Macroeconomic effects of lowering South Africa's inflation target: An SVAR analysis

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Abstract

We estimate the macroeconomic effects of shifting to a lower inflation target for South Africa, within a Structural Vector Autoregressive (SVAR) framework identified using the Max Share Identification strategy and estimated with Bayesian methods. We find that a decrease of 1% (in terms of percentage points change) in the inflation target leads to output expanding over the next few quarters after an initial muted response, with a peak of about 1.20% after about two years and remains positive and statistically significant for nearly three years after the shock. We also observe a short- and medium-term co-movement of inflation and the nominal policy rate in response to the inflation target shock, reminiscent of Neo-Fisherian effects. However, unlike most of the findings in the literature whereby the effects of inflation target shocks are persistent, we find that they are less persistent for the South African economy, with the target shock contributing only marginally to fluctuations in the country's long-term interest rates. This implies that the often-cited gains linked with permanent lower borrowing costs may not apply to South Africa. Finally, we investigate the transmission mechanism of the inflation target shock and find strongly operative sovereign credit risk and asset price channels through which a lower inflation target increases output. These findings are relevant for emerging markets where sovereign credit risks tend to be elevated compared to developed economies.

Keywords: Inflation target, Inflation expectations, Transmission channels, SVAR.

JEL classifications: E31, E52, E58.

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1 Introduction

Inflation targeting has become the preferred monetary policy implementation framework for many central banks and its price stabilization benefits relative to alternative frameworks are well documented (Mishkin and Schmidt-Hebbel (2007); Walsh (2009); Svensson (2007)). While an important strand of the literature suggests that the optimal inflation rate should be near zero percent, some central banks in advanced economies target 2% inflation (Diercks (2019) and references therein). Meanwhile, emerging market economies that adopted the inflation targeting framework initially had high targets, but then gradually shifted towards lower ones. In this regard, the macroeconomic effects of lowering the inflation target in emerging markets has received less attention in the literature. This paper aims to fill this gap by estimating the dynamic effects of shifting to a lower inflation target in South Africa as the country's central bank has made public calls of its desire to shift its inflation target from a range of $3-6\%$ to a point target of 3%.[1] Following the announcement of this policy change intention, an analysis by Honohan and Orphanides (2022) came to the conclusion that a 3% inflation target would bode well for growth and the value of the Rand.

The central bank's inflation target can vary over time due to reasons that include changes in the central bank's own beliefs about the short-term trade-off between inflation and output (Sargent, Williams and Zha (2006)). For instance, Honohan and Orphanides (2022) attributed South Africa's reluctance to lower inflation toward the midpoint of the $3-6\%$ official target range during the 2010-2019 period due to the belief that output underperformed relative to its potential. Other reasons for a varying inflation target are that central banks learn in real-time about changes in the structure of the economy (Primiceri

[1] A public lecture by Lesetja Kganyago Governor of the South African Reserve Bank

(2006)).[2] In practice, inflation targeting central banks can pursue a policy that partially accommodates inflation pressures in the short run to avoid the costs to output while committing to a medium-term inflation target (Galí (2008)).

In this paper, we use the Max Share Identification strategy first suggested by Uhlig (2004a), to identify inflation target shocks in a SVAR for South Africa and then estimate the macroeconomic effects of these shocks using Bayesian techniques. In the spirit of Mumtaz and Theodoridis (2023), our inflation target shocks are implicit in the sense that they are identified as innovations which make the largest contribution to future movements in medium-term inflation expectations. Along with Pirozhkova and Viegi (2023), this is one of the first studies, to the best of our knowledge, to assess the macroeconomic effects of shifting the target for an inflation targeting emerging market economy and to investigate various channels through which the target shock propagates to the economy. Importantly, our identification strategy rests on the assumption that changes in inflation expectations, in the medium to long run, approximate changes to the inflation target because shocks to inflation expectations from productivity, aggregate demand and monetary policy shocks dissipate over the medium to long-term if the central bank is deemed credible and reacts consistently to rein in inflation to its target. Mumtaz and Theodoridis (2023) exploit this assumption and identify the implicit inflation target innovations as the structural VAR innovations that make the largest contribution to the forecast error variance (FEV) of long-run inflation expectations at a long horizon which captures the systematic component of monetary policy. The Max Share Identification approach has recently gained popularity and has

[2] The author shows that the high US inflation during the 1960s and 1970s was due to an underestimation by the Fed of the persistence of inflation in the Phillips curve and the natural rate of unemployment, resulting in over-expansionary monetary policy. The central bank's learning about the structure of the economy introduces temporary deviations from the model's equilibrium, resulting in an inflation bias.

been extensively used in the identification of single dominant shocks to the variations in target variables with examples including the analyses of the main determinants of exchange rate shocks (Miyamoto, Nguyen and Oh (2023)), business cycles (Angeletos, Collard and Dellas (2020)), and news and uncertainty shocks (Cascaldi-Garcia and Galvao (2021)), among others. Moreover, as argued by Mumtaz and Theodoridis (2023), the Max Share Identification is agnostic with regards to the relationship between endogenous variables, placing only minimal identification restrictions on them compared to the strong assumptions made to both the inflation target process and the structure of the economy in studies using New Keynesian Dynamic Stochastic General Equilibrium (NK-DSGE) frameworks.

We estimate the model using quarterly data over the 2000Q3-2024Q3 period, including the highly volatile COVID-19 episode with extreme observations recorded in 2020, which we account for in our estimation strategy. We set the lag length to 4 and estimate the Bayesian VAR using a Markov Chain Monte Carlo (MCMC) Gibbs sampler. To control for the extreme observations witnessed during the COVID-19 pandemic, we follow the approach proposed by Cascaldi-Garcia (2024) and extend the Bayesian prior with time dummies that we adapt to our identification procedure and estimation setting. We then simulate the posterior distributions of the VAR parameters using the Gibbs sampling algorithm.

We find that a reduction in the inflation target by one percentage point will lead to growth in output over time after an initial muted response, with a peak of about 1.20% after 9 quarters, and remains positive and statistically significant for nearly three years. Our findings also suggest the existence of some variant of Neo-Fisherian effects whereby both inflation and the policy rate co-move in the short- and medium-run in response to the inflation target shock. However, we do not observe for South Africa the persistent effects found in similar studies focusing on developed economies such as the US. We also find that the South African inflation target shock contributes only marginally to fluctuations in the country's long-term interest rates, in contrast with Mumtaz and Theodoridis (2023)'s finding for the US whereby the target shock is shown to have significantly contributed to the persistent decline in the 10-year government bond yield. This implies that the often-cited gains linked with permanent lower borrowing costs may not apply to South Africa. Together, these results suggest that the amplification mechanism of the target shock is different depending on whether the investigation is conducted on developed or emerging countries, with our less persistent shock effects for South Africa providing a case that may be relevant for other emerging market economies. We also find that the less persistent effects of the inflation target shock are robust to using alternative identification schemes including a Cholesky ordering and narrative sign restrictions, therefore lending further support to our conclusion that this finding may be a specific pattern of the South African economy. Finally, we explore various transmission channels of the inflation target changes to the real economy, and find strongly operative sovereign credit risk and asset price channels through which a lower inflation target raises economic growth. These findings are relevant for emerging markets where sovereign credit risks tend to be elevated compared to developed economies.

The rest of the paper proceeds as follows. Section 2 relates our work to the literature. Section 3 presents descriptive analyses of survey-based measures of inflation expectations for South Africa. Section 4 describes the data and our empirical approach. Section 5 presents our results and robustness checks. Section 6 investigates the transmission channels of inflation target shocks. Section 7 concludes.

2 Literature

Our paper is related to several strands of the literature. First, we build on a recent rapidly growing empirical literature that identifies inflation target shocks in structural VAR models. In particular, our identified inflation target shock is similar to the one in the SVAR framework of Mumtaz and Theodoridis (2023) which singles out innovations to the Fed's inflation target as the main driver of long-horizon inflation expectations in the medium- and long-term. They identify these shocks as ones that make the largest contribution to the forecast error variance of a survey-based measure of long-run inflation expectations. Aside from survey-based measures of expected inflation, other papers use DSGE-based implicit inflation target series estimated from New Keynesian frameworks, in their empirical analyses. Works along these lines include Lukmanova and Rabitsch (2023) who include their estimated series of the inflation target in a standard three-variable monetary VAR as in Stock and Watson (2001) to investigate the transmission mechanism of monetary policy in response to an inflation target shock for the US economy. Unlike these model-implied inflation target series, our survey-based and therefore data-driven long-horizon inflation forecasts ensure we avoid using a subsidiary and potentially misspecified model linking short-run forecasts to long-run inflation expectations, with the corollary of additional assumptions made for the US economy that are not necessarily suited for a small open developing/emerging economy such as South Africa. Finally, other SVAR-based frameworks that do not make use of survey-related or model-derived proxies for the inflation target, consider core measures of inflation (e.g., CPI inflation) along with other nominal and real variables in settings with cointegration identified using long-run restrictions. For example, De Michelis and Iacoviello (2016) specify a vector error correction model for Japan, including core inflation, and identify inflation target shocks as innovations that cause both inflation and interest rates to increase by the same amount in the long run. However, Francis, Owyang, Roush and DiCecio (2014) show that the Max Share Identification strategy for identifying inflation target innovations has an advantage over the conventional long-run restrictions such as the ones used in De Michelis and Iacoviello (2016) because they can yield biased impulse responses in small samples. Finally, Uribe (2022) estimates the effects of permanent monetary policy shocks on post World War II US data by imposing among other restrictions, that both the nominal interest rate and inflation are cointegrated with the monetary shocks. With respect to all these aforementioned papers which focus on developed economies, our study estimates the macroeconomic impact of inflation target shocks for an emerging economy, thereby allowing us to compare the respective effects of these shocks across both types of economies.

Another strand of the literature investigates the effects for the economy of changes in the inflation target, using structural models. Some of these studies use dynamic optimizing models such as the DSGE framework, in which the inflation target is assumed to follow an exogenous time-varying random walk process. Such settings were pioneered by Ireland (2007) and extended by Cogley, Primiceri and Sargent (2010), with the central bank adjusting its inflation target in response to cost-push and technology shocks, while innovations to the inflation target are assumed to be serially uncorrelated. Fève, Matheron and Sahuc (2010) followed the same approach but assumed innovations to the inflation target were correlated to capture gradual shifts in the inflation target.

Finally, our work can also be related to a nascent empirical literature on emerging markets and/or developing economies that estimate the macroeconomic effects of changes to the inflation target. In particular, Ndou and Gumata (2024) show that lowering the inflation target reduces the pass-through of positive GDP shocks to inflation in South Africa, and that the lower the inflation target the lower the pass-through based on impulse responses from a VAR model. Meanwhile, Honohan and Orphanides (2022) analyze South Africa's monetary policy over the 2007-2021 period and argue that a point target of 3% would better promote growth and protect the value of the Rand. Compared with these studies, we systematically investigate various transmission channels via which the inflation target shock propagates through the economy. Lastly, Pirozhkova and Viegi (2023) find that South Africa's inflation and inflation expectations declined after the change in the inflation target in 2017 without a negative effect on output and employment, and attribute this to a reduction in the sovereign credit risk premium and a subsequent positive effect on asset prices. These findings which are more closely aligned with ours, are based on conditional forecast estimates using a Bayesian VAR which compares macroeconomic fluctuations after the South African Reserve Bank (SARB) transitioned to the 4.5% midpoint target in 2017 with those that were prevalent during the $3-6\%$ inflation target range era prior to 2017.

3 South Africa's measures of inflation expectations

In this section, we present descriptive analyses of different measures of expected inflation for South Africa, namely the Bureau of Economic Research (BER) survey-based measures. We also provide a quick assessment of how well these inflation expectations are anchored by considering whether they fall within the $3-6\%$ range of the target set by the SARB. We abstract from other expected inflation measures such as those proxied by empirical estimates of trend inflation, as well as market-based measures. The latter are the 5- and 10-year break-even inflation rates, defined as the difference between the yield on a long-term nominal bond and the yield on an inflation-indexed bond of the same maturity. However, these break-even inflation estimates might reflect factors other than just long-run inflation expectations such as liquidity or inflation risk premium, especially when the risk premium is time-varying. Notably, Faust and Wright (2013) find break-even inflation excessively volatile to be considered a good proxy for long-horizon inflation expectations.

Survey-based measures of inflation expectations

The BER conducts a quarterly survey on inflation expectations in South Africa, covering four groups, namely financial analysts, businesses, trade unions and households.[3] The survey asks the financial analysts, businesses and trade unions about their current year, one- and two-year ahead inflation expectations using the CPI measure of inflation, whereas households are only requested to assess the current year expected CPI inflation. From 2011Q3 onwards, the survey started to ask financial analysts, businesses and trade unions about 5-year ahead inflation expectations.[4] In the survey, respondents are asked to indicate *quantitatively* what they expect CPI inflation to be during the specific year, i.e., the current year, 1-, 2- and 5-year in the future. It is therefore different from its qualitative counterparts in which respondents are usually asked whether they expect prices to be up, the same or down, compared to the same time a year ago.[5]

Figure 1 displays the BER inflation expectations at various forecast horizons (one-, two- and five-year) together with actual inflation, overlaid by the SARB's $3-6\%$ inflation target range. Both the inflation expectations and actual inflation exhibit a strikingly high volatility over the 2000-2010 period. From 2010 onwards, the volatility of actual inflation

[3]The BER was commissioned to conduct the survey by the SARB to help carry out its inflation targeting mandate.

[4]This longer horizon expected inflation measure for households was only made available from 2022Q1.

[5]Further methodological details about the survey and related resources can be found at Inflation Expectation Survey.

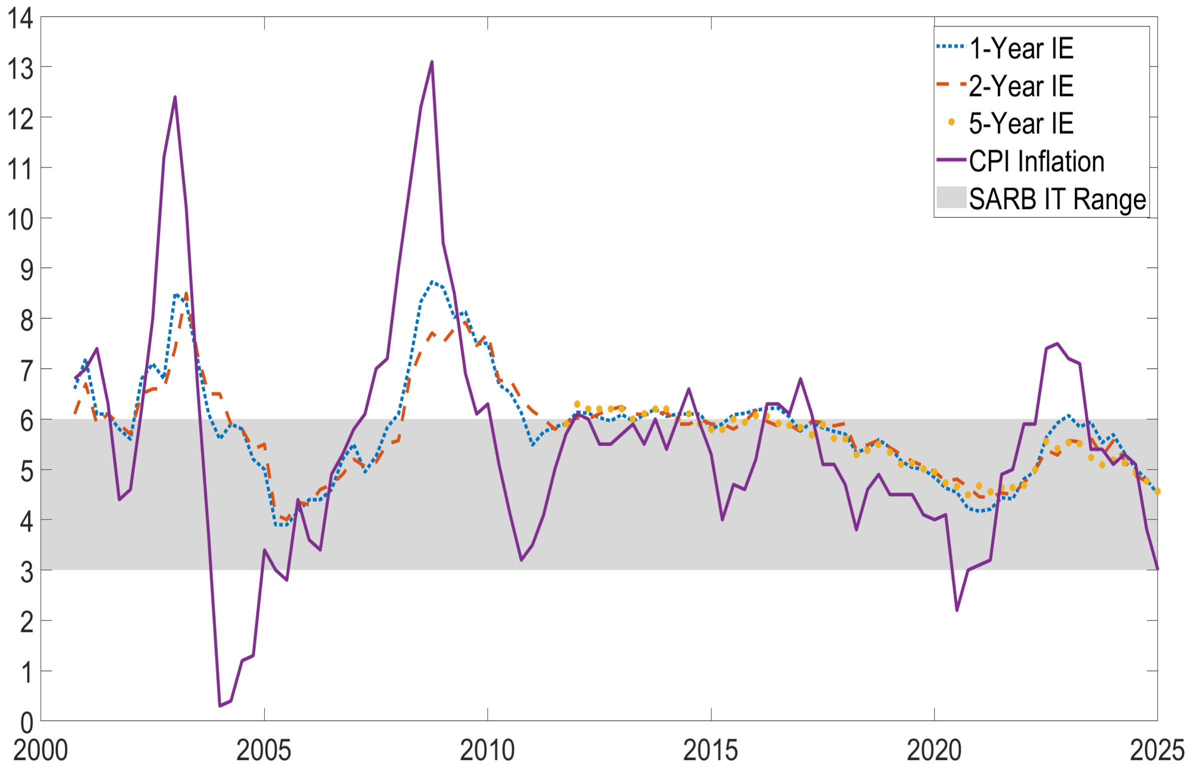

Figure 1: One-, two- and five-year ahead inflation expectations

Note: This figure reports the BER inflation expectations (1-5 year forecasts) over the 2000Q3-2024Q4 period, along with actual CPI inflation and the SARB's 3-6% inflation target range (grey band).

significantly slowed down and mostly remained within the $3-6\%$ range, along with the volatility of the different inflation expectations. This indicates that these expectations have become more anchored and closely tied with the SARB's objective of keeping the headline inflation within the $3-6\%$ range. In addition, despite the short-term volatility of the headline inflation within the target range during the less volatile post-2010 period, the inflation expectations have been quite stable, especially at the 2- and 5-year forecast horizons.

The visual observation that inflation expectations have become more anchored after the Great Recession as monetary policy credibility improved, has been confirmed by evidence from Coco and Viegi (2020), DuRand, Hollander and Van Lill (2023) and Kabundi, Schaling and Some (2019), among others. These works generally highlight how the SARB's monetary policy credibility has increased through communications and forward guidance (Coco and Viegi (2020)), a decline in inflation persistence (Kabundi et al. (2019)) as well as through a lower exchange rate pass through to domestic inflation (Kabundi and Mlachila (2018)) after the Global Financial Crisis, as illustrated in Figure 1. Our identification strategy below crucially relies on anchored inflation expectations and the central bank's credibility, with the post-2010 period in Figure 1 reasonably validating both assumptions.[6]

4 Methodology

This section lays out our empirical approach, including the VAR model specification, the identification strategy, the data to be included in the model, and the estimation steps.

4.1 Model, identification, and data

Theoretically, as in Mumtaz and Theodoridis (2023), long-run inflation expectations π^{LH} are driven by shocks to the central bank's inflation target $\varepsilon_t^{\pi^*}$ and a range of additional shocks $\tilde{\varepsilon}_t$ including technology, policy, and non-policy aggregate demand shocks:

$$\pi^{LH} = f(\varepsilon_t^{\pi^*}, \tilde{\varepsilon}_t) \tag{1}$$

Yet, over the medium- to long-run horizons, the contribution of $\varepsilon_t^{\pi^*}$ is higher in relative terms, compared to the other shocks. Specifically, if the central bank reacts systematically

[6]To support further our identification strategy and address potential concerns about the credibility of monetary policy authorities in emerging market economies, we perform a battery of robustness checks in section 5.2 below.

to changes in inflation and is, at least, perceived to be credible in the long run, then long-horizon inflation expectations would coincide with the inflation target, i.e., inflation expectations would be well anchored in the long-term. As a consequence, any further changes in long-horizon inflation expectations would reflect shocks to the inflation target. In the previous section, we argued that this appears to be the case for South Africa, with inflation expectations increasingly anchored from 2010 onwards.

We use the following VAR framework to approximate these economic disturbances:

$$Y_t = \alpha + \sum_{j=1}^{P} \beta_{t-j} Y_{t-j} + A_0 \varepsilon_t, \tag{2}$$

where Y_t includes a measure of long-horizon inflation expectations $\hat{\pi}^{LH}$ and a set of other endogenous variables with $\hat{\pi}^{LH}$ ordered first (for simplicity). α is a vector of intercepts, P the lag length, ε_t denotes the orthogonal shocks and A_0 is the contemporaneous impact matrix such that $A_0 A_0^{'} = \Sigma$, with Σ being the variance-covariance matrix of the reduced-form error $u_t = A_0 \varepsilon_t$. A_0 is not unique and the space spanned by these matrices can be written as $\tilde{A}_0 Q$ where Q is an orthonormal rotation matrix such that $Q^{'} Q = I$. If we re-write the VAR in equation (2) in structural moving average form, we get

$$Y_t = B(L) A_0 \varepsilon_t, \tag{3}$$

where $B(L)$ is the lag operator defined as the following matrix polynomial: $B(L) = I_K - B_1 L - ... - B_P L^P$, with $B_i,\ i = 1, ..., P$, the $K \times K$ parameter matrices.

The shock to the inflation target is then identified by imposing the restriction that this shock makes the largest contribution to the forecast error variance (FEV) of $\hat{\pi}^{LH}$. The k-period ahead forecast error of the ith variable is given by

$$Y_{it+k} - \hat{Y}_{it+k} = e_1 \left[\sum_{j=0}^{k-1} B_j \tilde{A}_0 Q \varepsilon_{t+k-j} \right], \tag{4}$$

where e_1 is a selection vector that picks out $\hat{\pi}^{LH}$ in the set of variables. The identification scheme thus amounts to finding the column of Q that solves the following maximization problem (Uhlig (2004a)):

$$\arg\max_{Q_1} e_1^{'}\left[\sum_{k=0}^{K}\sum_{j=0}^{k-1} B_j\tilde{A}_0 Q_1 Q_1^{'}\tilde{A}_0^{'}B_j^{'}\right]e_1 \tag{5}$$

subject to $Q_1^{'}Q_1 = 1$, with Q_1 being the column of Q that corresponds to the shock explaining the largest proportion of the FEV of the first variable in the VAR, i.e., $\hat{\pi}^{LH}$, and K the forecast horizon.

Following Uhlig (2004b), one can re-write the maximization problem as an eigenvalue-eigenvector problem:

$$\begin{aligned}\arg\max_{Q_1} e_1^{'}\left[\sum_{k=0}^{K}\sum_{j=0}^{k-1} B_j\tilde{A}_0 Q_1 Q_1^{'}\tilde{A}_0^{'}B_j^{'}\right]e_1 &= \sum_{k=0}^{K}\sum_{j=0}^{k-1} \text{trace}\Big[Q_1^{'}\tilde{A}_0^{'}B_j^{'}(e_1e_1^{'})B_j\tilde{A}_0Q_1\Big] \\ &= Q_1^{'}\Big[\sum_{k=0}^{K}\sum_{j=0}^{k-1}\tilde{A}_0^{'}B_j^{'}(e_1e_1^{'})B_j\tilde{A}_0\Big]Q_1 = Q_1^{'}SQ_1 \end{aligned} \tag{6}$$

where $S = \Big[\sum_{k=0}^{K}\sum_{j=0}^{k-1}\tilde{A}_0^{'}B_j^{'}(e_1e_1^{'})B_j\tilde{A}_0\Big]$. The Lagrangian for this maximization problem is given by

$$L = Q_1^{'}SQ_1 + \lambda(1 - Q_1^{'}Q_1)$$

and the resulting first order condition is $SQ_1 = \lambda Q_1$. This is the definition of an eigenvalue decomposition, with the solution Q_1 being the eigenvector of S associated with the largest eigenvalue λ.

As in Mumtaz and Theodoridis (2023), on top of the long-run inflation expectations variable π^{LH} which is ordered first, the other variables included in the baseline VAR are real GDP y_t which enters the model in log-levels, the end-of-period annualized CPI inflation π_t^a, the 10-year bond yield I_t, and the end-of-period repo rate R_t, which is the SARB policy rate.[7] We use the BER 2-year ahead expected inflation as our benchmark for long-run inflation expectations π^{LH}. Ideally, one would like to use the BER 5-year ahead expected inflation as our preferred baseline variable, but its sample only starts in 2011Q3. Yet, the BER 2-year ahead expected inflation is highly correlated (96.3%) with its 5-year counterpart over the sample period where both measures are available.[8]

4.2 Estimation approach

We use quarterly data over the 2000Q3-2024Q3 period. This sample includes the highly volatile COVID-19 episode with extreme observations recorded in 2020Q1, 2020Q2, 2020Q3, and 2020Q4, which we account for in our estimation strategy. We set the maximum lag length P to the conservative value of 4. In the robustness analyses below, we also experiment with lag lengths of 2 and 3. We estimate the reduced-form VAR in equation (2) using a Bayesian approach and a Markov Chain Monte Carlo (MCMC) Gibbs sampler to approximate the posterior distribution of the parameters.

In particular, as in Mumtaz and Theodoridis (2023) and Bańbura, Giannone and Reichlin (2010), we use the procedure developed by Litterman (1986), i.e., the Minnesota prior, along with a natural conjugate distribution. Specifically, we adopt the version of this prior discussed in Sims and Zha (1998) among others, which entails a random covariance matrix for the reduced-form VAR innovations. The prior specification incorporates the beliefs that the more recent lags should provide more reliable information than the more distant ones, and own lags should explain more of the variation of a given variable than the lags

[7]We check that using quarterly average series of the policy rate and annualized inflation does not affect our findings, as shown in Figure C13. Besides, we refer the interested readers to Mumtaz and Theodoridis (2023) for detailed theoretical and empirical justifications for the choice of the variables included in the model.

[8]Appendix A contains the details of all the variables used in the baseline and additional analyses as well as their data sources.

of other variables in the equation. Hence, the prior means for each endogenous variable are derived from OLS estimates of an AR(1) - for the first lag - and the sum of the lagged dependent variables, using a training sample. The prior tightness parameters are set close to standard values in the literature. To control for the extreme observations witnessed during the COVID-19 pandemic, we follow Cascaldi-Garcia (2024) by extending the prior with time dummies that we adapt to our identification scheme. Given the conjugate prior, we then simulate the conditional posterior distributions of the VAR parameters using the Gibbs sampling algorithm.[9]

5 Results

In this section, we first present the findings of our benchmark analysis, that is the baseline impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) to the inflation target shock, as well as bivariate correlations between this shock and standard business cycle shocks of the South African economy. We then perform a battery of robustness checks to test for the sensitivity of our main findings to various alterations of the baseline model.

5.1 Baseline findings

Figure 2 below shows the posterior median IRFs to a negative inflation target shock, along with the 68% error bands. An announcement by the central bank to lower the inflation target by one percentage point (1ppt) decreases long-horizon inflation expectations, as the monetary authority is deemed credible. This effect of the shock on inflation expectations persists for 11 quarters while reaching a trough of about -1.20% after 3 quarters. As one would expect, lower inflation expectations in turn result in a decrease in both actual

[9] We provide further details about the estimation in Appendix B.

inflation and the repo rate, i.e., the SARB short-term nominal policy rate. Because of nominal frictions in the short-run, inflation falls faster than the decline in the policy rate following the adverse inflation target shock, leading to a short-term increase in the real interest rate that lasts for a year with an impact response of about 1.70%. The larger decrease in inflation compared to the policy rate is a feature also observed in Mumtaz and Theodoridis (2023) and Lukmanova and Rabitsch (2023).[10] As a result, the level of output briefly contracts on impact, yet this short-lived contraction, referred to as the "sacrifice ratio", is not statistically significant. This muted output response echoes Pirozhkova and Viegi (2023)'s finding according to which the target shock has no negative effect on real output. Then, from one year after the shock, which also corresponds to the end of the real interest rate increase, output expands over the next few quarters, peaking at roughly 1.20% after about two years and remains positive and statistically significant for nearly three years before becoming non-significant.[11] Our output expansion finding is in line with Uribe (2022). Besides, output being demand driven in the short-run, the reduced real rate after a year has likely contributed to higher aggregate demand as we show later in section 6 where we investigate the transmission channels of the inflation target shock. Moreover, the long-term interest rate proxied by the 10-year sovereign bond yield temporarily decreases by approximately 0.80% on impact but is less persistent than the short-term interest rate. Remarkably, our findings show that a shift in the inflation target that translates into a persistent change in inflation expectations, causes a short- and medium-term positive co-movement of actual inflation and the policy rate, akin to Neo-Fisherian effects. This

[10]The large effects on inflation appear to be driven by goods inflation as can be seen in Appendix D4.

[11]These output level's dynamics are qualitatively similar to the ones observed for output growth when we re-estimate the baseline model with real GDP growth, as can be seen in Appendix C10.

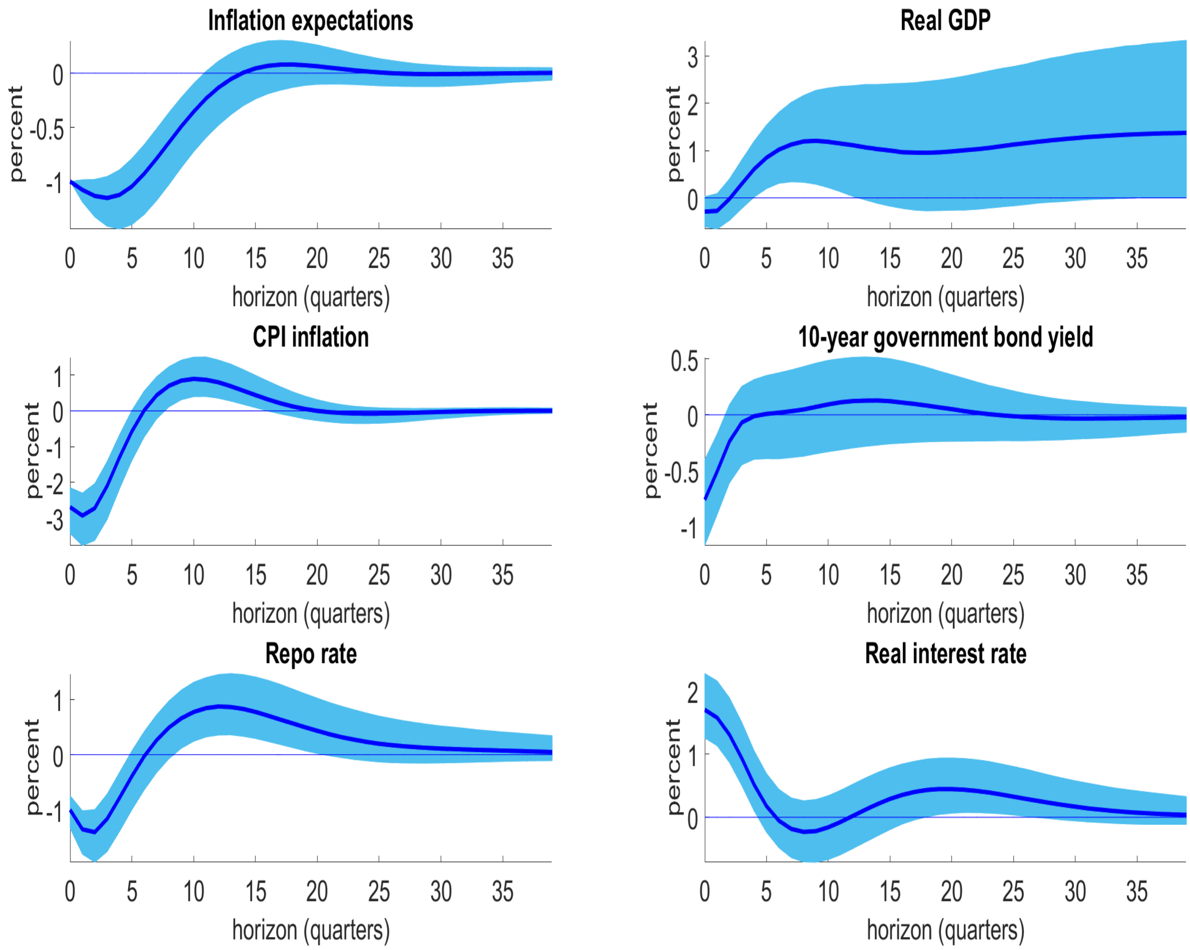

Figure 2: Baseline IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs (solid blue lines) of the benchmark model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

is qualitatively similar to evidence in Lukmanova and Rabitsch (2023), Mumtaz and Theodoridis (2023), Uribe (2022) and Garín, Lester and Sims (2018) among others, that analyze the effects of long-lasting monetary innovations including inflation target shocks.

However, unlike findings in the literature whereby the effects of inflation target shocks are persistent (Mumtaz and Theodoridis (2023) and Lukmanova and Rabitsch (2023) for the US, and De Michelis and Iacoviello (2016) for Japan), we find that they are less persistent for the South African economy. In particular, Mumtaz and Theodoridis (2023) find these effects to be highly persistent (i.e., at least 40 quarters) for inflation expectations, actual inflation, the short-term policy rate and the long-term interest rate, whereas we find the responses of the same variables to the inflation target shock to last for about 2 to 11 quarters only.[12] This finding suggests that the amplification mechanism of the shock is different depending on whether the investigation is conducted on developed or emerging countries. Our less persistent shock effects hence appear to provide a case that may be relevant for other emerging market economies. Lastly, Figure D2 in Appendix shows the structural inflation target shocks over the sample period. One can notice that they reflect quite well the lower volatility patterns observed in the data from 2010 onwards, as well as the recent post Covid-19 inflation surge and the higher inflation recorded during the Great Financial Crisis.

Figure 3 displays the contribution of the inflation target shock to the forecast error variances (FEV) of the baseline model's variables. By construction, the shock explains the bulk of the FEV of long-run expected inflation, with its highest contribution estimated to be over 92% at the 5-quarter horizon. Similarly to Mumtaz and Theodoridis (2023), our model suggests the shock contributes about only 7% to the FEV of output and just below 61% to

[12]To rule out suspicions that the less persistent effects of our inflation target shock could be due to our shorter sample, we re-estimate the model with Mumtaz and Theodoridis (2023) US data sample curtailed to 100 observations - ours is 98 - over the 1968-1992 period. The resulting IRFs still display much higher persistence compared with ours, despite a similar sample size. These IRFs are available upon request, we do not report them here in the interest of space.

that of inflation at the 2-year horizon. Its contribution to the FEV of the nominal policy rate is also substantial at short and medium forecast horizons, yet about twice less than inflation's volatility, with a peak contribution of just below 40% after about two quarters. These important contributions of the inflation target shock to the FEV of inflation and the policy rate are qualitatively in line with similar predictions in Uribe (2022) who finds that permanent non-stationary monetary shocks comparable to our inflation target shock, are a relevant source of movements in nominal variables. We also reach a similar conclusion when examining the contribution of the inflation target shock to the historical fluctuations of those two nominal variables as shown in Appendix D3. This figure plots the endogenous variables' detrended data along with their model-implied estimates based on the contributions of inflation target and non-inflation target shocks. Finally, the inflation target shock explains on average only 10% of the FEV of the 10-year government bond yield in the short-and medium-run, which is corroborated by the important contribution of the non-inflation target shocks to the historical fluctuations of this variable as illustrated in Appendix D3. This small contribution of the inflation target shock to the observed fluctuations in South Africa's long-term interest rates contrasts with Mumtaz and Theodoridis (2023)'s finding for the US whereby the inflation target shock is shown to have contributed substantially to the persistent decline observed in the 10-year US government bond yield.

5.2 Robustness analyses

In a first robustness exercise, we follow the now standard practice in the literature for partially identified shocks such as ours, and compute the bivariate cross-correlations between our estimated inflation target shock and each of a set of other structural shocks identified as being important for business cycle fluctuations. As Figure 4 below shows, these shocks

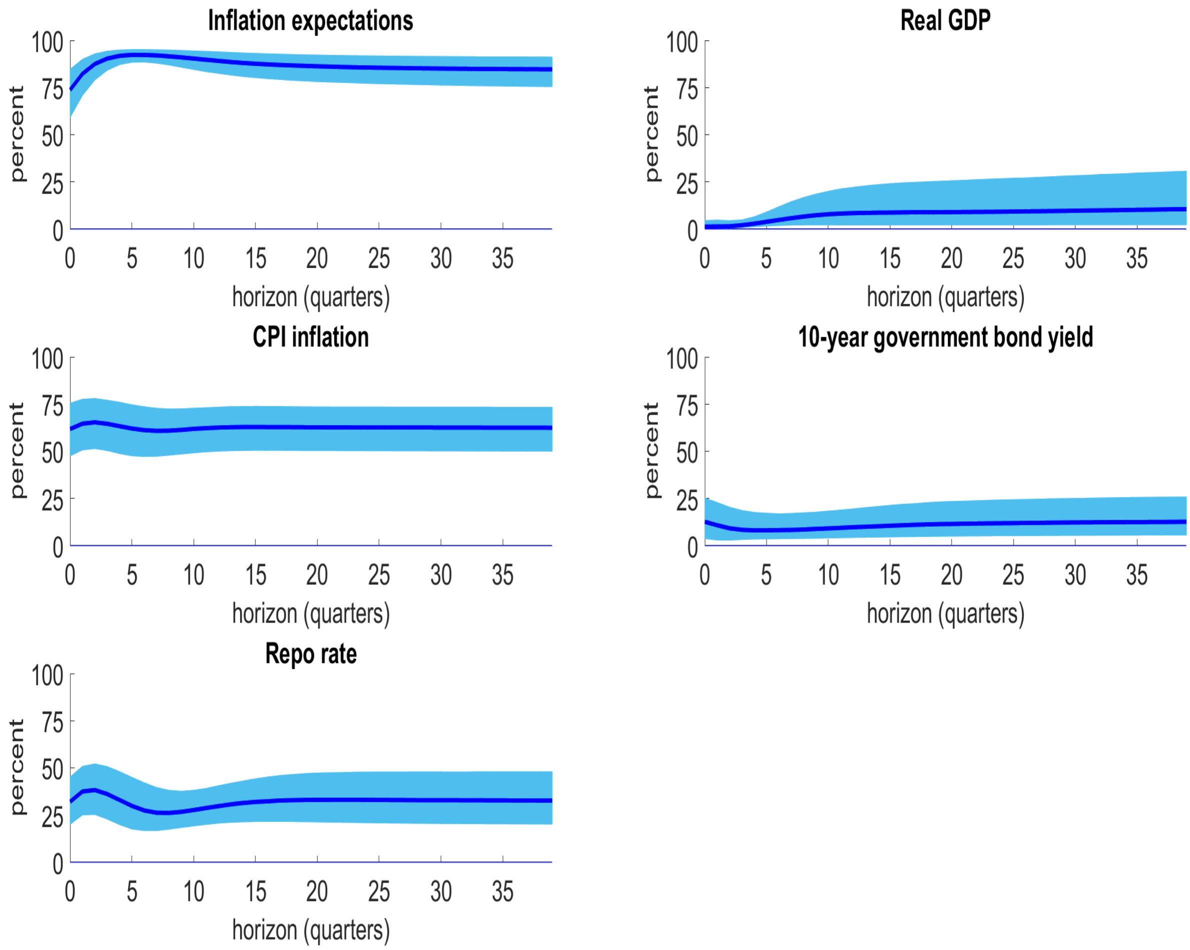

Figure 3: Baseline FEVDs to an inflation target shock

Note: This figure displays the median contributions (solid blue lines) of the inflation target shock to the FEV of the benchmark model variables, along with the 68% credible sets (blue error bands).

include innovations to monetary and fiscal policies, aggregate demand, oil, exchange rate, as well as uncertainty shocks, identified in various studies as significant for economic fluctuations in South Africa. In particular, monetary policy innovations are obtained using an adapted version of Romer and Romer (2004)'s approach as implemented in Merrino

(2022) for South Africa. Aggregate demand shocks are recovered from long-run identification restrictions in a bivariate VAR with gross national income and the unemployment rate following Blanchard and Quah (1989), with innovations in the unemployment rate used as proxy for aggregate demand shocks. Government spending and revenue shocks are estimated using the seminal three-variable structural VAR model of Blanchard and Perotti (2002), whereas the nominal bilateral Rand-US dollar exchange rate is used to estimate Rand shocks which are recovered from a sticky price monetary model developed by Dornbusch (1976), incorporating both short- and long-run determinants of exchange rate dynamics as in Frankel (1982).[13] Global oil price shocks are sourced from Baumeister (2023), and to retrieve the uncertainty shocks, we make use of the World Uncertainty Index (WUI) for South Africa and estimate a recursive SVAR as in Baker, Bloom and Davis (2016) with the following ordering: the WUI for South Africa, the JSE index, the repo rate, employment and the industrial production index.[14] Interestingly, Figure 4 shows not-statistically-different-from-zero weak correlations between our estimated inflation target shock and each of these other structural shocks at various leads and lags, despite our partial identification strategy. This serves as a strong evidence that our target shock is distinct from standard policy and non-policy innovations shown to be important for the South African economy.

In a second robustness test, we provide additional support for our identified shock and baseline findings. For that we identify the inflation target shock using a Cholesky identification scheme with the inflation expectations variable ordered first, followed by real

[13]The sticky price model builds on the the flexible price model of exchange rates with their fundamental determinants linked to money supply, real income and interest rate differentials. We augment the model with the South Africa's sovereign credit risk premium and gold price given that the Rand is considered a commodity currency (Ndlovu and Schaling (2018), Schaling, Ndlovu and Alagidede (2014), Sayed and Charteris (2022)). The model assumes purchasing power parity and uncovered interest rate parity hold at all times.

[14]The JSE index is the Johannesburg Stock Exchange price index for all shares.

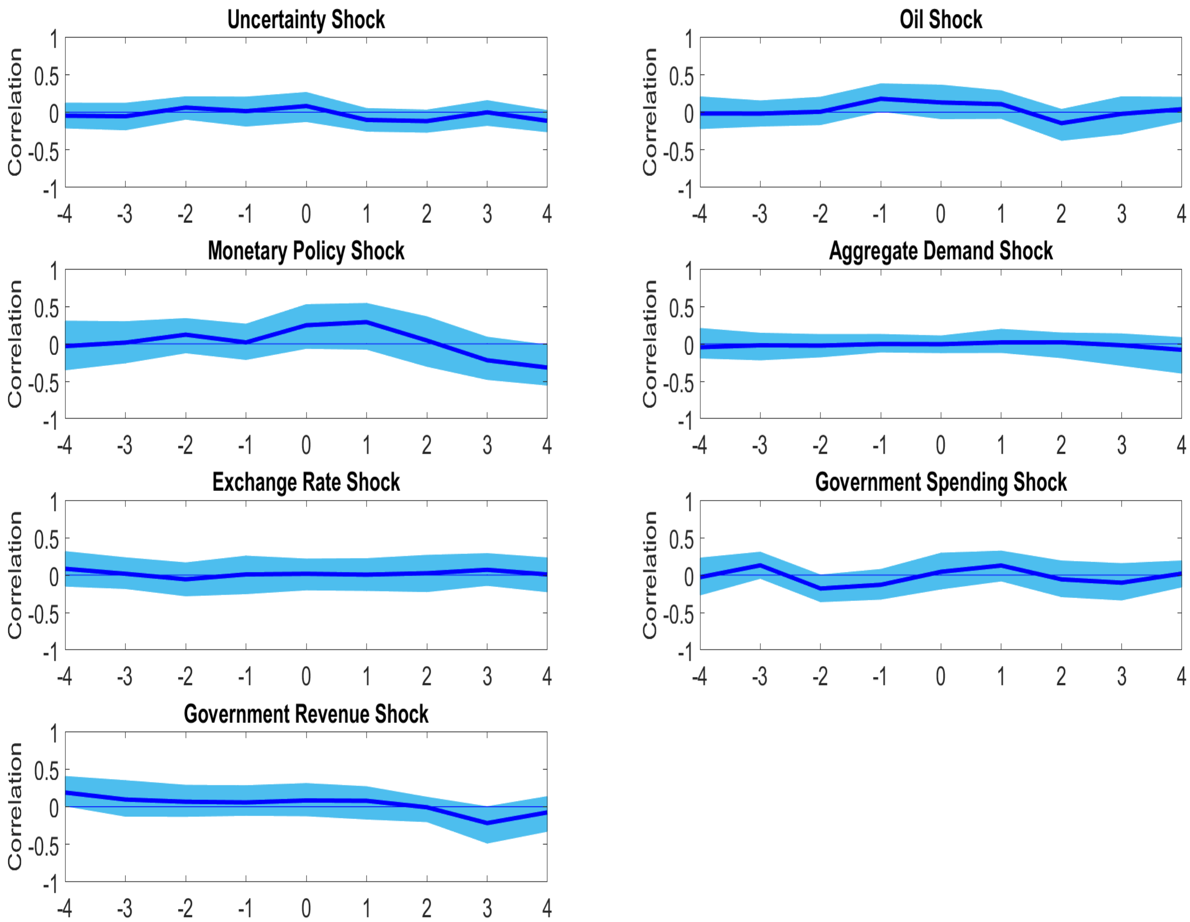

Figure 4: Correlations between the target shock and other structural shocks

Note: This figure displays the median correlations (solid blue lines) between the structural target shock and standard business cycle shocks of the South African economy, along with the 95% confidence intervals (blue error bands) obtained via bootstrap.

GDP, CPI inflation, the 10-year bond yield and the repo rate. As in the baseline setting, an inflation target shock is one that moves inflation expectations on impact. The model is then estimated using Bayesian methods with the same Minnesota-like conjugate distributions for the prior and posterior and a Gibbs sampler as before.[15] As can be seen in Figure 5 below, employing this alternative identification strategy generates IRFs that are qualitatively close to those in our baseline model. Importantly, one can notice that the IRFs from the Cholesky identification approach are not only in line with those in the baseline setting, but also mimic quite closely the less persistent effects of our inflation target shock identified using the Max Share identification strategy, hence lending support to our previous conclusion that the less persistent effects of the inflation target shock appear as a specific feature of the South African economy.

In another alternative identification robustness check, we proceed to identifying the inflation target shock using a state of the art identification scheme, that is Antolín-Díaz and Rubio-Ramírez (2018)'s narrative sign restrictions, shown to substantially minimize endogeneity and identification issues while also being highly informative about the shock of interest. In particular, we use as narrative restriction the announcement by the SARB in July 2017 of a change in its inflation target definition from the 3 - 6% range to the mid-point of the range, i.e., 4.5%. Before this announcement, the SARB's Monetary Policy Committee (MPC) expressed concerns that actual CPI inflation remained *"uncomfortably close to the upper end of the target range"* over the past few quarters prior to 2017Q3.[16] We therefore impose our narrative restriction over the 2017Q1-2017Q3 period, along with the

[15]In this specific experiment, we restrict our data sample to the 2000Q3-2019Q4 pre-Covid-19 period for simplicity, as Lenza and Primiceri (2022) show that dropping the Covid-19 episode extreme observations is acceptable for the purpose of parameter estimation and leads to the same inference as with the full sample including the highly volatile Covid-19 observations as in our baseline exercise. We check that this is effectively the case by re-estimating our baseline model using the pre-Covid-19 sample. Moreover, while we set some of the hyperparameters, namely the prior tightness parameter on the VAR's first lag coefficients and the one on the sum of the coefficients of the lagged dependent variables as in the baseline model, we choose the remaining hyperparameters to maximize the marginal density of the sample data (without loss of generality), and estimate the model using Ferroni and Canova (2025)'s toolbox.

[16]These concerns are relentlessly expressed in the MPC Statements released in January, March, and May 2017, among other prior statements (SARB's MPC statements)

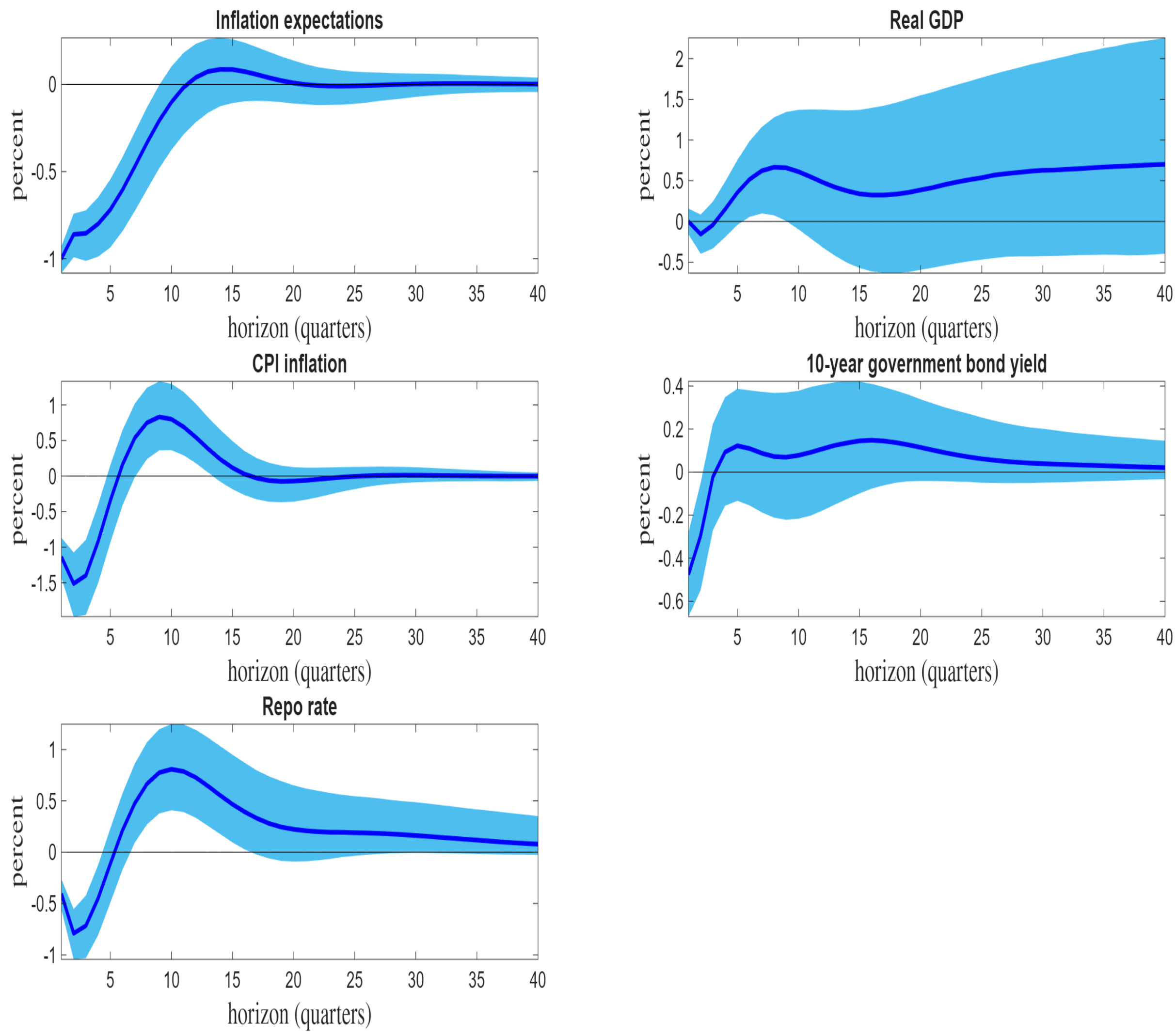

Figure 5: Cholesky identification's robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs (blue lines) for the robustness model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

additional sign restrictions that a positive inflation target shock leads to a positive impact (only) response for inflation expectations, CPI inflation, and the Repo Rate.[17] As in the

[17]We also obtain very similar results when we impose the narrative restriction only on 2017Q2 and 2017Q3.

previous robustness test, we also restrict our data sample to the 2000Q3-2019Q4 pre-Covid period and use the same Bayesian estimation settings. As can be seen in Figure C11 in Appendix C, imposing these narrative sign restrictions results in IRFs that are qualitatively close to those in our baseline model, though output response remains non-significant. In addition, as with the previous Cholesky identification scheme, one can notice that the IRFs from the narrative sign identification approach also mimic quite closely the less persistent effects of our inflation target shock identified using the Max Share identification strategy, hence lending an even stronger support to our previous conclusions that the inflation target shock is plausibly well identified and its less persistent effects appear as a specific feature of the South African economy.

Finally, we also test the sensitivity of our benchmark model to various other features, including changes in model specification (e.g., baseline model with 2 or 3 lag-lengths, alternative priors, etc.), different proxy variables (including other survey or non-model- and model-based inflation target series), and additional variables to the baseline, among others. As shown in Appendix C, these various sensitivity exercises do not significantly affect our baseline model's findings, an exception being the experiment whereby trend inflation is used as a proxy for inflation expectations, leading to a more persistent GDP response.

In these exercises, we follow Ferroni and Canova (2025) and use a version of the narrative sign identification approach that restricts structural parameters so that the structural shocks are of a particular sign for the narrative dates. Besides, Patel and Peralta-Alva (2025) provide evidence that these specific forms of narrative restrictions are less affected by the problem of foresight and invertibility; they argue that the quantitative importance of this problem is likely to be limited in settings such as ours that combine narrative and sign restrictions, relative to using the narrative events or shocks directly.

6 Transmission channels of inflation target shocks

In the previous section, we have shown that a lower inflation target for South Africa would entail a short-lived yet non-statistically significant contraction in output, before it sustainedly grows over time for about two years. In this section, we investigate through which channels these effects of the inflation target shock on the economy are transmitted. We perform these analyses by means of the traditional transmission channels as well as others that are relevant for small open economies, and relate them to the standard monetary policy shock transmission mechanism.

6.1 Interest rate and other asset prices channel

To understand some of the ways the inflation target shock affects the South African economy, we begin with the investigation of its effects through the real interest rate and other asset prices channel.[18] In the traditional direct interest rate channel, a contractionary monetary policy leads to a rise in real interest rates which raises the user cost of capital, thereby reducing spending and aggregate demand. However, our lower inflation target shock in Figure 6 implies a higher real rate with opposite effects. First, while a lower target leads to a decrease in inflation and the policy rate as one would expect, this does not translate into a lower real interest rate as suggested by the standard direct interest rate channel. Instead, the higher real interest rate implied by the inflation target shock, appears to suggest a

[18] In the standard monetary policy transmission mechanism whereby the central bank has direct control over a short-run policy rate, nominal wage and price rigidities imply that adjustments in the nominal policy rate not only directly affect the real interest rate, but also the values of other assets via the real rate, including stock and house prices, thereby influencing consumption and investment spending and hence aggregate demand. This channel operates through the user cost of capital and the closely related Tobin's q for investment, and through wealth and intertemporal substitution effects for consumption. Extensive details about the standard monetary policy transmission channels can be found in Boivin, Kiley and Mishkin (2010).

strong positive impact on asset prices, namely stock and house prices, with their real values remaining significantly above zero for about 20 quarters and 12 quarters, respectively. We interpret these asset price booms in light of the downward shift of the inflation target. The lower target reduces expected future inflation, which boosts investors' confidence and increases demand for assets, raising their values. These higher asset values may also have had an indirect mitigation effect that explains the muted output initial response and therefore the insignificant sacrifice ratio. These effects are also reminiscent of Pirozhkova and Viegi (2023) who show that the SARB 2017 target change led to non-negative output growth via a positive effect on asset prices.

Consistent with wealth and intertemporal substitution effects (Ando and Modigliani (1963)), investment and consumption spending by firms and households increases as a consequence of the higher asset values. In particular, the rise in the level of consumption peaks at 2.35% after 7 quarters, is more persistent and remains elevated for about 15 quarters. However the increase in the level of investment is transient, suggesting that the channel is stronger via consumption spending. In the context of South Africa, other studies that have highlighted the strong linkages between household spending and asset prices include Ncube and Ndou (2011) and Apergis, Simo-Kengne and Gupta (2014). However the muted response of investment during the first year, which coincides with the similar output reaction following the rise in the real rate, suggests the presence of a direct yet weaker interest rate channel via the user cost of capital, which may have contributed to the delayed effect on aggregate demand.

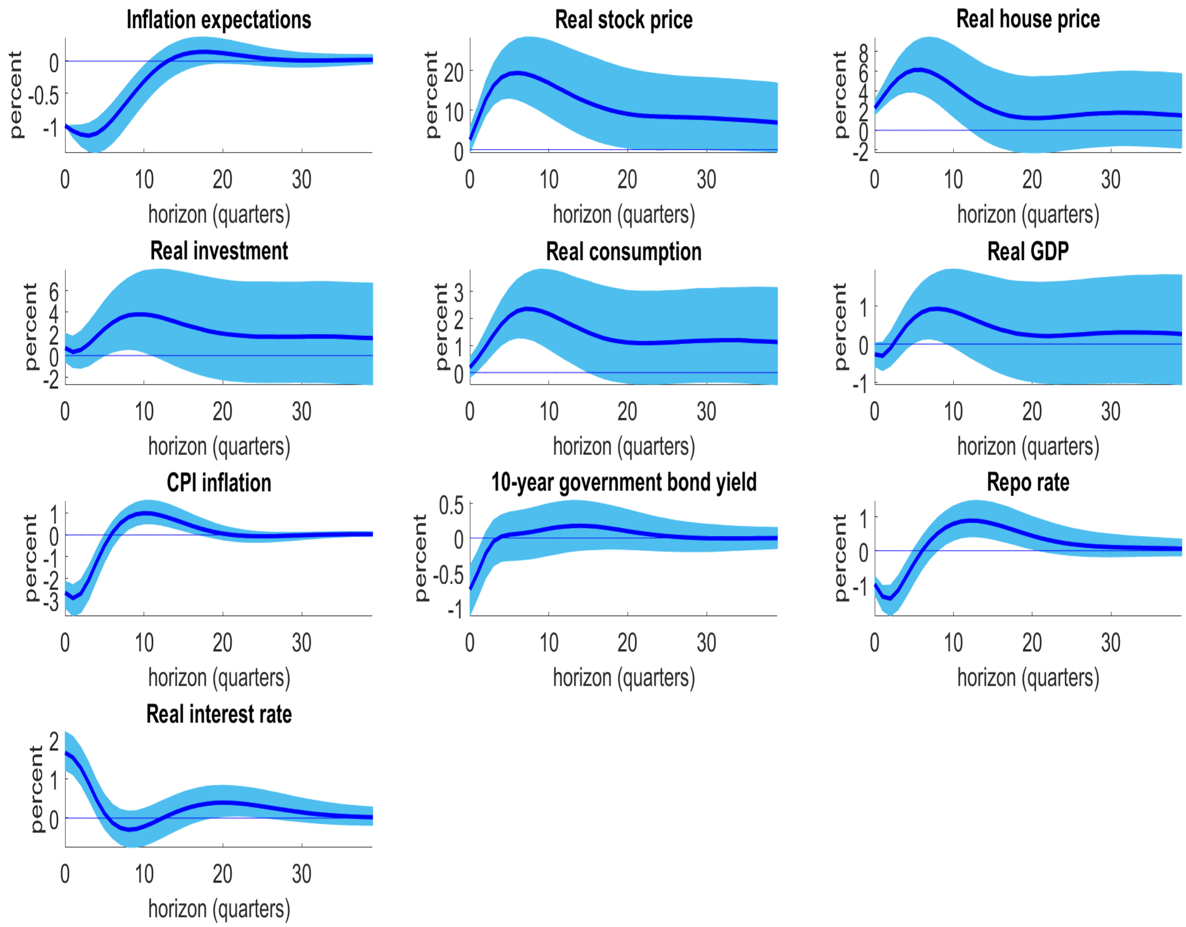

Figure 6: Interest rate and other assets price channel's IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs (solid blue lines) of the model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

6.2 Exchange rate channel

Figure 7 below illustrates how a downward shift in the inflation target affects net exports through variations in the exchange rate. As one can notice, lowering the inflation target by 1% will cause the real exchange rate to increase in the short-term but this increase is mostly not statistically significant. Similarly to the traditional exchange rate channel, the effect of a lower inflation target also operates through interest rate dynamics, with the rise in the real interest rate implying an appreciation of the rand, which then results in a fall in net exports. This is shown by the decline in the trade balance-to-GDP ratio that lowers aggregate demand, though the response is not statistically different from zero. This in turn suggests that the exchange rate channel may not be that strong within our setting. However, small open economies usually tend to see larger effects via this channel.[19]

One possible explanation for this weak exchange rate channel is that increased monetary policy credibility has helped reduce the pass-through of exchange rate movements to inflation, thereby mitigating their effects on the trade balance (Kabundi and Mbelu (2018), Kabundi and Mlachila (2018), Miyajima (2020)).

6.3 Credit channels: the balance sheet channel

The balance sheet channel arises from the presence of asymmetric information in credit markets, i.e., adverse selection and moral hazard problems, both of which are exacerbated when households' and firms' net worth falls. In particular, lower net worth means that the borrowing agents have less collateral, which not only increases adverse selection but also the incentive to take more risk, thus worsening the moral hazard problem. As a consequence, lenders tend to tighten access to credit by reducing loan supply or demanding a higher risk premium.

[19] Our measure of exchange rate is the real effective exchange rate which is obtained as a weighted average of the Rand relative to a basket of currencies from South Africa's major trading partners. We also check in Appendix D1 that our finding is unchanged when we make use of the ZAR/USD exchange rate, the US Dollar being the main currency for international trade.

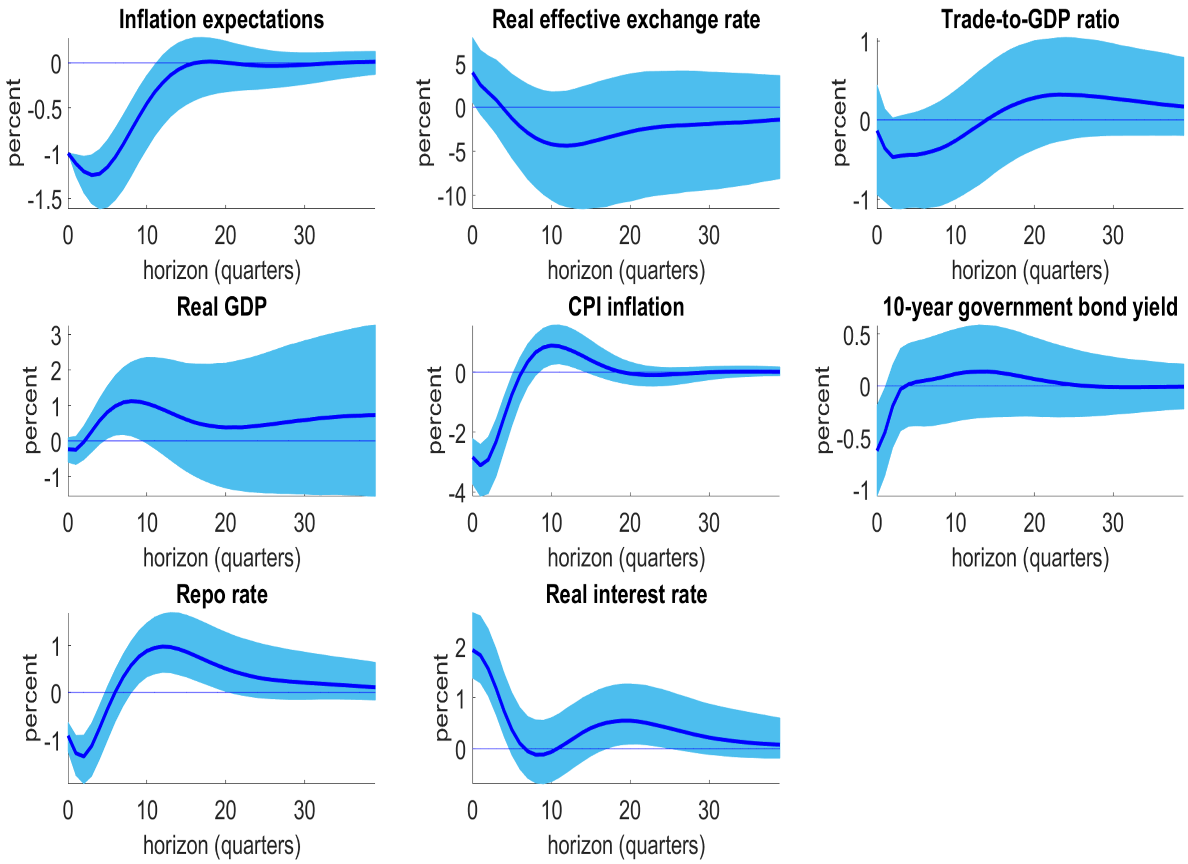

Figure 7: Exchange rate channel's IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs (solid blue lines) of the model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

Figure 8 provides some evidence of an operative balance sheet transmission channel of the inflation target shock. As in Figure 6, real equity and house prices increase in response to a reduction in the inflation target. Higher asset prices increase borrowers' net worth, leading to an increase in the value of the collateral they can provide to the lenders, thereby reducing adverse selection and moral hazard-related agency problems in credit markets.

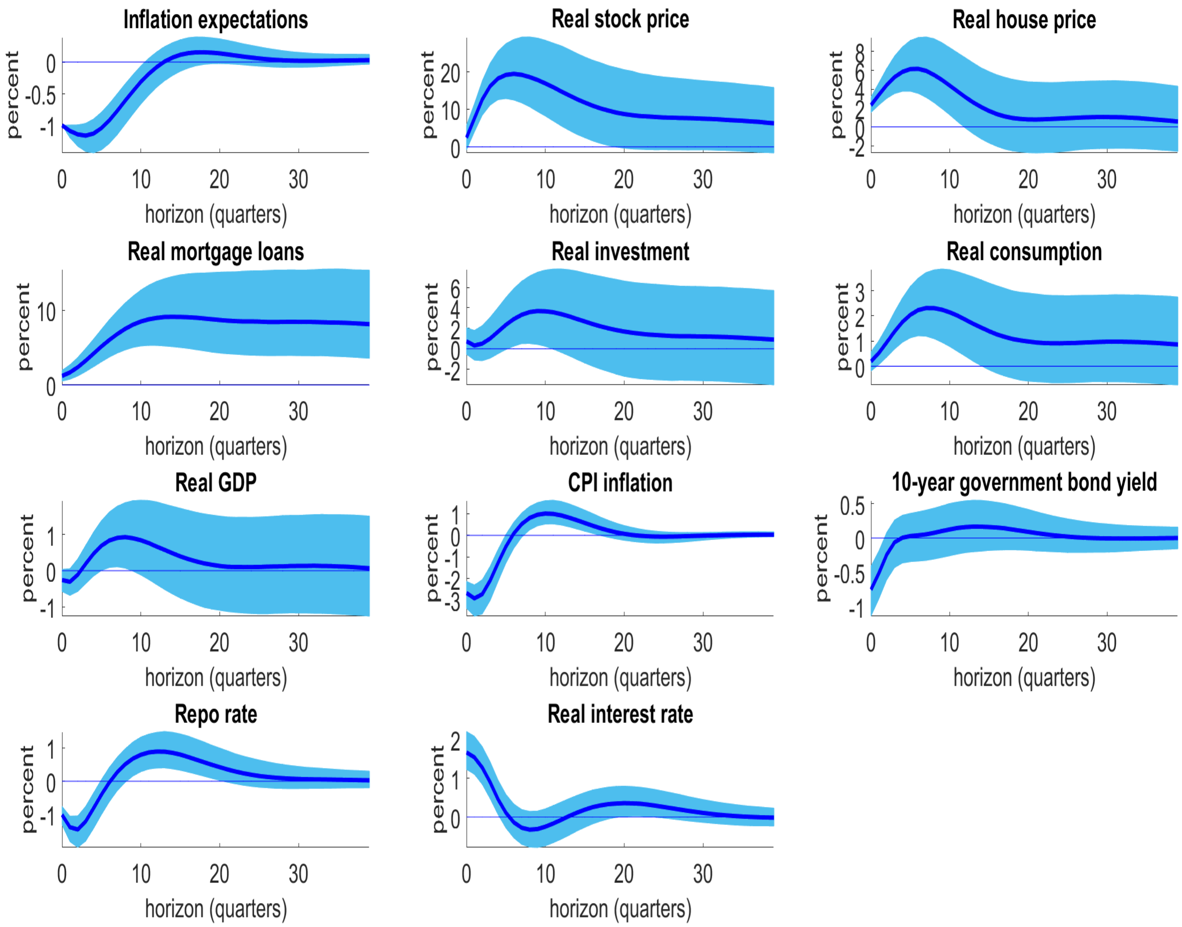

Figure 8: Balance sheet channel's IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs (solid blue lines) of the model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

This in turn leads to a lower external finance premium (Bernanke and Gertler (1989)) and increases loan demand. In particular, one can see from Figure 8 a large and persistent increase in real mortgage loans for credit-dependent firms and households, supporting higher spending and aggregate demand.[20]

6.4 Sovereign risk premium channel

Figure 9 illustrates the sovereign credit risk premium channel for the transmission of monetary policy shocks following evidence in Cantero-Saiz, Sanfilippo-Azofra, Torre-Olmo and López-Gutiérrez (2014) and Cantero-Saiz, Sanfilippo-Azofra and Torre-Olmo (2022). These papers show that banks in countries with a high sovereign credit risk reduce their loan supply relatively more when monetary policy tightens because elevated sovereign credit risk increases the cost of funding for banks. In the same vein, Olds and Steenkamp (2021) show that the increase in bank funding costs in South Africa during the COVID-19 crisis can be partly attributed to an increase in sovereign credit risk. In this context, we test the sovereign credit risk channel operating through the bank lending channel.[21] Our main variables include the debt-to-GDP ratio, credit default swap (CDS), and mortgage loans which captures the bank lending channel. The median IRFs show that a lower inflation target causes a sustained and persistent decline in the debt-to-GDP level after an initial short-lived positive impact of about 2.5% that lasted for a year. The sustained lower debt-to-GDP ratio translates into a decrease in the sovereign credit risk premium over 8 quarters as illustrated in the dynamics of the CDS, resulting in a strong and persistent increase

[20] We use mortgage loans because they represent a large share of household assets, and changes in house prices can affect household inter-temporal decisions on consumption and savings. In addition, the housing market plays a key role in business cycle fluctuations (Leamer (2007), Iacoviello and Pavan (2013), and Aye, Balcilar, Bosch and Gupta (2014) for South Africa). Data from the SARB show that home loans account for 58% of all extended credit. Besides, the banking sector alone accounts for over 90% of the home loans issued (Pirozhkova and Viegi (2024)).

[21] According to this channel, contractionary monetary policy affects the balance sheet health of banks, through its impact on leverage, profitability and asset quality; this in turn affects their marginal cost of funding given that banks also use market-based funding to credit extension, where credit risk matters. Key references on the bank lending channel include Bernanke and Blinder (1992), Kashyap and Stein (2000), Bernanke and Gertler (1995), Bernanke (2007), and Disyatat (2011), among others.

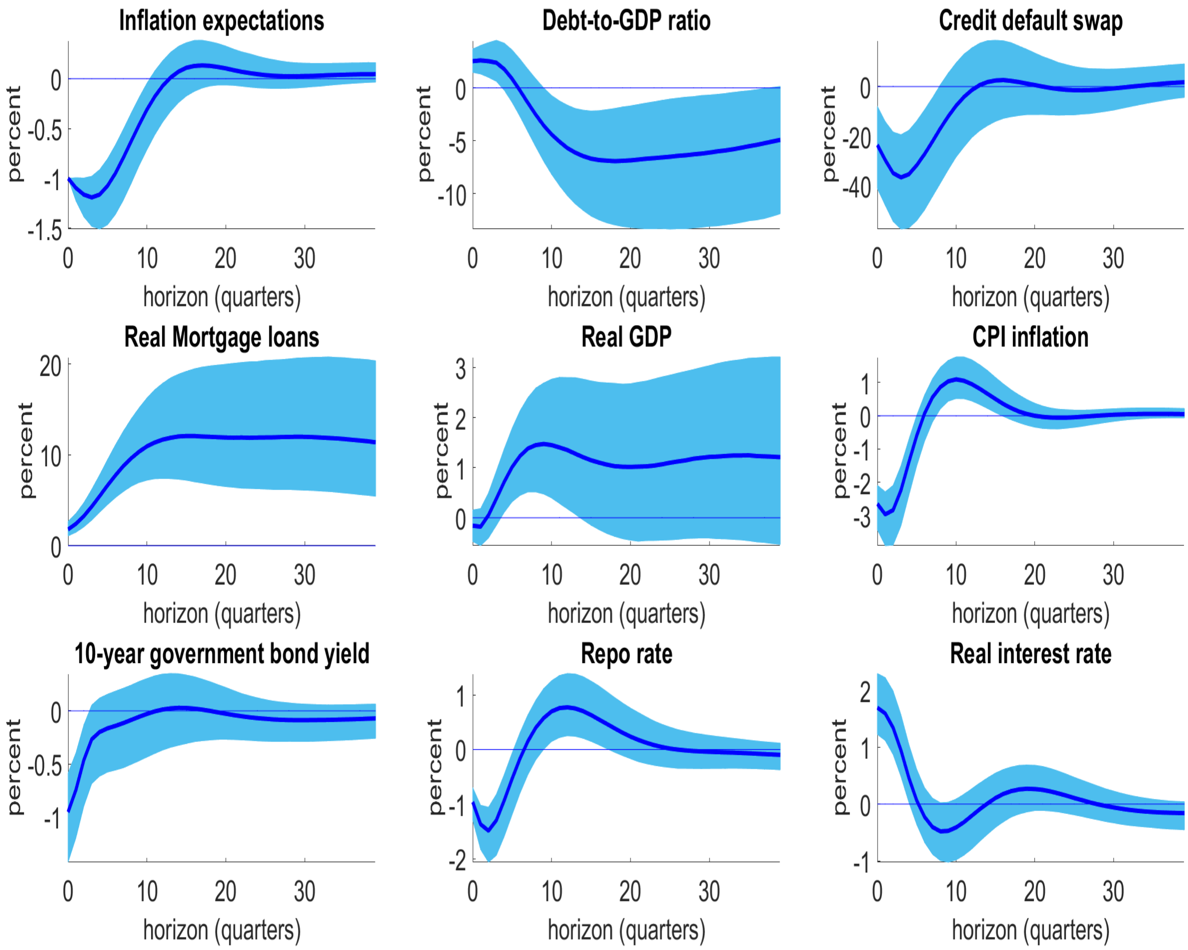

Figure 9: Sovereign debt risk premium channel's IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs (solid blue lines) of the model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

in mortgage loans. These results suggest that a lower inflation target will contribute to a reduction in South Africa's credit risk premium, which is also in line with Pirozhkova and Viegi (2023). The lower credit risk premium results in lower bank funding costs, therefore encouraging an increase in credit extension which in turn supports economic activity.

7 Conclusion

In summary, we identify shocks to the SARB's implicit inflation target as SVAR innovations that explain most of the forecast error variance of medium-term inflation expectations. We find that lowering the target leads to output growing over three years, driven by aggregate demand, and a co-movement of inflation and the repo rate akin to Neo-Fisherian effects, a feature also evidenced in other similar studies. Moreover, the inflation target shock substantially contributes to the fluctuations of both inflation and the policy rate. This latter feature along with the Neo-Fisherian effects, together imply that a central bank pursuing a lower inflation target in a context of high inflation and inflation expectations would need to devise a contractionary monetary policy by initially raising its policy rate in order to reverse inflation and inflation expectations' dynamics. As both of them decrease and agents increasingly learn about the lower inflation target, the policy rate would subsequently decrease as well.

Unlike findings on advanced economies whereby the effects of the target shock are persistent, we find that they are less persistent for South Africa with this finding being robust to alternative identification schemes including narrative restrictions. Moreover, the South African inflation target shock contributes only marginally to fluctuations in the country's long-term interest rates, in sharp contrast with findings for the US in which the target shock is shown to have significantly contributed to the persistent decline observed in the 10-year government bond yield. This implies that the often-cited gains linked with permanent lower borrowing costs may not apply to the South Africa economy. Together, all these findings suggest that the amplification mechanism of the inflation target shock may be different depending on whether one is dealing with developed or developing/emerging economies, implying different policy responses. In particular, our finding that innovations other than the inflation target shock contributed more substantially to fluctuations in South Africa's long-term government bond yield, appears to suggest that lowering the target might not necessarily lead to lower borrowing costs, especially in a context of rapidly increasing public debt with other factors offsetting the effects of the lower target.

Finally, an analysis of the transmission mechanism of the target shock to the economy reveals strongly operative sovereign credit risk and asset price channels. Meanwhile, the exchange rate channel is weakly operative, owing to increased central bank credibility that helped to reduce the pass-through of exchange rate movements to inflation, thereby mitigating their effects on the trade balance. The sovereign risk premium channel may be particularly relevant for developing and emerging markets where sovereign credit risks tend to be elevated compared to developed economies, especially with the increasing frequency of global shocks.

More work is needed to investigate further the effects of inflation target shocks and their transmission channels, particularly for developing and emerging economies, with a special attention to unanchored inflation expectations and the credibility concerns about their monetary authorities. One may also want to analyze how nominal and real variables in inflation targeting developing and emerging economies are affected by external or global shocks, including, e.g., US monetary policy shocks' spill-overs, the heightened uncertainty induced by Trump's trade wars or the recent geopolitical tensions.

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Appendix

Appendix A Data details

Table A1: Variables description and data sources

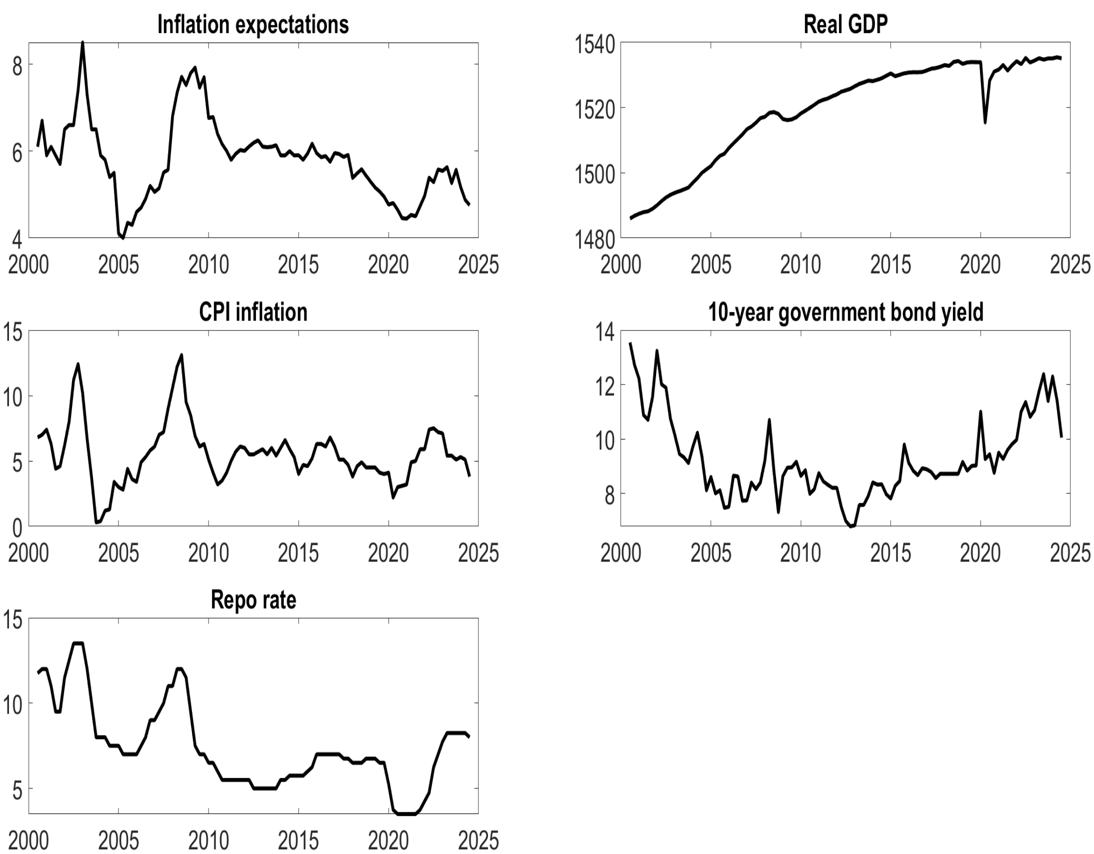
Name	Description	Source
Real GDP	Gross domestic product at constant prices	Statistics South Africa (Stats SA)
GDP deflator	Ratio of nominal GDP to real GDP	Stats SA
Debt-to-GDP ratio	Total government gross loan debt as a ratio of GDP	SARB Quarterly Bulletin
CPI inflation	Year-on-year growth rate in consumer price index	Stats SA
Trend CPI inflation	9-quarter moving average of CPI inflation rate	Authors calculations and Stats SA
ZAR/USD exchange rate	Rands per US dollar exchange rate	Bloomberg
REER	Real effective exchange rate	SARB Quarterly Bulletin
Oil price	Brent crude oil price (US$ per barrel)	Bloomberg
Repo rate	Repurchase rate (SARB policy rate)	SARB Quarterly Bulletin
10-year government bond yield	South Africa sovereign fixed bond yield	Bloomberg
JIBAR	3-month Johannesburg interbank rate	Bloomberg
JSE index	Johannesburg stock exchange index (all shares)	Bloomberg
House price index	FNB average house price index	S&P Global
Private investment	Gross fixed capital formation by private enterprises	Stats SA
Inflation expectations	BER survey-based measure of inflation expectations	BER
Business confidence index	Composite RMB/BER Business Confidence Index	BER
Consumer confidence index	FNB/BER Consumer Confidence Index	BER
Mortgage loans	Mortgage advances extended to the private sector	SARB Quarterly Bulletin
CDS spread	5-year credit default swap (CDS) spread	Bloomberg
Consumption expenditure	Final household consumption expenditure	Stats SA
Durable goods expenditure	Final household consumption expenditure for durable goods	Stats SA
Trade balance	Total export minus toal imports at constant prices	Stats SA
Bank loans	Total bank balance sheet - Assets: Total loans and advances to customers	SARB BA100 data
Bank deposits	Total bank balance sheet - Liabilities: Deposits, current accounts and other creditors	SARB BA100 data

Table A2: Decriptive statistics (2000Q3-2024Q3)

Variables	Observations	Standard deviation	Skewness	Kurtosis
Inflation expectations	97	0.900	0.512	3.324
Real GDP	97	15.289	-0.840	2.386
CPI inflation	97	2.278	0.860	4.973
10-year government bond yield	97	1.473	0.913	3.274
Repo rate	97	2.490	0.730	2.912

Note: This table shows the summary statistics of the variables used in the benchmark model

Figure A1: Time series plots of the data (2000Q3-2024Q3)



Note: This figure displays the time series plots of the variables used in the benchmark model

Appendix B Estimation details

We estimate the reduced-form VAR in equation (2) of the main text using a Bayesian method, via the imposition of prior beliefs on the VAR parameters. In setting the prior distributions, we follow Mumtaz and Theodoridis (2023) and Bańbura et al. (2010) by using Kadiyala and Karlsson (1997) and Sims and Zha (1998)'s modifications of the now standard procedure developed by Litterman (1986) - the so-called Minnesota prior - and adopt a natural conjugate prior.[22]

Intuitively, this prior specification incorporates the beliefs that the more recent lags should provide more reliable information than the more distant ones, and own lags should explain more of the variation of a given variable than the lags of other variables in the equation. Hence, we introduce a prior on the coefficients of the VAR's first lag, with the corresponding prior means obtained as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable using a training sample. Similarly, we also impose a prior belief on the sum of the coefficients of the lagged dependent variables, where the sample means of this prior for each endogenous variable are computed using the same training sample as before.

The prior tightness parameters or hyperparameters for the VAR coefficients, namely the tightness of the prior on the VAR's first lag coefficients and the tightness of the prior on the sum of the coefficients of the lagged dependent variables, are set close to standard values in the literature. Yet, we also experiment with lower and higher alternative values in

[22] The interested reader can refer to Bańbura et al. (2010)'s equations (1) to (9) for extensive technical details about the derivations of the prior and posterior.

the sensitivity analyses in Appendix C1 and C2 below. Moreover, we chose a flat prior for the tightness parameter of the prior on the VAR constant terms.

Furthermore, to control for the extreme observations witnessed during the pandemic, we follow Cascaldi-Garcia (2024) and extend the Minnesota prior with time dummies that we adapt to our identification scheme. These time dummies allow for the adjustment of the historical relationship among the variables for the extreme values linked with the Covid-19 episode observed in specific periods within our 2000Q3-2024Q3 sample, i.e., in 2020Q1, 2020Q2, 2020Q3, and 2020Q4, hence the name "Pandemic Priors".

Finally, given the natural conjugate prior extended with the pandemic priors, we then simulate the conditional posterior distributions of the VAR parameters using a Markov Chain Monte Carlo (MCMC) Gibbs sampling algorithm.

Appendix C Sensitivity analyses

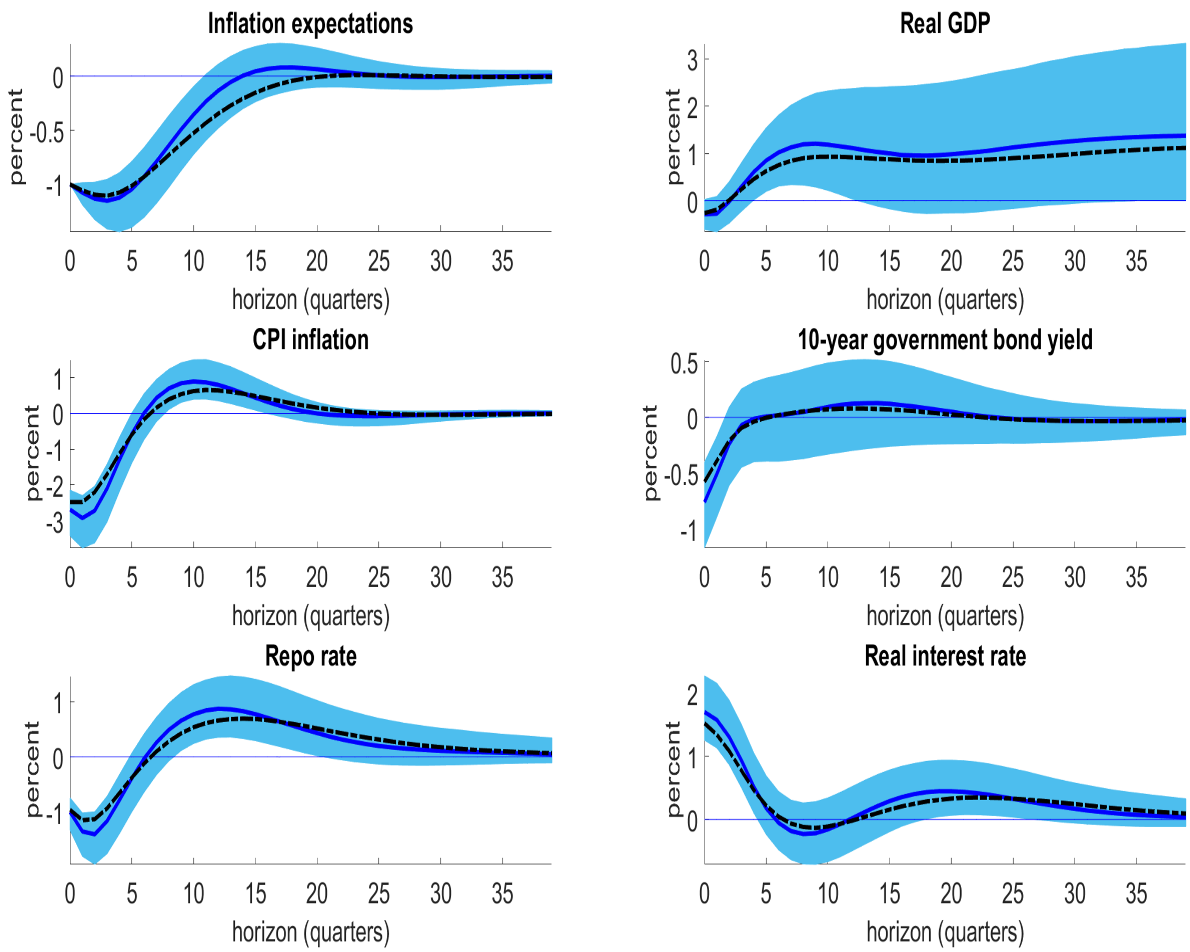


Figure C1: Joint baseline and lower alternative priors robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs both for the benchmark model (solid blue lines) and the robustness model (dash black lines) variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

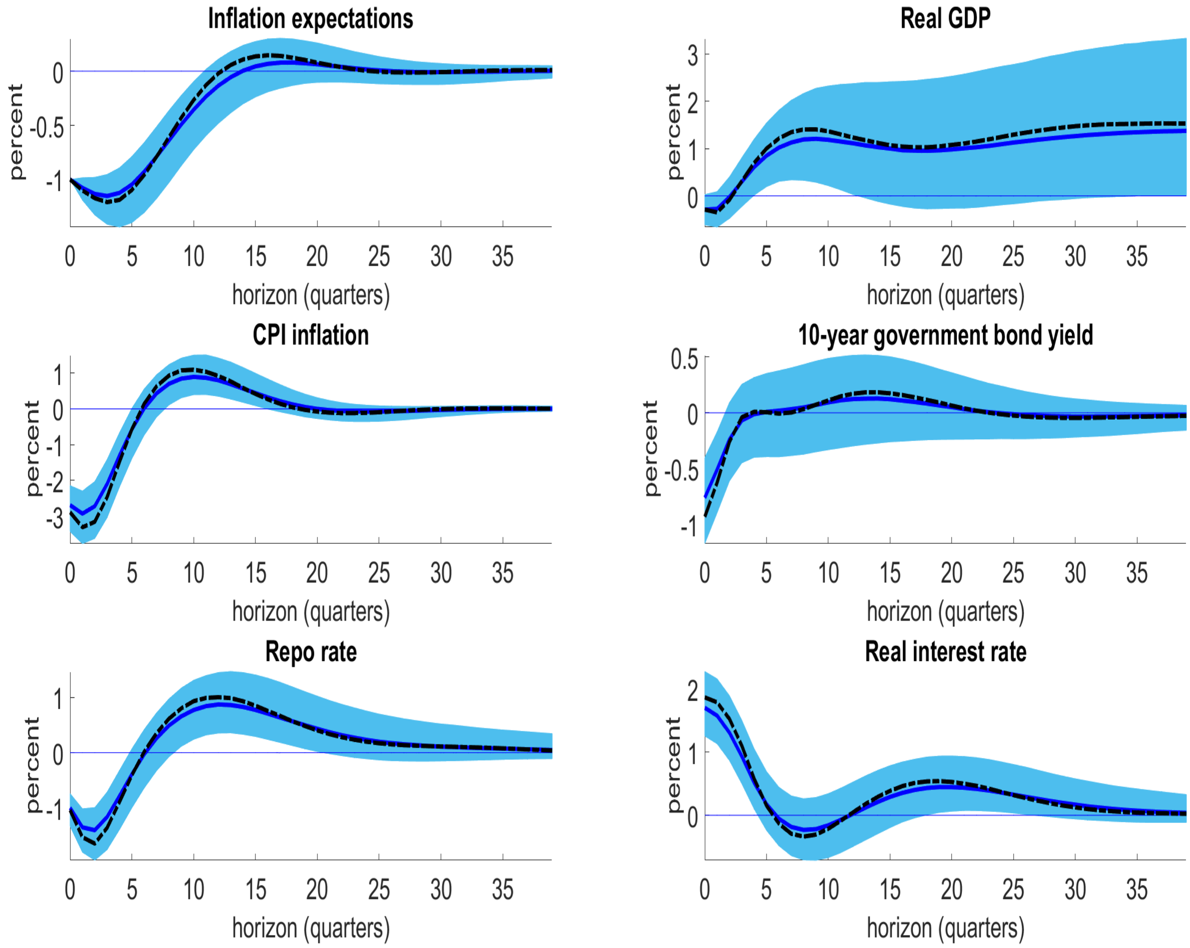


Figure C2: Joint baseline and higher alternative priors robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs both for the benchmark model (solid blue lines) and the robustness model (dash black lines) variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

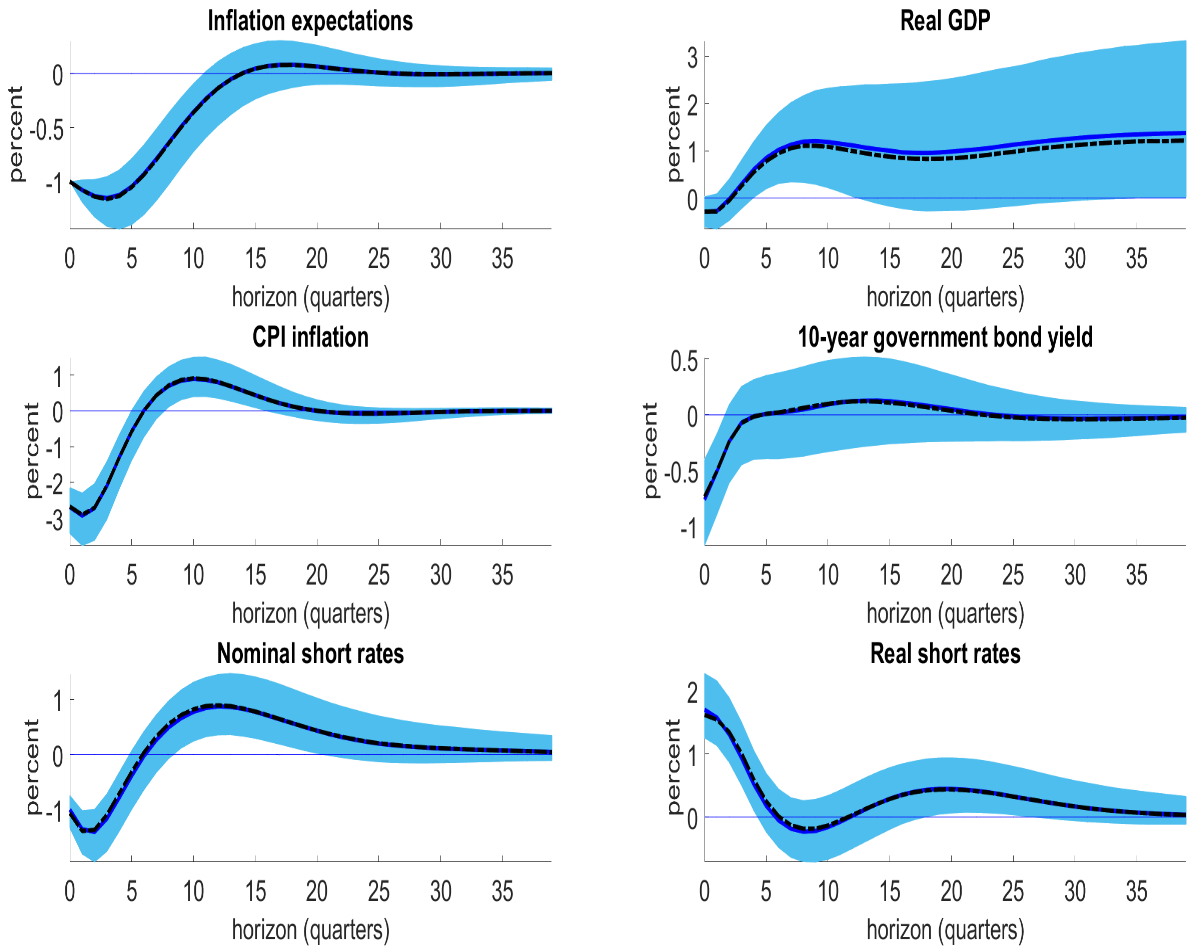


Figure C3: Joint baseline and Jibar as a proxy for the repo rate robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs both for the benchmark model (solid blue lines) and the robustness model (dash black lines) variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

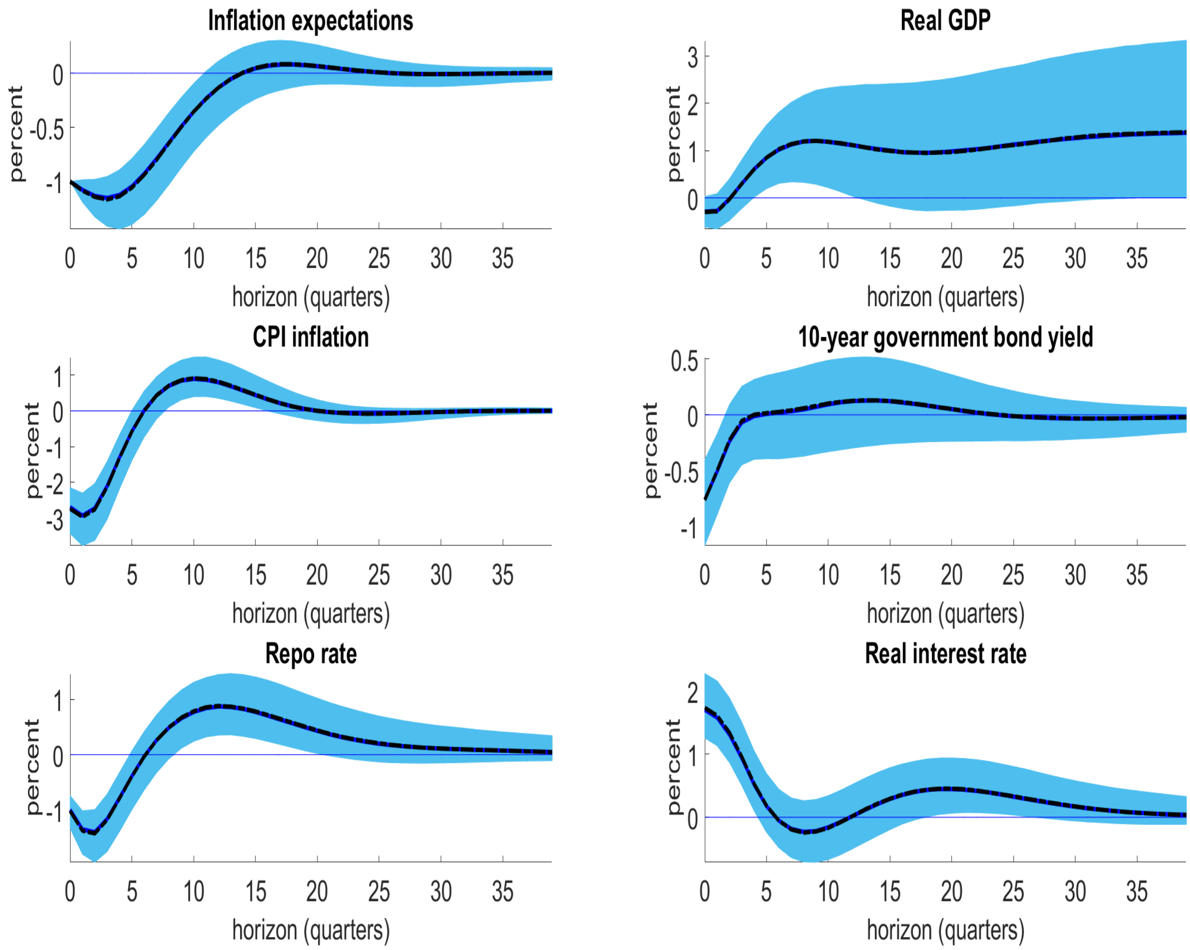


Figure C4: Joint baseline and the use of a 80 quarters horizon robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs both for the benchmark model (solid blue lines) and the robustness model (dash black lines) variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

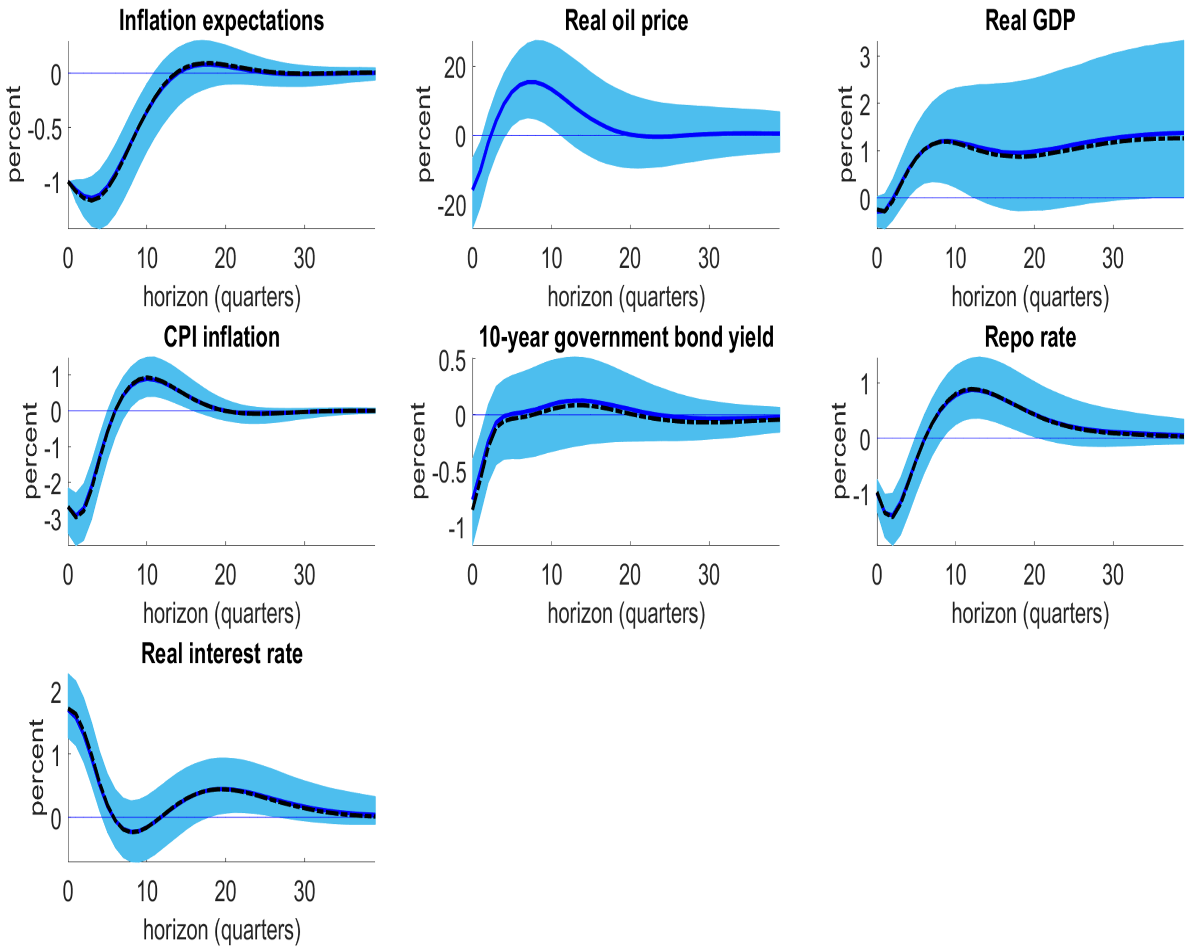


Figure C5: Joint baseline and the addition of real oil price robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs both for the benchmark model (solid blue lines) and the robustness model (dash black lines) variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

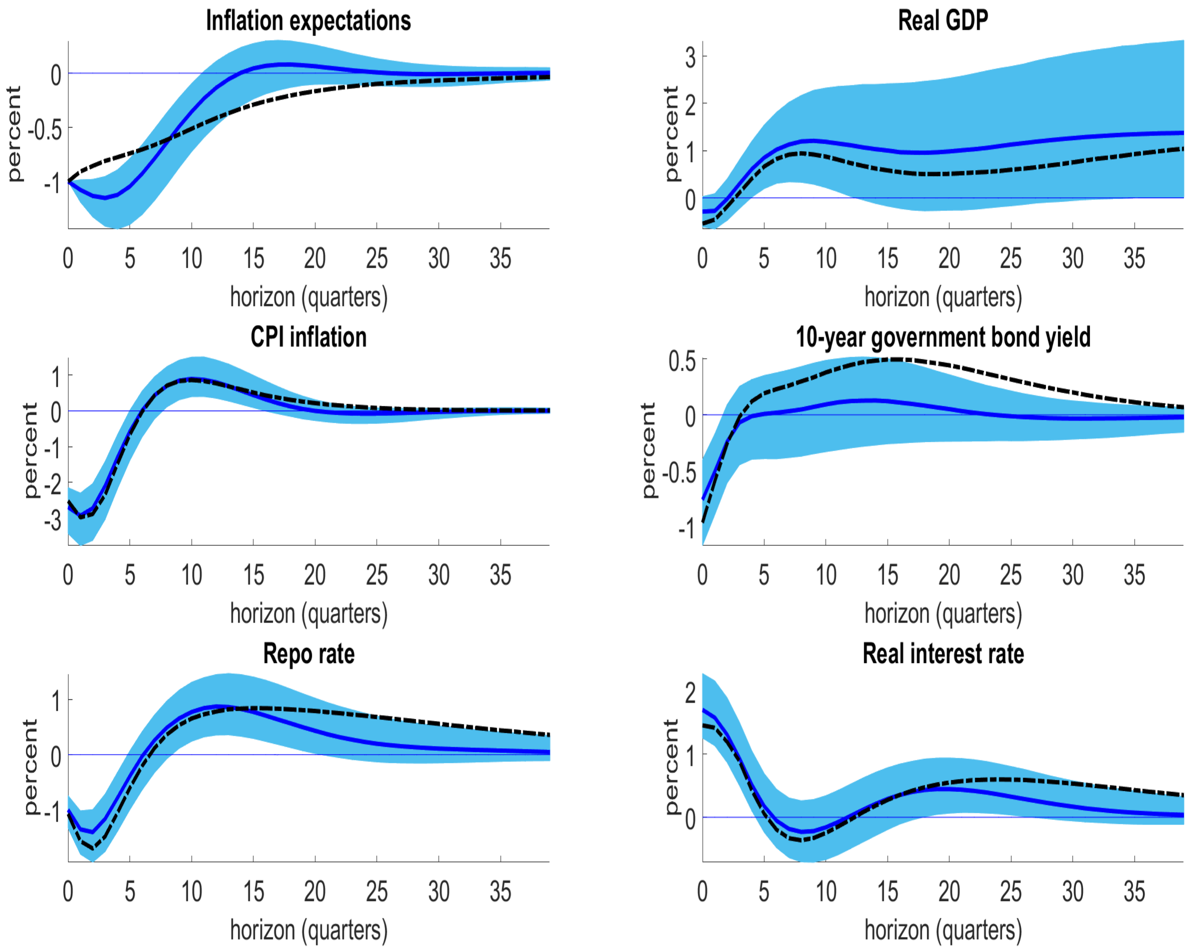


Figure C6: Joint baseline and Analysts inflation expectations as a proxy for inflation expectations robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs both for the benchmark model (solid blue lines) and the robustness model (dash black lines) variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

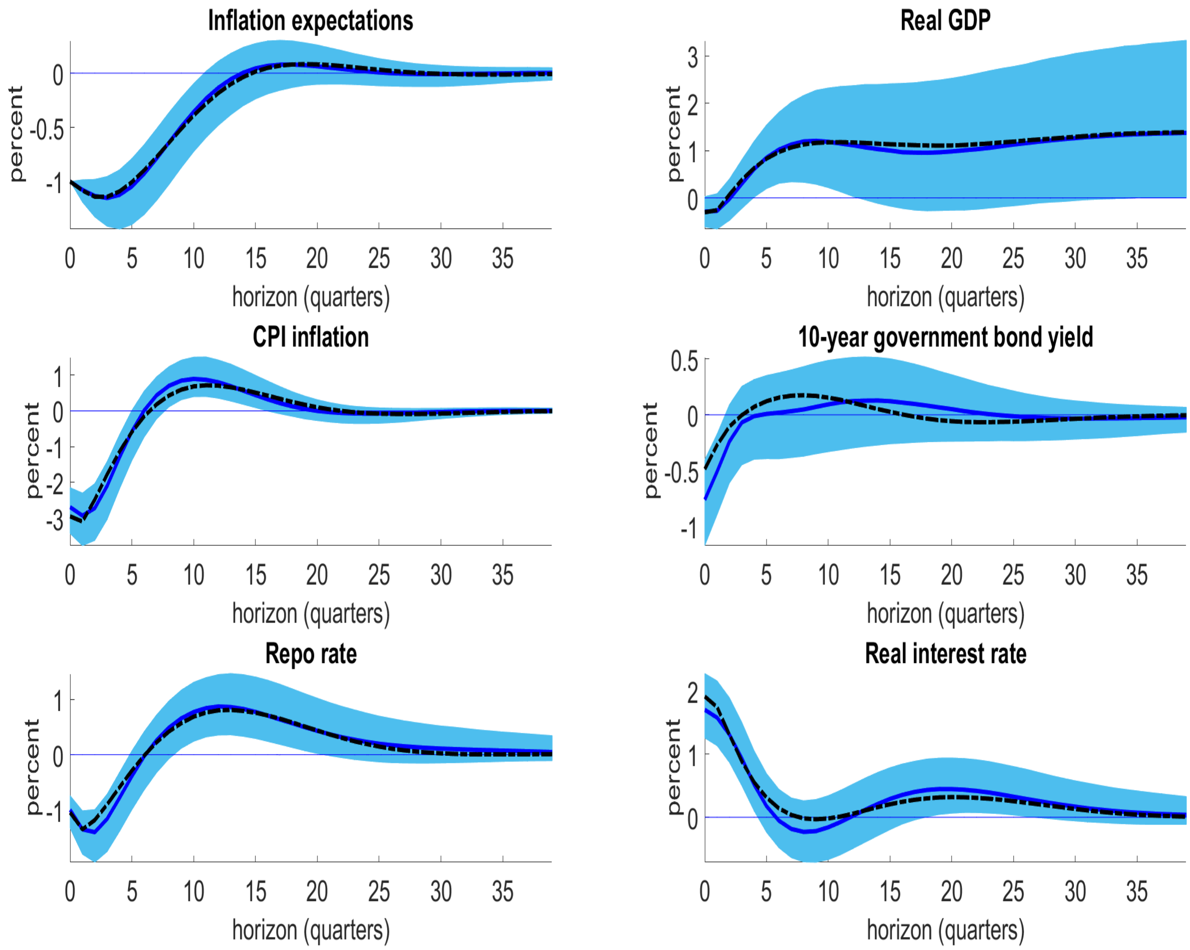


Figure C7: Joint baseline and alternative lag order L = 2 robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs for the robustness model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

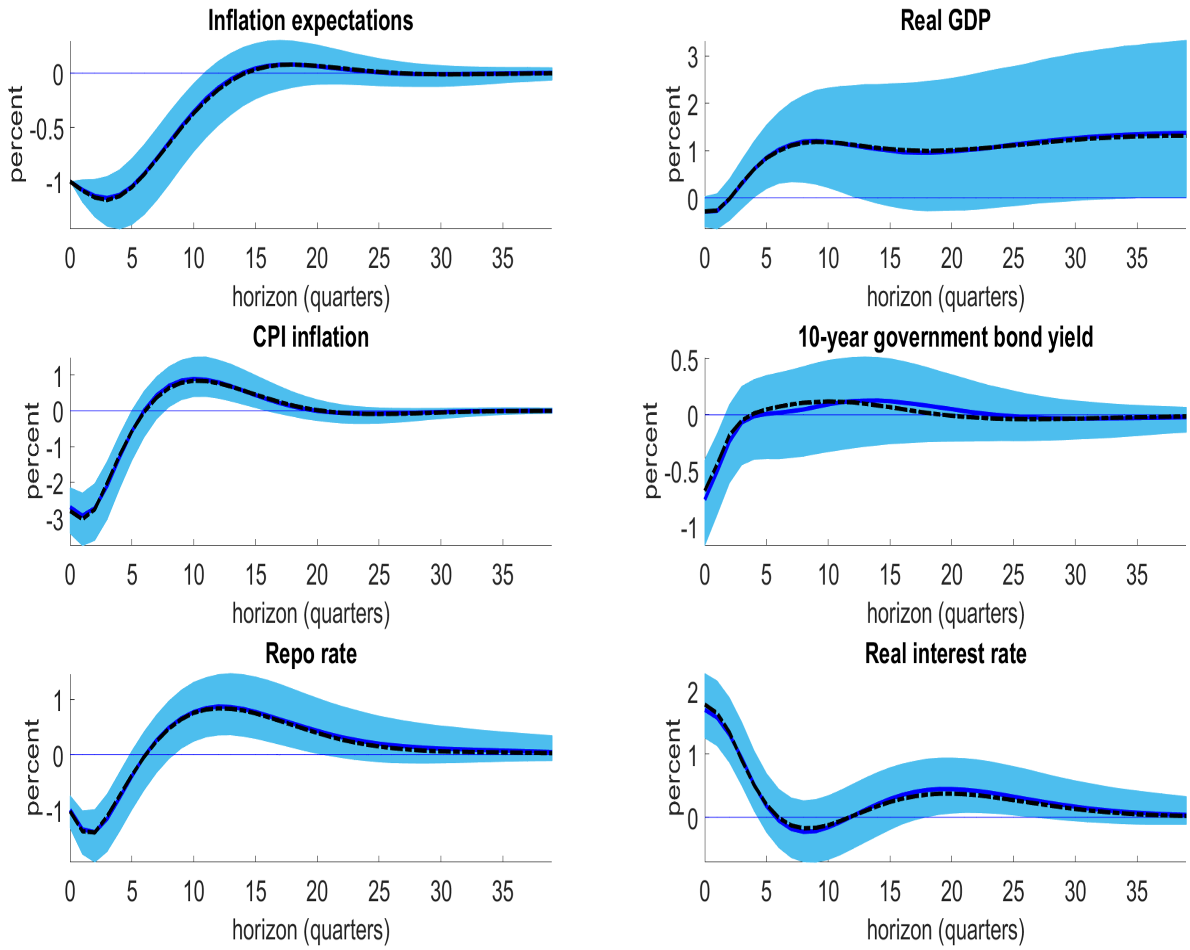


Figure C8: Joint baseline and alternative lag order L = 3 robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs for the robustness model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

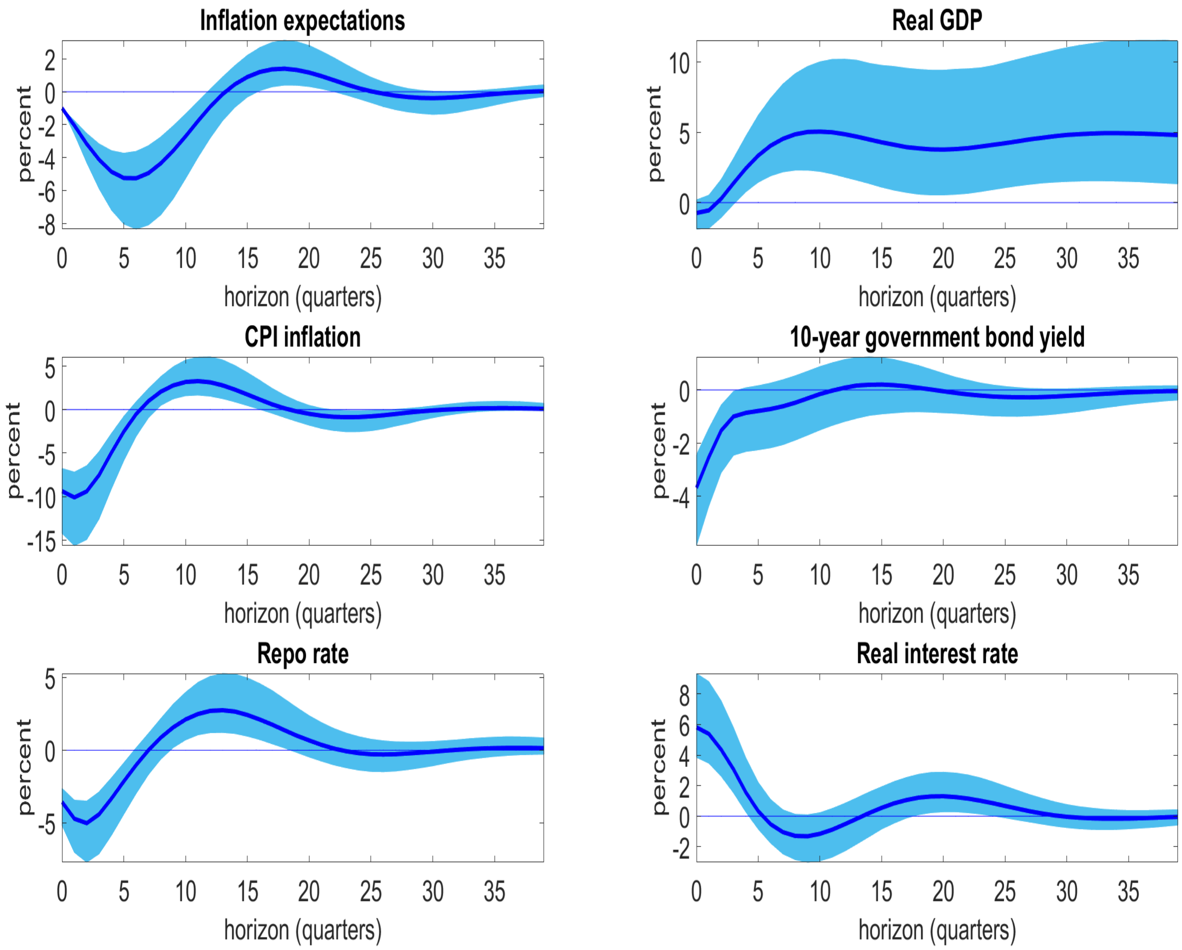


Figure C9: Trend inflation as proxy for inflation expectations robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs for the robustness model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

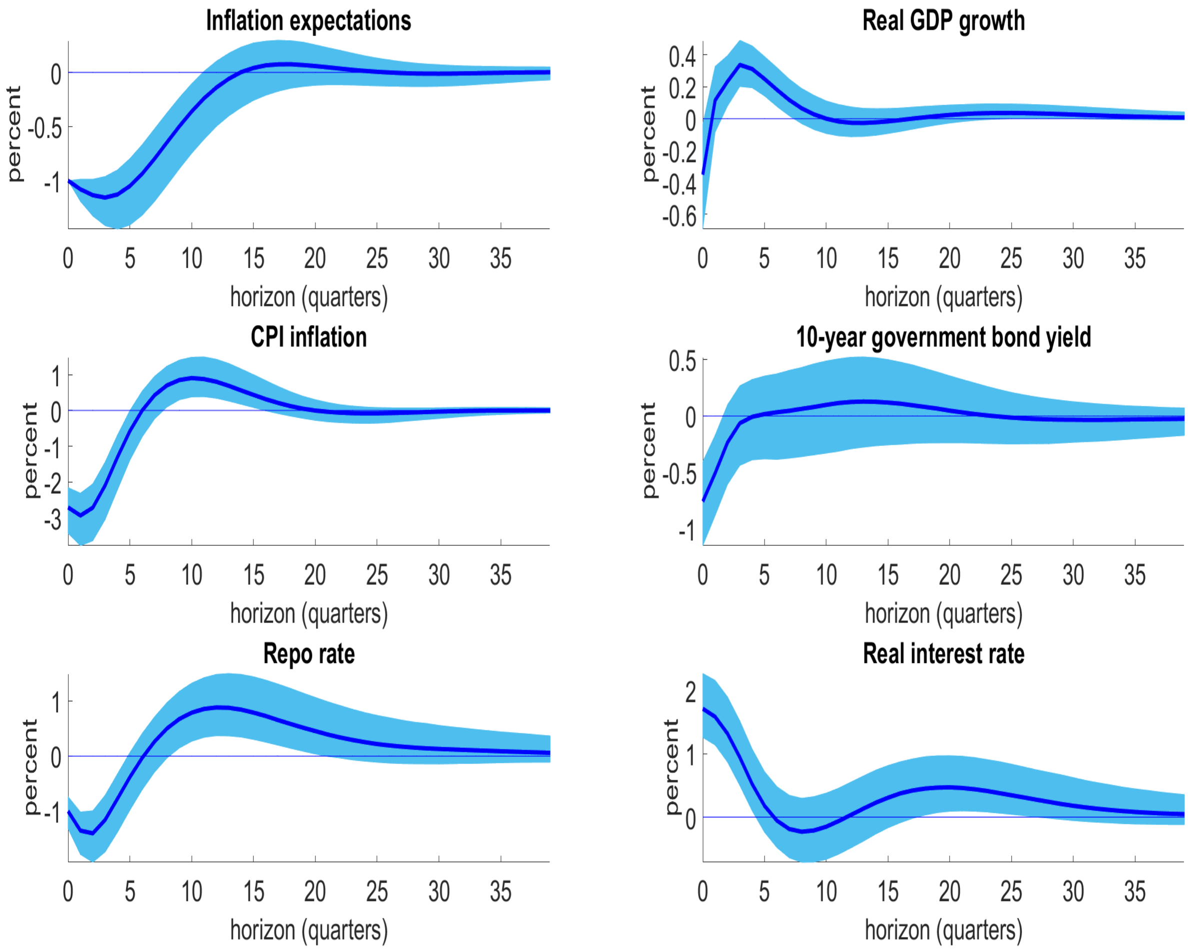


Figure C10: Baseline IRFs to an inflation target shock, using GDP growth

Note: This figure displays the posterior median IRFs (solid blue lines) of the model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

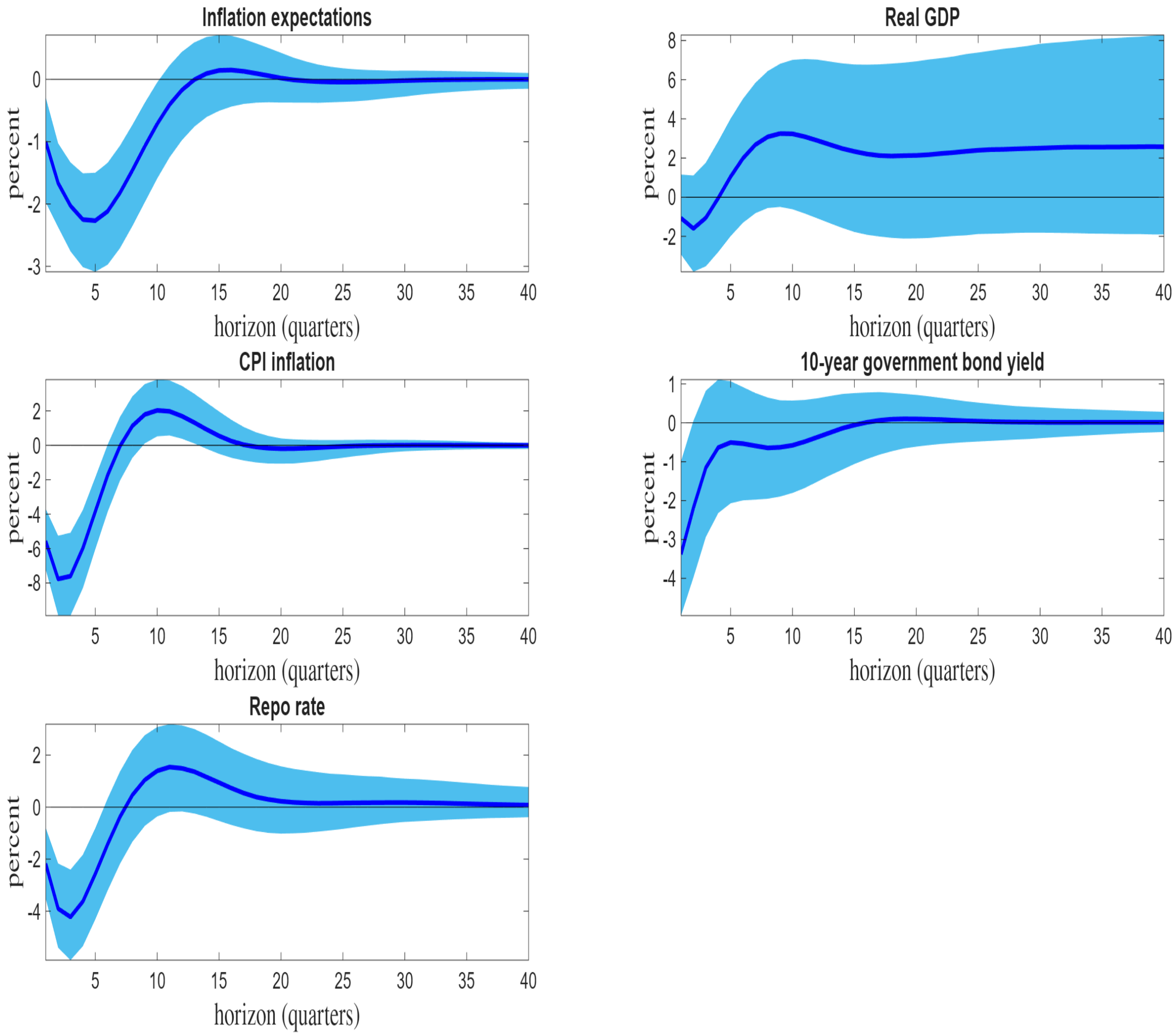


Figure C11: Narrative sign restrictions identification's robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs (blue lines) for the robustness model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

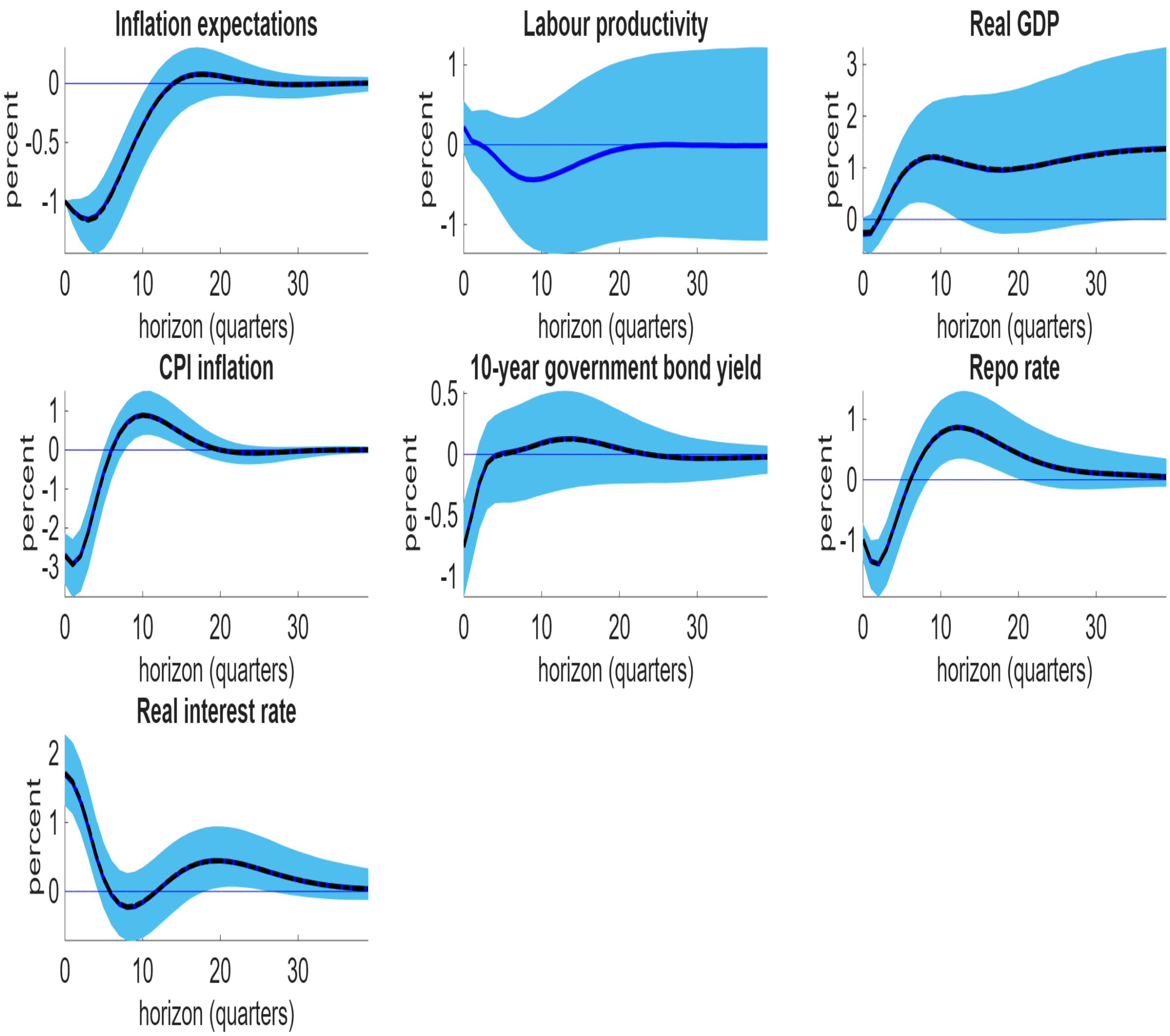


Figure C12: Joint baseline and the addition of labour productivity robustness IRFs to an inflation target shock

Note: This figure displays the posterior median IRFs both for the benchmark model (solid blue lines) and the robustness model (dash black lines) variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

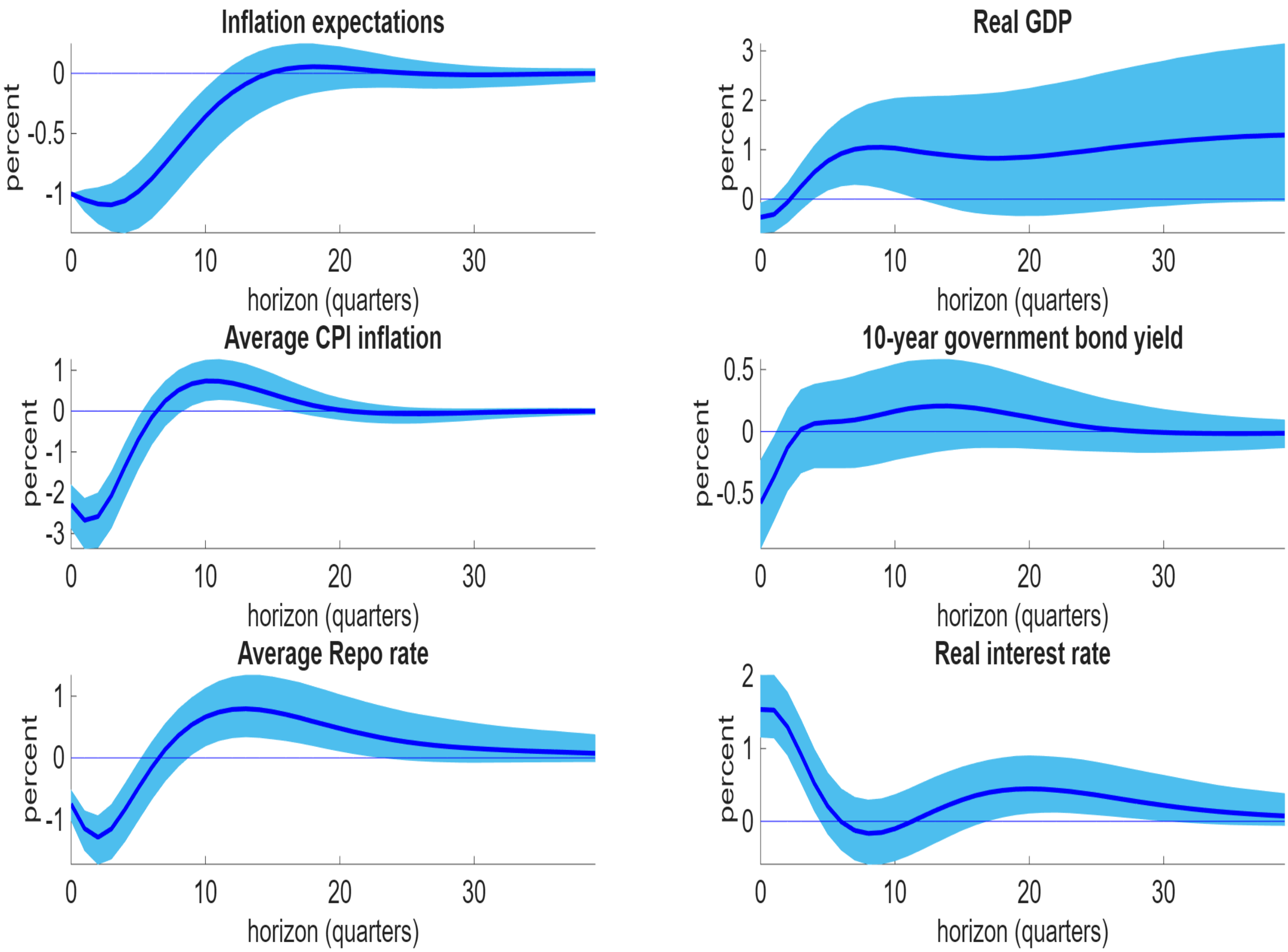


Figure C13: Baseline IRFs to an inflation target shock, using average inflation and repo rates

Note: This figure displays the posterior median IRFs (solid blue lines) of the model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

Appendix D Additional results

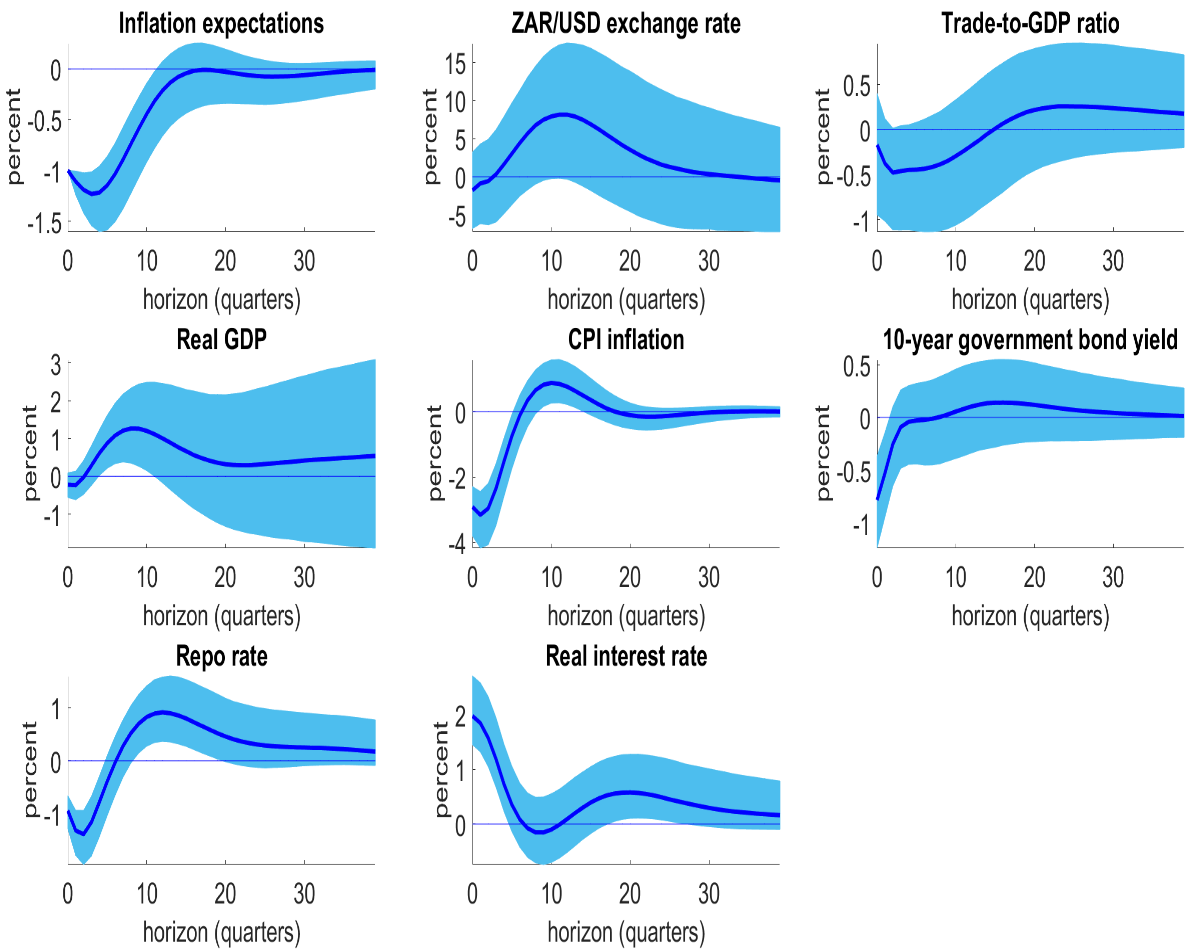


Figure D1: Exchange rate channel's IRFs to an inflation target shock, using the ZAR/USD exchange rate

Note: This figure displays the posterior median IRFs (solid blue lines) of the model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).

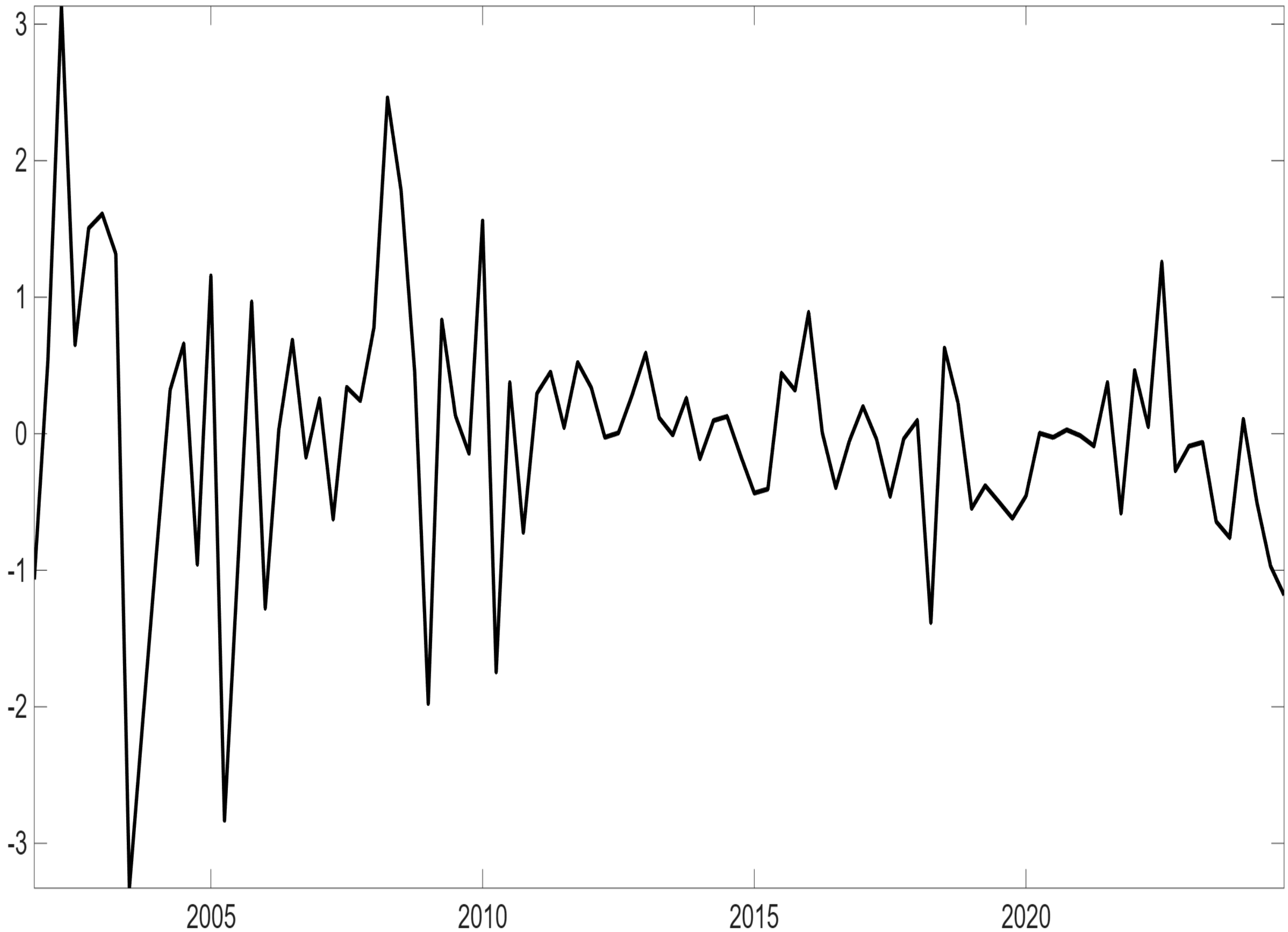


Figure D2: Structural inflation target shocks

Note: This figure displays our baseline model's structural inflation target shocks over the sample period.

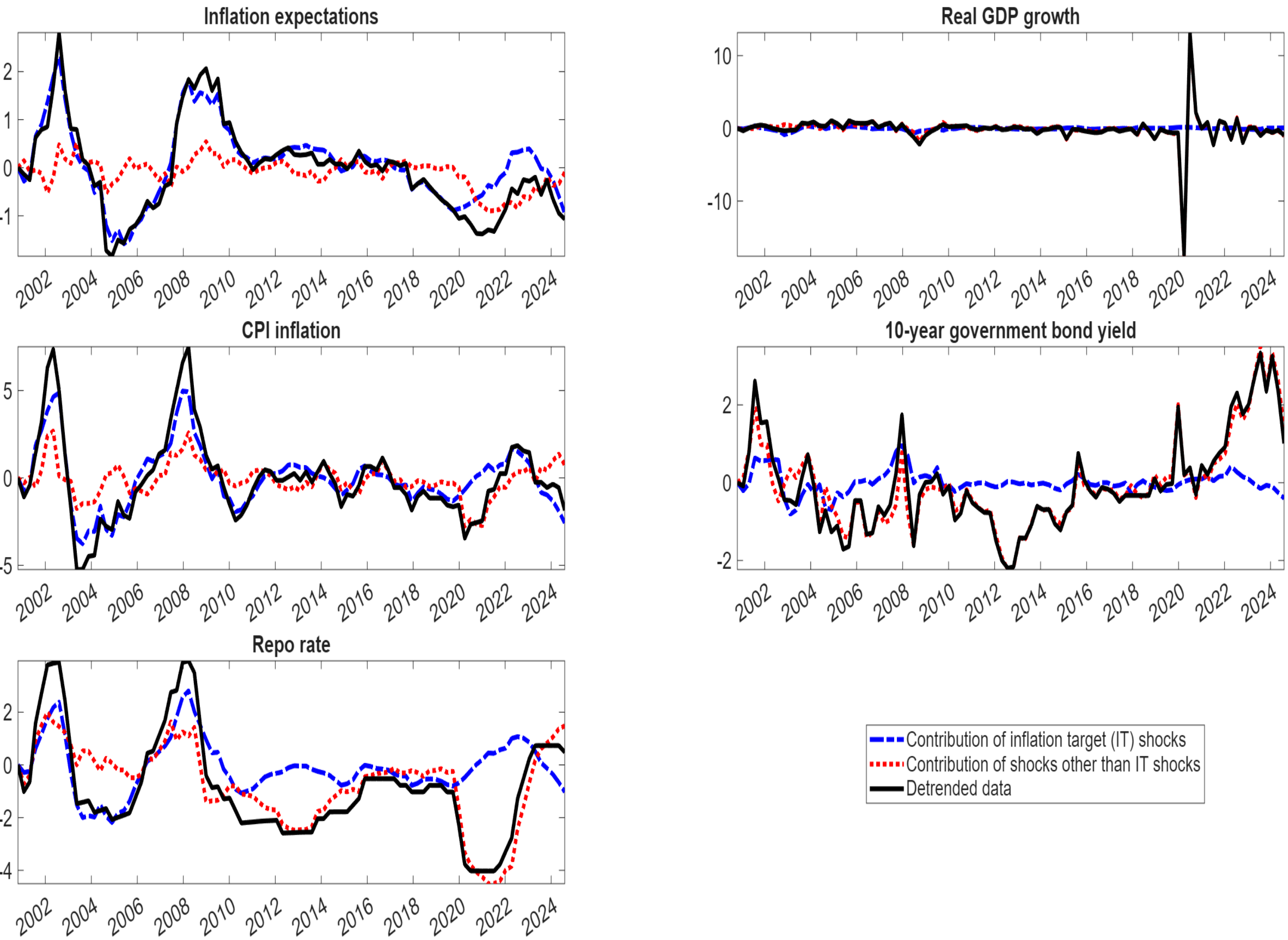


Figure D3: Contributions of inflation target (IT) and non-IT shocks to the de-trended data

Note: This figure shows the historical contributions of the IT and non-IT shocks to our baseline model variables over time. It plots each of the VAR variables' detrended data along with their model-implied counterparts based on the contributions of inflation target shocks and shocks other than inflation target shocks.

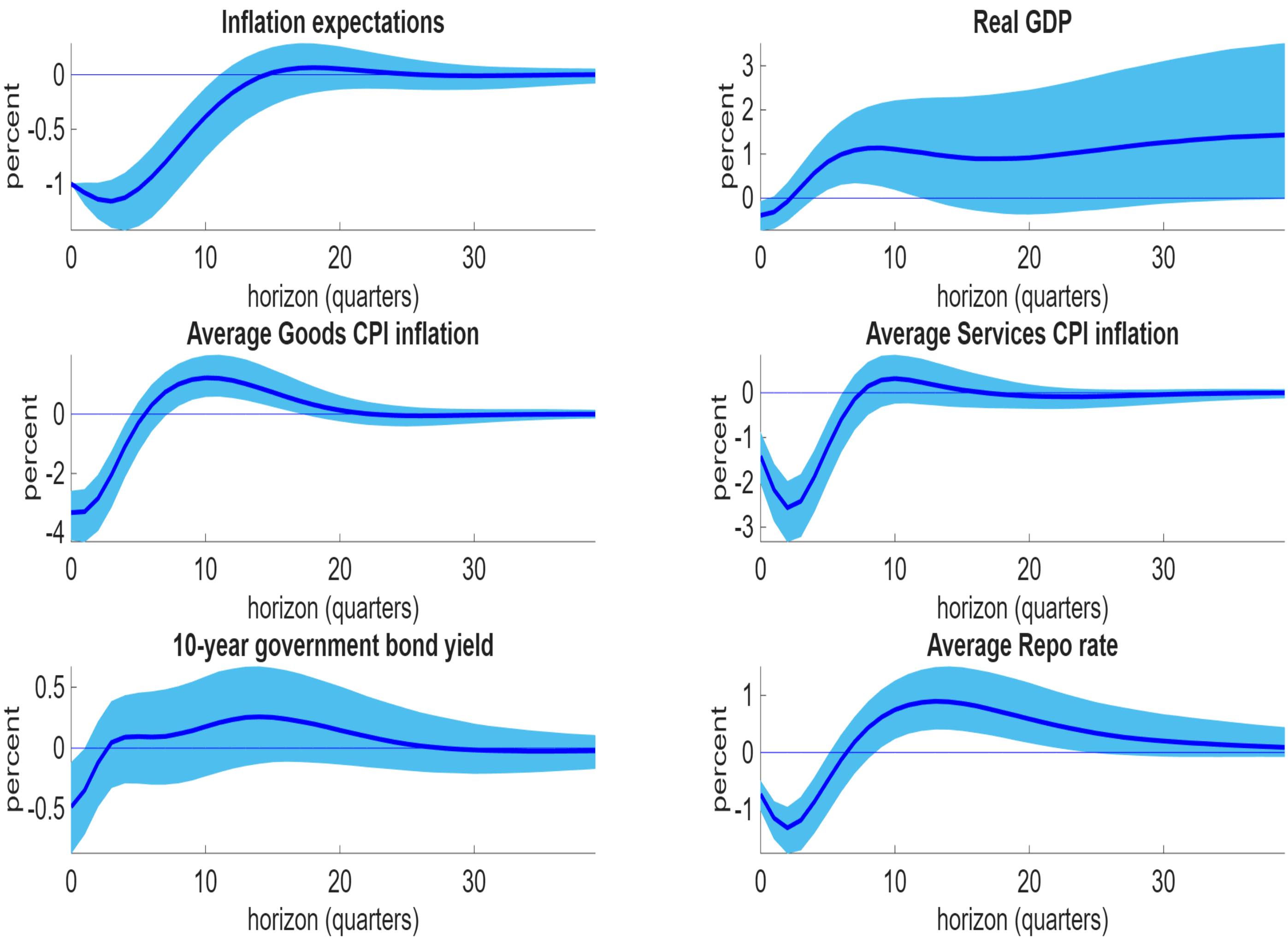


Figure D4: Baseline IRFs with core CPI inflation replaced by its goods and services counterparts

Note: This figure displays the posterior median IRFs (solid blue lines) of the model variables to a 1% negative inflation target shock, along with the 68% credible sets (blue error bands).