

Bank of England

Global-to-UK SVAR

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Clare Lombardelli

Deputy Governor for Monetary Policy

Bank of England

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Global-to-UK SVAR

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Abstract

This paper investigates how global shocks transmit to the UK economy. We build a Global-to-UK Bayesian structural vector autoregression model that identifies five global shocks using sign, ranking, and bound restrictions. We find that these shocks account for around half of the variation in UK GDP and CPI over the first year. World energy and world financial shocks are the main global drivers of UK inflation and economic activity overall, while world financial shocks explain most of the variation in fluctuations in Bank Rate. Building on the identified global shocks, we extend the analysis and investigate their transmission across a panel of advanced and emerging economies. Focusing on a common global financial shock, we find that responses are larger in more financially open economies, particularly for exchange rates and equity prices.

Key words: Bayesian SVAR, global shocks, world financial shocks, international transmission, cross-country heterogeneity.

JEL classification: C32, E32, F41, F44, G15.

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1 Introduction

Understanding how global shocks transmit to small open economies is among the most consequential questions in international macroeconomics. For the United Kingdom, whose deep integration into global trade and financial markets leaves it acutely exposed to external shocks, the question is even more pressing. Global disturbances differ in nature and origin (supply disruptions, swings in world demand, shifts in the monetary policy of large economies, changes in global financial conditions) – and they reach a small open economy through different channels (trade flows, interest rates, exchange rates, risk premia, and credit conditions). Distinguishing between these shocks is crucial for understanding the sources of fluctuations in UK activity and inflation.

This paper develops an empirical framework for identifying and estimating global shocks and their international transmission. We build on the UK structural VAR of [Brignone and Piffer \(2025\)](#), extending its identification of three global shocks to distinguish five sources of global fluctuations: on the supply side, a world supply shock and a world energy shock; on the demand side, a pure world demand shock, a US monetary policy shock, and a world financial shock. Disentangling global demand shocks raises challenges: a boom in world spending, an easing of US monetary policy, and a loosening of global financial conditions all push world output and prices in the same direction, yet they differ in their transmission and in the policy response they warrant. We separate them by combining sign, ranking, and bound restrictions, drawing on [Cesa-Bianchi and Sokol \(2022\)](#), [Amir-Ahmadi and Drautzburg \(2021\)](#), and [Kilian and Murphy \(2012\)](#). Our framework complements [Brignone and Piffer \(2025\)](#): while they distinguish domestic UK demand, supply and monetary policy shocks, we focus on separating global shocks and estimating their UK transmission. Domestic shocks therefore remain individually unidentified, avoiding the additional assumptions needed to distinguish their economic origins. We impose fewer restrictions on UK responses to global shocks, our principal object of interest, allowing them to be informed primarily by the data.

We find that global shocks account for roughly half of the variation in UK GDP and CPI within the first year of the shock, broadly consistent with [Brignone and Piffer \(2025\)](#). Extending the framework to distinguish a richer set of global shocks yields a more granular decomposition of the external forces shaping UK macroeconomic outcomes. World energy and world financial shocks are the largest global drivers of UK inflation and activity overall, though their relative importance differs across horizons and over time. World financial shocks, and to a lesser extent US monetary policy shocks, are the main global drivers of Bank Rate.

The historical decompositions show how the composition of global shocks differs across episodes. During the Global Financial Crisis (GFC), world financial shocks turned sharply

negative after the Lehman collapse and were the main drivers of the fall in UK inflation and activity. After the June 2016 UK referendum on EU membership, the global environment was instead dominated by the energy price cycle, while the pick-up in UK inflation from 2017 was largely domestic, consistent with the lagged pass-through of sterling’s post-referendum depreciation. In the post-pandemic surge, by contrast, no single shock dominated: inflation was pushed above trend by global and domestic shocks alike, with world energy shocks prominent early on. Each episode thus reflects a different configuration of shocks, and different policy trade-offs – distinctions that a composite demand shock would conflate.

Finally, the identified shocks can be used in a range of empirical applications. As an illustrative application, we employ the estimated world financial shock as a common exogenous driver in a panel of advanced and emerging economies. Feeding the shock into country-specific VARs with exogenous variables (VARX), we recover the domestic responses of real GDP, CPI, the nominal exchange rate against the US dollar, and a nominal equity price index. Descriptive evidence suggests that more financially open economies are more exposed to the shock, particularly through exchange rates and equity prices.

Using the model in practice. The Global-to-UK SVAR is designed to help policy-makers interpret global developments and assess their implications for the UK economy. A central application is disentangling different sources of external variation and quantifying their contributions to UK activity, inflation and financial conditions. By distinguishing between world demand, US monetary policy and world financial shocks, the model provides a framework for interpreting historical episodes and communicating how global shocks transmit to the UK economy. The framework has also been used in Monetary Policy Committee (MPC) communications; for example, [Greene \(2026\)](#) referred to the model to illustrate how US monetary policy shocks spill over to the UK economy, and [Mann \(2026\)](#) used impulse responses from the model in a presentation at the [Jackson Hole Economic Policy Symposium](#) to illustrate the effects of global financial intermediation shocks on UK output, inflation, Bank Rate and financial conditions.

The model can also be used to monitor global economic conditions in real time. The estimated structural shocks provide a model-based assessment of whether recent developments are primarily associated with changes in global demand, financial conditions, US monetary policy or supply-side factors. The posterior distributions of recent shocks presented in [Section 3.5](#) illustrate how the framework can be used to assess current global conditions and their implications for the UK outlook.

The framework also lends itself to further applications. The estimated impulse responses could inform assessments of how alternative global developments might affect

UK activity, inflation and financial conditions, including in scenario analysis.

Related Literature. This paper is related to the literature on shock transmission with a focus on the UK. Existing work has examined both the transmission of domestic UK shocks (Cesa-Bianchi et al., 2020; Braun et al., 2025) and the role of external developments in shaping UK macroeconomic and financial outcomes (Chowla et al., 2014; Forbes et al., 2018; Cesa-Bianchi et al., 2021). Methodologically, the analysis builds on sign-restricted SVAR approaches used to identify global demand, supply, commodity-price, financial and monetary policy shocks (Kilian, 2009; Cesa-Bianchi et al., 2018; Baumeister and Hamilton, 2019; Miranda-Agrippino and Rey, 2020; Ha et al., 2022; Brignone and Piffer, 2025, 2026). This literature shows that global shocks account for a substantial share of fluctuations in output, inflation and exchange rates in small open economies, with transmission effects varying by shock type (Forbes et al., 2020). By estimating these shocks within a single framework, this paper characterises the relative importance of global shocks for the UK economy and the channels through which global developments affect domestic outcomes.

The remainder of the paper proceeds as follows. Section 2 describes the data, the model specification, and the identification strategy. Section 3 presents the SVAR estimates, impulse responses, and variance decompositions, with a focus on the historical evolution of global shocks and their impact on UK macro-financial variables. Section 4 examines the propagation of the identified world financial shocks in a cross-country setup and documents how their transmission varies with financial openness. Section 5 concludes with implications for monitoring global developments and for the design of macroeconomic policy in small open economies.

2 Data and Methodology

This section lays out the empirical framework. Section 2.1 describes the data. Section 2.2 presents the SVAR model and its block-recursive structure. Section 2.3 details how the global shocks are identified through sign, ranking, and bound restrictions. Section 2.4 describes the prior and the posterior sampler.

2.1 Data

Table 1 lists the ten variables in the SVAR: five global variables and five UK variables. The global block contains world GDP, world CPI, the real price of oil, the US 1-year government bond yield, and the US borrowing rate. The world aggregates are weighted

TABLE 1 VARIABLES IN THE GLOBAL-TO-UK SVAR

Variable	Data Transformation
Real World GDP	$100 \cdot \log$
World CPI	$100 \cdot \log$
Real Oil Price	$100 \cdot \log$
US 1-Year Government Bond Yield	level
Borrowing Rate	level
Exchange-Rate Index (ERI)	$100 \cdot \log$
Bank Rate	level
UK CPI	$100 \cdot \log$
UK CPI Energy	$100 \cdot \log$
UK Real GDP	$100 \cdot \log$

NOTE: World GDP and CPI are UK-trade-weighted. The real price of oil is in sterling. The Bank of England exchange-rate index is a trade-weighted exchange value of sterling computed using bilateral exchange rates (a decrease in the index corresponds to a sterling depreciation). UK CPI Energy captures the combined contribution of oil and gas prices to the UK CPI.

using UK trade shares, and the real price of oil is denominated in sterling. The US 1-year government bond yield represents the short-term risk-free interest rate; the US borrowing rate is the sum of the US 10-year government bond yield and the corporate bond spread of [Gilchrist and Zakrajsek \(2012\)](#). The UK block contains the Bank of England’s effective exchange rate index, Bank Rate, UK CPI, UK CPI Energy, and UK real GDP. The effective exchange rate index is a trade-weighted measure of sterling, defined so that a decrease corresponds to a depreciation.

Relative to [Brignone and Piffer \(2025\)](#), we retain the eight-variable specification in their paper and expand the global block by adding the US 1-year government bond yield and the borrowing rate. The data are quarterly, and the estimation sample spans 1992Q1–2025Q4, covering several global episodes of interest for the UK economy, including the GFC and the Covid-19 pandemic. The three interest rates enter the SVAR in levels and the remaining seven variables in log levels (multiplied by 100).

2.2 Model

SVAR models capture the joint dynamics of a set of variables. The starting point is a vector $\mathbf{y}_t$ of k variables of interest, modelled as a function of its own past values. The goal is to trace how the underlying structural shocks $\boldsymbol{\varepsilon}_t$ drive the dynamics of these variables. Formally, the reduced-form representation of the model is given by

$$\mathbf{y}_t = \sum_{\ell=1}^p \boldsymbol{\Pi}_{\ell} \mathbf{y}_{t-\ell} + \mathbf{c} + \sum_{j=1}^q \boldsymbol{\delta}_j d_{j,t} + \mathbf{u}_t, \quad (1)$$

$$\mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}). \quad (2)$$

where $\mathbf{\Pi}_\ell$ are $k \times k$ matrices of autoregressive coefficients, $\mathbf{c}$ is a $k \times 1$ vector of constants, and $d_{j,t}$, $j = 1, \dots, q$, are pandemic-period dummies with $k \times 1$ coefficient vectors $\boldsymbol{\delta}_j$, described below. We assume that the $k \times 1$ vector of reduced-form innovations $\mathbf{u}_t$ follows a normal distribution with covariance matrix $\boldsymbol{\Sigma}$. The model is estimated on quarterly data with $p = 5$ lags¹. In addition to the autoregressive terms, we follow [Cascaldi-Garcia \(2022\)](#) and explicitly account for the Covid-19 episode by adding pandemic-period dummy variables for each quarter from 2020Q1 to 2021Q2 to the model. Because the dummy coefficients are shrunk towards zero with a tightness estimated from the data (Section 2.4), the data determine how far the pandemic observations inform the estimated dynamics.

These reduced-form innovations are linked to a $k \times 1$ vector of structural shocks through

$$\mathbf{u}_t = \mathbf{B}\boldsymbol{\varepsilon}_t, \quad (3)$$

where $\mathbf{B}$ is a $k \times k$ matrix and the structural shocks $\boldsymbol{\varepsilon}_t$ are normally distributed with identity covariance:

$$\boldsymbol{\varepsilon}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_k). \quad (4)$$

This implies that the reduced-form covariance matrix satisfies

$$\boldsymbol{\Sigma} = \mathbf{B}\mathbf{B}'. \quad (5)$$

We parameterise $\mathbf{B}$ by combining the lower-triangular Cholesky factor $\chi(\boldsymbol{\Sigma})$ with an orthogonal matrix $\mathbf{Q}$:

$$\mathbf{B} = \chi(\boldsymbol{\Sigma})\mathbf{Q}, \quad \mathbf{Q}\mathbf{Q}' = \mathbf{I}_k. \quad (6)$$

Any orthogonal $\mathbf{Q}$ delivers the same reduced-form fit, so restrictions on $\mathbf{B}$ (and on the impulse responses it generates) are what give the shocks their structural interpretation ([Rubio-Ramírez et al., 2010](#)).

The vector $\mathbf{y}_t$ is partitioned into a world block and a UK block, $\mathbf{y}_t = (\mathbf{w}'_t, \mathbf{x}'_t)'$, with $k_w = 5$ world variables ordered first and $k_{uk} = 5$ UK variables ordered last (Table 1). Consistent with this partition, we restrict $\mathbf{Q}$ to be block diagonal,

$$\mathbf{Q} = \begin{pmatrix} \mathbf{Q}_w & \mathbf{0} \\ \mathbf{0} & \mathbf{Q}_{uk} \end{pmatrix}, \quad \mathbf{Q}_w \in \mathcal{O}(k_w), \quad \mathbf{Q}_{uk} \in \mathcal{O}(k_{uk}), \quad (7)$$

where $\mathcal{O}(m)$ denotes the set of $m \times m$ orthogonal matrices. Because $\chi(\boldsymbol{\Sigma})$ is lower triangular and $\mathbf{Q}$ is block diagonal, the top-right $k_w \times k_{uk}$ block of $\mathbf{B}$ is exactly zero: the UK shocks have no contemporaneous impact on world variables. This block-recursive, small-open-economy structure holds by construction for every draw and is the only zero

¹We retain five quarterly lags for comparability with [Brignone and Piffer \(2025\)](#). This lag order is also used in the quarterly Bayesian VAR applications of [Giannone et al. \(2015\)](#).

restriction we impose.

2.3 Shock Identification in the Global-to-UK SVAR

We identify five global structural shocks in Eq. (3): world demand, world supply, world energy, US monetary policy (USMP), and world financial shocks; the five UK domestic shocks are separated from the world block but not individually identified. Identification combines three types of inequality restrictions on the contemporaneous impact matrix $\mathbf{B}$: (i) sign restrictions on impact responses; (ii) ranking restrictions that compare the impact response of a given variable across two shocks; and (iii) bound restrictions on ratios of impact responses. All restrictions are imposed on impact only, and each shock is normalised to one standard deviation with the sign convention of Table 2.

For UK shocks, we impose a small-open-economy assumption: domestic shocks have zero contemporaneous impact on global variables, as encoded in the block-recursive structure Eq. (7). This assumption is standard in small-open-economy SVARs; see, e.g., [Brignone and Piffer \(2025\)](#), [Cesa-Bianchi et al. \(2021\)](#), and [Forbes et al. \(2018\)](#). By contrast, the effects of global shocks on UK variables are largely estimated from the data. The only exceptions are the ranking and bound restrictions imposed on UK CPI in Panel B. Empty cells in Table 2 denote an unrestricted impact response.

Our identification scheme differs from that of [Brignone and Piffer \(2025\)](#) in four main respects. First, we identify five rather than three global shocks, separately distinguishing US monetary policy and world financial shocks from broader world demand disturbances. Second, we refine the identification of the global shocks, notably by using the opposing impact responses of the real oil price to distinguish world supply from world energy shocks. Third, while [Brignone and Piffer \(2025\)](#) identify UK demand, supply and monetary policy shocks through sign and zero restrictions on global and domestic variables, our five UK shocks are restricted only by the block-recursive zeros and are otherwise left unidentified. Finally, we supplement the sign and zero restrictions with ranking and bound restrictions on selected impact responses.

Sign restrictions. Our sign restrictions largely follow the empirical literature. In particular, a positive world supply shock and a positive world energy shock are both assumed to increase world real GDP and decrease world CPI. We distinguish world supply and energy shocks based on their impact on real oil prices. World supply shocks typically include supply-driven non-oil disturbances in cross-border value chains, labour, or product markets. For example, a positive world supply shock can be due to an increase in productivity, greater competition across firms, or lower marginal costs of production in general. Since higher productivity increases the demand for oil, the price of oil rises.

TABLE 2 RESTRICTIONS FOR SHOCK IDENTIFICATION

	Global shocks					UK shocks
	Demand	Supply	Energy	USMP	Financial	5 SOE shocks
<i>Panel A: sign and zero restrictions (impact)</i>						
Real World GDP	+	+	+	−	+	0
World CPI	+	−	−	−	+	0
Real Oil Price		+	−			0
US 1Y Govt Bond Yield	+			+	+	0
Borrowing Rate	+			+	−	0
UK ERI						
Bank Rate						
UK CPI						
UK CPI Energy						
UK Real GDP						
<i>Panel B: ranking and bound restrictions (impact)</i>						
(R1)	$ B_{\text{Oil, USMP}} < B_{\text{Oil, Energy}} $					
(R2)	$ B_{\text{UK-CPI, USMP}} < B_{\text{UK-CPI, Energy}} $					
(B1)	$0 < B_{\text{UK-CPI, Energy}} / B_{\text{Oil, Energy}} < 0.10$					

NOTE: ‘+’ (‘−’) denotes a positive (negative) sign restriction on the impact response, ‘0’ denotes a zero restriction, and blank entries indicate no restriction. All restrictions are imposed on impact only. USMP denotes a US monetary policy shock and SOE denotes small open economy. In Panel B, $B_{i,j}$ denotes the impact response of variable i to a one-standard-deviation shock j and $|\cdot|$ denotes the absolute value; “Oil” is the real oil price and “UK-CPI” is UK CPI (seasonally adjusted). The zero restrictions on the UK shocks are imposed through the block-recursive structure in Eq. (7); the UK shocks are otherwise unidentified.

By contrast, a world energy shock boosts oil supply or lowers energy costs, making oil prices fall. This opposite effect on real oil prices reflects the assumption that energy and technology are complementary.

On the demand side, we distinguish three shocks: a world demand shock, a US monetary policy shock, and a world financial shock. A positive world demand shock is assumed to have a positive impact on world GDP, world CPI, the US 1-year government bond yield, and the US borrowing rate. These shocks typically represent demand-driven non-monetary disturbances, such as an expansionary fiscal policy or an increase in agents’ marginal propensity to consume. Monetary policy authorities react to these developments by raising interest rates. A contractionary US monetary policy shock is defined as one that is accompanied by a higher US 1-year government bond yield and borrowing rate, but lower world GDP and world CPI.

World financial shocks typically lead to dynamics of output, consumer prices, and policy rates that are similar to those of aggregate demand shocks. This makes world financial shocks challenging to distinguish from world demand shocks. Financial shocks can be broadly thought of as exogenous changes to the net worth of financially constrained agents or their degree of risk aversion. Such disturbances can be a key driver of business-cycle fluctuations. We follow [Cesa-Bianchi and Sokol \(2022\)](#) that derive a minimal set of

restrictions that distinguishes a financial shock from a typical aggregate demand shock. To do so, they draw from theoretical models with sticky prices and a financial accelerator mechanism (Bernanke et al., 1999; Christiano et al., 2014). In these models, the borrowing rate on a loan of m -period maturity i_m^B is given by the sum of two components: the rate on a government bond of similar maturity i_m plus a spread that arises because of imperfect information in credit markets x_m . That is:

$$i_m^B = i_m + x_m. \quad (8)$$

In this class of models, the credit spread x_m endogenously responds to shocks in a countercyclical fashion, while the interest rate i_m is typically a moving average of short-term risk-free rates set by the central bank via a Taylor rule. Hence, in these models the equilibrium response of the borrowing rate i_m^B to demand and financial shocks is theoretically ambiguous. To see this, suppose that a positive demand or financial shock hits the economy, putting upward pressure on both economic activity and prices. In response to the shock, monetary policy becomes restrictive (i_m rises), while the credit spread decreases (x_m falls). Therefore, depending on (i) the monetary policy reaction function and (ii) the semi-elasticity of the credit spread to the shock, the borrowing rate prevailing in the economy might either increase or decrease.

The conjecture is that in the face of demand shocks, movements in the policy rate dominate movements in the credit spread, so that a positive demand shock leads to a rise in the borrowing rate. On the other hand, in the face of financial shocks, movements in the credit spread dominate movements in (current and future expected) policy rates, so that a positive financial shock leads to a decrease in the borrowing rate. Under such an assumption, we impose different sign restrictions on the borrowing rate to disentangle world demand from world financial shocks.

Ranking and bound restrictions. In addition to the sign restrictions in Panel A of Table 2, we impose two further classes of inequality restrictions on the impact matrix, reported in Panel B: ranking restrictions that compare impact responses across shocks, and bound restrictions on ratios of impact responses. As with the sign restrictions, both classes truncate the set of admissible rotations and the model remains set-identified.

The additional restrictions address an ambiguity that remains under sign restrictions alone. In particular, the sign-restricted model admits rotations in which a US monetary policy shock generates larger movements in oil prices and UK CPI than a world energy shock, making the two shocks difficult to distinguish along the commodity-price channel. The ranking restrictions rule out such rotations by assigning the larger contemporaneous oil price and UK CPI movements to the energy shock. Additionally, the bound restriction

disciplines the scale of the immediate pass-through from oil prices to headline CPI. Their purpose is therefore to sharpen the distinction and economic interpretation of the two shocks while preserving set identification.

The first class consists of between-shock *ranking restrictions*, following [Amir-Ahmadi and Drautzburg \(2021\)](#). Let $B_{i,j}$ denote the impact response of variable i to a one-standard-deviation shock j , with shocks signed as in Table 2 (a positive energy shock is expansionary and lowers oil prices; a positive USMP shock is a tightening). We impose

$$|B_{\text{Oil, Energy}}| - |B_{\text{Oil, USMP}}| > 0, \quad (9)$$

$$|B_{\text{UK-CPI, Energy}}| - |B_{\text{UK-CPI, USMP}}| > 0. \quad (10)$$

Both an expansionary energy shock and a US monetary tightening exert downward pressure on the real oil price and on UK consumer prices. Restrictions Eq. (9) and Eq. (10) – R1 and R2 in Table 2 – establish which of the two shocks dominates on impact: the energy shock moves the real oil price and UK CPI down by more than the USMP shock does. Since the responses of the real oil price and of UK consumer prices to the USMP shock are otherwise unrestricted, these rankings are what separate US monetary tightening from energy-price shocks along the commodity- and consumer-price dimension.

The second class consists of *bound restrictions* on ratios of impact responses, in the spirit of the elasticity bounds of [Kilian and Murphy \(2012\)](#). We bound the pass-through of oil prices to UK headline consumer prices under the world energy shock (restriction B1 in Table 2):

$$0 < \frac{B_{\text{UK-CPI, Energy}}}{B_{\text{Oil, Energy}}} < 0.10, \quad (11)$$

that is, UK CPI must move in the same direction as the oil price on impact, with a magnitude of at most 10% of the oil-price movement. The upper bound corresponds to the peak energy share of the UK CPI basket, so impact pass-through is capped at the mechanical, first-round effect of energy prices on headline CPI.²

Restrictions Eq. (9) to Eq. (11) are imposed jointly with the sign restrictions of Table 2 (Panel A): a draw of the reduced-form parameters and of $\mathbf{Q}$ is admissible only if it satisfies all of them simultaneously. Section 3.6 examines the sensitivity of the results to relaxing or removing these additional restrictions.

²Energy accounts for around 7% of the CPI basket on average over the sample period, with its combined expenditure weight reaching around 10% at its peak, based on ONS CPI expenditure weights.

2.4 Prior and Estimation

Prior. We estimate the reduced-form Eq. (1) and Eq. (2) with Bayesian methods, using a conjugate normal–inverse-Wishart prior of the Minnesota type (Litterman, 1986), implemented and optimised following Giannone et al. (2015). The prior shrinks the VAR coefficients towards univariate random walks, with overall tightness λ and lag-decay rate α , and it is augmented with two standard sets of dummy observations: sum-of-coefficients (no-cointegration) dummies with tightness μ (Doan et al., 1984) and a dummy-initial-observation (single-unit-root) prior with tightness θ (Sims, 1993). The coefficients δ_j on the pandemic dummies carry their own prior with a common tightness hyperparameter ϕ , following Cascaldi-Garcia (2022), so that the degree to which the 2020Q1–2021Q2 observations are discounted is itself estimated from the data rather than fixed a priori. In the hierarchical spirit of Giannone et al. (2015), the hyperparameters $(\lambda, \theta, \mu, \alpha, \phi)$ are treated as random, assigned Gamma hyperpriors, and set at the peak of their posterior by numerically maximising the product of the marginal likelihood and the hyperprior. Conditional on the hyperparameters, the prior is conjugate, so the posterior of $(\Pi, \mathbf{c}, \boldsymbol{\delta}, \Sigma)$ is normal–inverse-Wishart with closed-form parameters. Appendix A reports the hyperprior specification.

Posterior sampling of the structural parameters. Conditional on the reduced form, the identification scheme of Section 2.3 restricts, but does not point-identify, the rotation $\mathbf{Q}$ in Eq. (6). We complete the model with the conventional conditionally uniform (Haar) prior over the block-diagonal orthogonal matrices in Eq. (7), truncated to the set that satisfies the sign, ranking, and bound restrictions (Rubio-Ramírez et al., 2010; Arias et al., 2018). Sampling from the resulting posterior by accept–reject methods becomes impractical as inequality restrictions accumulate: the probability that an unrestricted draw satisfies all sign, ranking, and bound restrictions simultaneously is small, so standard algorithms discard the vast majority of candidate rotations. We therefore sample $(\Sigma, \mathbf{A}, \mathbf{Q})$ jointly, where $\mathbf{A}$ collects the reduced-form coefficients $(\Pi_1, \dots, \Pi_p, \mathbf{c}, \boldsymbol{\delta})$, using the elliptical-slice-within-Gibbs sampler of Arias et al. (2026) (henceforth ARRS). The ARRS algorithm reparameterises each of the three blocks as latent standard-normal vectors and updates them with elliptical slice steps (Murray et al., 2010) under an indicator likelihood that equals one on the admissible set and zero outside it. Every Gibbs sweep delivers an admissible draw by construction and targets the same posterior as accept–reject sampling. Within the indicator we also search over column permutations and sign flips of the candidate rotation, following Algorithm 1 of Chan et al. (2026), which further enlarges the set of latent draws consistent with the restrictions and thereby improves mixing. The block-recursive zeros are not checked but hold exactly, since the sampler draws $\mathbf{Q}_w$ and $\mathbf{Q}_{uk}$ separately as in Eq. (7). Draws that imply non-stationarity

are excluded. Details of the algorithm are in Appendix A.

All results are based on 1,000 retained posterior draws, obtained after a burn-in of 200 Gibbs sweeps. For each retained draw we compute impulse responses, forecast-error variance decompositions, structural shock series, and historical decompositions; we report pointwise posterior medians together with 68% and 90% credible bands.

3 Results

This section summarises the empirical evidence by examining the estimated shock series and their association with major global events. It then quantifies how much of the variation in UK variables is driven by global shocks and discusses their transmission through impulse response functions. Sections 3.4 and 3.5 focus on the interpretation of past episodes through historical decompositions, and the monitoring of current global conditions through the posterior distributions of the most recent shocks, respectively. Section 3.6 assesses the sensitivity of the results to the identifying restrictions and the pandemic prior.

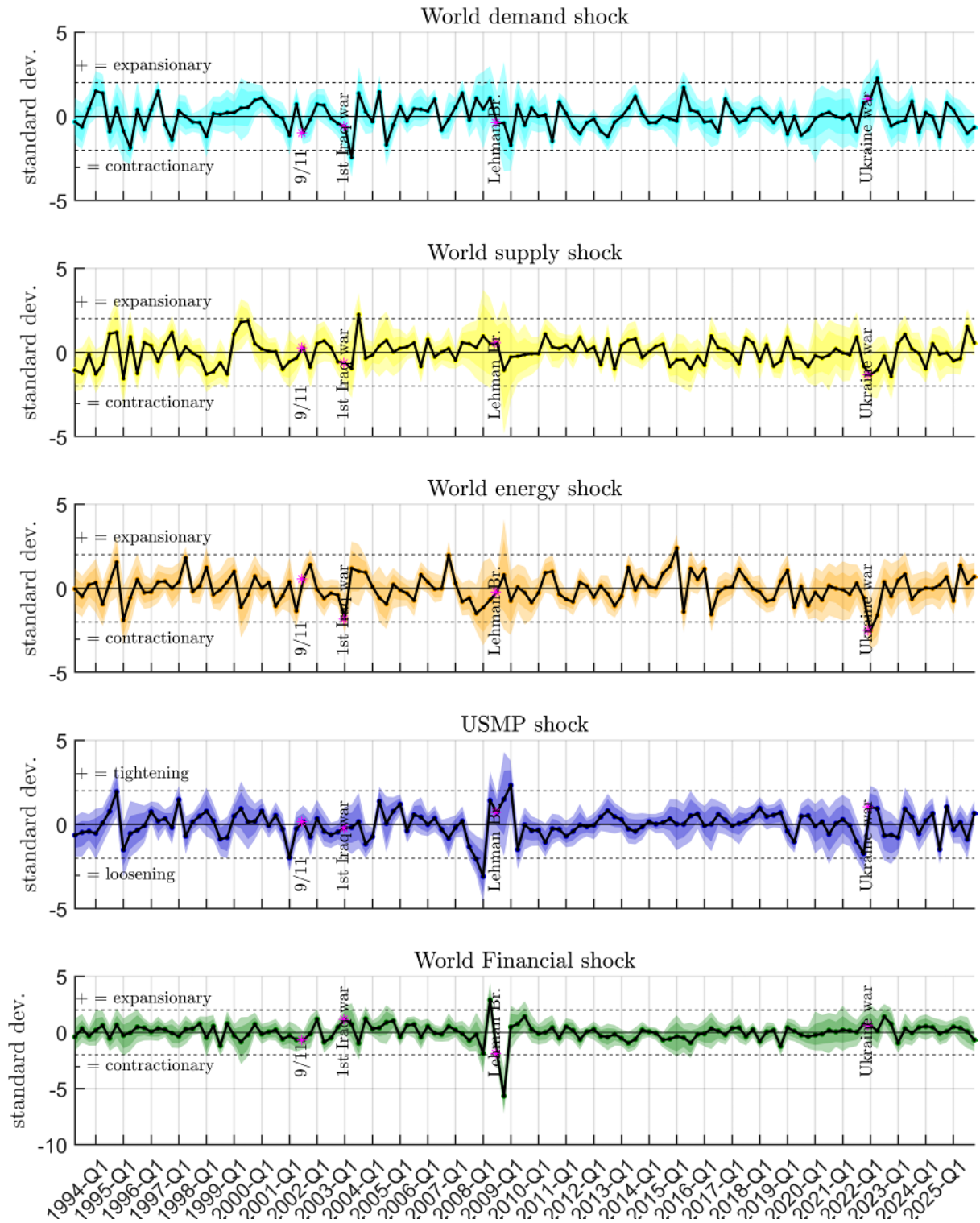
3.1 Estimated Global Shocks

Figure 1 shows the posterior median of five global shocks identified in our model, along with two-standard-deviation bands.

World energy and world supply shocks often coincide with geopolitical or commodity-driven events. Contractionary (negative) energy shocks appear around the 2003 Iraq invasion and in 2021–22 as European gas and oil prices surged ahead of and following Russia’s invasion of Ukraine. Expansionary (positive) energy shocks appear around 2015, when the US shale expansion and OPEC’s decision not to cut production drove oil prices down while world activity held up. World supply shocks are less volatile than energy shocks, with the largest declines occurring around global downturns.

The world demand, US monetary policy, and world financial shocks all operate through aggregate spending, and their historical patterns align with major macroeconomic events. World demand shocks were negative during the Asian financial crisis (1997–98), after 9/11 (2001), and in the 2008–09 GFC. US monetary policy shocks were most volatile in the mid-1990s, reflecting the 1994 tightening cycle and shifts in US policy during the transition to a low-inflation regime. The largest contractionary world financial shock in our sample occurred during the GFC. US monetary policy shocks followed a two-stage pattern: they were expansionary from 2007Q3 to 2008Q1, but contractionary from 2008Q2 to 2009Q1, before turning expansionary again. In late 2021, US monetary policy shocks

FIGURE 1 ESTIMATED GLOBAL SHOCKS



NOTE: This figure plots the five identified structural global shocks: world supply, world energy, world demand, US monetary policy, and world financial. Shocks are recovered from the Bayesian SVAR estimated over 1992Q1–2025Q4 using the sign, ranking, and bound restrictions of Section 2.3. The series shown are median posterior estimates with shaded regions showing the 68% and 90% credible bands based on 1,000 stable posterior draws.

indicated policy loosening, with policy rates remaining low while inflation picked up, and world demand shocks turned positive, reflecting post-pandemic reopening and stimulus.

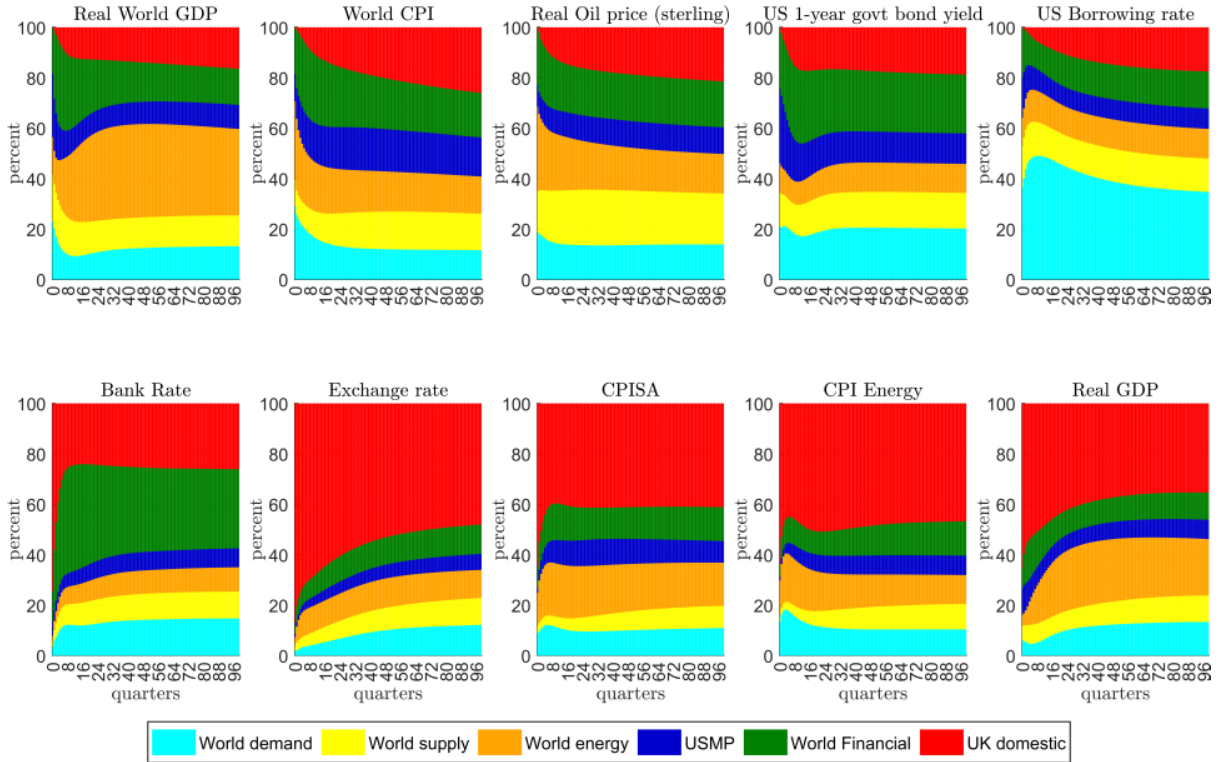
Major downturns thus typically combine several adverse demand-side shocks.

3.2 Forecast Error Variance Decomposition (FEVD)

To quantify the contribution of global shocks to fluctuations in UK variables, we compute the forecast-error variance decomposition, which measures the share of the forecast-error variance due to each shock. Figure 2 reports the posterior median share of each variable's forecast-error variance attributed to the five global shocks and to the UK-domestic block, at horizons up to 100 quarters.

Global shocks are important drivers of the UK economy, explaining around 47% of the variation in UK real GDP and 56% of the variation in UK CPI one year after the shocks. These shares are comparable to those found in previous Bank analysis (Cesa-Bianchi et al., 2021). More specifically, world energy shocks are the largest global contributor to UK CPI fluctuations at all horizons, accounting for around 13% on impact and 21% after 8 quarters. For UK real GDP, US monetary policy and world financial shocks are more important up to a year ahead, while world energy shocks become the largest global contributor after the first year, with their share rising from around 5% on impact to 23% after five years.

FIGURE 2 FORECAST ERROR VARIANCE DECOMPOSITION



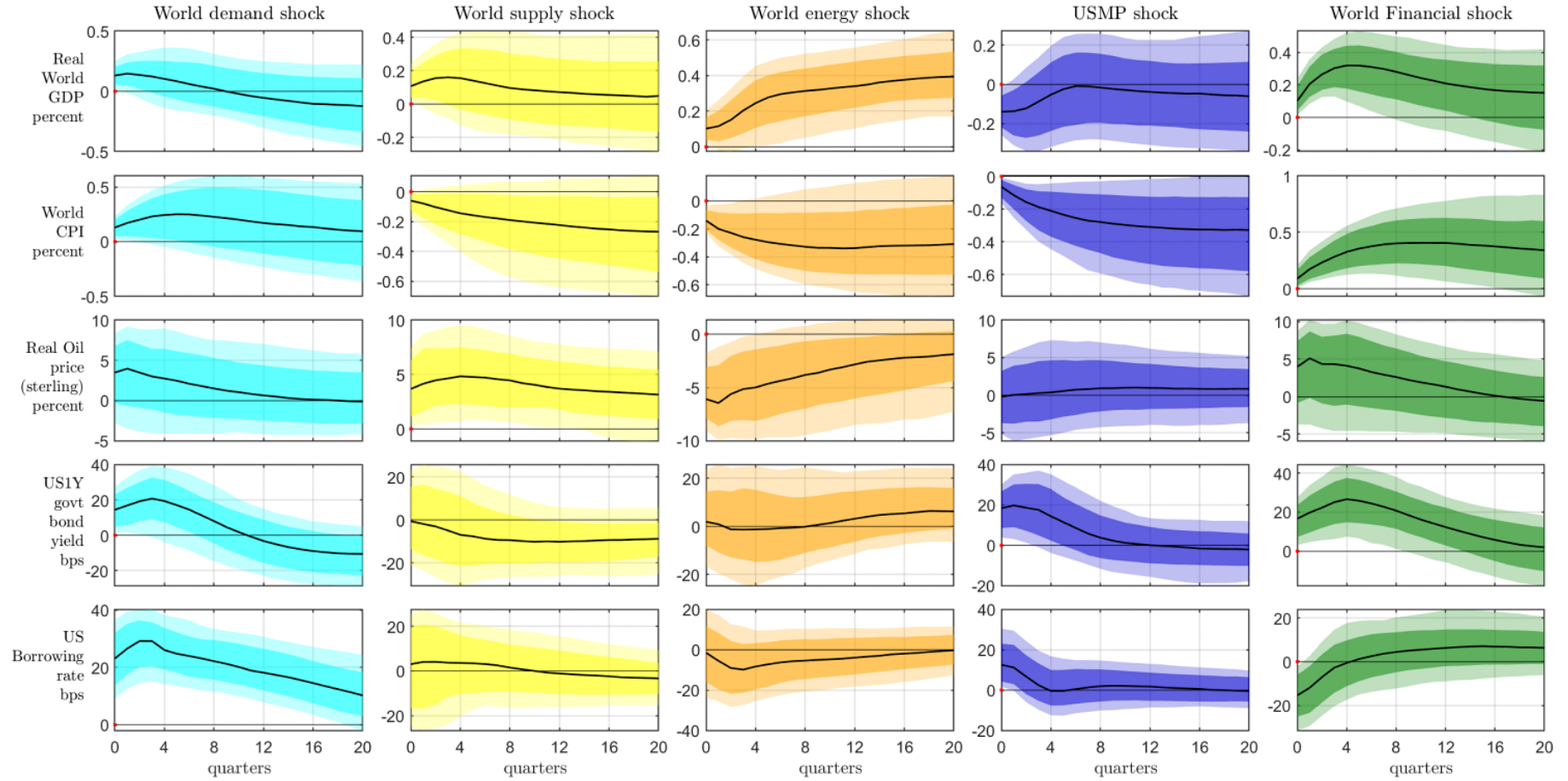
NOTE: The forecast-error variance decomposition reports the share of variance in the world and UK variables attributed to the identified global and domestic shocks. Results are based on the mean of 1,000 posterior draws from the Bayesian SVAR estimated over 1992Q1–2025Q4.

Global shocks also play a prominent role in Bank Rate fluctuations: their contribution rises from around 26% on impact to 74% after two years, of which around 47% is due to world financial and US monetary policy shocks together, with world financial shocks the largest single contributor. This is consistent with UK monetary policy responding to global developments. The global shocks explain a smaller proportion of fluctuations in the UK exchange-rate index, although the share steadily increases across horizons from around 13% on impact to 30% after two years. World energy shocks are the largest individual global contributor to the exchange rate at medium and longer horizons.

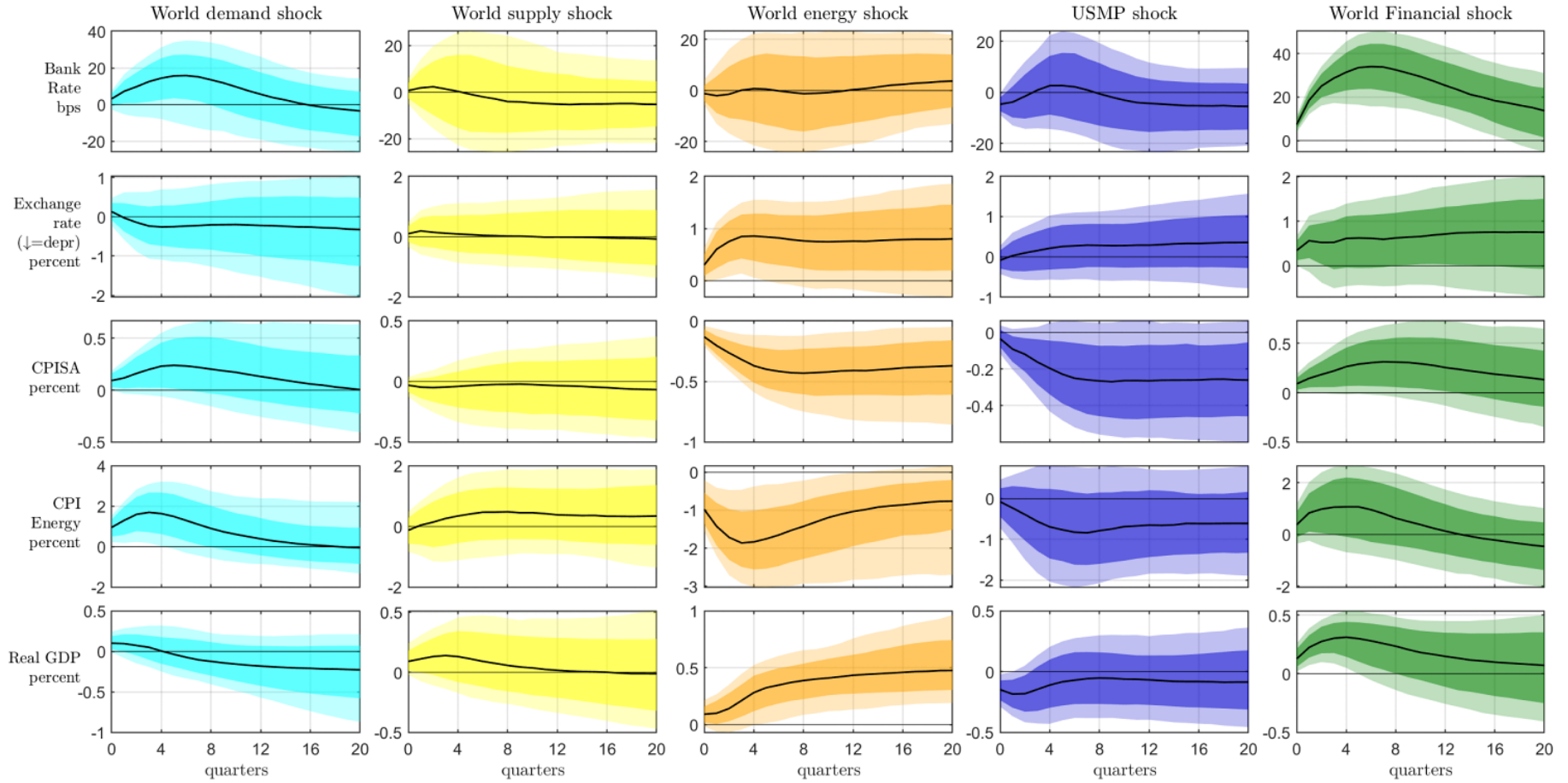
These results illustrate the importance of disentangling world financial shocks from world demand shocks: world financial shocks account for a larger share of Bank Rate and UK GDP fluctuations than world demand shocks, highlighting the relevance of foreign financial developments for UK monetary and broader economic conditions.

3.3 Impulse Response Functions (IRFs)

Figures 3 and 4 report the dynamic responses of the world and UK macroeconomic variables to the identified global shocks. The impulse responses trace the effects of each structural shock over time, with each shock normalised to one standard deviation. The solid lines show the pointwise posterior median responses, while the shaded areas represent the 68% and 90% credible bands based on 1,000 stable posterior draws.

FIGURE 3 IRFs: IMPACT OF GLOBAL SHOCKS ON WORLD VARIABLES

NOTE: This figure shows the impulse responses of world variables to the identified global shocks. The solid lines show the median dynamic response of each variable to a one-standard-deviation structural shock, with 68% and 90% posterior credible bands. All shocks are identified using the sign, ranking, and bound restrictions of Section 2.3. Responses are computed from 1,000 posterior draws.

FIGURE 4 IRFs: IMPACT OF GLOBAL SHOCKS ON UK VARIABLES

NOTE: This figure shows the impulse responses of domestic UK variables to the identified global shocks. The solid lines show the median dynamic response of each variable to a one-standard-deviation structural shock, with 68% and 90% posterior credible bands. All shocks are identified using the sign, ranking, and bound restrictions of Section 2.3. Responses are computed from 1,000 posterior draws.

On the global-supply side, an expansionary world supply shock raises real world GDP and oil prices, while world CPI declines gradually and persistently. A positive world energy shock also raises real world GDP, with the response building over time as lower energy costs support activity, and leads to persistent declines in world CPI and real oil prices, although the latter gradually unwinds. The median response of the US 1-year government bond yield differs across the two shocks: it declines progressively following a world supply shock, reaching around -10 basis points at longer horizons, whereas its response to a world energy shock is initially mixed but becomes positive at longer horizons, rising to around 6 basis points. However, the wide credible bands span zero, indicating substantial uncertainty about both the magnitude and direction of these responses.

On the global-demand side, an expansionary world demand shock initially raises global output and prices. The response of world GDP is short-lived, whereas world CPI rises more gradually and persistently. The shock increases the US 1-year government bond yield by around 14 basis points on impact, peaking at around 21 basis points after three quarters before gradually reversing. The borrowing rate rises by around 23 basis points on impact and remains positive throughout the reported horizon, with its 68% band remaining above zero. A tightening of US monetary policy increases the short-term bond yield by approximately 18 basis points and produces a short-lived 12 basis point increase in the borrowing rate. The contractionary shock has a negative but short-lived impact on real world GDP, and a fall in world CPI that increases over time and remains negative at longer horizons.

Following a positive world financial shock, both real world GDP and world CPI rise; the literature attributes such effects on real activity to looser credit constraints and higher net worth of borrowers (Eickmeier and Ng, 2015). The response of the 1-year government bond yield is positive as monetary policy leans against the rise in activity and prices. The credit spread moves by more than the policy rate, causing a short-lived fall in the borrowing rate that stimulates economic activity. Then, as the spread compression fades and policy tightening accumulates, the response of the borrowing rate turns positive after six quarters, consistent with the mechanism discussed in Section 2.3. Across the three global demand-side shocks, the responses of real oil prices are highly uncertain. The median response is initially positive following world demand and world financial shocks, peaking at around 4% and 5%, respectively. By contrast, the median response to a US monetary policy shock is zero on impact and increases at longer horizons. In all three cases, however, the credible bands span zero over the entire horizon.

We now turn to the responses of UK variables. The impulse responses indicate sub-

stantial spillovers from global shocks into UK economic conditions.³ A positive world supply shock produces a small and short-lived increase in UK real GDP, with the median response peaking at around 0.14% after three quarters. By contrast, a positive world energy shock generates a persistent increase in UK real GDP, rising from around 0.09% on impact to 0.48% at longer horizons, together with a persistent appreciation of sterling of around 0.8%. UK CPI and CPI Energy decline following the energy shock. The fall in headline UK CPI is bounded on impact by the first-round energy pass-through restriction in Eq. (11). Bank Rate responds only modestly to both supply-side shocks, with substantial uncertainty surrounding the responses, consistent with policy facing offsetting movements in activity and inflation.

An expansionary world demand shock produces a modest and short-lived rise in UK real GDP, with a median impact response of 0.1% that turns negative after four quarters. UK CPI rises more gradually, peaking at around 0.24% after five quarters, while CPI Energy increases by as much as 1.7% before declining. Bank Rate rises by around 3 basis points on impact and peaks at approximately 16 basis points after six quarters, although the response becomes increasingly uncertain thereafter. By contrast, a tightening of US monetary policy lowers UK real GDP by around 0.15% on impact and UK CPI by around 0.27% at its trough, consistent with evidence that US monetary policy transmits rapidly to foreign activity, prices and financial conditions (Georgiadis, 2016; Miranda-Agrippino and Rey, 2020). Bank Rate falls by around 5 basis points on impact, consistent with domestic policy loosening in response to imported disinflation and weaker external demand.

Following a positive world financial shock, Bank Rate rises by around 7 basis points on impact and peaks at approximately 34 basis points after six quarters. The response remains positive throughout all horizons and is larger and more persistent than the response to any other global shock. Sterling appreciates, with the median response increasing from around 0.35% on impact to 0.75% at longer horizons, consistent with risk-on behaviour by global investors. UK real GDP rises by around 0.31% at its peak after one year, while UK CPI increases more gradually, peaking after seven quarters. Together with the variance decomposition analysis, these results indicate that world financial shocks play a more important role in shaping Bank Rate than the separately identified world demand shock.

³Apart from the ranking and bound restrictions on the impact response of UK CPI (Panel B of Table 2), no restrictions are imposed on the responses of UK variables. Thus the responses of UK variables to the global shocks largely reflect the estimated transmission of the identified shocks rather than assumptions embedded in the identification scheme.

3.4 Interpreting the Past through the Lens of the Model

The FEVD and IRF results provide empirical evidence that global shocks matter quantitatively for UK macroeconomic fluctuations. We next use the estimated model to produce a historical decomposition of its time series. For each quarter, we calculate the contribution of each structural shock to the variables of interest. This yields a decomposition of year-on-year world and UK CPI inflation and GDP growth, shown as deviations from the deterministic component (initial conditions and constant). We focus on three periods – the GFC (2007Q4–2010Q4), Brexit (2015Q4–2018Q4), and post-Covid (2022Q1–2025Q4).

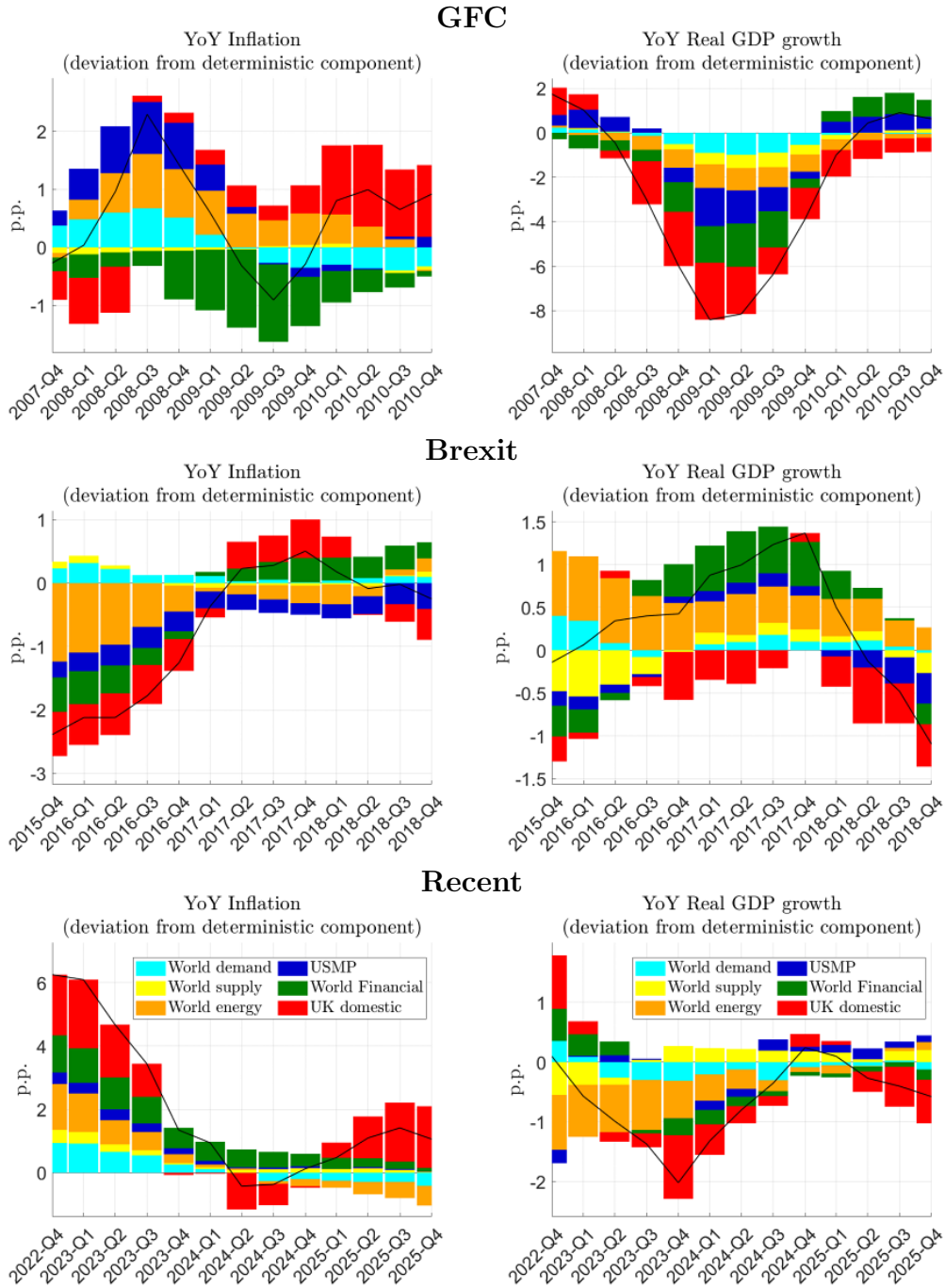
The historical decompositions (HDs) in Figures 5 and 6 describe how much of the realised path of each variable can be attributed to the identified structural shocks at every point in time. The results over the pre- and post-GFC subsamples, reported in Figures B.1 and B.2 in Appendix B, show that global shocks account for a substantial share of UK macroeconomic fluctuations. World energy and world financial shocks are the main global drivers of fluctuations in UK GDP growth and CPI inflation, while world financial shocks account for around 37% of Bank Rate fluctuations.

The size and composition of the spillovers of global shocks to the UK vary across different periods. During the GFC, world financial and US monetary policy shocks were prominent, jointly accounting for around 41% of UK real GDP and 44% of UK CPI fluctuations. In the recent post-Covid period, world energy shocks were the largest global contributor to fluctuations in UK real GDP (around 27%), while world financial shocks were the leading global driver of UK CPI and Bank Rate (Figure B.3), at around 21% and 38%, respectively. Global shocks also remain important outside these periods, explaining around 59% of UK real GDP fluctuations and 55% of UK CPI fluctuations in the pre-GFC sample. Overall, the results indicate that UK macroeconomic fluctuations are strongly influenced by global shocks, even though the relative importance of individual shocks changes across periods.

GFC (2007Q4–2010Q4). UK domestic shocks alongside world financial shocks pushed down on UK inflation at the beginning of this period, consistent with the domestic economy already softening ahead of the crisis. US monetary policy and world demand shocks pushed up UK inflation, while the contribution of world energy shocks increased during 2008. This initial positive contribution of US monetary policy shocks is consistent with the expansionary monetary policy shocks identified in late 2007 and early 2008, a period of Federal Reserve rate cuts and rising commodity prices.

Following the Lehman collapse, world financial shocks explained most of the fall in UK inflation below trend. For UK real GDP growth, the negative contributions from

FIGURE 5 HISTORICAL DECOMPOSITION OF UK VARIABLES



NOTE: The historical decomposition attributes observed fluctuations in year-on-year UK CPI inflation and UK GDP growth to the five identified global shocks and the aggregated UK-domestic block of the Global-to-UK SVAR. Bars show contributions measured relative to the deterministic component (initial conditions and constants). The figure highlights three key episodes of interest: the GFC, the Brexit period, and the most recent three-year window.

2008Q2 through 2009Q4 reflected both domestic and global shocks, with world financial and US monetary policy shocks explaining most of the variation during the most acute phase of the downturn. From 2010, the contributions of world financial and US monetary policy shocks to UK GDP turned positive, supporting the recovery, while the domestic drag persisted until the end of 2010.

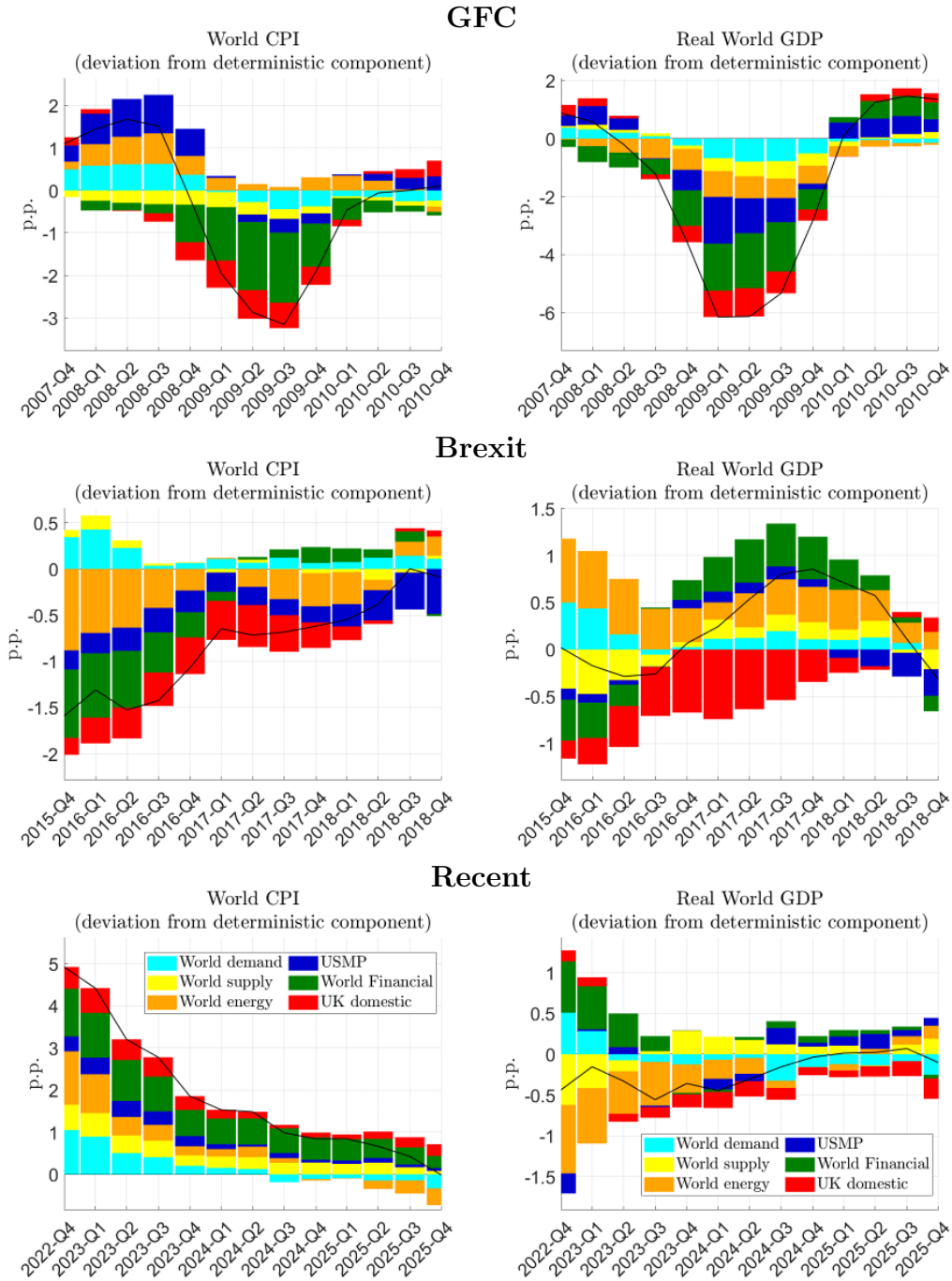
Globally, the world CPI and real world GDP panels show broadly similar dynamics, with world financial shocks becoming the largest negative global contributor to both variables during 2009⁴. For real world GDP, the drag from world financial and US monetary policy shocks subsequently reduced, and both contributions turned positive by 2010, while the contributions of world demand and world energy shocks remained negative. For world CPI, the negative contribution of world financial shocks also declined from late 2009, while the contributions of world demand and US monetary policy shocks followed different trajectories. This episode illustrates the value of disentangling demand-side shocks. Although all three shocks contributed to the downturn, their impact differed in magnitude and persistence. While the drag from world financial and US monetary policy shocks diminished and eventually turned into support for the recovery in GDP growth, world demand shocks remained negative for a prolonged period. Pooling them into a single global demand shock would conceal these nuances and make it harder to assess whether the recovery reflected improving financial conditions, monetary easing or a broader recovery in global demand.

Brexit (2015Q4–2018Q4). UK inflation remained below trend from 2015Q4 to 2016Q2, largely reflecting negative contributions from world energy shocks following the collapse in global oil prices in 2014–15. The global environment during this period was also marked by a tightening of US monetary conditions, whose effects our model allows us to identify and analyse. UK domestic, world financial and US monetary policy shocks added to the downward pressure during this period. From 2017Q2, UK domestic shocks pushed up on inflation, consistent in timing with the lagged pass-through of sterling’s post-referendum depreciation to consumer prices ([Forbes et al., 2020](#)). World financial shock contributions also turned positive from early 2017, while US monetary policy shocks continued to drag. For UK GDP growth, while UK domestic shocks started weighing down on activity towards the end of 2016, world energy shocks and world financial shocks supported UK economic activity for most of 2017, and US monetary policy shocks began to weigh down on domestic growth towards the end of 2017.

Over this period, world CPI inflation moved closer to trend as the negative contributions from world energy and financial shocks eased. Real world GDP growth strengthened through 2017, supported by improving global financial conditions and positive world energy shocks, before moderating in 2018. This moderation coincided with a period of US monetary policy normalisation, as the Federal Open Market Committee (FOMC) continued to raise interest rates and reduce the size of its balance sheet. The resulting tightening in global monetary and financial conditions increasingly weighed on both world activity

⁴The block-recursive zero restriction excludes contemporaneous effects of UK shocks on world variables but permits lagged effects. Past UK shocks can therefore contribute to current world-variable fluctuations in the historical decomposition.

FIGURE 6 HISTORICAL DECOMPOSITION OF WORLD VARIABLES



NOTE: The historical decomposition attributes observed fluctuations in year-on-year World CPI inflation and World GDP growth to the five identified global shocks and the aggregated UK-domestic block of the Global-to-UK SVAR. Bars show contributions measured relative to the deterministic component (initial conditions and constants). The figure highlights three key episodes of interest: the GFC, the Brexit period, and the most recent three-year window.

and inflation, while the support from world financial shocks weakened. For policymakers, the decomposition shows that the later slowdown did not simply reflect weaker global demand, but also the growing international effects of tighter US monetary policy.

Recent past (2022Q4–2025Q4). The fluctuations during this episode are considerably larger than in the GFC and Brexit subsamples. UK inflation stood more than 6 percentage points above trend in 2022Q4, with all identified global and domestic shocks pushing up simultaneously. World energy and UK domestic shocks were the main drivers, but world demand, world supply, US monetary policy and world financial shocks also added to inflation, indicating that the surge reflected a broad combination of external and domestic pressures rather than a single dominant source. World CPI displayed a similar pattern, standing almost 5 percentage points above trend in 2022Q4, with world energy and financial shocks among the largest contributors. This is consistent with the global energy-price volatility and widespread supply and demand imbalances that followed the pandemic and Russia’s invasion of Ukraine.

Disinflation began during 2023 as the contributions of most of the shocks started to unwind. The effects of world energy, world demand and world financial shocks faded both globally and in the UK, while the domestic contribution to UK inflation fell sharply and turned negative during 2024. By 2025, however, the composition of UK inflation had changed: world demand and energy shocks were pushing down on inflation, whereas domestic shocks had again become strongly inflationary. This distinction matters for policy because the initial fall in inflation reflected the unwinding of several external and domestic pressures, while its subsequent persistence was increasingly associated with domestic forces.

The activity decompositions point to weak growth. UK economic activity weakened markedly during 2023, mainly because of adverse world energy and domestic shocks, compounded by weaker world demand and, later in the year, world financial shocks. Although the energy and broader supply shocks supported growth, domestic weakness intensified again in 2025, while world financial shocks also remained negative. Real world GDP followed a similar but less pronounced path, with the drag from world energy and supply shocks easing after 2022 but weakness in world demand persisting through much of the period. Overall, the decompositions suggest that post-pandemic disinflation was accompanied by weak activity, but that the sources of inflation and output weakness evolved considerably over time.

The role of financial shocks across different periods. The contribution of global demand-side shocks varies considerably across the three episodes, illustrating why distinguishing world financial shocks from US monetary policy and broader world demand shocks is important for policy analysis. During the GFC, world financial shocks were the largest global source of weakness once the crisis intensified, making substantial negative contributions to world activity and inflation and to UK GDP and inflation. US monetary policy shocks followed a different path: they initially supported UK inflation and

activity, but subsequently contributed to the downturn before turning positive during the recovery. In the Brexit period, world financial shocks supported UK and world GDP through much of 2017, with a smaller positive contribution to inflation. By contrast, US monetary policy shocks dragged persistently on UK and world inflation and, as US monetary policy normalisation progressed, increasingly weighed down on activity during 2018. In the post-pandemic period, world financial and US monetary policy shocks initially pushed up on inflation, but their contributions eased over time. World financial shocks, in particular, shifted from supporting UK and global activity to making negative contributions later in the period.

Across the three episodes, pooling these disturbances into a single global demand shock would conceal these nuances. This distinction is relevant for monetary policy because a tightening of credit conditions, a change in the US monetary policy stance and a shift in broader world demand transmit differently to the UK and may therefore warrant different monetary policy responses. It also matters for monitoring the near term: with structural forces, such as the AI-driven investment boom and the reconfiguration of energy markets, now reshaping the global economy, disentangling the effects of world financial conditions, broader global demand and US monetary policy becomes even more relevant.

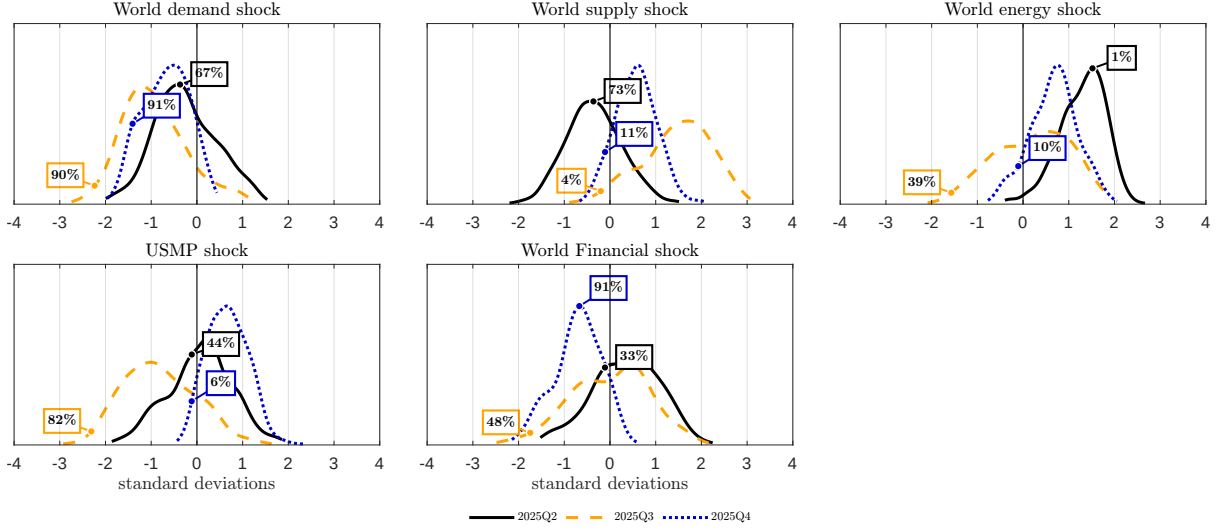
3.5 Monitoring Economic Conditions in Real Time

Beyond interpreting past episodes, the model can be used to monitor global conditions in real time and to support the policy narrative around current economic developments. By tracking the evolution of the estimated structural shocks each quarter, the Global-to-UK SVAR provides a model-based assessment of the global environment at any point in time: whether recent movements are driven by demand-side or supply-side disturbances, and what role financial shocks play. Figure 7 plots the posterior distributions of the five identified global shocks for 2025Q2–2025Q4 in standard-deviation units. The percentage shown in each panel indicates the posterior probability mass below zero.

On the demand side, the US monetary policy shock is centred near zero in 2025Q2 (44% below zero), moves into accommodative territory in 2025Q3 (around 82% below zero, with mode near -1) as the Federal Reserve began cutting rates in September, and returns above zero in 2025Q4 (around 6% below zero, with mode near $+1$) as the October and December cuts were largely anticipated and interpreted as relatively hawkish.⁵ The world financial shock also changes over this period, shifting from relatively looser financial conditions (i.e., positive world financial shocks) in 2025Q2 (33% below zero) through broadly neutral conditions in 2025Q3 (48%) to tighter financial conditions in 2025Q4

⁵See FOMC statements and minutes, September–December 2025.

FIGURE 7 RECENT GLOBAL SHOCKS: POSTERIOR DISTRIBUTIONS



NOTE: This figure shows the posterior distributions of the five identified global shocks, expressed in standard-deviation units. Each line represents the posterior distribution of the shock in a given quarter between 2025Q2 and 2025Q4. All shocks are identified using the sign, ranking, and bound restrictions of Section 2.3. The percentage in each panel is the posterior probability mass below zero. Distributions are based on 1,000 posterior draws.

(around 91% below zero). The world demand shock remains persistently weak throughout the year, with between 67% and 91% of posterior mass below zero. On the supply side, world supply and energy shocks follow different trajectories during the year but both are estimated to be positive by the end of 2025, with a probability of around 89% and 90%, respectively, of being above zero in 2025Q4.

Taken together, the shock estimates point to a global environment of persistently weak external demand during 2025, improving supply conditions towards year-end, and financial conditions that tightened at the end of the year. Their significance for the UK, however, depends not only on how precisely the structural shocks are identified but also on their magnitude and transmission. Figure 7 summarises the sign and posterior uncertainty of each shock, while the historical decomposition in Figure 5 quantifies its contribution to UK inflation and activity. A shock may therefore be signed with high posterior probability yet have only a modest macroeconomic effect if it is small or offset by other disturbances. On this basis, global developments exerted limited upward pressure on UK inflation over the period, while weak world demand continued to weigh on UK activity.

3.6 Sensitivity Analysis

To assess the role of the identifying restrictions, we re-estimate the model under six alternative specifications. Table 3 reports the results alongside those from the baseline model. We first tighten, relax, and remove the bound restriction. We then remove the

ranking restrictions on impact responses, before removing both the bound and ranking restrictions so that identification relies only on sign restrictions. Finally, we re-estimate the baseline specification without the pandemic prior. All alternative specifications retain the same set of sign restrictions.

TABLE 3 SUMMARY OF RESULTS ACROSS MODELS

Models/shocks	Peak response		FEVD: 1 year	HD: leading global driver
	USMP	Financial	Global	
<i>Panel A: UK GDP</i>				
Baseline	-0.18	0.31	46.66	Energy
bound ≤ 0.07	-0.17	0.28	44.18	Financial
bound ≤ 0.15	-0.17	0.29	44.85	Energy
Without bound	-0.18	0.27	46.04	Energy
Without ranking	-0.14	0.27	44.57	Fin./Energy
Without pandemic dummy	-0.12	0.27	40.36	Energy
Sign only	-0.15	0.27	45.76	Energy
<i>Panel B: UK CPI</i>				
Baseline	-0.27	0.31	56.31	Energy/Fin.
bound ≤ 0.07	-0.33	0.31	56.40	Energy/Fin.
bound ≤ 0.15	-0.34	0.35	56.17	USMP/Energy
Without bound	-0.30	0.39	56.25	Energy
Without ranking	-0.43	0.32	58.39	USMP
Without pandemic dummy	-0.36	0.29	57.88	Energy
Sign only	-0.44	0.33	58.29	Financial

Note: All specifications share the same sign restrictions, but differ in the feature named in the row label. Peak responses are posterior medians (%) to a one-standard-deviation structural shock, taken over the first five years. FEVD is the one-year share of the global shocks. The “leading driver” column reports the largest-contributing global shock (“A/B” where the top two are within 1pp).

The main findings are robust across the alternative specifications. The signs of the key spillovers remain unchanged: a contractionary US monetary policy shock lowers both UK GDP and UK CPI, with the peak GDP response ranging between -0.12% and -0.18% , while a positive world financial shock raises both variables, with the peak UK GDP response ranging from 0.27% to 0.31% . As shown in Appendix Figures B.4 and B.5, the median impulse responses from all alternative models lie within the 68% credible intervals of the baseline model. The variance decompositions are similarly stable: the global contribution to the forecast-error variance of UK CPI varies by around 2 percentage points across specifications, while the corresponding contribution to UK GDP varies by roughly 6 percentage points. The result that global shocks account for roughly half of

the variation in UK output and CPI therefore holds across specifications. World energy and world financial shocks also remain the leading global drivers of UK CPI and GDP in the baseline model and most alternatives. Overall, neither the ranking nor the bound restriction materially affects the signs of the responses or the aggregate importance of global shocks.

Two alternative specifications generate somewhat larger departures from the baseline. First, removing the pandemic prior has the greatest impact on the estimated importance of global shocks for UK activity. It reduces the one-year global FEVD for UK GDP from 47% to 40% and reduces the magnitude of the GDP response to a US monetary policy shock by around one-third. This suggests that, without the pandemic prior, the extreme observations of 2020–21 are attributed to a larger extent to the UK-domestic block. Second, removing the ranking restrictions strengthens the peak response of UK CPI to a US monetary policy tightening, from -0.27% to -0.43% , and elevates the US monetary policy shock to the largest global contributor to UK inflation. This reflects the role of our ranking restrictions, which separate the US monetary policy shock from the world energy shock more sharply than sign restrictions alone.

Even so, the sign and qualitative pattern of every response are unchanged, and only their magnitudes and the marginal ranking of the leading driver shift. This pattern highlights the role of the ranking and bound restrictions in sharpening the economic interpretation of the identified shocks while leaving the key findings intact.

4 Cross-country Heterogeneity following a Global Financial Shock

The shocks identified in Section 2.3 are objects of independent interest. Once estimated, the shock series can be used in other empirical settings as observable measures of common, exogenous global disturbances, and to address questions that the Global-to-UK model is not itself designed to answer. We illustrate this here by asking which economies are most exposed to a world financial shock. We feed the world financial shock series into country-specific VARs for a broad panel of advanced and emerging economies and trace how the shock transmits domestically.

More specifically, for each country i we estimate by OLS, equation by equation, the VARX

$$X_{it} = c_i + d_i t + e_i t^2 + \sum_{\ell=1}^5 \Phi_{i\ell} X_{i,t-\ell} + b_i s_t + u_{it}, \quad (12)$$

where X_{it} contains real GDP, the CPI, the nominal exchange rate against the US dollar

and a nominal equity price index. The variables enter in log levels, without differencing or filtering; low-frequency movements are absorbed by the country-specific constant, linear trend and quadratic trend.⁶ The world financial shock s_t is the pointwise posterior median of the identified world financial structural shock from the Global-to-UK SVAR. The shock enters contemporaneously only, so its dynamic effects propagate through the autoregressive part of the model. Samples run from 1996Q3 to 2019Q4, except where a later start is indicated (Table C.1). Each equation has 24 regressors, and the effective sample is 89 quarters for countries with data over the full period. We assume that u_{it} is normally distributed with mean zero and covariance matrix $\Sigma_{u,i}$. The covariance matrix is estimated using the standard degrees-of-freedom adjustment, dividing the sum of squared residuals by the number of observations minus the number of regressors. All 34 country models pass a stability screen (largest modulus of the companion-matrix eigenvalues below 0.999), so $N = 34$. A detailed description of the data, sources, sample coverage, and variable construction is provided in Appendix C.

Impulse responses and variance decomposition. Let $\theta_{ik,h}$ denote the response of variable k in country i at horizon h to a unit impulse in s_t , in percent, with $h = 0$ the impact quarter, and let $\theta_{i,h}$ collect the responses of the four variables: $\theta_{i,0} = b_i$ and $\theta_{i,h} = JF_i^h J' b_i$, where F_i is the companion matrix of Eq. (12) and $J = [I_4 \ 0]$ selects its first four rows. Since s_t is treated as exogenous in Eq. (12), it is orthogonal to u_{it} by assumption, and its share of the forecast-error variance of variable k at horizon h is

$$\omega_{ik,h} = \frac{\sigma_s^2 \sum_{j=0}^h \theta_{ik,j}^2}{\sigma_s^2 \sum_{j=0}^h \theta_{ik,j}^2 + \sum_{j=0}^h [\Psi_{ij} \Sigma_{u,i} \Psi_{ij}']_{kk}}, \quad (13)$$

where $\Psi_{ij} = JF_i^j J'$ are the reduced-form moving-average coefficients and σ_s^2 is the sample variance of s_t over the country's estimation sample.

Mean-group estimator. The mean-group estimates are the cross-country averages

$$\bar{\theta}_{k,h} = \frac{1}{N} \sum_{i=1}^N \theta_{ik,h}, \quad \bar{\omega}_{k,h} = \frac{1}{N} \sum_{i=1}^N \omega_{ik,h},$$

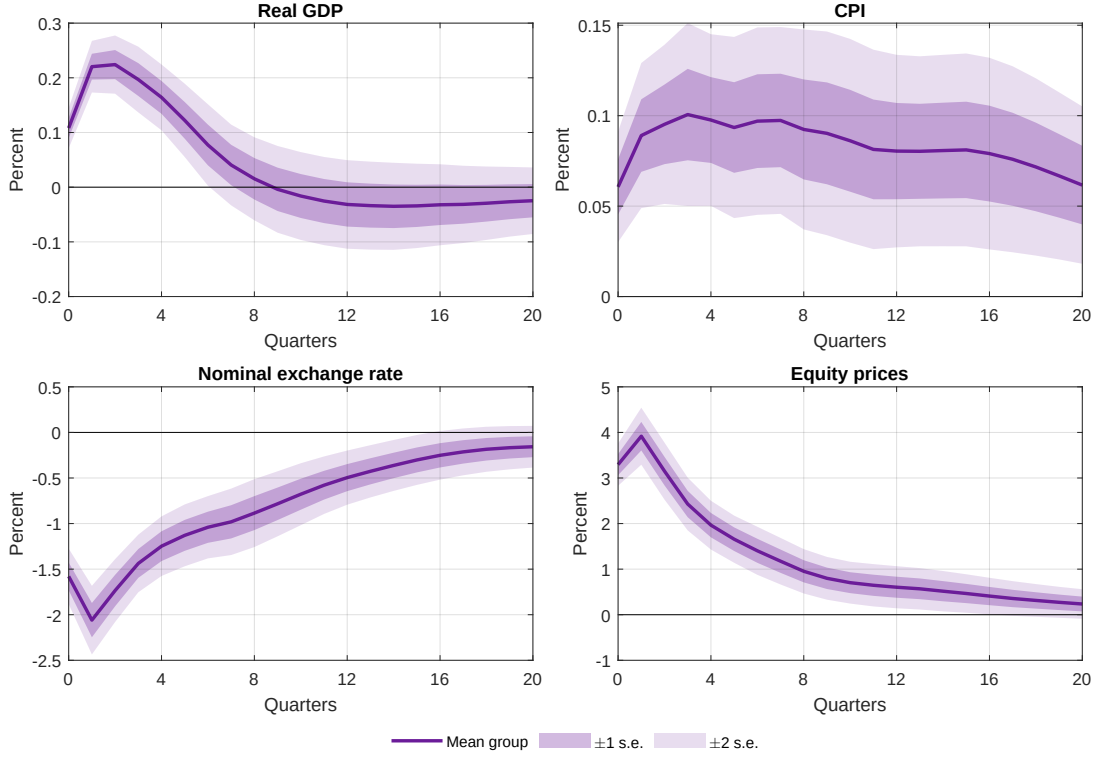
with standard errors equal to the cross-country standard deviation divided by $\sqrt{N}$ (Pesaran and Smith, 1995). These standard errors reflect the dispersion of the country estimates; they do not account for the estimation uncertainty in s_t , which is treated as

⁶We include country-specific linear and quadratic trends to flexibly account for the heterogeneous long-run dynamics observed across the economies in our sample, particularly among emerging market economies. Appendix C shows that the results are robust to a more parsimonious specification with only country-specific linear trends.

observed.

Results. Figure 8 summarises the mean-group responses to a unit world financial shock. On impact, a unit shock raises equity prices by 3.3 percent and appreciates local currencies against the dollar by 1.6 percent; both responses peak after one quarter, at 3.9 percent and a 2.1 percent appreciation, respectively, and then decay gradually. Real GDP rises by 0.11 percent on impact, peaks at 0.22 percent after two quarters and returns to zero after about two years. The CPI rises more gradually, reaches 0.10 percent after three quarters, remains close to this level for about two years and stays above zero over the 20-quarter horizon.

FIGURE 8 MEAN-GROUP RESPONSES TO A WORLD FINANCIAL SHOCK

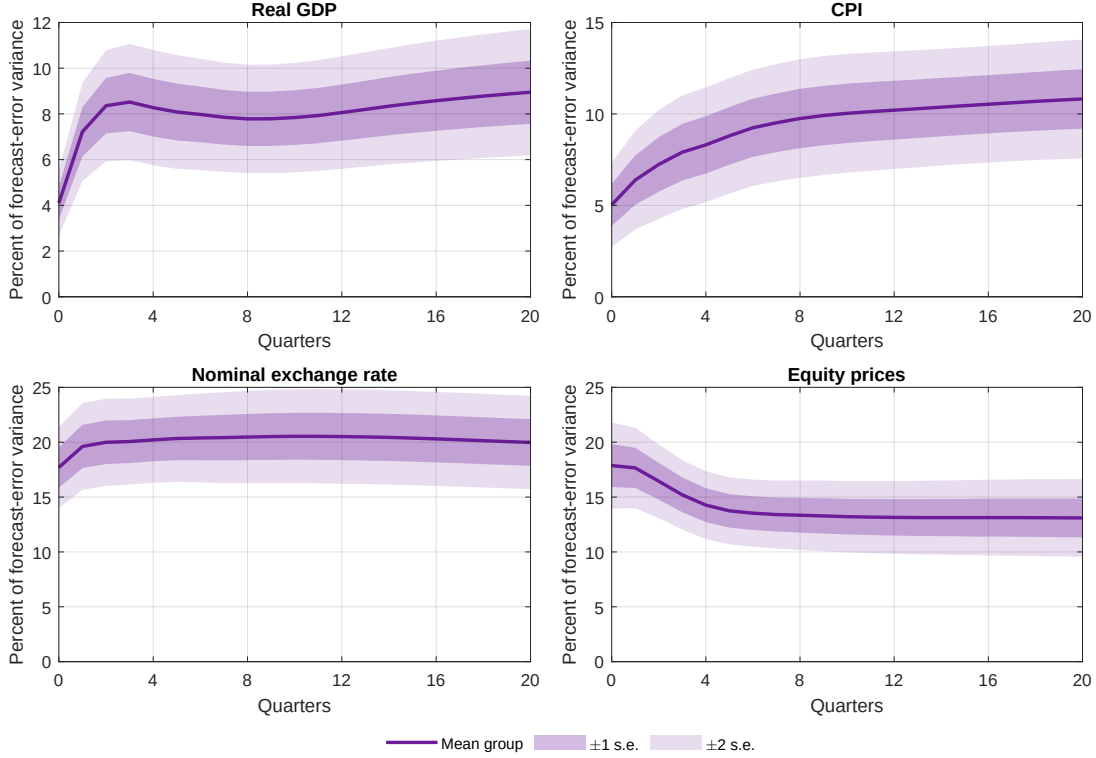


NOTE: This figure shows the mean-group impulse responses $\bar{\theta}_{k,h}$ of real GDP, the CPI, the nominal exchange rate against the US dollar (local currency per dollar, so that a decline is an appreciation) and equity prices to a unit impulse in the world financial shock s_t , in percent. The horizontal axis is in quarters, with $h = 0$ the impact quarter. The shock s_t is the world financial shock identified in the Global-to-UK SVAR (median rotation across accepted posterior draws, as described in Sections 2 and 3); its sample standard deviation over 1996Q3–2019Q4 is 0.90. The country responses $\theta_{ik,h}$ are computed from the VARX in Eq. (12), estimated by OLS for each of the $N = 34$ countries over 1996Q3–2019Q4 or the longest available sample (Table C.1). The solid line is the cross-country average; the shaded areas are ± 1 and ± 2 mean-group standard errors, equal to the cross-country standard deviation divided by $\sqrt{N}$, which do not account for the estimation uncertainty in s_t . Individual country responses are shown in Figure C.2.

Figure 9 plots the mean-group share of the forecast-error variance of each variable due to the world financial shock, $\bar{\omega}_{k,h}$ in Eq. (13). At $h = 8$, the shock accounts on average for 7.8 percent of the forecast-error variance of real GDP, 9.7 percent of that of the CPI, 20.5 percent of that of the exchange rate and 13.3 percent of that of equity prices. For

the exchange rate and equity prices the share is already large on impact (17.7 and 17.9 percent, respectively), whereas for GDP and the CPI it builds up over the first quarters, from 4.1 and 5.0 percent on impact.⁷

FIGURE 9 MEAN-GROUP FORECAST ERROR VARIANCE SHARES



NOTE: This figure shows the mean-group share $\bar{\omega}_{k,h}$ of the forecast-error variance of real GDP, the CPI, the nominal exchange rate against the US dollar and equity prices due to the world financial shock, in percent. The horizontal axis is the forecast horizon in quarters, with $h = 0$ the impact quarter. The country shares $\omega_{ik,h}$ are computed from Eq. (13), with σ_s^2 the sample variance of s_t over each country's estimation sample, from the VARX in Eq. (12) estimated by OLS for each of the $N = 34$ countries. The solid line is the cross-country average; the shaded areas are ± 1 and ± 2 mean-group standard errors, defined as in Figure 8. Individual country shares are shown in Figure C.3.

4.1 Cross-Country Evidence

Figures 10 and 11 relate two country-level statistics to financial openness⁸: the average response over impact and the following eight quarters, $\frac{1}{9} \sum_{h=0}^8 \theta_{ik,h}$, and the variance share $\omega_{ik,8}$. For each variable k , these statistics are plotted against financial openness of each country i (FO_i), together with the OLS fit on FO_i (in logs) and a 90% band based on HC1 standard errors and Student- t critical values with $N - 2$ degrees of freedom.

⁷Figures C.2 and C.3 in the appendix show the individual country estimates, which are dispersed around the mean group.

⁸Financial openness is taken from the External Wealth of Nations database, January 2025 release (Lane and Milesi-Ferretti, 2018). It is the ratio of external assets (excluding gold) plus external liabilities to GDP, all in US dollars, where each of the three series is averaged over 1996–2019 before the ratio is taken.

For all four variables, the point estimates indicate larger responses in absolute value in more financially open economies, but the relation is statistically significant only for the exchange rate and equity prices. For the exchange rate, the correlation between the average response and log openness is -0.56 (HC1 t -statistic -4.1), so that more open economies experience a larger appreciation and a doubling of financial openness is associated with an average appreciation larger by 0.46 percentage points. The correlation is 0.44 for equity prices ($t = 2.8$), and 0.25 for both real GDP and the CPI ($t = 1.1$ and 1.5). The variance shares in Figure 11 are positively correlated with openness for all four variables, with correlations between 0.38 (equity prices; $t = 1.8$) and 0.63 (exchange rate; $t = 4.1$). For the exchange rate, a doubling of financial openness is associated with a variance share that is higher by 7.2 percentage points.⁹

These cross-country correlations are descriptive: they do not identify a causal effect of financial openness, which may proxy for other country characteristics. They nonetheless suggest that domestic structural features shape the transmission of world financial shocks, and provide a basis for a more formal investigation in future work.

5 Conclusion

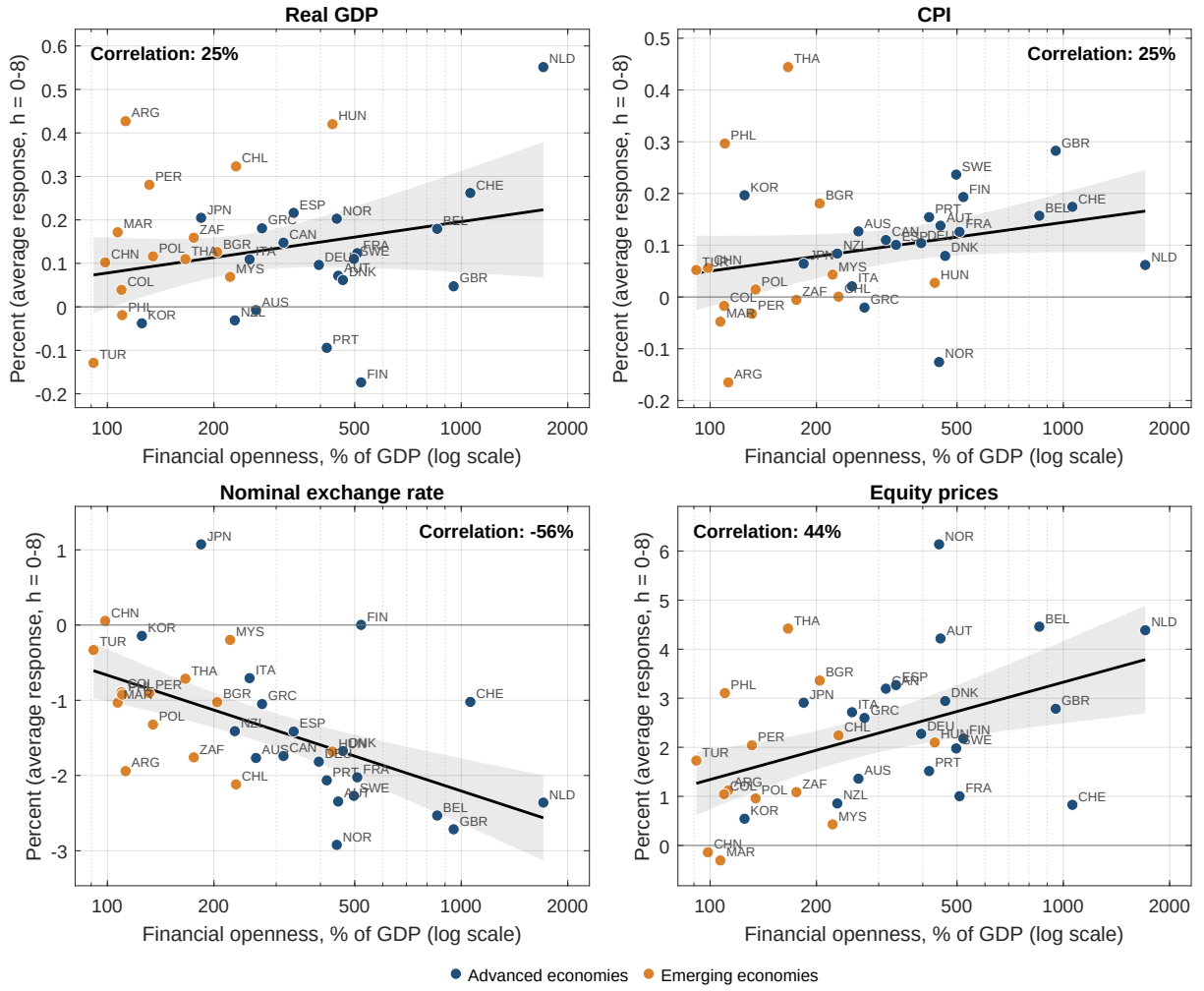
This paper studies the role of global shocks in shaping UK macroeconomic outcomes. Using a Global-to-UK SVAR, we show that global shocks account for around half of the variation in UK GDP and CPI within the first year. More importantly, the composition of these shocks matters. Distinguishing between world supply, world energy, world financial, world demand, and US monetary policy shocks reveals important differences in the drivers of UK inflation, activity, and monetary policy. It also sheds light on the external forces behind major economic episodes and the trade-offs they imply.

We also show that the identified shocks provide a useful input to broader analyses of international transmission. Applying the world financial shock to a panel of advanced and emerging economies reveals substantial heterogeneity in transmission: responses are larger in more financially open economies, particularly for exchange rates and equity prices.

These results point to two implications for policymakers in small open economies. First, distinguishing between different sources of global fluctuations is important for interpreting economic developments and assessing the appropriate policy response, as different shocks generate different trade-offs. Second, country-specific characteristics, such

⁹Figures C.4 and C.5 in the appendix repeat the VARX analysis with a constant and a linear trend only. Under this specification the models for Australia, Chile, Korea and Thailand fail the stability screen, so $N = 30$. The relationships between the variance shares and financial openness are robust; the minor differences that arise reflect both the change in sample and the change in specification.

FIGURE 10 AVERAGE RESPONSES AND FINANCIAL OPENNESS



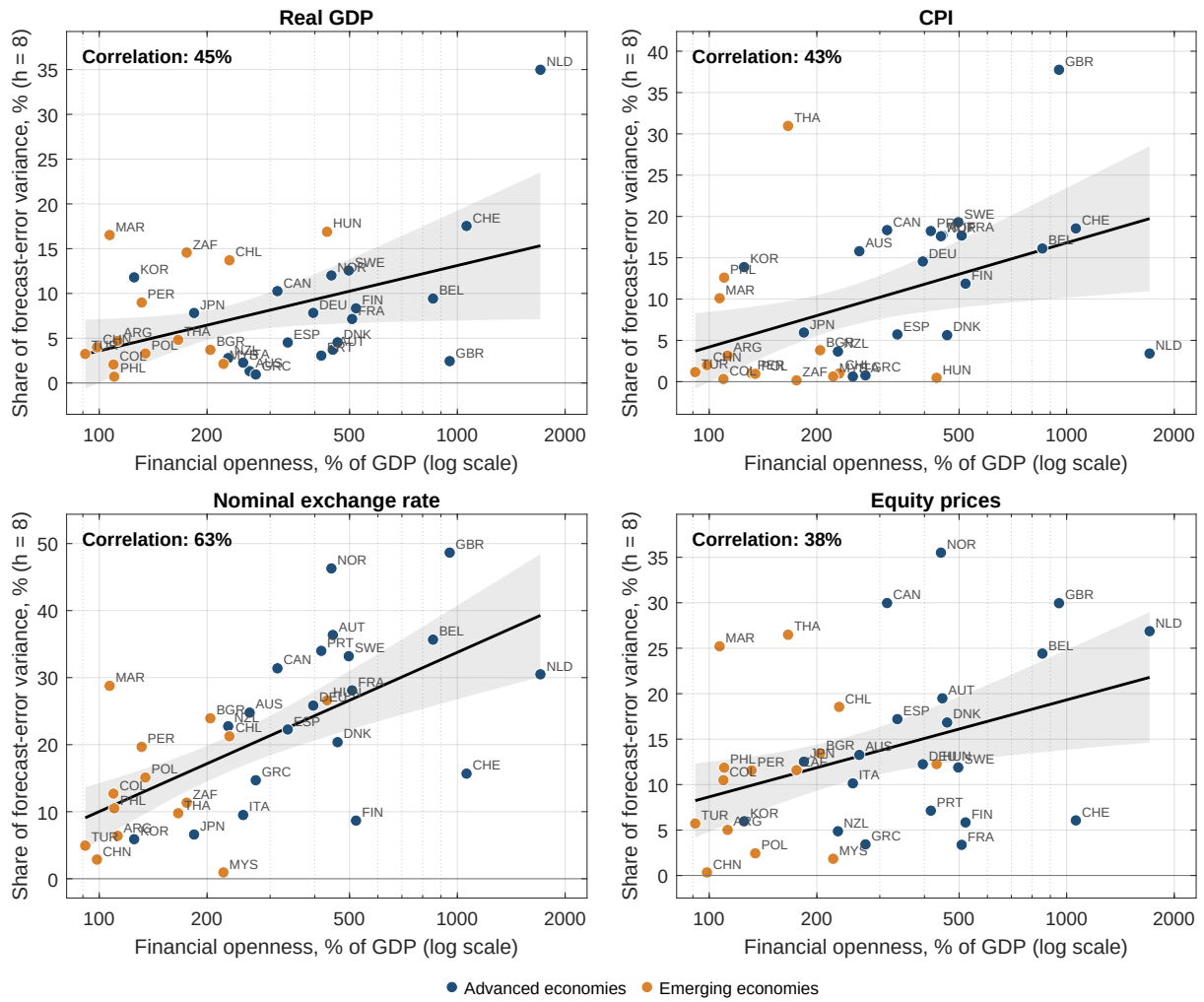
NOTE: This figure plots, for each of the $N = 34$ countries, the average response to a unit world financial shock over impact and the following eight quarters, $\frac{1}{9} \sum_{h=0}^8 \theta_{ik,h}$, in percent (vertical axis), against financial openness FO_i on a log scale (horizontal axis). Financial openness is the ratio of external assets (excluding gold) plus external liabilities to GDP, in percent, with each series averaged over 1996–2019, from the External Wealth of Nations database (Lane and Milesi-Ferretti, 2018). Markers distinguish advanced and emerging economies, following the IMF World Economic Outlook classification, and are labelled with ISO country codes. The solid line is the OLS fit of the country statistic on $\ln FO_i$; the shaded area is the 90% confidence band based on HC1 standard errors and Student- t critical values with $N - 2$ degrees of freedom. Each panel reports the Pearson correlation between the country statistic and $\ln FO_i$. The country responses $\theta_{ik,h}$ are computed from the VARX in Eq. (12).

as financial openness, shape the transmission of global shocks and are therefore important for assessing cross-country spillovers. The framework can support further work on historical interpretation, real-time monitoring, scenario analysis, and the resilience of open economies to global shocks.

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FIGURE 11 FORECAST ERROR VARIANCE SHARES AND FINANCIAL OPENNESS



NOTE: This figure plots, for each of the $N = 34$ countries, the share of the forecast-error variance at horizon $h = 8$ due to the world financial shock, $\omega_{ik,8}$ in Eq. (13), in percent (vertical axis), against financial openness FO_i on a log scale (horizontal axis). Financial openness, markers, fitted line, confidence band and reported correlation are defined as in Figure 10.

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A Estimation Details

A.1 Prior Specification and Hyperparameters

The conjugate prior for the VAR in Eq. (1) is $\Sigma \sim \mathcal{IW}(\Psi, d)$ and $\text{vec}(\mathbf{A}) \mid \Sigma \sim \mathcal{N}(\text{vec}(\mathbf{A}_0), \Sigma \otimes \Omega_0)$, where $\mathbf{A}$ collects $(\Pi_1, \dots, \Pi_p, \mathbf{c}, \delta)$. We set $d = k + 2$, the smallest integer degrees of freedom for which the prior mean of Σ exists; Ψ is diagonal, scaled so that this prior mean equals the residual variances of univariate AR(4) regressions, variable by variable. The prior mean $\mathbf{A}_0$ centres the first own lag of each variable at one and all other coefficients at zero. The prior variance of the coefficient on lag ℓ of variable i in any equation is proportional to $\lambda^2 / (\ell^\alpha \psi_i)$, where ψ_i is the i -th diagonal element of Ψ ; the intercept carries a diffuse prior. The sum-of-coefficients and dummy-initial-observation components enter as dummy observations with tightnesses μ and θ , respectively, constructed from the averages of the initial p observations (Doan et al., 1984; Sims, 1993). The pandemic dummy coefficients δ_j have conditionally normal priors centred at zero, with prior variance governed by a common tightness ϕ (Cascaldi-Garcia, 2022).

Following Giannone et al. (2015), the hyperparameters are assigned independent Gamma hyperpriors with modes (standard deviations) λ : 0.2 (0.4); μ : 1 (1); θ : 1 (1); α : 2 (0.5); and ϕ : 0.2 (1). The vector $(\lambda, \theta, \mu, \alpha, \phi)$ is set at its posterior peak by numerically maximising the log marginal likelihood (which is available in closed form under conjugacy) plus the log hyperprior. Conditional on the maximised hyperparameters, the posterior of $(\mathbf{A}, \Sigma)$ is normal-inverse-Wishart with the usual closed-form updates.

A.2 The Elliptical-Slice-within-Gibbs Sampler

We sample from the joint posterior of $(\Sigma, \mathbf{A}, \mathbf{Q})$ subject to the identification restrictions using Algorithm 2 of Arias et al. (2026), adapted to the block-recursive structure Eq. (7). The three parameter blocks are reparameterised as latent standard-normal vectors:

- **Rotation block.** A latent vector $\mathbf{x}_Q \in \mathbb{R}^{k_w^2 + k_{uk}^2}$ is mapped to $\mathbf{Q} = \text{blkdiag}(\mathbf{Q}_w, \mathbf{Q}_{uk})$ by reshaping its two sub-vectors into $k_w \times k_w$ and $k_{uk} \times k_{uk}$ matrices and applying a QR decomposition with the sign normalisation $\text{diag}(\mathbf{R}) > 0$ to each. Under this map, $\mathbf{x}_Q \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ induces the Haar (uniform) measure on each orthogonal block.
- **Covariance block.** A latent matrix of standard normals is mapped to Σ through the Bartlett-type decomposition of the inverse-Wishart posterior of Σ .
- **Coefficient block.** A latent vector $\mathbf{x}_A \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ is mapped to $\mathbf{A} = \bar{\mathbf{A}} + \text{chol}(\bar{\Omega}) \text{mat}(\mathbf{x}_A) \text{chol}(\Sigma)'$, where $\bar{\mathbf{A}}$ and $\bar{\Omega}$ are the posterior mean and scale of the matrix-variate normal posterior of $\mathbf{A}$ given Σ .

Each Gibbs sweep updates the three latent blocks in turn with an elliptical slice step (Murray et al., 2010), using as “likelihood” the indicator function that equals one if and only if the implied $(\Sigma, \mathbf{A}, \mathbf{B})$ satisfies all active restrictions: stability of the companion matrix; the on-impact sign restrictions of Table 2, checked up to column permutations and sign flips within each block as in Algorithm 1 of Chan et al. (2026); the between-shock ranking restrictions Eq. (9) and Eq. (10); and the bound restriction Eq. (11). Because

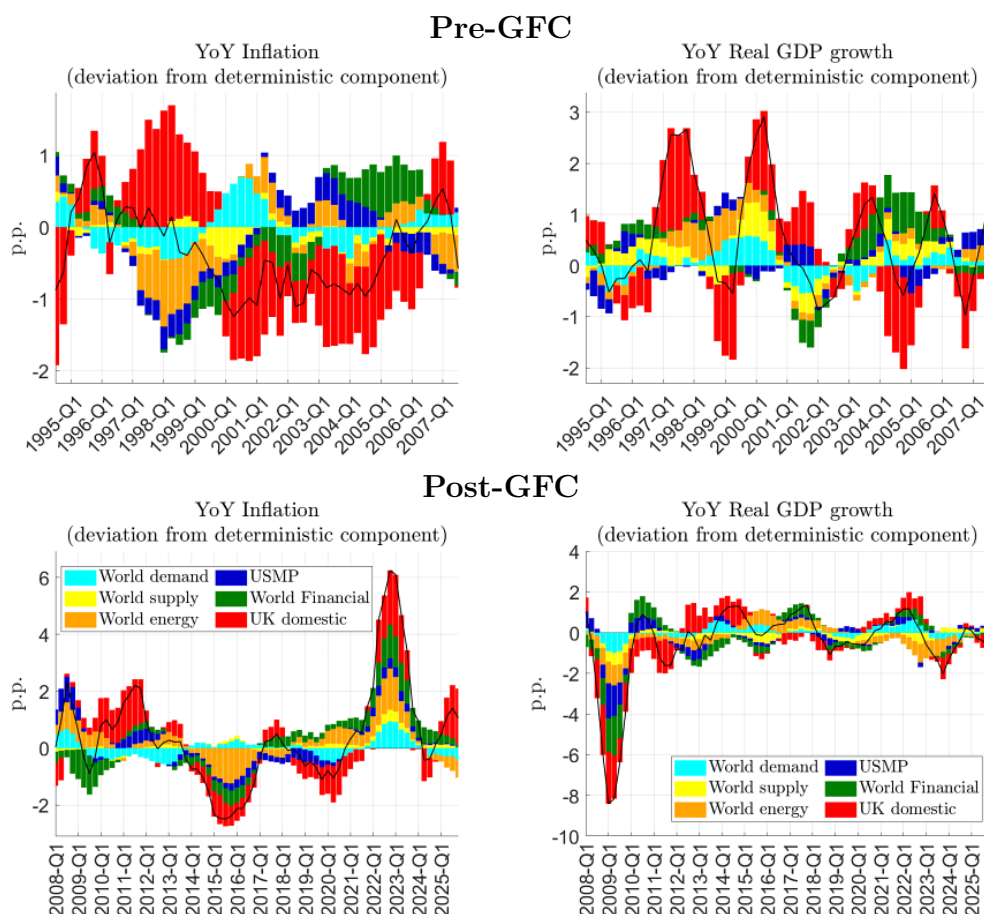
the elliptical slice step shrinks its proposal bracket until the indicator is satisfied, every sweep returns an admissible draw and the algorithm has an acceptance rate of one. The chain is initialised at an admissible point obtained by accept–reject sampling, run for 200 burn-in sweeps, and the subsequent 1,000 sweeps are retained.

B Global-to-UK SVAR

B.1 Historical Decompositions over Longer Subsamples

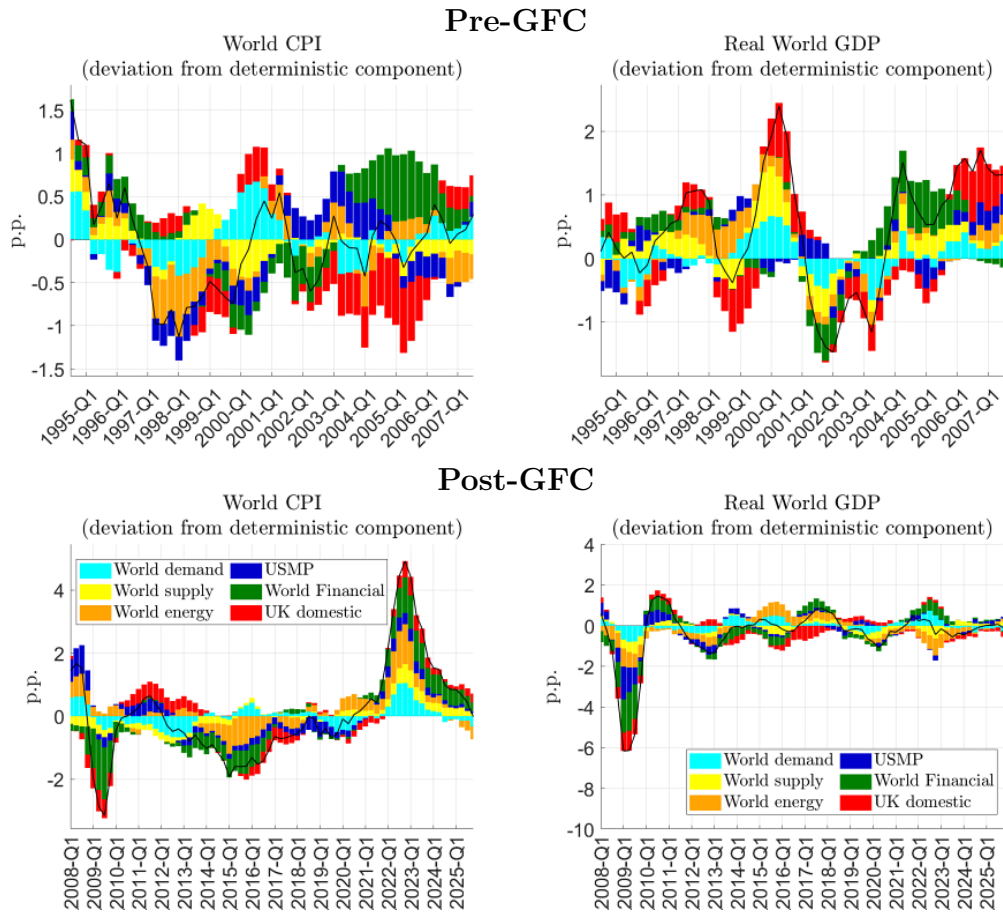
This appendix complements the episode-specific historical decompositions of Section 3.4 with decompositions over two longer subsamples. Figures B.1 and B.2 report the historical decompositions of UK and world variables, respectively, over the pre-GFC (1994Q3–2007Q4) and post-GFC (2008Q1–2025Q4) periods. As in Figures 5 and 6, the bars attribute observed fluctuations in year-on-year CPI inflation and GDP growth to the five identified global shocks and the aggregated UK-domestic block, measured relative to the deterministic component.

FIGURE B.1 HISTORICAL DECOMPOSITION OF UK VARIABLES: SUBSAMPLES



NOTE: The historical decomposition attributes observed fluctuations in year-on-year UK CPI inflation and UK GDP growth to the five identified global shocks and the aggregated UK-domestic block of the Global-to-UK SVAR. The Pre-GFC panel covers 1994Q3–2007Q4 and the Post-GFC panel covers 2008Q1–2025Q4. Bars show contributions measured relative to the deterministic component (initial conditions and constants). See Figure 5 for the GFC, Brexit, and Recent episodes.

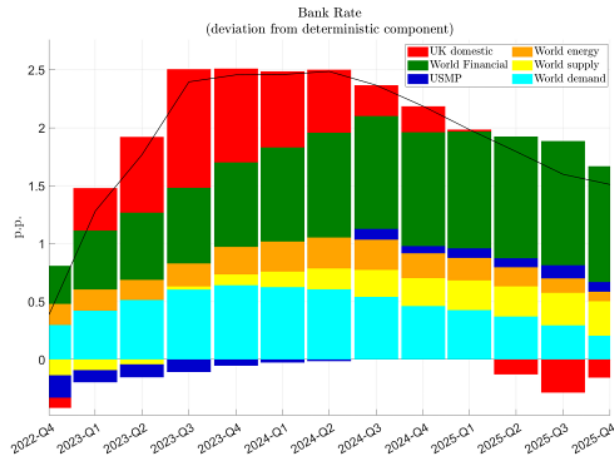
FIGURE B.2 HISTORICAL DECOMPOSITION OF WORLD VARIABLES: SUBSAMPLES



NOTE: The historical decomposition attributes observed fluctuations in year-on-year World CPI inflation and World GDP growth to the five identified global shocks and the aggregated UK-domestic block of the Global-to-UK SVAR. The Pre-GFC panel covers 1994Q3–2007Q4 and the Post-GFC panel covers 2008Q1–2025Q4. Bars show contributions measured relative to the deterministic component (initial conditions and constants). See Figure 6 for the GFC, Brexit, and Recent episodes.

B.2 Historical Decomposition of Bank Rate in the Recent Past

FIGURE B.3 HISTORICAL DECOMPOSITION OF BANK RATE

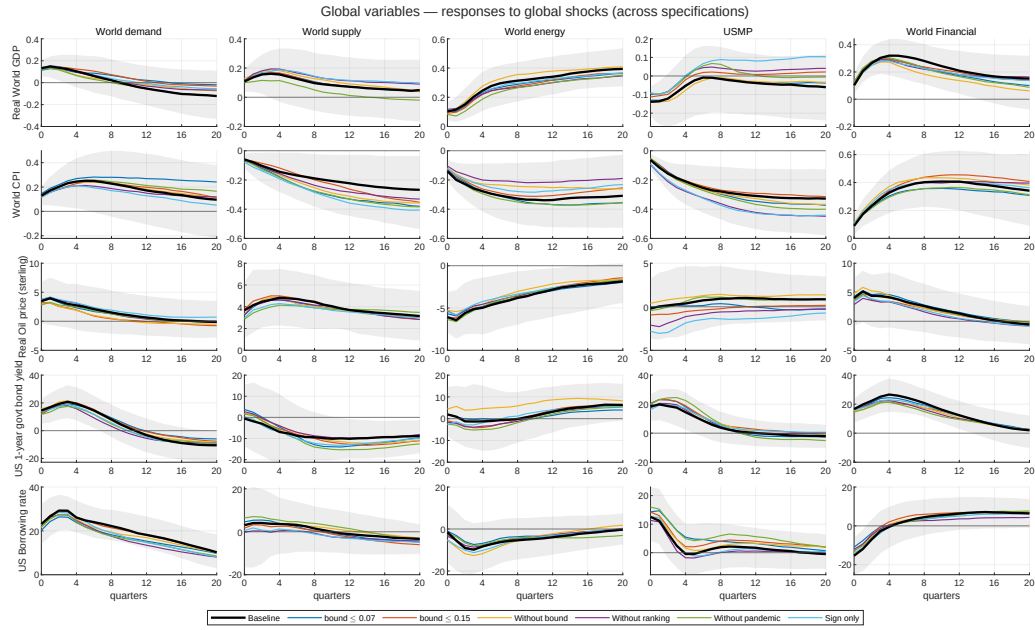


NOTE: The historical decomposition attributes observed fluctuations in Bank Rate to the five identified global shocks and the aggregated UK-domestic block of the Global-to-UK SVAR. Bars show contributions measured relative to the deterministic component (initial conditions and constants). The figure highlights the most recent three-year window from 2022Q4 to 2025Q4.

B.3 Robustness of Impulse Responses across Specifications

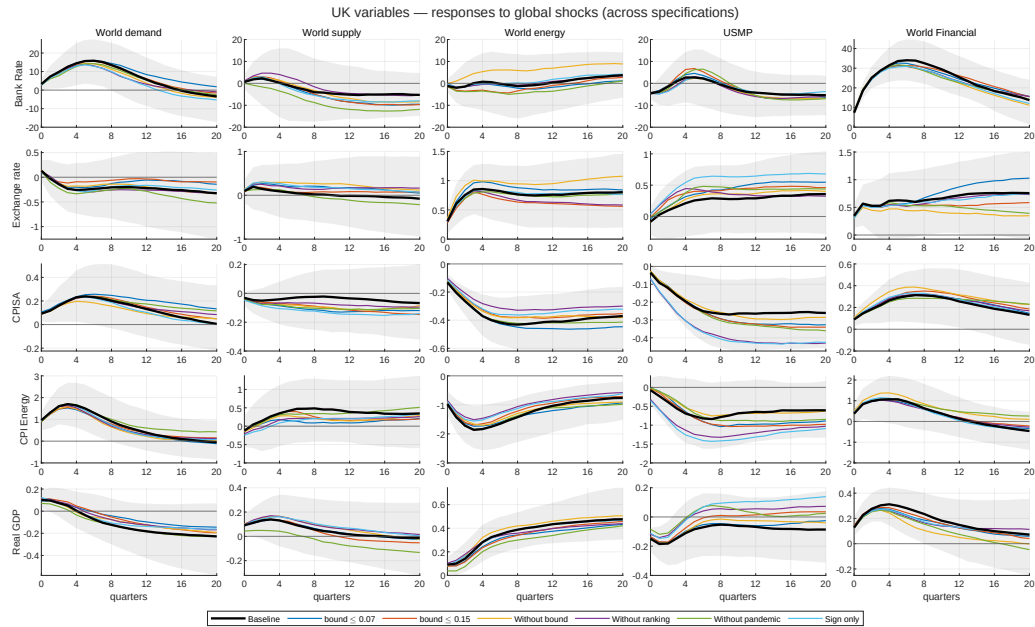
Figures B.4 and B.5 report the impulse responses of the world and UK variables under the alternative specifications summarised in Table 3 and discussed in Section 3.6.

FIGURE B.4 RESPONSES OF GLOBAL VARIABLES ACROSS SPECIFICATIONS



NOTE: This figure shows the impulse responses of the world variables (rows) to the five identified global shocks (columns) across specifications of the Global-to-UK SVAR estimated over 1992Q1–2025Q4. Each shock is normalised to one standard deviation; the horizontal axis is in quarters. The solid black line and the shaded area are the posterior median and the 68% credible band of the baseline specification; the coloured lines are the posterior medians under the alternative specifications listed in Table 3, which share the sign restrictions of the baseline and differ in the bound restriction, the ranking restriction or the pandemic dummy. Responses are in percent, except for the US 1-year government bond yield and the borrowing rate, which are in basis points.

FIGURE B.5 RESPONSES OF UK VARIABLES ACROSS SPECIFICATIONS



NOTE: This figure shows the impulse responses of the UK variables (rows) to the five identified global shocks (columns) across specifications of the Global-to-UK SVAR estimated over 1992Q1–2025Q4. Each shock is normalised to one standard deviation; the horizontal axis is in quarters. The solid black line and the shaded area are the posterior median and the 68% credible band of the baseline specification; the coloured lines are the posterior medians under the alternative specifications listed in Table 3, defined as in Figure B.4. Responses are in percent, except for Bank Rate, which is in basis points.

C Cross-Country Spillovers

C.1 Data

Macroeconomic data. The data are quarterly, 1996Q3–2019Q4, for 34 countries: 20 advanced and 14 emerging economies, following the IMF World Economic Outlook classification (Table C.1). For each country we use real GDP, the CPI, the nominal exchange rate against the US dollar (local currency per dollar, so that an increase is a depreciation) and a nominal equity price index. All series were downloaded from Datastream on 11 September 2026; Table C.2 reports the Datastream ticker and the original source of each series. The original sources are the OECD, the IMF International Financial Statistics, national statistical offices and central banks, and Oxford Economics; the equity price indices are Datastream total-market indices. For Argentina, Australia, Chile, China, Malaysia, Peru, the Philippines, Thailand and Turkey the CPI is taken from the OECD, Oxford Economics or national sources, because the corresponding IMF series is unavailable, starts after 1996 or is reported with insufficient precision. The exchange rate and equity prices are quarterly averages of the underlying higher-frequency series, as are the monthly CPI series for Malaysia, Peru, the Philippines, Thailand and Turkey. Series that are not seasonally adjusted at source, namely the CPI for 32 countries and real GDP for eight countries, are seasonally adjusted with the Datastream seasonal-adjustment function SAM#. All variables enter the analysis in natural logarithms. The samples for Bulgaria, Colombia and Morocco start later, in 2000Q4, 2005Q1 and 2007Q1, respectively; all samples end in 2019Q4 and contain no gaps.

TABLE C.1 COUNTRIES

Advanced economies (20)		Emerging economies (14)	
AUS	Australia	ARG	Argentina
AUT	Austria	BGR	Bulgaria (from 2000Q4)
BEL	Belgium	CHL	Chile
CAN	Canada	CHN	China
DNK	Denmark	COL	Colombia (from 2005Q1)
FIN	Finland	HUN	Hungary
FRA	France	MYS	Malaysia
DEU	Germany	MAR	Morocco (from 2007Q1)
GRC	Greece	PER	Peru
ITA	Italy	PHL	Philippines
JPN	Japan	POL	Poland
KOR	Korea	ZAF	South Africa
NLD	Netherlands	THA	Thailand
NZL	New Zealand	TUR	Turkey
NOR	Norway		
PRT	Portugal		
ESP	Spain		
SWE	Sweden		
CHE	Switzerland		
GBR	United Kingdom		

Note: Samples run from 1996Q3 to 2019Q4, except where a later start is indicated. Classification follows the IMF World Economic Outlook.

World financial shock. The world financial shock s_t is the shock identified in the Global-to-UK SVAR (pointwise posterior median). It is common to all countries; over 1996Q3–2019Q4 its sample mean is -0.07 and its sample standard deviation is 0.90 .

Financial openness. Financial openness FO_i is taken from the External Wealth of Nations database, January 2025 release (Lane and Milesi-Ferretti, 2018). It is the ratio of external assets (excluding gold) plus external liabilities to GDP, all in US dollars, where each of the three series is averaged over 1996–2019 before the ratio is taken. Figure C.1 shows that the ten most open economies are all advanced, while the emerging economies are concentrated at the bottom of the ranking, with Hungary the main exception.

TABLE C.2 DATA SOURCES

Country	ISO	Datastream ticker	Original source
<i>Real GDP</i>			
Argentina	ARG	AGOCMP03G	National Accounts, OECD
Australia	AUS	AUOCMP03G	National Accounts, OECD

Table C.2 (continued)

Country	ISO	Datastream ticker	Original source
Austria	AUT	OEOCMP03G	National Accounts, OECD
Belgium	BEL	BGOCMP03G	National Accounts, OECD
Bulgaria	BGR	BLI99.37C†	IFS, IMF
Canada	CAN	CNOCMP03G	National Accounts, OECD
Chile	CHL	CLOCMP03G	National Accounts, OECD
China	CHN	CHXGDPR.C†	Oxford Economics
Colombia	COL	CBOCMP03G	National Accounts, OECD
Denmark	DNK	DKOCMP03G	National Accounts, OECD
Finland	FIN	FNOCMP03G	National Accounts, OECD
France	FRA	FROCMP03G	National Accounts, OECD
Germany	DEU	BDNA0000G	Deutsche Bundesbank
Greece	GRC	GRXGDPR.D	Oxford Economics
Hungary	HUN	HNOCMP03G	National Accounts, OECD
Italy	ITA	ITOCMP03G	National Accounts, OECD
Japan	JPN	JPI99BVRG	IFS, IMF
Korea	KOR	KOOCMP03G	National Accounts, OECD
Malaysia	MYS	MYXGDPR.C†	Oxford Economics
Morocco	MAR	MCXGDSA.C	Oxford Economics
Netherlands	NLD	NLGDP...C†	CBS, Netherlands
New Zealand	NZL	NZOCMP03G	National Accounts, OECD
Norway	NOR	NWOCMP03G	National Accounts, OECD
Peru	PER	PEGDP...C†	Central Reserve Bank of Peru
Philippines	PHL	PHI99B.PC†	IFS, IMF
Poland	POL	POOCMP03G	National Accounts, OECD
Portugal	PRT	PTOCMP03G	National Accounts, OECD
South Africa	ZAF	SAOCMP03G	National Accounts, OECD
Spain	ESP	ESOCMP03G	National Accounts, OECD
Sweden	SWE	SDOCMP03G	National Accounts, OECD
Switzerland	CHE	SWOCMP03G	National Accounts, OECD
Thailand	THA	THGNP...C†	NESDB, Thailand
Turkey	TUR	TKOCMP03G†	National Accounts, OECD
United Kingdom	GBR	UKOCMP03G	National Accounts, OECD
<i>Consumer price index</i>			
Argentina	ARG	AGXCPI.F†	Oxford Economics
Australia	AUS	AUCCPI.E	ABS, Australia
Austria	AUT	OEQ64...F†	IFS, IMF
Belgium	BEL	BGQ64...F†	IFS, IMF
Bulgaria	BGR	BLQ64...F†	IFS, IMF
Canada	CAN	CNQ64...F†	IFS, IMF

Table C.2 (continued)

Country	ISO	Datastream ticker	Original source
Chile	CHL	CLCONPRCF†	INE, Chile
China	CHN	CHQCP009F†	Main Economic Indicators, OECD
Colombia	COL	CBQ64...F†	IFS, IMF
Denmark	DNK	DKQ64...F†	IFS, IMF
Finland	FIN	FNQ64...F†	IFS, IMF
France	FRA	FRQ64...F†	IFS, IMF
Germany	DEU	BDQ64...F†	IFS, IMF
Greece	GRC	GRQ64...F†	IFS, IMF
Hungary	HUN	HNQ64...F†	IFS, IMF
Italy	ITA	ITQ64...F†	IFS, IMF
Japan	JPN	JPQ64...F†	IFS, IMF
Korea	KOR	KOQ64...F†	IFS, IMF
Malaysia	MYS	MYCONPRCF†	Department of Statistics, Malaysia
Morocco	MAR	MCQ64...F†	IFS, IMF
Netherlands	NLD	NLQ64...F†	IFS, IMF
New Zealand	NZL	NZI64...F†	IFS, IMF
Norway	NOR	NWQ64...F†	IFS, IMF
Peru	PER	PECCPI..E	INEI, Peru
Philippines	PHL	PHCONPRCF†	Philippine Statistics Authority
Poland	POL	POQ64...F†	IFS, IMF
Portugal	PRT	PTQ64...F†	IFS, IMF
South Africa	ZAF	SAQ64...F†	IFS, IMF
Spain	ESP	ESQ64...F†	IFS, IMF
Sweden	SWE	SDQ64...F†	IFS, IMF
Switzerland	CHE	SWQ64...F†	IFS, IMF
Thailand	THA	THCONPRCF†	Bureau of Trade and Economic Indices, Thailand
Turkey	TUR	TKOCP009F†	Main Economic Indicators, OECD
United Kingdom	GBR	UKQ64...F†	IFS, IMF
<i>Nominal exchange rate (local currency per USD)</i>			
Argentina	ARG	AGL..RF.	IFS, IMF
Australia	AUS	AUL..RF.	IFS, IMF
Austria	AUT	OEOCC015	Main Economic Indicators, OECD
Belgium	BEL	BGOCC015	Main Economic Indicators, OECD
Bulgaria	BGR	BLI..RF.	IFS, IMF
Canada	CAN	CNL..RF.	IFS, IMF
Chile	CHL	CLI..RF.	IFS, IMF
China	CHN	CHI..RF.	IFS, IMF
Colombia	COL	CBL..RF.	IFS, IMF
Denmark	DNK	DKL..RF.	IFS, IMF

Table C.2 (continued)

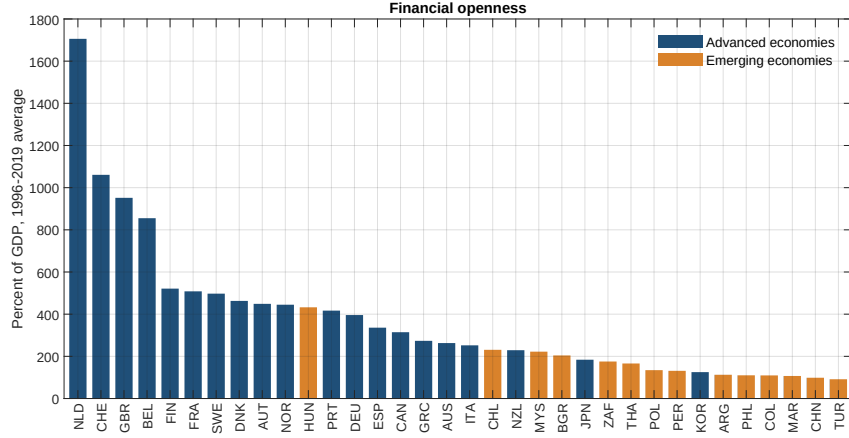
Country	ISO	Datastream ticker	Original source
Finland	FIN	FNOCC015	Main Economic Indicators, OECD
France	FRA	FROCC015	Main Economic Indicators, OECD
Germany	DEU	BDOCC015	Main Economic Indicators, OECD
Greece	GRC	GROCC015	Main Economic Indicators, OECD
Hungary	HUN	HNL.RF.	IFS, IMF
Italy	ITA	ITOCC015	Main Economic Indicators, OECD
Japan	JPN	JPL.RF.	IFS, IMF
Korea	KOR	KOL.RF.	IFS, IMF
Malaysia	MYS	MYL.RF.	IFS, IMF
Morocco	MAR	MCL.RF.	IFS, IMF
Netherlands	NLD	NLOCC015	Main Economic Indicators, OECD
New Zealand	NZL	NZL.RF.	IFS, IMF
Norway	NOR	NWL.RF.	IFS, IMF
Peru	PER	PEL.RF.	IFS, IMF
Philippines	PHL	PHL.RF.	IFS, IMF
Poland	POL	POL.RF.	IFS, IMF
Portugal	PRT	PTOCC015	Main Economic Indicators, OECD
South Africa	ZAF	SAI.RF.	IFS, IMF
Spain	ESP	ESOCC015	Main Economic Indicators, OECD
Sweden	SWE	SDL.RF.	IFS, IMF
Switzerland	CHE	SWL.RF.	IFS, IMF
Thailand	THA	THL.RF.	IFS, IMF
Turkey	TUR	TKL.RF.	IFS, IMF
United Kingdom	GBR	UKL.RF.	IFS, IMF
<i>Equity price index</i>			
Argentina	ARG	TOTMKAR	Datastream
Australia	AUS	TOTMKAU	Datastream
Austria	AUT	TOTMKOE	Datastream
Belgium	BEL	TOTMKBG	Datastream
Bulgaria	BGR	TOTMKBL	Datastream
Canada	CAN	TOTMKCN	Datastream
Chile	CHL	TOTMKCL	Datastream
China	CHN	TOTMKCA	Datastream
Colombia	COL	TOTMKCB	Datastream
Denmark	DNK	TOTMKDK	Datastream
Finland	FIN	TOTMKFN	Datastream
France	FRA	TOTMKFR	Datastream
Germany	DEU	TOTMKBD	Datastream
Greece	GRC	TOTMKGR	Datastream

Table C.2 (continued)

Country	ISO	Datastream ticker	Original source
Hungary	HUN	TOTMKHN	Datastream
Italy	ITA	TOTMKIT	Datastream
Japan	JPN	TOTMKJP	Datastream
Korea	KOR	TOTMKKO	Datastream
Malaysia	MYS	TOTMKMY	Datastream
Morocco	MAR	TOTMKMC	Datastream
Netherlands	NLD	TOTMKNL	Datastream
New Zealand	NZL	TOTMKNZ	Datastream
Norway	NOR	TOTMKNW	Datastream
Peru	PER	TOTMKPE	Datastream
Philippines	PHL	TOTMKPH	Datastream
Poland	POL	TOTMKPO	Datastream
Portugal	PRT	TOTMKPT	Datastream
South Africa	ZAF	TOTMKSA	Datastream
Spain	ESP	TOTMKES	Datastream
Sweden	SWE	TOTMKSD	Datastream
Switzerland	CHE	TOTMKSW	Datastream
Thailand	THA	TOTMKTH	Datastream
Turkey	TUR	TOTMKTK	Datastream
United Kingdom	GBR	TOTMKUK	Datastream

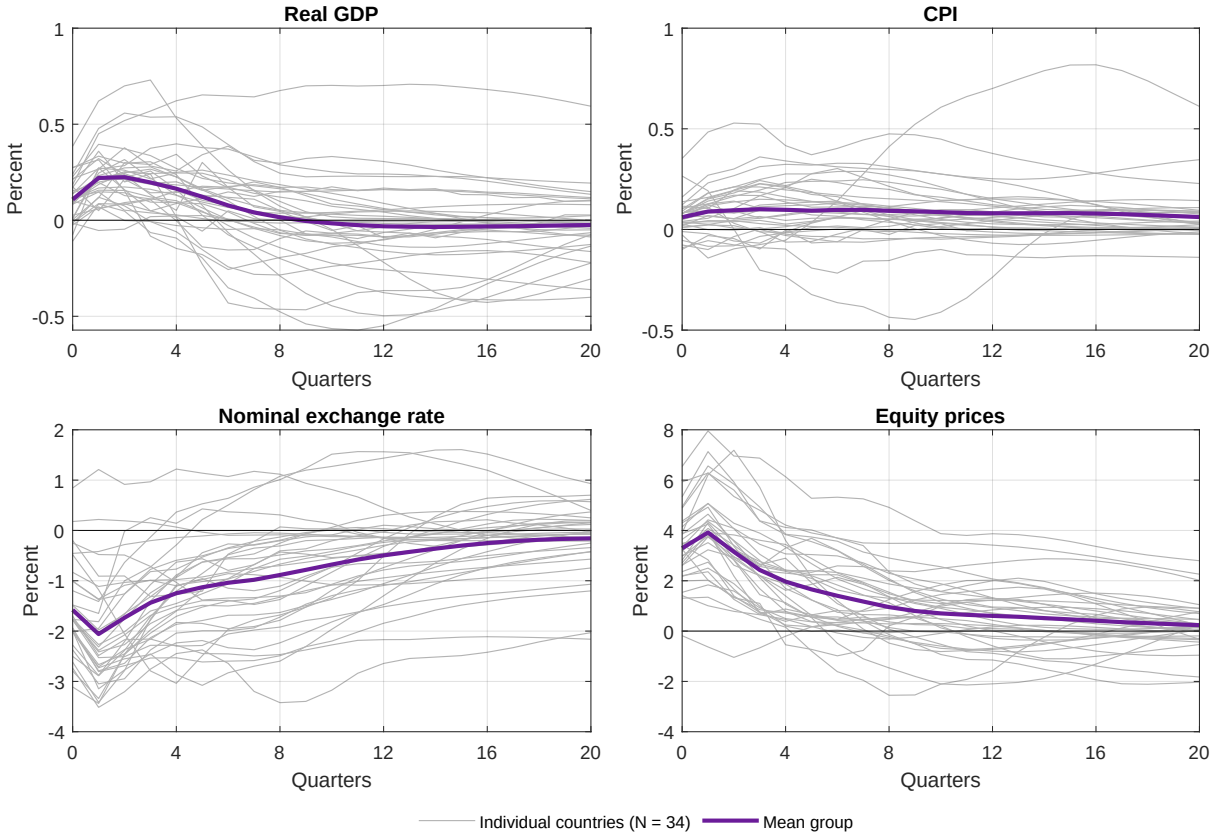
Note: Original source as reported by Datastream; the equity price indices are Datastream total-market indices. †: not seasonally adjusted at source; seasonally adjusted with the Datastream function SAM#. Data downloaded on 11 September 2026.

FIGURE C.1 FINANCIAL OPENNESS



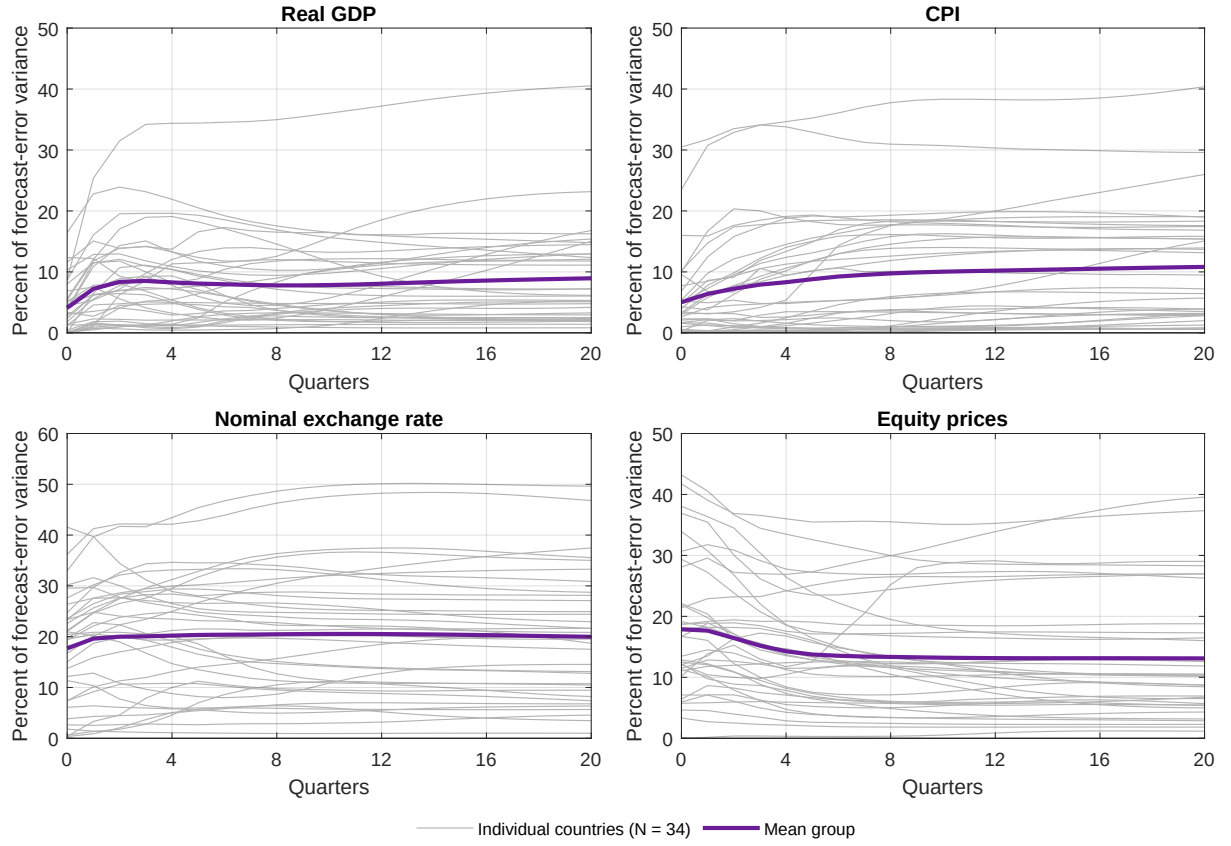
NOTE: This figure shows financial openness FO_i for the $N = 34$ countries in the sample, ranked from the most to the least open. Financial openness is the ratio of external assets (excluding gold) plus external liabilities to GDP, in percent, all in US dollars, with each of the three series averaged over 1996–2019 before the ratio is taken. Data are from the External Wealth of Nations database, January 2025 release (Lane and Milesi-Ferretti, 2018). Countries are labelled with ISO codes; colours distinguish advanced and emerging economies, following the IMF World Economic Outlook classification (Table C.1).

FIGURE C.2 COUNTRY RESPONSES TO A WORLD FINANCIAL SHOCK



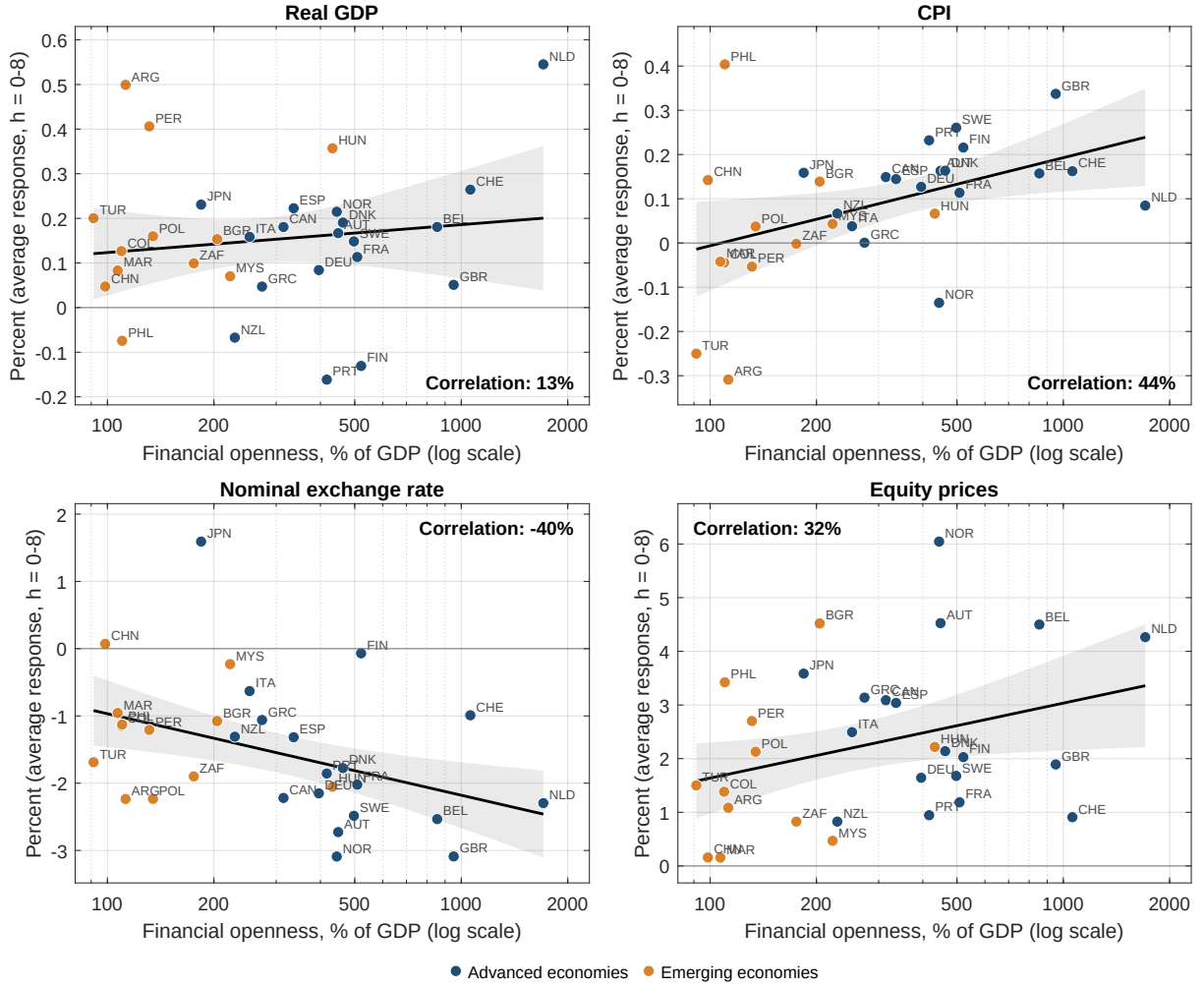
NOTE: This figure shows the impulse responses $\theta_{ik,h}$ of real GDP, the CPI, the nominal exchange rate against the US dollar (local currency per dollar, so that a decline is an appreciation) and equity prices to a unit impulse in the world financial shock s_t , in percent. The horizontal axis is in quarters, with $h = 0$ the impact quarter. The grey lines are the responses of the $N = 34$ individual countries, computed from the VARX in Eq. (12) estimated by OLS for each country over 1996Q3–2019Q4 or the longest available sample (Table C.1); the purple line is the mean-group response $\bar{\theta}_{k,h}$ shown in Figure 8.

FIGURE C.3 COUNTRY FORECAST ERROR VARIANCE SHARES



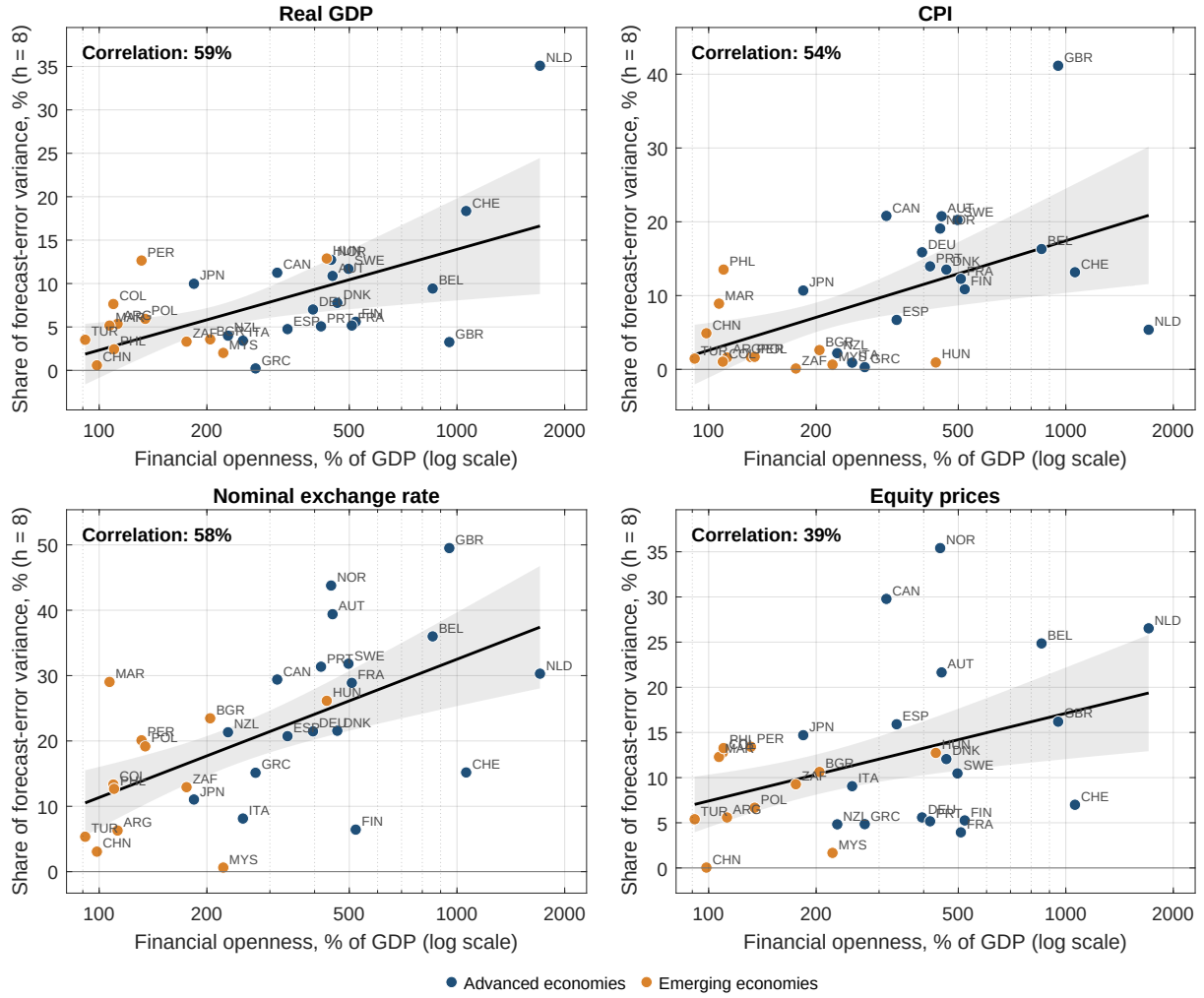
NOTE: This figure shows the share $\omega_{ik,h}$ of the forecast-error variance of real GDP, the CPI, the nominal exchange rate against the US dollar and equity prices due to the world financial shock, in percent, computed from Eq. (13). The horizontal axis is the forecast horizon in quarters, with $h = 0$ the impact quarter. The grey lines are the shares of the $N = 34$ individual countries, from the VARX in Eq. (12); the purple line is the mean-group share $\bar{\omega}_{k,h}$ shown in Figure 9.

FIGURE C.4 AVERAGE RESPONSES AND FINANCIAL OPENNESS: LINEAR TREND



NOTE: This figure repeats Figure 10 with the country VARX in Eq. (12) estimated with a constant and a linear trend only, that is, without the quadratic trend; the lag order and the sample are unchanged. Under this specification the models for Australia, Chile, Korea and Thailand fail the stability screen (largest modulus of the companion-matrix eigenvalues below 0.999), so that $N = 30$. The vertical axis is the average response to a unit world financial shock over impact and the following eight quarters, $\frac{1}{9} \sum_{h=0}^8 \theta_{ik,h}$, in percent; the horizontal axis is financial openness FO_i on a log scale. Markers, fitted line, 90% confidence band and reported correlation are defined as in Figure 10.

FIGURE C.5 VARIANCE SHARES AND FINANCIAL OPENNESS: LINEAR TREND



NOTE: This figure repeats Figure 11 with the country VARX in Eq. (12) estimated with a constant and a linear trend only, so that $N = 30$ (Figure C.4). The vertical axis is the share of the forecast-error variance at horizon $h = 8$ due to the world financial shock, $\omega_{ik,8}$ in Eq. (13), in percent; the horizontal axis is financial openness FO_i on a log scale. Markers, fitted line, 90% confidence band and reported correlation are defined as in Figure 10.