n^l \varepsilon_{t-l}^n + \sum_{j=1}^2 \beta_{kjn} \sum_{l=0}^{\infty} \vartheta_{jn}^l \varepsilon_{t-l}^n \right] \end{aligned}$$

where $\beta_{kn} = \sum_{j=1}^2 \psi_{knj}$ and $\beta_{kjn} = -\frac{\psi_{knj} \vartheta_{jn}}{\rho_n}$. Their nowcast is

$$\bar{\mathbb{E}}_t^g a_{jt} = \sum_n \left(1 - \frac{\lambda_{gn}}{\rho_n}\right) \frac{L h_{jn}(L)(1 - \rho_n \lambda_{gn}) - \lambda_{gn} h_{jn}(\lambda_{gn})(1 - \rho_n L)}{(1 - \lambda_{gn} L)(L - \lambda_{gn})} n_t$$

Hence, we can write,

$$\begin{aligned} a_{g,t} - \bar{\mathbb{E}}_t^k a_{g,t} &= \sum_n \left\{ h_{gn}(L) \left[1 - \frac{(\rho_n - \lambda_{kn})L(1 - \rho_n \lambda_{kn})}{\rho_n(1 - \lambda_{kn}L)(L - \lambda_{kn})} \right] + h_{gn}(\lambda_{kn}) \frac{(\rho_n - \lambda_{kn})\lambda_{kn}(1 - \rho_n L)}{\rho_n(1 - \lambda_{kn}L)(L - \lambda_{kn})} \right\} n_t \\ &= \sum_n \frac{\lambda_{kn}(1 - \rho_n L)}{\rho_n(1 - \lambda_{kn}L)(L - \lambda_{kn})} [h_{gn}(L)(L - \rho_n) + h_{gn}(\lambda_{kn})(\rho_n - \lambda_{kn})] n_t \\ &= \sum_n \frac{\lambda_{kn}}{\rho_n(1 - \lambda_{kn}L)(L - \lambda_{kn})} [h_{gn}(L)(L - \rho_n) + h_{gn}(\lambda_{kn})(\rho_n - \lambda_{kn})] \varepsilon_t^n \\ &= \sum_n \frac{\lambda_{kn}}{\rho_n(1 - \lambda_{kn}L)(L - \lambda_{kn})} \sum_{j=1}^2 \left[\frac{\psi_{gnj}(\rho_n - \vartheta_{jn})(L - \rho_n)}{\rho_n(1 - \vartheta_{jn}L)} + \frac{\psi_{gnj}(\rho_n - \vartheta_{jn})(\rho_n - \lambda_{kn})}{\rho_n(1 - \vartheta_{jn}\lambda_{kn})} \right] \varepsilon_t^n \\ &= \sum_n \frac{\lambda_{kn}}{\rho_n(1 - \lambda_{kn}L)(L - \lambda_{kn})} \sum_{j=1}^2 \frac{\psi_{gnj}(\rho_n - \vartheta_{jn})}{\rho_n} \left[\frac{(L - \rho_n)}{1 - \vartheta_{jn}L} + \frac{\rho_n - \lambda_{kn}}{1 - \vartheta_{jn}\lambda_{kn}} \right] \varepsilon_t^n \end{aligned}$$

$$\begin{aligned}
&= \sum_n \frac{\lambda_{kn}}{\rho_n(1-\lambda_{kn}L)(L-\lambda_{kn})} \sum_{j=1}^2 \frac{\psi_{gnj}(\rho_n - \vartheta_{jn})}{\rho_n} \frac{(L-\lambda_{kn})(1-\rho_n\vartheta_{jn})}{(1-\vartheta_{jn}L)(1-\lambda_{kn}\vartheta_{jn})} \varepsilon_t^n \\
&= \sum_n \sum_{j=1}^2 \frac{\lambda_{kn}\psi_{gnj}(\rho_n - \vartheta_{jn})(1-\rho_n\vartheta_{jn})}{\rho_n^2(1-\lambda_{kn}\vartheta_{jn})} \frac{1}{(1-\vartheta_{jn}L)(1-\lambda_{kn}L)} \varepsilon_t^n \\
&= \sum_n \sum_{j=1}^2 \frac{\lambda_{kn}\psi_{gnj}(\rho_n - \vartheta_{jn})(1-\rho_n\vartheta_{jn})}{\rho_n^2(1-\lambda_{kn}\vartheta_{jn})} \left(\frac{\lambda_{kn}}{\lambda_{kn}-\vartheta_{jn}} \frac{1}{1-\lambda_{kn}L} - \frac{\vartheta_{jn}}{\lambda_{kn}-\vartheta_{jn}} \frac{1}{1-\vartheta_{jn}L} \right) \varepsilon_t^n \\
&= \sum_n \left[\sum_{j=1}^2 \frac{\lambda_{kn}^2 \psi_{gnj}(\rho_n - \vartheta_{jn})(1-\rho_n\vartheta_{jn})}{\rho_n^2(1-\lambda_{kn}\vartheta_{jn})(\lambda_{kn}-\vartheta_{jn})} \sum_{l=0}^{\infty} \lambda_{kn}^l \varepsilon_{t-l}^n - \sum_{j=1}^2 \frac{\lambda_{kn}\vartheta_{jn} \psi_{gnj}(\rho_n - \vartheta_{jn})(1-\rho_n\vartheta_{jn})}{\rho_n^2(1-\lambda_{kn}\vartheta_{jn})(\lambda_{kn}-\vartheta_{jn})} \sum_{l=0}^{\infty} \vartheta_{jn}^l \varepsilon_{t-l}^n \right] \\
&= \sum_n \gamma_{gkn} \sum_{l=0}^{\infty} \lambda_{kn}^l \varepsilon_{t-l}^n + \sum_n \sum_{j=1}^2 \gamma_{gkjn} \sum_{l=0}^{\infty} \vartheta_{jn}^l \varepsilon_{t-l}^n
\end{aligned}$$

where $\gamma_{gkn} = \sum_{j=1}^2 \frac{\lambda_{kn}^2 \psi_{gnj}(\rho_n - \vartheta_{jn})(1-\rho_n\vartheta_{jn})}{\rho_n^2(1-\lambda_{kn}\vartheta_{jn})(\lambda_{kn}-\vartheta_{jn})}$ and $\gamma_{gkjn} = -\frac{\lambda_{kn}\vartheta_{jn} \psi_{gnj}(\rho_n - \vartheta_{jn})(1-\rho_n\vartheta_{jn})}{\rho_n^2(1-\lambda_{kn}\vartheta_{jn})(\lambda_{kn}-\vartheta_{jn})}$. We also have

$$v_t - \mathbb{E}_{t-1}^k v_t = \left[\frac{1}{1-\rho_v L} - \left(1 - \frac{\lambda_{kv}}{\rho_v}\right) \frac{\rho_v L}{(1-\lambda_{kv}L)(1-\rho_v L)} \right] \varepsilon_t^v = \sum_{l=0}^{\infty} \lambda_{kv}^l \varepsilon_{t-l}^v$$

Applying these expressions to households, $k = c$, the monetary policy surprise can finally be written as

$$\begin{aligned}
\text{mps}_t^c &= \phi_\pi \left[\sum_n \gamma_{\pi cn} \sum_{l=0}^{\infty} \lambda_{cn}^l \varepsilon_{t-l}^n + \sum_n \sum_{j=1}^2 \gamma_{\pi cjn} \sum_{l=0}^{\infty} \vartheta_{jn}^l \varepsilon_{t-l}^n \right] \\
&\quad + \phi_y \left[\sum_n \gamma_{ycn} \sum_{l=0}^{\infty} \lambda_{cn}^l \varepsilon_{t-l}^n + \sum_n \sum_{j=1}^2 \gamma_{ycjn} \sum_{l=0}^{\infty} \vartheta_{jn}^l \varepsilon_{t-l}^n \right] + \sum_{l=0}^{\infty} \lambda_{cv}^l \varepsilon_{t-l}^v \\
&= \sum_n \left[\gamma_{cn} \sum_{l=0}^{\infty} \lambda_{cn}^l \varepsilon_{t-l}^n + \sum_{j=1}^2 \gamma_{cjn} \sum_{l=0}^{\infty} \vartheta_{jn}^l \varepsilon_{t-l}^n \right]
\end{aligned}$$

where $\gamma_{cv} = \phi_\pi \gamma_{\pi cv} + \phi_y \gamma_{ycv} + 1$, $\gamma_{cn} = \phi_\pi \gamma_{\pi cn} + \phi_y \gamma_{ycn}$ for $n \neq v$, and $\gamma_{cjn} = \phi_\pi \gamma_{\pi cjn} + \phi_y \gamma_{ycjn}$. Its variance is

$$\mathbb{V}(\text{mps}_t^c) = \sum_n \left(\frac{\gamma_{cn}^2}{1-\lambda_{cn}^2} + 2 \sum_{j=1}^2 \frac{\gamma_{cn} \gamma_{cjn}}{1-\lambda_{cn} \vartheta_{jn}} + \sum_{j=1}^2 \frac{\gamma_{cjn}^2}{1-\vartheta_{jn}^2} + 2 \frac{\gamma_{c1n} \gamma_{c2n}}{1-\vartheta_{1n} \vartheta_{2n}} \right) \sigma_n^2.$$

By (A.13), the forecast revision of group k at $t+h$ is a moving average of $\varepsilon_{t+h}^n, \varepsilon_{t+h-1}^n, \dots$ with weights $\zeta_{kgn} \lambda_{kn}^m$. Its covariance with each component of the surprise therefore decays at rate λ_{kn} , and

$$\mathbb{C} \left[\mathbb{E}_{t+h}^k a_{g,t+1+h} - \mathbb{E}_{t-1+h}^k a_{g,t+1+h}, \text{mps}_t^c \right] = \sum_n \zeta_{kgn} \lambda_{kn}^h \left(\frac{\gamma_{cn}}{1-\lambda_{kn} \lambda_{cn}} + \sum_{j=1}^2 \frac{\gamma_{cjn}}{1-\lambda_{kn} \vartheta_{jn}} \right) \sigma_n^2.$$

The OLS coefficient is $\beta_{\text{FR},kg}^h = \mathbb{C} \left[\mathbb{E}_{t+h}^k a_{g,t+1+h} - \mathbb{E}_{t-1+h}^k a_{g,t+1+h}, \text{mps}_t^c \right] / \mathbb{V}(\text{mps}_t^c)$. When revisions and surprise

refer to the same group, $k = c$, the first term in parentheses reduces to $\gamma_{cn}/(1 - \lambda_{cn}^2)$.

To proceed in a similar way with the OLS coefficient of policy rate forecast revisions, we first compute

$$\bar{\mathbb{E}}_{t+h}^k v_{t+1+h} - \bar{\mathbb{E}}_{t-1+h}^k v_{t+1+h} = \left[\frac{\rho_v - \lambda_{kv}}{1 - \lambda_{kv}L} v_{t+h} - \frac{\rho_v(\rho_v - \lambda_{kv})}{1 - \lambda_{kv}L} v_{t-1+h} \right] = \frac{\rho_v - \lambda_{kv}}{1 - \lambda_{kv}L} \varepsilon_{t+h}^v = (\rho_v - \lambda_{kv}) \sum_{j=0}^{\infty} \lambda_{kv}^j \varepsilon_{t-j+h}^v$$

and hence,

$$\begin{aligned} \beta_{FR,ki}^h &= \frac{\mathbb{C} \left[\bar{\mathbb{E}}_{t+h}^k i_{t+1+h} - \bar{\mathbb{E}}_{t-1+h}^k i_{t+1+h}, \text{mps}_t^c \right]}{\mathbb{V}(\text{mps}_t^c)} = \phi_{\pi} \beta_{FR,k\pi}^h + \phi_y \beta_{FR,ky}^h + \frac{\mathbb{C} \left[\bar{\mathbb{E}}_{t+h}^k v_{t+1+h} - \bar{\mathbb{E}}_{t-1+h}^k v_{t+1+h}, \text{mps}_t^c \right]}{\mathbb{V}(\text{mps}_t^c)} \\ &= \phi_{\pi} \beta_{FR,k\pi}^h + \phi_y \beta_{FR,ky}^h + \frac{(\rho_v - \lambda_{kv}) \lambda_{kv}^h \left(\frac{\gamma_{cv}}{1 - \lambda_{kv} \lambda_{cv}} + \sum_{j=1}^2 \frac{\gamma_{c j v}}{1 - \lambda_{kv} \vartheta_{jv}} \right) \sigma_v^2}{\mathbb{V}(\text{mps}_t^c)} \end{aligned}$$

Let us now focus on the aggregate IRF to monetary shocks. We can write

$$\begin{aligned} \mathbb{C} \left[a_{g,t+h}, \text{mps}_t^c \right] &= \sum_n \left\{ \left[\frac{\gamma_{cn} \rho_n^h}{1 - \rho_n \lambda_{cn}} + \sum_{j=1}^2 \frac{\gamma_{c j n} \rho_n^h}{1 - \rho_n \vartheta_{j n}} \right] \beta_{gn} + \left[\frac{\gamma_{cn} \vartheta_{1n}^h}{1 - \lambda_{cn} \vartheta_{1n}} + \frac{\gamma_{c1n} \vartheta_{1n}^h}{1 - \vartheta_{1n}^2} + \frac{\gamma_{c2n} \vartheta_{1n}^h}{1 - \vartheta_{1n} \vartheta_{2n}} \right] \beta_{g1n} \right. \\ &\quad \left. + \left[\frac{\gamma_{cn} \vartheta_{2n}^h}{1 - \lambda_{cn} \vartheta_{2n}} + \frac{\gamma_{c1n} \vartheta_{2n}^h}{1 - \vartheta_{1n} \vartheta_{2n}} + \frac{\gamma_{c2n} \vartheta_{2n}^h}{1 - \vartheta_{2n}^2} \right] \beta_{g2n} \right\} \sigma_n^2 \end{aligned}$$

where $\beta_{gn} = \sum_{j=1}^2 \psi_{gnj}$ and $\beta_{gjn} = -\frac{\psi_{gnj} \vartheta_{jn}}{\rho_n}$. The OLS coefficient is given by

$$\beta_{IRF,g}^h = \frac{\mathbb{C} \left[a_{g,t+h}, \text{mps}_t^c \right]}{\mathbb{V}(\text{mps}_t^c)}$$

To proceed in a similar way with the OLS coefficient of policy rate IRFs, we first compute

$$\mathbb{C}[v_{t+h}, \text{mps}_t^c] = \left(\frac{\gamma_{cv}}{1 - \rho_v \lambda_{cv}} + \sum_{j=1}^2 \frac{\gamma_{c j v}}{1 - \rho_v \vartheta_{jv}} \right) \rho_v^h \sigma_v^2$$

hence,

$$\beta_{IRF,i}^h = \frac{\mathbb{C} \left[i_{t+h}, \text{mps}_t^c \right]}{\mathbb{V}(\text{mps}_t^c)} = \phi_{\pi} \beta_{IRF,\pi}^h + \phi_y \beta_{IRF,y}^h + \frac{\mathbb{C}[v_{t+h}, \text{mps}_t^c]}{\mathbb{V}(\text{mps}_t^c)}.$$

□

COROLLARY A1. (i) The reaction of group- k forecast revisions to “cleaned” monetary policy surprises, $\phi_v \varepsilon_t^v$, is given by the OLS coefficients

$$\beta_{FR,ky,\varepsilon}^h = \frac{\mathbb{C} \left[\bar{\mathbb{E}}_{t+h}^k \tilde{y}_{t+1+h} - \bar{\mathbb{E}}_{t-1+h}^k \tilde{y}_{t+1+h}, \phi_v \varepsilon_t^v \right]}{\mathbb{V}(\phi_v \varepsilon_t^v)} = \frac{\zeta_{kyv} \lambda_{kv}^h}{\phi_v}$$

$$\beta_{FR,k\pi,\varepsilon}^h = \frac{\mathbb{C} \left[\bar{\mathbb{E}}_{t+h}^k \pi_{t+1+h} - \bar{\mathbb{E}}_{t-1+h}^k \pi_{t+1+h}, \phi_v \varepsilon_t^v \right]}{\mathbb{V}(\phi_v \varepsilon_t^v)} = \frac{\zeta_{k\pi v} \lambda_{kv}^h}{\phi_v}$$

$$\beta_{FR,ki,\varepsilon}^h = \frac{\mathbb{C} \left[\bar{\mathbb{E}}_{t+h}^k i_{t+1+h} - \bar{\mathbb{E}}_{t-1+h}^k i_{t+1+h}, \phi_v \varepsilon_t^v \right]}{\mathbb{V}(\phi_v \varepsilon_t^v)} = \phi_\pi \beta_{FR,k\pi,\varepsilon}^h + \phi_y \beta_{FR,ky,\varepsilon}^h + \frac{(\rho_v - \lambda_{kv}) \lambda_{kv}^h}{\phi_v}$$

(ii) The reaction of aggregate macro variables to “cleaned” monetary policy shocks is given by the OLS coefficients

$$\beta_{IRF,y,\varepsilon}^h = \frac{\mathbb{C} [\tilde{y}_{t+h}, \phi_v \varepsilon_t^v]}{\mathbb{V}(\phi_v \varepsilon_t^v)} = \frac{\beta_{yv} \rho_v^h + \sum_{j=1}^2 \beta_{yvj} \vartheta_{jv}^h}{\phi_v}$$

$$\beta_{IRF,\pi,\varepsilon}^h = \frac{\mathbb{C} [\pi_{t+h}, \phi_v \varepsilon_t^v]}{\mathbb{V}(\phi_v \varepsilon_t^v)} = \frac{\beta_{\pi v} \rho_v^h + \sum_{j=1}^2 \beta_{\pi vj} \vartheta_{jv}^h}{\phi_v}$$

$$\beta_{IRF,i,\varepsilon}^h = \frac{\mathbb{C} [i_{t+h}, \phi_v \varepsilon_t^v]}{\mathbb{V}(\phi_v \varepsilon_t^v)} = \phi_\pi \beta_{IRF,\pi,\varepsilon}^h + \phi_y \beta_{IRF,y,\varepsilon}^h + \frac{\rho_v^h}{\phi_v}$$

where ζ_{kgv} , β_{gv} and β_{gfv} are defined in Proposition A1.

Appendix C. Model Derivation

C.1. Households

Let us now focus on the budget constraint. Define $A_{it} = R_{t-1} B_{i,t-1}$ as consumer i 's initial asset position in period t . Rewrite (7) at $t+1$

$$(A.14) \quad C_{it+1} + B_{it+1} = R_t B_{i,t} + W_{it+1}^r N_{it+1} + D_{it+1}$$

Combining (7) and (A.14) we can write $C_{it} + (C_{it+1} + B_{it+1})R_t^{-1} = A_{it} + W_{it}^r N_{it} + D_{it} + (W_{it+1}^r N_{it+1} + D_{it+1})R_t^{-1}$. Doing this until $T \rightarrow \infty$ we obtain $\sum_{k=0}^{\infty} \prod_{j=1}^k \frac{1}{R_{t+j-1}} C_{it+k} = A_{it} + \sum_{k=0}^{\infty} \prod_{j=1}^k \frac{1}{R_{t+j-1}} (W_{it+k}^r N_{it+k} + D_{it+k})$. Log-linearizing the above condition around a zero inflation steady-state we obtain

$$(A.15) \quad \sum_{k=0}^{\infty} \beta^k c_{it+k} = a_{it} + \Omega_i \sum_{k=0}^{\infty} \beta^k (w_{it+k}^r + n_{it+k}) + (1 - \Omega_i) \sum_{k=0}^{\infty} \beta^k d_{it+k}$$

where a lower case letter denotes the log deviation from steady state, i.e., $x_t = \log X_t - \log X$, except for the initial asset position, defined as $a_{it} = A_{it}/C_i$; and Ω_i denotes the labor income share for household i .

We want to obtain the optimal expenditure of household i in period t as a function of the current a future expected wages, dividends and real interest rates. Using (16) and taking expectations, we can rearrange (A.15) as

$$(A.16) \quad \sum_{k=0}^{\infty} \beta^k \mathbb{E}_{it} c_{it+k} = a_{it} + \Omega_i \sum_{k=0}^{\infty} \beta^k \mathbb{E}_{it} \left(\frac{1+\varphi}{\varphi} w_{it+k}^r - \frac{\sigma}{\varphi} c_{it+k} \right) + (1 - \Omega_i) \sum_{k=0}^{\infty} \beta^k \mathbb{E}_{it} d_{it+k}$$

$$= \frac{\varphi}{\varphi + \sigma \Omega_i} a_{it} + \sum_{k=0}^{\infty} \beta^k \mathbb{E}_{it} \left[\frac{\Omega_i(1+\varphi)}{\varphi + \sigma \Omega_i} w_{it+k}^r + \frac{(1 - \Omega_i)\varphi}{\varphi + \sigma \Omega_i} d_{it+k} \right]$$

Let us now focus on the left-hand side. Taking individual expectations, we can rewrite it as $\sum_{k=0}^{\infty} \beta^k \mathbb{E}_{it} c_{it+k}$. Keeping this aside, we can rearrange (17) as $\mathbb{E}_{it} c_{it+1} = c_{it} + \frac{1}{\sigma} \mathbb{E}_{it} r_t$. Iterating (17) one period forward, we can similarly write $\mathbb{E}_{it} c_{it+2} = c_{it} + \frac{1}{\sigma} \mathbb{E}_{it} (r_t + r_{t+1})$ and, for a general k , $\mathbb{E}_{it} c_{it+k} = c_{it} + \frac{1}{\sigma} \sum_{j=0}^k \mathbb{E}_{it} r_{t+j}$. That is, we can write

$$\sum_{k=0}^{\infty} \beta^k \mathbb{E}_{it} c_{it+k} = \sum_{k=0}^{\infty} \beta^k c_{it} + \frac{1}{\sigma} \sum_{k=0}^{\infty} \sum_{j=0}^k \beta^k \mathbb{E}_{it} r_{t+j} = \frac{1}{1-\beta} c_{it} + \frac{\beta}{\sigma(1-\beta)} \sum_{k=0}^{\infty} \beta^k \mathbb{E}_{it} r_{t+k}$$

Inserting this last condition into (A.16), we can write

$$c_{it} = -\frac{\beta}{\sigma} \sum_{k=0}^{\infty} \beta^k \mathbb{E}_{it} r_{t+k} + \frac{\varphi(1-\beta)}{\varphi + \sigma\Omega} a_{it} + \sum_{k=0}^{\infty} \beta^k \mathbb{E}_{it} \left[\frac{\Omega_i(1+\varphi)(1-\beta)}{\varphi + \sigma\Omega} w_{it+k}^r + \frac{(1-\Omega_i)\varphi(1-\beta)}{\varphi + \sigma\Omega} d_{it+k} \right]$$

Aggregating, using the fact that assets are in zero net supply, $\int_{j_h} a_{it} di = a_t = 0$,

$$(A.17) \quad c_t = -\frac{\beta}{\sigma} \sum_{k=0}^{\infty} \beta^k \bar{\mathbb{E}}_t^h r_{t+k} + \sum_{k=0}^{\infty} \beta^k \left[\frac{\Omega(1+\varphi)(1-\beta)}{\varphi + \sigma\Omega} \bar{\mathbb{E}}_t^h w_{t+k}^r + \frac{(1-\Omega)\varphi(1-\beta)}{\varphi + \sigma\Omega} \bar{\mathbb{E}}_t^h d_{t+k} \right]$$

where $\bar{\mathbb{E}}_t^h(\cdot) = \int_{j_c} \mathbb{E}_{it}(\cdot) di$ is the average household expectation operator in period t .

C.2. Firms

Aggregate Price Level Dynamics. As in the benchmark NK model, price rigidities take the form of Calvo-lottery friction. At every period, each firm is able to reset their price with probability $(1-\theta)$, independent of the time of the last price change. That is, only a measure $(1-\theta)$ of firms is able to reset their prices in a given period, and the average duration of a price is given by $1/(1-\theta)$. Such an environment implies that aggregate price level dynamics are given (in log-linear terms) by

$$(A.18) \quad \pi_t = \int_{j_f} \pi_{jt} dj = (1-\theta) \left[\int_{j_f} p_{jt}^* dj - p_{t-1} \right] = (1-\theta) (p_t^* - p_{t-1})$$

Optimal Price Setting. A firm re-optimizing in period t will choose the price p_{jt}^* that maximizes the current market value of the profits generated while the price remains effective. Formally, $p_{jt}^* = \arg \max_{p_{jt}} \sum_{k=0}^{\infty} \theta^k \mathbb{E}_{jt} \left\{ \Lambda_{t,t+k} \frac{1}{p_{t+k}} \left[p_{jt} Y_{j,t+k|t} - c_{t+k}(Y_{j,t+k|t}) \right] \right\}$ subject to the sequence of demand schedules $Y_{j,t+k|t} = \left(\frac{p_{jt}}{p_{t+k}} \right)^{-\epsilon} C_{t+k}$, where $\Lambda_{t,t+k} \equiv \beta^k \left(\frac{C_{t+k}}{C_t} \right)^{-\sigma}$ is the stochastic discount factor, $c_t(\cdot)$ is the (nominal) cost function, and $Y_{j,t+k|t}$ denotes output in period $t+k$ for a firm j that last reset its price in period t . The First-Order Condition is $\sum_{k=0}^{\infty} \theta^k \mathbb{E}_{jt} \left[\Lambda_{t,t+k} Y_{j,t+k|t} \frac{1}{p_{t+k}} \left(p_{jt}^* - \mathcal{M} \Psi_{j,t+k|t} \right) \right] = 0$, where $\Psi_{j,t+k|t} \equiv c_{t+k}^T(Y_{j,t+k|t})$ denotes the (nominal) marginal cost for firm j , and $\mathcal{M} = \frac{\epsilon}{\epsilon-1}$. Log-linearizing around the zero inflation steady-state, we obtain the familiar price-setting rule

$$(A.19) \quad p_{jt}^* = (1-\beta\theta) \sum_{k=0}^{\infty} (\beta\theta)^k \mathbb{E}_{jt} \left(\psi_{j,t+k|t} + \mu \right)$$

where $\psi_{j,t+k|t} = \log \Psi_{j,t+k|t}$ and $\mu = \log \mathcal{M}$.

C.3. Equilibrium

Market clearing in the goods market implies that $Y_{jt} = C_{jt} = \int_{\mathcal{J}_h} C_{ijt} di$ for each j good/firm. Aggregating across firms, we obtain the aggregate market clearing condition: since assets are in zero net supply and there is no capital, investment, government consumption nor net exports, production equals consumption: $\int_{\mathcal{J}_f} Y_{jt} dj = \int_{\mathcal{J}_h} \int_{\mathcal{J}_f} C_{ijt} dj di \implies Y_t = C_t$. Aggregate employment is given by the sum of employment across firms, and must meet aggregate labor supply $N_t = \int_{\mathcal{J}_h} N_{it} di = \int_{\mathcal{J}_f} N_{jt} dj$. Using $Y_{jt} = A_t N_{jt}$ and (6) together with goods market clearing, $N_t = \int_{\mathcal{J}_f} \left(\frac{Y_{jt}}{A_t}\right)^{\frac{1}{1-\alpha}} dj = \left(\frac{Y_t}{A_t}\right)^{\frac{1}{1-\alpha}} \int_{\mathcal{J}_f} \left(\frac{P_{jt}}{P_t}\right)^{-\frac{\epsilon}{1-\alpha}} dj$. Log-linearizing the above expression yields $n_t = \frac{1}{1-\alpha}(y_t - a_t)$.

The (log) marginal cost for firm j at time $t+k|t$ is $\psi_{j,t+k|t} = w_{t+k} - m p n_{j,t+k|t} = w_{t+k} - [a_{t+k} - \alpha n_{j,t+k|t} + \log(1-\alpha)]$, where $m p n_{j,t+k|t}$ and $n_{j,t+k|t}$ denote (log) marginal product of labor and (log) employment in period $t+k$ for a firm that last reset its price at time t , respectively. Let $\psi_t \equiv \int_{\mathcal{J}_f} \psi_{jt}$ denote the (log) average marginal cost. we can then write $\psi_t = w_t - [a_t - \alpha n_t + \log(1-\alpha)]$. Thus, the following relation holds

$$(A.20) \quad \psi_{j,t+k|t} = \psi_{t+k} + \alpha(n_{j,t+k|t} - n_{t+k}) = \psi_{t+k} + \frac{\alpha}{1-\alpha}(y_{j,t+k|t} - y_{t+k}) = \psi_{t+k} - \frac{\alpha\epsilon}{1-\alpha}(p_{jt}^* - p_{t+k})$$

Introducing (A.20) into (A.19), we can rewrite the firm price-setting condition as

$$(A.21) \quad p_{jt}^* = (1-\beta\theta) \sum_{k=0}^{\infty} (\beta\theta)^k \mathbb{E}_{jt} (p_{t+k} - \Theta \hat{\mu}_{t+k}),$$

where $\hat{\mu} = \mu_t - \mu$ is the deviation between the average and desired markups, where $\mu_t = -(\psi_t - p_t)$, and $\Theta = \frac{1-\alpha}{1-\alpha+\alpha\epsilon}$.

Individual and Aggregate Phillips curve. Note that we can write the deviation between average and desired markups as

$$\begin{aligned} \mu_t &= p_t - \psi_t = p_t - w_t + w_t - \psi_t = -(w_t - p_t) + w_t - [w_t - a_t + \alpha n_t - \log(1-\alpha)] \\ &= -(\sigma y_t + \varphi n_t) + [a_t - \alpha n_t + \log(1-\alpha)] = -\left(\sigma + \frac{\varphi + \alpha}{1-\alpha}\right) y_t + \frac{1+\varphi}{1-\alpha} a_t + \log(1-\alpha) \end{aligned}$$

As in the benchmark model, under flexible prices ($\theta = 0$) the average markup is constant and equal to the desired μ . Consider the natural level of output, y_t^n as the equilibrium level under flexible prices and FIRERE. Rewriting the above condition under the natural equilibrium, $\mu = -\left(\sigma + \frac{\varphi + \alpha}{1-\alpha}\right) y_t^n + \frac{1+\varphi}{1-\alpha} a_t + \log(1-\alpha)$, which we can write as $y_t^n = \psi a_t + \psi y$, where $\psi = \frac{1+\varphi}{\sigma(1-\alpha)+\varphi+\alpha}$ and $\psi y = -\frac{(1-\alpha)[\mu - \log(1-\alpha)]}{\sigma(1-\alpha)+\varphi+\alpha}$. Therefore, we can write $\hat{\mu}_t = -\left(\sigma + \frac{\varphi + \alpha}{1-\alpha}\right) \tilde{y}_t$, where $\tilde{y}_t = y_t - y_t^n$ is defined as the output gap. Finally, plugging this expression into (A.21) yields the Phillips curve in (23).

Individual and Aggregate DIS curve. In order to derive the DIS curve, let us first log-linearize the profit of the monopolist. The profit D_{jt} of monopolist j at time t is $D_{jt} = \frac{1}{P_t} (P_{jt} Y_{jt} - W_t N_{jt}) = \frac{P_{jt}}{P_t} Y_{jt} - W_t^r N_{jt}$. Log-linearizing

around a zero-inflation steady state, $D_j d_{jt} = \frac{P_j}{P} Y_j (p_{jt} + y_{jt} - p_t) - \frac{W^r}{P} N_j (w_t^r + n_{jt})$. Aggregating the above expression across firms

$$(A.22) \quad y_t = \frac{W^r N}{Y} (w_t^r + n_t) + \frac{D}{Y} d_t = \Omega (w_t^r + n_t) + (1 - \Omega) d_t$$

Aggregating the labor supply condition (16) across households, and using the goods market clearing condition $w_t^r = \sigma y_t + \varphi n_t$. Inserting the above condition in (A.22), we can write $y_t = \frac{\Omega(1+\varphi)}{\varphi+\Omega\sigma} w_t^r + \frac{(1-\Omega)\varphi}{\varphi+\Omega\sigma} d_t$. Introducing this last expression into the aggregate consumption function (A.17), using again the goods market clearing condition

$$(A.23) \quad y_t = -\frac{\beta}{\sigma} \sum_{k=0}^{\infty} \beta^k \bar{\mathbb{E}}_t^h r_{t+k} + (1 - \beta) \sum_{k=0}^{\infty} \beta^k \bar{\mathbb{E}}_t^h y_{t+k}$$

Let us now derive the DIS curve. Subtracting the natural level of output from (A.23), we obtain

$$(A.24) \quad \tilde{y}_t = -\frac{\beta}{\sigma} \sum_{k=0}^{\infty} \beta^k \bar{\mathbb{E}}_t^h (r_{t+k} - r_{t+k}^n) + (1 - \beta) \sum_{k=0}^{\infty} \beta^k \bar{\mathbb{E}}_t^h \tilde{y}_{t+k}$$

We now need to derive an expression for the natural real interest rate. Recall that in a natural equilibrium with no price nor information frictions, the natural real interest rate is given by

$$(A.25) \quad r_t^n = \sigma \mathbb{E}_t \Delta y_{t+1}^n = \sigma \psi \mathbb{E}_t \Delta a_{t+1} = \sigma \psi (\rho_a - 1) a_t$$