

Nonlinearities with de-anchored inflation expectations ^{*}

Stefano Fasani^a
Lancaster University

Mirela Miescu^b
Lancaster University

Lorenza Rossi^c
Lancaster University

February 4, 2026

Abstract

Using a nonlinear VAR, we examine the asymmetric effects of shocks to long-run inflation expectations. Negative shocks, which temporarily lower long-run inflation expectations, have a stronger and more persistent impact on output, investment, and firm entry compared to positive shocks. We provide a novel theoretical explanation, demonstrating how these shocks influence the second-order components of the model, shaping firms' "wait-and-see" behavior - particularly along both the intensive and extensive margins of the investment channel.

Keywords: Inflation Expectations, Threshold VAR, VARX, Sign Asymmetry, Investments, Firm Dynamics.

JEL codes: C5, E1, E5, E52

^{*}We are particularly grateful to Klaus Adam, Guido Ascari, Francesco Bianchi, Efrem Castelnuovo, Luca Gambetti, Domenico Giannone, Yuriy Gorodnichenko, Refet Gurkaynak, Leonardo Melosi, Haroon Mumtaz, Giorgio Primiceri, and Giovanni Ricco, with whom we have had several discussions and received valuable feedback. We also thank the participants in the Mannheim CEPR-EABCN Workshop on "New Challenges in Monetary Economics," the Workshop on "Advances in Structural Shocks Identification" at the Barcelona Summer Forum 2024, the Bank of England, Bank of Italy, and Dutch Central Bank Seminar Series, the University of Konstanz Macro Seminar Series, the University of Nottingham Seminar Series, the University of York seminars, the 1st NLMacro Workshop, the 2023 Padova Macro Talks, the 26th Conference T2M, the Barcelona Workshop on "Expectations in Dynamic Macroeconomic Models," the BSE Summer Forum 2023, the 8th SEM Conference, and the 54th MMF Conference.

^aE-mail address: s.fasani@lancaster.ac.uk

^bE-mail address: m.miescu@lancaster.ac.uk

^cCorresponding author: Lancaster University, LA1 4YX, UK. E-mail: l.rossi@lancaster.ac.uk

1 Introduction

Long-run inflation expectations play a crucial role in monetary policy, as their anchoring to the inflation target is essential for maintaining price stability. Recent empirical literature shows that shocks increasing long-run inflation expectations are inflationary and expansionary (Mumtaz and Theodoridis, 2023, Neri, 2023, Lukmanova and Rabitsch, 2020, and Uribe, 2022). However, do shocks that decrease long-run inflation expectations generate effects of equal magnitude in the opposite direction? In other words, are these effects symmetric?

This is a key question for monetary authorities seeking to manage inflation expectations and enhance policy effectiveness. However, the literature lacks studies that address this issue. Although previous research highlights the macroeconomic relevance of long-run inflation expectation shocks, the analysis has been limited to linear models.¹ This paper aims to fill this gap by examining the asymmetric effects of such shocks. Our contribution is twofold.

The first contribution is empirical and consists in documenting robust sign asymmetries in the transmission of shocks to long-run inflation expectations across a range of empirical frameworks. To this end, we follow a multi-dimensional empirical strategy. We begin with a Threshold Vector Autoregression (TVAR), which provides a flexible environment to allow for sign-dependent impulse responses to shocks to perceived long-run inflation expectations. We then complement this analysis with evidence from alternative specifications—including nonlinear VARs with exogenous variables (VARX) and linear and nonlinear local projections (LP)—to assess the robustness of the results across different modeling approaches.

Across all specifications, shocks are identified as disturbances to the Federal Reserve’s implicit inflation target (PTR), using an identification strategy that isolates innovations making the largest contribution to future movements in long-term inflation expectations.² The consistency of the results across models highlights that the documented asymmetries are a feature of the data rather than an artifact of any particular empirical framework.

The TVAR framework allows for nonlinear transmission through state dependence and is therefore suitable for analyzing sign asymmetries in the response to inflation-target shocks. Within this framework, we apply a max-share identification strategy based on the generalized forecast error variance, adapting it to settings that allow for nonlinear propagation in order to ensure consistency between identification and estimation.

¹For example, Uribe (2022) shows that such shocks account for more than 40% of inflation variation.

²Throughout the paper, we use the terms “target shocks” and “long-run inflation expectation shocks” interchangeably. As clarified in Section 2.2.2 Narrative for Structural Shocks” and Section 3 Theoretical Model”, these shocks should be interpreted broadly as shocks that affect agents’ perceived inflation target, rather than strictly as a shock to the Federal Reserve’s target. Goncharenko and Lukmanova (2022) and Uribe (2022) refer to these shocks as “persistent monetary policy shocks” to capture the idea of a temporary yet highly persistent monetary shock, which they also synthesize as a shock to the inflation target in their theoretical model. Mumtaz and Theodoridis (2023) use the same identification strategy, but in a linear context.

Applying this approach to U.S. quarterly data (1962–2019), our main TVAR results can be summarized as follows: positive shocks (i.e., increases in long-term expectations) lead to inflationary expansion, while negative shocks cause recessionary deflation, consistent with prior literature. However, we find that these effects are notably asymmetric, with negative shocks having a stronger impact on output, investment, and firm entry than positive shocks. Furthermore, we show that the observed asymmetries are primarily derived from both the extensive and intensive margins of investment, measured by net firm entry and capital investment, respectively.

To interpret these shocks, we provide narratives for six major events, three large positive and three large negative shocks. Further, we show that our identified shocks are orthogonal to various other policy and non-policy shocks previously documented in the literature.

To rule out other potential drivers of asymmetries, such as nominal wage rigidity and the zero lower bound (ZLB), we conduct robustness checks for the TVAR findings: (i) excluding the ZLB period and (ii) incorporating nominal wages. Even after removing the ZLB period, real GDP and real investment—both the extensive margin, i.e. investment in capital, and the intensive margin, i.e. investment in new firms—exhibit asymmetric responses. In contrast, nominal wages respond symmetrically to positive and negative shocks, suggesting that nominal rigidities are not the main driver of asymmetries. Furthermore, we consider different sub-samples to show that the sign asymmetry is not a result of the disinflation period of the 1980s nor confined to the Great Moderation period.

To ensure robustness, we also identify our shocks using two alternative measures in place of the Federal Reserve’s implicit inflation target to capture unexpected movements in long-run inflation expectations: (i) a measure based on Blue Chip Economic Indicators and the Livingstone Survey, and (ii) the trend inflation measure recently developed by [Uribe \(2022\)](#).

We complement the TVAR analysis with a nonlinear VARX model that incorporates the squared value of the shocks into the standard VARX framework, following [Forni et al. \(2025\)](#) and [Forni et al. \(2024\)](#).³ Results from the nonlinear VARX regressions indicate that the coefficient on the nonlinear term, that is the squared shock, is negative for real variables, particularly for output, investment, and firm entry. This effect, which adds to that obtained from the linear term, implies that negative inflation-target shocks generate stronger effects than positive ones. This finding is especially relevant because it aligns with our theoretical model, in which a second-order approximation of the policy functions—dynamically influenced by both the level and the square of the shock—produces the same asymmetric responses.

The second contribution is theoretical. We develop a medium-scale model that incorporates both intensive and extensive margins of investment, that is, capital investment by incumbents

³We also provide robustness checks using local projections augmented with squared terms, as recommended by [Caravello and Martinez-Bruera \(2024\)](#), and we additionally compute a test showing that the identified shocks are symmetrically distributed.

and new plant investment by entrants. In our model, we allow the central bank’s inflation target to temporarily deviate from its long-run value, capturing medium-term adjustments made by the policy authority to balance its dual mandate. At the same time, we assume that agents do not observe the true inflation target but the perceived inflation target, which is estimated by the agent following a feedback equation similar to [Gürkaynak et al. \(2005\)](#) and [Neri \(2023\)](#). As in [Bianchi et al. \(2022\)](#), agents receive a signal on the true target, but the signal is not fully informative. The perceived target is a weighted average of the trend implied by the constant gain function and the central bank’s true announced target. The perceived target may deviate from the true one at any time actual inflation remains persistently distant from the target or because the central bank’s announcement of the target is not perceived as fully credible. We solve the model using a second-order approximation to account for nonlinearities ([Fernández-Villaverde et al., 2015](#) and [Fernández-Villaverde et al., 2016](#)). The nonlinear model is then estimated using limited-information IRF-matching techniques ([Christiano et al., 2005](#), [Christiano et al., 2010](#)). Model simulations show that target shocks, which influence agents’ long-term inflation estimates, replicate the empirical responses from the TVAR.⁴ In particular, model simulations confirm that negative inflation target shocks have stronger effects than positive ones.

The investment channel plays a crucial role in these asymmetric effects. Positive inflation target shocks temporarily lower real interest rates, stimulating both intensive and extensive investment margins. This increases aggregate demand, leading to expansion. Under a first-order approximation, negative shocks would have symmetric effects of the same magnitude but in the opposite direction. However, under a second-order approximation, the uncertainty introduced by the shock, and more precisely the square of the shock in the policy functions, alters investment dynamics. Increased uncertainty prompts firms to adopt a “wait-and-see” approach, delaying investments of incumbent and entry of new firms and amplifying negative shocks’ contractionary effects. In contrast, uncertainty dampens the expansionary impact of positive shocks. This explains the stronger effects of negative shocks relative to positive ones.

We further use the model to analyse sign asymmetry in shock transmission through nonlinear local projections on simulated data, assess alternative specifications of long-run inflation-expectations shocks, and evaluate the robustness of our findings under different parameter calibrations.

Taken together, our empirical evidence and theoretical analysis indicate that innovations that lower long-run inflation expectations exert stronger and more persistent effects on output, investment, and firm entry than those that raise them. This asymmetry implies a clear policy message: central banks should place greater emphasis on avoiding credibility losses and expectation under-

⁴In the theoretical model, the shock is introduced as a temporary shock to the inflation target, as in [Cogley et al. \(2010\)](#) affecting agents’ estimation of the target. In a rational expectation model, long-term inflation expectations coincide with the target. We assume that agents have partial information. They do not know the target and need to estimate it in the same vein as in [Gürkaynak et al. \(2005\)](#).

shooting than on episodes of moderate overshooting.

Related literature The recent and thriving literature on inflation expectations provides a host of seminal results on the importance of inflation expectations on agents' decisions (see, for example, [Coibion et al. \(2022\)](#) and [D'Acunto et al. \(2022\)](#) for a survey of the literature).

Exogenous changes in inflation expectations affect fundamental economic decisions by agents, such as household spending (see [Coibion et al., 2022](#)) and investment and pricing decisions of firms (see [Coibion et al., 2019](#)). We complement them by providing a macroeconomic framework that is relevant to policy that models the relevant channel (investment) through which asymmetric effects materialize.

[Bianchi et al. \(2021\)](#) argue that, although an explicit 2% target was formally announced on January 25, 2012, inflation did not stabilize around this target, suggesting that the private sector began losing confidence in the central bank's ability to return inflation to its target even during economic expansions. While "confidence" shocks, i.e. shocks to the agents' perceived target have been certainly relevant, we argue that the shock we examine can encompass both a shock to the agents' perceived target and an actual target shock. Concerning the latter shock, recently [Shapiro and Wilson \(2022\)](#) and [Cieslak et al. \(2024\)](#) show that the Fed's communication about its flexible inflation target may have temporarily surprised agents, leading to uncertainty about the central bank's true target and the expected timeline for achieving it. Recently, [Uribe \(2022\)](#) uses long-run and sign restrictions to separate permanent and transitory monetary shocks, supporting the Neo-Fisherian effects. Unlike [Uribe \(2022\)](#), we focus on the implicit inflation target without imposing restrictions on the interest rate equation in the SVAR and we provide evidence of the asymmetric effect of our identified shock.

The literature has recently stressed the importance of the state-dependency and nonlinearity of several shocks, for example, fiscal and monetary policy shocks ([Auerbach and Gorodnichenko, 2012](#), [Ramey and Zubairy, 2018](#), [Barnichon et al., 2022a](#), [Ben Zeev et al., 2023](#), [Barnichon and Matthes, 2018](#), [Debortoli et al., 2020](#), [Ghassibe and Zanetti, 2022](#)), oil shocks ([Forni et al., 2025](#) and [Miescu et al., 2024](#)), and financial shocks ([Barnichon et al., 2022b](#) and [Forni et al., 2025](#)). Sources of nonlinearity have been found in the ZLB ([Caggiano et al., 2017](#)), the downward wage rigidity ([Shen and Yang, 2018](#), [Abbritti and Fahr, 2013](#)), state-dependent pricing ([Devereux and Siu, 2007](#)) and firm "wait-and-see" behavior ([Bloom et al., 2007](#)). Our paper is closely related to [Debortoli et al. \(2020\)](#), who study sign asymmetries to monetary shocks relying on nominal wage rigidities as a source of asymmetry. With respect to them, we analyze a different shock, using different econometric techniques and we propose an alternative and complementary explanation for the asymmetry results, based on the second-order effects of the shock on the influencing firms' "wait-and-see" behavior, particularly along the intensive and extensive margins of the investment channel.

Despite the importance of entry costs in shaping the extensive margin of investments (Gourio et al., 2016, Hamano and Zanetti, 2017, Giannoulakis, 2021 and Ascari et al., 2023) and the overall macroeconomic dynamics (Gutiérrez et al., 2021), their role as a possible source of asymmetric transmission of the shocks is largely unexplored both in the theoretical and empirical literature.

From a methodological perspective, we relate to Caldara et al. (2021) who propose an algorithm to extend the max share identification to a nonlinear model featuring stochastic volatility. We differ from that paper, as we employ a TVAR model. By maximizing the generalized forecast error variance (GFEV), our approach takes into account the possibility of endogenous regime changes at the identification stage as well, not only at the impulse response analysis.

The remainder of the paper is organized as follows. Section 2 presents the empirical analysis. While Section 2.1 describes the TVAR model and the data used, Section 2.2 shows the results from the TVAR. In the same section, among the robustness analysis, it is studied an alternative model for nonlinearities is studied: a VARX model with polynomial transformations of the identified shocks. Section 3 introduces the theoretical model used to rationalize the empirical results. Section 3.1 shows the dynamics of the model and provides an estimate of the model to quantitatively assess the sign asymmetries of a shock to the inflation target and the ability to replicate the empirical results. The same section also inspects the theoretical mechanisms driving the sign asymmetry of the shock. Section 4 concludes. All the robustness checks of the empirical part and further details on the theoretical part are left to the Supplementary Appendix.

2 Empirical Analysis

Our empirical analysis consists of the estimation of a TVAR model in Section 2.1, whose main results are shown in Section 2.2. We test the robustness of our empirical findings over several dimensions. Specifically, we describe the VARX model with square transformation of the identified shocks to capture sign asymmetries in Section 2.2.4.

2.1 TVAR Analysis

To investigate the nonlinearities in the effects of a shock to long-run inflation expectations, we estimate the following Threshold VAR model:

$$Y_t = \left[c_1 + \sum_{j=1}^P B_{1,j} Y_{t-j} + \Omega_1^{1/2} e_t \right] S_t + \left[c_2 + \sum_{j=1}^P B_{2,j} Y_{t-j} + \Omega_2^{1/2} e_t \right] (1 - S_t) \quad (1)$$

where

$$S_t = 0 \Leftrightarrow Z_{t-d} \leq Z^* \quad (2)$$

Y_t is the $N \times 1$ vector of endogenous variables, which includes a measure of long-horizon inflation expectations and a set of macroeconomic and financial variables. $B_{i,j}$, with $i = 1, 2$, denotes the

$N \times (NP + 1)$ matrix of coefficients in regime i , while Ω_i , with $i = 1, 2$, is the covariance matrix of the residuals in regime i . Given the quarterly frequency of the data, we choose a lag length of $P = 4$, so that $j = 1, \dots, 4$. By introducing S_t we allow for the existence of two economic regimes characterized by potentially different dynamics. The regimes are determined by the level of the threshold variable Z_{t-d} relative to the threshold level Z^* . In our analysis, the threshold variable is assumed to be the d^{th} lag of the annual growth in the US CPI index. Therefore, the regimes identified by this specification are high and low inflation regimes.⁵ Importantly, both the threshold level Z^* and the delay parameter d are unknown and estimated in the model.

We estimate the model using Bayesian methods, as in [Alessandri and Mumtaz \(2019\)](#). Details of the priors and the MCMC algorithm are available in Section A “Bayesian TVAR: estimation” in the Supplementary Appendix. The main intuition behind it is straightforward. Given a draw for the threshold level Z^* and the delay parameter d , the model is split into two linear VARs, one for each regime. The conditional posterior of the delay parameter is a multinomial distribution, while the threshold value can be drawn from its non-standard posterior via a Metropolis step. Once the posterior distribution of all parameters is available, “generalized” identification and impulse responses are obtained using Montecarlo integration, as described in Section [2.1.1](#).

The TVAR model is particularly well-suited for our application, as it captures nonlinearities at both the identification and estimation stages. Moreover, its ability to accommodate regime-specific VAR parameters and variance–covariance matrices makes it especially appropriate for modelling periods marked by heightened volatility in long-run inflation expectations, such as the Global Financial Crisis and the COVID-19 period.⁶

Data The baseline empirical specification includes five US variables, at a quarterly frequency, running from 1962:Q1 to 2019:Q4 as follows:

⁵Although we recognize the importance of alternative regime specifications, we have chosen to focus on the high and low inflation regimes to examine the impact of inflation target shocks. This choice is primarily motivated by the fact that periods of particularly low or high inflation often trigger renewed debates about the optimal inflation target. During such periods, central banks may find it difficult to maintain their inflation targeting frameworks in the medium term. For instance, following the Great Recession, scholars such as [Blanchard et al. \(2010\)](#), [Ball \(2014\)](#), and [Krugman \(2014\)](#) proposed increasing the inflation target to address the zero lower bound (ZLB) on interest rates. More recently, the post-COVID-19 inflation surge has sparked a similar debate, with Olivier Blanchard suggesting that a 3% inflation target might be more appropriate for economies like the US. Section [2.1.2](#) demonstrates that our chosen regimes are preferred over alternative specifications, such as boom and bust regimes.

⁶The TVAR framework can readily be extended to include the COVID-19 period—though our baseline estimation ends in 2019:Q4 for consistency with the other empirical models we use, which are less well equipped to handle the COVID-19 recession. In Figure 5 of the Supplementary Appendix, we show that extending the TVAR sample to 2022:Q4 leaves the impulse responses essentially unchanged.

$$Y = \begin{bmatrix} \text{PTR} \\ \log(\text{real GDP}) \\ \log(\text{CPI}) \\ \text{3 Months T-bill rate} \\ \text{10 Year bond yield} \end{bmatrix}$$

As in [Mumtaz and Theodoridis \(2023\)](#), our benchmark proxy for the inflation target is a spliced survey-based measure of long horizon PCE inflation expectations used in the Federal Reserve board model. This measure (with mnemonic PTR) is available on a quarterly basis. [Figure 1](#) shows it from 1962:Q1 to 2019:Q4. The PTR measure is derived from the Federal Reserve Board of Governors’ estimate and corresponds to the inflation target estimate generated by the FRB/US model.⁷ FRB/US model is a medium-scale model, estimated on macro data, including observables for forward-looking inflation expectations. The time series is publicly available on the Federal Reserve Board of Governors’ website. [Figure 1](#) in the Supplementary Appendix compares PTR with two alternative proxies for the inflation target we consider in the robustness analysis: the inflation trend measure by [Uribe \(2022\)](#), and a measure of long-run inflation expectations based on Blue Chip forecasts.⁸

Finally, to gain a more comprehensive understanding of the nonlinear association between shocks to inflation expectations and the overall macroeconomy, we examine the impact of these shocks on three additional variables.

$$\begin{bmatrix} \log(\text{Firms' Net Entry}) \\ \log(\text{Consumption}) \\ \log(\text{Investment}) \end{bmatrix}$$

To generate the impulse responses for the expanded model, we introduce one additional variable at a time to the baseline TVAR model. Details on the transformations and sources of the data are available in [Table 1](#) of the Supplementary Appendix.

2.1.1 Shock identification

We extend the identification approach of [Mumtaz and Theodoridis \(2023\)](#) to a nonlinear framework to identify shocks to the inflation target based on the maximization of the forecast error

⁷In the earlier part of the sample PTR uses estimates of inflation expectations from [Kozicki and Tinsley \(2001\)](#). Data for the The 1980s is obtained from the discontinued Decision Makers poll (DMP). Published by Richard Hoey, this survey aimed to capture the 5 to 10-year ahead expectations of participants in the financial markets. From 1991:Q4 onwards, the series is based on 1 to 10-years ahead inflation expectations taken from the Survey of Professional Forecasters.

⁸While the [Uribe \(2022\)](#)’s inflation trend measure spans over the same sample period as the PTR, the measure of long-run inflation expectations based on Blue Chip forecasts is only available from 1980. Therefore, while we test the former alternative measure both in TVAR and LP analysis, we assess robustness for the long-run inflation expectations measure based on Blue Chip forecast only in the LP analysis due to shorter data available.

variance (FEV) of the PTR over a 10-year horizon.⁹

The main idea is that although various factors such as technology shocks, policy shocks, and non-policy aggregate demand shocks can influence the central bank’s inflation target, it is primarily shocks to the inflation target itself that drive inflation expectations in the medium to long term. Put simply, if the monetary authority consistently and systematically responds to changes in inflation and is viewed as credible over the long run, long-term inflation expectations will align with the inflation target. Consequently, any subsequent adjustments in long-term inflation expectations indicate the presence of shocks impacting the inflation target.

Extending the max share identification to a nonlinear framework adds complexity to the problem in two ways. Firstly, when considering nonlinear models, the appropriate measures to use are the generalized impulse response functions (GIRF) and generalized FEV (GFEV) instead of the standard impulse responses and FEV, as discussed in [Koop et al. \(1996\)](#). Secondly, in a nonlinear model, the GIRFs and, consequently, the GFEV cannot usually be expressed in a closed form. Instead, their effects depend on the size and sign of the shock, as well as the historical context, requiring the use of simulation methods. GIRFs of variable i to shock j is defined as follows:

$$GIRF_{ij}^S(k, \Psi_t, e_j, Y_{t-1}^S) = E(Y_{i,t+k} | \Psi_t, Y_{t-1}^S, e_j^S = A_0^{-1}u^S) - E(Y_{i,t+k} | \Psi_t, Y_{t-1}^S) \quad (3)$$

where k is the forecasting horizon under consideration, Ψ_t denotes all the parameters and hyper-parameters of the model, e_j is the shock of interest (in our case the inflation target shock), $S = 0, 1$ denotes the regime of high or low inflation, while Y_{t-1}^S denotes the specific history of the system prior to the shock. A_0^{-1} is the impact vector that maps the regime specific residuals u^s into the structural shocks e_j .

In particular, the regime specific variance-covariance matrix Σ^S can be rewritten as follows:

$$\Sigma^S = (Aq)(Aq)' \quad (4)$$

where A is a lower triangular matrix and q is a column of the family of orthogonal matrices of size N , satisfying $q'q = I_N$. By considering all possible values of q , the matrix Aq spans the space of all possible contemporaneous matrices. The structural shocks of the VAR model e_j are defined as

$$e_j^S = A_0^{-1,S}u^s, \quad (5)$$

⁹As shown by [Mumtaz and Theodoridis \(2023\)](#), the FEV-based identification remains robust across several alternative schemes, including: (i) zero long-run restrictions on the effects of the target shock on real variables; (ii) orthogonality to the natural interest rate; and (iii) multi-shock identification with monetary, oil, and TFP news shocks. They further demonstrate its superiority to the long-run restriction approach of [De Michelis and Iacoviello \(2016\)](#) and validate it in DSGE models featuring imperfect information and regime changes, showing that the method reliably recovers the true responses to target shocks.

where $A_0^S = Aq$. Equation (3) characterizes the GIRF as the difference between two conditional expectations, one in which we condition on the structural shock e_j , and one in which we assume the shock to be equal to zero.

The corresponding GFEV component for horizon $k = 0 : K$ in state S is described as follows:

$$GFEV_{ij}^S(K, \Psi_t, e_j, Y_{t-1}^S) = \frac{\sum_{k=0}^K GIRF_{ij}^2(k, \Psi_t, e_j, Y_{t-1}^S)}{\sum_{j=1}^N \sum_{k=0}^K GIRF_{ij}^2(k, \Psi_t, e_j, Y_{t-1}^S)} \quad (6)$$

Thus, shock e_j^S is defined such that it maximizes the generalized forecast error variance of variable j , over the forecasting horizon $k = 0 : K$, in state S . As a robustness check, we also test our results by setting a fixed forecasting horizon $k = 40$ (see Section 2.2.3).¹⁰ The generalized extension of the max share identification amounts to finding the column j of matrix Q that solves the following maximization problem:¹¹

$$\begin{aligned} & \underset{q_j}{\text{maximize}} && GFEV_{ij}^S(k, \Psi_t, e_j, Y_{t-1}^S) \\ & \text{subject to} && q_j' q_j = 1 \end{aligned} \quad (7)$$

The maximization outlined in equation (7) yields an impact column $A_{0,j}^S$, corresponding to a shock e_j^S that maximizes the GFEV of the PTR measure over a 10-year forecasting horizon, thus with $K = 40$, in state S . Estimating this requires conducting Monte Carlo simulations, where the GFEV is calculated for each regime by considering all possible values, i.e. all histories Y_{t-1}^S , of that specific regime S . The goal is to maximize the average forecast error variance conditioned on that regime over the 10-year horizon. Once the impact vectors are determined, the Generalized IRFs are computed using Equation (3).

Two key points deserve emphasis. Firstly, in this application, the transition between regimes is considered endogenous. This means that the economy has the freedom to switch between high and low inflation dynamics, depending on the magnitude and direction of the shock, throughout the simulation period. Therefore, the simulation takes into account the dynamics of both endogenous variables and the parameters governing the system. This holds true for both the shock identification stage as well as the computation of the generalized impulse responses. Consequently, the sign asymmetry of shocks in our application stems from the ability of the shock to trigger a change in regime.

Secondly, even within a given initial regime, denoted by S , the responses to the shock depend on the specific history of the system prior to the occurrence of the shock, represented as Y_{t-1}^S . Intuitively, the economy may react differently when the inflation indicator is at its historical minimum compared to when it is just below its critical threshold Z^* , despite both instances being characterized as “low inflation.” Finally, the response to positive and negative shocks is calculated

¹⁰See Dou et al. (2024) and Dieppe et al. (2021) for a discussion on this alternative strategy.

¹¹Notice that GFEV is a function of the impact matrix A_0 since the structural shock $e_t = A_0^{-1}u_t$.

as the average response to the shock across all historical paths falling within both regimes. By averaging over multiple historical paths, our aim is to obtain a representative description of the dynamics associated with each regime.

Additionally, we test the stability of the GFEV-based identification across regimes by performing a diagnostic analysis illustrated in Section B.4.1 of the Supplementary Appendix.

2.1.2 Model selection analysis

We initiate our empirical analysis by investigating the presence of nonlinearity in the data. Specifically, we compare the TVAR model with its linear counterpart, employing the Deviance Information Criterion (DIC) introduced by Spiegelhalter et al. (2002). DIC is calculated based on the average likelihood of a model and incorporates a penalty correction that considers the model’s complexity, quantified by the effective parameters it employs. This criterion is particularly well-suited for scenarios where the models under scrutiny are highly nonlinear or differ significantly in terms of complexity, as in this case. Smaller values of the criterion indicate a preference for the corresponding models.

To evaluate the overall significance of nonlinearities in the data, we compare the benchmark TVAR model with inflation regimes with two alternative specifications, namely the linear VAR model and a TVAR model featuring boom-bust regimes. The DIC supports that the baseline TVAR model with inflation regimes is preferred over the alternative specifications. We report the DIC for each specification in Table 2 in Section B.1 of the Supplementary Appendix.

2.1.3 Inflation regimes

The TVAR model identifies two CPI inflation regimes determined based on the threshold variable, specifically the year-on-year growth in CPI at time $t - d$. The estimated median threshold level is 3.9%.¹² The median estimate for the delay parameter (d) is one quarter, indicating that the economy tends to enter the high inflation regime promptly after surpassing the threshold.

The inflation regimes identified by the empirical model correspond to notable historical events that have been well-documented. We report the regimes for the baseline TVAR specification with five variables over the extended sample period 1962:Q1-2019:Q4 in Figure 1 along with the CPI annual growth rate and PTR measure. The red bands indicate periods when CPI inflation is above the threshold level Z^* , referred to as the high inflation regime. Results are nearly identical when additional variables are included or when the sample is extended to 1962:Q1–2022:Q4 -see Figure 1 in the Supplementary Appendix.

Unsurprisingly, the high inflation regime covers substantial periods during the Great Inflation era, following the breakdown of the Bretton Woods system and the occurrence of the two major

¹²Using a different econometric framework Pfäuti (2023) estimates a threshold value of about 4% as an attention threshold at an inflation rate, which indicates that agents start to consider inflation relevant and therefore relatively high, when above the 4%. He shows that agents’ attention doubles when inflation exceeds this threshold.

oil crises. Furthermore, it encompasses three smaller inflation spikes around the early 1990s, just before the Global Financial Crisis, and during the post-Covid-19 period. Conversely, the low inflation regime is marked by the post-Volker era, the Great Moderation period, the Zero Lower Bound, and the pre-Covid-19 period, extending until the end of 2019.

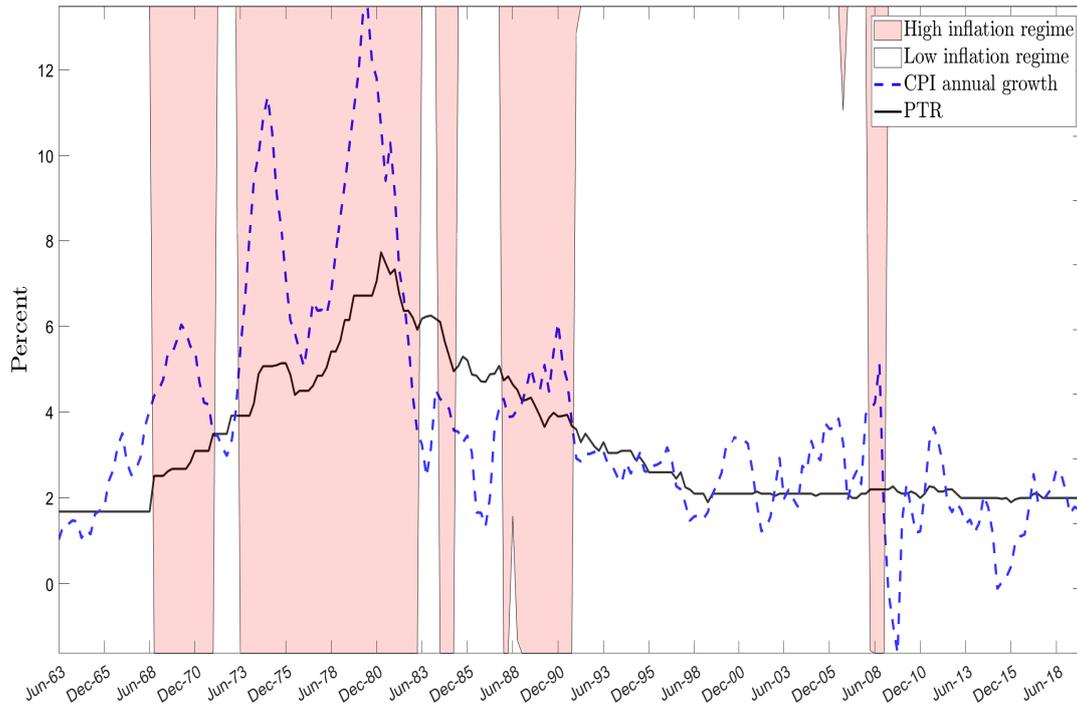


Figure 1: **Estimated CPI inflation regimes in the baseline TVAR model with five variables.** CPI inflation (blue dashed line) and long-run inflation expectations (black solid line) on the left axis, alongside the high- and low-inflation regimes, shown by red and white bands respectively.

2.2 Structural analysis

The next two subsections investigate how the impact of a shock to the inflation target varies based on the direction of the shock and provide a narrative for the structural shocks identified in the TVAR.

2.2.1 Impulse Responses and Sign Asymmetry

To analyze the sign asymmetry it is necessary to employ generalized impulse response functions, as defined in equation (3). In our framework, the sign asymmetry arises from the shock capacity to bring about a shift in the inflation regime. For example, a significant positive shock to the inflation target can lead to an increase in CPI inflation and potentially trigger a shift from a low inflation regime to a high inflation regime. Consequently, if the impulse responses differ between the two regimes, this will result in both sign and size asymmetry.

Figure 2 in Section B.2 of the Supplementary Appendix reports the responses to an inflation target shock in high and low inflation regimes. Empirical evidence supports the regime dependency of the impulse responses, but only for nominal variables (inflation and the nominal interest rate), whereas real variables do not show any regime dependency.¹³

Next, we analyze and compare the effects of positive and negative shocks on the inflation target. Figure 2 reports the generalized impulse responses of two distinct scenarios: a positive shock that raises the PTR measure by 1 percentage point (red line) and a negative shock that decreases the PTR measure by 1 percentage point (blue line). The third column (magenta line) illustrates the difference between the responses to negative and positive shocks. The shaded areas represent the 68% Highest Posterior Density Intervals (HPDI). Both shocks are normalized to increase the PTR by 1 pp on impact, and for easier comparison, the IRFs to a negative shock are multiplied by -1. Averages across all histories are reported.

Notably, in both scenarios, the shocks lead to inflationary and expansionary effects, prompting a tightening of monetary policy.¹⁴ However, a crucial observation is that a decrease in the inflation target results in more pronounced changes in output, consumption, investment, and net entry compared to an equal-sized increase in PTR. Interestingly, the nominal variables do not exhibit significant sign asymmetry in response to the shocks.

2.2.2 Narrative for Structural Shocks

As an output of the TVAR estimation, we obtain the series of identified structural shocks. This section will provide a narrative for the most significant shocks identified using our baseline TVAR.

¹³To isolate the specific dynamics of each inflation regime, we maximize the GFEVD and then compute the classical IRFs without incorporating regime switches caused by shocks. This ensures that the IRFs accurately capture the distinct effects within each regime, providing a clear understanding of the dynamics in each setting without mixing the two.

¹⁴Notice that, a negative shock is in reality a recessionary and deflationary shock, however, given that our IRFs are multiplied by -1 we interpreted it as expansionary and inflationary.

The vector of structural shocks from the TVAR, $e_t = (A_0^S)^{-1}u_t$, is a function of the impact matrix A_0^S , and thereby depends on which regime, denoted by S , prevails when they occur. Although it would be impractical, considering the inherent nature of shocks, to explain every target shock, we aim to examine whether it is feasible to provide anecdotal ex-post justifications for certain peaks in the series, serving as a basic sanity check. The shocks are measured in standard deviations. Since our model features two regimes, we have distinct impact matrices for each. To provide further intuition, a 1 standard deviation target shock increases the PTR on impact by approximately 6.5 basis points in the low-inflation regime and 10 basis points in the high-inflation regime. Consequently, if we take 2008:Q4 as a period, which is in the high-inflation regime, the 3.6 standard deviation shock observed at that date is expected to reduce the PTR by around 36 basis points.

The median of the identified inflation target structural shocks, along with the CPI inflation regimes for the baseline TVAR specification, is shown in Figure 3. In the same figure, we highlight some of the largest spikes in the series of structural shocks. These shocks are emphasized using blue dots, whereas their narrative is provided below, reporting in bold the year and the quarter of the identified shock.

1972:Q4. In the fourth quarter of 1972, the United States experienced a notable surge in inflation. This period was characterized by President Richard Nixon’s implementation of wage and price controls, known as Phase II, aiming to curb inflation. However, these controls were largely ineffective, leading to increased inflationary pressures.

The Federal Reserve’s response during this period was relatively muted. Under Chairman Arthur Burns, the Fed maintained an accommodative monetary policy, partly due to political pressures and a desire to support economic growth ahead of the 1972 presidential election (Drechsel, 2024). This lack of decisive action contributed to a shift in long-term inflation expectations, as businesses and consumers began to anticipate continued inflation, leading to behaviors that perpetuated rising prices.

This period is often cited as a precursor to the stagflation of the 1970s, where simultaneous high inflation and unemployment challenged traditional economic policies (Reis, 2022). The experience underscored the importance of central bank independence and the need for credible anti-inflationary policies to anchor long-term expectations.

The FOMC minutes and supporting documents from this period, especially the November and December 1972 meetings, reveal the Fed’s struggle to adjust its strategy amid mounting challenges, as it sought to balance inflation control with economic stability.¹⁵ This delicate balancing act

¹⁵For additional detailed minutes and specific economic discussions from the Fed’s perspectives in late 1972, refer to the FOMC meeting’s Memoranda of Discussion [here](#). For example, Mr Holmes, from the NY FED said: *If the recent strength in the aggregates tends to persist, we may be in for a difficult period. It would be most helpful if, in their policy deliberations, members of the Committee would indicate how they would prefer to see the Account*

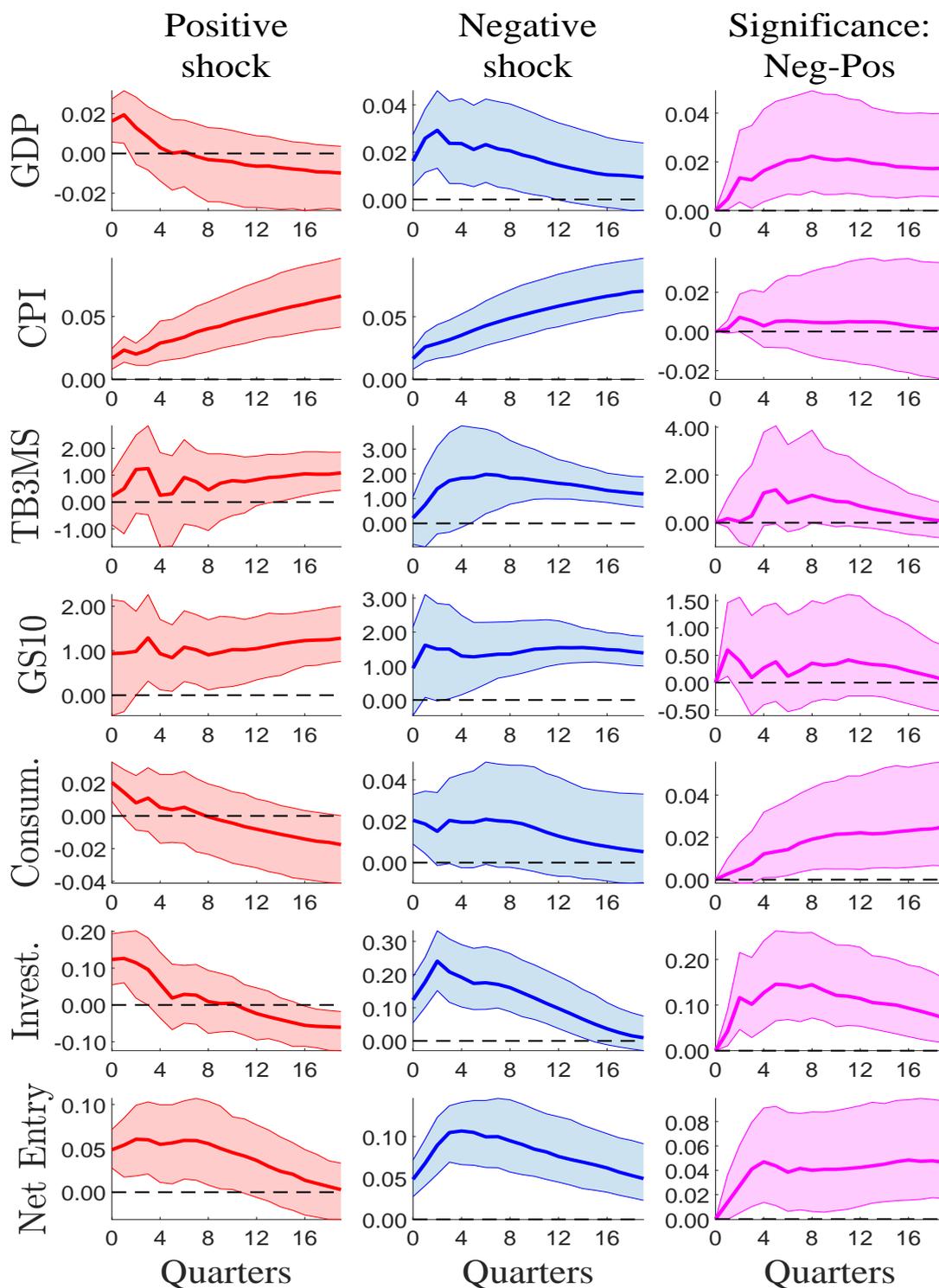


Figure 2: **GIRFs to positive (red) and negative (blue) inflation target shocks.** Responses are in percent, except interest rates (pp). The shock is normalized to raise the PTR by 1 pp on impact. Shaded areas show 68% Highest Posterior Density Intervals (HPDI).

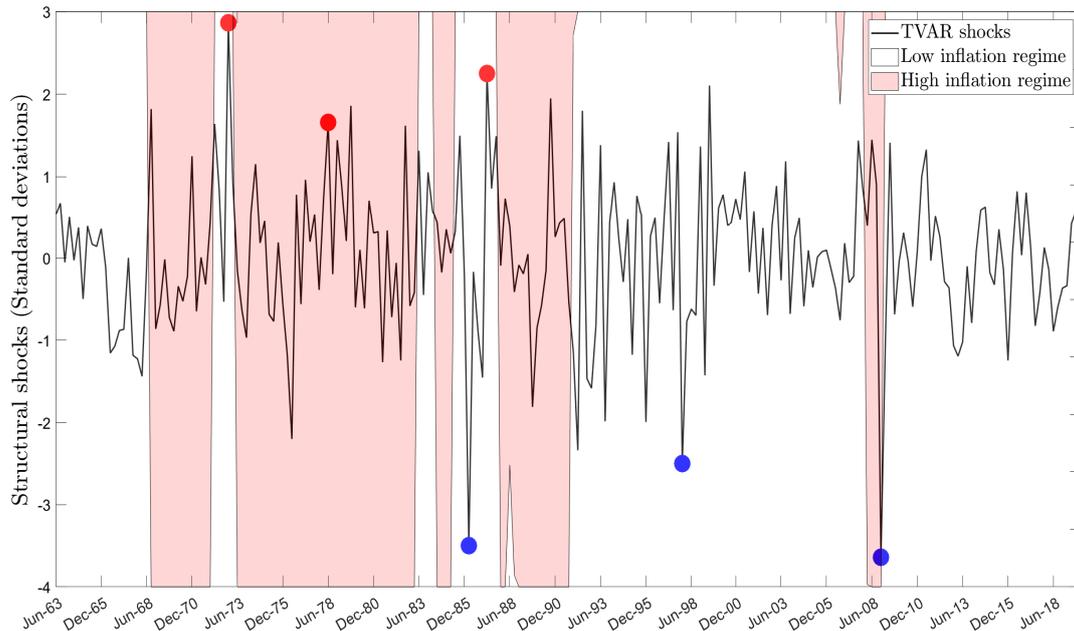


Figure 3: **Estimated CPI inflation regimes and PTR identified structural shocks.** Structural shocks (black line, left axis), with blue dots marking some large negative spikes and red dots marking some large positive spikes, alongside the high- and low-inflation regimes, shown by red and white bands respectively.

could have led to slight leniency on inflation targeting as the Fed was navigating dual mandates under considerable external pressures. This may justify the positive inflation target shock.

1978:Q2. The late 1970s saw high inflation due to cost-push factors, particularly the second wave of the oil crisis. Although the second oil shock officially occurred in 1979, energy prices were already rising in 1978, contributing to inflationary pressures and expectations of further price increases. In March 1978, G. William Miller assumed the role of Chairman of the Federal Reserve, succeeding Arthur Burns. This transition led to uncertainties regarding the Fed’s policy direction, reinforcing perceptions of a weakened commitment to combating inflation. Market participants feared that the Fed was not taking aggressive action to curb inflation, leading to higher inflation expectations. In his first appearance before the House Committee on Banking, Finance, and Urban Affairs, Chairman Miller acknowledged that “the rate of inflation remained disturbingly high.” He noted recent economic weaknesses but did not directly address how to control increasing inflation expectations in his prepared remarks (see The Statement of March 9, 1978, [Federal Reserve Bank of St. Louis](#)). This omission signaled uncertainty regarding the

Management respond to any potential conflict between even keel considerations and more rapid than desired growth in the aggregates.

implementation of an effective monetary policy stance, which has persistent effects and may explain the positive inflation target shock in the second quarter of 1978.

Subsequent retrospective analyses indicate that during Miller’s tenure, inflation continued to rise, and inflation expectations became unanchored. For example, [Hetzl \(2023\)](#) notes that *as inflation rose, inflationary expectations became untethered*, suggesting a loss of a stable nominal anchor during William Miller’s mandate.

1986:Q1. The first large negative shock occurred in the first quarter of 1986. During that period, the United States experienced notably low inflation, with the annual inflation rate for the year standing at 1.86%—a significant decline from the higher rates observed in previous years.

A retrospective analysis by the Federal Reserve Bank of Richmond, published in the Winter of 1993,¹⁶ examined how the Federal Reserve addressed the inflation scare problem between 1979 and 1992. Notably, the report argued that by the spring of 1986, the long-term interest rate was three percentage points lower than at the onset of the 1983 scare.

From a Fisherian perspective, this decline in long-term interest rates may indicate that the Fed successfully contained the inflation scare, reinforcing public confidence in a reduction of the inflation trend. Notably, in 1986:Q1, the Cleveland Federal Reserve’s 10-year expected inflation measure recorded its steepest non-recessionary decline in the series.¹⁷

1987:Q1. One year later, in the first quarter of 1987, the economic situation in the US changed dramatically. Inflation skyrocketed, and the surge involved inflation expectations as well. To measure the latter, FED economists looked at the yield curve, which is an imperfect but good indicator of inflation expectations. The Fisher effect implies that an increase in expected inflation could steepen the yield curve by raising the expected level of future short-term interest rates. In a report published by the Federal Reserve of Kansas City analyzing the US yield curve in 1987 ([Garner, 1987](#), page 7), this point is made explicitly. In the first half of 1987, the yield curve steepened sharply as long-term interest rates rose more significantly than short-term rates. One argument made by Fed analysts to explain this steepening was the substantial deterioration in the long-term inflation outlook, which occurred without decisive intervention from the central bank. This situation may also account for the upward shock to the implicit inflation target. This may justify the negative inflation target shock.

2008:Q4. Not surprisingly, the Great Financial Crisis led to heightened volatility in the time series of structural shocks. During the fourth quarter of 2008, the financial crisis was unfolding

¹⁶See the document: "Interest Rate Policy and the Inflation Scare Problem: 1979-1992," *FRB Richmond Economic Quarterly* 79.1 (1993): 1-23, [Goodfriend \(1993\)](#).

¹⁷See <https://fred.stlouisfed.org/series/EXPINF10YR>.

its catastrophic consequences, prompting policy institutions to take decisive actions to protect the U.S. economy.¹⁸ The structural shocks exhibit the largest drop in the series.

In the last quarter of 2008, the effective federal funds rate reached the zero lower bound. The economy was plummeting, and real GDP hit the trough of the recession in that quarter. During the FOMC meeting held on December 15-16, 2008, participants acknowledged the possibility of a prolonged contraction and emphasized the importance of monitoring inflation expectations for signs of disinflationary dynamics. However, the discussion also focused on the potential benefits of improving Federal Reserve communication. Specifically, it was suggested that a more explicit indication of the Fed’s long-run inflation target might enhance clarity and help prevent inflation expectations from falling further.¹⁹

This discussion signaled concerns among FOMC members that, during the peak of the Great Financial Crisis, financial markets perceived a lower Federal Reserve inflation target, and a lack of clarity may have exacerbated expectations. This concern could be reflected in the strong negative shock to the PTR in 2008:Q4.

Taking the narrative evidence together, we interpret the PTR shock broadly as a belief-driven disturbance to the perceived long-run inflation target, rather than as a pure exogenous change in the central bank’s actual policy rule. We show that this shock captures episodes in which private agents revise their views about the central bank’s commitment to its long-run inflation objective—whether due to policy inaction, communication frictions, or credibility losses.²⁰ Under this interpretation, large negative shocks, such as those in 2008:Q4 or 2020:Q2—see Figure 11 in Section “B.4 TVAR Structural Shocks” of the Supplementary Appendix, which reports on TVAR with estimation ending in 2022:Q4—reflect periods in which markets perceived a temporary weakening of the central bank’s resolve to maintain its long-run target, while positive shocks, such as those in 1972:Q4 or 1978:Q2, correspond to episodes of increased inflation tolerance or diminished anti-inflationary credibility.

2.2.3 Robustness analysis

We assess the robustness of TVAR findings using various alternative specifications. As a sanity check, we also compare our identified shocks with those from the related literature. In this section, we summarize the key findings, while more details on the impulse response functions and

¹⁸On October 3, 2008, the Emergency Economic Stabilization Act of 2008 was approved. Moreover, after the summer of 2008, the Federal Reserve began increasing its total assets from approximately 900 billion in September to about 2,000 billion in November. See [Federal Reserve Board](#).

¹⁹“Another possible form of communication that participants discussed was a more explicit indication of their views on what longer-run rate of inflation would best promote their goals of maximum employment and price stability. The added clarity in that regard might help forestall the development of expectations that inflation would decline below desired levels, and hence keep real interest rates low and support aggregate demand.” Source: Minutes of the Federal Open Market Committee, December 2008. See [FOMC Minutes, December 2008](#).

²⁰Such belief revisions are, for instance, consistent with the “confidence” or “credibility” shocks discussed in recent work (e.g., [Uribe, 2022](#), [Shapiro and Wilson, 2022](#)).

cross-correlations are provided in Sections B.3 and B.4 of the Supplementary Appendix.

Alternative TVAR specifications First, we address concerns that our analysis might overlook important sources of nonlinearities, such as constraints within the labor market. To explore this, we add nominal wages to the set of endogenous variables. Reassuringly, Figure 3 of the Supplementary Appendix shows that the responses of nominal wages to both positive and negative shocks to the inflation target are not statistically significant, supporting the robustness of our findings.

Second, we test the robustness of the max-share approach in identifying the true shock of interest, e_j^S . Specifically, following Dou et al. (2024), we re-estimate the TVAR model by modifying the horizon used to identify the shock. Instead of maximizing the generalized forecast error variance over the benchmark range $k = 0 : 40$, we apply a fixed horizon of $k = 40$. This alternative specification allows us to assess whether the approach still captures the same underlying economic dynamics. The results, illustrated in Figure 4 in the Supplementary Appendix, confirm that the impulse response functions for GDP, investment, and net entry remain consistently positive regardless of the chosen horizon. This suggests that the identified shock is robust to changes in the identification horizon and does not significantly alter the core findings.

Third, we examine whether our analysis might inadvertently capture factors beyond the distinction between high and low inflation regimes, such as financial distress, zero lower bound constraints, or periods of high versus low volatility. To mitigate these concerns, we restrict the sample period to end in 2007, aiming for a more balanced distribution of high and low inflation regimes. Figure 5 in the Supplementary Appendix shows the differences between the responses to negative and positive shocks for selected variables, specifically for the real GDP, investments and net entry.

Fourth, to ensure that the higher magnitude of negative shocks is not simply due to greater volatility in one regime, we estimate a model where the variance-covariance matrix is fixed across regimes. Figure 6 in the Supplementary Appendix shows that our results persist under this specification, supporting the robustness of our findings.

Fifth, we check the sensitivity of our results to the thresholds defining high and low inflation regimes. Specifically, we adjust the threshold level first to 6%, increasing observations in the low inflation regime, and then to 3%, which results in more observations in the high inflation regime. In both cases, our main results continue to hold, with negative shocks exhibiting a larger magnitude of effects than positive shocks. Figure 7 in the Supplementary Appendix shows the differences between the responses to negative and positive shocks for the same selected variables used for all the other robustness.

Sixth, we examine if our findings hold when using the PTR in levels for consistency with other variables, which are also in levels. Figure 8 in the Supplementary Appendix shows that our main

conclusions remain unchanged under this alternative specification.

Seventh, we verify the robustness of our results by using an alternative measure of the inflation trend. Specifically, we employ the permanent component of inflation estimated by [Uribe \(2022\)](#), who estimates a latent model that imposes a cointegration relationship between inflation and a latent permanent monetary shock. This shock is then rescaled and interpreted as the permanent component of inflation. The results, presented in Figure 9 in the Supplementary Appendix, confirm that our findings remain robust under this alternative inflation trend measure. This outcome is particularly reassuring given the consistency between our identification strategy and that of [Uribe \(2022\)](#), the interpretation of the shock as an inflation target shock, and the similarity of results in the linear framework between [Uribe \(2022\)](#), [Mumtaz and Theodoridis \(2023\)](#), and our results.

Structural shocks Following [Ben Zeev and Pappa \(2017\)](#) we analyze the cross-correlation between our target shock and various shocks identified in the literature as significant for business cycle fluctuations (e.g., oil, TFP, monetary, financial, and fiscal shocks). The correlations, reported in Figure 10 in Supplementary Appendix B.4, are predominantly insignificant and of small magnitude across most cases. While we observe some mild correlations with [Känzig \(2021\)](#)'s oil news shocks and the [Gertler and Karadi \(2015\)](#)'s monetary policy shocks, these are expected given that all these shocks are generated regressors and subject to measurement errors due to model misspecifications in the identification processes.

2.2.4 TVAR versus Polynomial Specifications

A recent and promising approach to modeling nonlinearities in sign and size consists of augmenting local projections or VARX models with polynomial transformations of the identified shocks. Even transformations (e.g., squared or absolute values) capture sign asymmetries, while odd transformations (e.g., cubic terms) capture size nonlinearities—differences in the marginal effects of small versus large shocks (see, for example, [Caravello and Martinez-Bruera, 2024](#), [Forni et al., 2025](#), [Forni et al., 2024](#)). Polynomial specifications thus offer a flexible and tractable way to allow for smooth departures from linearity, producing impulse responses that vary continuously with the sign or magnitude of the shock.

Our baseline model is a Threshold VAR, where the structural shock is identified by maximizing the generalized forecast error variance decomposition of the target variable. In this setup, sign asymmetry arises endogenously through state dependence: positive and negative shocks may move the system into different regimes, generating asymmetric transmission mechanisms.

We complement the TVAR analysis by estimating a nonlinear VARX model in which asymmetry originates directly from the shock rather than from regime changes. Following [Forni et al. \(2025\)](#) and [Forni et al. \(2024\)](#), we augment the VARX with even (squared) transformations of

the identified shock to capture sign asymmetry:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + B_1 s_t + B_2 s_t^2 + u_t, \quad u_t \sim (0, \Omega). \quad (8)$$

In this specification, asymmetry arises from the nonlinear propagation of the shock itself rather than from state-dependent regime switches. This allows us to study sign-dependent effects while retaining a standard VAR structure.

Crucially, we account for nonlinear transmission channels already at the identification stage. Specifically, we extend the approach of [Forni et al. \(2025\)](#) by selecting the shock that maximizes its contribution to the generalized forecast error variance (GFEV) of the perceived inflation target (PTR), explicitly taking into account both the linear and nonlinear components of the VARX. The identification algorithm is described in detail in Section B.5 of the Supplementary Appendix.

Impulse responses in the VARX framework are straightforward to interpret relative to the generalized impulse responses of the TVAR. They are computed as the sum of the coefficients on the linear and nonlinear terms: for positive shocks as $\mathbf{B}_1 + \mathbf{B}_2$, and for negative shocks as $\mathbf{B}_1 - \mathbf{B}_2$. For comparison with the TVAR results, we report responses to negative shocks as $-(\mathbf{B}_1 - \mathbf{B}_2)$.

We adopt the VARX specification for two main reasons. First, it preserves internal consistency between identification and estimation: the same nonlinear channels that govern transmission are explicitly accounted for when selecting the shock that maximizes its variance contribution. Second, it aligns naturally with our DSGE framework, in which the squared component of the inflation-target shock dampens expansionary effects of positive shocks while amplifying contractionary effects of negative ones.

This formulation introduces nonlinear transmission mechanisms while retaining a direct link between impulse responses, variance decompositions, and the innovation covariance matrix. Following [Forni et al. \(2024\)](#), the forecast error at horizon h can be written as

$$e_{t+h} = \sum_{k=0}^{h-1} \alpha_k u_t + \sum_{k=0}^{h-1} \beta_k g(u_t) + \sum_{k=0}^{h-1} \Gamma_k \xi_t, \quad (9)$$

where $\{\alpha_k\}$ and $\{\beta_k\}$ denote the linear and nonlinear impulse responses, and ξ_t collects other innovations. The share of forecast error variance explained by the shock and its nonlinear component is then defined as

$$\text{VD}_y(h) = \frac{\text{Var}_t(e_{t+h}^s)}{\text{Var}_t(e_{t+h})}, \quad e_{t+h}^s = \sum_{k=0}^{h-1} \alpha_k u_t + \sum_{k=0}^{h-1} \beta_k g(u_t). \quad (10)$$

Building on Equation (10), we perform identification by selecting the shock that maximizes the share of forecast error variance explained in the PTR over a 40-quarter horizon, as recommended

by [Mumtaz and Theodoridis \(2023\)](#). By explicitly incorporating the nonlinear term in both estimation and identification, this procedure ensures consistency between the identified shock, impulse responses, and variance decompositions.

For comparability with the TVAR analysis, we first estimate the VARX model on a baseline five-variable system including the PTR, log real GDP, log CPI, the 3-month Treasury bill rate, and the 10-year government bond yield. We then augment this baseline specification by adding one variable at a time from the following set: log consumption, log investment, and log firms' net entry. The data are quarterly, and since the VARX framework does not allow for regime changes, the sample ends in 2019Q4.

Figure 4 reports the impulse responses obtained from the nonlinear VARX specification. The first column (red) shows the responses to positive shocks, the second (blue) to negative shocks, and the third (magenta) displays the contribution of the nonlinear term—the squared shock—which captures sign asymmetry. Negative shocks exert stronger effects than positive ones on real variables such as GDP, consumption, investment, and net entry, while the difference is less pronounced for nominal variables. These findings closely mirror the results from the TVAR, reinforcing the evidence of asymmetric transmission mechanisms.

Overall, the VARX model provides a coherent and theoretically grounded framework that (i) preserves the FEVD-maximizing identification central to our baseline, (ii) captures nonlinear transmission channels, and (iii) allows for the analysis of sign asymmetries not driven by regime switching. Hence, Figure 4 confirms that our conclusions are robust to employing polynomial specifications to detect sign asymmetry, offering an internally consistent alternative to the regime-switching TVAR.

We provide further robustness to our empirical finding by following the approach proposed by [Caravello and Martinez-Bruera \(2024\)](#) to nonlinear local projections—namely, local projections augmented with the squared shock term. We also adopt a more conservative parametrization in which the local projections remain linear but allow for separate responses to positive and negative realizations of the shock, following [Tenreyro and Thwaites \(2016\)](#).

We report on the local projections estimation in Section B.6 and B.7 of the Supplementary Appendix. Notably, our estimated results are fully consistent with those obtained from the VARX and TVAR frameworks.

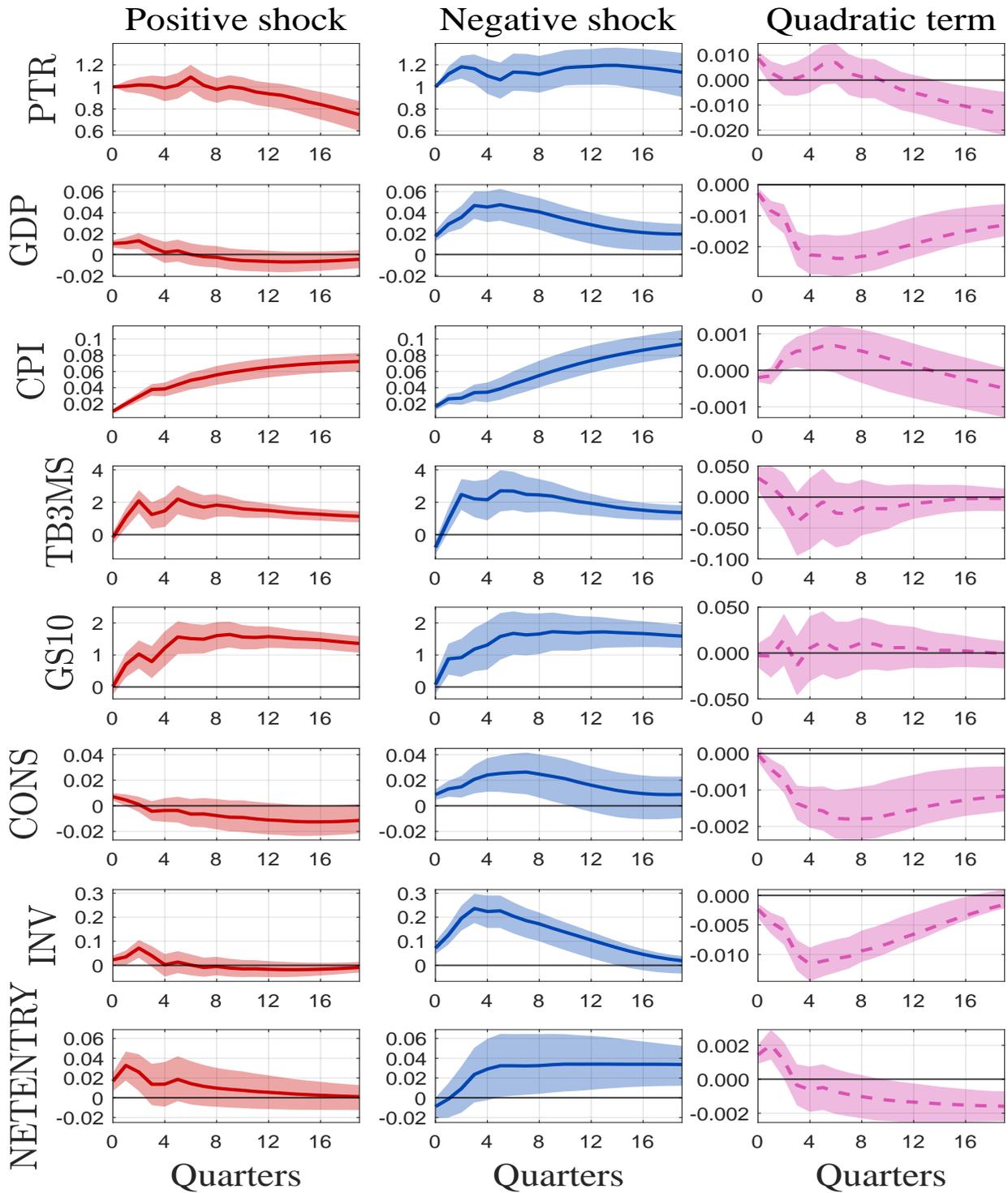


Figure 4: **Impulse responses from the nonlinear VARX model.** Responses to positive (red) and negative (blue) inflation-target shocks. Column 3 (magenta) shows the effect of the squared shock capturing sign asymmetry. IRFs are expressed in percent; shaded areas denote 68% confidence intervals.

3 Theoretical Model

In this section, we summarize the theoretical framework of the baseline model considered all along the paper (labeled as *Baseline* henceforth). The Baseline model is a modified version of a standard medium-scale model considered by Fasani et al. (2023). The main ingredients of the medium-scale model and its micro-foundations are well known in the literature (Christiano et al., 2005; Smets and Wouters, 2007), so the details are not discussed here. We assume sticky nominal wages and prices as in Rotemberg (1982), adjustment costs and capacity utilization for capital, and external habit persistence. On top of that, we introduce firm endogenous entry and exit dynamics in the intermediate sector to capture the extensive margin of investment dynamics.

The model consists of a closed economy composed of four agents: households, firms, monetary authority, and fiscal authority. A full description of the model, underlying how it differs from the standard medium-scale model can be found in Fasani et al. (2023).

Below, we describe the novel part of the model, namely the firms' price-setting mechanisms, which departs from Fasani et al. (2023). This part includes the equation for how agents estimate the Central Bank's inflation target -the perceived inflation target- and the equations describing the monetary policy rule and the inflation target shock. Agents have incomplete information about the Central Bank's inflation target and must estimate its value, following the approach of Gürkaynak et al. (2005) and more recently Neri (2021) and Bianchi et al. (2021). In the Supplementary Appendix Section "C.1 System of equations" (see Tables 3-4), we report the full list of the equations characterizing the model.

Price Setting and Perceived Inflation Target The intermediate sector is composed of a continuum of N_t intermediate firms that compete under monopolistic competition and flexible prices to sell the intermediate goods to a continuum of measure one of the retailers. Each $k \in (0, 1)$ retailer buys intermediate goods from the intermediate sector and differentiates them with a technology that transforms the intermediate goods into an aggregate industry good, $Y_t^I(k)$, solving a minimum expenditure problem. Retailers sell the differentiated industry goods to households, competing with other retailers under monopolistic competition. They face Rotemberg (1982) adjustment costs so that, due to the monopolistic competition structure, the second optimization problem gives rise to the price NKPC.

The price adjustment cost of retailers is: $\Gamma_{i,t} = \frac{\phi_p}{2} \left(\frac{P_{i,t}}{(\pi_t^*)^\gamma P_{i,t-1}} - 1 \right)^2$, where $\phi_p \geq 0$ measures the magnitude of the adjustment cost and π_t^* denotes the firm's estimate of the inflation target of the Central Bank. Finally, γ is the degree of indexation of the estimated inflation target. As in Neri (2023) we set $\gamma = 1$, that is we do not include indexation to past inflation on the basis of the findings in Benati (2008), which shows that estimates of the indexation parameter in hybrid NK Phillips curves are close to zero in inflation-targeting regimes.

Firms rely on their estimate of the inflation target π_t^* , which we label as the perceived inflation target. The equation estimated by firms is in the spirit of [Gürkaynak et al. \(2005\)](#), and recently [Neri \(2023\)](#) and [Bianchi et al. \(2022\)](#). The estimate of the target evolves according to the following equation, in which the variables are expressed as log-deviations from the steady state:

$$\widehat{\pi}_t^* = (1 - \lambda_{\pi^*}) \left[\rho_{\pi^*} \widehat{\pi}_{t-1}^* + \mu_{\pi^*} \left(\frac{1}{4} \sum_{i=1}^4 \widehat{\pi}_{t-i-1} - \widehat{\pi}_{t-1}^* \right) \right] + \lambda_{\pi^*} \widehat{\pi}_t, \quad (11)$$

where $\widehat{\pi}_t^* = \log\left(\frac{\pi_t^*}{\pi}\right)$, $\widehat{\pi}_t = \log\left(\frac{\pi_t}{\pi}\right)$, $\widehat{\pi}_t = \log\left(\frac{\pi_t}{\pi}\right)$ are the deviations from the steady-state value of the perceived inflation target, current inflation, and target inflation, respectively. The persistence in the perceived inflation target is captured by $\rho_{\pi^*} \in (0, 1)$. The parameter μ_{π^*} is the gain, which measures the strength with which firms revise their estimate of the target based on the deviations of past inflation from the previous period estimate. As in [Bianchi et al. \(2022\)](#), agents get a signal about the true inflation target: $\lambda_{\pi^*} = 1$, if the signal is completely informative, while $\lambda_{\pi^*} = 0$, if the signal is uninformative. Overall, the perceived target is a weighted average of the trend implied by the constant gain learning rule and the Central Bank's inflation target. Notice that when actual inflation remains substantially distant from the target for a long period of time agents see it as a temporary change in the central bank's target.

The retailer's optimal price decision rule implies the following NKPC:

$$1 = \frac{\theta_p}{\theta_p - 1} \rho_t^I - \frac{\phi_p}{\theta_p - 1} \left(\frac{\pi_t}{\pi_t^*} - 1 \right) \frac{\pi_t}{\pi_t^*} + \frac{\phi_p}{2} \left(\frac{\pi_t}{\pi_t^*} - 1 \right)^2 + \frac{\phi_p}{\theta_p - 1} E_t \left\{ \beta \frac{\lambda_{t+1}}{\lambda_t} \left(\frac{\pi_{t+1}}{\pi_{t+1}^*} - 1 \right) \frac{\pi_{t+1}}{\pi_{t+1}^*} \frac{Y_{t+1}}{Y_t} \right\}, \quad (12)$$

with ρ_t^I as the relative price $\frac{P_t^I(k)}{P_t}$, and $\lambda_{t,t+1}$ as the consumption marginal utility. By symmetry among the retailers, it holds $Y^R(k) = Y_t$ and $P^R(k) = P_t$. Hence, $\pi_t = \frac{P_t}{P_{t-1}}$ is the gross inflation rate.

Monetary Authority and Inflation Target Shock To close the model we specify an equation for the behavior of the Central Bank. We simply assume that the monetary authority sets the nominal net interest rate i_t according to the following Taylor rule,

$$\log\left(\frac{1+i_t}{1+i}\right) = \phi_R \log\left(\frac{1+i_{t-1}}{1+i}\right) + (1 - \phi_R) \left(\phi_\pi \log\left(\frac{\pi_t}{\pi}\right) + \phi_y \log\left(\frac{Y_t}{Y}\right) + \phi_{dy} \log\left(\frac{Y_t}{Y_{t-1}}\right) \right), \quad (13)$$

where ϕ_π , ϕ_y and ϕ_{dy} are the elasticities of the nominal interest rate to the deviation of the

inflation from their time-varying inflation target $\bar{\pi}_t$, to the deviation of output from its steady-state value and the output growth rate. The parameter ϕ_R is the interest rate smoothing parameter. Following [Cogley et al. \(2010\)](#) the inflation target is time-varying and follows an AR(1) process with $\sigma_{\bar{\pi}}$ standard deviation and $\rho_{\bar{\pi}}$ persistence:

$$\ln\left(\frac{\bar{\pi}_t}{\pi}\right) = \rho_{\bar{\pi}} \ln\left(\frac{\bar{\pi}_{t-1}}{\pi}\right) + \sigma_{\bar{\pi}} u_{\bar{\pi},t} \quad (14)$$

The inflation targeting innovation $u_{\bar{\pi},t}$ evolves following a Normal white noise process with zero mean.

3.1 Model Dynamics

To study the dynamics of the DSGE model, we solve it using a second-order approximation, which allows for nonlinear effects. We follow the procedure suggested by [Fernández-Villaverde et al. \(2015\)](#) to compute impulse response functions (IRFs) as deviations from the stochastic steady state. By resorting to a second-order approximation of the policy functions, we can analyse the effects of a level shock to the inflation target within a nonlinear framework. Our analysis consists of three subsections.

First, we quantitatively validated our model by estimating a subset of structural parameters, while calibrating the remaining parameters according to the literature. We then simulated the model to study the dynamics of the impulse response functions (IRFs) and the sign asymmetry of the inflation target shock. In line with the empirical evidence, a shock that lowers the central bank's inflation target has more pronounced effects on real macroeconomic variables such as output, consumption, investment, and firm entry.

Second, we inspect the main mechanism driving the sign asymmetry in response to the inflation target shock. By focusing on key elements such as capital accumulation and firm dynamics, we identify how these factors contribute to the observed asymmetries in economic responses.

Third, we exploit the model to examine (i) sign asymmetry in shock transmission using simulated data in nonlinear local projections, (ii) alternative specifications of the long-run inflation expectations shock, and (iii) alternative calibrations of the structural parameters.

3.1.1 Model Estimation and IRFs Dynamics

In this section, we bring the model to the data and estimate a set of structural parameters using the TVAR-implied IRFs as the data counterpart. Specifically, we keep fixed a predetermined set of parameters, while the remaining parameters are estimated using limited information impulse response matching techniques, following the spirit of [Christiano et al. \(2005\)](#), [Basu and Bundick \(2017\)](#). The second set of parameters are estimated by matching the first 12 periods of the quarterly TVAR-implied IRFs of real GDP, price level, consumption, investments, and net entry. As our empirical counterpart allows us to compare the effects of positive and negative shocks,

differently from the papers above, we exploit this information in the estimation of the theoretical model. Data counterparts in the impulse response matching are the responses of the variables to shocks that both raise and decline the PTR measure. With the estimated parameters in hand, obtained using the second-order solution of the model, we simulate the models and calculate the dynamic responses of the variables to an unexpected increase and decrease in the inflation target.

Calibrated Parameters The calibration of the DSGE model is set at a quarterly frequency. The discount factor, β , is set at 0.99, corresponding to an annualized real interest rate of about 4%. The capital-income share α is set to 0.33, whereas the depreciation rate of the physical capital, δ_k , is set to 0.0067, which is equivalent to around 2% every quarter. The output in the steady state is normalized to 1. The steady-state value of the exit probability η is set to match the U.S. quarterly establishments' death ratio, which is at around 9% for the period considered in the VAR analysis. The parameter of the elasticity of substitution among intermediate goods, θ_p , is set equal to 4.3, corresponding to a steady state price markup of around 30%. This value is in line with the literature on firm dynamics (Ghironi and Melitz, 2005, Bilbiie et al., 2012). We set the markup in the labor market as the benchmark for the good market, so that the elasticity of substitution among labor types θ_w is fixed to 4.3. The shape parameter of the Pareto distribution ξ is set equal to 6.51 to satisfy the steady state value of the exit rate. This value also guarantees that the condition for well-behaved average productivity, i.e. $\xi > \theta_p - 1$, is satisfied. The lower bound of productivity distribution, z_{\min} , is equal to 1. The variable components of entry and exit costs, ec and xc , are set, respectively, to 1.6% and 1.2% of the GDP in steady state. The indexation parameter, γ is set equal to 1. The remaining constant component of the entry cost, f^E , and the parameters Θ^e and Θ^x are endogenously determined. The share of the fixed entry cost of the exiting firms rebated to the households is fixed to 25% so that the parameter τ is set to 0.75. The rest of the parameters are estimated starting from an initial guess as described below.

Estimated Parameters In what follows we report the initial guess used to estimate the remaining parameters. The initial guess for the coefficient of the relative risk aversion, σ_C , is set to 1.5, while the elasticity of labor supply, σ_L , to 5. The habits persistence parameter is set to 0.6. The parameter measuring the elasticity of the capital utilization adjustment cost function, γ_2 , is set initially to be 0.54 as in the corresponding specification used in Smets and Wouters (2007). The capital adjustment costs parameter, ϕ_K , is set to 4, as in Christiano et al. (2005). The elasticity of entry and exit congestion externality, ς_e and ς_x , is set to 2 and 1 respectively. Both the variable components of sunk costs and congestion externalities are set slightly higher for entry than for exit, which is consistent with the estimates in Casares et al. (2020). Parameters describing the price and wage setting are initially set as follows. We set the initial guess for

Rotemberg parameter of price adjustment cost ϕ_p and of the of nominal wage adjustment cost ϕ_w both equal to 40. Finally, we set the initial values of the coefficients in the Taylor rule as $\phi_R = 0$, $\phi_\pi = 1.5$, $\phi_y = 0.01$ and $\phi_{dy} = 0.05$, being roughly in the range of the values estimated for the U.S. economy. We set the initial guess for parameter measuring the persistence in the perceived inflation target, ρ_{π^*} , is calibrated to 0.9, and for μ_{π^*} to 0.01, following Neri (2023). Finally, following Bianchi et al. (2021) we set the guess of λ_{π^*} to 0.013. Table 1 presents the list of estimated parameters.

Table 1: Estimated Model Parameters

Parameter	Description	Estimate
Adjustment cost parameters		
ϕ_p	Rotemberg adjustment cost - Price	47.0604
ϕ_w	Rotemberg adjustment cost - Wage	56.8071
ϕ_K	Capital adjustment cost	3.3176
Shock parameters		
$\sigma_{\bar{\pi}}$	Standard deviation of inflation target shock	0.0062
$\rho_{\bar{\pi}}$	Persistence inflation target shock	0.8862
ρ_{π^*}	Persistence estimated inflation target	0.9500
Taylor rule parameters		
ϕ_π	Inflation feedback coefficient	3.1602
ϕ_y	Output feedback coefficient	0.0106
ϕ_{dy}	Output growth feedback coefficient	0.0319
ϕ_R	Interest rate smoothing	0.0001
Other parameters		
γ_2	Capital utilization coefficient	1.0173
ς_e	Entry congestion coefficient	2.1226
ς_x	Exit congestion coefficient	1.1051
σ_C	Inverse elasticity of substitution	1.0010
σ_L	Labor supply elasticity	2.0475
h	Consumption habit coefficient	0.4074
μ_{π^*}	Gain in perceived inflation target	0.0145
λ_{π^*}	Signal parameter in in perceived inflation target	0.0165

Notes: Parameters are estimated via impulse response matching.

The estimates suggest a lower degree of price rigidity than wage rigidity, consistent with the empirical literature emphasizing the relatively higher importance of wage rigidity. The parameter of the capital adjustment cost is higher but close to [Basu and Bundick \(2017\)](#), who use the same specification of capital adjustment costs set by [Hayashi \(1982\)](#). The estimated steady-state standard deviation of the inflation expectations shock, $\sigma_{\bar{\pi}}$, is 0.0062, while the persistence of the shock, $\rho_{\bar{\pi}}$, is estimated at 0.89. Concerning the Taylor rule, model estimation basically implies an inflation-targeting policy with a low response to output growth and a muted response to output. The interest rate smoothing, ϕ_R , is estimated to be very low, but this reconciles with the shock, which instead shows high persistence and enters the Taylor rule shown in equation (13). The rest of the parameters of the Taylor rule are in line with the literature. The capital utilization adjustment parameter, γ_2 , is estimated close to [Smets and Wouters \(2007\)](#). The estimated elasticity of entry and exit congestion externality, ς_e and ς_x , align with [Casares et al. \(2020\)](#), who find higher congestion externalities for entry than for exit. Even the parameters of the utility function are consistent with the related literature. While the intertemporal elasticity of substitution and the elasticity of labor supply are respectively slightly below and above the estimates in [Smets and Wouters \(2007\)](#), the model calls for a habit parameter of 0.4 which is lower than the usual estimates, but bigger than the lower bound in the existing literature. Finally, in the perceived inflation target equation, the gain, μ_{π^*} , is estimated to be 0.015, close to the 0.01 estimated in [Neri \(2023\)](#), while ρ_{π^*} , is estimated to 0.95. The signal parameter, λ_{π^*} , is 0.017 close to the calibration in [Bianchi et al. \(2022\)](#).

IRFs Dynamics and Sign Asymmetry Figure 5 illustrates the dynamics of the model when positive and negative shocks to the inflation target are simulated, with structural parameters calibrated following the estimates based on the impulse response matching. For the sake of comparison, Figure 5 shows the responses obtained when simulating a shock that increases the inflation target in a red solid line, while those obtained when simulating a shock that decreases the inflation target are in a blue dotted line and multiplied by -1 . For interpreting the results we also report the IRFs of the linear counterpart (black dotted line).

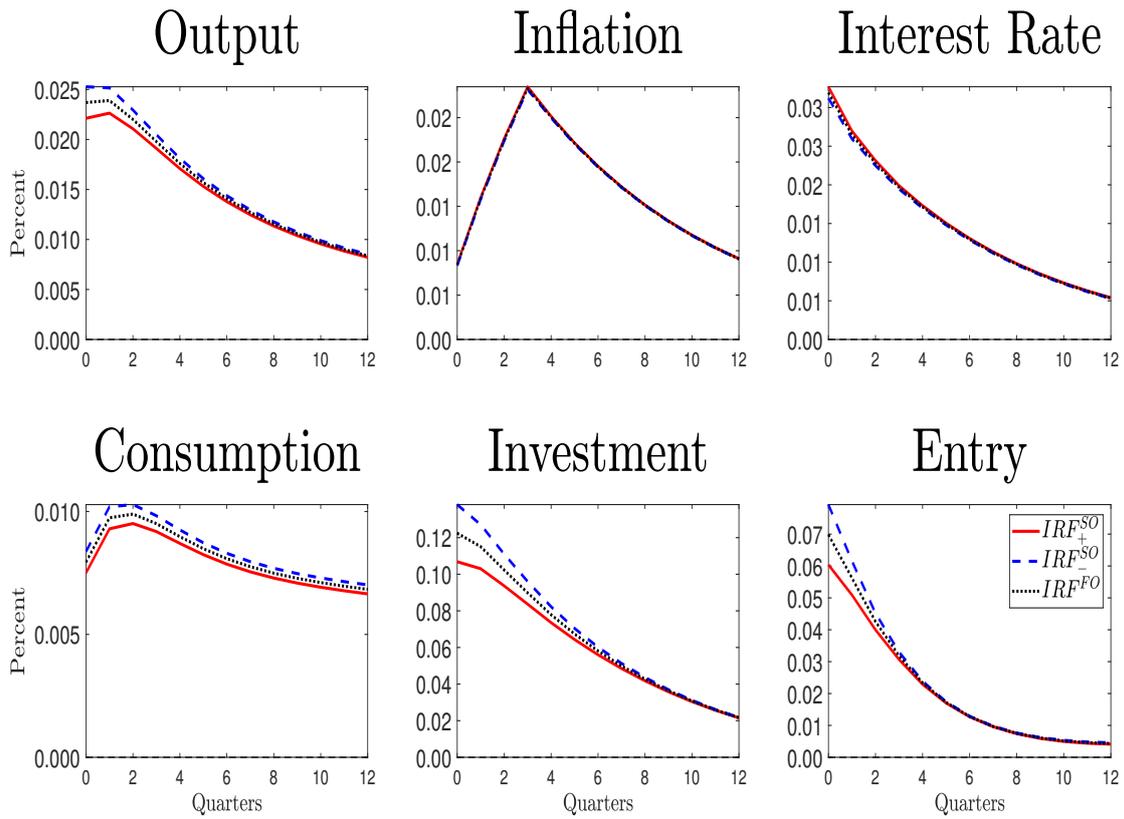


Figure 5: **Model Dynamics with estimated parameters:** responses to a one percent increase (decrease) in the *inflation target shock* (red solid lines), IRF_+^{SO} , (blue dashed lines, IRF_-^{SO}) for the *non-linear* model. Responses to a negative innovation are multiplied by -1 . Black dotted lines, IRF^{FO} , for the *linear* model.

Let’s consider first the transmission of a positive shock to the inflation target. Red lines in Figure 5 show that a shock increasing the inflation target is inflationary and expansionary in the nonlinear model. The Central Bank initially accommodates the shock. While the nominal interest rate increases, the real one declines as the shock transmits and inflation is high. The demand for consumption and investment goods thus increases and fosters aggregate demand. Firms set higher prices sustaining the surge in inflation. Overall, the shock acts as a positive demand shock with rising output and inflation. Firms’ expected profits increase too. This enhances the firms’ value and the number of new entrants, bringing about an increase in the extensive margin of investment.

The responses for the linear model (black dotted lines) in Figure 5 show the same qualitative results. However, the expansionary effect of the shock in the first-order solution is stronger than what is implied by the second-order solution (red solid lines).

The presence of uncertainty in the second-order approximation dampens the expansionary effect of the shock. The uncertainty introduced by the shock interacts with the convexity of firm profits, inducing a “wait-and-see” mechanism of incumbent firms and potential entrants, resulting in a lower demand for capital and lower entry than in a first-order solution.

Blue lines in Figure 5 show the responses in the nonlinear model of a shock that declines the inflation target. These responses are multiplied by -1 for comparability with those showing the IRFs to a shock that increases the inflation target (red lines). Remarkably, they show that the effects are larger for real variables in the case of negative shock. The reason lies in the contribution of the variance of the shock in the nonlinear model. In a second-order approximation, the variance of the shock interacts negatively with real variables, independently of the sign of the shock. In contrast, there is no contribution of the variance of the shock and in the linear model, which shows symmetric responses to positive and negative shock.

In Supplementary Appendix (Section “C.4 Model solution”), we further inspect the first- and second-order model solutions to provide an analytical investigation of the contribution of the variance of the shock to explain the asymmetry in the response.

For a quantitative assessment of the DSGE model, the Supplementary Appendix (Section “C.5 Model estimation”, Figure 24) reports the match between empirical IRFs and theoretical IRFs for the variables used in the limited-information IRF-matching: real GDP, the price level, consumption, investment, and net entry. Overall, the model provides a strong quantitative fit. Firm entry shows greater persistence in the TVAR than in the model, which can be attributed to the simplified modelling of firm dynamics.

3.1.2 Inspecting the Mechanisms Driving the Results

This section examines the main mechanisms in the model that drive the asymmetry results. By focusing on key elements such as capital accumulation and firm dynamics, we identify how these

factors contribute to the observed asymmetries in economic responses. To do this, we compare the dynamics of three alternative models: (i) the baseline model; (ii) the baseline model without firm dynamics; and (iii) the model without firm dynamics and capital accumulation.

Figure 6 shows what we define as $\Delta IRF = (-)IRF_-^{SO} - IRF_+^{SO}$, which represents the difference between the absolute value of the responses of the variable of interest to a negative inflation target shock and a positive inflation target shock. A positive response of the ΔIRF indicates that the responses to a negative shock are stronger than those to a positive shock. The figure shows the ΔIRF s for output and investments: magenta solid lines represent the baseline model; green dashed lines represent the baseline model without firm dynamics; and black dotted lines represent the model without capital accumulation and firm dynamics. It is clear from the figure that capital accumulation is the main driver of the asymmetric response of the variables. In the model without capital, the differences in the IRFs become negligible. Firm entry amplifies the responses and generates a more prolonged effect on output and investments in line with what is found in the empirical section.

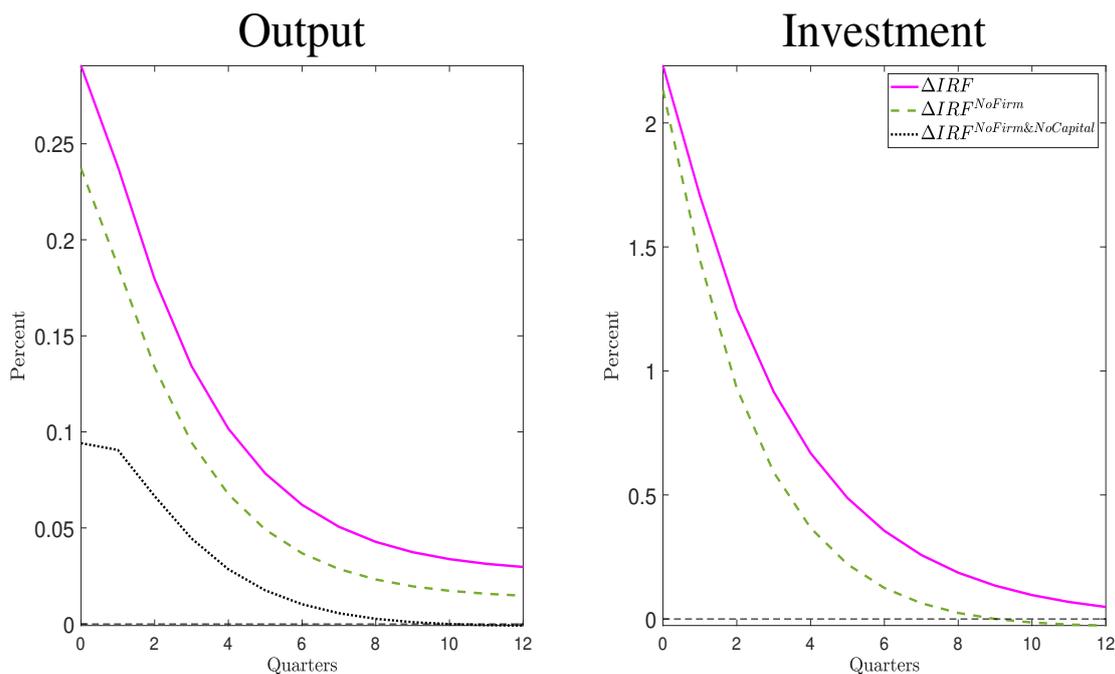


Figure 6: **Model Dynamics with estimated parameters:** Differences between the responses to a one percent decrease and the responses to a one percent increase in the *inflation target shock* for the *non-linear* model. Responses to a negative innovation are multiplied by -1 . Responses differences in the baseline model in magenta solid lines, ΔIRF , in the model with frictionless firm entry in green dashed lines, ΔIRF^{NoFirm} , in the model with frictionless firm entry and no capital in black dotted lines, $\Delta IRF^{NoFirm\&NoCapital}$.

3.1.3 Model robustness

Sign asymmetry with Simulated Data We use our DSGE model as a data-generating process to test our empirical approach. Specifically, we feed the series of empirical structural shocks into our DSGE model,²¹ solve the model to a second-order approximation, and simulate a series of macroeconomic variables. We then estimate nonlinear local projections following the approach proposed by [Caravello and Martinez-Bruera \(2024\)](#) to capture sign asymmetries in the responses. Estimates of nonlinear local projections using DSGE-generated data confirm our empirical findings.

As shown in the Supplementary Appendix (Section “C.2 Nonlinear Local Projections Using DSGE-Generated Data”), a decrease in the inflation target induces more pronounced changes in output, consumption, investment, and entry relative to an increase in the target. This is evident from the local projection coefficients on the nonlinear term associated with the squared shock, which capture sign asymmetry in the shock transmission. The estimates suggest that we can reject the null of linearity for all real variables, consistent with our empirical findings.

Inflation Target Shocks versus Perceived Inflation Target Shock We test our DSGE model to examine whether an alternative specification of the long-run inflation expectations shock can replicate the empirical evidence as effectively as the inflation target shock. A natural candidate is an exogenous component of the perceived inflation target shock—introduced by adding a shock, $u_{\pi^*,t}$, to equation 11—that is independent of monetary policy actions.

As documented in the Supplementary Appendix (Section “C.3.1 Target shock versus Perceived Target shock”), we assess the differential macroeconomic effects of inflation target shocks and perceived inflation target shocks by conducting a Monte Carlo simulation following the approach of [Canova and Paustian \(2011\)](#). We generate 5,000 draws for a subset of structural parameters from uniform distributions and compute impulse responses to both shocks. While both shocks are inflationary, only the inflation target shock consistently produces expansionary effects across parameterizations. In contrast, the perceived target shock is typically contractionary unless the monetary policy rule is sufficiently accommodative, that is, characterized by a very low inflation feedback parameter -lower than 1- and high persistence in agents’ perceived target. These results underscore that the monetary policy environment plays a critical role in shaping macroeconomic outcomes to the perceived target shock.

As a further check, in the same appendix, we test whether the asymmetric responses observed for the target shock also arise for the perceived target shock. We find similar asymmetries, though with smaller magnitudes. In both cases, higher shock variance consistently dampens the effects of expansionary shocks and amplifies those of recessionary shocks for real variables such as output,

²¹We use the shock series from a five-variable linear VAR following [Mumtaz and Theodoridis \(2023\)](#), which is regime-free, allowing us to validate our model in a purely regime-independent setting.

investment, and entry.

Model Sensitivity Analysis We further test our DSGE model under different parameter calibrations. As shown in the Supplementary Appendix (Section “C.3.2 Model Sensitivity Analysis”), we use the DSGE-based Monte Carlo framework described above to assess sign asymmetry under thousands of alternative calibrations for key nonlinear parameters—such as the learning gain, price rigidity, and capital adjustment costs. We find that, across all parameter ranges, negative inflation-target shocks systematically generate stronger and more persistent effects on output, investment, and entry than positive shocks. We also re-evaluate the model under full-information rational expectations, where agents observe the true inflation target in the price and wage NKPC. Although the magnitude of the responses is smaller under full information, the qualitative asymmetry remains: recessionary shocks continue to have larger real effects than expansionary shocks. Overall, these robustness exercises confirm that the asymmetry is an intrinsic feature of the model’s transmission mechanism rather than a consequence of particular parameter calibrations.

4 Conclusions

Using a non linear VAR, we analyze the asymmetry by the sign of shocks to long-run inflation expectations interpreted as a shock to the “inflation target”. We identify the shock as the VAR innovation that makes the largest contribution to the medium- to the long-term horizon of the GFEVD of the Fed’s implicit inflation target. Our findings indicate that these shocks have significant asymmetric effects. Specifically, negative shocks to the inflation target have a stronger and more prolonged impact on output, investments, and the net entry of firms compared to positive shocks. We rationalize these results through the lens of a medium-scale model with endogenous firm entry and exit. We demonstrate that the uncertainty introduced by the shock, combined with the convexity of firm profits and the entry cost channel, plays a crucial role in shaping the asymmetric responses of the extensive margin of investments, which in turn drives the asymmetric responses in total investments and overall economic activity. Ultimately, our paper highlights the importance for central banks to be particularly attentive to negative shocks in the long-run inflation target.

Our empirical and theoretical findings suggest that central banks should place greater emphasis on avoiding credibility losses and expectation under-shooting than on moderate overshooting. The revised version also links this interpretation to ongoing debates on asymmetric inflation targets, forward guidance, and communication policies, highlighting how managing expectation asymmetries can enhance the effectiveness of monetary policy at the lower bound.

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