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WORKING PAPER SERIES

Are Hysteresis Effects Nonlinear?

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2025/32 September 2025
ISSN(ONLINE): 2284-0400
DOI: 10.57838/sssa/a8az-kv29

Are Hysteresis Effects Nonlinear?*

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September 2025

Abstract

Do temporary aggregate demand shocks have lasting effects, and are they asymmetric between contractions and expansions? Using U.S. data from 1983:Q1-2019:Q4, we identify demand shocks with potential long-run consequences via a Bayesian SVAR and trace their propagation with nonlinear local projections. We find that negative shocks dominate in the short run, but positive shocks build up over time and by the medium run generate equally persistent effects on output. We investigate the mechanisms behind this result and argue that positive hysteresis is transmitted primarily through the labor market channel: expansions durably lower long-term unemployment and raise labor force participation. By contrast, the capital accumulation and R&D channels transmit predominantly negative hysteresis.

Keywords: Hysteresis, SVAR, Nonlinear Local Projections, Asymmetry
JEL codes: C32, E12, E24, E32

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We are grateful to Haroon Mumtaz, Andrea Carriero, and Alessio Moneta for their guidance, and to Giovanni Caggiano, Efrem Castelnuovo, Elena Pesavento, and Alessio Volpicella for their insightful discussions. For helpful comments and suggestions, we thank Davide Cassese, Mario Forni, Pascal Frank, Francesco Furlanetto, Luca Gambetti, Jonas Hölz, Francesco Lamperti, Mario Martinoli, Gianluca Pallante, Andrea Roventini, and Maria Enrica Virgillito, as well as participants at the 2024 Sant'Anna PhD Workshop, the 17th UniTO–Collegio Carlo Alberto PhD Workshop in Economics, the 1st Junior Milan Time Series Workshop, the 3rd UEA Time Series Workshop, the 2025 Trans-Atlantic Doctoral Conference (TADC) at London Business School, the 13th Conference of the International Association for Applied Econometrics (IAAE 2025), and the 13th SIdE Workshop for PhD students in Econometrics and Empirical Economics (WEEE 2025). Finally, we are thankful to the International Association for Applied Econometrics (IAAE) for awarding this paper an honorable mention at the IAAE 2025. Figures are best viewed on-screen or in color print.

1 Introduction

Can temporary shocks to aggregate demand exert long-run effects? If so, is such persistence asymmetric — arising only from demand contractions — or can expansions also generate lasting gains? The idea that fluctuations in demand can have long-run effects on the economy — a phenomenon known in macroeconomics as 'hysteresis' — remains contested (see Cerra et al., 2023, for a recent review). Especially after the slow recovery from the 2007–08 Great Recession, much of the debate focused on *negative hysteresis* — the view that demand-driven recessions leave lasting scars on the economy. By contrast, considerably less attention has been devoted to *positive hysteresis*, the idea that aggregate demand expansions may also generate persistent gains. This notion, however, has recently attracted the attention of policymakers. In a 2016 speech, then-Federal Reserve Chair Janet Yellen remarked:

> *"If we assume that hysteresis is in fact present to some degree after deep recessions, the natural next question is to ask whether it might be possible to reverse these adverse supply-side effects by temporarily running a 'high-pressure economy,' with robust aggregate demand and a tight labor market"* (Yellen, 2016).

In 2018, her successor as Federal Reserve Chair, Jerome Powell, revisited the same concern:

> *"While persistently strong economic conditions can pose risks to inflation and perhaps financial stability, we can also ask whether there may be lasting benefits. [...] All told, though, the persistence of any such 'positive hysteresis' benefits is uncertain, since, again, the historical evidence is sparse and inconclusive"* (Powell, 2018).

The uncertainty around the potential benefits of "running the economy hot" also reflects the limited research on the topic: *"Whether hysteresis is only negative or also positive is an empirical question that remains to be settled"* (Alves and Violante, 2024).

The contribution of our paper is to shed light on this underexplored question and study whether the long-term effects of aggregate demand operate only through the scarring impact of negative shocks, or whether positive shocks also produce lasting benefits. We test whether any asymmetric behavior emerges, and, when it does, we investigate the mechanisms driving it.[1]

The empirical investigation involves two steps. We first identify an aggregate demand shock with potential long-run consequences using a Bayesian structural VAR (BVAR) estimated on U.S. data, in the sample 1983:Q1-2019:Q4 (Furlanetto et al., 2025). In a second step, we trace the effects of the demand shock — which we term *hysteresis* shock — using state-of-the-art nonlinear local projections (LP) (Caravello and Martinez-Bruera, 2024; Gonçalves et al., 2021). The resulting sign-dependent impulse response functions (IRFs) allow us to test, without imposing it ex ante, whether positive and negative shocks exhibit persistent asymmetric impacts.

Although the literature largely frames hysteresis as a recession phenomenon, our main results suggest a more nuanced picture: not only do negative shocks leave lasting scars, but positive demand shocks also build up over time and yield persistent gains. More specifically, we show that hysteresis shocks persistently affect GDP, employment, and investment, explaining

[1] Empirically, it is challenging to distinguish between permanent and very persistent hysteresis effects (see Cerra et al. (2023, Section 3.3)). We therefore interpret our framework as one in which temporary demand shocks may influence the economy for longer than standard models suggest. Accordingly, we use terms such as *persistent*, *medium run*, *long lasting*, and *long horizons* interchangeably to describe dynamics beyond business-cycle frequencies.

a sizable share of their fluctuations for as long as ten years. When we decompose the linear effects into positive and negative realizations, we find that negative shocks dominate in the short term (about 2–3 years), but positive shocks emerge in the medium run and ultimately exert statistically significant effects alongside negative shocks.

Our second key finding is that the emergence of positive hysteresis in the aggregate is driven primarily by the labor market, one of the two main channels through which hysteresis can arise. In this channel, recessions (expansions) persistently increase (reduce) unemployment, eroding (strengthening) skills and attachment to the labor force. Sign-dependent IRFs show that contractionary shocks initially dominate, whereas expansionary shocks build gradually and deliver medium-run increases in participation and declines in both the unemployment rate and the fraction of long-term unemployed.

The second channel operates through capital accumulation and innovation: weak aggregate demand lowers expected profits and discourages productivity-enhancing investment, eroding the long-run productive capacity of the economy. Similarly, demand stimulus may encourage firms to upgrade technologies and increase productivity. For this channel, the evidence points mainly to negative hysteresis: contractions reduce R&D expenditures and the capital stock persistently, whereas expansions do not generate comparable gains. The protracted decline in R&D translates into a negative response of aggregate productivity, albeit only at long horizons and with considerable statistical uncertainty. Innovation is also persistently affected, albeit more symmetrically.

Our main findings are robust to (i) a richer lag structure in the VAR and LP, (ii) extending the sample to 2024:Q4, and (iii) a richer set of controls in the LPs. We also confirm that the sign-dependent results are not driven by size effects: the distinction between large and small shocks plays only a minor role in the propagation of hysteresis. Similarly, when we interact sign asymmetry with the business-cycle state — comparing positive and negative hysteresis shocks in recessions versus booms — we find little evidence of state dependence in their transmission.

Finally, given the central role of the labor market in our results, we examine it more closely by disaggregating outcomes by gender and race and by analyzing the intensive margin of labor market adjustments. We find that disadvantaged groups — most notably African American and Hispanic workers — are more sensitive to both positive and negative hysteresis shocks than White workers. On the intensive margin, hysteresis shocks persistently reduce average hours worked while increasing involuntary part-time employment.

2 Aggregate Demand, Hysteresis, and Nonlinearity

Our paper builds on the recent call by Blanchard (2025) for a deeper understanding of "the macroeconomics of the medium run" — that is, the potential linkages between the business cycle and long-run trends. Macroeconomic theory has long assumed that output follows a supply-determined trend, with demand driving only temporary fluctuations around it (Solow, 1997). The slow recovery from the Great Recession challenged this separation, raising the possibility that demand shocks can also affect long-run outcomes. This phenomenon, known as hysteresis, implies a violation of the "independence hypothesis" according to which the cycle is orthogonal to the trend (Blanchard, 2018). We contribute to this debate by examining whether such persistent effects arise only from recessions or also from demand expansions. More specifically, our contribution relates to several strands of the literature.

First, we contribute to the empirical literature on estimating hysteresis effects. Existing studies either focus exclusively on scarring effects from contractionary shocks (Cerra and Saxena, 2008; Blanchard et al., 2015; Fatás and Summers, 2018), or rely on linear frameworks that identify demand shocks without testing for asymmetry. For instance, Furlanetto et al. (2025) estimate generic demand shocks in a linear VAR and find evidence of hysteresis in GDP, investment, and employment, whereas Benati and Lubik (2022), using a cointegrated structural VAR and a different sample, finds only a limited role for hysteresis.[2] As for specific demand shocks, government spending — particularly when tilted toward R&D — and corporate tax shocks have been shown to raise output, innovation, and productivity in the medium run (Fieldhouse and Mertens, 2023; Antolin-Diaz and Surico, 2025; Cloyne et al., 2024). For monetary policy, Jordà et al. (2024) find persistent long-run effects on GDP and productivity in a panel of 18 advanced economies, and Ma and Zimmermann (2023) find significant effects on U.S. innovative activities.[3] However, if nonlinearities exist, linear models may underestimate the effects of hysteresis. Relative to this literature, we move beyond linear models and, using asymmetric local projections, show that *both* contractionary and expansionary shocks can generate hysteresis. The only paper that allows for asymmetric hysteresis effects is Jordà et al. (2024) on monetary policy shocks. Their key finding is that over the full sample (1900–2015), only monetary tightenings have lasting effects. In the post-WWII period, however, they show that expansionary shocks also generate persistent increases in GDP that remain detectable for up to 12 years, albeit with smaller magnitudes than tightenings.[4] Our findings partly relate to the subsample analysis of Jordà et al. (2024), as we document the presence of positive hysteresis in the U.S. economy, though over a shorter sample than the post-WWII period. However, unlike that paper, our results highlight the labor market — in addition to the productivity channel — as a relevant mechanism to rationalize hysteresis in output.

Second, our paper relates to contributions focusing on the asymmetric effects of specific demand shocks at business cycle frequencies. Examples include Barnichon et al. (2022a) and Ben Zeev et al. (2023) for fiscal policy shocks; Cover (1992), Weise (1999), Ravn and Sola (2004), Lo and Piger (2005), Tenreyro and Thwaites (2016), Angrist et al. (2018), and Barnichon and Matthes (2018) for monetary policy shocks; Barnichon et al. (2022b) and Forni et al. (2024) for financial shocks. We differ from previous works in two main respects. First, rather than isolating specific shocks, we consider a generic aggregate demand shock, grouping different types together. While each shock has unique features, this approach is more directly aligned with hysteresis theory, which emphasizes that the demand structure of the economy — not only supply factors — can shape its long-run trajectory. Second, our focus is on the *persistence* of aggregate demand shocks and its asymmetry by sign, rather than short-run asymmetries. To achieve this objective, our sign-dependent specification leverages recent advances in nonlinear local projections to cleanly distinguish between sign and size asymmetries and to compute nonlinear impulse responses consistently (Gonçalves et al., 2021, 2024; Kolesár and Plagborg-Møller, 2025; Caravello and

[2] See also Maffei-Faccioli (2025) for evidence on super-hysteresis, i.e. the idea that aggregate demand may permanently affect the growth rate, rather than just the level, of GDP (Ball, 2014).

[3] Similar results can be found in Moran and Queralto (2018) and Garga and Singh (2021). The idea that monetary policy can have supply-side effects dates back at least to the work of Evans (1992). Recent evidence can also be found in Meier and Reinelt (2024).

[4] See Appendix Figure A.8 in Jordà et al. (2024).

Martinez-Bruera, 2024). To the best of our knowledge, this is the first study to test for *asymmetry in persistence* in the propagation of aggregate demand shocks.

Third, we contribute to the literature on asymmetry in business cycle persistence. Ball and Onken (2022) examine asymmetry in unemployment persistence and find that persistence is stronger following a decrease in unemployment than after an increase.[5] Beaudry and Koop (1993) show that negative shocks to GDP tend to be temporary, while positive shocks have more persistent effects, suggesting that persistent changes in output are more significant during expansions. In contrast, Aikman et al. (2022) provide reduced-form evidence suggesting that recessions are the primary drivers of persistence, with a strong size dependence: only large recessions lead to lasting output losses. However, the limitation of these works is their reduced-form nature, as they infer persistence from the statistical properties of single time series (e.g. the unemployment rate, the NAIRU, or output). This approach prevents them from distinguishing the *sources* of persistence, that is whether it arises from demand or supply shocks. This distinction is crucial because persistence in output fluctuations is consistent with two contrasting theoretical accounts: the Real Business Cycle perspective, where technological supply-side shocks drive both cyclical and trend dynamics, as opposed to the hysteresis hypothesis, where aggregate demand shocks can influence an economy's potential. Each view implies vastly different policy conclusions. While we share the focus on nonlinearities with these studies, our structural approach enables us to identify the underlying drivers of long-term trends, highlighting a critical role for persistent aggregate demand shocks.

Fourth, we provide evidence on asymmetric hysteresis effects through specific transmission channels. One channel suggests that firms' investments in R&D, technology adoption, and productivity growth respond to changes in aggregate demand (Huber, 2018; De Ridder, 2019), especially during periods of tightened credit conditions (Duval et al., 2020). Another channel focuses on the scarring effects of recessions on labor market outcomes, drawing on the seminal work of Blanchard and Summers (1986). Recent evidence supporting this channel is provided in Yagan (2019) and Hershbein and Stuart (2024). What is particularly relevant for our paper is that similar mechanisms may operate in reverse, following positive large demand shocks. Baqaee et al. (2024) show that a monetary expansion can improve aggregate productivity by reallocating resources from low- to high-markup firms.[6] Ilzetzki (2024) provide causal evidence that positive aggregate demand shocks can have long-term effects by enhancing the productivity of capacity-constrained firms through a 'learning by necessity' mechanism. Girardi et al. (2020) document for a panel of OECD countries that aggregate demand expansions persistently impact GDP, participation rate, and capital stock. On the labor market side, the seminal contribution of Okun (1973) shows that 'running an economy hot' has the potential to persistently improve the economic conditions of disadvantaged workers. Building on this work, Aaronson et al. (2019) provide evidence of persistent gains in employment and labor force participation during economic booms. Similarly, Bluedorn and Leigh (2019) exploit revisions in professional forecasts in a panel of advanced economies and find that labor market booms driven by demand generate persistent effects. Relative to these contributions, we find that hysteresis via R&D and capital accumulation are predominantly on the downside, with only modest effects on productivity. By

[5] Earlier studies addressing both positive and negative unemployment persistence include Ball (1999) and Ball (2009).

[6] Similarly, González et al. (2024) use data from nearly the entire universe of Spanish firms and document aggregate productivity increases after an expansionary monetary policy due to a reduction in capital misallocation.

contrast, labor-market dynamics propagate both positive and negative shocks, with positive hysteresis playing a particularly important role.

Lastly, although our paper is purely empirical, it is motivated by theoretical models in which trend and cycle interact through feedback mechanisms between aggregate demand and the supply side of the economy. Early examples of such models include Stadler (1990), Stiglitz (1993), and Comin and Gertler (2006). More recent developments can be found in agent-based models (Dosi et al., 2010, 2018), post-Keynesian theory (Fazzari and González, 2025; Lavoie, 2022), and New Keynesian models with endogenous productivity (Benigno and Fornaro, 2018; Moran and Queralto, 2018; Anzoategui et al., 2019; Bianchi et al., 2019; Guerron-Quintana and Jinnai, 2019). In these models, aggregate demand can affect an economy's potential through productive investment, learning-by-doing, the speed of adoption of new technologies, and the entry or exit dynamics of firms.[7] Other models instead focus on the labor market channel, usually linked to the insider-outsider dynamics in the wage setting process or the de-skilling of long-term unemployed people (Galí, 2022; Alves and Violante, 2024, 2025). We empirically show that, although often framed in terms of negative shocks, similar mechanisms can also arise on the upside.[8]

Outline of the paper. Section 3 outlines the empirical strategy, including identification and estimation. Section 4 presents the main results, and Section 5 reports robustness checks that support the baseline findings. Section 6 provides a more granular perspective on the labor market channel. Section 7 examines size nonlinearity, and how sign asymmetry interact with state dependence. Section 8 discusses broader implications of our findings. Finally, section 9 concludes.

3 Empirical Strategy

To explore the potentially nonlinear effects of persistent aggregate demand shocks, we employ a two-step methodology. First, we use the SVAR framework of Furlanetto et al. (2025) to isolate a demand shock with potential long-term effects, which we define as our hysteresis shock. In the second step, we use this shock in a nonlinear local projection framework. This approach allows us to disentangle the potentially different effects of expansionary versus contractionary shocks. To bridge step 1 and step 2, we follow Debortoli et al. (2024) and assume partial invertibility of the hysteresis shock — namely, that the shock is an *informationally sufficient* linear combination of the current and lagged endogenous variables in the VAR. With this assumption, identification in step 1 does not require nonlinear dependencies among variables; we introduce them only in step 2 to evaluate potential asymmetries using local projections. Importantly, we test the partial invertibility assumption by applying the informational sufficiency test of Forni and Gambetti (2014) to the identified shock. In Appendix A, we provide a detailed discussion on the suitability of our methodology for capturing asymmetric dynamics and the challenges that traditional nonlinear VARs face in this regard.

[7] To be more exhaustive, hysteresis can also arise through other mechanisms. For example, Fernández-Villaverde et al. (2025) show that persistent effects from recessions can be generated in a model with search complementarities.

[8] Notably, Alves and Violante (2025) argue that their framework produces both 'uplifting effects' after expansions and 'scarring effects' after recessions.

3.1 SVAR model

The traditional approach to identify shocks with persistent effects on output originates with Blanchard and Quah (1989), who impose long-run restrictions on GDP to separate demand from supply disturbances. In this framework, demand shocks are mechanically constrained to have short-run effects, while supply shocks drive long-run dynamics in output. Furlanetto et al. (2025) generalize this framework by allowing demand shocks to exert persistent effects on output, alongside traditional demand and supply shocks. We adopt their methodology as a first step. Specifically, consider the reduced-form VAR:

$$\mathbf{y}_t = \boldsymbol{\mu} + \sum_{i=1}^{P} B_i \mathbf{y}_{t-i} + \mathbf{u}_t, \tag{1}$$

where $\mathbf{y}_t$ is an $N \times 1$ vector of endogenous variables, $\boldsymbol{\mu}$ is an $N \times 1$ vector of constants, and B_i $(i = 1, \dots, P)$ are $N \times N$ coefficient matrices, with P denoting the lag length. The reduced-form errors $\mathbf{u}_t$ are assumed to be normally distributed, $\mathbf{u}_t \sim \mathcal{N}(0, \Sigma)$, with Σ the $N \times N$ variance-covariance matrix. Structural shocks $\boldsymbol{\varepsilon}_t$ are identified by imposing restrictions on the mapping from reduced-form errors, $\mathbf{u}_t = A_0^{-1}\boldsymbol{\varepsilon}_t$, specifically through assumptions on the impact matrix A_0^{-1}. The lag order is set to $P = 3$ based on the Akaike information criterion (AIC).

Estimation is conducted in a Bayesian framework using a Normal–Inverse Wishart prior over the reduced-form parameters (B, Σ). In this setup, the covariance matrix of the error term follows an Inverse-Wishart distribution, $\Sigma \sim IW(S, d)$, while the regression coefficients conditional on Σ follow a multivariate normal distribution, $B \mid \Sigma \sim \mathcal{N}(\bar{\mathbf{B}}, \Sigma \otimes \Omega)$. [9] To improve inference, we also employ the Minnesota priors (Litterman, 1979), which shrink coefficients toward zero at a rate that increases exponentially with lag length. Moreover, we adopt a sum-of-coefficients prior (Doan et al., 1984) to mitigate the influence of initial conditions — consistent with our focus on the long-run effects of demand shocks — and to reduce the estimation uncertainty of the model's deterministic component (Bergholt et al., 2025). The hyperparameters are selected following the data-driven approach proposed by Giannone et al. (2015). Estimation is conducted using 201,000 Gibbs sampling draws, discarding the first 1,000 as burn-in, and thinning by retaining every 100th draw, yielding 2,000 posterior draws of the shocks.

The model features output growth, inflation, employment and investment, and is identified by combining long-run zero and sign restrictions using the algorithm of Arias et al. (2018). The identification strategy is exemplified in Table 1. Short-run (SR) sign restrictions (imposed over the first two quarters) distinguish demand from supply shocks, based on the intuition that demand shifts move prices and quantities in the same direction, whereas supply shocks move them in opposite directions (Wolf, 2022; Giannone and Primiceri, 2025). Long-run zero

[9] Here $(S, d, \bar{\mathbf{B}}, \Omega)$ are the priors' hyperparameters. d and S denote, respectively, the degrees of freedom and the scale of the prior Inverse-Wishart distribution for the variance-covariance matrix of the residuals. $\bar{\mathbf{B}}$ is the prior mean of the VAR coefficients, and Ω acts as a prior on the variance-covariance matrix of the dummy regressors. For the sum-of-coefficients prior, we calibrate the dummy initial observation using pre-sample averages calculated over the period 1949:Q1 to 1983:Q1.

	Demand Temporary		Supply Temporary		Demand Permanent *(hysteresis shock)*		Supply Permanent	
Variable	SR	LR	SR	LR	SR	LR	SR	LR
Output growth	−	0	−	0	−		−	
Inflation	−		+		−		+	
Employment		0		0				
Investment								

Table 1: Long-run zero and short-run sign restrictions as in Furlanetto et al. (2025). SR = Short Run; LR = Long Run.

restrictions (LR) are imposed on output to distinguish permanent from temporary shocks.[10] The zero long-run restriction on employment sharpens identification but is not strictly necessary.

The adopted empirical strategy enables the identification of a demand shock with potentially long-run effects — the hysteresis shock — alongside a more traditional supply shock in the spirit of Blanchard and Quah (1989).[11] The main focus of our analysis will be on the asymmetric transmission of the hysteresis shock.

Test for informational sufficiency Once the structural hysteresis shock is identified in the first step, we employ it as a regressor within a local projection framework. A potential concern with this hybrid VAR–LP approach is model misspecification: if the data are generated by a nonlinear process, the linear SVAR in Eq. (1) may fail to capture relevant nonlinearities, leading to imprecisely estimated shocks (Barnichon et al., 2022b). To address this concern, we follow Born et al. (2024), Debortoli et al. (2024), and Forni et al. (2024), who show that even when the focus is on asymmetries in transmission mechanisms, consistent estimates of shocks can still be obtained from a linear SVAR, provided that the shock of interest can be expressed as a linear combination of the current and past values of the variables in $\mathbf{y}_t$ — that is, the shock is informationally sufficient.[12]

Specifically, Born et al. (2024) identify a government spending shock in a linear panel VAR and then include it in a nonlinear LP framework, justifying their approach by assuming that the underlying fiscal rule spanning the government spending shock is linear in observables — an assumption supported by Monte Carlo evidence. Debortoli et al. (2024) identify a monetary policy shock in a linear proxy-SVAR, and then analyze nonlinear transformations of that shock within a nonlinear proxy SVARX, arguing that the monetary authority follows a linear Taylor rule. Similarly, Forni et al. (2024) identify a financial shock in the recursive linear VAR of Gilchrist and Zakrajšek (2012) and investigate its nonlinear propagation within nonlinear SVARX,

[10] We acknowledge the ongoing debate regarding the conventional practice of imposing a uniform prior on the orthogonal rotation matrix when identifying structural VARs with sign (and zero) restrictions. Baumeister and Hamilton (2015) and Watson (2020) raise concerns that such a prior may lead to spuriously informative posterior inference about impulse responses. In a recent contribution, Arias et al. (2025) clarify that the uniform prior over the set of orthogonal matrices is not only sufficient but also necessary to have uniform joint prior and posterior distributions over the identified set for the vector of impulse responses. In addition, Inoue and Kilian (2025) show that when identification is sufficiently tight, posterior inference based on the uniform prior provides a reasonably accurate approximation.

[11] A similar set of restrictions is used by Benati and Lubik (2022), although with slightly different variables and within a cointegration framework.

[12] Forni and Gambetti (2014) and Beaudry et al. (2019) provide a detailed discussion of information sufficiency in VARs.

justifying the approach by assuming that the nonlinear term linking the financial shock to observables enters only the fast-moving equations and thus nonlinearities do not play any role in the estimation phase.

In our case, we justify the linearity assumption on the grounds that our hysteresis shock — being an aggregate demand shock — likely combines monetary, fiscal, and financial disturbances, for which the two-step approach has already been shown to be valid. Importantly, however, we do not take this assumption for granted: we also subject it to a formal test.

Because a small-scale VAR may lack the information on state variables needed to accurately identify the underlying structural shocks, Forni and Gambetti (2014) propose a test to assess whether additional information contained in principal components can Granger-cause the VAR disturbances. To implement this test, we use the FRED-QD database (McCracken and Ng, 2020) and extract the first seven factors based on the Bai and Ng (2002) criterion.[13] We then evaluate the orthogonality of the hysteresis shock by regressing it on the lags of the principal components and conducting an F-test, using one to six lags of between one and seven factors.

3.2 Nonlinear local projections

To study whether hysteresis shocks have asymmetric effects on key macroeconomic variables, we use the shock extracted from the SVAR as a regressor in nonlinear local projections. While local projections are flexible due to their semi-parametric nature, in our context we face two main challenges. First, sign asymmetry can be confounded with size asymmetry, particularly when the shock distribution is skewed.[14] For example, if contractionary shocks are on average larger than expansionary shocks, an apparent sign asymmetry may simply reflect differences in magnitude rather than sign. Second, as shown by Gonçalves et al. (2021), standard estimators of nonlinear IRFs might not recover the population impulse responses if conditional expectations are incorrectly calculated, and can thus deliver inconsistent estimates.

To address these two issues, we (i) leverage the separation results of Caravello and Martinez-Bruera (2024) to distinguish *pure* sign nonlinearity from size nonlinearity, and (ii) use the *plug-in estimator* proposed by Gonçalves et al. (2021) to consistently estimate asymmetric IRFs.

Formally, denote the previously estimated hysteresis shock as ε_t. We specify local projections (Jordà, 2005) of the form

$$y_{t+h} - y_{t-1} = \alpha^h + \beta_1^h \varepsilon_t + \beta_2^h f(\varepsilon_t) + \sum_{l=1}^{k} \gamma_l^h \Delta y_{t-l} + u_{t+h}, \quad h = 0, 1, \ldots, H \tag{2}$$

where $y_{t+h} - y_{t-1}$ denotes the long-difference of the dependent variable of interest[15], α^h is an horizon-specific constant, $f(\cdot)$ represents a nonlinear function specified by the researcher, k denotes the number of lags of the dependent variable, and h is the impulse-response horizon. For the projection residual u_{t+h}, given that ε_t is plausibly exogenous, it holds that $\mathbb{E}(\varepsilon_t, u_{t+h}) = 0$.

[13] Details on the factor estimation are provided in Appendix D.

[14] Size dependence occurs when the proportional effect of a shock, i.e., $\frac{E(y_{t+h}|\varepsilon_t=a)-E(y_{t+h}|\varepsilon_t=0)}{a}$, depends on the size of the shock, a. For example, a two-percentage-point increase in interest rates need not equal twice the effect of a one-percentage-point increase.

[15] Specifying local projections in levels (y_{t+h}) or long-difference ($y_{t+h} - y_{t-1}$) produces asymptotically equivalent results (Jordà and Taylor, 2025). However, Piger and Stockwell (2025) show that the long difference specification with lags of the first-differenced dependent variable as controls largely suppresses small-sample estimation bias.

Caravello and Martinez-Bruera (2024) show that under the assumption of a symmetric distribution of the shock, it is possible to separately test for sign nonlinearities by estimating a local projection that includes an even transformation of the shock. Our choice for the even function to be specified in Equation (2) is the absolute value of the shock $f_{sign}(\varepsilon_t) = |\varepsilon_t|$.

Following Gonçalves et al. (2021), we estimate Equation (2) and compute the response of y_t to a shock of size δ at horizon h as follows:

$$\mathrm{IRF}_{h,\delta} = \beta_1^h \,\delta + \beta_2^h \,\mathbb{E}[\,|\varepsilon_t + \delta| - |\varepsilon_t|\,]\,. \tag{3}$$

Intuitively, the IRF compares the expected path of y_t when the system is subjected to a shock of size δ at time t to the path in the absence of that shock. The term $\mathbb{E}[\,|\varepsilon_t + \delta| - |\varepsilon_t|\,]$ captures the expected change in the transformed regressor $|\varepsilon_t|$ induced by δ. Because the absolute value is a nonlinear transformation, this expectation does not reduce to δ itself.

Importantly, the IRFs are sign-dependent: setting $\delta = 1$ yields the contractionary response, whereas $\delta = -1$ yields the expansionary response, with both normalized to a one–standard-deviation shock.[16] Under the i.i.d. assumption for ε_t, the expectation in Equation (3) can be approximated in finite samples by the sample average $T^{-1}\sum_{t=1}^{T}\left(|\varepsilon_t + \delta| - |\varepsilon_t|\right)$. [17]

We estimate the local projection in (2) using Bayesian methods to be consistent with the first step. We assign a noninformative Normal–Wishart prior to the coefficients and the error covariance matrix, and then draw directly from the posterior, which under conjugacy is Normal for the coefficients and Inverse–Wishart for the covariance matrix. As the shock in the first step is set-identified, we account for shock-identification uncertainty in the second step by repeatedly drawing the shock from its posterior distribution, thus computing IRFs from Equation (3) conditional on each draw.[18] We set the maximum horizon H to 40 quarters as in the VAR. To address serial correlation in the LP residuals, we include three lags of the dependent variable as controls, consistent with the suggestion by Montiel Olea and Plagborg-Møller (2021)[19].

3.3 Data

In the VAR we include quarterly data on real GDP per capita (output growth), the PCE deflator (inflation), the employment-to-population ratio (employment), and real investment per capita (investment) over the sample period 1983:Q1-2019:Q4. All variables enter the model in first differences.

In the nonlinear local projections, we use quarterly data expressed in log-levels (with the exception of ratios, which enter in levels), over the same sample period, and group the variables into three categories. First, we assess the impact of hysteresis shocks on key macroeconomic

[16] In the VAR, we normalize the shock so that positive realizations (e.g., $\delta = +1$) are contractionary; conversely, negative realizations (e.g., $\delta = -1$) are expansionary.

[17] In Appendix E.7, we sketch the derivation of Eq. (3), compare it with the conventional estimator, and report results under both estimators. A recent application of Gonçalves et al. (2021)'s estimator to characterize nonlinear impulse responses is Alessandri et al. (2025).

[18] Our procedure also accounts for the fact that the estimated shocks used in the second-step are generated regressors. However, following Pagan (1984), Coibion and Gorodnichenko (2012) argue that the generated-regressor issue is limited when the regressor is a residual rather than a fitted value; see also Born et al. (2024).

[19] Montiel Olea and Plagborg-Møller (2021) show that augmenting local projections with lags of the variable of interest yields robust frequentist inference. Although there is no formal Bayesian justification for lag augmentation, Cloyne et al. (2024) conduct Monte Carlo experiments to assess the coverage rates in their Bayesian LP with lag augmentation. They find that the benchmark model delivers satisfactory coverage rates — with distortions below 10% even at long horizons.

aggregates, focusing on real GDP per capita, real investment per capita and consumption per capita. Second, we examine the capital accumulation and innovation channel by analyzing the responses of R&D expenditure, capital stock, and total factor productivity. Additionally, we examine how innovative activity responds to persistent shocks in aggregate demand. To do so, we aggregate the *Patent-based Innovation Index* developed by Kogan et al. (2017) following the methodology of Cascaldi-Garcia and Vukotić (2022). This index measures the GDP-weighted sum of the market value associated with patents granted each quarter, based on stock market reactions to the firms receiving the patents. It captures the forward-looking assessment of the economic significance of newly granted patents, thereby providing a market-based estimate of the expected real impact of innovation.

Finally, we examine both the extensive and intensive margins of the labor market in response to our identified persistent demand shock. On the extensive margin, we analyze the responses of unemployment, labor force participation, and long-term unemployment. Following the approach of Aaronson et al. (2019), we disaggregate these variables by gender and race to provide a more granular perspective. For the intensive margin, we focus on average hours worked and distinguish between voluntary and involuntary part-time employment, capturing adjustments in labor input beyond headcount changes. A detailed description of the variables, their transformations, and sources can be found in Appendix B.

4 Main Results

4.1 Linear VAR and informational sufficiency test

We first report the results from the linear SVAR. In Figure 1, we present the cumulative IRFs for our shock of interest — the hysteresis shock (or permanent demand shock) — alongside those of the permanent supply shocks.[20] Dark lines represent pointwise posterior medians, while the shaded bands denote 68% posterior credible intervals. Consistent with Furlanetto et al. (2025), we find that the long-term aggregate demand shock exhibits persistent effects on GDP, investment, and employment, while having a minimal impact on labor productivity (first column of Figure 1). The forecast error variance decomposition (FEVD) in Figure 2 shows that the hysteresis shock is not only statistically significant but also economically relevant. The long-term demand shock accounts for the majority of employment fluctuations across all horizons, and it also plays a significant role in driving fluctuations in GDP and investment, explaining over 50% of output variations at all horizons. Overall, our findings support Furlanetto et al. (2025)'s conclusion that aggregate demand shocks propagate in the long run, thus displaying hysteresis effects. In Appendix C.1, we plot the identified shock against NBER recession dates to illustrate its behavior over the business cycle, we compare it to standard proxies for demand shocks, and argue that it is unlikely to be contaminated by supply-side disturbances.

Turning to the informational sufficiency test, Table 2 reports the p-values obtained using the median of the distribution of the hysteresis shock. P-values higher than a chosen critical value

[20] We do not report the IRFs for temporary shocks, as they are not the focus of this study. For a detailed discussion on those results, see Furlanetto et al. (2025).

indicate that the null hypothesis of no predictability of the hysteresis shock cannot be rejected. In all cases, the F-test of joint significance yields p-values above the 10% level.[21]

	First 3 Factors, l lags			First 7 Factors, l lags		
	$l = 1$	$l = 3$	$l = 6$	$l = 1$	$l = 3$	$l = 6$
p-value	0.2591	0.2840	0.1946	0.3663	0.6577	0.1990

Table 2: Median F-test p-values for lags $\ell \in \{1, 3, 6\}$ and factor sets (first 3 and first 7) extracted from FRED-QD (McCracken and Ng, 2020).

We next ask whether the observed persistence is driven by expansionary or contractionary shocks. To isolate sign nonlinearity from size effects, we first verify that the shock distribution is symmetric (Caravello and Martinez-Bruera, 2024). Appendix C.2 documents this symmetry, confirming that our asymmetric LPs capture genuine sign-dependent responses rather than differences in shock magnitude.

4.2 Asymmetry in the macro

We examine how nonlinear hysteresis effects transmit to the aggregate economy, focusing on GDP, investment and consumption per capita. Figure 3 (and subsequent figures) present the results in three columns: the first column reports linear coefficients β_1^h; the second column displays the nonlinear coefficients, β_2^h, which capture deviations from linearity at each horizon; and the third column shows results from the sign-dependent specification using $f_{\text{sign}}(\varepsilon_t) = |\varepsilon_t|$, where the responses to expansionary hysteresis shocks are multiplied by -1 to aid comparability.

The main findings are as follows. The hysteresis shock exhibits persistent effects across the three macro aggregates. Decomposing by sign reveals an expected short-run asymmetry: contractionary demand shocks generate larger impact responses than expansionary shocks, consistent with evidence that contractionary fiscal and monetary policies have stronger effects at business-cycle frequencies (Tenreyro and Thwaites, 2016; Barnichon et al., 2022a; Jordà et al., 2024). Yet the subsequent dynamics diverge: as shown in the middle panels of Figure 3, the nonlinear coefficient reverts toward baseline within 5 to 15 quarters. This is due to negative shocks progressively losing persistence, whereas expansionary shocks — smaller on impact — accumulate and persist. At long horizons, credible sets for both signs overlap. Nevertheless, positive shocks contribute more to the medium-run persistence observed in the linear IRF. This implies that persistence is not driven solely by negative shocks; positive hysteresis shocks account for a substantial share of the overall effect. This is our central finding. The next sections examine the channels through which this asymmetric behavior arises.

[21] Because the SVAR is set-identified, we obtain 2,000 draws of the hysteresis shock. To ensure that the orthogonality test is informative for the entire distribution, Appendix D.1 reports results also for the 16$^{\text{th}}$ and 84$^{\text{th}}$ percentiles of the empirical distribution. These results confirm the informational sufficiency of the hysteresis shock.

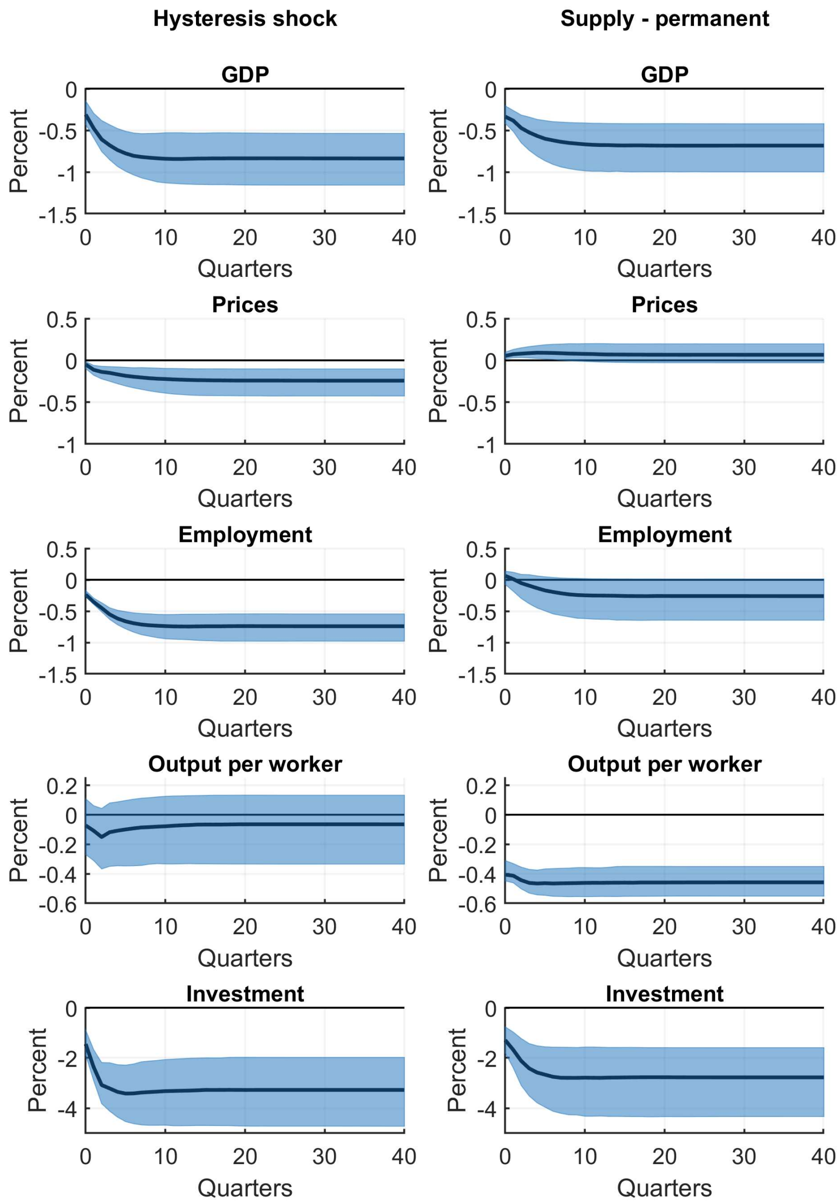

Figure 1: **IRFs to the Hysteresis and Supply Permanent Shocks.** Plots show percent changes in levels. Dark lines denote pointwise posterior medians. Bands denote 68% posterior credible intervals.

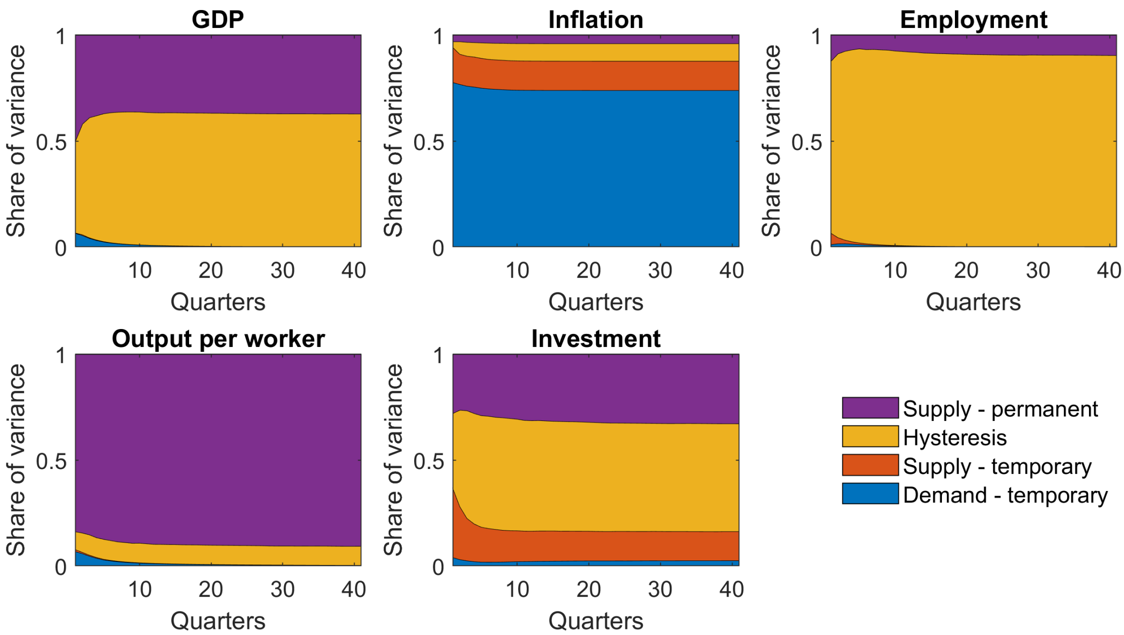

Figure 2: **Forecast Error Variance Decomposition.** FEVDs are based on pointwise median impulse responses on the levels of the variables.

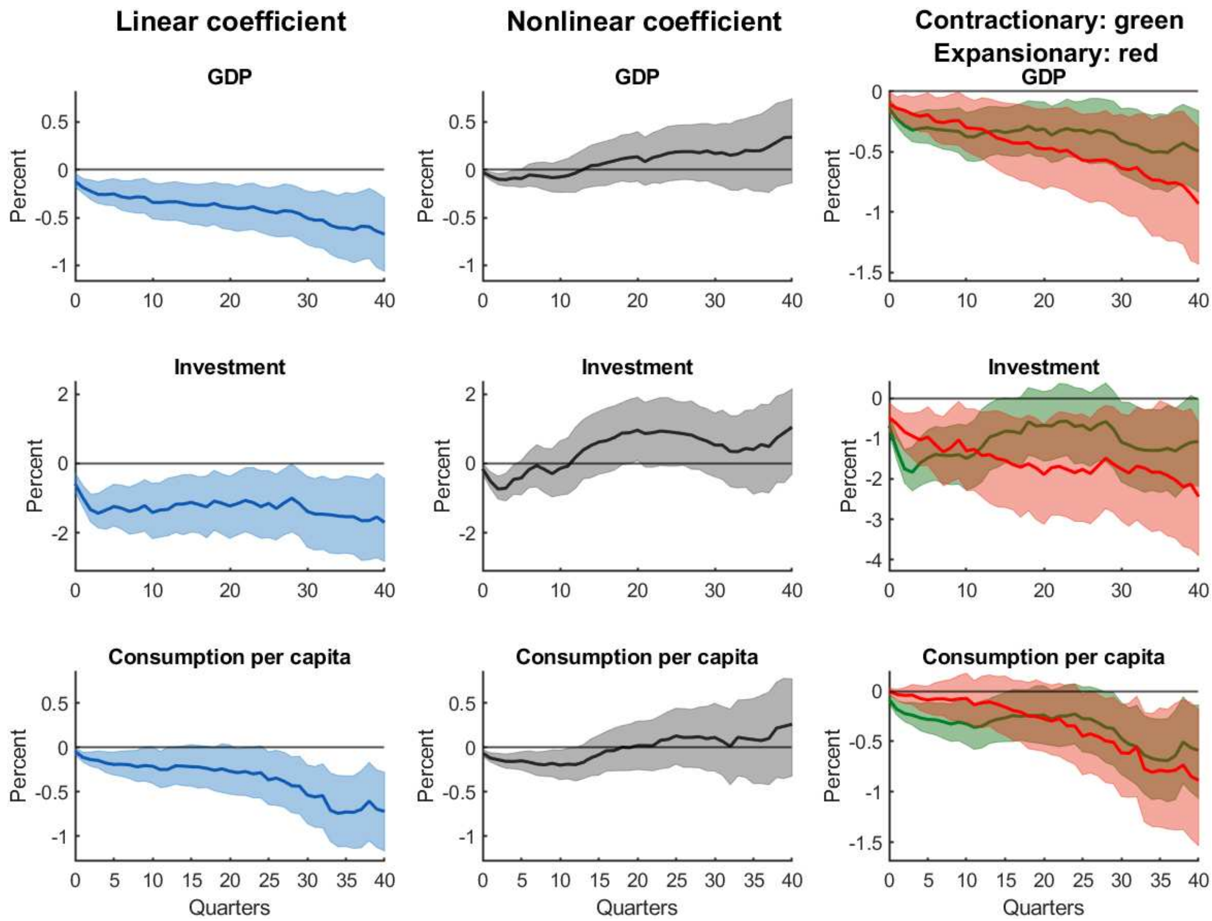

Figure 3: **Linear and Nonlinear IRFs for Aggregate Macroeconomic Variables.** The first column reports the linear coefficients β_1 and the second the nonlinear coefficients β_2, both estimated from Eq. (2). The third column shows the sign-specific IRFs implied by Eq. (3). Contractionary shocks are shown in green, expansionary in red (with the latter plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals.

4.3 Asymmetry in the channels

In this section, we connect the findings on aggregate dynamics to two key channels through which hysteresis may operate: (i) capital accumulation, innovation, and productivity, and (ii) the labor market.

Capital accumulation, innovation, and productivity. The basic rationale behind this channel rests on the procyclicality of variables tied to long-run growth (such as R&D expenditures) over the business cycle. If the engines of growth respond to cyclical conditions — and those conditions are shaped by aggregate demand — then demand disturbances can transmit to the supply side. Since at least Stadler (1990) and Stiglitz (1993), this line of work has argued that recessions lower profit expectations and lead firms to cut back on productivity-enhancing activities, including R&D and innovation more generally. As a result, the adverse effects of a temporary downturn may permanently depress the economy's growth path (Benigno and Fornaro, 2018; Anzoategui et al., 2019; Bianchi et al., 2019; Schmöller and Spitzer, 2021). Related work emphasizes the link between aggregate demand and capital accumulation: persistent weak demand results in protracted underutilization of capacity, ultimately inducing firms to scale back their capital stock (Fatás, 2000; Girardi et al., 2020). By the same token, these mechanisms can operate during demand expansions: robust aggregate demand stimulates R&D expenditure and technological innovation, while procyclical investment creates additional installed capacity and increases the capital stock (Dosi et al., 2018, 2023; Girardi et al., 2020).[22]

In this section, we examine this channel by analyzing the responses of R&D expenditure, the capital stock, productivity, and an aggregate innovation index to our hysteresis shock. Results are shown in Figure 4. In the first column, we show that R&D expenditures, capital stock, and the patent-based innovation index all display persistent linear responses to the hysteresis shock. By contrast, total factor productivity (TFP) trends downward but with substantial statistical uncertainty over the entire impulse–response horizon. The third column reveals that the persistent declines in R&D and capital stock are predominantly driven by contractionary shocks, with R&D decline remaining statistically significant at long horizons, whereas the capital stock effect is less persistent. Expansionary shocks, by comparison, have negligible effects. The productivity IRF to negative shocks is initially positive, consistent with short-run "cleansing" effects (e.g., reallocation away from less productive firms). This effect is temporary, however: at longer horizons the point estimate turns negative, plausibly reflecting the downward trend in R&D, so that the longer-run consequences of recessions ultimately outweigh any initial gains. These dynamics are in line with the evidence reported by Acabbi et al. (2024) and Haltiwanger et al. (2025), although the uncertainty surrounding the productivity response precludes firm statistical conclusions about its magnitude.

Finally, we consider an innovation indicator that is tightly linked to patenting activity — another important mechanism through which fluctuations in aggregate demand can affect long-run economic performance. Specifically, we examine the impulse response of the patent-based innovation index constructed by Kogan et al. (2017). The persistence observed in the linear response is initially driven by negative shocks, in line with the R&D results. The asymmetry is, however, less pronounced than for R&D, as indicated by the nonlinear coefficient in column two.

Taken together, this channel of hysteresis operates mainly through negative shocks; expansionary shocks play no quantitatively meaningful role. The dynamics of R&D and the capital stock — where negative shocks dominate — and the ambiguous effects on productivity closely mirror the findings of Barnichon et al. (2022b), who show that the persistence identified in linear models of financial shocks is largely attributable to their negative component. Thus, the results in this section are compatible with interpreting the hysteresis shock as a negative financial shock that depresses innovative investment. The ambiguous productivity response may reflect the need to account for delayed effects that lie beyond the IRF horizon we consider: for example, Fieldhouse and Mertens (2023) report IRFs up to 60 quarters (in a much larger sample), with productivity responding only after roughly 30–35 quarters, consistent with our finding that longer-run effects emerge with substantial delay.

These results also indicate that this hysteresis channel does not rationalize the positive shocks we document in GDP. We therefore turn to the labor market channel to examine whether it can account for these patterns.

[22] Similar mechanisms linking monetary policy and firms' automation decisions are discussed in Fornaro and Wolf (2021).

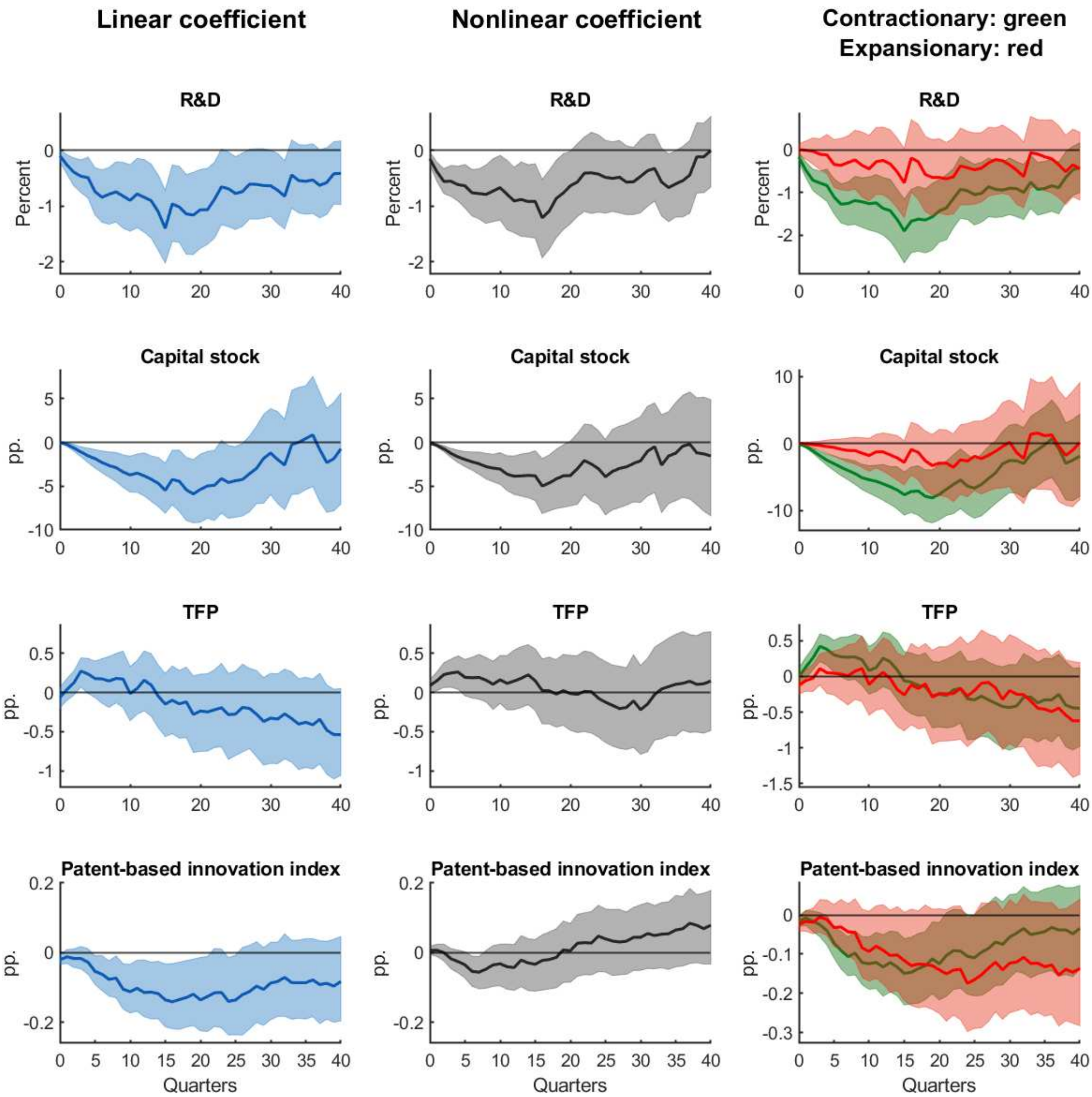

Figure 4: **Linear and Nonlinear IRFs for the Innovation and Productivity Channel Variables.** The first column reports the linear coefficients β_1 and the second the nonlinear coefficients β_2, both estimated from Eq. (2). The third column shows the sign-specific IRFs implied by Eq. (3). Contractionary shocks are shown in green, expansionary in red (with the latter plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals.

Labor market. The seminal contribution of Blanchard and Summers (1986) identifies the labor market as a key channel for the propagation of negative hysteresis, emphasizing insider–outsider wage setting as an explanation for unemployment persistence.[23] More recently, a growing literature has highlighted human-capital depreciation and declining labor-force attachment as additional sources of hysteresis.

Results from the VAR provide aggregate validation of this labor market channel, with employment being permanently affected (Furlanetto et al., 2025; Yagan, 2019). We then zoom in

[23]Galí (2022) provides a modern treatment of this mechanism and shows that monetary policy shocks can have long-run effects on the natural rate of unemployment and potential output.

on the extensive margin examining our sign-dependent local projections. Figure 5 reports LP estimates for the unemployment rate, long-term unemployment, and the labor-force participation rate. In the first column, all three series exhibit pronounced hysteresis: participation declines steadily over the impulse response horizon, while the unemployment rate and long-term unemployment both peak around fifteen quarters and remain persistently elevated. Peak responses are about 0.5 percentage points for the unemployment and participation rates and nearly 4 percentage points for long-term unemployment, highlighting the severe scarring effect.

The third column documents sign-dependent nonlinearities: contractionary shocks account for most of the hysteresis in long-term unemployment and participation over the first fifteen quarters (and in the unemployment rate over the first few quarters). Beyond this horizon, the effects of negative shocks persist, although they are no longer statistically distinguishable from those of positive shocks. The presence of persistent negative shocks is consistent with a mechanism in which a fall in aggregate demand raises unemployment and, as joblessness persists, workers lose skills and some exit into non-participation. Once out of the labor force, individuals often remain detached for extended periods, further eroding human capital and reinforcing labor market detachment. Consequently, even short-lived demand shocks can have long-lasting macroeconomic effects — reducing labor-force participation, keeping unemployment elevated, and ultimately lowering aggregate output (Alves and Violante, 2024; Ball and Onken, 2022).

However, the main result of this section is the emergence of positive hysteresis. In fact, column two shows that the nonlinear coefficient is significant only at short horizons — signaling stronger effects from negative shocks — but converges toward zero as the horizon lengthens. This pattern reflects the behavior of positive demand shocks in column three: their effects accumulate gradually and ultimately become highly persistent for the three variables of interest. This evidence aligns with the view that robust aggregate demand can deliver lasting benefits. A plausible mechanism is that strong demand induces firms to upgrade matches — moving workers into more productive roles — and draws nonparticipants back into the labor force. Moving into employment builds skills and improves future labor prospects. When this dynamic is at work, cyclical gains cumulate into longer-run improvements in workers' outcomes and — by lowering unemployment and lifting labor-force participation — may raise the economy's potential (Aaronson et al., 2019; Okun, 1973). We therefore document responses consistent with persistent positive spillovers from expansions, especially along the participation margin.

In sum, while negative shocks are the main drivers of persistent effects on R&D and the capital stock, positive shocks play a substantial medium-run role for labor market outcomes. Taken together, these patterns point to the labor market channel as the key mechanism behind the aggregate asymmetry documented in Section 4.2.

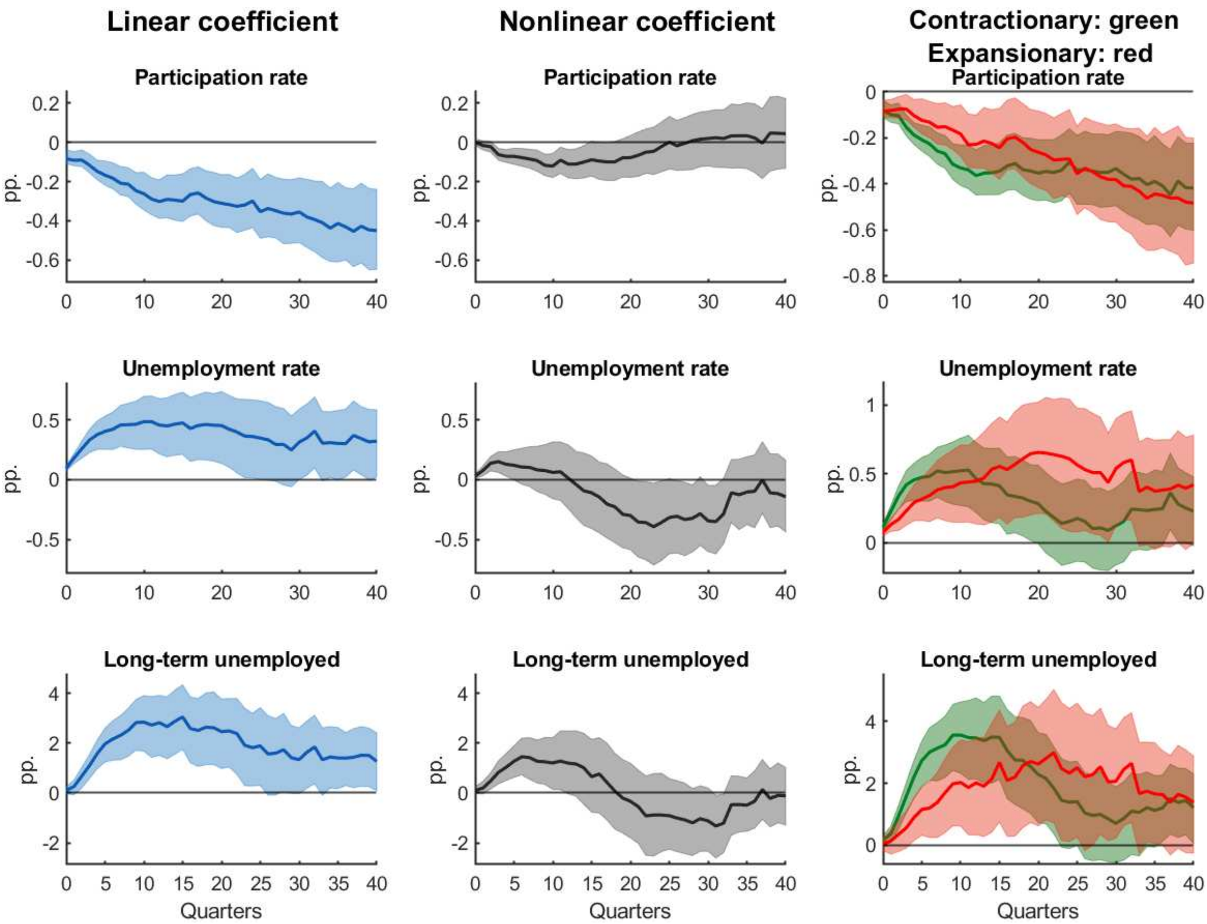

Figure 5: **Linear and Nonlinear IRFs for the Extensive Margin of Labor Market Adjustment.** The first column reports the linear coefficients β_1 and the second the nonlinear coefficients β_2, both estimated from Eq. (2). The third column shows the sign-specific IRFs implied by Eq. (3). Contractionary shocks are shown in green, expansionary in red (with the latter plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals.

5 Robustness of the Main Results

In this section, we assess the robustness of our main findings to alternative specifications of the VAR and LPs, as well as to extensions in the sample.

5.1 Different lag structures in the VAR and LP

Our baseline results are robust to richer lag specifications. We first assess whether the VAR is dynamically misspecified — that is, whether omitted lags distort long-horizon impulse responses by forcing extrapolation from only the initial set of autocovariances (Montiel Olea et al., 2025). In Appendix E.1 we show that the VAR results continue to hold when the lag length is set equal to 8 and 12, as opposed to the baseline of 3 lags. We also estimate a VAR with 40 lags (equal to the IRF impulse-response horizon), as recommended by Baumeister (2025) and implemented by Antolin-Diaz and Surico (2025). The baseline results hold in this case as well. Although robustness to the inclusion of 40 lags may seem surprising, De Graeve and Westermark (2025) show in a simulation study that longer lag structures can mitigate model misspecification and counteract the increased uncertainty due to overparameterization. Importantly, as in Antolin-Diaz and Surico (2025), our BVAR estimation employs a Minnesota prior, which shrinks distant lags toward zero unless the data provide strong evidence to the contrary. This prior, however, does not mechanically constrain low-frequency dynamics from playing any role. In this regard, De Graeve and Westermark (2025) show that the point estimates of the monetary policy effects in Miranda-Agrippino and Ricco (2021) are quantitatively different when their BVAR (which employs the Minnesota prior) is estimated with a more generous lag structure.

After establishing robustness of the BVAR to richer lag specifications, we next show that the LP results remain robust when the hysteresis shock is extracted from a BVAR with lag length $P \in \{8, 12\}$. The Appendix E.2 reports the corresponding nonlinear impulse responses from Eq. (3), keeping the LP lag length fixed at the baseline $k = 3$.

As a final exercise, we estimate the LP with a richer lag structure — up to six lags (baseline: three) — while holding fixed the baseline BVAR from which the hysteresis shock is extracted, and obtain similar conclusions (see Appendix E.3). We explore with a few additional lags in the LP because this class of models has been shown to be relatively robust to lag misspecification in small samples (Li et al., 2024; Montiel Olea et al., 2025).

5.2 Sample: including post-pandemic data

We extend the baseline sample to include post-pandemic data through 2024:Q4. To accommodate the extreme macroeconomic volatility around the pandemic, we follow Lenza and Primiceri (2022). In the BVAR, the autoregressive coefficients are estimated as in normal times, while the reduced-form innovation variance–covariance matrix is inflated by a large scale factor in 2020:Q2. However, the inferred hysteresis shock still shows substantial variability in 2020:Q2 and 2020:Q3. Prior to using this series as a regressor in the LP, we adjust it analogously to the BVAR, employing instead the iterative procedure proposed by Hamilton (2025). [24] Results for both the VAR and the LP are reported in Appendix E.4. While the LP estimates are somewhat more jagged due to the inherent volatility of the data, the qualitative conclusions are unchanged relative to the baseline.

5.3 Additional controls in the LP

In the baseline specification, the LP includes only lags of the dependent variable as controls, addressing serial correlation of the regression residuals. This parsimonious approach is justified because the hysteresis shock extracted from the linear structural BVAR already conditions on the VAR information set. However, as Montiel Olea et al. (2025) argue, the inclusion of additional controls may increase estimation efficiency and guard against minor misspecifications of the shock measure. To guide the choice of controls, we draw on the findings of McCracken and Ng (2020), who show that the first three factors extracted from FRED-QD — a database also used in our informational sufficiency test —capture economically interpretable variation, in contrast to the remaining four factors whose interpretation is less clear. McCracken and Ng (2020) show that factor 1 captures real activity, as it correlates strongly with series in the Employment and Industrial Production groups; factor 2 is a forward-looking factor associated with interest rate term spreads as well as housing permits and starts; and factor 3 is essentially a consumer price index factor, with its highest loadings concentrated in the Prices group. As a robustness check, we therefore augment the LP with these three factors, estimating the specification with three

[24] Further details on the procedure used to remove the pandemic outlier from the hysteresis shock are provided in Appendix E.4.

lags as in the baseline. The resulting IRFs (Appendix E.5) confirm our baseline conclusion that positive hysteresis in output arises from lasting improvements in labor market outcomes.

5.4 Different nonlinear transformation of the shock in the LP

In this subsection, we experiment with an alternative nonlinear transformation of the shock in Eq. (2). Specifically, we replace the absolute value of the shock, $|\varepsilon_t|$, with its square, ε_t^2. The results, reported in Appendix E.6, confirm the robustness of our baseline findings, indicating that sign dependence is well captured whenever an even transformation of the shock is used (Caravello and Martinez-Bruera, 2024).

5.5 Alternative estimator for computing nonlinear IRFs

In the baseline, we compute nonlinear impulse responses using the plug-in estimator of Gonçalves et al. (2021). Many papers instead rely on the conventional estimator; see, e.g., Tenreyro and Thwaites (2016); Caravello and Martinez-Bruera (2024). Appendix E.7 details both estimators and shows that our conclusions are robust to the choice of either of them.

6 Unpacking the Labor Market Channel

6.1 Disaggregation by gender and race

We identify the labor market as the key channel through which positive hysteresis shocks emerge alongside negative ones. These results connect to the "high-pressure economy" hypothesis — first articulated by Okun (1973) — where robust aggregate demand and a tight labor market can yield persistent benefits. A key characteristic of these dynamics is heterogeneity across workers, with disadvantaged groups typically the most responsive to fluctuations in aggregate demand. The underlying idea is that, in a high-pressure economy, firms struggle to fill vacancies at prevailing wages and thus relax hiring thresholds, broaden recruitment, and invest more in training. This, in turn, improves employment prospects for disadvantaged workers, enabling job entry, skill accumulation, and advancement up the job ladder.

To investigate this hypothesis, we build on Aaronson et al. (2019) and Furlanetto et al. (2025) and disaggregate the responses of the unemployment rate, the employment-to-population ratio, and the labor-force participation rate by gender and race.[25]

Figure 6 presents disaggregated unemployment responses. The linear estimates indicate that both men and women experience a similar peak increase in unemployment — approximately 0.5 percentage points. Racial disparities are instead more pronounced: Black and Hispanic workers face the largest increases, with unemployment peaking around 1 percentage point, while White workers experience a smaller peak increase of roughly 0.5 percentage points. Turning to the sign-dependent specification, contractionary shocks result in larger medium-term increases in unemployment across all groups. Although the effects of expansionary shocks are initially muted, their impact grows over time, consistent with the aggregate labor market dynamics evidenced in Section 4.3. Importantly, the larger linear impact observed for Black and Hispanic workers is driven by their heightened sensitivity to both negative and positive shocks.

We now examine the disaggregated dynamics of the employment-to-population ratio. This variable is especially informative, as recent evidence points to persistent declines following

[25] Data series for long-term unemployment disaggregated by gender and race are not available.

recessions (Hershbein and Stuart, 2024), with recession-induced employment losses found to be larger among lower-earning individuals (Yagan, 2019). Figure 7 reports the results. Following Furlanetto et al. (2025), we compute relative employment for each group of workers as the deviation of that group's employment-to-population ratio from the aggregate employment-to-population ratio. In the first column, the employment-to-population ratio for men falls more than that of women for roughly twenty quarters before converging, whereas Black and Hispanic workers experience disproportionately larger declines than White workers. Interestingly, in the sign-dependent specification showed in column three, responses are broadly symmetric: both contractionary and expansionary shocks exhibit persistence over time.

We also report in Appendix F the labor-force participation responses disaggregated by gender and race. the linear LP results reveal that the persistent decline in participation over the impulse-response horizon, when conditioning by gender, is driven primarily by women. Their responses fall steadily throughout, whereas men's participation dips by around 0.3 percentage points at its peak before stabilizing at that lower level. When disaggregating by race, Black or African American workers experience the largest initial drop — peaking at roughly 0.5 percentage points around 15–20 quarters-, while White and Hispanic or Latino workers exhibit smaller but still persistent declines that mirror the aggregate pattern. Introducing sign-dependence in column three reveals that contractionary shocks drive most of the persistence over the first twenty quarters, while expansionary shocks gradually accumulate.

Taken together, this additional evidence confirms our interpretation that the labor market is a key channel through which aggregate demand hysteresis is transmitted. We find that asymmetries across groups are particularly pronounced when conditioning by race in unemployment, and more muted for employment and participation. We also confirm that persistence is especially strong in participation, pointing to labor-force entry and exit as key margins for interpreting the effects of demand shocks on labor supply.

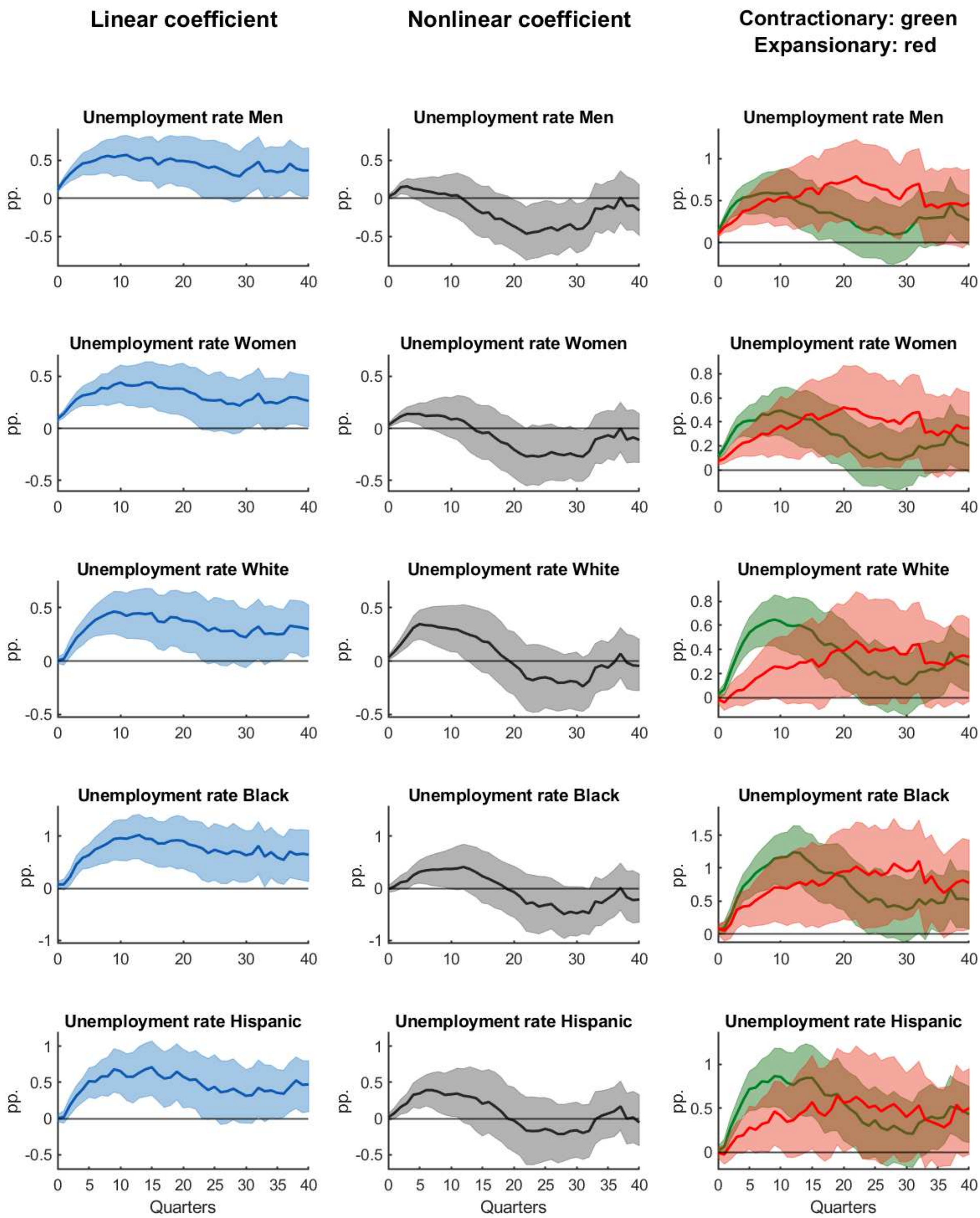

Figure 6: **Linear and Nonlinear IRFs for Unemployment Rate by Gender and Race.** The first column reports the linear coefficients β_1 and the second the nonlinear coefficients β_2, both estimated from Eq. (2). The third column shows the sign-specific IRFs implied by Eq. (3). Contractionary shocks are shown in green, expansionary in red (with the latter plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals.

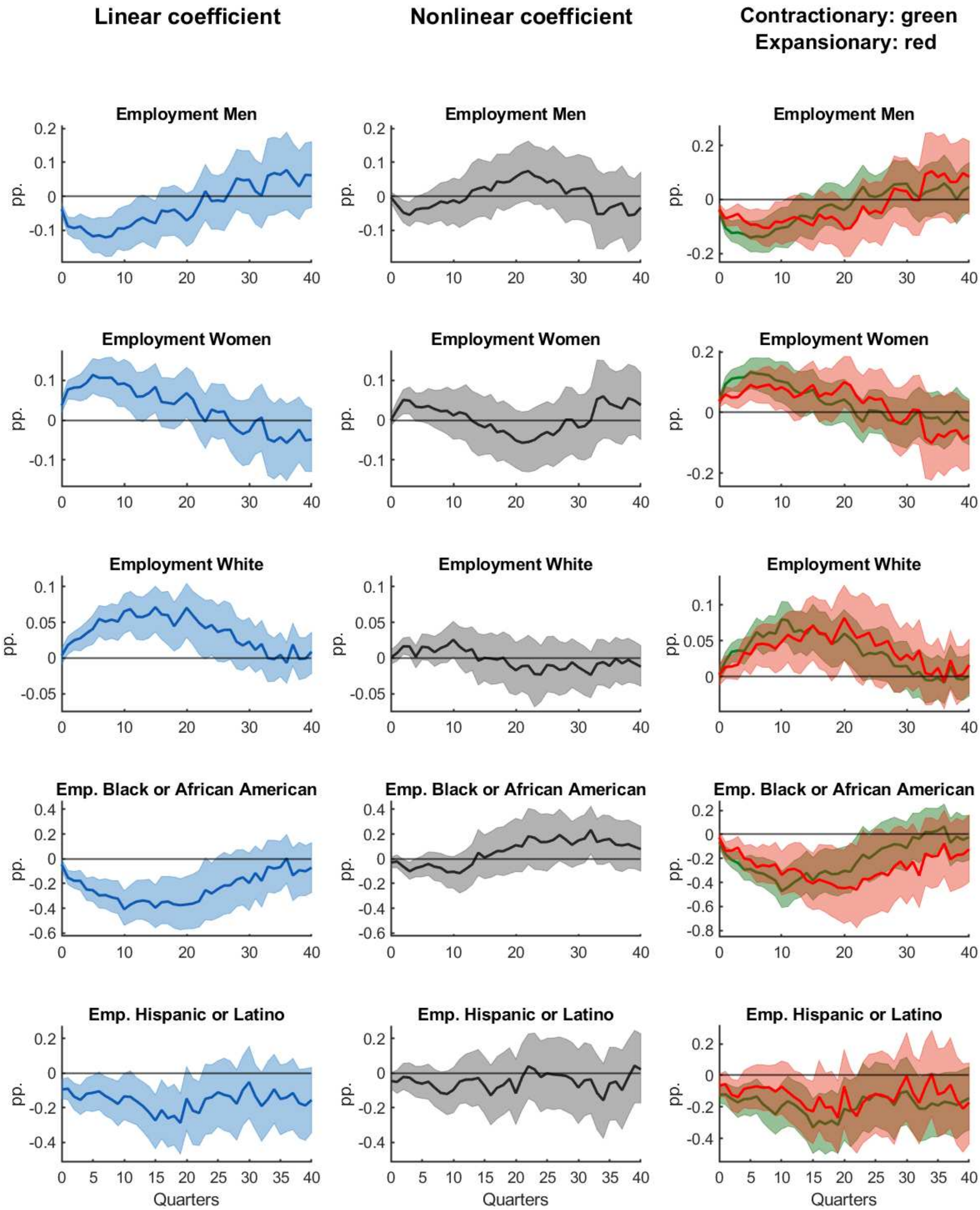

Figure 7: **Linear and Nonlinear IRFs for Employment-to-Population ratios by Gender and Race.** The first column reports the linear coefficients β_1 and the second the nonlinear coefficients β_2, both estimated from Eq. (2). The third column shows the sign-specific IRFs implied by Eq. (3). Contractionary shocks are shown in green, expansionary in red (with the latter plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals.

6.2 Intensive Margin of Labor Market Adjustments

In the aftermath of a severe downturn, firms not only operate along the extensive margin by firing workers, but often cut hours or shift workers into part-time roles — thus operating adjustments along the intensive margin, which is what happened in the aftermath of the Great Financial Crisis (Kudlyak, 2019; Valletta et al., 2020). Figure 8 presents evidence on the *intensive margin* of labor market adjustments. In column one, we find that the hysteresis shock reduces average hours worked during the first fifteen quarters, which is somewhat consistent with Cantore et al. (2022), who document, through a linear framework, long-lasting US monetary policy contractions on hours worked. [26] Interestingly, Cantore et al. (2022) also find that hours worked by low-income individuals are procyclical, rising after a contraction. We confirm this nuance by examining the response of part-time employment to the decline in average hours worked. Specifically, the decline maps into distinct patterns across part-time categories: voluntary part-time employment falls after a contraction—procyclical and consistent with aggregate hours—whereas involuntary part-time employment is countercyclical (Borowczyk-Martins and Lalé, 2019). This countercyclicality indicates a compositional effect within part-time work: increases in involuntary part-time during downturns are concentrated in sectors with weaker labor-market attachment and lower pay (e.g., retail and hospitality) (Valletta et al., 2020). Kudlyak (2019); Canon et al. (2014); Valletta et al. (2020) show that involuntary part-time work remained structurally elevated after 2008, even as unemployment normalized, due to a shortage of full-time positions. This points to involuntary part-time employment as a crucial measure of labor underutilization beyond the unemployment rate and essential for understanding both cyclical and structural dynamics in the labor market.

In column three, our sign-dependent estimates reveal familiar dynamics from the extensive margin: contractionary shocks drive more persistent effects over the first five to ten quarters, echoing the financial crisis narrative (with the exception of voluntary part-time work, where the effects are mostly symmetric at the beginning of the impulse response horizon). However, expansionary shocks gain importance later in the horizon and this asymmetry remains statistically significant even in the long run (column two). These results underscore again the importance of studying the direction of hysteresis shocks, which is masked by the linear specification.

[26] Cantore et al. (2022) construct aggregate hours from the CPS and CEX surveys, while we employ the measure *Average Weekly Hours for All Workers* provided by FRED, see Appendix B for more details.

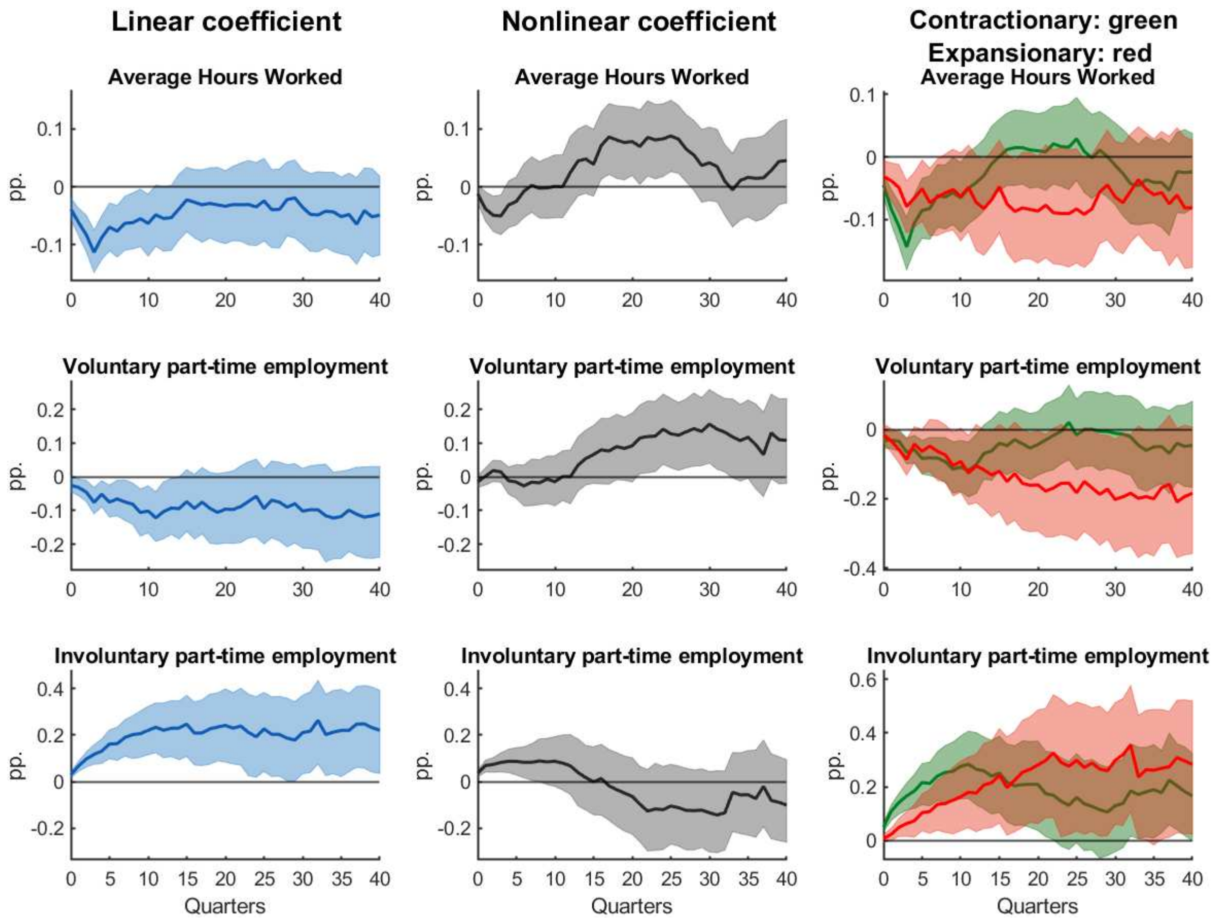

Figure 8: **Linear and Nonlinear IRFs for the Intensive Margin of Labor Market adjustments.** The first column reports the linear coefficients β_1 and the second the nonlinear coefficients β_2, both estimated from Eq. (2). The third column shows the sign-specific IRFs implied by Eq. (3). Contractionary shocks are shown in green, expansionary in red (with the latter plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals.

7 The role of Nonlinearity by Size and State

Size-dependence. One potential concern with our sign-asymmetric results is that we may be conflating the effects of size and sign. In section 3.2 we argued that the symmetry of the shock enables us to leverage the separation result proposed by Caravello and Martinez-Bruera (2024) and avoid contamination of nonlinearities between size and sign. Nevertheless, assessing whether hysteresis effects depend on the size of demand shifts is interesting in its own right: only sufficiently large shocks may trigger changes in firms' technological choices or labor force participation that give rise to persistent effects. To test this possibility, we replace the absolute value transformation of the shock with the odd function $f_{size}(\varepsilon_t) = \varepsilon_t|\varepsilon_t|$ in equation (2). Results are presented in Appendix G.1. We report only the nonlinear coefficient to test the null hypothesis of no deviation from linearity. The estimates provide limited evidence of size asymmetries in the transmission of the hysteresis shock, concentrated in the first few quarters.[27]

[27] The odd function $\varepsilon_t|\varepsilon_t|$ is employed for example by Ascari and Haber (2022). Results are the same if we use the cube of the shock ε_t^3 as in Tenreyro and Thwaites (2016).

State-dependence. Focusing on differences between positive and negative shocks, implicitly averages the effects over all economic conditions. However, the degree of hysteresis might also depend on the initial state of the economy. For example, does a positive shock in a recession (high slack) yield bigger long-run gains than a positive shock in an already tight economy? To answer these questions, we interact sign asymmetry with state dependence in equation (2).[28] In particular, we estimate the following

$$
\begin{aligned}
y_{t+h} - y_{t-1} = H_{t-1}\big[\alpha^{R,h} + \beta_1^{R,h}\varepsilon_t + \beta_2^{R,h}|\varepsilon_t| + \sum_{l=1}^{k}\gamma_l^{R,h}\Delta y_{t-l}\big] \\
+ (1 - H_{t-1})\big[\alpha^{B,h} + \beta_1^{B,h}\varepsilon_t + \beta_2^{B,h}|\varepsilon_t| + \sum_{l=1}^{k}\gamma_l^{B,h}\Delta y_{t-l}\big] + u_{t+h}, \qquad h = 0, 1, \ldots, H.
\end{aligned}
\tag{4}
$$

$y_{t+h} - y_{t-1}$ is the long difference of y_t; H_{t-1} is a dummy variable equal to 1 when unemployment is above its sample mean (recession state), i.e., $H_{t-1} = \mathbf{1}\{\text{Unemp}_{t-1} > \overline{\text{Unemp}}\}$. The coefficients of interest are $\beta_1^{R,h}$ and $\beta_2^{R,h}$ — where R denotes the recession state — and $\beta_1^{B,h}$ and $\beta_2^{B,h}$ — where B denotes boom. The Gonçalves et al. (2021) estimator in this context is going to be state-specific, in particular

$$
\text{IRF}^R_{h,\delta} = \beta_1^{R,h}\,\delta + \beta_2^{R,h}\,\mathbb{E}[\,|\varepsilon_t + \delta| - |\varepsilon_t|\,], \qquad \text{IRF}^B_{h,\delta} = \beta_1^{B,h}\,\delta + \beta_2^{B,h}\,\mathbb{E}[\,|\varepsilon_t + \delta| - |\varepsilon_t|\,]. \tag{5}
$$

where setting $\delta = -1$ yields the state-specific impulse responses for expansionary shocks, while setting $\delta = +1$ yields the state-specific impulse responses for contractionary shocks (with the shock normalized to one standard deviation).

Results are presented in Figures 21 and 22. Comparing positive and negative hysteresis shocks across recessions and expansions, we find limited evidence of state dependence. In the second column of Figure 21, the difference between contractionary shocks in recessions and in booms generally crosses zero. The same pattern holds for expansionary shocks (Figure 22). In the latter case, the point estimate in the third column of Figure 22 suggests that positive shocks in booms may be larger than in recessions, consistent with Okun's "high-pressure economy" hypothesis — when the labor market is strong, further strengthening delivers extra gains for workers and the broader economy (Aaronson et al., 2019; Alves and Violante, 2025). However, the wide statistical uncertainty around these estimates prevents us from drawing sharp conclusions. The large uncertainty associated with the joint state-and-sign decomposition likely reflects the difficulty of estimating a highly nonlinear model, such as Equation 4, with a limited sample spanning fewer than 40 years. To further explore this issue, it is necessary to either use a longer sample or exploit cross-sectional variation in economic conditions (e.g., across US states, as in Ahn and Eo (2025)).

8 Discussion

Our findings show that focusing only on short-run effects can understate the long-run consequences of aggregate demand shocks and, in particular, the potential for reverse hysteresis.

[28] A similar exercise combining state and sign dependence can be found in Barnichon et al. (2022a) and Born et al. (2024) for fiscal shocks.

These results carry potential policy implications. However, absent a structural model, we treat them as suggestive and primarily as directions for future research.

First, in the presence of hysteresis, the costs of cyclical demand shocks can be substantially larger. During recessions, inaction by aggregate demand policy can compound these losses (Fatás and Singh, 2024), whereas tightening too early in expansions can hinder positive labor market developments.

Second, although positive demand shocks may yield persistent benefits, they can also generate persistent inflation, which poses a trade-off for policymakers. On this point, Lepetit (2023) finds that the expected change in inflation caused by persistent demand shocks is smaller than that associated with temporary demand shocks, because in the former case the supply side responds endogenously, easing inflation pressures. Whether this holds for both positive and negative shocks is an important question for future research.

Third, our results speak to recent works on adopting an asymmetric monetary-policy strategy that focuses on shortfalls of employment from its maximum level rather than symmetric deviations. Kiley (2024) develops a model in which the monetary authority follows an asymmetric rule and shows that, if demand is neutral in the long run, such policies have unintended consequences — exacerbating activity shortfalls and creating an inflationary bias. If hysteresis is present but only on the downside, the asymmetric approach worsens scarring and can be even more adverse for activity shortfalls than under long-run neutrality. However, if positive hysteresis is also present, an asymmetric strategy may be justified: responding more forcefully in recessions while accommodating expansions can durably lift labor market trajectories for low-wage workers (Alves and Violante, 2025).

Beyond policy, our findings also speak to macroeconomic modeling. The asymmetric results we find for R&D and capital stock are consistent with models in which recessions leave lasting scars by depressing innovation and slowing capital accumulation (Benigno and Fornaro, 2018; Anzoategui et al., 2019; Garga and Singh, 2021, just to name a few). The importance we find for the labor market channel is consistent with model where micro hysteresis in employment and participation scales up to macro hysteresis for the aggregate economy (Alves and Violante, 2024). The initial labor market asymmetry — negative shocks mattering more than positive shocks — is in line with models featuring asymmetric effects of demand shocks in general and policy shocks in particular. Such asymmetries are typically associated with downward nominal wage rigidity (DNWR) and with occasionally binding constraints such as the zero lower bound (see Bundick et al. (2025) for an extensive account of mechanisms generating asymmetries in business-cycle models). A representative example for labor market hysteresis is provided by Abbritti et al. (2021), where DNWR amplifies scarring effects from negative shocks but limits hiring and job creation after positive shocks because nominal wages react faster on the upside. While the short-run asymmetries we document in labor market outcomes may be consistent with this mechanism, the emergence of persistent positive effects over the medium term calls for models in which such asymmetry dissipates through labor-force expansion and skill upgrading, potentially with larger gains for disadvantaged workers.

9 Conclusions

Do contractionary demand shocks have lasting effects on the economy's potential? Conversely, can expansionary demand shocks reverse these effects and generate sustained positive outcomes?

In this paper, we address these questions by combining a vector autoregression identified through zero and sign restrictions with nonlinear local projections to measure sign-dependent impulse responses resulting from hysteresis shocks. Our results indicate that contractionary demand shocks tend to have stronger immediate effects than expansionary ones. However, this asymmetry often reverses over longer horizons, with this reversal being mostly driven by labor market variables.

We view this research as an initial step toward a deeper understanding of nonlinear hysteresis. Future work could benefit from a more granular analysis of the transmission mechanisms, allowing for asymmetric effects across the skill and earnings distribution of workers — in the labor market channel — and across firm characteristics, such as financing constraints — within the capital accumulation and innovation channels. Additionally, cross-country comparisons, such as between the U.S. and EU countries, could provide valuable insights into how different institutional settings, labor market dynamics, and policy frameworks affect the asymmetry, propagation and persistence of aggregate demand shocks.

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Online Appendix

Are Hysteresis Effects Nonlinear?

Damiano Di Francesco   Omar Pietro Carnevale

Contents

A Sign Nonlinearity in VAR and LP

In this section, we clarify the rationale for our two-step methodology and explain why traditional nonlinear VAR methods cannot easily capture asymmetric impulse response functions.

The applied macroeconomic literature has traditionally used regime-switching VARs — such as threshold VARs, smooth-transition VARs, and Markov-switching VARs — to capture certain forms of nonlinearity (see Kilian and Lütkepohl, 2017, for a review). These models are well suited to *state dependence* — where IRFs vary with the prevailing state of the economy when the shock hits — but they cannot capture *sign asymmetry*, whereby the impulse response varies with the sign of the shock. To capture sign dependence in VARs, some studies use censored variables or nonlinear transformations of observables (Kilian and Vigfusson, 2011). While this is a viable approach when the asymmetry of interest concerns an observed regressor, it is not suitable when, as in this paper, the focus is on the asymmetric effects of an unobserved structural shock, which must first be identified. In principle, one would need a regime-switching VAR with the shock itself as the state. This entails two problems: (i) the state (the shock) is unobserved and must be estimated, creating a circular identification–estimation issue; (ii) regime-switching VARs assume a finite number of regimes with fixed coefficients, whereas asymmetric impulse responses generally imply dependence on the entire history of shocks — effectively requiring a continuum of regimes (as shown by Barnichon and Matthes, 2018, Appendix, Section 9).

An alternative is the Functional Approximation of Impulse Responses (FAIR) of Barnichon and Matthes (2018), which directly estimates the vector moving-average (VMA) representation of the data, thereby allowing for flexible nonlinear specifications, including sign dependence (Barnichon et al., 2022a,b). While attractive, FAIR relies on a tightly parameterized functional forms — typically Gaussian basis functions — to approximate nonlinear IRFs and, more importantly, is not designed to accommodate the mix of sign and long-run zero restrictions that underpins our identification strategy. More broadly, once endogenous regime switching is allowed and structural impulse responses are nonlinear, long-run restrictions become infeasible because there is no closed-form solution for IRFs (Kilian and Lütkepohl, 2017).

To accommodate our complex identification scheme with sign dependence, we therefore adopt the two-step methodology in Section 3. Our approach builds on Debortoli et al. (2024), who represent the economy with a structural vector moving average (SVMA) that includes nonlinear functions of the shock of interest.[29] We depart from that framework by modeling asymmetry via *asymmetric LPs* rather than a VARX. We prefer LPs because (i) in small samples they are better suited to estimating medium- and long-horizon dynamics than VARs (Jordà et al., 2024); (ii) LPs let us analyze many outcomes without overparameterizing a VAR or re-estimating multiple VARs that add variables one by one; (iii) they allow us to exploit the separation results of Caravello and Martinez-Bruera (2024) to disentangle pure sign from size asymmetry; and (iv) combined with the *plug-in* estimator of Gonçalves et al. (2021), LPs flexibly handle nonlinearity while delivering consistent asymmetric IRFs. Importantly, there is supportive simulation evidence for this two-step design. Examples are Born et al. (2024), where the first step is set-identified VAR and the second step is a nonlinear LP — exactly as in our application — and Debortoli et al. (2024) where the second step is a VARX. Moreover, Barnichon et al. (2022b) find that a VAR–LP approach delivers asymmetric responses comparable to those obtained with FAIR.

[29] See also Forni et al. (2024, 2025) for related frameworks.

B Data

B.1 Variables in the BVAR and LP

Variable	Description
GDP	Real Gross Domestic Product, 2017$ chn. bn, SA
Inflation	PCE (implicit price deflator), 2017=100, SA.
Employment	Employment-Population ratio, 2017Q1=100, SA.
Investment	Real Gross Private Domestic Investment, 2017$ chn. bn, SA

Table 3: Variables in the VAR. *Source*: FRED

Variable	Description
Consumption per capita	Personal Consumption Expenditures over Total Population, $ /person, SA
R&D per capita	GDP: Research and Development over Total Population, $ /person, SA.
Capital Stock	Capital input, Perpetual inventory stocks, Level, Fernald (2014)
TFP	Utilization adjusted Business sector TFP, Level, Fernald (2014)
Patent-based Innovation index*	Aggregate innovation measure from Kogan et al. (2017), Percent
Participation Rate	Labor Force Participation Rate, Percent, SA
Participation Rate Men	Labor Force Participation Rate, Men, Percent, SA
Participation Rate Women	Labor Force Participation Rate, Women, Percent, SA
Participation Rate White	Labor Force Participation Rate, White, Percent, SA
Participation Rate Black or African American	Labor Force Participation Rate, Black or Afr., Percent, SA
Participation Rate Hispanic or Latino	Labor Force Participation Rate, Hisp., Percent, SA
Unemployment Rate	Unemployment Rate, Percent, SA
Unemployment Rate Men	Unemployment Rate, Men, Percent, SA
Unemployment Rate Women	Unemployment Rate, Women, Percent, SA
Unemployment Rate White	Unemployment Rate, White, Percent, SA
Unemployment Rate Black or African American	Unemployment Rate, Black or Afr., Percent, SA
Unemployment Rate Hispanic or Latino	Unemployment Rate, Hisp., Percent, SA
Employment Men	Employment-Population ratio, Men, 2017Q1=100, SA.
Employment Women	Employment-Population ratio, Women, 2017Q1=100, SA.
Employment White	Employment-Population ratio, White, 2017Q1=100, SA.
Employment Black or African American	Employment-Population ratio, Black or Afr., 2017Q1=100, SA.
Employment Hispanic or Latino	Employment-Population ratio, Hisp., 2017Q1=100, SA.
Long-term unemployed	Unemployed for 27 Weeks over Unempl. Level, Th.
Average Hours worked	Nonfarm Business Sector: Average Weekly Hours for All Workers, 2017=100, SA
Voluntary part-time employment*	Labor utilization measure from Borowczyk-Martins and Lalé (2020), Percent
Involuntary part-time employment*	Labor utilization measure from Borowczyk-Martins and Lalé (2020), Percent

Table 4: Variables in the LP. The construction of variables indicated with '*' is detailed in the next paragraphs. *Source*: FRED, Fernald (2014); Kogan et al. (2017); Borowczyk-Martins and Lalé (2020).

B.2 Construction of the Innovation measure

The *Patent-based Innovation Index* is an updated quarterly measure of the annual innovation measure proposed by Kogan et al. (2017). The quarterly transformation is obtained along the lines of Cascaldi-Garcia and Vukotić (2022). In particular, we first downloaded patent level panel data from 1926 to 2023 from https://github.com/KPSS2017. We then run the routine in the replication code of Cascaldi-Garcia and Vukotić (2022) to (i) aggregate firm-level information as the sum of the value of all patents granted in year t to the firms in the sample, scaled by aggregate output; and (ii) to obtain a quarterly index from the annual measure.

B.3 Construction of the Part-time Employment Variables

Voluntary and involuntary part-time employment measures are constructed in Borowczyk-Martins and Lalé (2019) and retrieved from Borowczyk-Martins' website. Voluntary and involuntary part-time employment are measured using CPS basic-monthly (BM) and Annual Social and Economic Supplement (ASEC) files. Individuals are classified as part-time if they usually work under 35 hours per week (in the CPS reference week for BM or in more than half of their weeks in the year for ASEC), and as involuntary part-timers if, when reporting under 35 hours, they cite inability to find full-time work or poor business conditions as their main reason. Because the 1994 CPS redesign introduced a structural break in part-time and involuntary part-time measurement, the authors implement a calibration adjustment — using ASEC-based benchmarks to reweight the basic-monthly series — so as to bridge the pre- and post-redesign data into a single, consistent time series.

C Descriptive statistics of the hysteresis shock

C.1 Hysteresis Shock over business cycles

The hysteresis shock estimated in our analysis is an aggregate demand shock, with "hysteresis" referring to its persistent effects on the examined economic variables. Figure 9 plots the shock from the baseline VAR. The blue bands denote the distribution of the set-identified shock. Shaded regions mark NBER recessions, illustrating the shock's behavior over the business cycle.

First, the shock displays clear demand-like features: it reaches negative peaks around the 1990, 2001, and 2008 recessions, with an especially sharp decline during the Great Recession. We next look at whether the hysteresis shock correlates with known demand proxies related to monetary policy, fiscal policy, and financial shocks. For monetary policy, the strongest correlation is with the Nakamura and Steinsson (2018) shock (0.24)[30]. We also find 0.21 for Jarociński and Karadi (2020) and 0.20 for the path component of Gürkaynak et al. (2005). Correlations with the narrative measures of Romer and Romer (2004) and Aruoba and Drechsel (2025) are lower—0.07 and 0.09, respectively. With respect to financial shocks, the correlation with the Excess Bond Premium of Gilchrist and Zakrajšek (2012) is 0.29. On the fiscal side, the values are 0.18 for Auerbach and Gorodnichenko (2012) and 0.13 for the military-expenditure news shock of Ramey (2011). Some of these correlations are non-negligible, indicating that the hysteresis shock is an aggregate-demand disturbance that bundles different shock types.[31] At the same time, the correlations are not large, suggesting that the hysteresis shock is a particular kind of demand shock with long-run effects, whereas the previously cited proxies are typically associated with short-run macroeconomic fluctuations.

One concern is that the long-run effects we document could reflect supply-shock contamination. We view this as unlikely. First, sign restrictions on prices and quantities — used to distinguish demand from supply — are a standard VAR identification device. Consistent with

[30] Correlations are Pearson coefficients, computed for each draw of the hysteresis shock over each proxy's available sample window and then averaged across draws.

[31] In this correlation exercise, we exclude discount-factor and confidence shocks, which are also instances of demand shocks.

this, the price IRFs in Figure 1 have opposite signs for the hysteresis shock and the permanent supply shock. Output per worker also behaves differently, with its long-run movements driven largely by supply shocks. For additional robustness to guard against potential shock contamination, see Section V of Furlanetto et al. (2025).

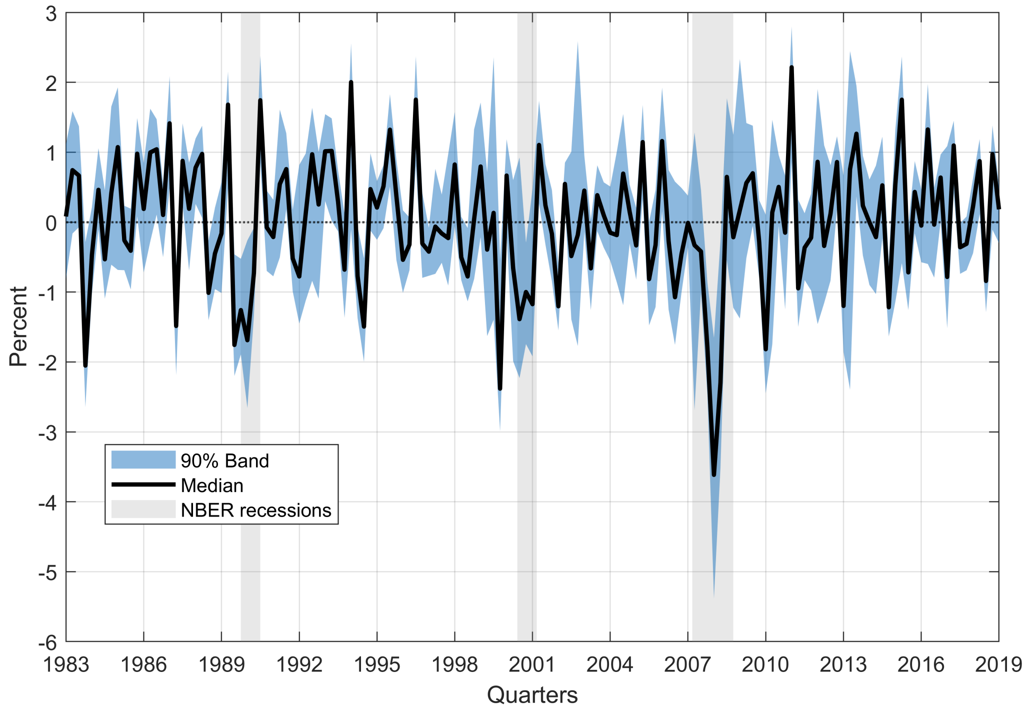

Figure 9: **Hysteresis shock (baseline model).** Black line: pointwise posterior median. Blue bands: 90% posterior credible interval. Gray shading: NBER recessions.

C.2 Symmetry of the shock distribution

We assess whether the shock distribution is symmetric using the nonparametric triples test of Randles et al. (1980). The null hypothesis H_0 is symmetry about an unknown median, and the alternative H_1 is asymmetry. The test orders the sample and, for every triple $i < j < k$, checks whether the middle observation tends to lie closer to the lower or to the upper value; under symmetry, the counts of "leftward" and "rightward" triples balance and the test statistic centers near zero. We conduct the test at the 5% significance level for the median and for the 16^{th} and 84^{th} percentiles of the hysteresis shock distribution. The two-sided p-values are 0.32 (median), 0.29 (16^{th} percentile), and 0.47 (84^{th} percentile). Hence, we fail to reject H_0 and conclude that the shock distribution is symmetric. Figure 10 displays the histogram of the shock distribution based on the median, visually corroborating the result of the statistical test.

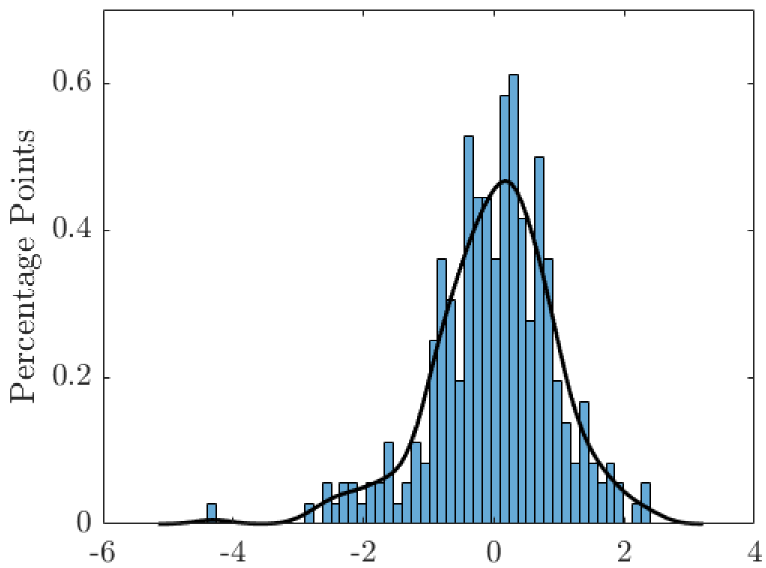

Figure 10: **Distribution of the Hysteresis Shock.** Bins correspond to the histogram, whereas the black line is the estimated density via kernel.

D Factor Estimation using FRED-QD

Factors are extracted from the FRED-QD database (McCracken and Ng, 2020), following the original paper's variable transformations to ensure stationarity. Principal Component Analysis (PCA) is conducted while accounting for missing values, using the factor-based imputation method proposed by Bai and Ng (2021). The number of factors is selected based on the criterion of Bai and Ng (2002), and estimation is conducted over the same sample used for the BVAR estimation. The criterion selects 7 factors as in McCracken and Ng (2020). The entire procedure is implemented using the MATLAB routine provided by the authors, available at the St. Louis Fed website.

D.1 Results of the test for different percentiles of the set-identified hysteresis shock

Median

	First 3 Factors, l lags			First 7 Factors, l lags		
	$l = 1$	$l = 3$	$l = 6$	$l = 1$	$l = 3$	$l = 6$
p-value	0.2591	0.2840	0.1946	0.3663	0.6577	0.1990

16% Percentile

	First 3 Factors, l lags			First 7 Factors, l lags		
	$l = 1$	$l = 3$	$l = 6$	$l = 1$	$l = 3$	$l = 6$
p-value	0.1079	0.2068	0.1090	0.1826	0.5702	0.1279

84% Percentile

	First 3 Factors, l lags			First 7 Factors, l lags		
	$l = 1$	$l = 3$	$l = 6$	$l = 1$	$l = 3$	$l = 6$
p-value	0.4310	0.3598	0.3774	0.5955	0.7235	0.3313

Table 5: F-test p-values (median, 16th, and 84th percentiles) for lags $l \in \{1, 3, 6\}$ and factor sets (first 3, first 7).

E Robustness of Main Results

E.1 BVAR with varying lags

In this section, we show that the baseline results — based on the BVAR in Eq. (1) with lag length $P = 3$ — are robust when the BVAR is estimated with $P \in \{8, 12, 40\}$.

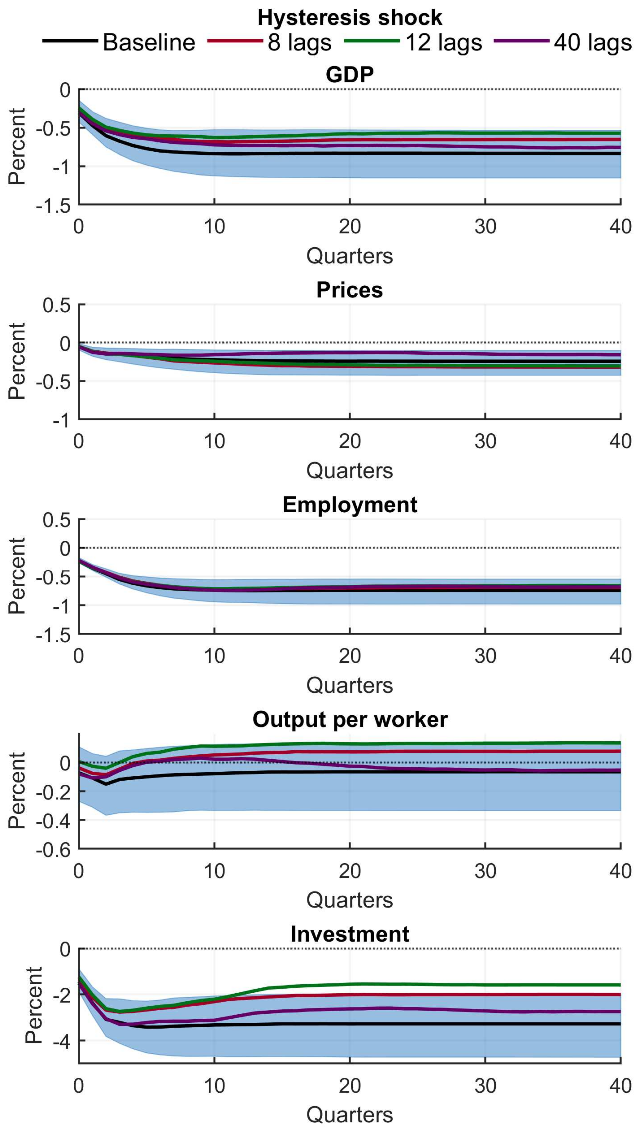

Figure 11: **IRFs to the Hysteresis shock for different lags in the BVAR.** Plots show percent changes in levels. Black lines denote pointwise posterior medians for the baseline model with 3 lags, red lines for the model with 8 lags, green lines for the model with 12 lags, and purple lines for the model with 40 lags. Bands denote 68% posterior credible intervals for the baseline model.

E.2 LP with a varying number of lags in the BVAR

In the preceding exercise we varied the BVAR lag length and showed robustness of baseline findings. In this robustness check, we vary the VAR lag length over $P \in \{3, 8, 12\}$ and report the nonlinear impulse responses from Eq. (3), keeping the LP lag length fixed at the baseline $k = 3$. Baseline findings remain materially unchanged across these alternative VAR lag choices.

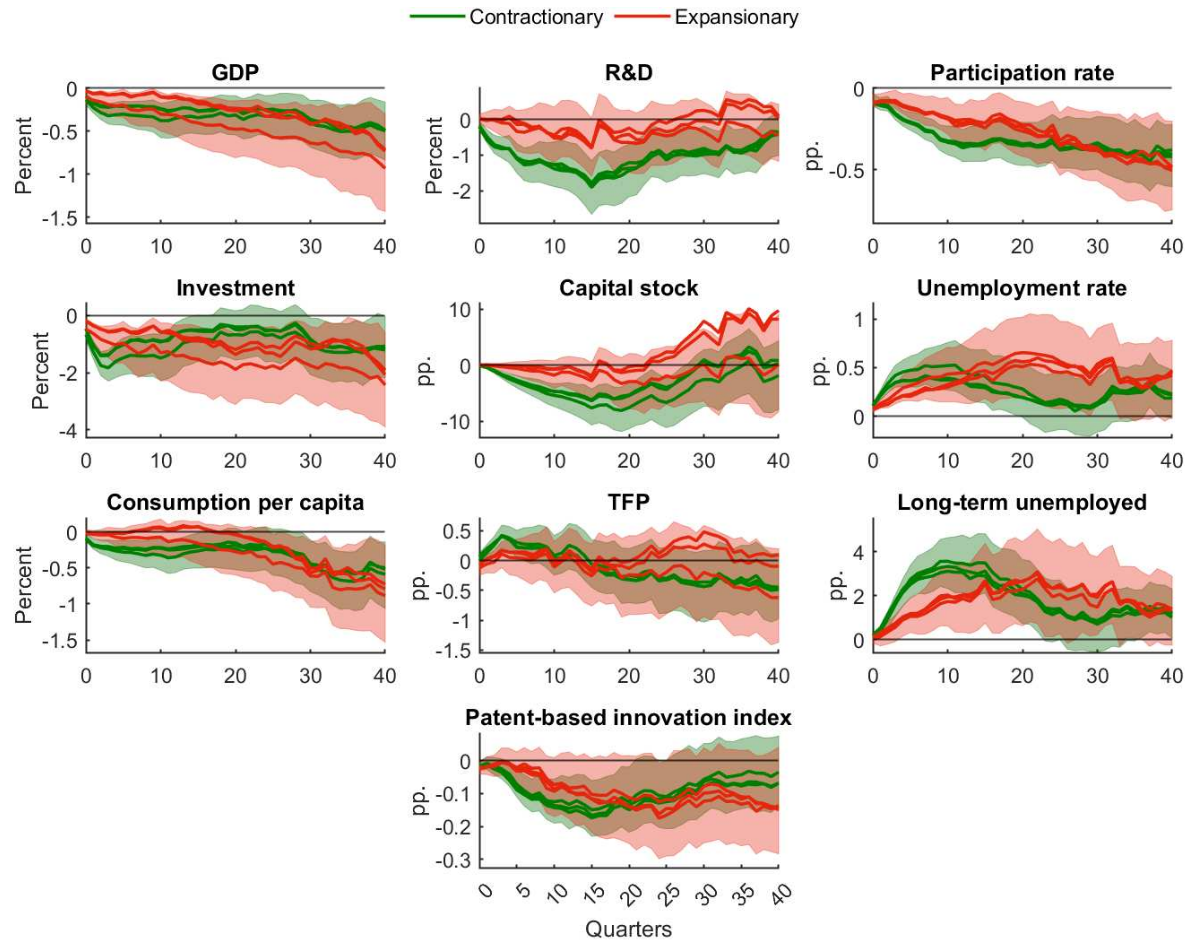

Figure 12: **Nonlinear IRFs for different number of lags in the VAR.** Each panel shows the sign-specific IRFs implied by Eq. (3) for number of lags P in the VAR, with $P \in (3, 8, 12)$ and $k = 3$ number of lags in the LP. Contractionary shocks are shown in green, expansionary in red (with the latter plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals for $P, k = 3$ (baseline).

E.3 LP with varying lags

In this section, we estimate the LP with a richer lag structure, $k \in \{2, 3, 4, 5, 6\}$, while holding fixed the baseline BVAR from which the hysteresis shock is extracted. Baseline results are robust to this richer lag specification.

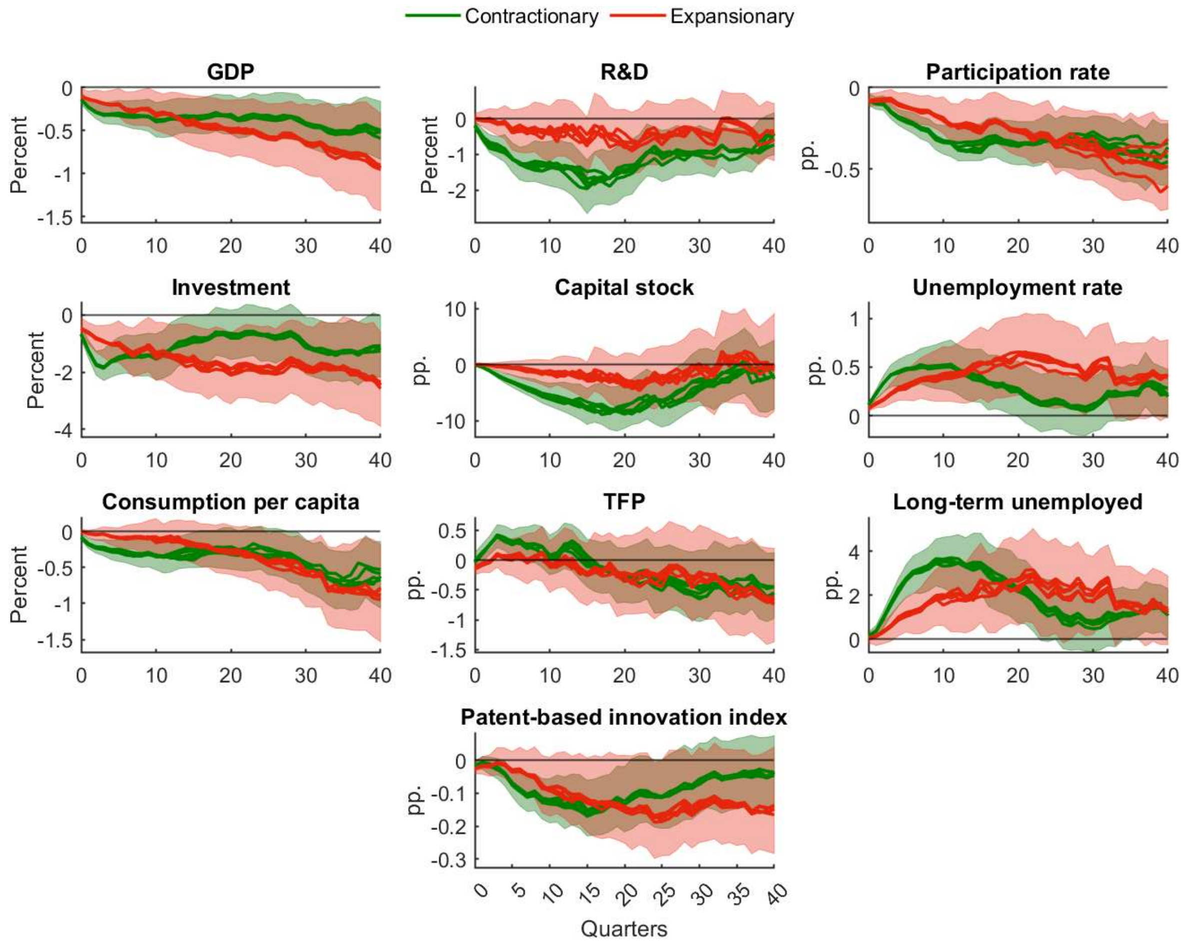

Figure 13: **Nonlinear IRFs for different number of lags in the LP.** Each panel shows the sign-specific IRFs implied by Eq. (3) for number of number of lags k in the LP, with $k \in (2, 3, 4, 5, 6)$. Contractionary shocks are shown in green, expansionary in red (with the latter plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals for $k = 3$.

E.4 Extended sample: 1983:Q1-2024:Q4

In the main text we explain that, to estimate both the VAR and LPs through 2024:Q4, we need to accommodate the extreme macroeconomic volatility surrounding the pandemic. For the VAR, we rely on the procedure outlined by Lenza and Primiceri (2022). Since the estimated hysteresis shock to be used in the LP still displays substantial variability in 2020:Q2 and 2020:Q3, we apply a related adjustment to the distribution of the hysteresis shock, following the GLS-based approach proposed by Hamilton (2025). Below we outline the formal procedure.

Consider the following VAR

$$\mathbf{y}_t \;=\; B_{s_t}\,\mathbf{y}_{t-1} \;+\; \mathbf{u}_t, \qquad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0},\, \boldsymbol{\Sigma}_{s_t}), \tag{6}$$

where $s_t \in \{1,2\}$ denotes the regime: $s_t = 1$ for normal times and $s_t = 2$ for the pandemic.

Although one could estimate $(B_1, \boldsymbol{\Sigma}_1)$ for normal times, the limited number of pandemic observations prevents reliable estimation of $(B_2, \boldsymbol{\Sigma}_2)$. Following Lenza and Primiceri (2022), we assume instead that autoregressive coefficients are unchanged across regimes ($B_2 = B_1$), while the covariance matrix is inflated by a scale factor $\delta^2 > 1$:

$$\boldsymbol{\Sigma}_2 \;=\; \delta^2 \boldsymbol{\Sigma}_1.$$

Likelihood. Conditional on $\{s_t\}$, the Gaussian log-likelihood is

$$\begin{aligned} L(B_1, \boldsymbol{\Sigma}_1, \delta) = -\frac{TN}{2}\log(2\pi) \;-\; \frac{T_2 N}{2}\log\delta^2 \;-\; \frac{T}{2}\log\left|\boldsymbol{\Sigma}_1\right| \\ -\tfrac{1}{2}\sum_{t=1}^{T}\left(\mathbf{y}_t^* - B_1\mathbf{y}_{t-1}^*\right)'\boldsymbol{\Sigma}_1^{-1}\left(\mathbf{y}_t^* - B_1\mathbf{y}_{t-1}^*\right), \end{aligned} \tag{7}$$

where $\mathbf{y}_t^* = \mathbf{y}_t/\delta_{s_t}$, $\mathbf{y}_{t-1}^* = \mathbf{y}_{t-1}/\delta_{s_t}$, and $T_2 = \sum_{t=1}^{T}\mathbf{1}(s_t = 2)$ is the number of pandemic observations. Thus δ effectively downweights pandemic observations rather than discarding them.

Estimating $(B_1, \boldsymbol{\Sigma}_1)$. For known δ, the MLE of the coefficients and covariance matrix is obtained by weighted least squares:

$$\hat{B}_1(\delta) = \left(\sum_{t=1}^{T}\mathbf{y}_t^*\mathbf{y}_{t-1}^{*\prime}\right)\left(\sum_{t=1}^{T}\mathbf{y}_{t-1}^*\mathbf{y}_{t-1}^{*\prime}\right)^{-1}, \tag{8}$$

$$\hat{\boldsymbol{\Sigma}}_1(\delta) = \tfrac{1}{T}\sum_{t=1}^{T}\left(\mathbf{y}_t^* - \hat{B}_1\mathbf{y}_{t-1}^*\right)\left(\mathbf{y}_t^* - \hat{B}_1\mathbf{y}_{t-1}^*\right)'. \tag{9}$$

Estimating δ. For given $(B_1, \boldsymbol{\Sigma}_1)$, the MLE of δ^2 is

$$\hat{\delta}^2(B_1, \boldsymbol{\Sigma}_1) \;=\; \frac{1}{T_2 N}\sum_{t=1}^{T}\left(\mathbf{y}_t - B_1\mathbf{y}_{t-1}\right)'\boldsymbol{\Sigma}_1^{-1}\left(\mathbf{y}_t - B_1\mathbf{y}_{t-1}\right)\mathbf{1}(s_t = 2). \tag{10}$$

Zigzag algorithm. The likelihood expressions suggest the following iterative GLS procedure, termed *zigzag algorithm* by Hamilton (2025):

1. Initialize with a guess $\hat{\delta}^{(0)}$.
2. Given $\hat{\delta}^{(j)}$, rescale the data and update $\left(\hat{B}_1^{(j)}, \hat{\mathbf{\Sigma}}_1^{(j)}\right)$ using the weighted regression formulas.
3. Given $\left(\hat{B}_1^{(j)}, \hat{\mathbf{\Sigma}}_1^{(j)}\right)$, update the scale factor $\hat{\delta}^{(j+1)}$ using the expression for $\hat{\delta}^2$.
4. Iterate until convergence.

The fixed point yields the maximum-likelihood estimates $\left(\hat{B}_1, \hat{\mathbf{\Sigma}}_1, \hat{\delta}\right)$, efficiently incorporating all observations while appropriately downweighting the pandemic period. We apply this procedure to the 2,000 posterior draws of our hysteresis shock before employing them in the LPs.

In the next page, we report the robustness of our main results when extending the sample through 2024:Q4 in both the BVAR and LP.

VAR: 1983:Q1-2024:Q4

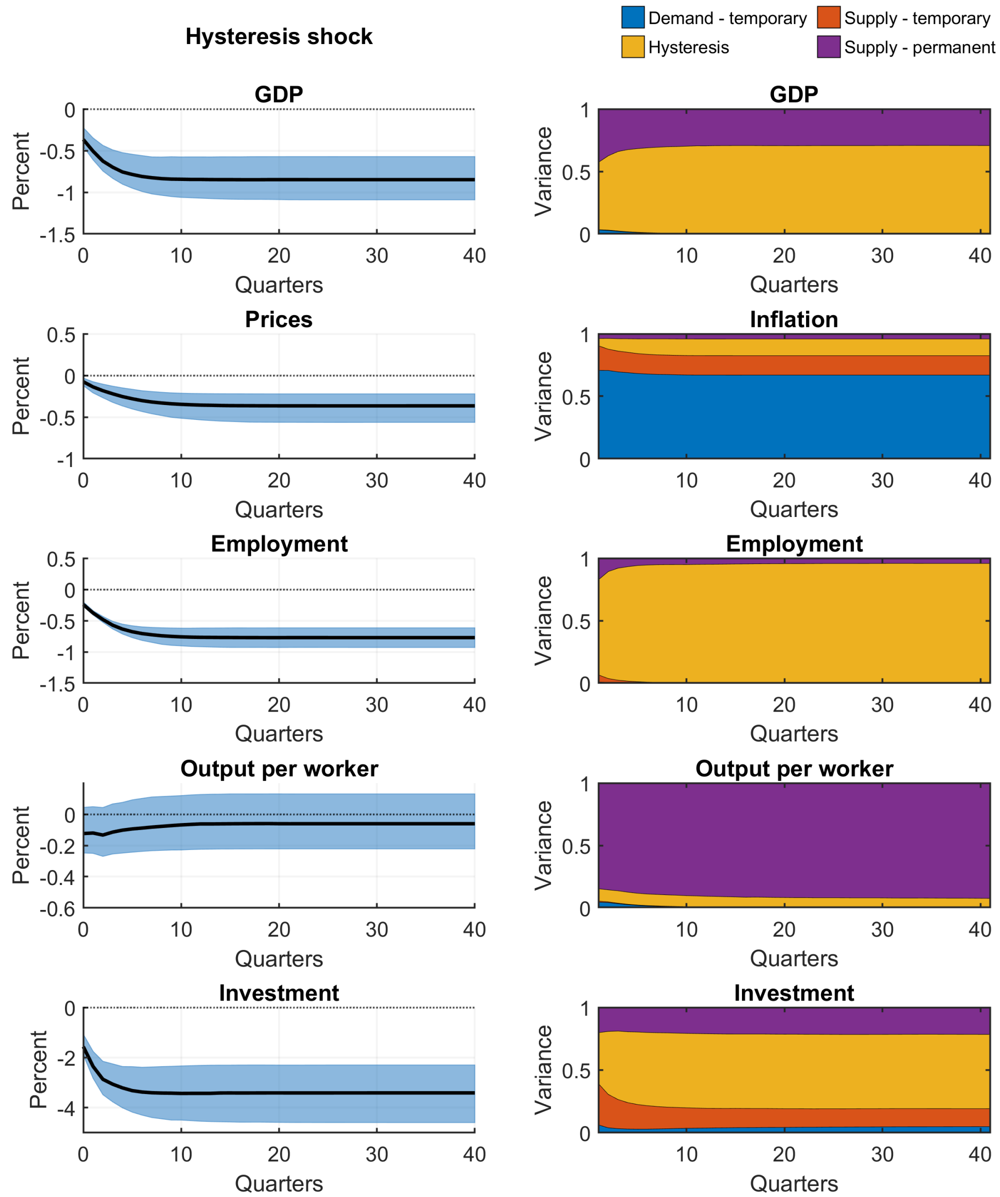

Figure 14: **IRFs and FEVD to the Hysteresis shock**. Sample:1983:Q1-2024:Q4. The BVAR is estimated as explained in the main text, and it also features the pandemic correction proposed by Lenza and Primiceri (2022). Plots show percent changes in levels. Dark lines denote pointwise posterior medians. Bands denote 68% posterior credible intervals.

LP:1983:Q1-2024:Q4

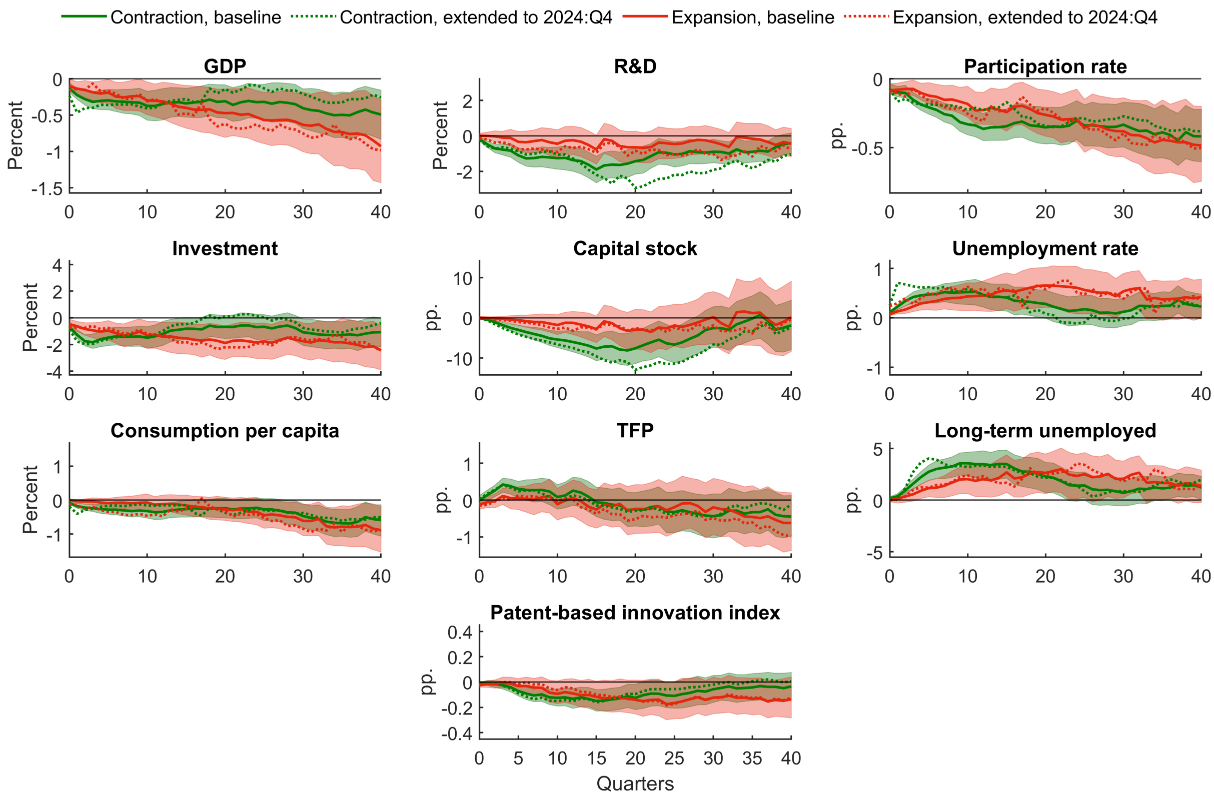

Figure 15: **Nonlinear IRFs — Sample extended through 2024:Q4.** Each panel shows the sign-specific IRFs implied by Eq. (3) for two cases: the baseline sample (1983:Q1–2019:Q4) and the extended sample (1983:Q1–2024:Q4). Contractionary shocks are shown in green, expansionary in red (with the latter plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals for the baseline sample.

E.5 Additional controls in the LP

In this section we enrich the LP specification in Equation (2) by adding additional controls:

$$y_{t+h} - y_{t-1} = \alpha^h + \beta_1^h \varepsilon_t + \beta_2^h f(\varepsilon_t) + \sum_{l=1}^{k} \gamma_l^h \Delta y_{t-l} + \sum_{l=1}^{k} \delta_l^h PC_{t-l} + u_{t+h}, \quad h = 0, 1, \dots, H \tag{11}$$

where PC_{t-l} stacks the first three factors also employed in the informational sufficiency test described in Section 4.1. We set the LP lag length to $k = 3$ as in the baseline estimation. All other terms are as defined in Equation (2). While the estimated responses to contractionary shocks are somewhat attenuated, the baseline conclusions remain essentially unchanged under this augmented specification.

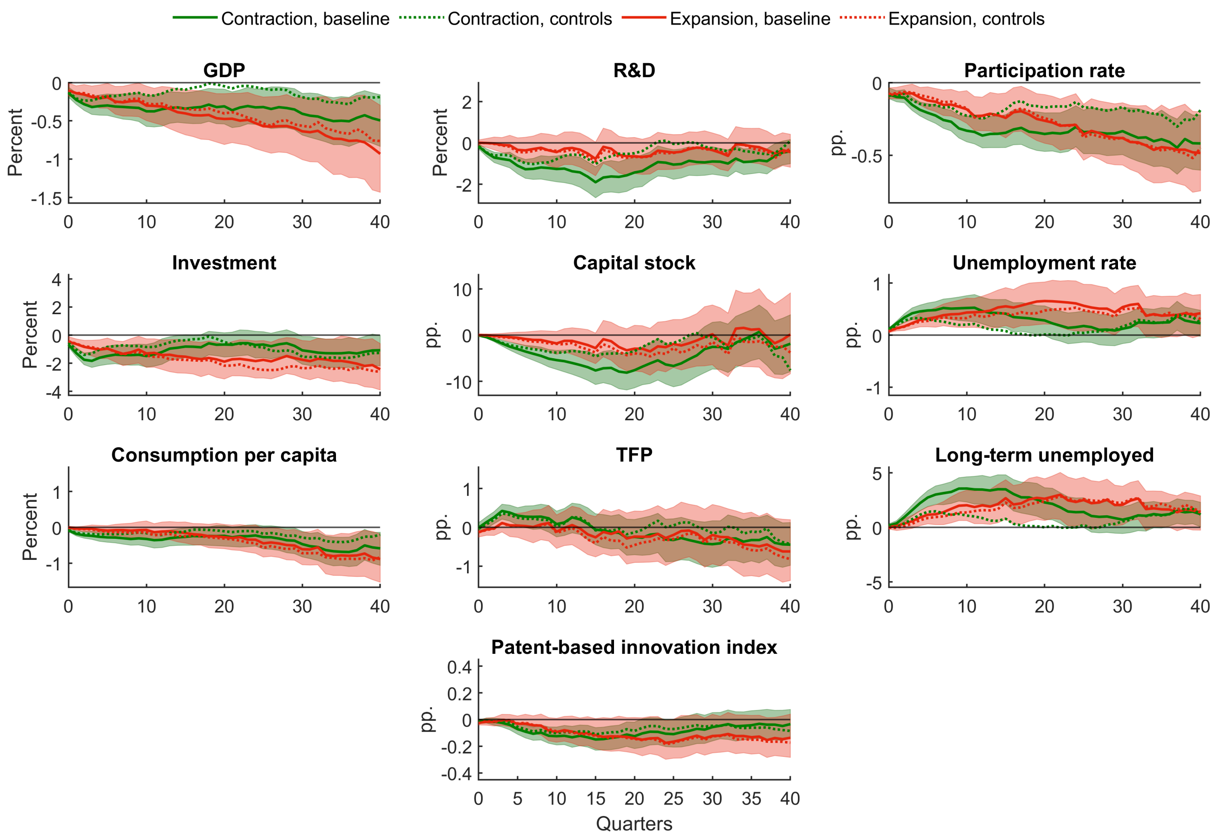

Figure 16: **Nonlinear IRFs — LP with additional controls.** Each panel shows the sign-specific IRFs for two cases: the baseline specification in Eq. (3), which includes only lags of the dependent variable as controls, and the augmented specification in Eq. (11), which additionally includes the first three factors. Contractionary shocks are shown in green, expansionary shocks in red (plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals for the baseline specification.

E.6 Different nonlinear transformation of the shock in the LP

In this section we report the results for the LP in Equation (2) when replacing the absolute value of the shock, $|\varepsilon_t|$, with its square, ε_t^2. Our baseline results are robust to this alternative specification.

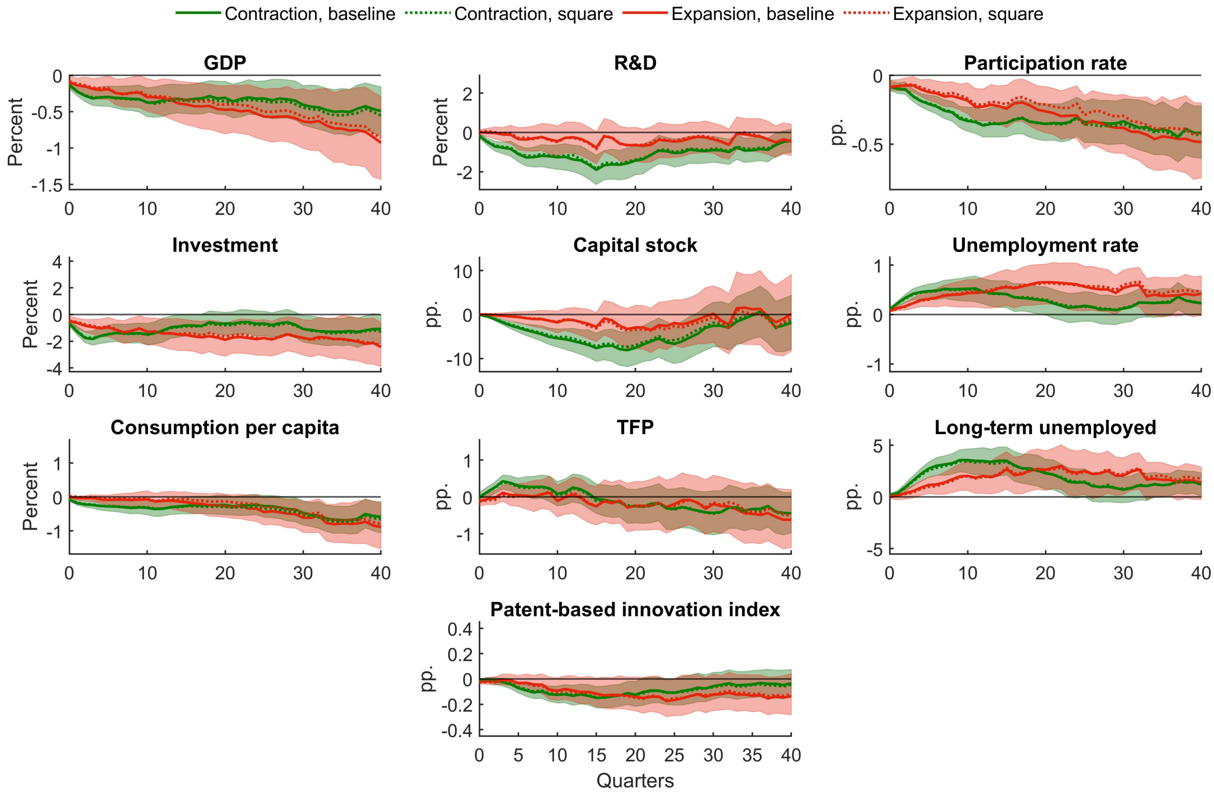

Figure 17: **Nonlinear IRFs — LP with alternative transformation of the shock.** Each panel shows the sign-specific IRFs implied by Eq. (3) for two cases: the baseline specification, which uses the absolute value of the hysteresis shock as the nonlinear transformation, and an alternative specification, which instead uses its square. Contractionary shocks are shown in green, expansionary shocks in red (plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals for the baseline specification.

E.7 Comparing Gonçalves et al. (2021) with the conventional estimator

In this section, we outline the intuition behind the Gonçalves et al. (2021)'s estimator and contrast it with the conventional estimator. We also show that the baseline results obtained with Gonçalves et al. (2021) are robust when computed with the conventional estimator. To do so, we adopt a potential outcomes framework to clarify and formalize the definitions of nonlinear impulse responses commonly used in the literature (Gonçalves et al., 2024a,b; Kolesár and Plagborg-Møller, 2025).

The idea is to compare two sample paths for the variable of interest: one where ϵ_t is subject to a particular realization of the shock of size δ at time t, and another where no such shock occurs. The difference between the values of the outcome variable over time, across these two scenarios, provides a measure of the impulse response function.

Formally, let Y_{t+h} denotes the long difference $y_{t+h} - y_{t-1}$. In our model, we compare the following two potential outcomes:

$$Y_{t+h}(\epsilon_t) = \alpha^h + \beta_1^h \epsilon_t + \beta_2^h |\epsilon_t| + \sum_{l=1}^{k} \gamma_l^h \Delta y_{t-l} + u_{t+h} \quad \text{(Observed)} \tag{12}$$

$$Y_{t+h}(\epsilon_t + \delta) = \alpha^h + \beta_1^h (\epsilon_t + \delta) + \beta_2^h |\epsilon_t + \delta| + \sum_{l=1}^{k} \gamma_l^h \Delta y_{t-l} + u_{t+h} \quad \text{(Counterfactual)} \tag{13}$$

The causal dynamic effect is defined as the difference between (13) and (12):

$$Y_{t+h}(\epsilon_t + \delta) - Y_{t+h}(\epsilon_t) = \beta_1^h \delta + \beta_2^h \left(|\epsilon_t + \delta| - |\epsilon_t|\right). \tag{14}$$

The conventional estimator sets ϵ_t to its mean. When the shock is modeled as an i.i.d. white noise process, as in our case, this implies a mean of zero. This corresponds to a *marginal* response function (Kolesár and Plagborg-Møller, 2025; Gonçalves et al., 2024a). Starting from $\epsilon_t = 0$, Equation (14) simplifies to:

$$Y_{t+h}(\epsilon_t + \delta) - Y_{t+h}(\epsilon_t) = \beta_1^h (\delta) + \beta_2^h |\delta|. \tag{15}$$

Specifically, the impulse response functions to a contractionary shock ($\delta = 1$) and an expansionary shock ($\delta = -1$), both of 1 standard deviation, are given by:

$$\begin{aligned} IRF(\delta = 1) &= \beta_1^h + \beta_2^h, \\ IRF(\delta = -1) &= -\beta_1^h + \beta_2^h. \end{aligned} \tag{16}$$

Gonçalves et al. (2021) note that the conventional estimator derived from Eq. (15) does not integrate $|\varepsilon_t|$ over all the possible values of ε_t after the shock δ occurs. Thus the conventional estiator does not consistently recover the unconditional *average* response. [32] Gonçalves et al. (2021)'s approach consists in taking the expected value of Equation (14), which results in the nonlinear IRF we report as Eq. (3) in the main text:

$$E\left[Y_{t+h}(\epsilon_t + \delta) - Y_{t+h}(\epsilon_t)\right] = \beta_1^h \delta + \beta_2^h E\left[|\epsilon_t + \delta| - |\epsilon_t|\right]. \tag{17}$$

[32] Importantly, the two definitions of impulse responses are equal in a linear local projection framework (Gonçalves et al., 2024a).

Below we compare nonlinear IRFs computed using the baseline definitions in Eqs. (3) and (17) with those obtained from the conventional estimator in Eq. (16). The results are pretty much similar, showing that the choice of which estimator to use does not drive our results.

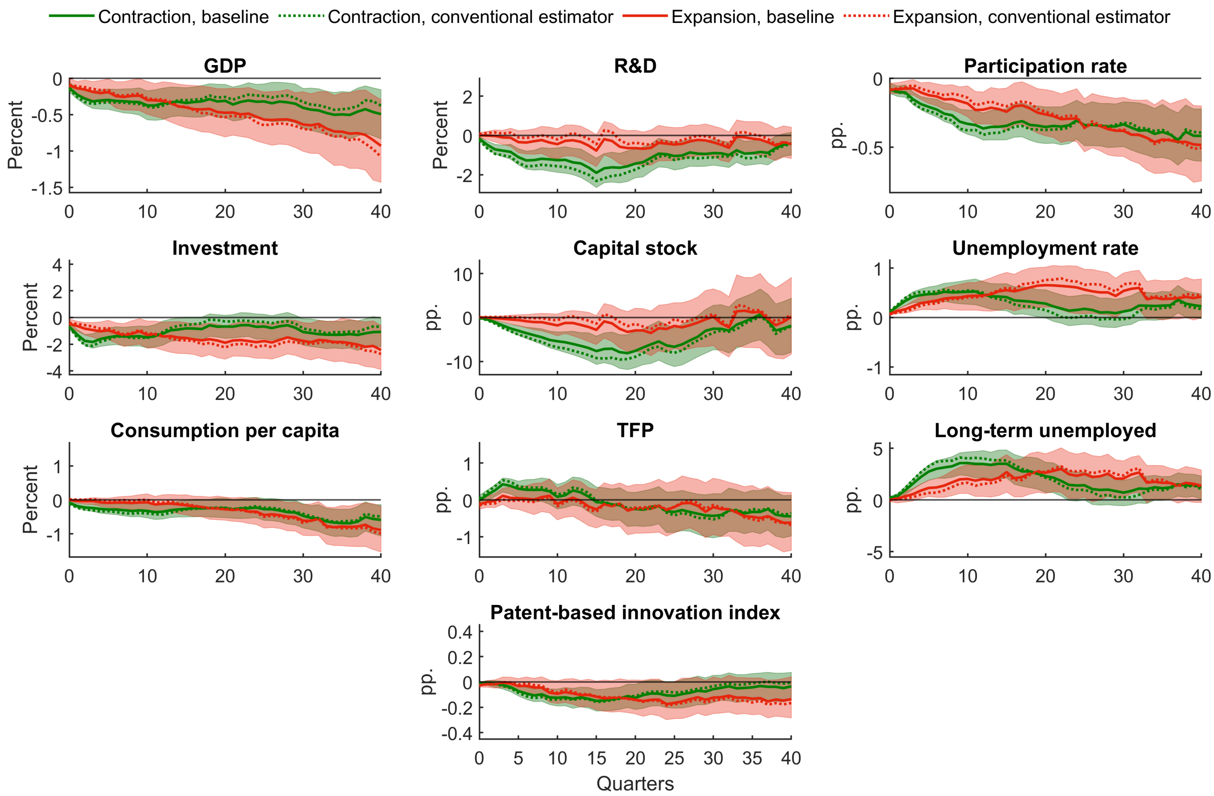

Figure 18: **Nonlinear IRFs — comparing Gonçalves et al. (2021)'s and the conventional estimator.** Each panel shows the sign-specific IRFs for two cases: the baseline specification implied by Eq. (3), and the conventional estimator implied by Eq. (16). Contractionary shocks are shown in green, expansionary shocks in red (plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals for the baseline specification.

F Additional Results on Disaggregated Participation Rates

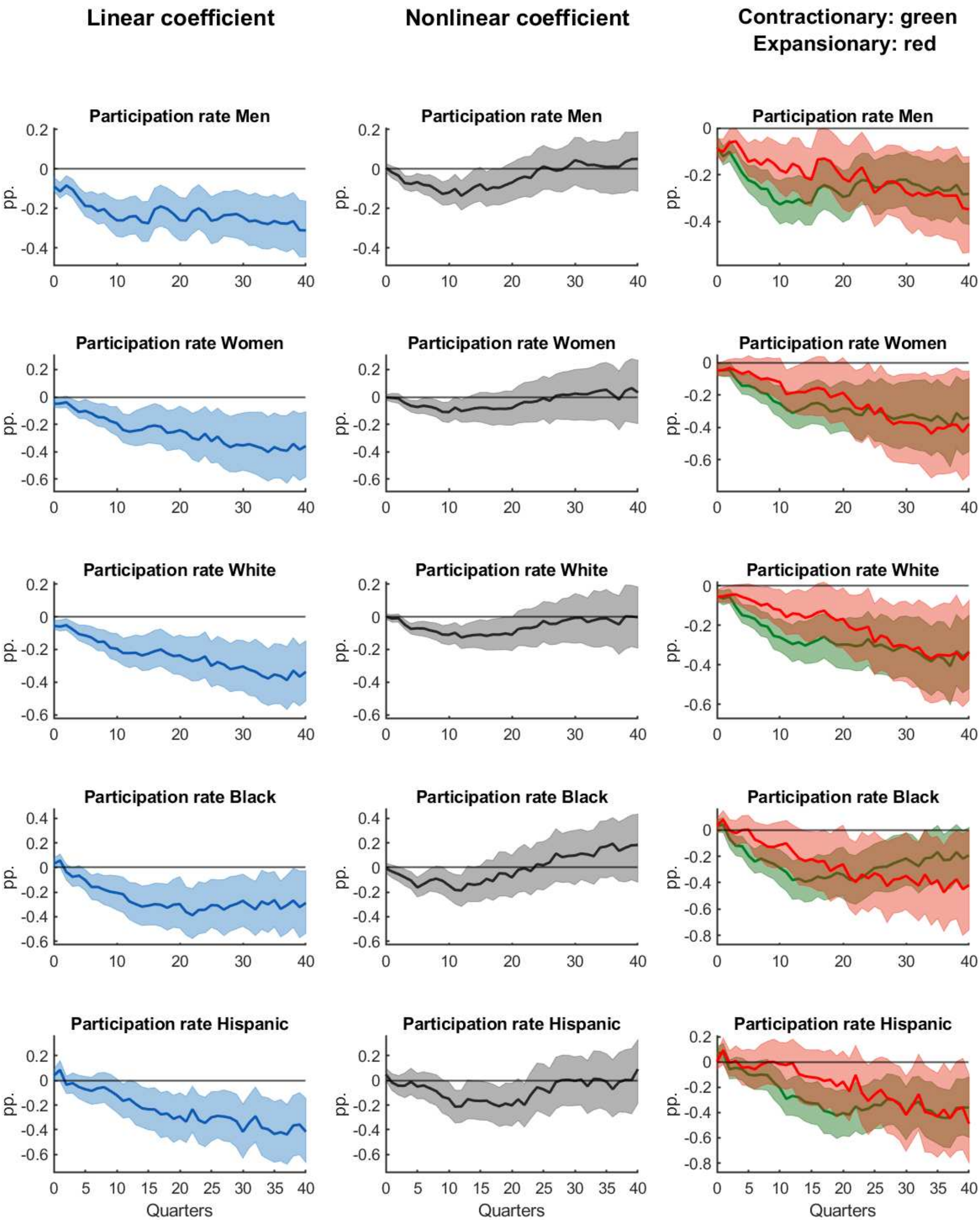

Figure 19: **Linear and Nonlinear IRFs for Participation rates by Gender and Race.** The first column reports the linear coefficients β_1 and the second the nonlinear coefficients β_2, both estimated from Eq. (2). The third column shows the sign-specific IRFs implied by Eq. (3). Contractionary shocks are shown in green, expansionary in red (with the latter plotted with inverted sign for comparability). Shaded bands denote 68% credible intervals.

G Other nonlinearities in LPs

G.1 Size dependence

In this section, we examine whether there is evidence of size asymmetry in the transmission of the hysteresis shock. To this end, we estimate Eq. (2) using the nonlinear transformation of the shock $f(\varepsilon_t) = \varepsilon_t|\varepsilon_t|$. We report the nonlinear coefficients β_2^h, which exhibit considerable statistical uncertainty, and conclude that there is little evidence of size dependence.

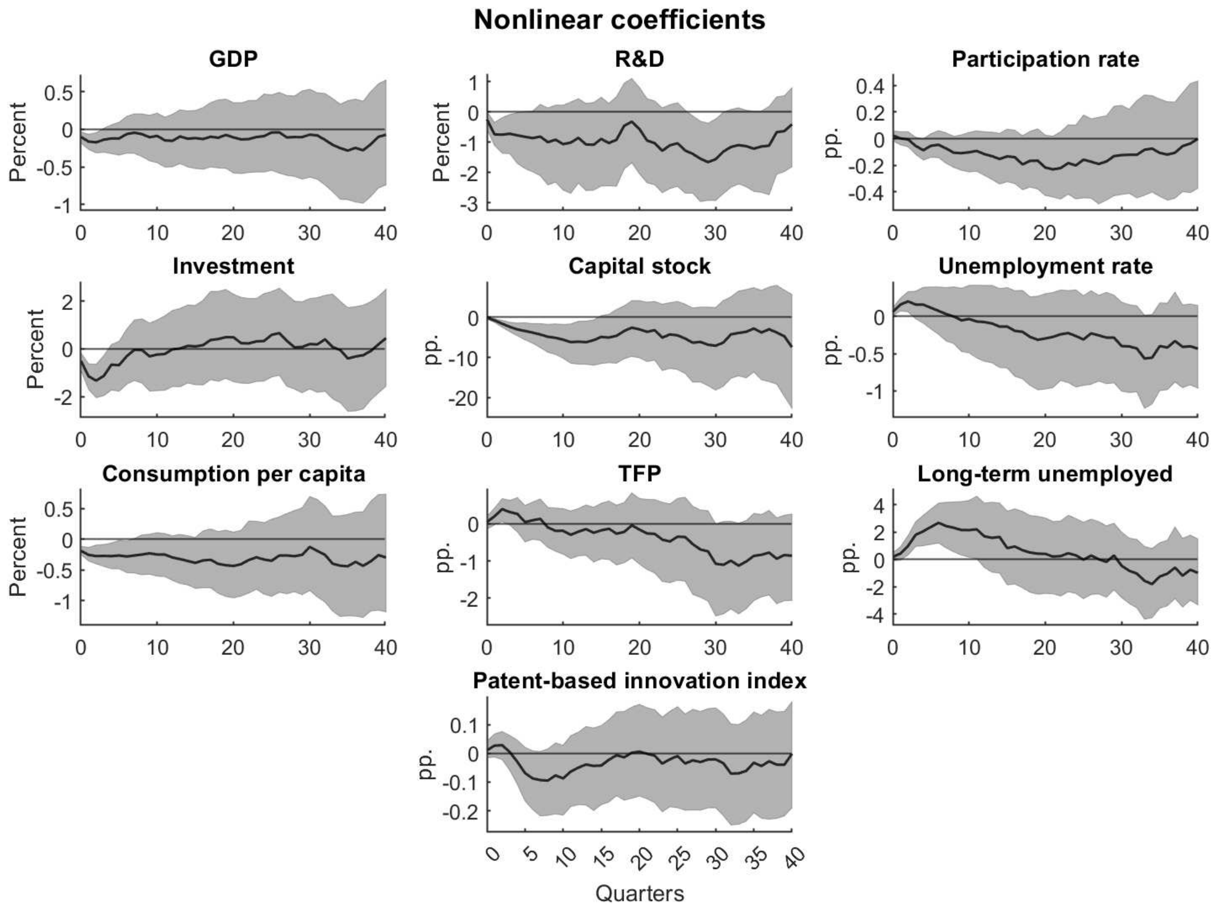

Figure 20: **Nonlinear coefficients across groups of variables — size dependence.** Each panel reports the nonlinear coefficients from the size-dependent specification, where the nonlinear transformation of the shock $f(\epsilon_t)$ in Eq. (2) is $|\varepsilon_t|\,\varepsilon_t$. Shaded areas indicate 68% credible intervals.

G.2 State and sign dependence

In this section, we present the state- and sign-dependent impulse responses introduced in Section 7, as given by Equations (4) and (5).

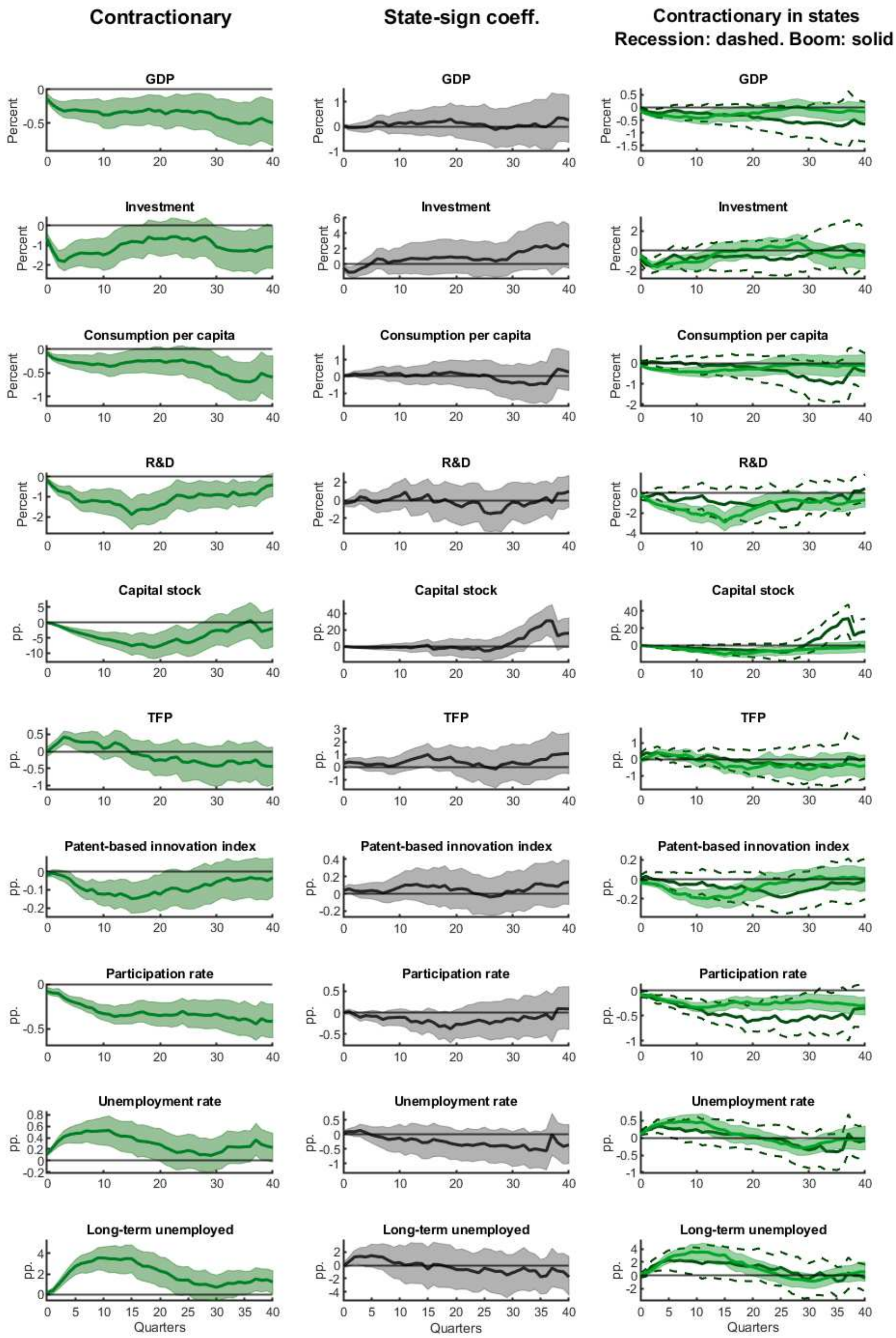

Figure 21: **State-dependent Contractionary IRFs** The first column reports the sign-dependent contractionary IRF from Eq. (3). The second column reports the across-state difference (boom − recession) of the implied contractionary IRFs from Eq. (5) (parameters estimated via Eq. (4)). The third column shows the state-specific contractionary IRFs: recession (dark green, dashed) and boom (light green, solid). Both sets of credible intervals are at the 68% level.

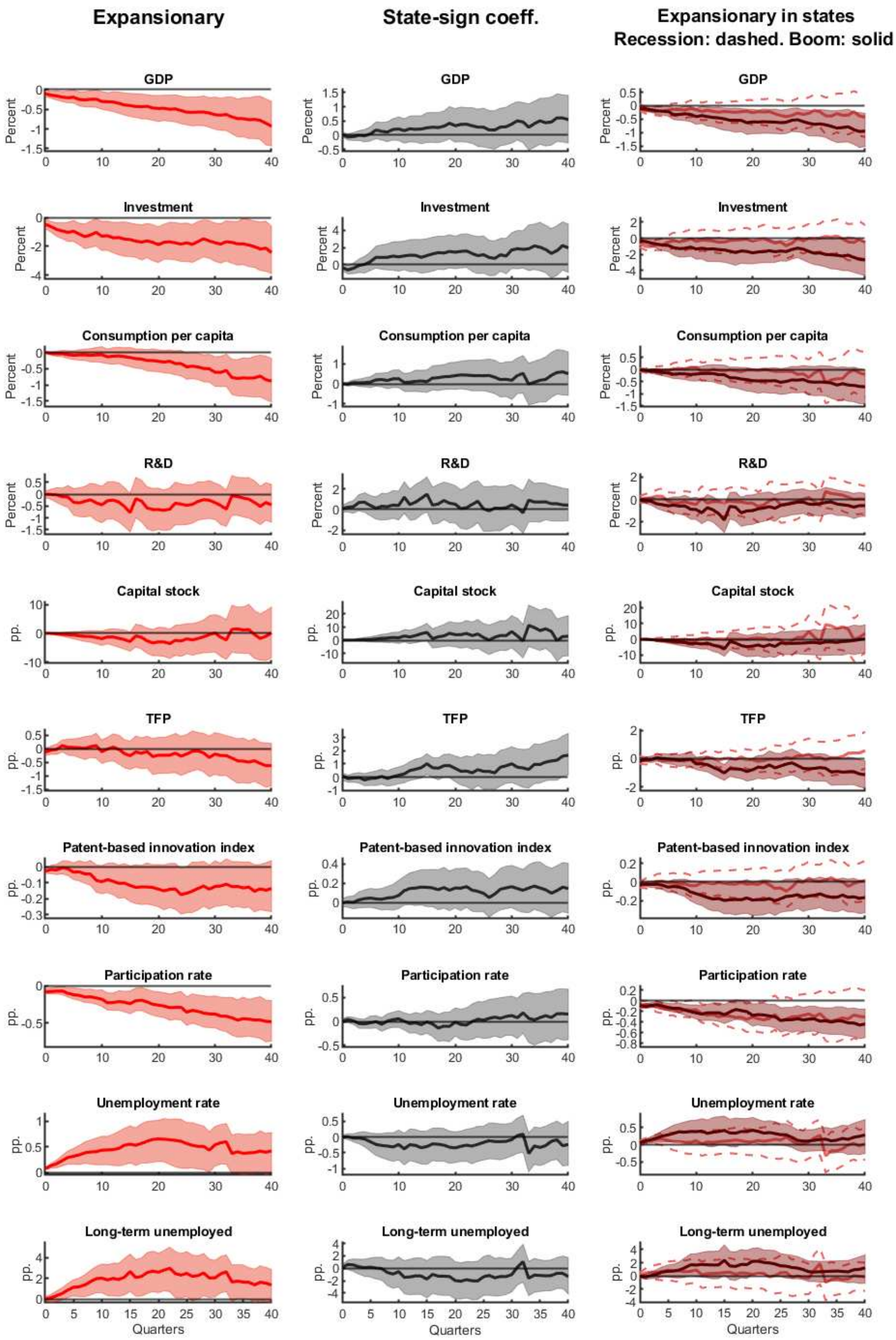

Figure 22: **State-dependent Expansionary IRFs** The first column reports the sign-dependent expansionary IRF from Eq. (3). The second column reports the across-state difference (boom − recession) of the implied expansionary IRFs from Eq. (5) (parameters estimated via Eq. (4)). The third column shows the state-specific expansionary IRFs: recession (light red, dashed) and boom (dark red, solid). Both sets of credible intervals are at the 68% level.

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