Bank of England

Workshop on Analysing the Information Content of Money

Central Bank Practice and Recent Academic Research

Bank of England, 4th March 2026

"It is clearly desirable to arrive at an early understanding of what we mean by money. There is no very general agreement upon this point; but as with so many other economic terms, it does not matter very much what meaning we adopt as long as we stick to it, or at any rate do not change it without being aware that we are doing so" **Dennis Robertson (1922)**.

"The relationship between changes in the stock of money and changes in other economic variables... is far from simple or mechanical. The velocity of circulation of money... is not a constant; it is a sensitive variable that reflects the decisions of millions of individuals."" **Friedman and Schwartz (1963)**

"Any observed statistical regularity will tend to collapse once pressure is placed upon it for control purposes." **Charles Goodhart (1975)**

"We didn't abandon [the monetary aggregates], [they] abandoned us" **Gerald Bouey (1983)**

"The use of quantity of money as a target has not been a success……I'm not sure I would as of today push it as hard as I once did." **Milton Friedman (FT, 7 June 2003).**

Agenda

9:30	**Registration and coffee**
10:00-10:15	**Opening remarks/welcome – Huw Pill** (Bank of England)
10:15-11:15	**Central Bank Show and Tell Part 1** Chair: Juan Castañeda (Vinson Centre, Buckingham University) • BoE analysis 30mins - **Ryland Thomas** (Bank of England) • SNB analysis 30mins - **Samuel Reynard** (Swiss National Bank)
11:15-11:30	**Coffee**
11:30-12:30	**Central Bank Show and Tell Part 2** Chair: John Power (CCBS, Bank of England) • ECB analysis - **Miguel Boucinha** (European Central Bank) • RBI analysis - **Soumya Bhadury** (Reserve Bank of India)
12:30-12:40	**Results from a Deep Learning Model - John Duca** (Oberlin College and Emeritus Economist, Dallas Fed) and Kenean Kejela (Google)
12:40-13:00	**Discussion of CB analysis and audience participation**
13:00-14:00	**Lunch**

Agenda

14:00-14:50 **Keynote –** *The future of monetarism after Milton Friedman*

Michael Bordo (Rutgers University)

Chair: Samuel Reynard (Swiss National Bank)

14:50-15:00 **Comfort Break**

15:00-16:00 **Paper session I – Using Money/Divisia to identify shocks**

Chair: Costas Milas (University of Liverpool)

- *From the monetary pillar to the monetary and financial analysis*:
  Martin Mandler (Bundesbank) and Michael Scharnagl (Bundesbank)
- *Identifying monetary policy shocks with Divisia money in the United Kingdom*:
  Jane Binner (University of Birmingham), Rakesh Bissoondeeal (Aston University) , Barry Jones (Binghamton University) and Victor Valcarcel (University of Texas)

16:00-16:30 **Coffee break**

Agenda

16:30-17:30 **Paper Session II - Using velocity gaps to predict inflation**

Chair: Chris Yeates (Bank of England)

- *Broad Divisia Money, Supply Pressures, and U.S. Inflation Following the COVID-19 Recession*, Michael Bordo (Rutgers University), **John Duca** (Oberlin College and Emeritus Economist, Dallas Fed) and Barry Jones (Binghamton University)
- *Sectoral money and prices*
  Juan Castañeda (University of Buckingham), Jose Luis Cendejas (Universidad Francisco de Vitoria), Florian Horber (Swiss National Bank) and Samuel Reynard (Swiss National Bank)

17:30-17:40 **Comfort Break**

17:40-18:30 **Policy Panel and discussion**

How should central banks assess and communicate the risks around money growth given the experience of the post-pandemic inflation ?

Chair: Ryland Thomas (Bank of England)

- **Huw Pill** (Bank of England)
- **Charles Goodhart** (LSE)
- **Lawrence Goodman** (Centre for Financial Stability)

18:30 **Workshop ends**

Participants - In person

First Name	Last Name	Ticket	Job Title	Company
Ryland	Thomas	In-person	Senior Research Advisor	Bank of England
Samuel	Reynard	In-person	Economic Advisor	Swiss National Bank
Huw	Pill	In-person	Chief Economist and Executive Director Monetary Analysis and Research	Bank of England
Sam	Christie	In-person	Economist	Bank of England
Mike	Ellington	In-person	Senior Lecturer in Finance	University of Liverpool
Jagjit	Chadha	In-person	Professor	University of Cambridge
Alec	Chrystal	In-person	Professor of Money and Banking	Bayes Business School, City University of London.
Costas	Milas	In-person	Professor of Finance	University of Liverpool
Gabriel	Stein	In-person	Founder	Stein Brothers (UK)
John	Duca	In-person	Danforth-Lewis Professor of Economics and Emeritus Economist	Oberlin College and Federal Reserve Bank of Dallas
Juan	Castaneda	In-person	Director, Vinson Centre	University of Buckingham
Martin	Mandler	In-person	Senior Economist	Deutsche Bundesbank
Charles	Goodhart	In-person	Professor Emeritus	London School of Economics
Tim	Congdon	In-person	Chair	Institute of International Monetary Research
Rakesh	Bissoondeeal	In-person	Senior Lecturer in Economics	Aston University
Barry	Jones	In-person	Professor	Binghamton University
John	Power	In-person	Head of Division	BoE
Richard	Sparkes	In-person	PhD student	University of St. Andrews
Jamie	Dannhauser	In-person	Chief economist	Ruffer
Jane	Binner	In-person	Chair of Finance	Birmingham Business School
Miguel	Boucinha	In-person	Head of Section	ECB
Michael	Oliver	In-person	Senior Lecturer in Finance	Open University
Gary	Harper	In-person	Manager - Data and Statistics Division	Bank of England
Michael	Leftley	In-person	Analyst - Data and Statistics	Bank of Engalnd
John	Greenwood	In-person	Chief Economist	International Monetary Monitor Ltd
Chris	Yeates	In-person	Senior Manager, Monetary & Financial Conditions Division	Bank Of England
Milena	Mazzoli	In-person	Programmes and Research officer	Institute of Economic Affairs
Jacob	Ponte	In-person	Senior Analyst	BoE
Kavya	Saxena	In-person	Private Secretary, MA	Bank of England
Iryna	Kaminska	In-person	Adviser	BoE
Peter	Denton	In-person	Analyst	BoE
Lord Brian	Griffiths	In-person	Member of House of Lords	House of Lords
Eugenio	Sanchez	In-person	Manager	Bank of England
Ewan	Stewart	In-person		University of Buckingham
Kenean	Kejela	In-person		Google
Dragos	Gorduza	In-person	Reaserch	BoE

Participants - Virtual

Lawrence	Goodman	Virtual	President	Center for Financial Stability
Michael	Bordo	Virtual	Distinguished Professor of Economics Emeritus	Rutgers University
Aaron	Clements-Partridge	Virtual	Senior Economist	Bank of England
Soumya	Bhadury	Virtual	Senior Economist	Reserve Bank of India
Victor	Valcarcel	Virtual	Professor	University of Texas at Dallas
Jim	Swofford	Virtual	Professor	University of South Alabama
Harry	Rigg	Virtual	Senior Economist	Bank of England
Peter	Spencer	Virtual	Emeritus professor	University of York
Florian	Horber	Virtual	Intern Monetary Policy Analysis	Swiss National Bank
Jose Luis	Cendejas	Virtual	PhD	Francisco de Vitoria University
Michael	Scharnagl	Virtual		Bundesbank
Bernhard	Winkler	Virtual		ECB

Bank of England

Staff Analysis of Money Data at the Bank of England

Workshop on Analysing the Information Content of Money

Bank of England 4th March 2026

Sam Christie, Aaron Clements-Partridge and Ryland Thomas*

*The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or its committees

Plan

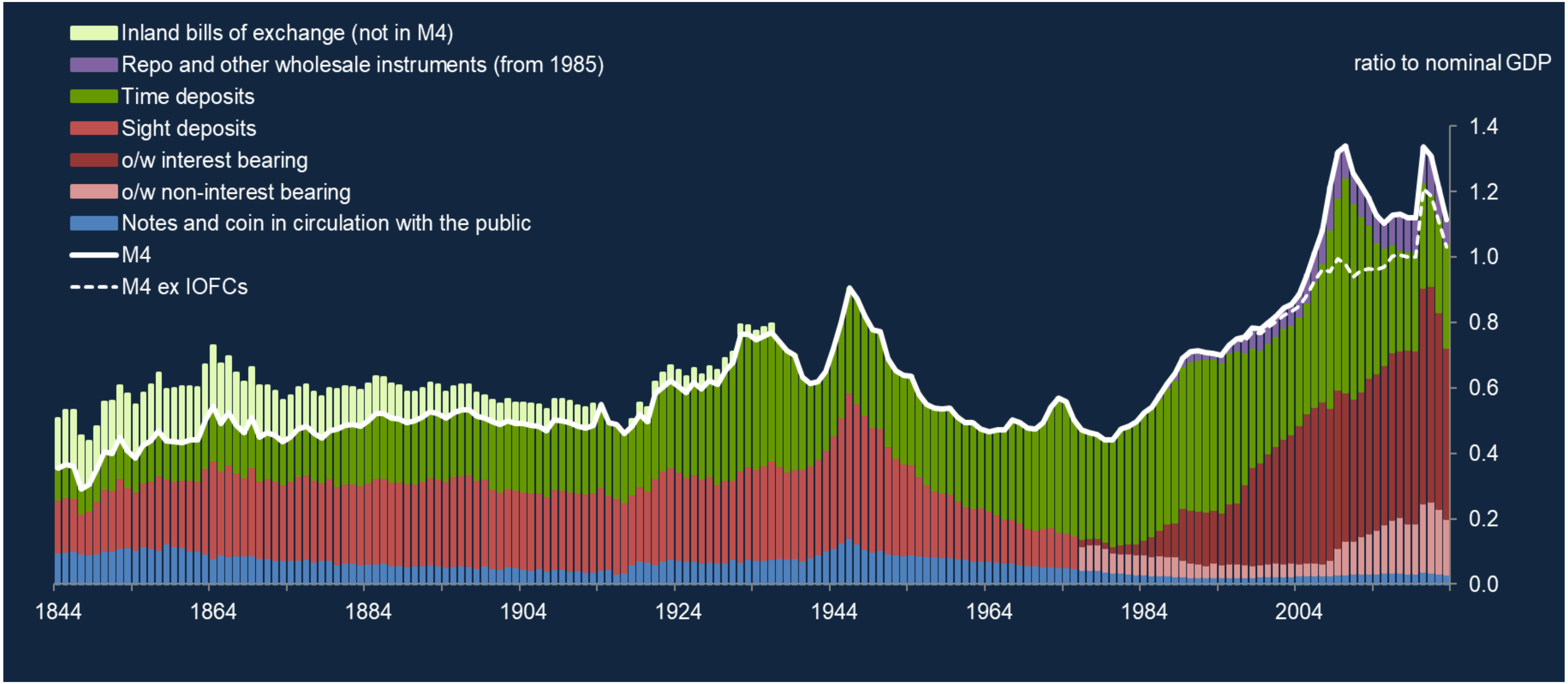
- How do we think about money creation and what measures do we focus on ?
- Money and nominal spending in the short and long-run
- How does money feed into the forecast and MPC process ?
- What were the key issues and problems assessing the signal from money during Covid and what did we learn ?
- Current live issues and plans for assessing the risks from money growth

Bank of England staff analysis focuses on broad measures of money

Table 1 Popular monetary aggregates that can be constructed from available UK data[(a)]

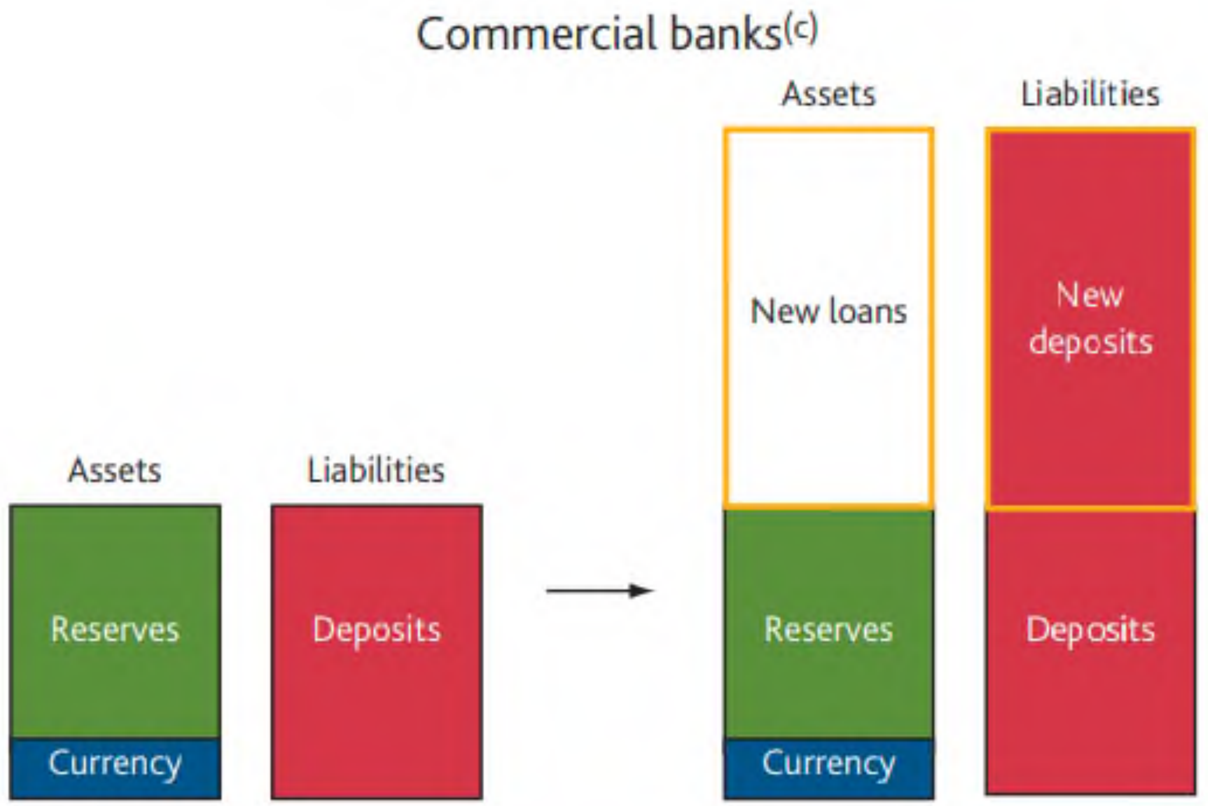
Name	Definition	Description[(b)]	Availability
Notes and coin	Notes and coin in circulation outside the Bank of England.	The narrowest measure of money and used as an indicator of cash-based transactions.	1870–present[(c)]
M0	Notes and coin plus central bank reserves.	Historically the base measure of money used in money multiplier calculations. Often used as an approximate measure of the size of the Bank of England's balance sheet. *No longer published by the Bank of England but can be reconstructed.*[(d)]	1870–present[(c)]
Non-interest bearing M1	Notes and coin plus non-interest bearing sight deposits held by the non-bank private sector.	An indicator of transactions in goods and services in the economy, less useful now since most sight deposits pay some form of interest. *Not published by the Bank of England but can be constructed from published components.*	1921–present[(c)]
MZM	Notes and coin plus all sight deposits held by the non-bank private sector.	An indicator of transactions in goods and services in the economy. *Not published by the Bank of England but can be constructed from published components. The Bank also produces a measure based on an ECB definition of M1.*	1977–present
M2 or retail M4	Notes and coin plus all retail deposits (including retail time deposits) held by the non-bank private sector.	A broader measure of money than MZM encompassing all retail deposits. The key additions are household time deposits and some corporate retail time deposits. *Published by the Bank of England. The Bank also produces a measure based on an ECB definition of M2.*	1982–present
M3	Notes and coin plus all sight and time deposits held with banks (excluding building societies) by the non-bank private sector.	Up until 1987 the headline broad monetary aggregate constructed by the Bank of England. *The Bank also produces a measure based on an ECB definition of M3.*	1870–1990[(c)]
M4	Notes and coin, deposits, certificates of deposit, repos and securities with a maturity of less than five years held by the non-bank private sector.	Up until 2007 the headline broad monetary aggregate constructed by the Bank of England.	1963–present
$M4^{ex}$	M4 excluding the deposits of IOFCs.	Since 2007 the headline broad monetary aggregate constructed by the Bank of England.	1997–present
Divisia	A weighted sum of different types of money.	Aims to weight the component assets of broad money according to the transactions services they provide.[(e)]	1977–present

Breakdown of Broad money/M4ex since 1844



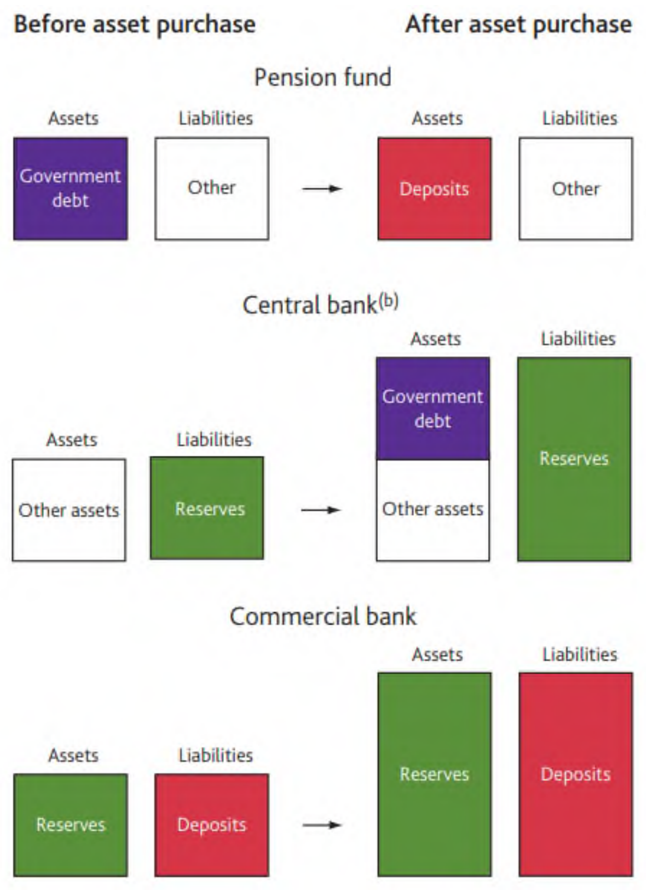
Money creation in the modern economy (BEQB 2014)

- Focus on broad money measures
- Bank deposits account for 97% of the "money supply" (M4ex)
- Banks create money through lending - "Loans creates deposits" not the other way around
- Through setting interest rates, the Bank of England controls the money supply by affecting the incentives for banks to make additional loans

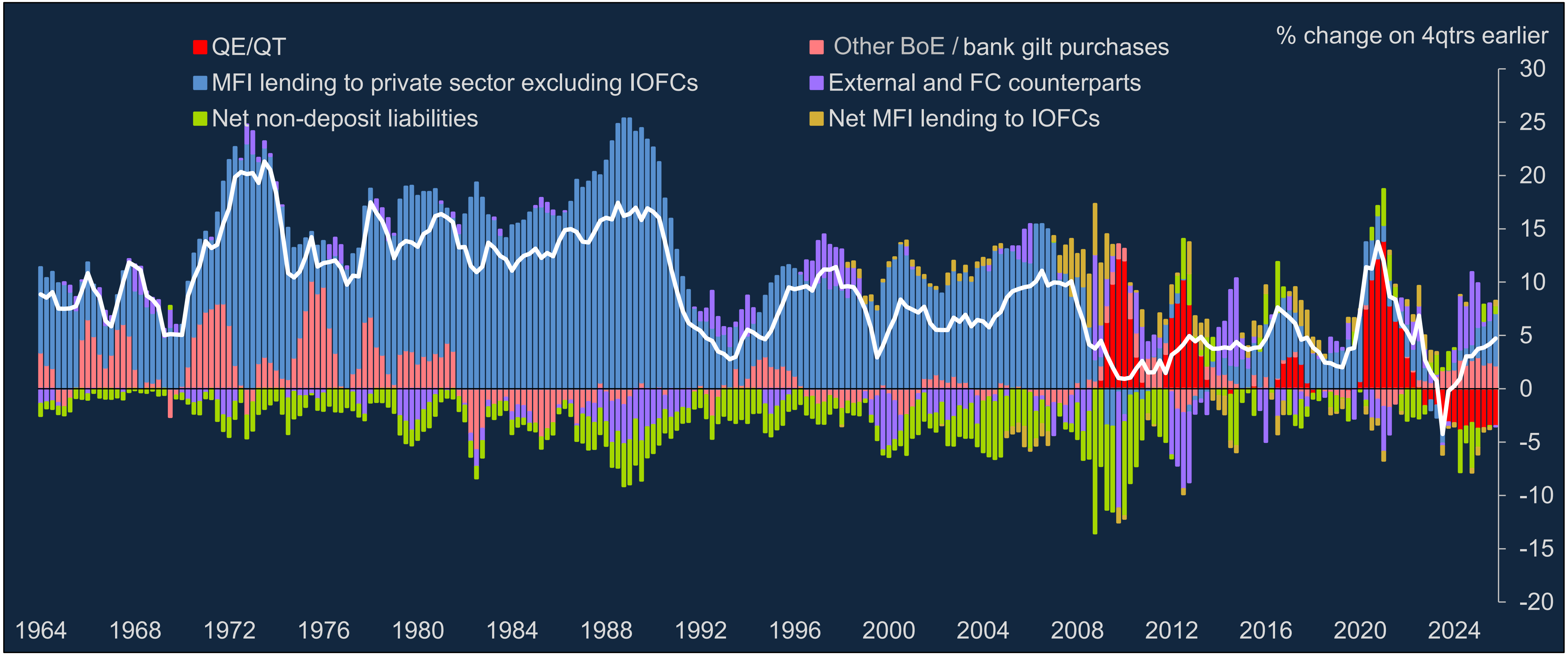


Money creation in the modern economy (BEQB 2014)

- **Central bank asset purchases (QE) can increase the money supply "create deposits" directly when the economy hits the ELB/ZLB**
- QE "works around the banking system" public sector creates money directly
- Aim to lower yields in government bond and capital markets and increase asset prices

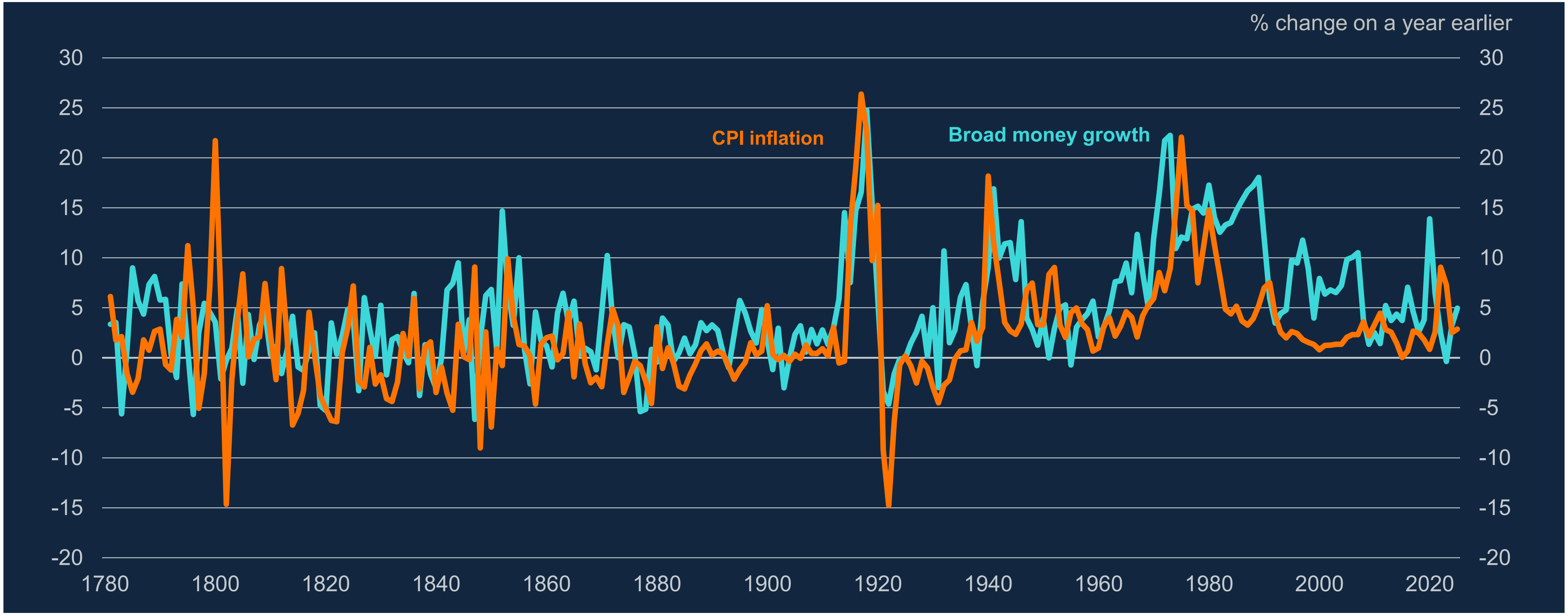


Historical M4ex Counterparts – contributions to M4ex growth



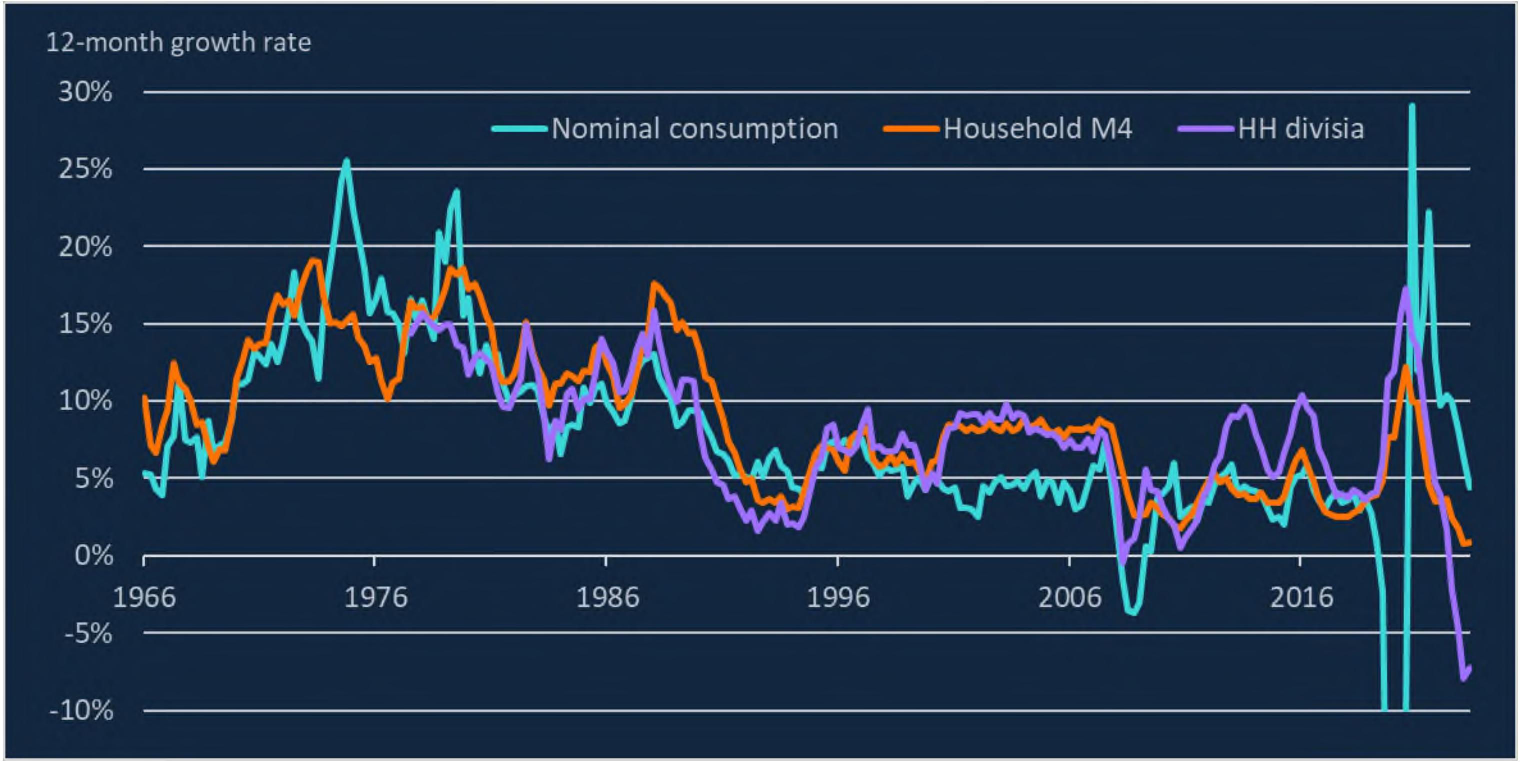
- Historically M4ex driven by lending to private sector (blue bars) and MFI purchases of govt. debt (pink and red bars)

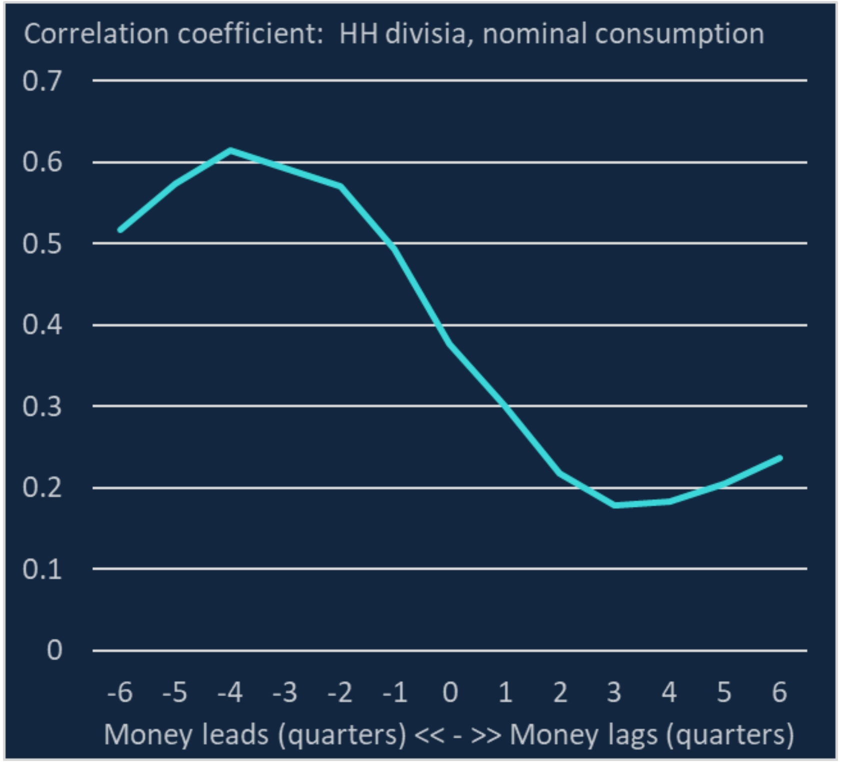
Aggregate Broad Money Growth and CPI inflation since 1780



- Link between broad money growth and inflation/nominal spending not always obvious in the headline data, notably the 1980s to the early 2000s

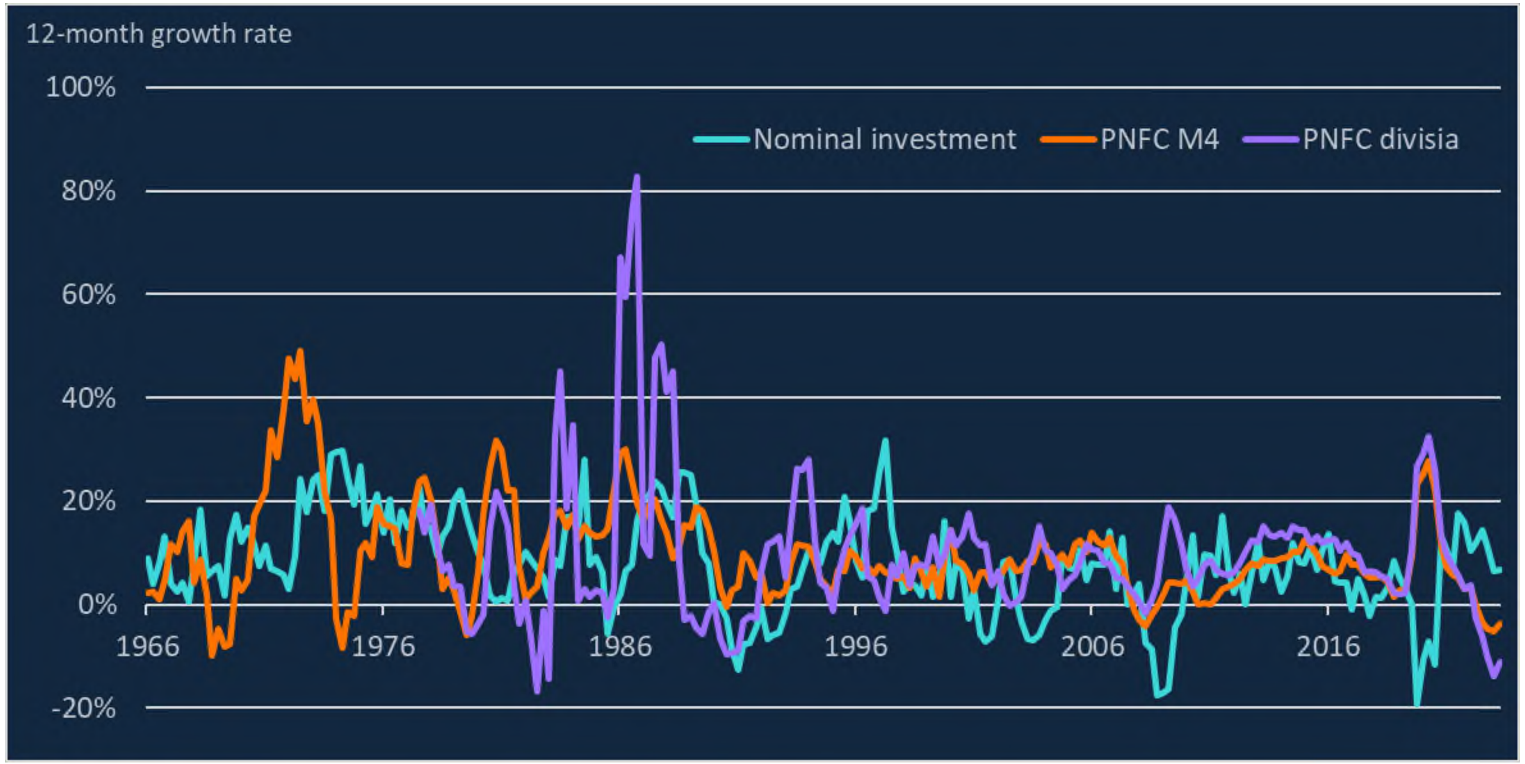
Relationships more obvious at sector level and/or using weighted Divisia indices rather than simple sum

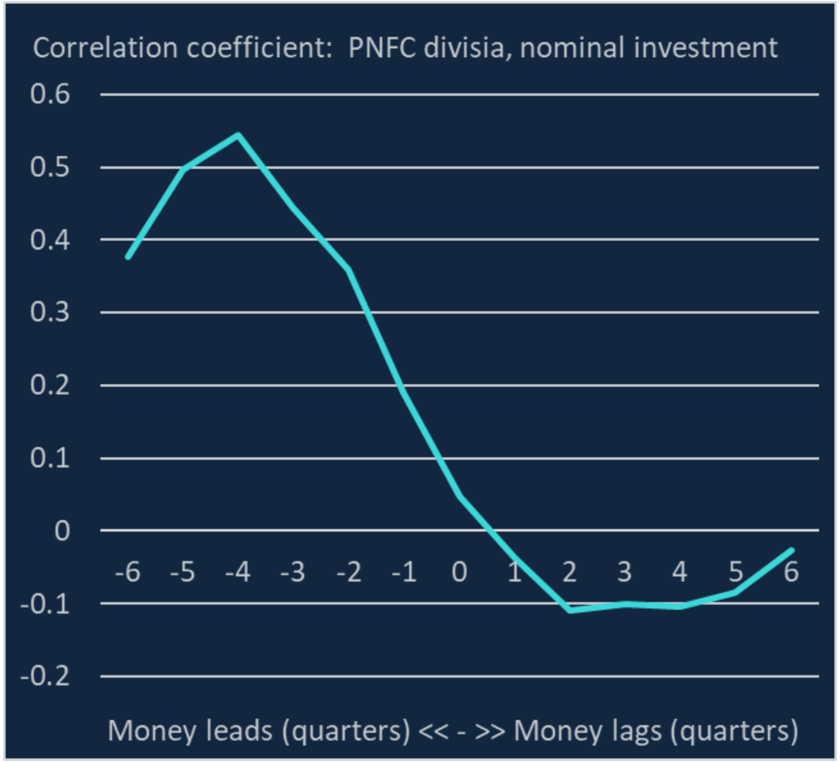




- Household M4/Divisia and consumption are reasonably well correlated
- Household money/Divisia often appears as a significant term in estimated consumption equations
- Divisia predicted turning points in the GFC
- But since GFC/low-rate environment Divisia more volatile than simple sum M4 related to consumption

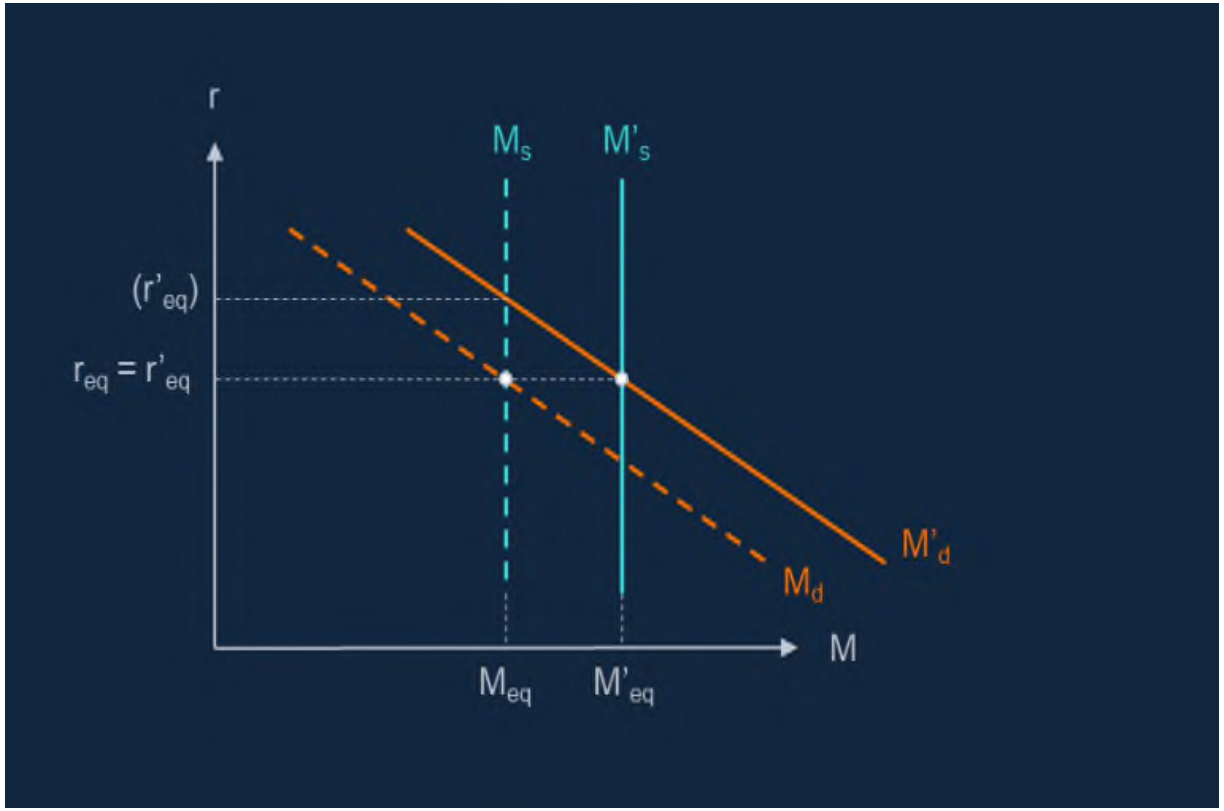
Previous work has found evidence that PNFC money is a leading indicator of investment

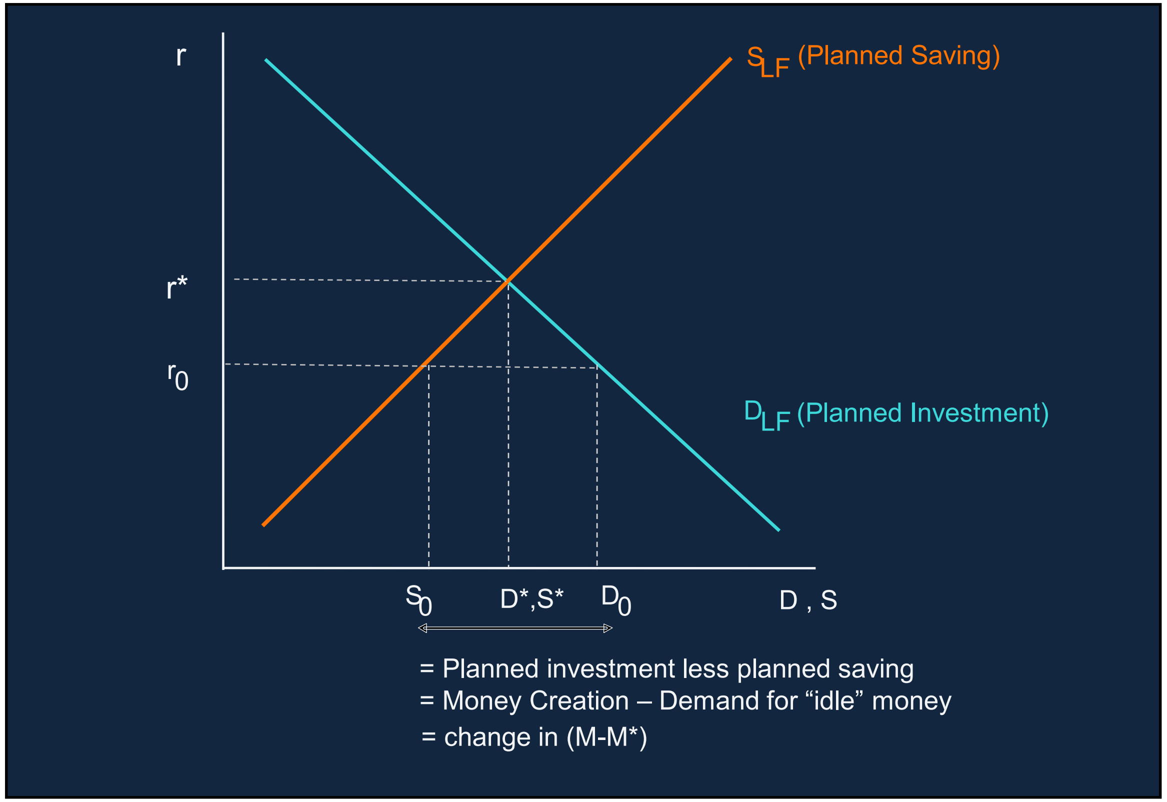




- Thomas (1997), Bridgen and Mizen (2004) and Cloyne et al. (2015)

Money overhangs (M-M*) rather than growth are a better reflection of monetary conditions





- A shift in the money supply in response to a shift in money demand will not imply a loosening of monetary conditions
- Loose monetary conditions will be indicated by money supply growth in excess of underlying demand for money (M*).

Implications

- At any one time the money supply is pinned down by provision of credit to public and private sector

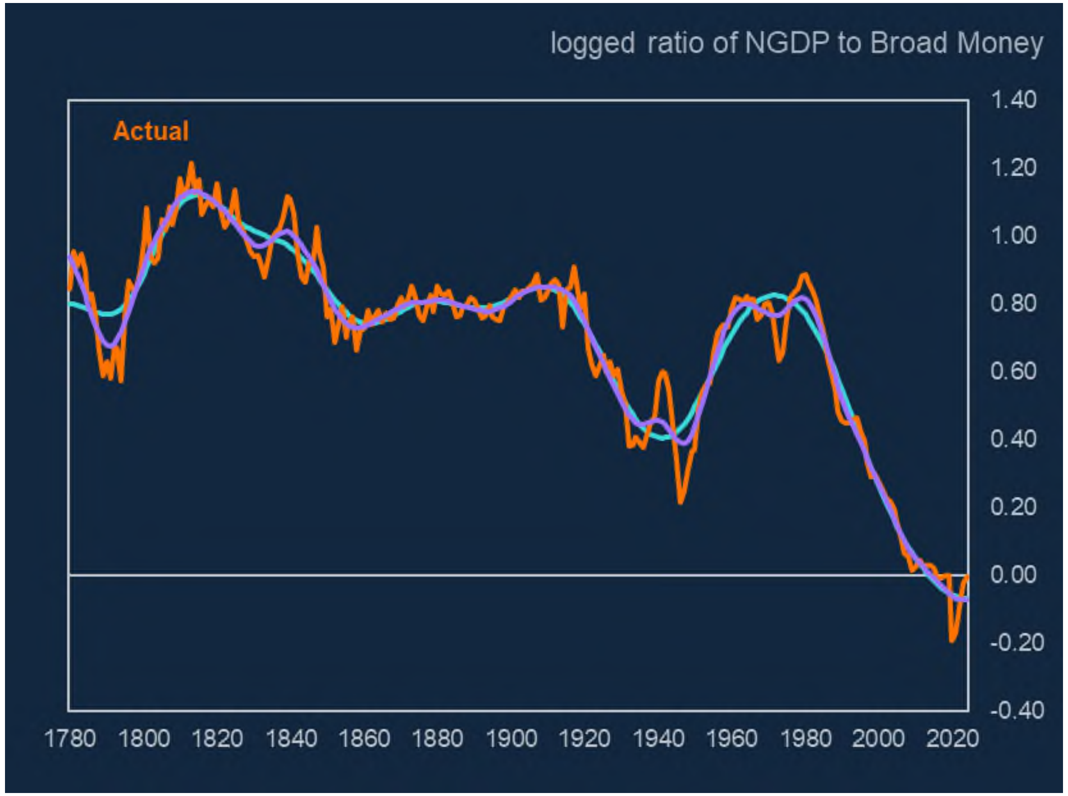
- This might differ from the “demand for money” over the longer term by different sectors
  - Buffer-stock ideas: money “accepted” in SR but not necessarily demanded
  - Demand for money an average/target amount of money, “M*”
  - Individual agent versus aggregate adjustment: hot potato effects

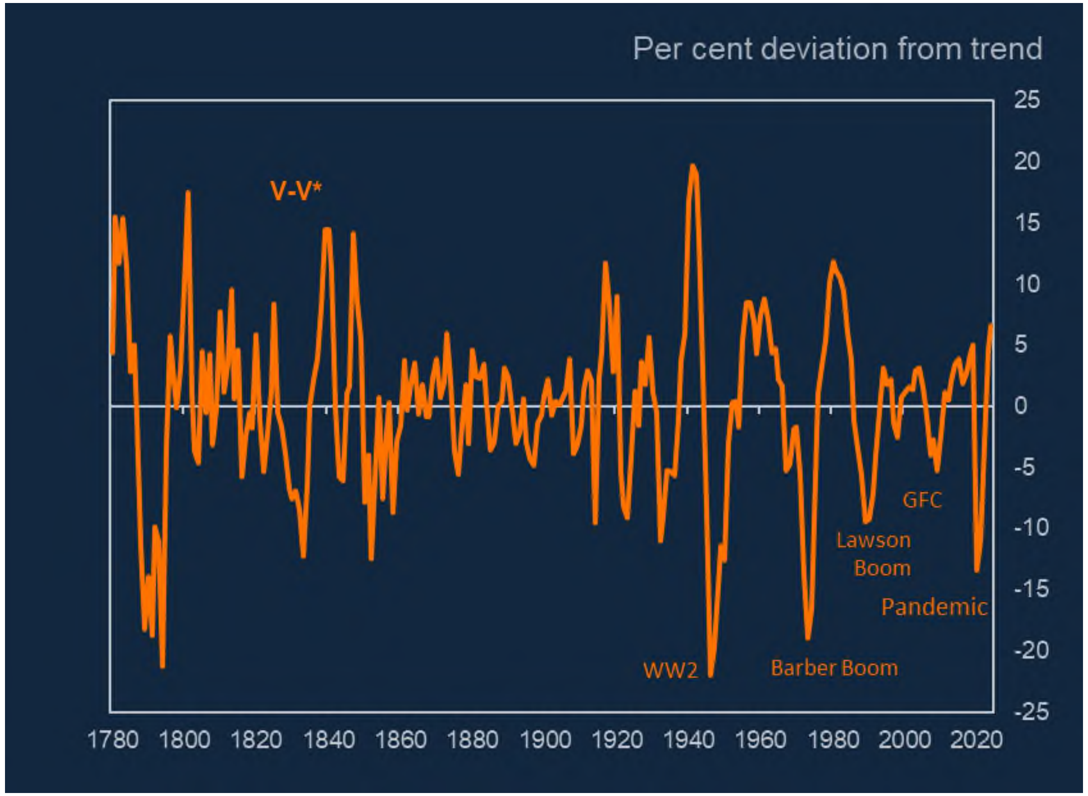
- But the demand for money M* will depend on
  - Expected/Planned Nominal spending
  - Relative rates of return/Divisia user costs
  - Structural factors (often picked up by a filter)
  - Uncertainty/precautionary behaviour (difficult “will-o’-the-wisp” factors to pick up e.g. dash for cash)

- Balance of Ms and Md summarised by “monetary overhangs” or “velocity gaps”

- Do these gaps have incremental information for demand and inflation over and above yields and interest rates or do they merely corroborate ?

Velocity gaps in UK history





- Bordo and Jonung (1981) discuss U shape trends in velocity reflecting waves of financial deepening and innovation
- Deviations from trend show lots of "V's" in velocity, but speed and nature of adjustment varies
- How do M and NGDP adjust to velocity gaps ? Why are there long and variable lags ?
- Thomas (forthcoming) provides some simple reduced-form metrics

Does the money supply or the economy make the adjustment ?

- Reduced-form cointegrated VAR/VECM in money gap space (inverse velocity)

$$\begin{bmatrix} \Delta m4x_t \\ \Delta ngdp_t \\ \Delta rgdp_t \end{bmatrix} = \; lags \; + \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} [m4x_{t-1} - ngdp_{t-1} - trend] + \varepsilon_t$$

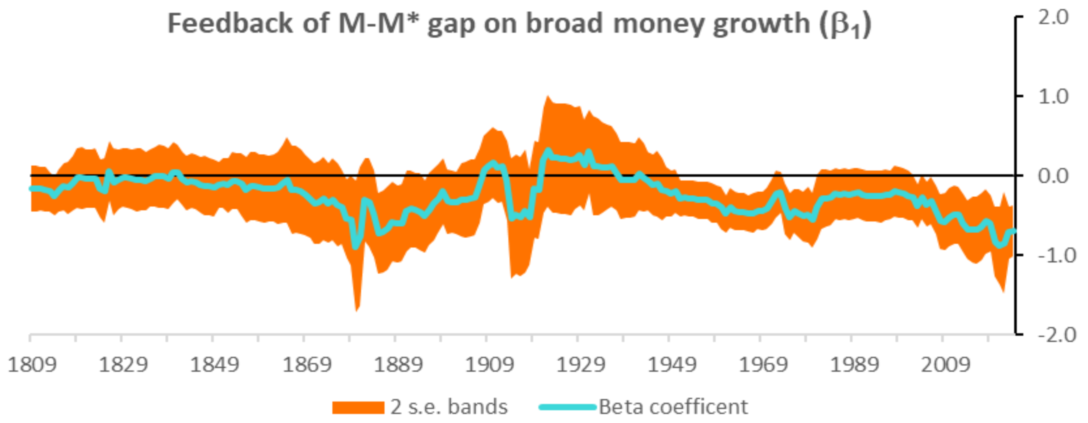
- If there is a money gap does NGDP (and in short run) RGDP adjust to return velocity to equilibrium ?
  - Monetarist hypothesis $\beta_2 > 0$, $\beta_3 > 0$

- Or does money growth subsequently fall back ? $\beta_1 < 0$
  - Normal reflux, firms repay debt with lag "real bills doctrine"/"Kaldor effect"
  - Monetary policy acts in time to prevent activity and inflation from picking up, "monetary policy acts as a stabiliser".
  - Financial crisis occurs before there is a chance of boom in output and inflation occurring

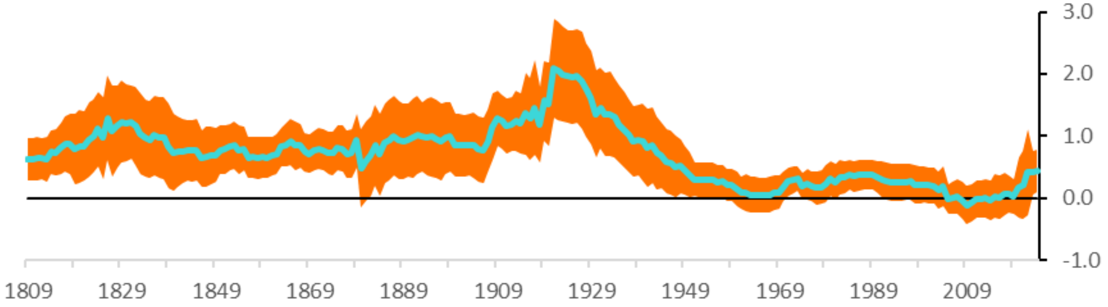
- Maybe little feedback happens because of unobservable shifts in the demand for money not captured by velocity trend $\beta_{1,2,3} \approx 0$ but gap based on velocity trend used earlier does appear stationary.

Feedbacks from the money gap

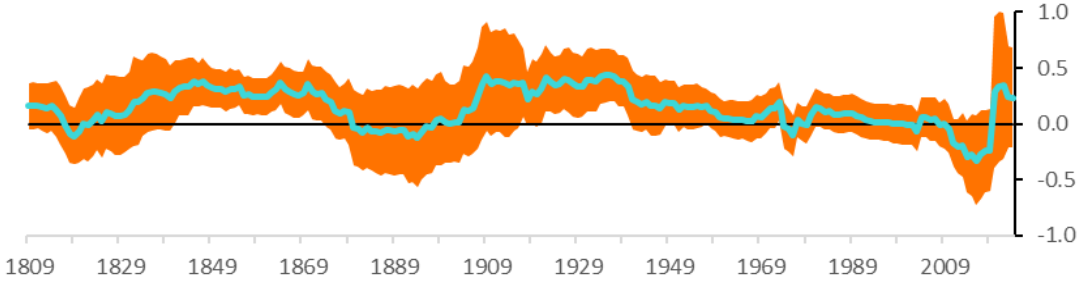
Feedback of M-M* gap on broad money growth (β_1)



Feedback of M-M* on NGDP growth (β_2)

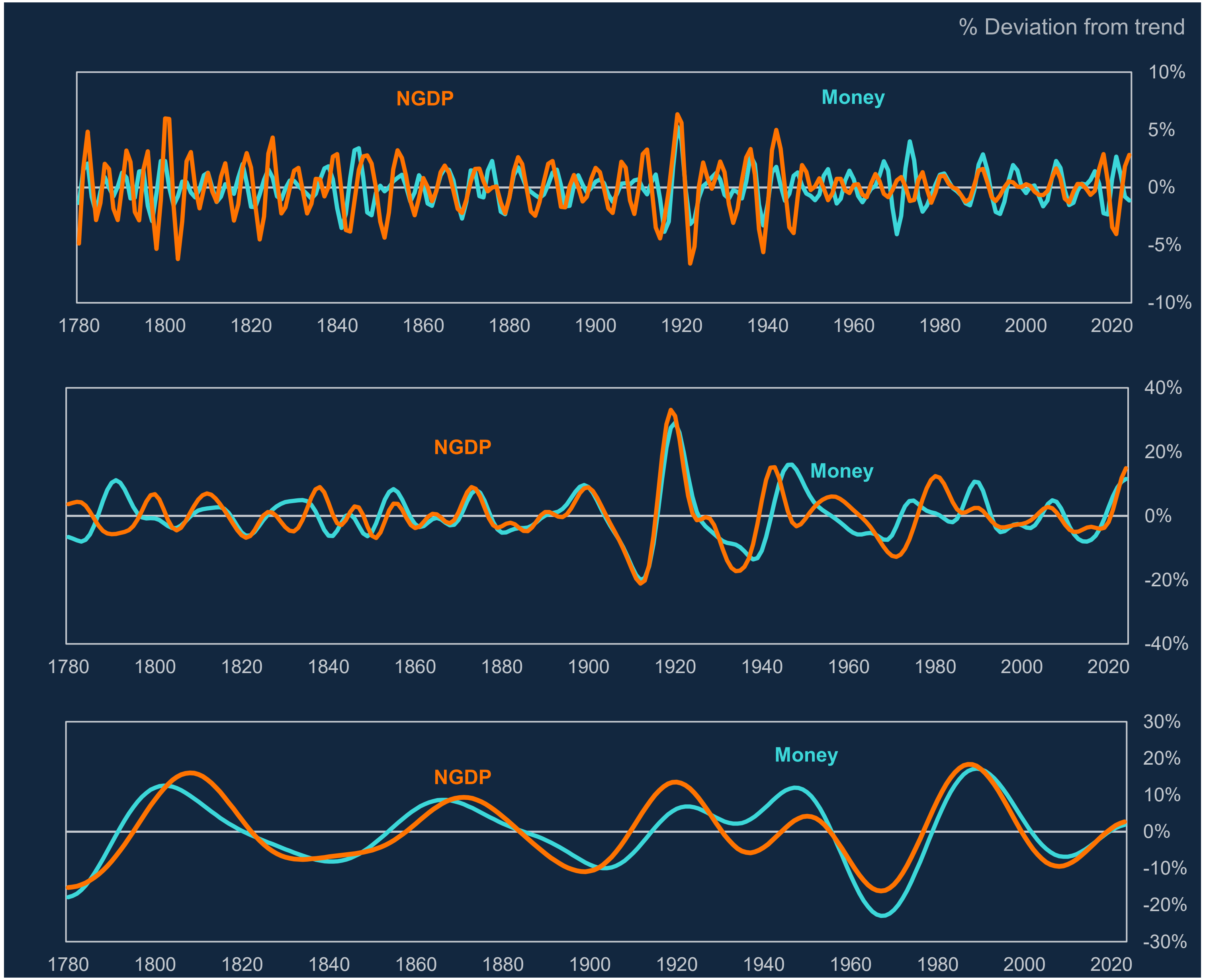


Feedback of M-M* on RGDP growth (β_3)



- Rolling VECM regressions over 30 years
- Negative feedback on money growth often insignificant particularly in C18th and early C19th, but appears significant during fixed exchange rate regimes and for most of post-war period. Increases during IT regime.
- Nominal and Real GDP significantly and positively affected by money gaps on average over whole sample. But relationship largely driven by pre-WW2 data, though note the tick up in significance post-pandemic period
- Periods when both money and spending react significantly to money gaps, appears to be true of recent period

Money and Nominal GDP more correlated at lower frequencies



Business cycle

(4-8 years)

r_{xy} = 0.35

Credit cycle

(8-32 years)

r_{xy} = 0.67

Long cycle

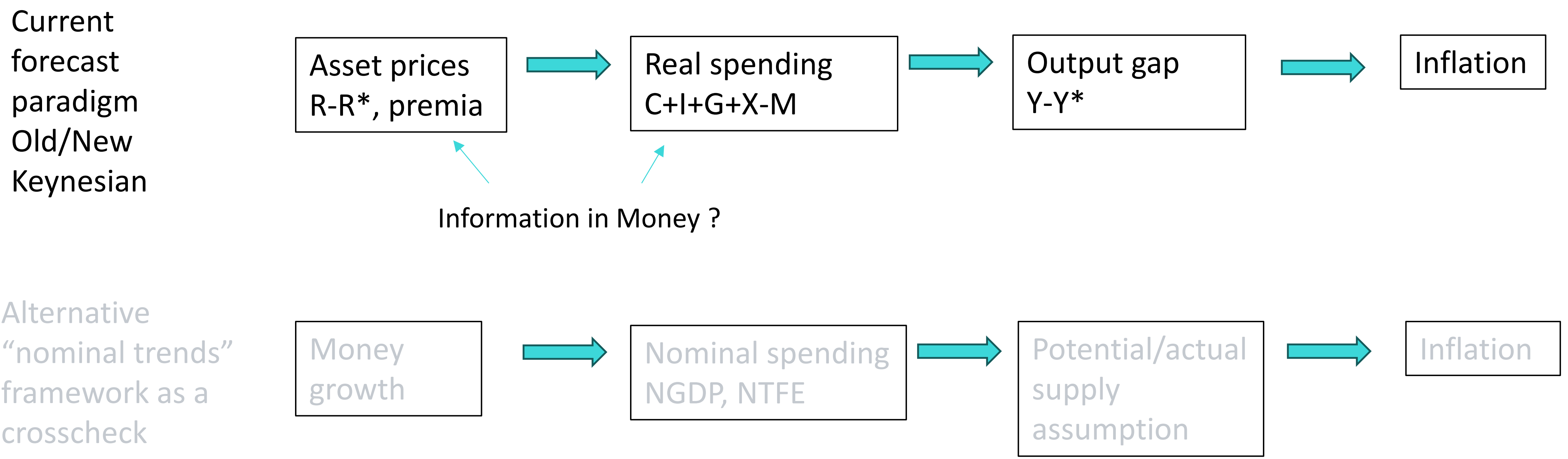
(32-64 years)

r_{xy} = 0.86

QE1

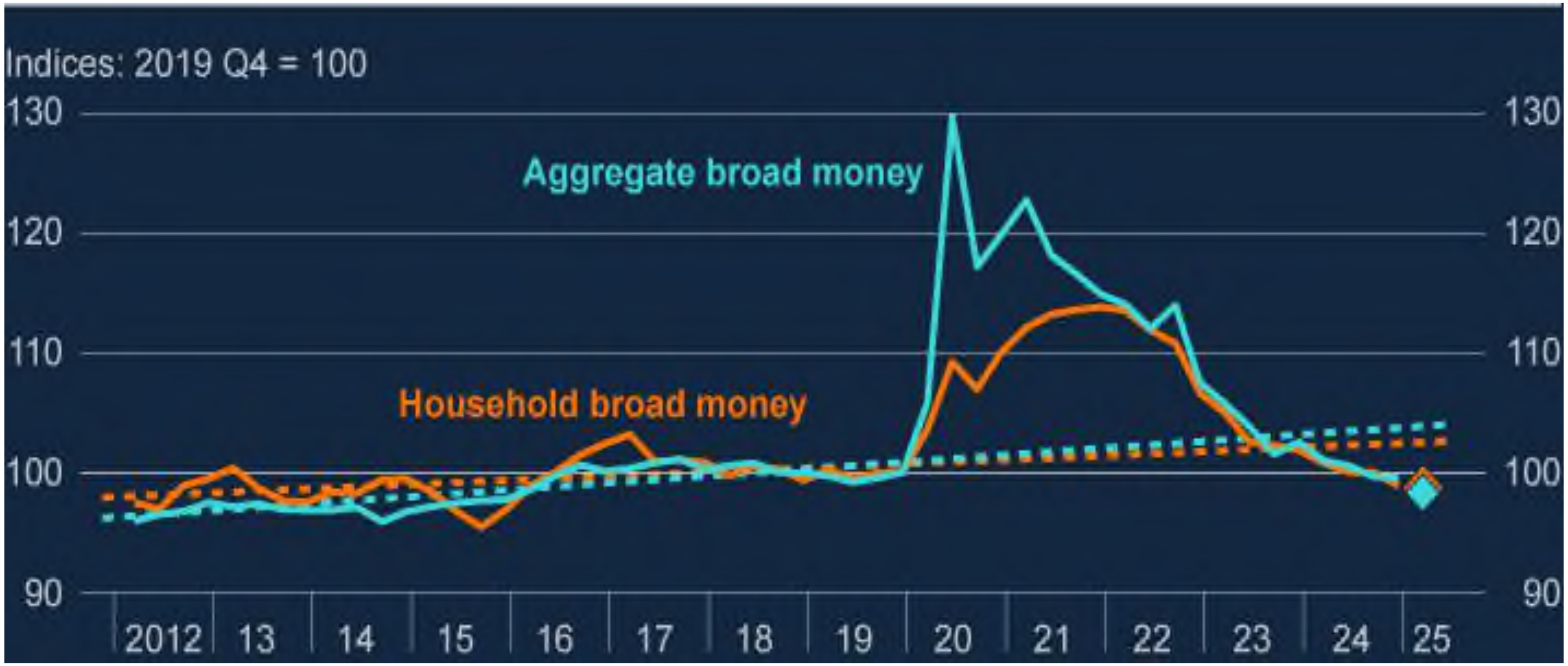
Money and monetary policy in practice at the BoE

Money in the MPC forecast process



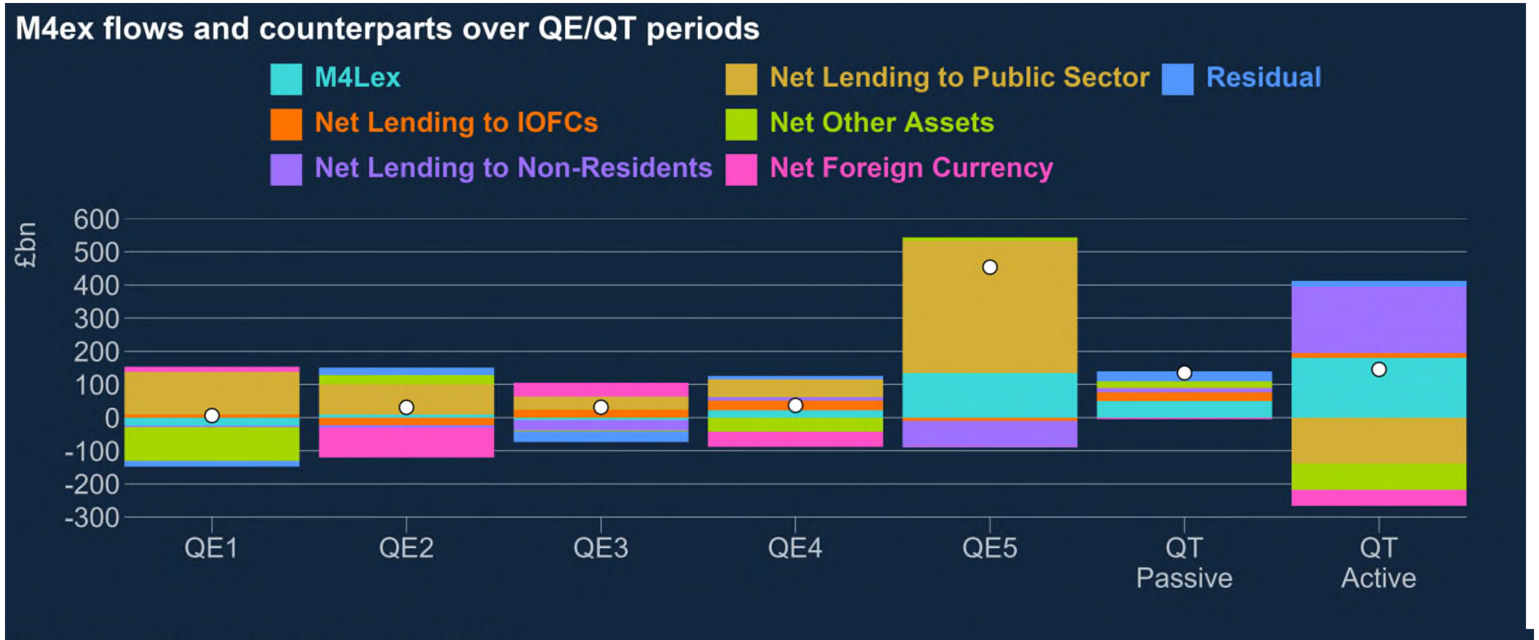
- Typically analysis of money and credit has fed into what is essentially a Keynesian paradigm
- Sectoral money and credit as additional variables in consumption and investment equations
- Money and credit in SVAR analysis to help identify shocks to the banking system/credit spreads and QE
- Forecast is conditioned on asset prices/yields, so captures any effects of money already embodied in them

2020: the emergence of the money overhang in the pandemic



- A significant overhang emerged in 2020 and 2021 in both aggregate and sectoral measures of money
- This followed £440bn of QE gilt purchases (QE5) over two years (18% of M4ex)
- The pick up in nominal spending in 2022 and 2023 led to closure of the money gap
- How was this analysed at the time?

2020: The link between QE and broad money was uncertain



Source: Bank of England. Latest data up to 31 Jan 2026. QE1 data covers the period only from July 2009 when monthly flows of M4ex are available.

Table A Estimated impact of QE1 and QE2 on broad money[a]

Factor	QE1[b] (£ billions)	QE2[c] (£ billions)
Direct effect of asset purchases	200	125
minus corporate substitution from bank loans to capital markets attributable to QE	16	8
minus purchases of debt and equity issued by banks attributable to QE	62	0
minus purchases of non-resident assets attributable to QE	0	16
minus bank sales of government debt attributable to QE	0	31
Estimated impact of QE net of indirect leakages	122	70
Impact of QE on broad money as a percentage of asset purchases	**61%**	**56%**
Actual broad money flow	13	31
Implied counterfactual flow	-109	-38

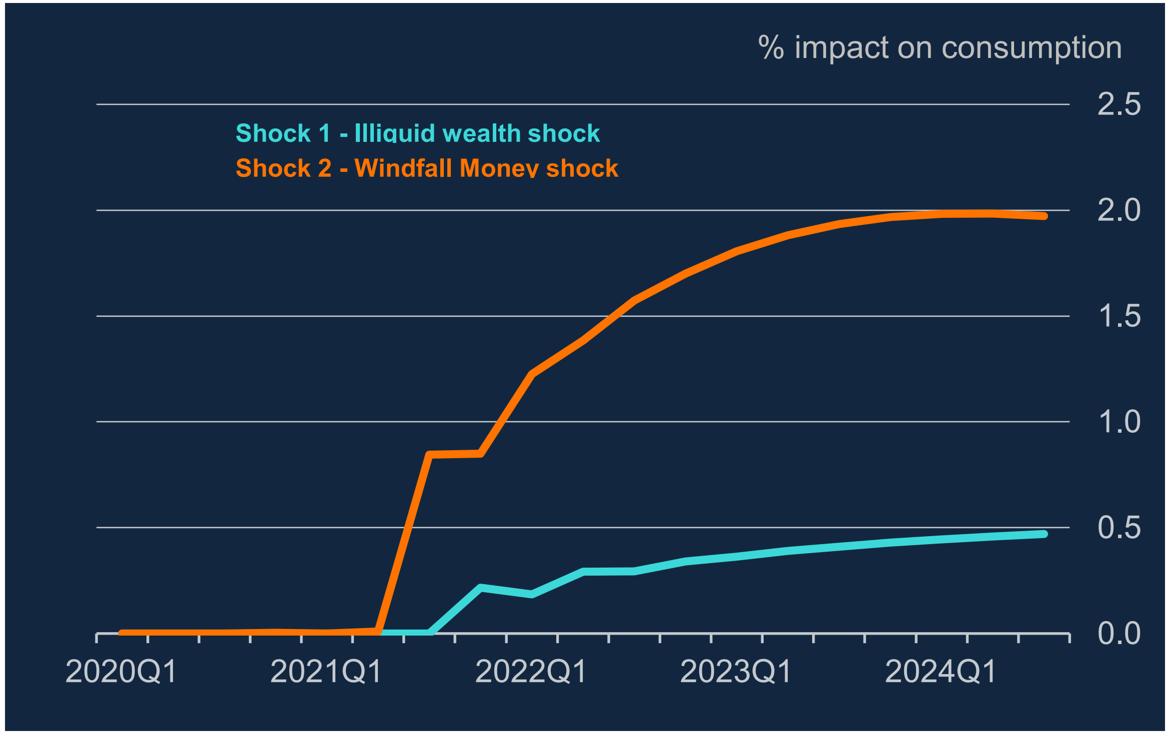
Sources: Bank of England, Bridges and Thomas (2012) and Bank calculations.

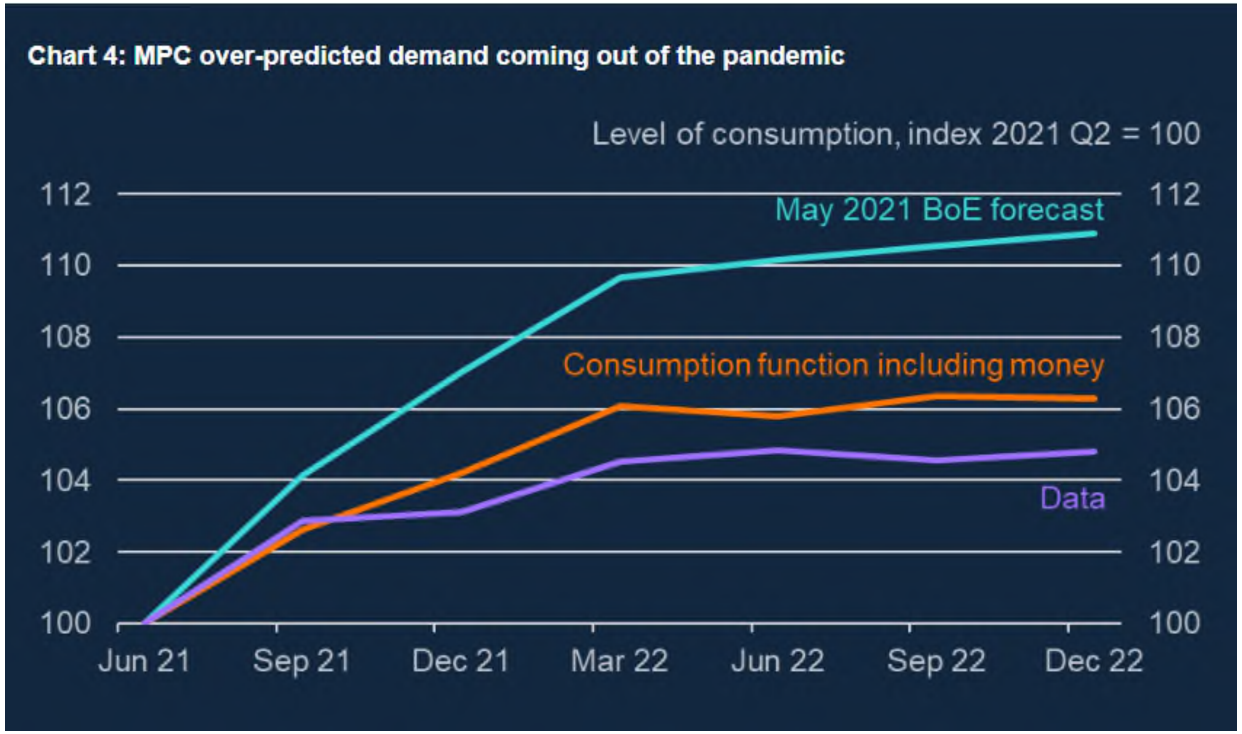
(a) M4ex — that is M4 excluding intermediate 'other financial corporations'.
(b) The period covers 2009 Q2 to 2010 Q1 as monthly data were not available.
(c) The period covers October 2011 to April 2012.

Source: BEQB by Butt et al. (2012)

- Initial rounds of QE had little impact on broad money because of other offsetting factors on banks' balance sheets
- Some factors may be endogenous response to QE, others bespoke factors operating independently of QE
- Each round of QE has led to different balance sheet counterparts, which may be indicative of state contingency
- QE1 to 4 our ready reckoner was that £xbn of QE led to 0.6 x £bn on broad money
- QE5 however did not exhibit any net leakages

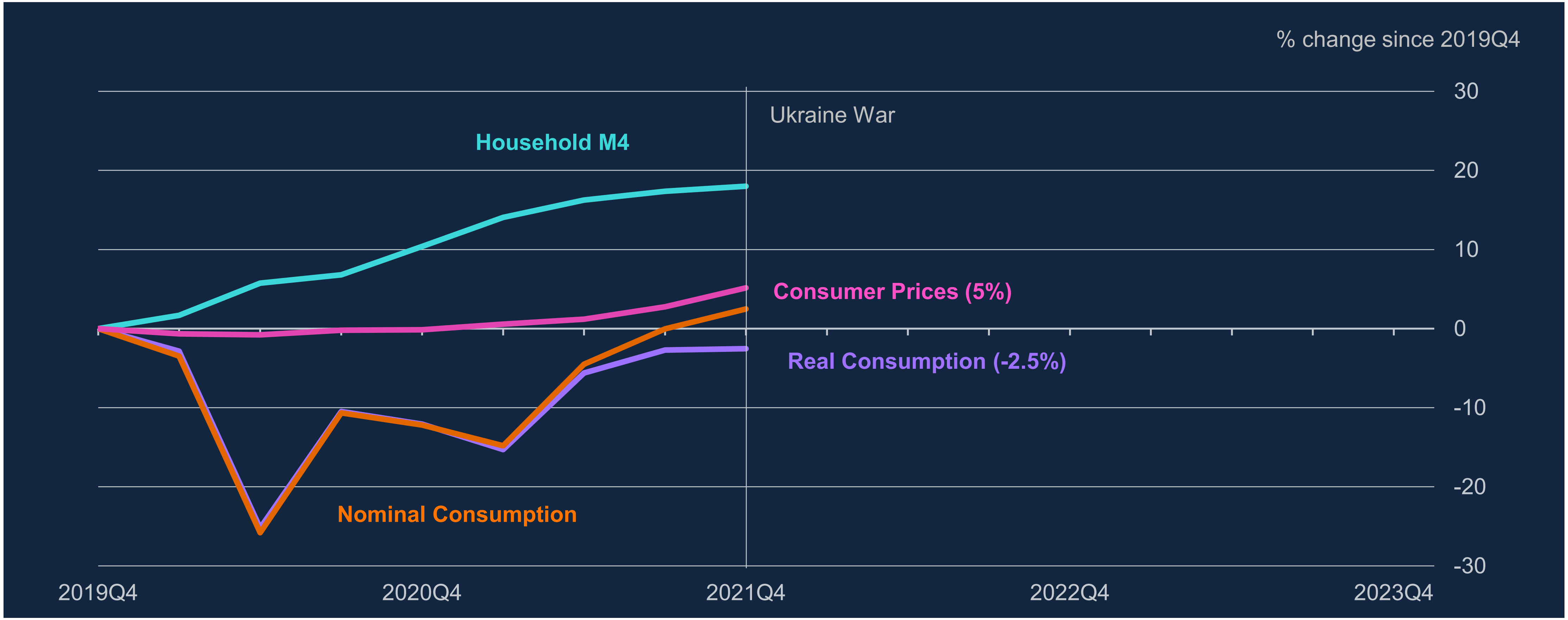
II 2021: Impact of the money overhang in the pandemic





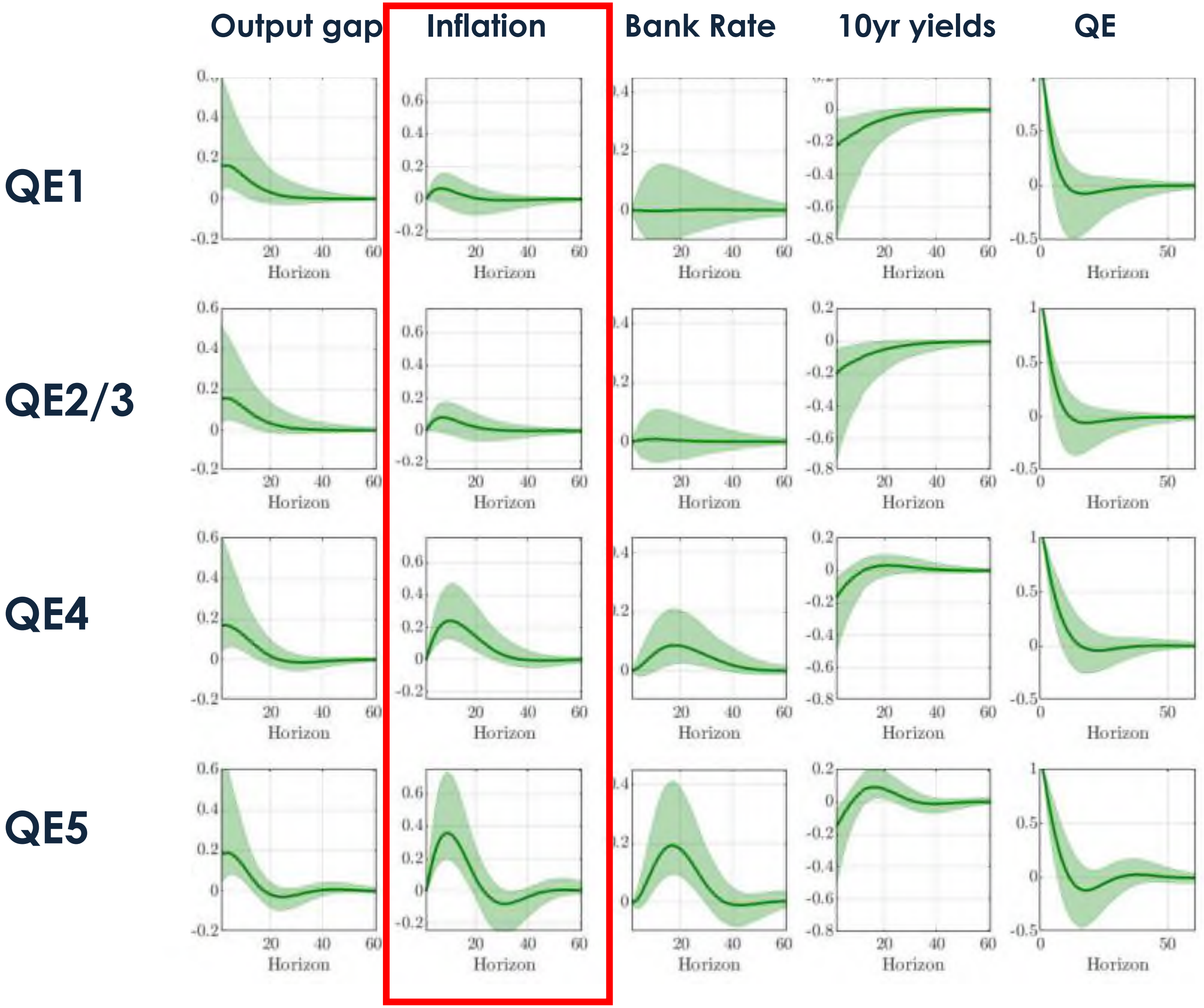
- Our models that contained money had stronger effect on consumption than treating it as an illiquid wealth/annuity value impact (LHS chart)
- However, such models overpredicted <u>real</u> consumption (RHS chart) in 2021 and 2022

III Late 2021 and 2022 – too much money or too few goods ?



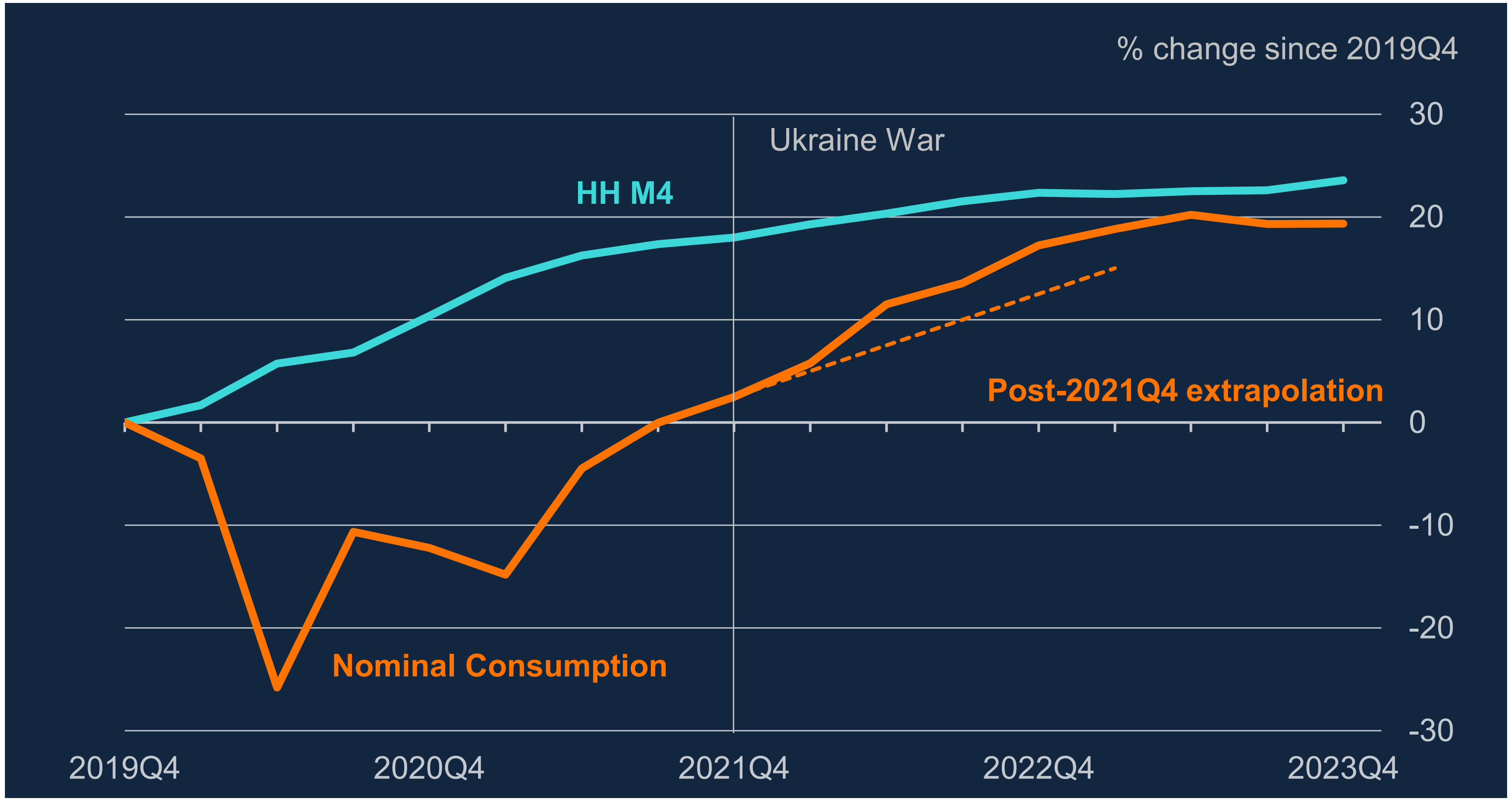
- At the end of 2021 nominal consumption no higher than pre-pandemic and well-below pre-pandemic trend, despite near 20% increase in HH money. Inflation pick up was due to weak supply, real consumption was lower than 2019Q4 and consumer prices higher as a result.

State contingency of QE – Impact of QE worth 1pp of M4ex



- TVP-SVAR analysis of different QE episodes using money data suggests large increase in slope of Phillips curve in QE5
- Ellington, Milas and Thomas (SWP forthcoming)

III Did energy prices trigger a larger adjustment in velocity ?



- Would nominal spending growth have been weaker in absence of Ukraine War ?
- Was it the spark that forced adjustment of velocity ?
- Is the impact of a given money gap state contingent and interacting with relative price movements ?

Key points/Lessons

- Important to analyse apparent money overhangs/underhangs when they emerge "Canary in the coalmine"

- MPC *were* looking at money gaps during the pandemic but MPR language couched in terms of "cumulative savings" and impact on real consumption
  - The discussion was not visible in the MPR, role of money and nominal adjustment risks not articulated

- Keynesian framework may have suggested there was more time to react to any inflationary impulse from the money overhang
  - Focus on real demand/output can be misleading in a system with supply chain pressures
  - Lags to prices can be short and variable !

Going forward: Nominal Trends Framework useful as a crosscheck

Current forecast paradigm

Asset prices R-R*, premia → Real spending C+I+G+X-M → Output gap Y-Y* → Inflation

Information in Money ?

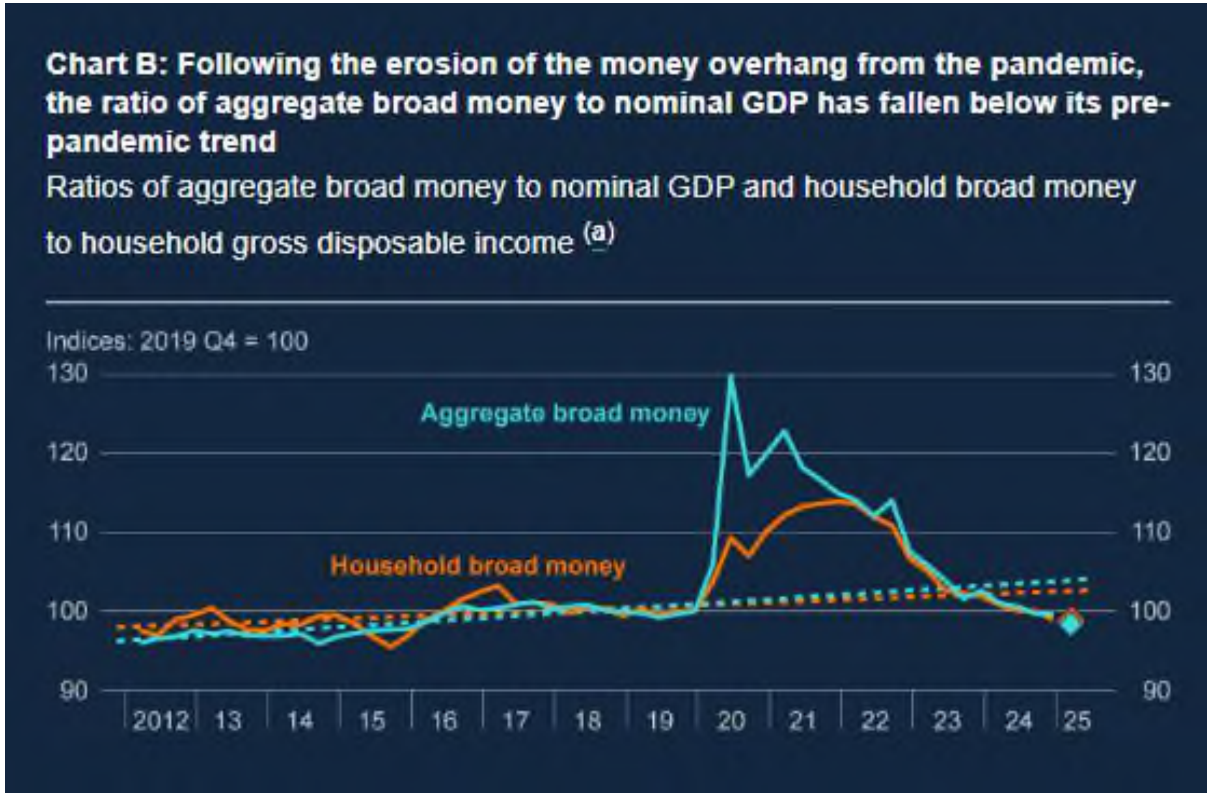
Alternative “nominal trends” framework as a crosscheck to assess risks

Money growth → Nominal spending NGDP, NTFE → Potential/actual supply assumption → Inflation

- Useful to use money as a part of a nominal trends framework as a crosscheck to assess risks rather than shoe-horn money into a Keynesian framework

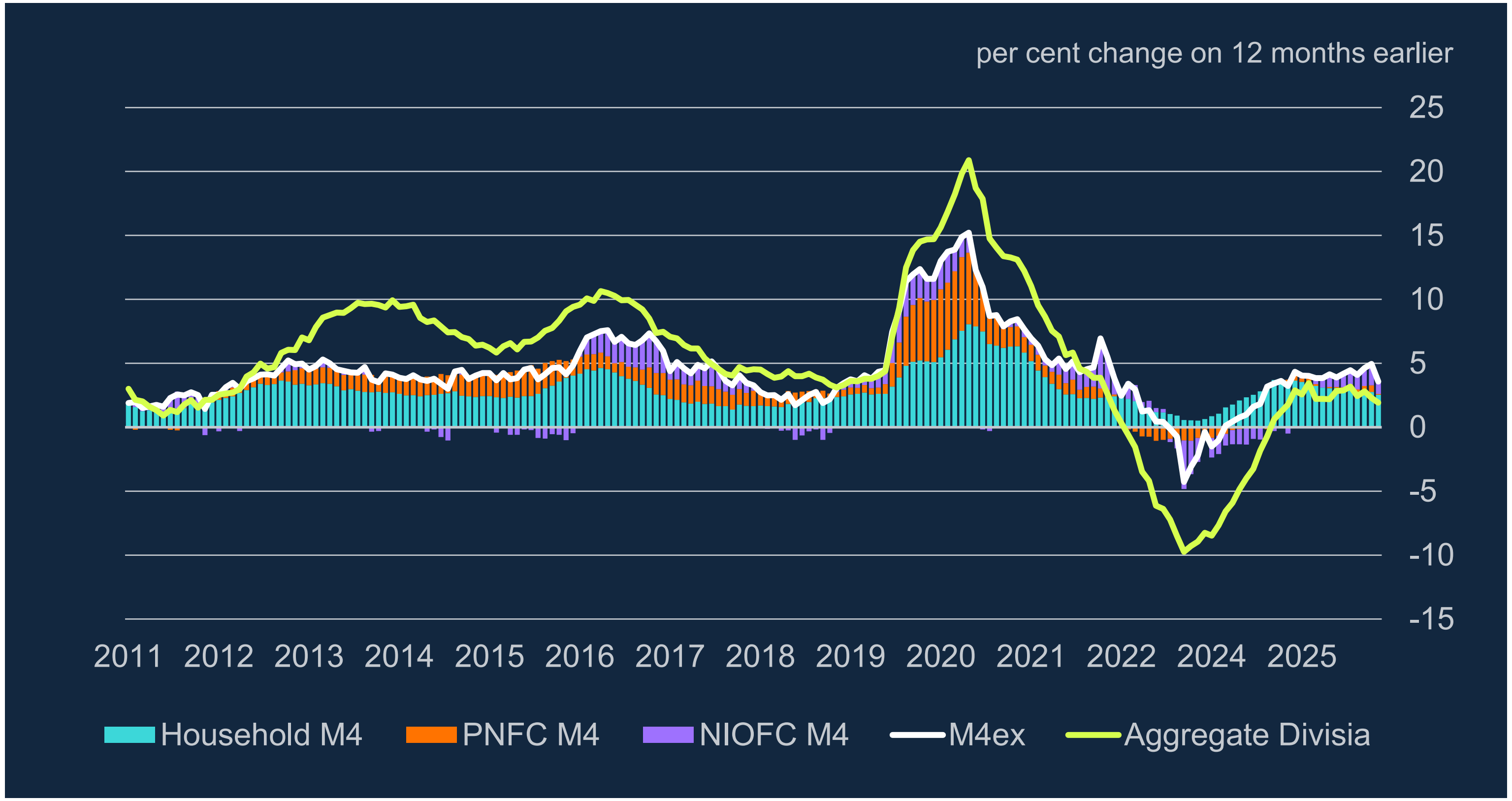
Recent developments and going forward

- Since 2024 we have introduced a regular box in the MPR assessing monetary trends



- Analysis is based around simple money gap estimates, “canary in the coalmine”
- Last year’s box highlighted the possibility of a money “underhang” emerging based on an extrapolation of simple trends for velocity, albeit respecting the considerable uncertainty about M*

Current trends in money growth



- Aggregate and HH M4 growth is growing roughly in line with rates consistent with inflation at target despite QT dragging on money.
- NIOFC borrowing and deposits have been volatile, strong at the end of last year but now have unwound a bit in the latest data
- Divisia growth weaker than simple sum aggregates at around 2%. Money gap is further “under water” on this measure
- **Future development.** Need explicit projections of money growth and the money gap to assess risks

ECB Monetary Analysis

Miguel Boucinha
ECB, DG Monetary Policy

Analysing the Information Content of Money –
central bank practice and recent academic research

The views expressed in this presentation are my own and do not necessarily reflect the views of the European Central Bank or the Eurosystem

Bank of England
4 March 2026

Outline

1 Beyond a single indicator, a consistent framework

- ❑ From bi-variate relationships between headline series…
- ❑ … to “looking under the hood”

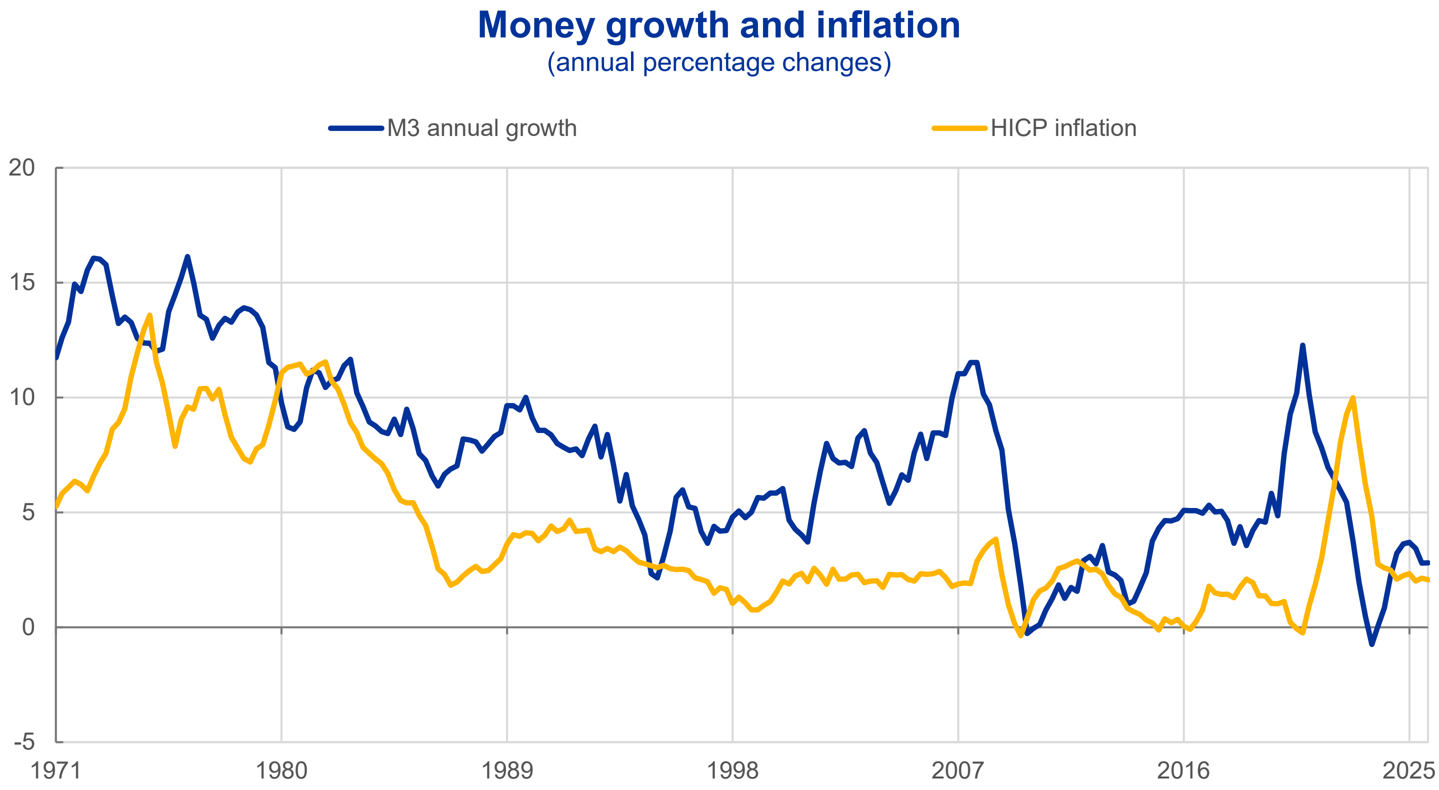
2 Signals from monetary analysis in the current setting

- ❑ Drivers or monetary flows and their implications
- ❑ Assessment of credit dynamics
- ❑ Risks for transmission

3 New forms of money and their implications for transmission

- ❑ How do stablecoins affect banks?
- ❑ Can they affect monetary policy transmission?
- ❑ Does the currency of denomination matter?

Money growth and inflation

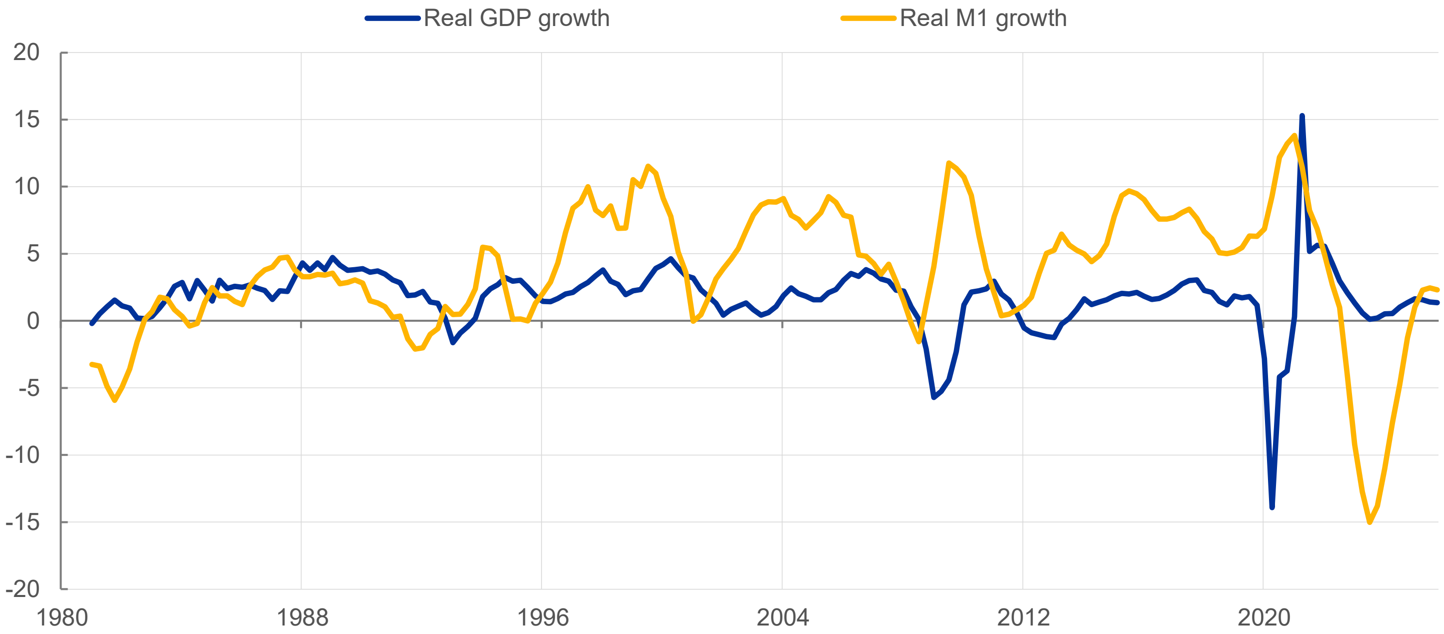


Sources: ECB (BSI), Eurostat and ECB calculations.
The latest observations are for Q4 2025.

M1 and real economic activity

M1 and GDP

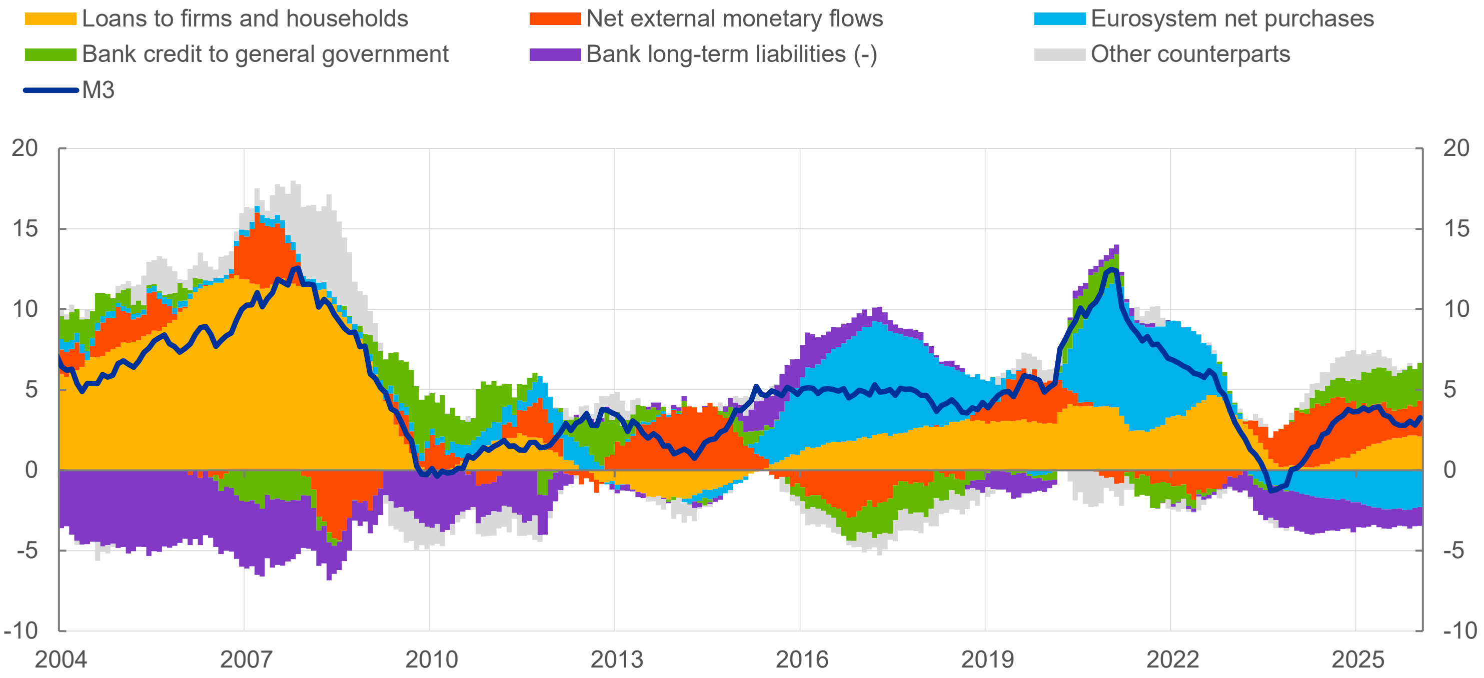
(annual percentage changes)



Sources: ECB (BSI), Eurostat and ECB calculations.
The latest observations are for Q4 2025.

Sources of money creation

(annual percentage changes; p.p. contributions)



Sources: ECB (BSI).
The latest observations are for January 2026.

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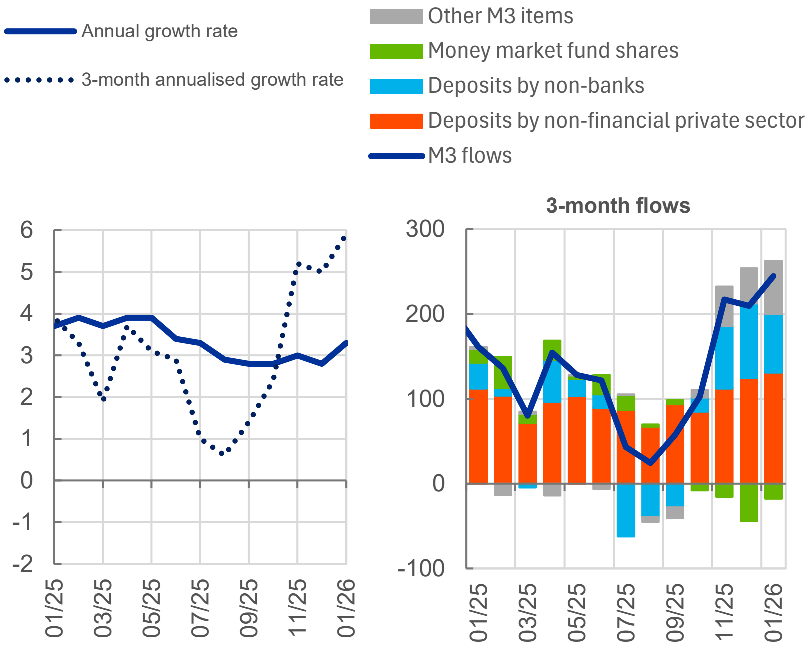
Recent pick-up in M3 driven by non-bank deposits and household portfolio rebalancing

M3 and deposits by sector

(left panel: annual percentage changes, right panel: quarterly flows in EUR bn)



Sources: ECB (BSI) and ECB calculations.
The latest observations are for January 2026
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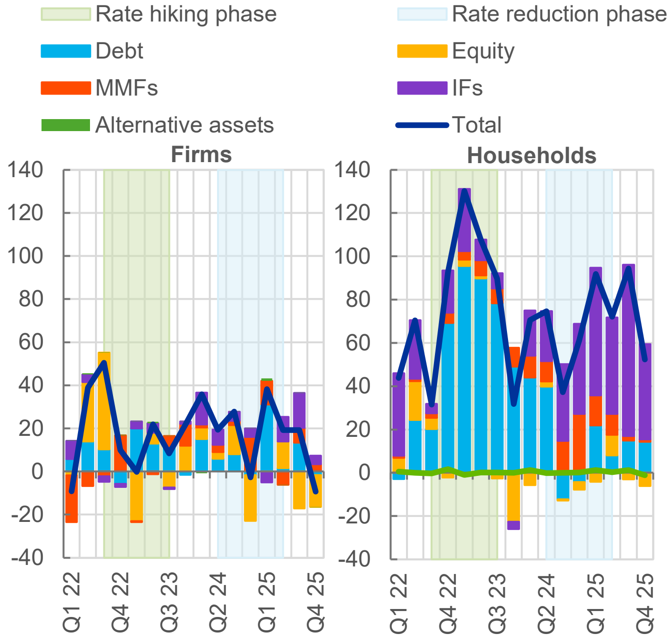
Net purchases of securities by euro area firms and households

(quarterly flows in EUR bn)

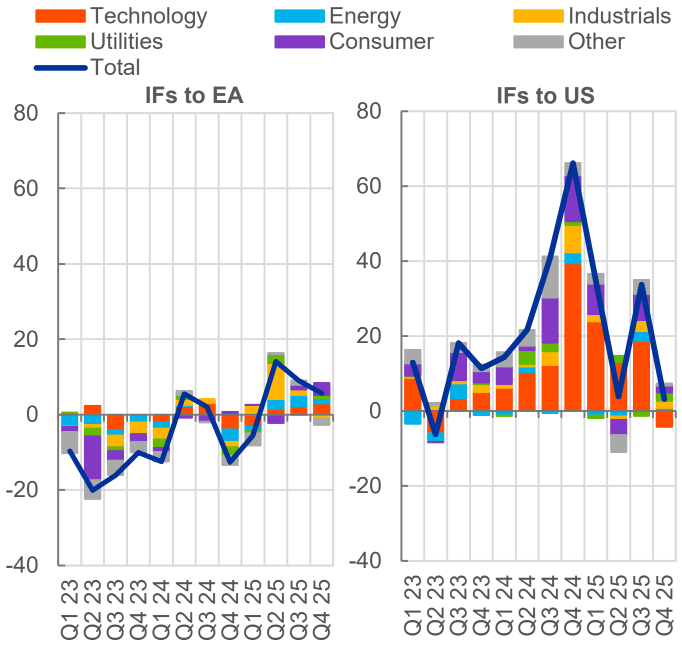


Sources: ECB (SHSS, CSDB) and ECB calculations.
Notes: Alternative assets comprise crypto and gold-related securities.
The latest observations are for Q4 2025.

Euro area investment funds tilted to US equity, amid sustained foreign demand

Net purchases of EA and US corporate listed shares by EA investment funds

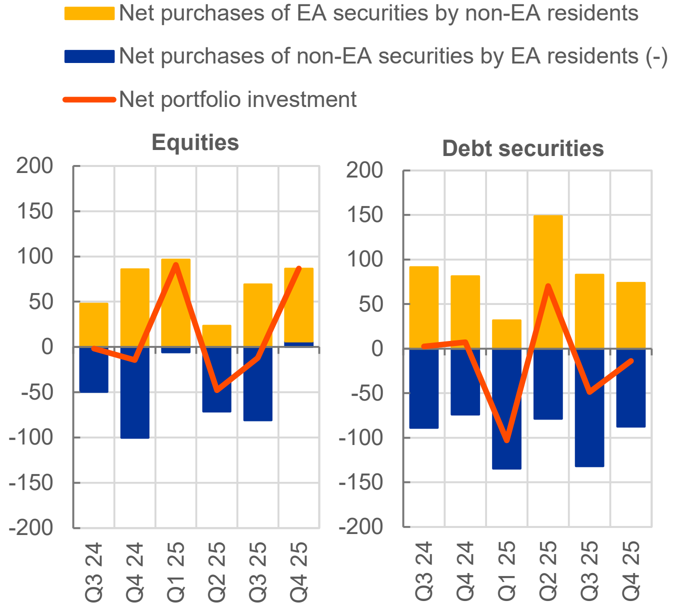
(quarterly flows in EUR bn)



Sources: ECB (SHSS), LSEG Data & Analytics and ECB calculations.
Notes: For the US, “Other” include Academic and Educational Services, Basic Materials, Financials, Healthcare, Institutions, Associations & Organizations and Real Estate. For the EA, “Other” include Academic and Educational Services, Basic Materials, Financials, Government Activity, Healthcare, Institutions, Associations & Organizations and Real Estate.
The latest observations are for Q4 2025.

Portfolio investment by EA non-MFIs and foreign investors

(quarterly flows in EUR bn)

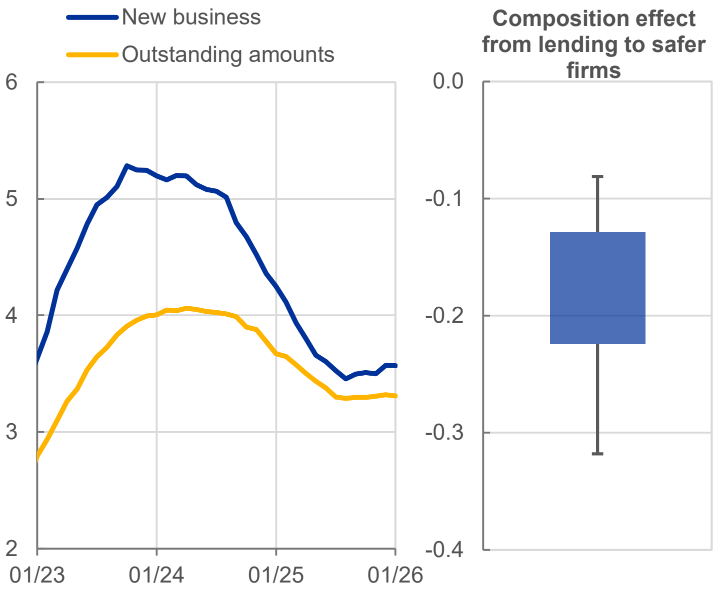


Sources: ECB (BPS) and ECB calculations.
Notes: The signs matche the related monetary flows, i.e. monetary inflows are shown with a positive sign, monetary outflows are shown with a negative sign.
The latest observations are for December 2025.

Lending rates influenced by composition effects and yield-curve steepening

Lending rates to firms

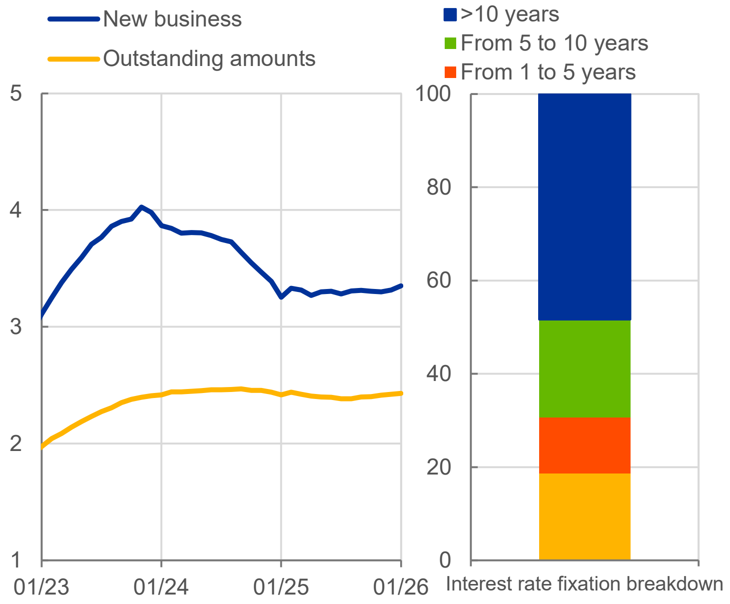
(lhs panel: percentages p.a., rhs panel: percentage points p.a.)



Sources: ECB (MIR, AnaCredit) and ECB calculations.
Notes: The right panel shows a range of impacts based on the reduction in loan growth to risky but viable firms, translated into a downward pressure on lending rates using elasticities from the literature. Whiskers are min/max, area represents the interquartile range. The latest observations are for January 2026 for the left panel and June 2025 for the right panel.

Lending rates for housing loans

(lhs panel: percentages p.a., rhs panel: percentages of outstanding loans)

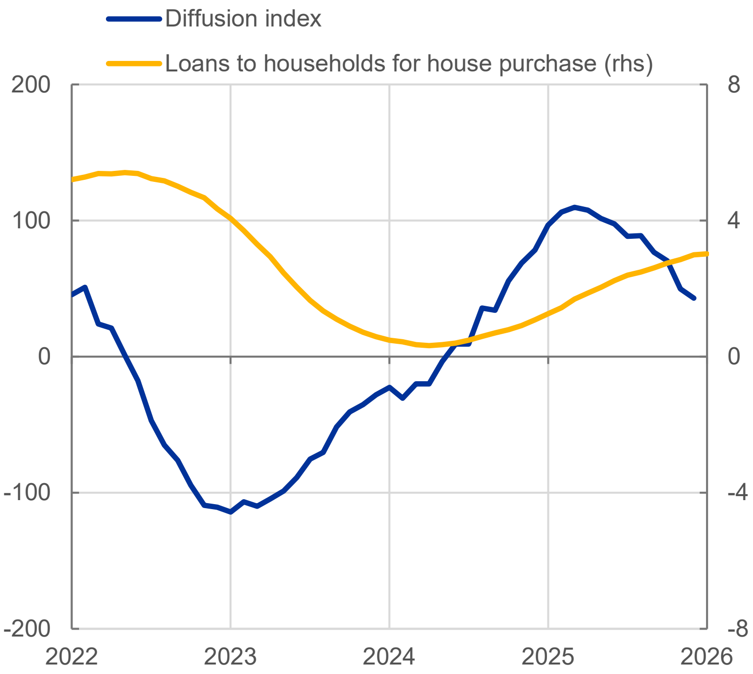


Sources: ECB (MIR), ESCB (MPC Task Force on Banking Analysis) and ECB calculations.
The latest observations are for January 2026 for interest rates and June 2024 for rate fixation.

Household lending dynamics continue to recover but with lower momentum

Loans for house purchase and diffusion index

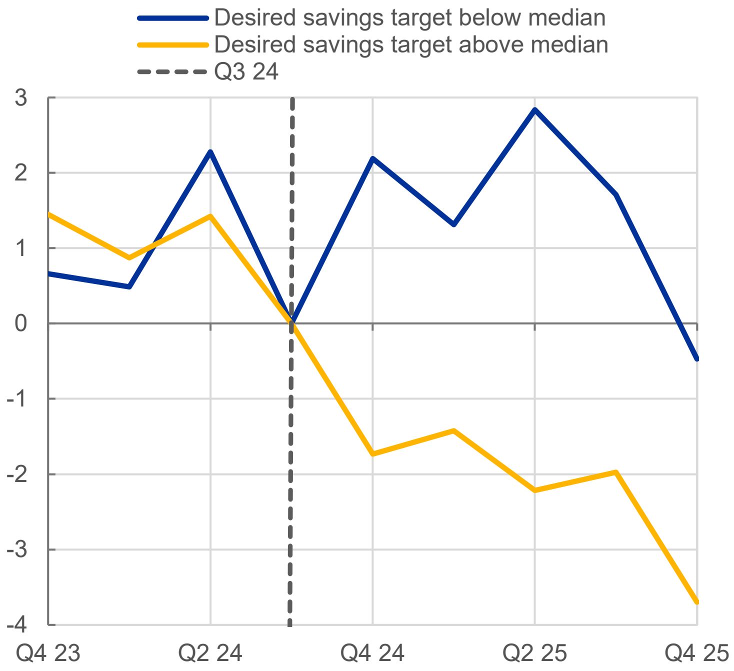
(lhs panel: percentages p.a., rhs panel: percentage points p.a.)



Sources: ECB (MIR) and ECB calculations.
The latest observations are for January 20265.

Precautionary savings targets and credit applications

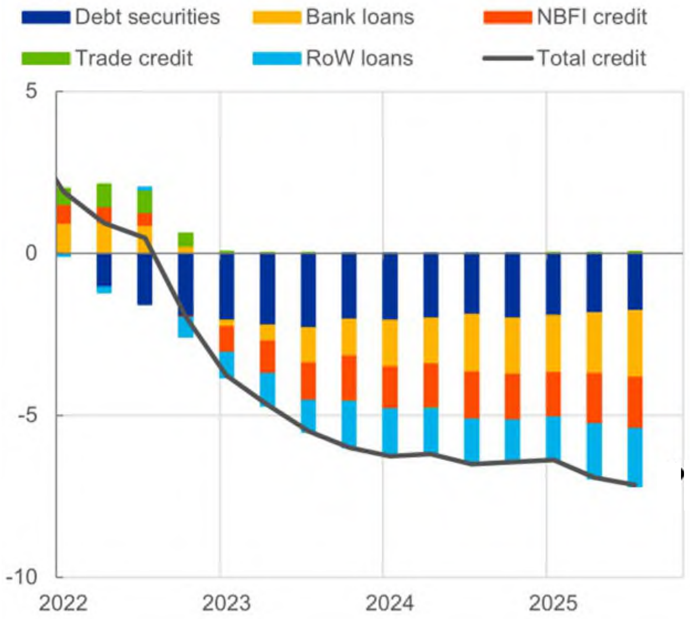
(percentage points)



Sources: ECB (CES) and ECB calculations.
The latest observations are for January 2026

Credit to firms recovered since the policy rate cuts, but remains contained

Firm credit-to-GDP gap
(percentages of annualised GDP)



Sources: ECB (QSA) and ECB calculations.
Notes: The credit-to-GDP gap is calculated using an extended version of the trend-cycle BVAR model by Del Negro et al. (2017).
The latest observations are for Q3 2025.
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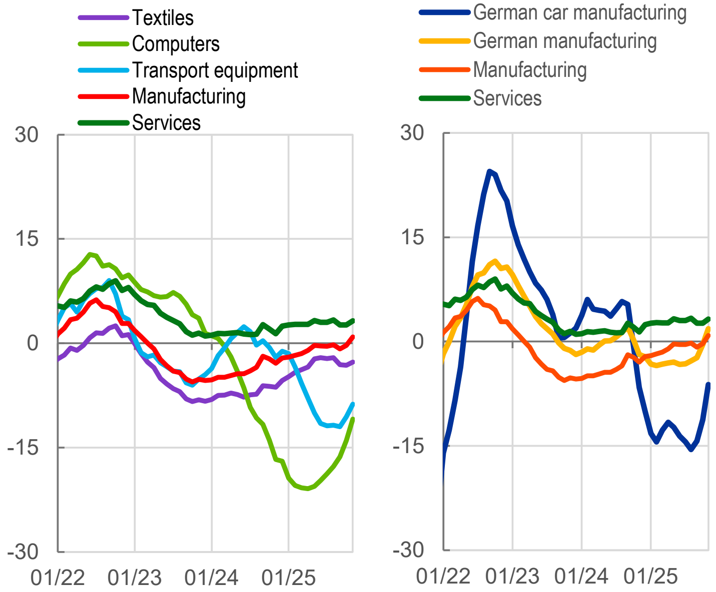
Lending to firms across sectors
(percentages per annum)

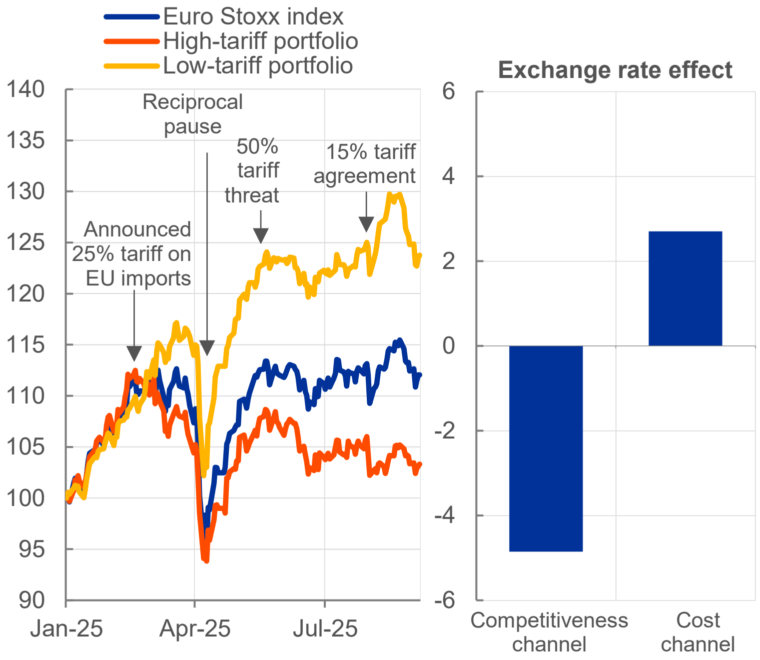


Sources: ECB (AnaCredit) and ECB calculations.
Notes: The latest observations are for November 2025.

Risks for transmission to firms and households

Risks for firms based on tariffs and euro appreciation

(lhs: index =100 on 01 Jan 2025, rhs: percentage points)

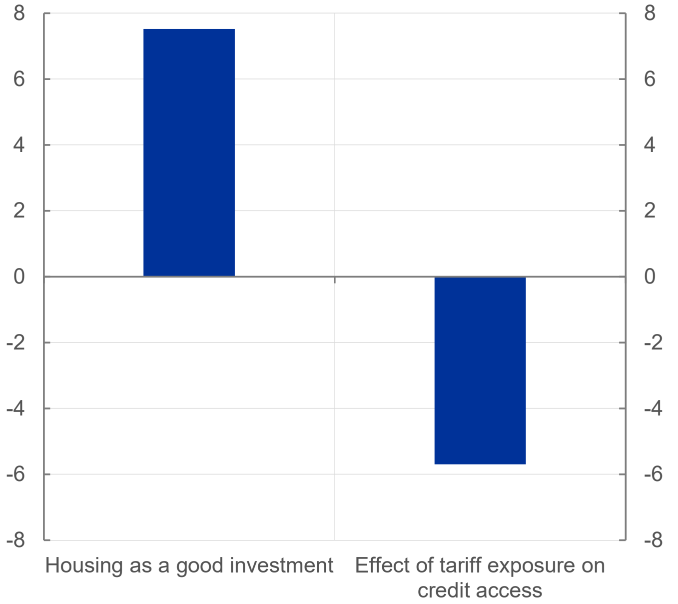


Sources: LSEG, Eurostat and ECB calculations. Notes: In the lhs panel, the two portfolios sort Euro Stoxx firms into an upper and lower quartile based on their share of revenue from Americas. In the rhs panel the exchange rate effect refers to the change in the euro/dollar exchange rate since 1 January 2025. The competitiveness channel is based on the link between firms' excess returns and euro appreciation, purged from changes in firms' dollar-denominated costs, proxied by oil prices (Brent). The cost channel considers the fourth quartile of the distribution of benefits from exchange rate appreciations.

Latest observations: 5 September 2025.

Risks for households based on tariffs and defence spending

(differences in net percentage of respondents)



Sources: ECB (CES) and ECB calculations.

Notes: The lhs bar shows the difference in the average net percentage of respondents agreeing that housing is a good investment between July 2025 and the 6 months before the first rate cut (December 2023 - May 2024). The rhs bar shows the estimated change in expected credit access over the next 12 months following the April US tariff announcement for households reporting that they are negatively affected by tariffs relative to other households.

Latest observations: July 2025.

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Developing European market for digital assets

- The financial ecosystem of tomorrow is likely to host multiple forms of money, both public and private. But the stability and integration of that ecosystem will continue to rely on central bank money remaining the trusted anchor for settlement.

- To ensure central bank money remains an anchor for stability and trust in a digital economy:

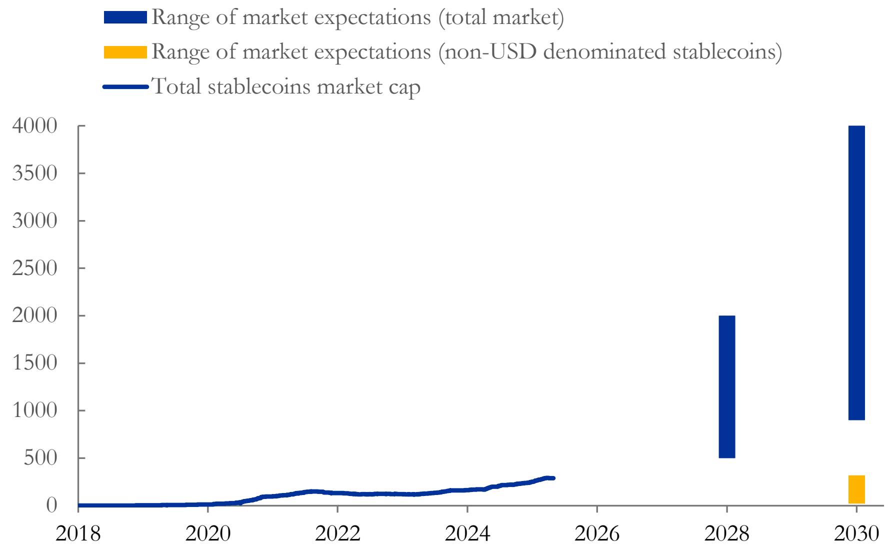
  ✓ Digital euro:
  - reduce dependence on external providers, support innovative, pan-European payment solutions

  ✓ Central bank money to settle wholesale transactions in DLT platforms:
  - Short-term track (Pontes) to link between DLT platforms and TARGET services by end Q3-2026
  - Long-term track (Appia) to shape future-ready, innovative and integrated financial ecosystems

- Stablecoins may play a role in domestic and cross-border settlements. In this paper we assess:
  - How do stablecoins affect banks?
  - Can they affect monetary policy transmission?
  - Does the currency of denomination matter?

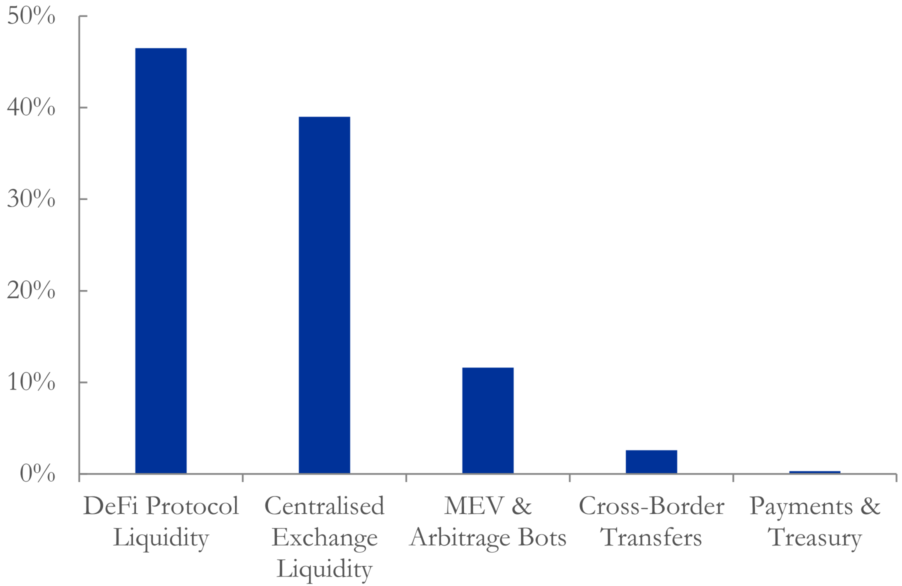
Stablecoin market developments

Actual and expected market capitalisation
(USD bn)



Source: Altavilla C., Boucinha M., Burlon L., Adalid R., Fortes R., Maruhn F. (2026) Stablecoins and monetary policy transmission, ECB Working Paper No 3199.
Note: The chart displays the historical evolution of total stablecoin market capitalisation in USD billions (blue line), alongside two ranges of market estimates (blue bars) for expected total market capitalisation in 2028 and 2030. The yellow bar represents market expectations for non-USD-denominated stablecoins..

Stablecoin use cases
(percentages)



Sources: Altavilla C., Boucinha M., Burlon L., Adalid R., Fortes R., Maruhn F. (2026) Stablecoins and monetary policy transmission, ECB Working Paper No 3199.
Note: Share by functional activity. Harmonised snapshot combining 2024/25 datasets, percentage. Based on data from Artemis, BCG, McKinsey, Visa Onchain.

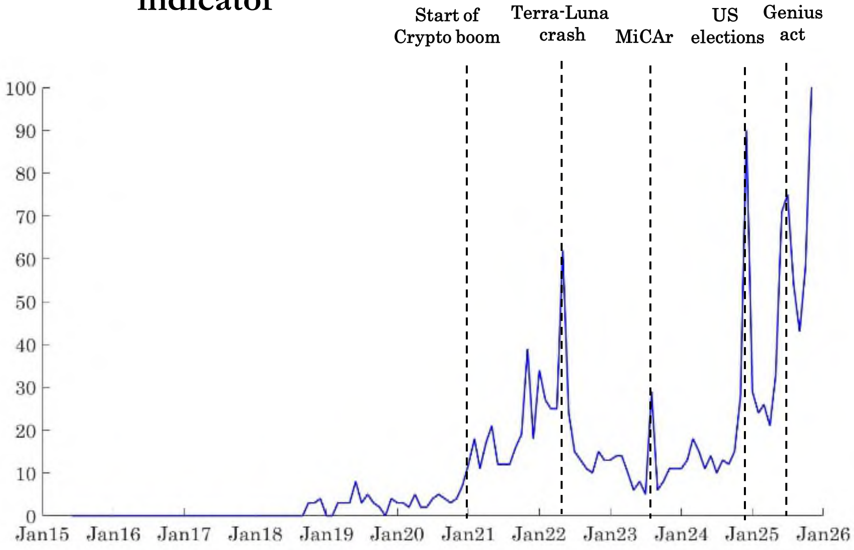
A BVAR model

$$y_t = \binom{z_t}{X_t} = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t$$

z_t "stablecoin innovations" from Google Trends data

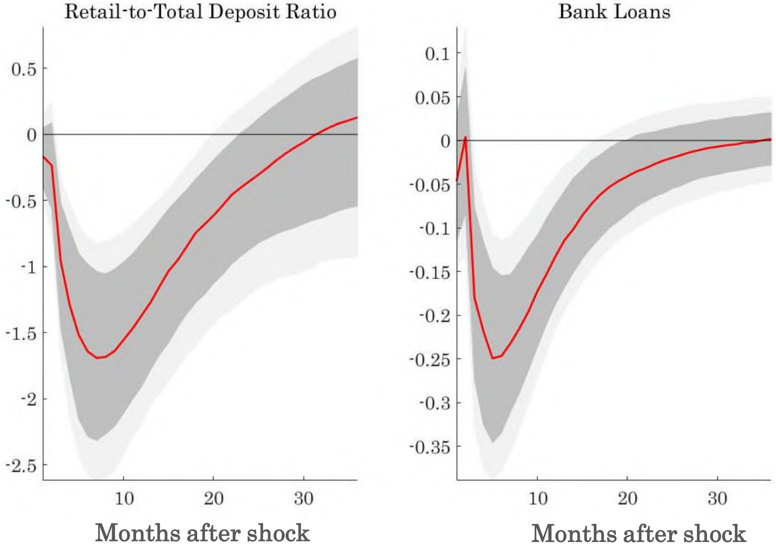
X_t [stablecoin market capitalisation, ratio of retail to total deposits, loans to non-financial firms, unemployment rate]

Stablecoin Google Trend indicator



Source: Altavilla C., Boucinha M., Burlon L., Adalid R., Fortes R., Maruhn F. (2026) Stablecoins and monetary policy transmission, ECB Working Paper No 3199

Response to a positive shock in the stablecoin indicator



Source: Altavilla C., Boucinha M., Burlon L., Adalid R., Fortes R., Maruhn F. (2026) Stablecoins and monetary policy transmission, ECB Working Paper No 3199.

Response to a contractionary monetary policy shock

$$Y_{b,t+h} = \beta^h \widehat{MP}_t + \gamma^h Y_{b,t-1} + X_{b,t} + \mu_b^h + u_{b,t}^h$$

Responses of loan growth to a contractionary monetary policy shock depending on crypto exposure of current customers

	(1) Low crypto	(2) High crypto	(3) Low crypto	(4) High crypto
$\widehat{MP}_t$	-1.027**	-0.193	-0.847**	0.074
	(0.417)	(0.773)	(0.376)	(0.758)
Loan demand (BLS)			0.745**	1.015
			(0.368)	(0.683)
Bank controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	3592	1104	3592	1104
Adjusted R^2	0.347	0.215	0.354	0.230

Source: Altavilla C., Boucinha M., Burlon L., Adalid R., Fortes R., Maruhn F. (2026) Stablecoins and monetary policy transmission, ECB Working Paper No 3199

$$Y_{b,t+h} = \beta^h \widehat{MP}_t + \gamma^h Y_{b,t-1} + X_{b,t} + \mu_b^h + u_{b,t}^h$$

Monetary policy impact on loan growth for banks with high wholesale funding depending on USD exposure

	(1)	(2)	(3)	(4)
	Low USD	High USD	Low USD	High USD
$\widehat{MP}_t$	-1.590**	-0.064	-1.330**	0.293
	(0.617)	(0.578)	(0.596)	(0.540)
Loan demand (BLS)			1.288	1.157
			(0.797)	(0.735)
Bank controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	2574	1754	2574	1754
Adjusted R^2	0.310	0.097	0.317	0.105
F-Stat: low vs. high USD	3.36*		4.20**	

Source: Altavilla C., Boucinha M., Burlon L., Adalid R., Fortes R., Maruhn F. (2026) Stablecoins and monetary policy transmission, ECB Working Paper No 3199

What we do/find

❑ How do stablecoins affect banks?

- ✓ The growth of stablecoins triggers a **deposit-substitution mechanism:** funds shift from retail bank deposits toward digital assets.
- ✓ This reallocation increases banks' **reliance on wholesale funding** and ultimately constrains their intermediation capacity.
- ✓ but the **effect is nonlinear** and depends heavily on their scale, design, and regulatory treatment.

❑ What does this mean for monetary policy?

- ✓ They can interfere with multiple transmission channels, potentially making monetary policy **transmission less predictable.**

❑ Why does the currency denomination of stablecoins matter?

- ✓ The **risks** to monetary transmission are **amplified** for **non-euro-denominated stablecoins.**

Divisia Monetary Aggregates for India and Emerging Markets

Policy applications for monetary analysis, FX monitoring, and forecasting

Soumya S. Bhadury (Reserve Bank of India)

Roadmap: Measurement, Identification, Robustness, Policy Use

Measurement
Divisia as aggregation-theoretic money

Identification
India SVAR puzzles & transmission

Robustness
Bootstrap + rolling windows (breaks)

Policy use
Stance, FX surveillance, forecasting

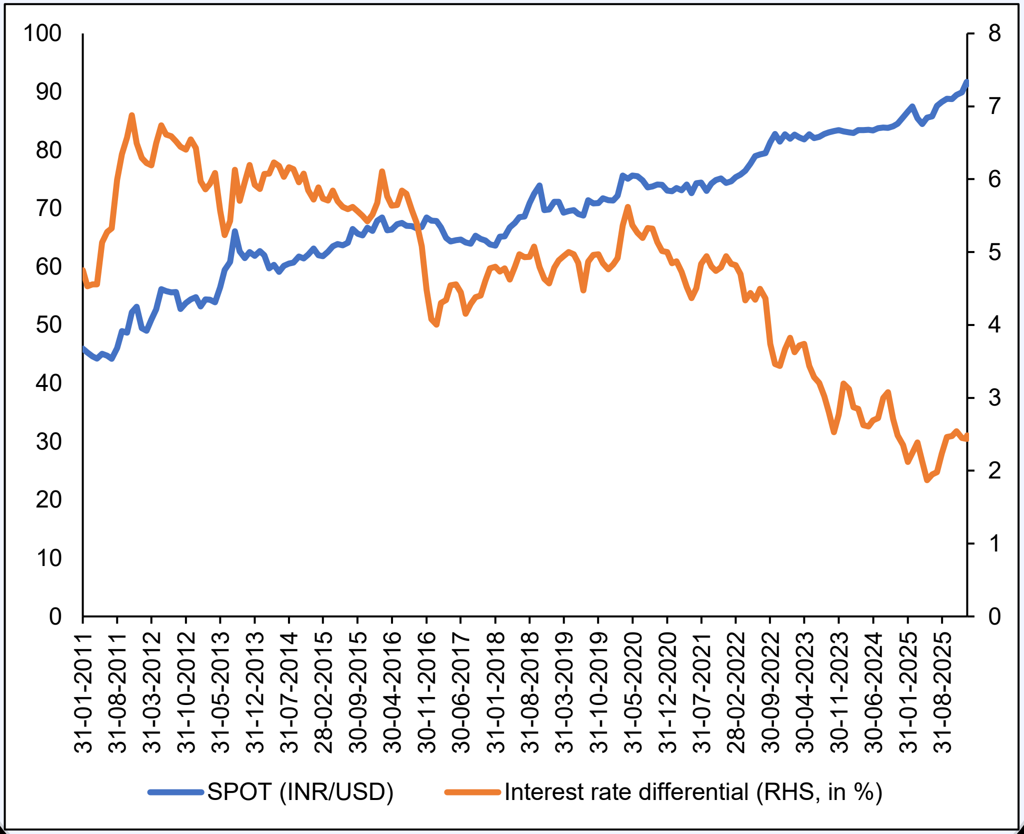
- **Measurement**: Why Divisia instead of simple-sum money
- **Identification**: India SVAR evidence on transmission and puzzles
- **Robustness**: Bootstrap and rolling-window evidence across countries
- **Policy use**: How Divisia can complement existing central-bank indicators

Why Rates Alone May Be Incomplete in an Open Economy

Problem: Rates can be an incomplete read of the stance in open economy

- Under unconventional/constrained regimes (e.g., near ZLB), short-term rates may be less informative about stance
- Rates may not fully summarize monetary conditions
- When rates are constrained and less information, complementary monetary indicators
- Money measurement matters because substitution across monetary assets varies over time
- Divisia is proposed as a theoretically consistent complement

Interest differential and INR/USD Exchange rate



Predictor Screening

Problem: Rates can be an incomplete read of the stance in open economy

- **Forward stepwise selection ranks predictors by incremental in-sample fit**
- **Excluding FX curve measures brings macro-financial variables back into the ranking**
    - But for monthly changes their cumulative explanatory power remains modest (**$R^2 \approx 0.385$**)
- **From a surveillance perspective, short-tenor market prices are the strongest near-term anchors,**
    - While macro-financial variables are used as conditioning inputs for ranges and scenarios

INR/USD: Predictor screening (Forward Stepwise Selection)

Specification	Step 1 (ΔR^2; R^2-after)	Step 2 (ΔR^2; R^2-after)	Step 3 (ΔR^2; R^2-after)	Management takeaway
Levels — Full set (incl. FW/NDF/CF)	CF1M (0.9999; 0.9999)	CF3M (0.0000; 0.9999)	FW1M (0.0000; 0.9999)	FX-curve prices are near re-expressions of spot-in levels; rankings mainly reflect redundancy/co-movement.
Differences — Full set (incl. FW/NDF/CF)	CF1M (0.9922; 0.9922)	FW1M (0.0020; 0.9942)	Sensex (0.0001; 0.9943)	Short-tenor market price dominates monthly moves; other covariates add only marginal incremental fit.
Levels — Restricted (excl. FW/NDF/CF)	CPI (0.9559; 0.9559)	Sensex (0.0110; 0.9669)	DXY (0.0022; 0.9692)	Conventional variables explain level co-movement once FX-curve prices are removed (interpret levels cautiously).
Differences — Restricted (excl. FW/NDF/CF)	Sensex (0.2965; 0.2965)	CPI (0.0410; 0.3375)	DXY (0.0096; 0.3471)	Macro/risk drivers matter for monthly changes, but overall fit remains modest ($R^2 \approx 0.385$ after 10 vars).

CF = INR/USD currency futures rate (tenor shown: 1M/3M/6M/12M). | FW = INR/USD deliverable forward rate (1M/3M/6M). | NDF = INR/USD offshore non-deliverable forward rate (1M/3M/6M). | DXY = US Dollar Index; VIX = CBOE Volatility Index; Brent = Brent crude oil price. | Interest rate differential = India 10Y G-sec yield minus US 10Y Treasury yield. | CPI = Consumer Price Index; EPU = Economic Policy Uncertainty index. | CAD = current account deficit proxy; CAP = capital account / capital flows proxy. | Intervention = FX intervention proxy (as constructed in the dataset). | Sensex = BSE Sensex equity index.

Why Divisia Instead of Simple-Sum Money?

Core idea

- Simple-sum assumes monetary assets are perfect substitutes
- Divisia weighs assets by monetary services flow, using the user-cost logic
- When asset composition changes, Divisia tracks monetary conditions more accurately
    - Weights move with user costs and relative returns, so growth can diverge from simple-sum in regime change.

What changes mechanically

- The empirical question is whether that improves identification and forecasting in policy models.

Empirical Design: No-money vs Simple-sum vs Divisia

Core Idea:

- A clean horse race across no-money, simple-sum, and Divisia specifications
- Both recursive and non-recursive identification schemes are examined
- The objective is to separate identification effects from money-measurement effects

Model setup

Model No.	Model Structu	World Variab	Monetary Aggrega	Identification Typ	Variable Set
Model 1	NR	OIL	DM3	Non-Recursive	oilp, rfed, iip, π, DM3, rdom, ER
Model 2	NR	OIL	M3	Non-Recursive	oilp, rfed, iip, π, M3, rdom, ER
Model 3	NR	OIL	M1	Non-Recursive	oilp, rfed, iip, π, M1, rdom, ER
Model 4	NR	OIL	DL1	Non-Recursive	oilp, rfed, iip, π, DL1, rdom, ER
Model 5	NR	OIL	DM2	Non-Recursive	oilp, rfed, iip, π, DM2, rdom, ER
Model 6	NR	COM	DM3	Non-Recursive	wcom, rfed, iip, π, DM3, rdom, ER
Model 7	NR	COM	M3	Non-Recursive	wcom, rfed, iip, π, M3, rdom, ER
Model 8	NR	COM	M1	Non-Recursive	wcom, rfed, iip, π, M1, rdom, ER
Model 9	NR	COM	DL1	Non-Recursive	wcom, rfed, iip, π, DL1, rdom, ER
Model 10	NR	COM	DM2	Non-Recursive	wcom, rfed, iip, π, DM2, rdom, ER
Model 11	R	OIL	DM3	Recursive (Cholesky)	oilp, rfed, iip, π, DM3, rdom, ER
Model 12	R	OIL	M3	Recursive (Cholesky)	oilp, rfed, iip, π, M3, rdom, ER
Model 13	R	OIL	M1	Recursive (Cholesky)	oilp, rfed, iip, π, M1, rdom, ER
Model 14	R	OIL	DL1	Recursive (Cholesky)	oilp, rfed, iip, π, DL1, rdom, ER
Model 15	R	OIL	DM2	Recursive (Cholesky)	oilp, rfed, iip, π, DM2, rdom, ER
Model 16	R	OIL	X (No Money)	Recursive (Cholesky)	oilp, rfed, iip, π, rdom, ER

India Open-Economy SVAR: Question and Structure

Questions revisited for India

- India setting revisit familiar monetary transmission puzzles
  - Inflationary (price) puzzle and exchange-rate puzzle under some identifications
- World variables, domestic macro variables and the exchange rate are modelled jointly
- The key question is whether identification and money measurement alter inference
  - Evidence from the transmission in policy shock responses

Stylised SVAR block

World variables → Domestic block (output, prices, policy rate, money) → Exchange rate

Policy equation: interest rate reaction function; money equation: money demand (output, price, rates).

Puzzles that have Plagued Exchange Rate Literature

Puzzle	What the model shows	Why it is called a puzzle	What it suggests
Liquidity puzzle	A contractionary monetary policy shock is followed by a **fall** in the short-term interest rate, instead of a rise.	This is contrary to the intended policy action: a tightening shock should push the policy/market rate up, at least initially.	Likely misspecification in identification, timing restrictions, or poor separation of policy and non-policy shocks.
Price puzzle	After a monetary tightening, the **price level / inflation rises** instead of falling.	Standard theory predicts that tighter policy should eventually reduce inflation, not increase it on impact in a sustained way.	Often reflects omitted information (for example, policy reacting to future inflation) or weak identification.
Exchange-rate puzzle	After a monetary tightening, the domestic currency **depreciates** instead of appreciating.	In a standard open-economy setting, higher interest rates should support the currency, at least initially.	May reflect poor identification, intervention effects, risk-premium shocks, or exchange-rate smoothing by the central bank.
Delayed overshooting puzzle	The exchange rate responds only weakly on impact and the main adjustment comes with a delay, rather than immediate overshooting.	In standard Dornbusch-type logic, the exchange rate should jump immediately and then partially reverse.	Suggests sluggish transmission, intervention, capital controls, or model structure that does not capture financial-market adjustment well.
Forward discount / exchange-rate disconnect (broader empirical puzzle)	Interest-rate differentials do not reliably predict exchange-rate movements in the expected direction.	Conventional uncovered interest parity logic often fails in the data.	Reinforces the need for broader monetary/financial indicators beyond short-term rates alone.

Identification Strategies In Addressing Puzzles

Paper	Core identification idea	Key restrictions / assumptions	Why it helps with the exchange-rate puzzle
Kim & Roubini (2000, JME)	**Non-recursive SVAR with short-run contemporaneous restrictions**	Replace mechanical recursive ordering with theory-based impact restrictions; foreign / external variables are treated as relatively exogenous to the domestic block; sluggish macro variables (especially output/prices) are not assumed to jump freely on impact, while financial variables can adjust faster.	Avoids the distortions created by a pure Cholesky ordering and helps eliminate the liquidity, price, and exchange-rate puzzles in open-economy VARs. (ScienceDirect)
Bjørnland (2009, JIE)	**Allow contemporaneous rate–exchange-rate interaction + long-run restriction**	Do not impose a zero contemporaneous restriction between the policy rate and the exchange rate; instead, allow them to react simultaneously, and identify the monetary policy shock by imposing that it has no long-run effect on the real exchange rate.	This restores the possibility of immediate exchange-rate appreciation after a tightening shock, so the empirical response is much more consistent with Dornbusch-style overshooting. (ScienceDirect)

Identification matters Before We Judge the Monetary Aggregate

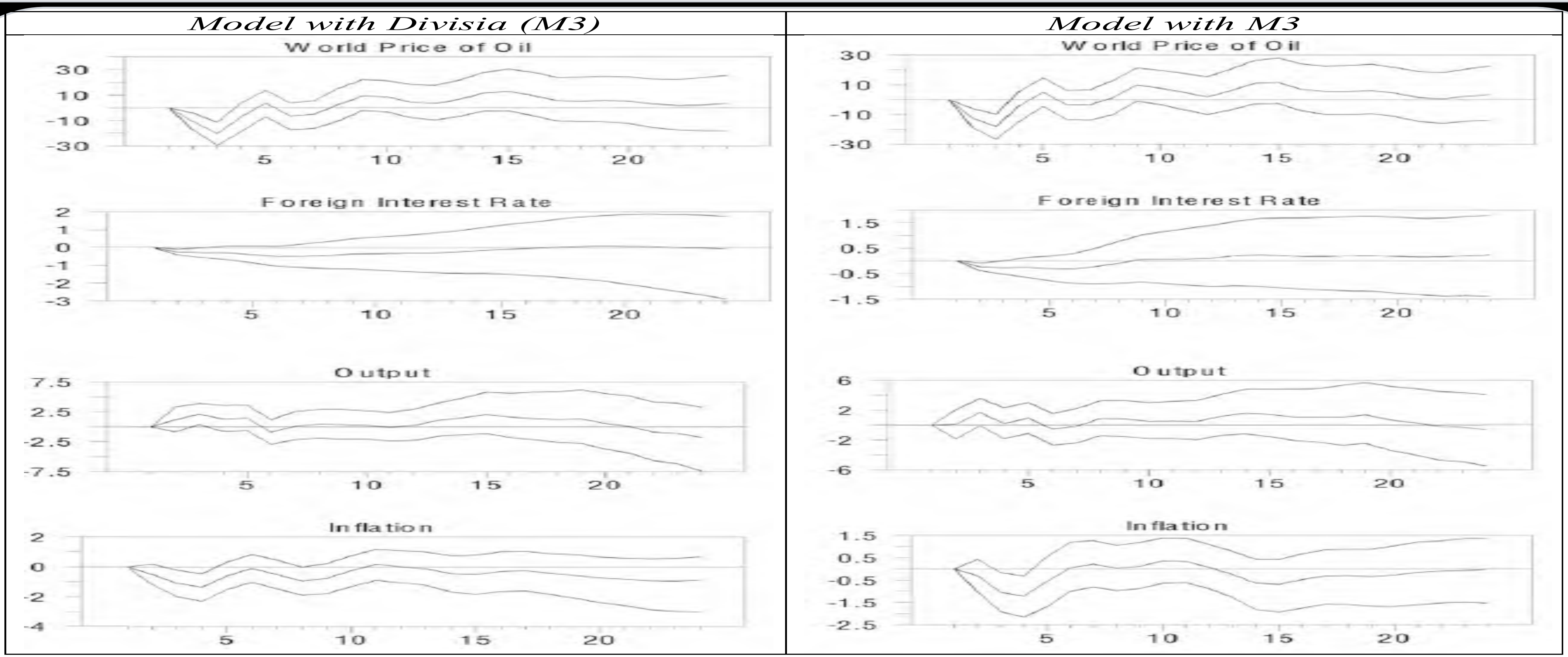
Key point

- Recursive specifications are more prone to liquidity, price and exchange rate puzzles
- Non-recursive specification reduce these distortions
- Identification must be addressed before comparing money measures

Model & Code	Liquidity Puzzle	Price Puzzle	Exchange Rate Puzzle	Forward Discount Bias Puzzle
1 (NR,OIL,DM3)	Slight to none	None	None	None
2 (NR,OIL,M3)	Insignificant	None	Slight to None	None
3 (NR,OIL,M1)	Yes	Yes	None	None
4 (NR,OIL,DL1)	Slight to none	None	None	None
5 (NR,OIL,DM2)	Slight to none	None	None	None
6 (NR,COM,DM3)	Slight to none	Slight to none	None	None
7 (NR,COM,M3)	Insignificant	Insignificant	None	None
8 (NR,COM,M1)	Insignificant	None	None	None
9 (NR,COM,DL1)	Insignificant	Insignificant	None	None
10 (NR,COM,DM2)	Insignificant	None	None	None
11 (R,OIL,DM3)	Yes	Yes	Slight to None	Yes
12 (R,OIL,M3)	Insignificant	Yes	Yes	Yes
13 (R,OIL,M1)	None	Yes	Yes	Yes
14 (R,OIL,DL1)	Yes	Yes	Slight to None	Yes
15 (R,OIL,DM2)	Yes	Yes	Slight to None	Yes
16 (R,OIL,X)	Yes	Yes	Yes	Yes

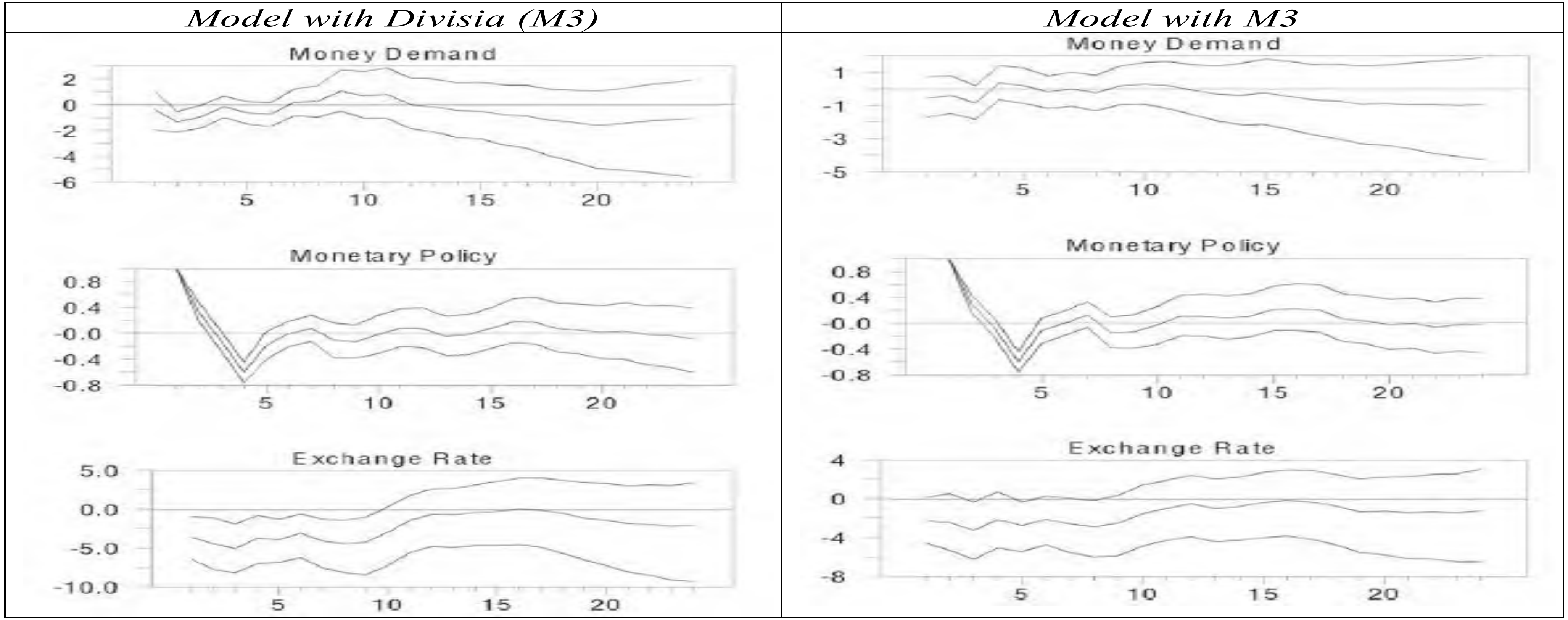
Once Identification Improves, Divisia Outperforms Simple-Sum

- Under non-recursive identification, the comparison becomes economically meaningful
- Divisia M3 delivers relatively impulse responses than simple-sum M3
- Better money measurement improves the model’s signal



Divsia Improves Forecast Accuracy in the India Model

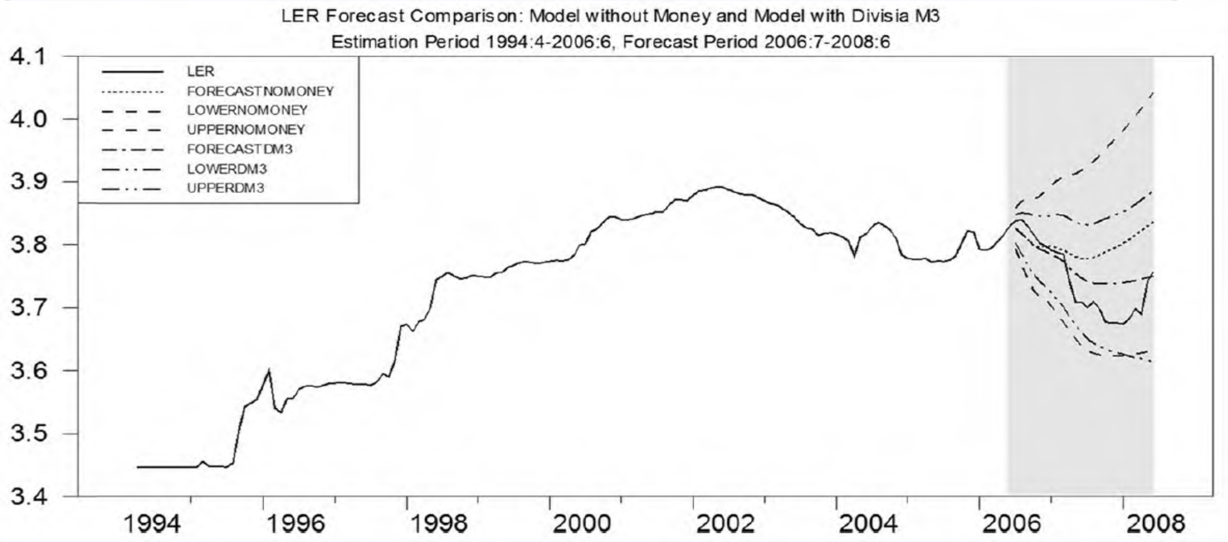
- Models with money outperform the no-money benchmark
- Performance gap becomes relatively clearer at longer horizons
- Divisia M3 yields lower forecast errors than simple-sum M3

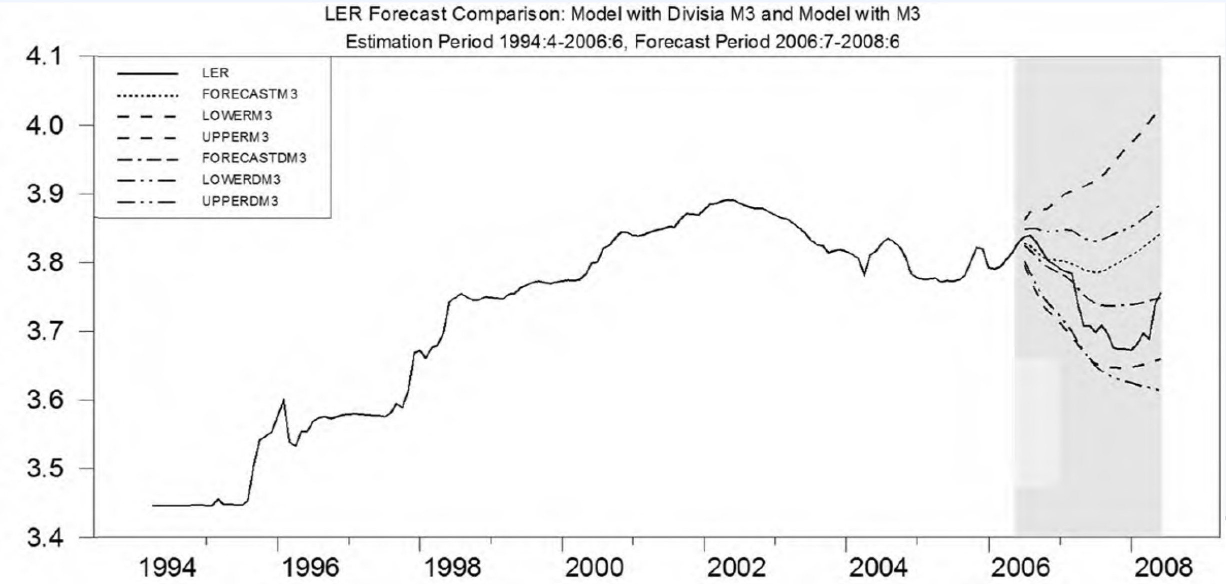


Forecast Paths: Divisia Tracks the Exchange Rate More Closely

Key findings

- Divisia-based forecast stays closer to the realized exchange-rate path
- Prediction bands are usually tighter than in the no-money and simple-sum alternatives
- However, the differences fade out in the in-sample exercises





From One-Country Mechanism to Cross-Country Evidence

What we do next

- While the earlier study provides structural evidence within India
- Next question is whether Divisia contains broader exchange-rate information
  - Specifically, does Divisia contain FX signal more broadly, and does it persist under breaks/instability?
- In doing so, bootstrap and rolling fixed-window Granger causality tests are performed across countries.

Key distinction

- SVAR evidence is structural within a model; Granger evidence is predictive content (not structural causality).
- Together they triangulate mechanism + external validity + time variation.

Cross-country Framework: Bootstrap and Rolling-Window Inference

What they do

- Full-sample residual-bootstrap Granger causality tests (REER and NER).
- Rolling fixed-window bootstrap to address parameter instability and structural breaks.
- Compare three indicators: Divisia money, simple-sum money, and short-term interest rates.
- Fixed window length: 100 observations (robustness at 60 and 80).
- 2000 bootstrap draws; lags via AIC; p-value plots for rolling windows.

Bivariate Bootstrap Granger Causality Test

India bivariate bootstrap granger causality.

Null Hypothesis: The row variables do not Granger cause exchange rate

Estimation Period 1994 April to 2008 June

	Lags = 6			Lags = 12		
REER						
	F-Value	Significance Level	Bootstrapped p-value	F-Value	Significance Level	Bootstrapped p-value
Interest Rate	0.70	0.65	0.70	0.80	0.65	0.68
M1	1.19	0.32	0.40	1.64	0.09***	0.10
M3	1.19	0.32	0.41	2.12	0.02**	0.03**
DL1	2.18	0.05**	0.08***	2.96	0.00*	0.00*
DM2	2.18	0.05**	0.08***	2.88	0.00*	0.00*
DM3	2.18	0.05**	0.08***	2.96	0.00*	0.00*
NER						
Interest Rate	0.90	0.49	0.52	1.08	0.38	0.41
M1	0.85	0.54	0.65	1.44	0.16	0.23
M3	0.44	0.85	0.89	1.34	0.20	0.27
DL1	0.70	0.65	0.72	1.50	0.13	0.17
DM2	1.22	0.30	0.39	1.54	0.12	0.16
DM3	0.70	0.65	0.73	1.50	0.13	0.17

Poland bivariate bootstrap granger causality.

Null Hypothesis: Row variables do not Granger cause exchange rate

Estimation Period 2001 January to 2015 June

	Lags=6			**Lags=12**		
REER						
	F-Value	Significance Level	Bootstrapped p-value	F-Value	Significance Level	Bootstrapped p-value
Interest Rate	1.27	0.28	0.31	0.88	0.61	0.57
M1	2.70	0.02**	0.02**	1.33	0.20	0.24
M2	2.09	0.06***	0.08***	2.60	0.00*	0.01**
M3	1.85	0.09***	0.12	2.32	0.01**	0.02**
Div1	2.36	0.03**	0.04**	1.22	0.27	0.31
Div2	3.82	0.00*	0.00*	2.67	0.00*	0.01**
Div3	3.78	0.00*	0.00*	2.61	0.00*	0.01**
NER						
	F-Value	Significance Level	Bootstrapped p-value	F-Value	Significance Level	Bootstrapped p-value
Interest Rate	1.26	0.28	0.33	0.62	0.81	0.84
M1	1.55	0.16	0.23	1.00	0.45	0.55
M2	1.27	0.27	0.34	1.49	0.13	0.18
M3	1.26	0.28	0.35	1.48	0.14	0.19
Div1	1.65	0.14	0.19	1.02	0.44	0.53
Div2	2.36	0.03**	0.06***	1.81	0.05***	0.08***
Div3	2.34	0.03**	0.05***	1.78	0.06***	0.09***

India in the Cross-Country Evidence: REER Signal is Stronger than NER

What they do

- In the reported full sample, Divisia shows stronger and more predictive content than short-term rates
- Divisia significantly Granger causes REER/NER for Israel, Poland, the UK, and the US.
- For India, Divisia significantly predicts the REER although NER results is weaker
- This is consistent with a managed FX volatility regime, where nominal rate predictability may be muted.

Bivariate Bootstrap Granger Causality Test

UK bivariate bootstrap granger causality.

Null Hypothesis: Row variables do not Granger cause exchange rate

Estimation Period 1999 January to 2013 December

	Lags=6			Lags=12		
NER						
	F-Value	Significance Level	Bootstrapped p-value	F-Value	Significance Level	Bootstrapped p-value
Interest Rate	1.20	0.31	0.40	1.01	0.44	0.52
M1	0.90	0.50	0.58	1.12	0.35	0.43
M3	1.40	0.23	0.32	0.64	0.80	0.85
Divisia	4.67	0.00*	0.00*	3.13	0.00*	0.00*
REER						
	F-Value	Significance Level	Bootstrapped p-value	F-Value	Significance Level	Bootstrapped p-value
Interest Rate	3.33	0.00*	0.00*	2.10	0.02*	0.02*
M1	1.62	0.14	0.36	1.71	0.07**	0.16
M3	5.04	0.00*	0.00*	3.02	0.00*	0.00*
Divisia	5.37	0.00*	0.00*	3.49	0.00*	0.00*

US bivariate bootstrap granger causality.

Null Hypothesis: Row variables do not Granger cause exchange rate

Estimation Period 1994 January to 2017 February

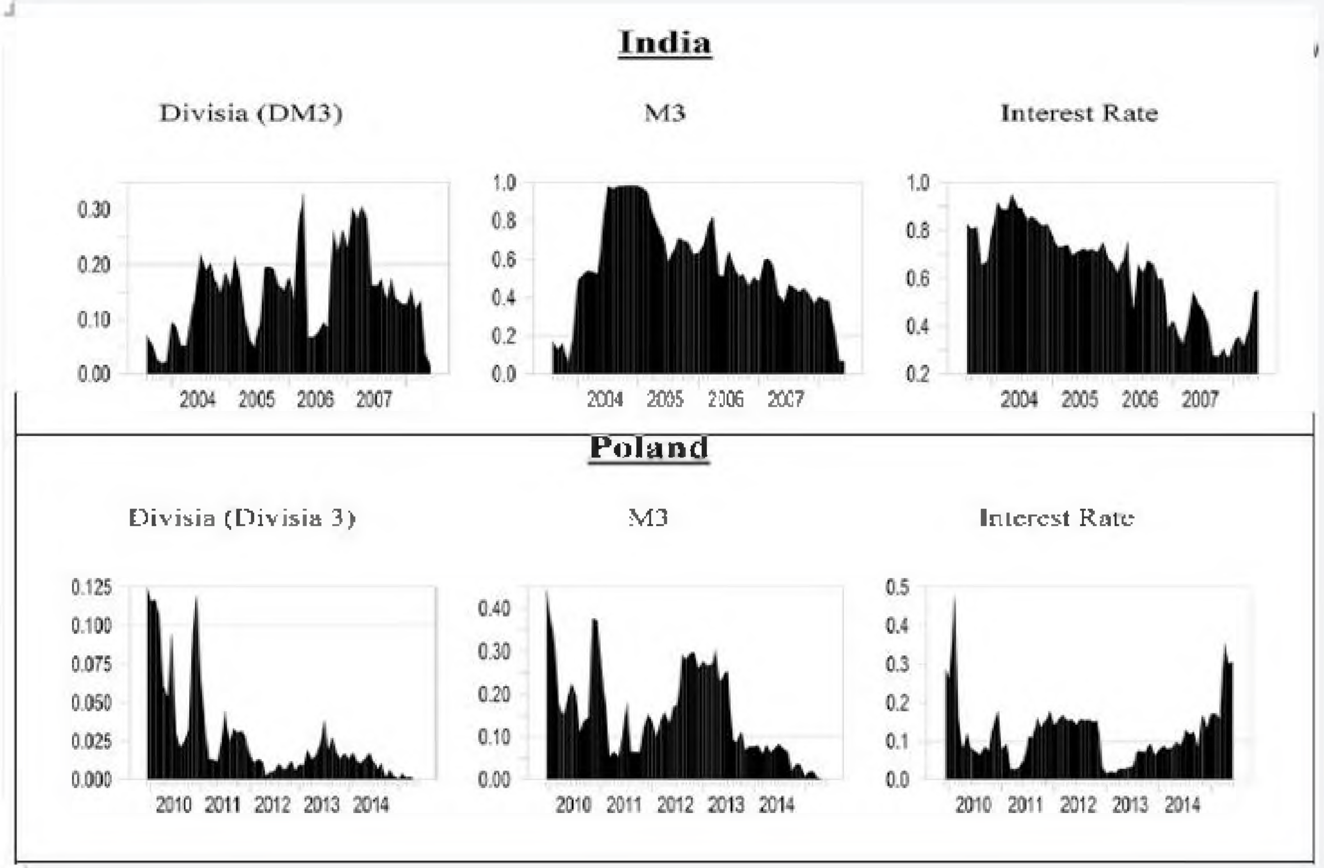
	Lags=6			Lags=12		
REER						
	F-Value	Significance Level	Bootstrapped p-value	F-Value	Significance Level	Bootstrapped p-value
Interest Rate	0.57	0.75	0.80	1.21	0.33	0.27
M1	0.82	0.56	0.66	1.01	0.44	0.54
M3	1.52	0.17	0.27	0.90	0.55	0.64
DivisiaM1	0.90	0.50	0.62	0.76	0.69	0.76
DivisiaM2	1.74	0.11	0.19	1.26	0.24	0.33
DivisiaALL	1.52	0.17	0.28	1.13	0.34	0.44
DivisiaM3	3.78	0.01**	0.02**	2.25	0.01**	0.03**
DivisiaM4-	2.43	0.03**	0.06***	1.88	0.03**	0.06***
DivisiaM4	2.50	0.02**	0.05***	1.93	0.03**	0.06***

India’s Predictive Relationship is Time-Varying, Not Constant

Empirical findings

- Rolling-window methods are necessary because full-sample tests can hide structural change
- Predictive content for the REER is episodic rather than permanent
- Divisa’s significance strengthens in some windows and weakens in others
- Interpretation offered: FX management aimed at orderly conditions can weaken nominal exchange-rate predictability.

Rolling Causality Test

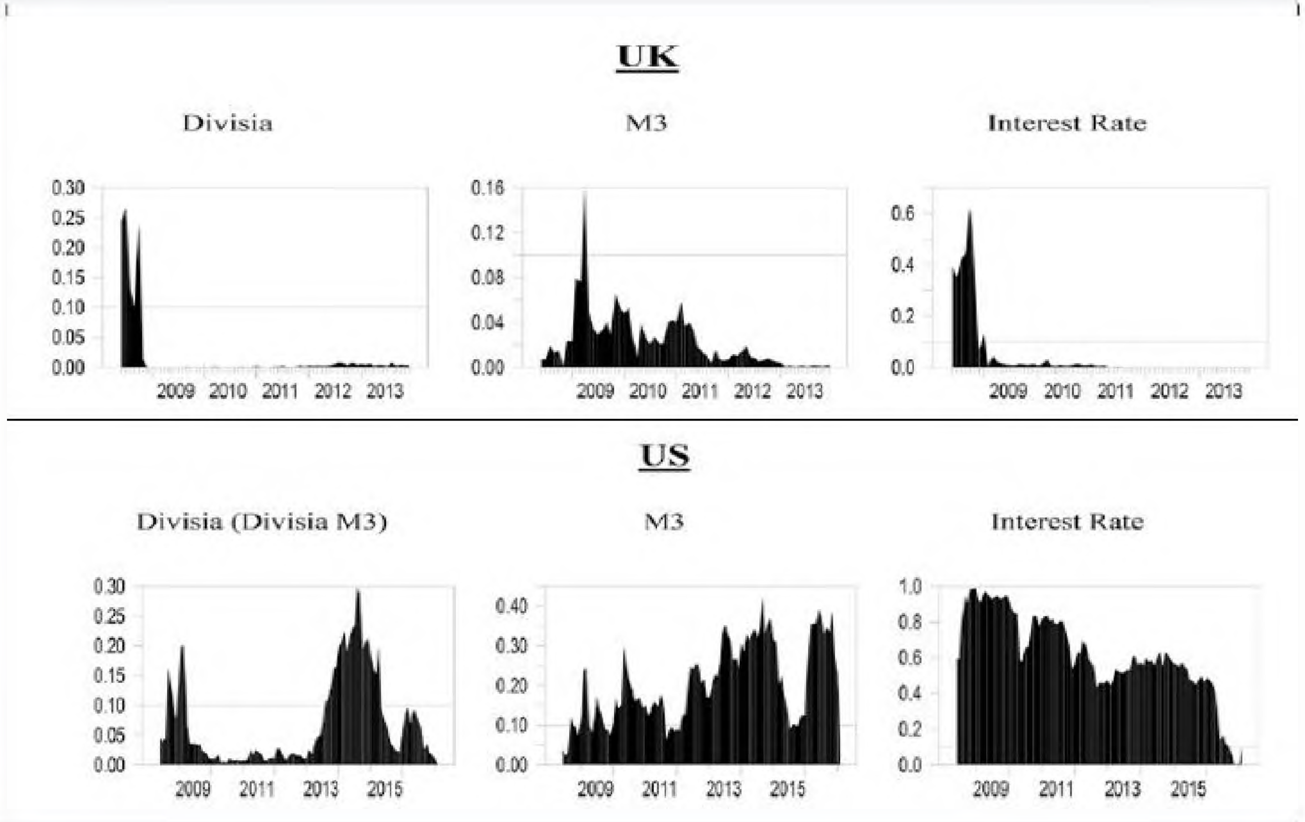


Rolling Causality Test Results: India and Beyond

Empirical findings

- Divisia is the most informative monetary indicator in the rolling tests, especially when policy rates are constrained
- Divisia's predictive power for the REER is strongest in more open financial systems
- For the NER as well, Divisia generally outperforms simple-sum money and interest rates

Rolling Causality Tests



How Central Banks Can use Divisia in Practice

- **Use Divisia as a complementary policy signal** for stance monitoring, especially when short-term rates are constrained or less informative, and for liquidity assessment in India and other EMs.

- **Add Divisia to FX surveillance and forecast models**: it often carries stronger predictive content for exchange rates than conventional short-term rates, with time variation best handled through bootstrap and rolling-window approaches.

- **The broader lesson is that both identification and measurement matter**: recursive structures can generate price/FX puzzles, while Divisia improves model performance relative to simple-sum and no-money specifications, including out-of-sample forecasting.

Does Money Help Forecast (U.S.) Nominal GDP in Deep Learning Models?*

Does Money Help Forecast (U.S.) Core Inflation in Deep Learning Models?*

Kenean Yemane Kejela
Software Engineer
Google

John V. Duca
Danforth-Lewis Professor, Oberlin College and
Emeritus Economist, Federal Reserve Bank of Dallas

*The views expressed are those of the authors and are not necessarily those of the Federal Reserve Bank of Dallas, the Federal Reserve System, or Google. Any errors are our own.

Introduction

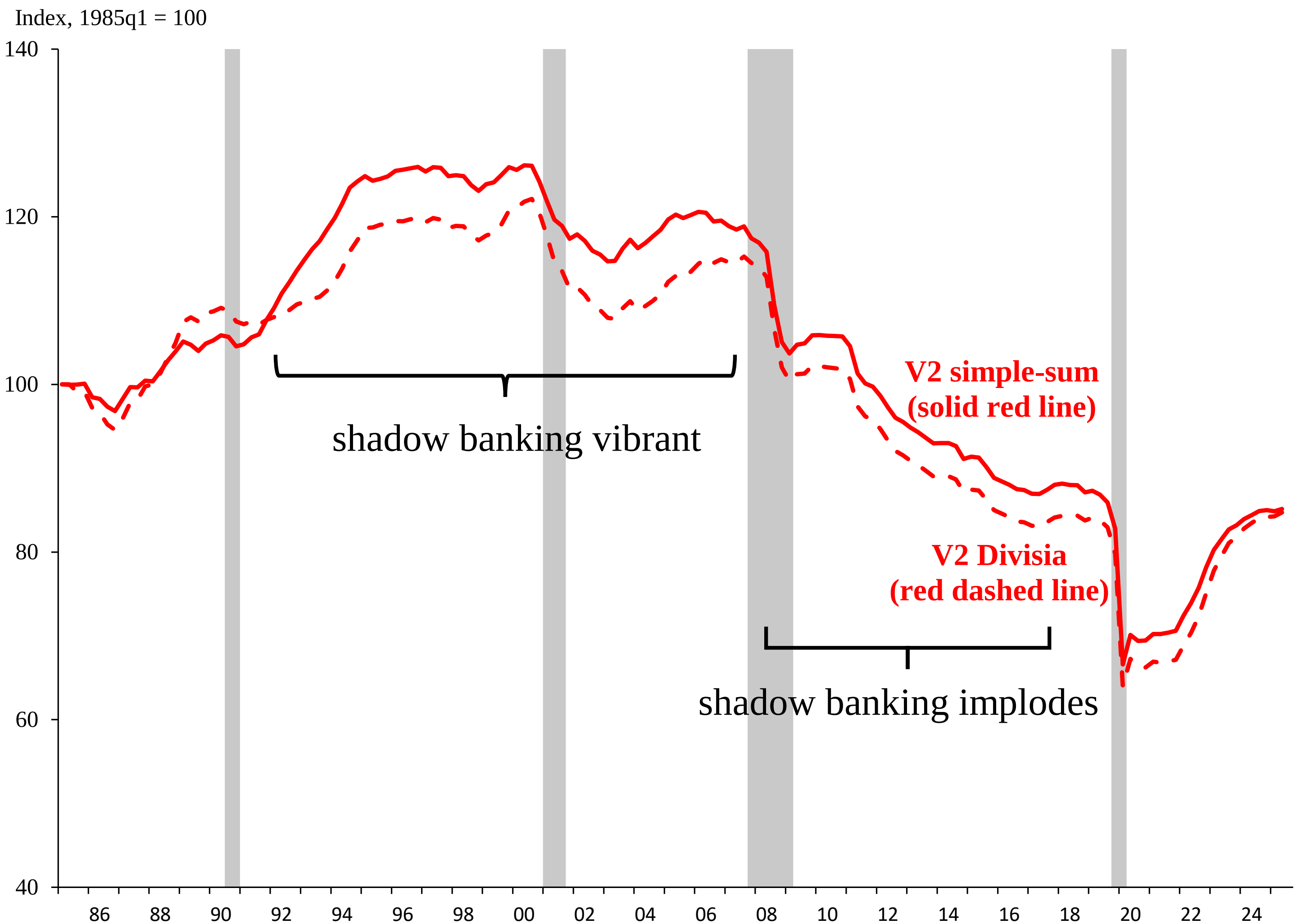
Strong US nominal GDP growth in 2021-22 coincided with inflation rising above 2% => a role for demand, not just supply.

Two oversimplified ways of tracking nominal aggregate demand:

$$\underbrace{C + I + G + \text{net } X}_{\text{expenditure approach}} \quad = \quad PY \quad = \quad \underbrace{MV}_{\text{monetarist approach}}$$

Expenditure approach uses multi-equation models hurt by unusual COVID era shocks: hard-to-forecast fiscal policy & unconventional M policy effects not fully tracked by interest rates; e.g., corporate bond facilities prevent financial accelerator effects (Bordo/Duca, 2021, 2022) and quantities provide information when ZLB binding.

Old Chicago view relied on stable V ($\equiv PY/M$). Money growth surged 2020-22. Many ignored simple-sum money measures whose past large V shifts made them unreliable. Partly owed to M2 not internalizing the rise and fall of US shadow banking. Why post-2020 inflation surprised many who overlooked rapid money growth.

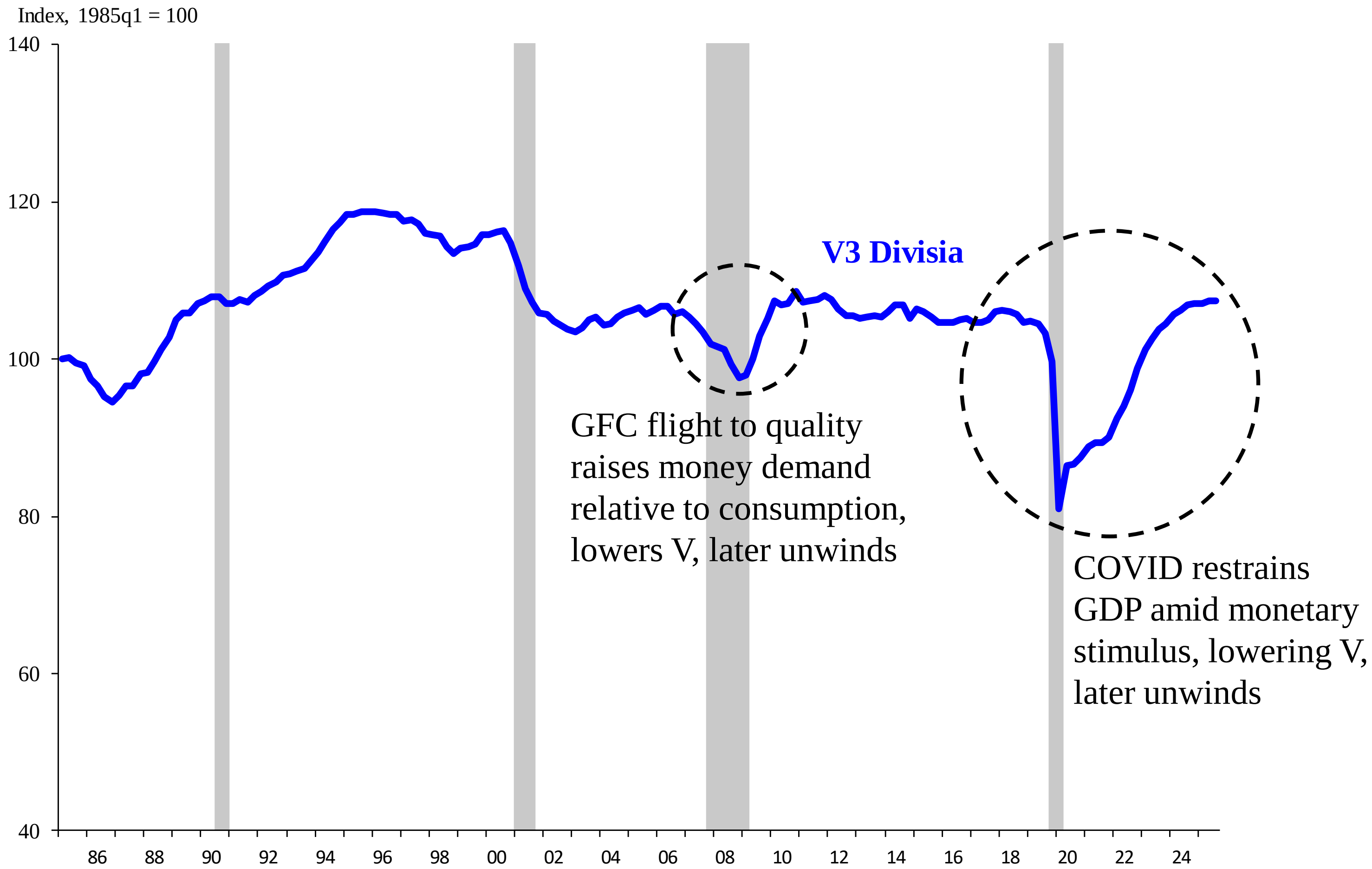


Since early 1990s, the Velocity of M2 <u>And</u> Divisia M2 Very Unstable

(Sources: CFS, Federal Reserve, Bordo & Duca, 2023, and authors' calculations.)

Introduction

Divisia M3 has a stable long-run V. Divisia indexes more precisely measure the liquidity of money components and M3 internalizes shifts between M created by commercial banks & shadow banks.



Since early 1990s, the Velocity of Divisia M3 Stable in Long-Run

(Sources: CFS, Federal Reserve, Bordo & Duca, 2023, and authors' calculations.)

Introduction

Divisia M3 has a stable long-run V. Divisia measures more precisely measure the liquidity of money components and M3 internalizes shifts between M created by commercial banks & shadow banks.

Bordo & Duca (2024) model Div. M3 velocity with mutual fund costs to track liquidity of assets outside Div M3 & COVID mobility restrictions. Using structural model of V forecast nominal GDP.

Bordo, Duca, & Jones (2025) find Div. M3 V well modeled with stock mutual fund loads & using V model better predicts inflation than using an HP of V in a P* model where M affects P in long-run.

An artifact of their structural models? **No. adding Div. M3 & mutual fund costs to a standard dataset (FRED) improves deep learning forecasts of U.S. nominal GDP and core PCE inflation.**

Methodology: Use LSTMs a type of RNN

For forecasting Recurrent Neural Networks (RNN's) effective at learning temporal dependencies, nonlinearities, trends, & seasonality

LSTMs selectively store & forget information, capture long-term dependencies and limit vanishing gradient problem that can overly downgrade signals from older data. Helps us identify l-run velocity.

Compare LSTM results from data including or omitting Divisia M and mutual fund costs. Tests if Divisia M and mutual fund costs add information for forecasting nominal GDP and core PCE prices.

Some references:

LSTM forecasts: Zhang et al. (2022) on Chinese GDP, Longe et al. (2022) on US GDP, Stoneman & Duca (2024) for core PCE inflation

Step 1: Create Datasets for Nom. GDP, Core PCE

- From FRED, fetch & clean, find 7,491 continuous series 1984-2024, avoid mismeasurement of Divisia before 1984
- Avoid overfitting with Scikit-Learn's Mutual Information regression to select 1,500 most informative FRED variables omitting nominal GDP or price components, as appropriate. Done separately for nominal GDP and core PCE prices.
- Normalize variables using Scikit-Learn's StandardScaler
- **FRED includes simple-sum monetary aggregates but omits Divisia money and mutual fund costs.** Add 3 different Divisia measures (**Center for Financial Stability, CFS**) tracking money services from different liquid assets:

DM3: M2, institutional money funds, large time deposits

DM4-: to DM3 adds services from commercial paper

DM4: to DM4- adds services from Treasury bills

Step 1: Create Datasets: for Nominal GDP, Assessed Three COVID Control Variables

- By unusually affecting spending COVID can induce V shifts.
- ***GSTR:*** Oxford Blatavnik Index gov't imposed restrictions
- Vaccines affect spending. ***VaxFull*** % fully vaccinated adults. Can combine: $\boldsymbol{GSTR}_t$ x (1-$\boldsymbol{VaxFull}_{t-1}$)
- Help explain V **contemporaneously** (Bordo & Duca, 2024). Unclear if helpful for forecasting when they enter with at least a t-1 lag as in our exercise. <u>This is an empirical issue</u>.
- Adding COVID controls reduces LSTM forecast accuracy
  - Such controls are not predictive likely since COVID was not forecastable, so the models miss the COVID dip in nom. GDP.
- Did not use COVID variables for forecasting core PCE.

Step 1: Create Datasets (continued)

- **Nominal GDP** assessed 8 data sets: Baseline with or without
  - COVID Controls
  - 1 of 3 Divisia Money and common Mutual Fund (MF) Costs

  Did so forecasting nominal GDP 1- and 4-quarters ahead

- **Core PCE**: <u>plan</u> to assess 8 data sets: Baseline with or without
  - 1 of 3 Divisia Money and common Mutual Fund (MF) Costs
  - FRBNY's index of global supply pressures

Thus far forecasted Core PCE prices 1- and 4-quarters ahead using Baseline dataset with and without Divisia M3 and mutual fund costs

Step 2: Training, LSTM Architecture & Parameters

- Train data over 1984-2013.
  - Pre-1984 regulation-related measurement problems w/ Divisia
  - Spans the Great Moderation and Great Recession
- Testing or forecast period 2014-2024 spans expansion, then COVID Recession & Recovery
  - Forecasts of nominal GDP or core PCE 1-quarter ahead
  - Forecasts of nominal GDP or core PCE 4-quarters ahead
- LSTM architecture affects performance, involving # of neurons, # & types of hidden layers, learning rates, sequential length (# prior quarters used to learn).
- Use hyperparameter tuning to find best combination of parameters to optimize performance for each baseline.

Model Performance Across Data Sets: 1-Quarter Ahead Nominal GDP Forecasts

(Sources: CFS, FRED, and authors' calculations)

Dataset	R^2	MAPE
Baseline	0.89	5.13%
add DivM3 & MF costs	0.97	1.82%
add DivM4- & MF costs	0.99	1.10%
add DivM4 & MF costs	0.97	2.59%

1-quarter horizon: R^2 rises by about 8 to 10 percentage points

1-quarter horizon: MAPE falls by 2.4 to 4 percentage points

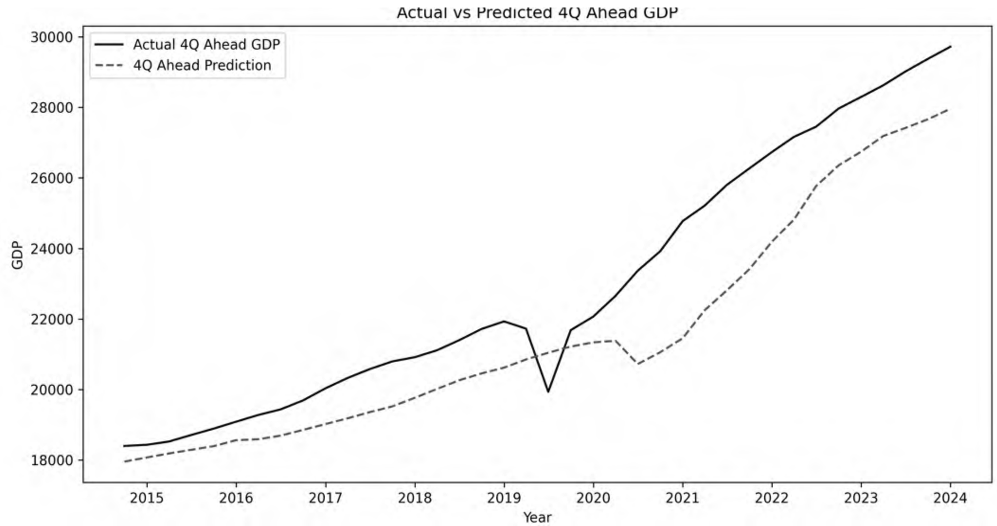
Model Performance Across Data Sets: 4-Quarter Ahead Nominal GDP Forecasts

(Sources: CFS, FRED, and authors' calculations)

Dataset	R^2	MAPE
Baseline	0.79	5.93%
add DivM3 & MF costs	0.94	2.90%
add DivM4- & MF costs	0.91	3.06%
add DivM4 & MF costs	0.94	2.50%

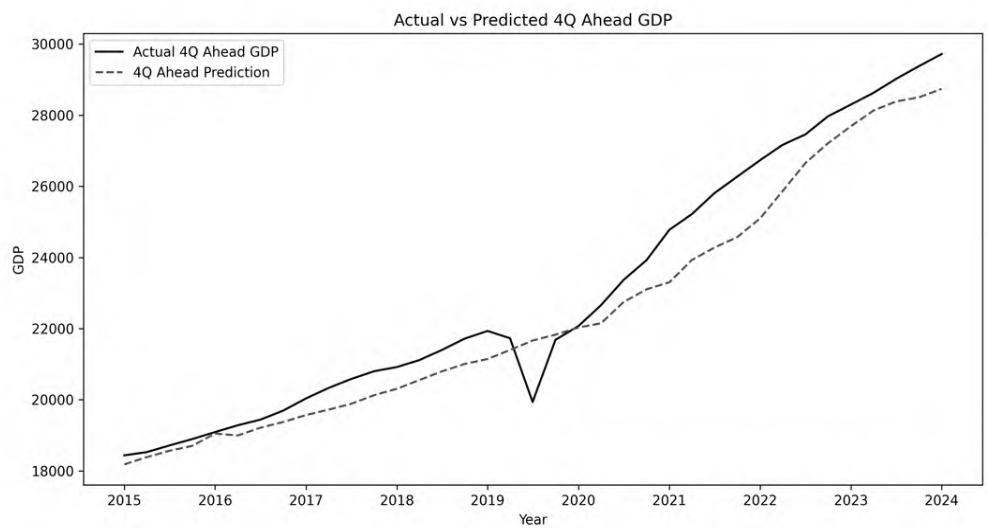
4-quarter horizon: R^2 rises by about 12 to 15 percentage pts.

4-quarter horizon : MAPE falls by 1.9 to 3.4 percentage pts.



4-Qtr. Ahead Forecast of Nominal GDP **EX**cluding Div. M's and Mutual Fund Costs

(sources: CFS, FRED, and authors' calculations)



4-Qtr. Ahead Forecast of Nominal GDP **IN**cluding Div. M3 and Mutual Fund Costs

(sources: CFS, FRED, and authors' calculations)

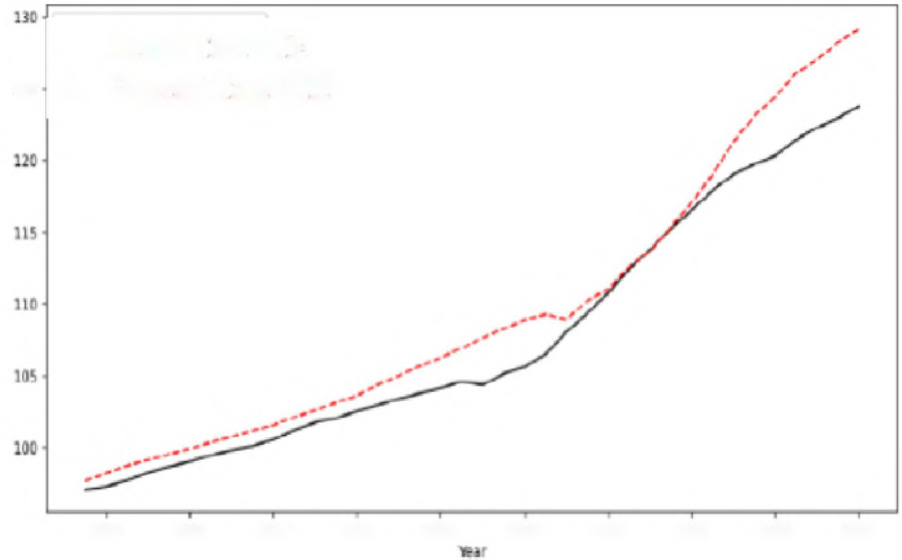
Model Performance Across Data Sets: Core PCE Forecasts

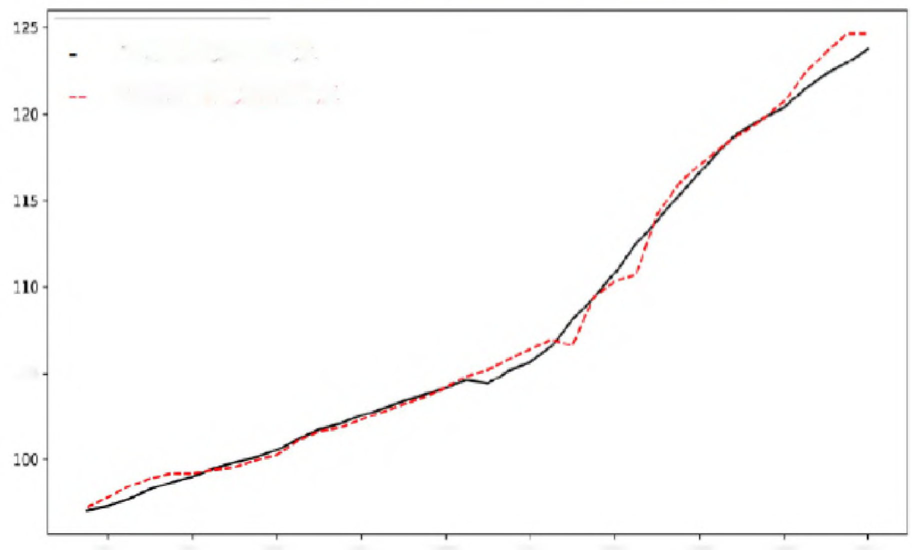
(Sources: CFS, FRED, and authors' calculations)

Dataset	R^2	MAPE
1-Quarter Ahead Forecasts		
Baseline	0.90	2.32%
add Div. M3 & MF costs	0.97	1.34%
4-Quarter Ahead Forecasts		
Baseline	0.92	1.63%
add Div. M3 & MF costs	0.99	0.44%

1-quarter horizon: R^2 rises by about 7 percentage points
1-quarter horizon: MAPE falls by 1 percentage point

4-quarter horizon: R^2 rises by about 7 percentage points
4-quarter horizon: MAPE falls by 1.2 percentage points


130
120
115
110
105
100
Year


125
120
115
110
100

Concluding Comments

- Using LSTM Deep-Learning models including broad Divisia Money and mutual fund costs in datasets improves forecasts of 1- and 4-quarter ahead nominal GDP and core PCE.
- Results imply Bordo & Duca ('25), & Bordo, Duca, & Jones (2025) findings that these variables help forecast nom. GDP & core PCE prices are **not** artifacts of structural models.
- Why? Perhaps since broad Divisia M reflects many factors: interest rates, uncertainty, unconventional monetary actions (QE, forward guidance, credit easing), health of commercial & shadow banks that create money. As such, Div. M more endogenous and may be less "controllable" than simple-sum money aggregates. But they are useful information variables.

Some Related Papers

- Barnett, William A. 1980. "Economic Monetary Aggregates: An Application of Index Number and Aggregation Theory." *Journal of Econometrics* 14(1): 11–48.
- Belongia, Michael T. and Peter N. Ireland. 2017. “Circumventing the Zero Lower Bound with Monetary Policy Rules based on Money.” *Journal of Macroeconomics* 54: 42-58.
- Bordo, Michael D. and John V. Duca. 2022. “How New Fed Corporate Bond Programs Cushioned the Covid-19 Recession,” *Journal of Banking and Finance* 136: 1-22.
- Bordo, Michael D. and John V. Duca. 2021. “An Overview of The Fed’s New Credit Policy Tools and Their Cushioning Effect on the COVID-19 Recession.” *Journal of Government Economics* 3: 1-10.
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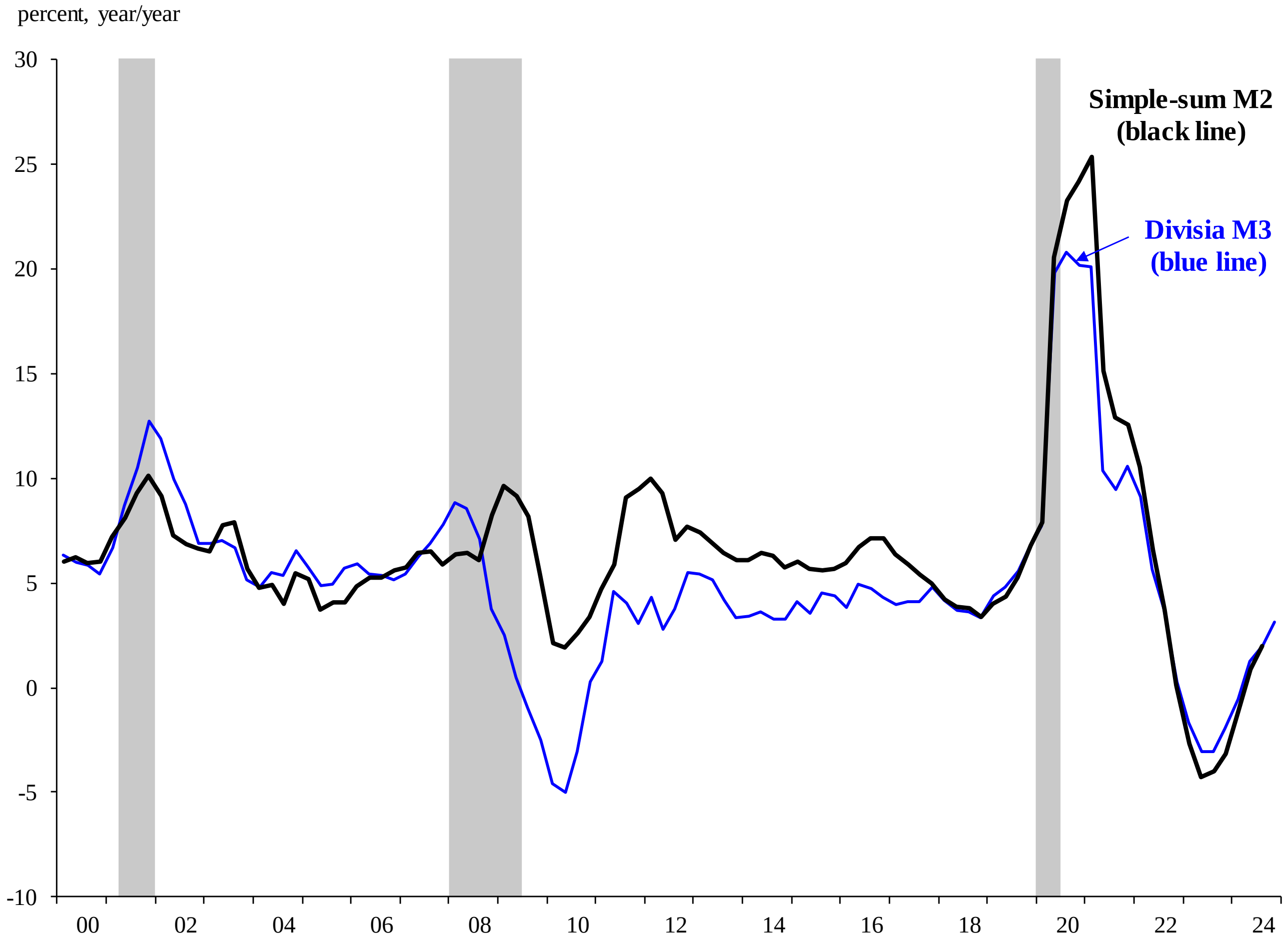
- Bordo, Michael D., John V. Duca, and Barry E. Jones. 2025." Broad Divisia Money, Supply Pressures, and U.S. Inflation Following the COVID-19 Recession." *Macroeconomic Dynamics* 29: 1-35.
- Congdon, Tim. 2025. *Money and Inflation at the Time of Covid*. Edgar Elger: Cheltenham, UK and Northampton, MA, U.S.A.
- Duca, John V. 2000. “Financial Technology Shocks and the Case of the Missing M2.” *Journal of Money, Credit, and Banking* 32 (4, Part 1): 820-39.
- Ireland, Peter 2024. “Money Growth and Inflation in the Euro Area, UK, and USA: Measurement Issues and Recent Results.” *Macroeconomic Dynamics*: 1-28.
- Jadidzadeh, Ali and Apostolos Serletis. 2019. “The Demand for Assets and Optimal Monetary Aggregation.” *Journal of Money, Credit, and Banking* 51(4): 929-52.
- Stoneman, David and John V. Duca. 2024. "Using Deep (Machine) Learning to Forecast US Inflation in the COVID-19 Era." *Journal of Forecasting* 43(4): 894–902.

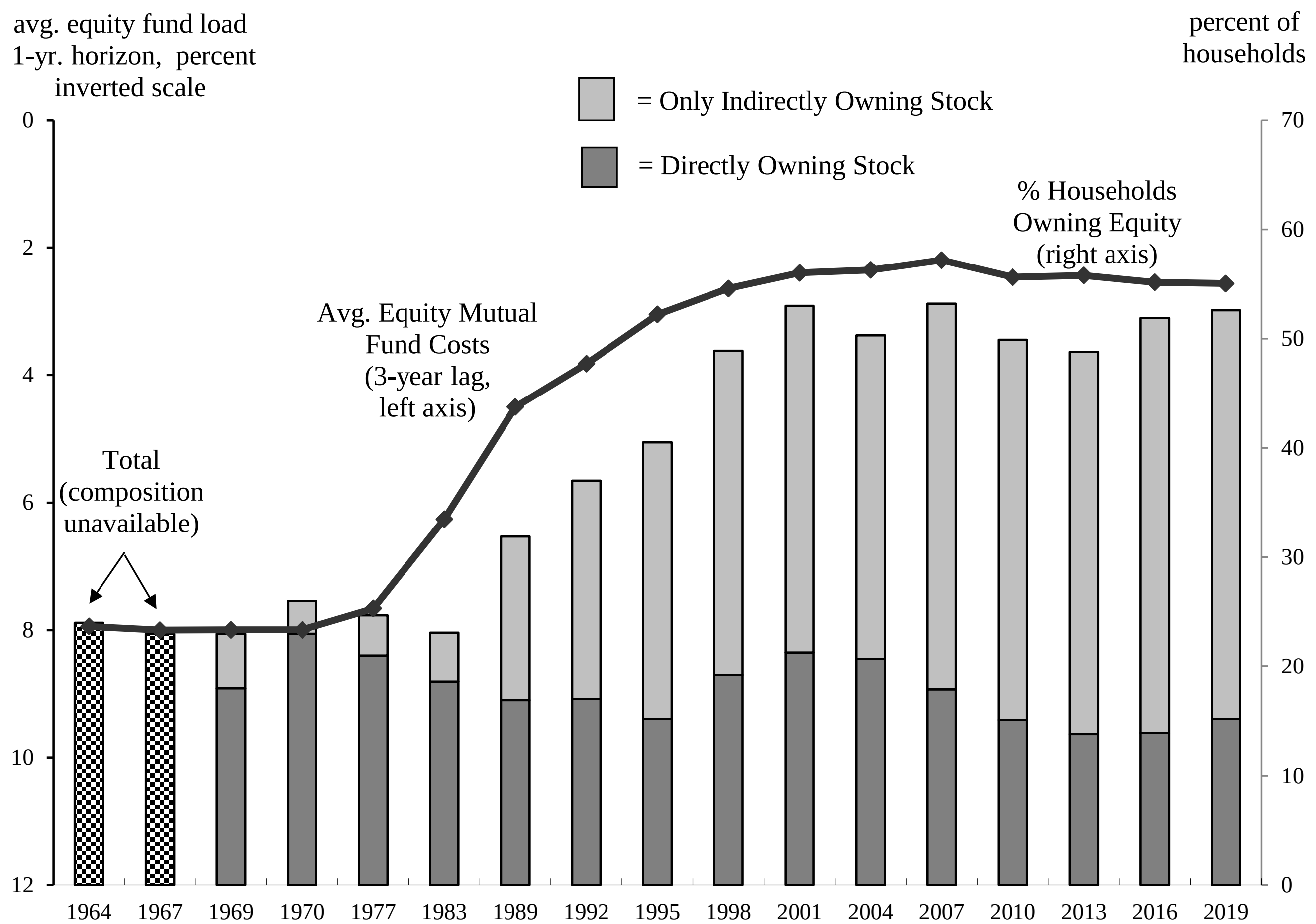
Back-up Slides



Money Growth Surges During the COVID Pandemic

(Sources: Center for Financial Stability, Federal Reserve, and authors' calculations.)

Inverted Stock Mutual Fund Costs Very Correlated with Stock Ownership Rates (Duca&Walker, '22)



Sources: Various Surveys of Consumer Finances reported in *Federal Reserve Bulletin* articles and authors' calculations.

Overview of Divisia Monetary Aggregates (indexes)

Data from CFS Divisia measures are okay after deposit deregulation:

DivM2: liquidity services from M2 balances

DivM3 adds services from LTDs, institutional MMMFs, RPs

DivM4- further adds services from commercial paper

DivM4+ further adds services of T-bills

Stable broad divisia velocity in deregulated deposit era.

Divisia tracks the evolving liquidity of monetary components.

Divisia M3 internalizes nonbank money created by money funds. For example, institutional MMMFs bought commercial paper and s-run debt financing many subprime investments, which fell in the subprime bust.

Broad Divisia V falls in crises, but later recovers, imparting long & variable lags in the effects of swings associated with money growth.

The Future of Monetarism after Milton Friedman

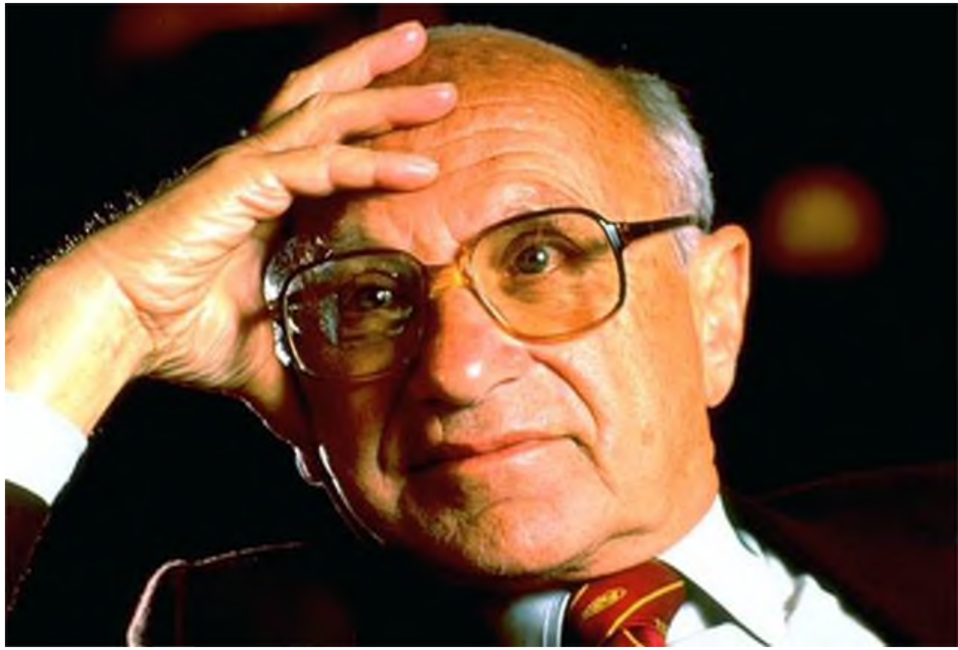
Bank of England workshop “ Analysing the Information Content of Money—Central bank Practice and recent academic research”

London, England March 4 2026

Michael D Bordo, Rutgers University, Hoover Institution, Stanford University, Griswold Center, Princeton University, and NBER

The Future of Monetarism after Milton Friedman

- I reflect on Milton Friedman’s legacy to monetarism-- one of his key contributions to economics, fifty years later
- MF’s “The Quantity Theory of Money—A Restatement (1956)” led to a new paradigm in macroeconomics, later called monetarism, that was ascendant in the 1960s and 70s
- Friedman (and Anna Schwartz) attributed the US record of business cycle instability, inflations and deflations in the nineteenth and twentieth centuries to variations in the growth of the money supply, largely attributable to actions by the monetary authorities
- His views challenged the prevailing Keynesian orthodoxy and influenced the Federal Reserve in 1979 to end the Great Inflation and pivot to a strategy of credibility for low inflation
- His views have a strong footprint in the present New Keynesian macro models used by central banks
- His legacy continues in the watchdog Shadow Open Market Committee, which has projected many of his views through the lens of modern macroeconomics
- Although money growth is no longer at the forefront of modern policymaking, it still has resonance as a cross-check of monetary policy, especially in periods of incipient inflation.



I.Friedman’s monetarism

- Following a long tradition at the University of Chicago (Tavlas 2024)
- Milton Friedman in 1956 revived the quantity theory of money in a new form, “ The Quantity Theory of Money—a Restatement”
- According to Friedman, the core of his QT is a stable long-run demand for money as a function of a limited number of salient variables (wealth, rates of return on various assets)

Friedman’s monetarism

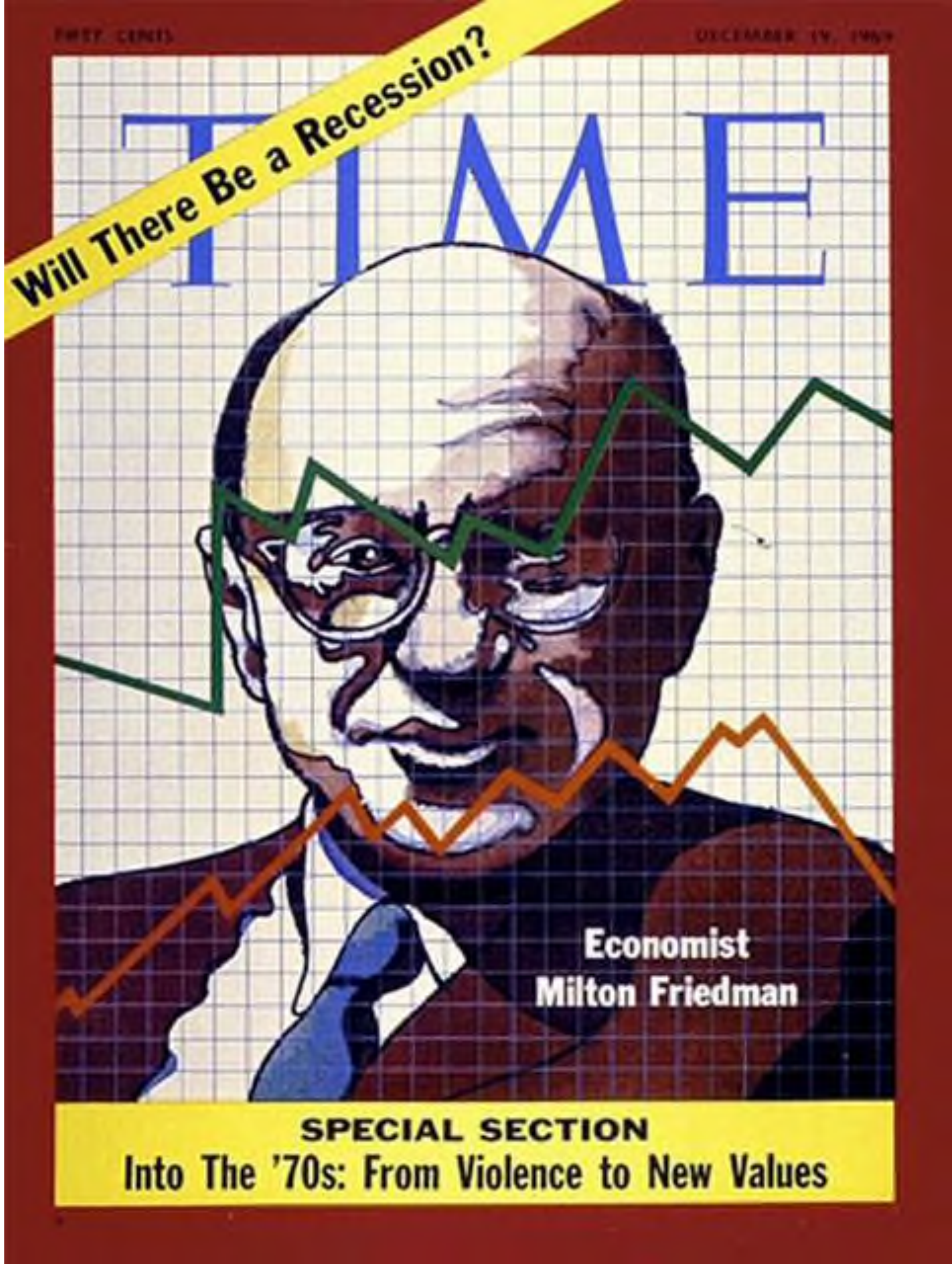
- The interaction between the stock of money (M), predominantly determined by the monetary authorities’ actions, and the demand for money would determine the level of nominal income
- With real income determined by market forces, and a stable demand for M (also velocity), the price level (P) would be determined by M
- MF posed his QT as an alternative to the prevailing Keynesian approach that national income was determined by autonomous expenditures (Investment and Fiscal policy)
- And that money demand was unstable (absolute liquidity preference and impotent monetary policy)

Friedman's monetarism

- Milton Friedman and Anna Schwartz provided a massive amount of evidence (empirical and historical) for the QT
- Their key findings on business cycles (FS 1963a) were that changes in M would first impact y with a 1 to 2 Q lag (reflecting nominal rigidities) and then would be fully reflected in changes in P (M neutrality)
- FS's key work was in *A Monetary History of the US* (AMH) (1963b)
- They developed their narrative approach to identify unique natural experiments of monetary change under varying historical and institutional circumstances (e.g., gold std, Greenbacks, silver, the Fed)
- To make the case that monetary change was the key cause of US monetary and financial turbulence (Bordo and Rockoff 2013)

Friedman's monetarism

- According to FS, the Great Contraction of 1929 to 1933, was the Fed's worst unforced error by not acting as a LOLR and offsetting four banking panics
- The Fed's poor record led MF to make the case for his k% monetary rule against Fed fine-tuning/discretion
- In the 1960s and 70s he criticized the Fed for generating and exacerbating the Great Inflation
- His views led Congress in 1978 to require the Fed to report on its M targets
- His lessons were heeded in the Volcker shock of 1979
- MFs (1968) AEA Presidential address, with his NRH, severely challenged the prevailing Phillips curve tradeoff



Friedman’s monetarism

- However, the Fed and other CBs' adoption of M targeting foundered on short-run instability in the Md function they used, reflecting financial innovation in the face of rising and then falling inflation.
- MF in the mid 80s famously forecasted a burst in inflation that never occurred
- Leading to the economics profession and the Fed turning away from monetarism
- The Fed (and other CBs) restored interest rates as their policy tool and abandoned M targeting

II. MF’s legacy 50 years later

- While MF’s monetarism has long been forgotten by the mainstream, his views have prevailed and are still relevant
- His monetarist legacy has two channels: 1.**theoretical** through the development of modern macro by his student Robert Lucas and others, followed by the New Keynesian model (NK)
- 2. a **policy** channel through the Shadow Open Market Committee in the US and via the hard currency central banks of Europe(DBB and SNB)

II.1 The Theoretical Channel

- FS 1963a and 1963b evidence that M policy first affected y via nominal rigidities and P reflecting M neutrality
- As well as the role of expected inflation and the NRH in MF (1968)
- In addition to MF's (1960) case for an M rule over fine-tuning/discretion
- Became the bedrock for the now prevailing NK model
- Lucas (1972) and Sargent (1971) extended MF's NRH to the "policy invariance hypothesis"
- Under rational expectations, monetary policy actions would not influence the real economy because agents understand the Fed's model, and have full information
- Would completely adjust their expectations, obviating the effects of the CB's policy

II.1 The Theoretical Channel

- This classical model was extended to include nominal rigidities via staggered wage and price contracts (Fischer, Taylor, Calvo)
- MF’s case for rules was superseded by the approaches of Kydland and Prescott (1977) and Barro and Gordon (1982)
- That central banks would be prevented by rational agents from following time-inconsistent/ discretionary policies to alter the Phillips’ curve tradeoff
- Only by following a credible commitment device (rule) would inflation be anchored

II.1 The Theoretical Channel

- John Taylor’s (1993) rule with the policy interest rate as the instrument (rather than M)
- Reacting to a function with the dual mandate of stable P and maximum N output
- And following the Taylor principle, the CB would need to alter its nominal policy rate more than the rate of expected inflation to change the real rate
- Became a key building block to anchor credibility for low inflation
- These modern tools, derived from MF’s monetarism, became the equations of the New Keynesian model
- Which became the workhorse for both policymakers and academic economists
- Of note, very different from MF’s monetarism, M does not appear directly in the model
- It is buried in the cash-in-advance assumption underlying the NK framework

The Policy Channel: The Shadow Open Market Committee

- The Shadow Open Market Committee (SOMC) was founded in 1973 by Karl Brunner, Alan Meltzer, and Anna Schwartz to serve as an outside watchdog of the Fed.
- They were highly critical of the pattern of ever-rising inflation in the 1970s.
- Their policy recommendation was a gradual decline of the monetary base to reduce inflation
- They were successful in using the media to influence Congress to convey their message: the 1977 and 1978 Acts requiring the Fed to report monetary aggregate target ranges
- They may have influenced Volcker's shock

The Policy Channel: The SOMC

- During the Great Moderation, the SOMC still kept recommending monetary base targeting when the Fed and the profession had shifted to interest rates
- This reduced its standing
- Beginning in the 1990s, new members, Charles Plosser and Bennett McCallum, were at the forefront of new research using rational expectations and real business cycles
- They advocated the Fed’s adherence to systematic interest rate rules
- Lee Hoskins, a member in the 90s, was a pioneer in advocating inflation targeting
- While Marvin Goodfriend made a strong case for a transparent, accountable, rules-based independent central bank to maintain credibility for low inflation

The Policy Channel: The SOMC

- Later in the twenty-first century, two former Fed Presidents (Jeffrey Lacker and Jim Bullard) joined the group.
- New members (Michael Bordo, Peter Ireland, Andrew Levin, Athanasios Orphanides, Charles Calomiris, and Deborah Lucas) joined
- The revived SOMC, following its successful analysis of the Great Inflation, was prescient in predicting and criticizing the Fed's role ("too low for too long" in the debt-financed housing bubble leading to the GFC of 2007-2008
- And more recently, the Fed's role in generating the recent pandemic inflation("team transitory") and its still being behind the curve (Bordo and Levy 2022)
- The SOMC has carried forward a modern rendition of Friedman's monetarist message

The Policy Channel: The Hard Currency European central banks

- Two European central banks(the Bundesbank and the Swiss National Bank) were direct descendants of Friedman's monetarism
- Both followed "the stability culture" of sound money and price stability
- Both CBs avoided the Great Inflation of the 70s and kept targeting monetary aggregates long after the Fed(and others) had given up
- The European Central Bank (ECB), established in 1999, kept a strong role for the monetary aggregates
- Otmar Issing, chief economist of the Bundesbank and then of the ECB, originated the ECB's "Two Pillar Strategy" to fulfill its mandate of price stability.

The Policy channel: The ECB

- Pillar one was based on the Bundesbank’s successful twentieth-century monetary targeting record -- to monitor monetary aggregates to ensure long-run price stability, mainly to prevent outbreaks of high inflation
- Pillar Two was to use real and financial analysis (conventional Macro modelling) to ensure stable prices in the short to medium term
- The pillars were later reversed

What about the M’s

- Anna Schwartz, at the end of her life in 2012, asked me, “Michael, what about the M’s? Will they ever be given attention by the Fed?”
- Several FOMC members continue to do research using the aggregates in the spirit of F and S.
- They use the Center of Financial Stability’s (CFS) Divisia indexes of monetary services based on concepts by Friedman and Schwartz (1970) and Barnett (1980)
- The choice of the correct monetary aggregate to use in MQT analysis was the combination of monetary assets (currency, deposits, MMFs, etc.) that provided the most accurate flow of monetary services.
- Barnett (1980) constructed a weighted average of monetary components where the weights are the expenditure shares of the component services
- The prices of these services within these shares are measured by their user cost prices
- User cost prices are proportional to the difference between the rate of return on pure capital and the return paid on the different components of money

What about the M's?

- Peter Ireland and Michael Belongia (2016) used CFS Divisia M2 to revisit FS's (1963a) work on "Money and Business Cycles"
- They find that the original FS correlations between money growth and real output and inflation, which broke down in the 80s, are completely restored using data to the present
- John Duca and I (2025), using CFS Divisia M3, developed a stable long-run money demand function 1984 to 2023
- Which corrects for both the changes in financial innovation and regulation that derailed earlier monetarist work
- Interacting our money demand (velocity) function with the actual growth rates of Divisia M3 closely tracks the path of nominal GDP growth from the 1980s through the recent pandemic

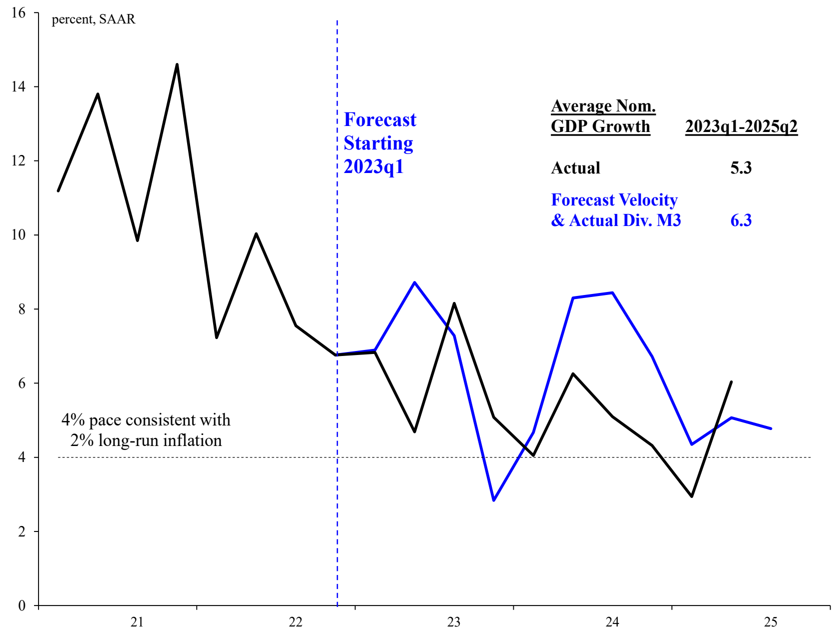


Figure 1: Bordo-Duca Model Forecasted Somewhat Higher Nominal GDP Growth Since the COVID-19 Pandemic

(Sources: BEA, Federal Reserve, CFS, Oxford's Blavatnik Center, and authors' calculations)

What about the M's ?

- Further work with Duca and Barry Jones (2025) combines our Divisia M3 money demand analysis into the Fed's P-star model (Hallman, Porter, and Small 1991) based on the MQT
- We track the recent post-pandemic inflation episode closely
- Our analysis suggests that monetary aggregates, when properly measured to reflect the flow of monetary services (as first discussed by FS 1970)
- Can be a very useful cross-check to the Fed's interest rate policy based on the NK and other non-monetarist models
- This supplements the approach taken in Europe

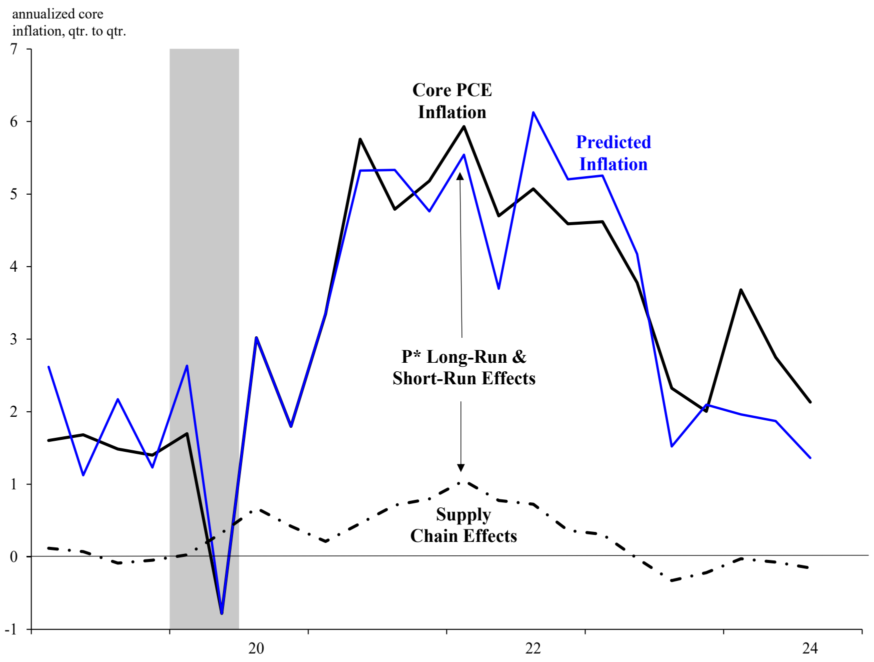


Figure 2: Bordo-Duca-Jones Core PCE Inflation Predictions
(Sources: BEA, Federal Reserve, CFS, Oxford's Blavatnik Center, and authors' calculations)

Conclusion

- MF's legacy is very much present in today's money macro models
- The need to follow systematic (Taylor-type) rules to achieve low and stable inflation has its roots in FS (1963a and b), in MF's case for M rules (1960), and in his NRH (1968)
- The SOMC's watchdog approach keeps the MF tradition very much alive
- Although the M aggregates no longer play a direct role in modern central banking, monitoring them as a cross-check can help CBs from generating high inflation
- Indeed, every measure of the M's ballooned in 2021 as a clear red flag of an impending inflationary surge
- Yet the Fed, to its peril, ignored the M data

From the Monetary Pillar to Monetary and Financial Analysis: money and the identification of (financial) shocks

Workshop on Analysing the Information Content of Money – central bank practice and recent academic research, Bank of England, 4 March 2026

Martin Mandler[a][b] and Michael Scharnagl[a], [a]Deutsche Bundesbank, [b]Justus-Liebig-Universität Gießen

Introduction

- Initial focus of Eurosystem monetary analysis on **money growth**.
  - Deviation of annual growth rate of monetary aggregate M3 from reference value.
  - Long-run (trend) relationship between money growth and inflation (“underlying money growth”).
- **Problems**:
  - Short-run deviations of money growth from reference value with little information content for future inflation.
  - Weakening of empirical correlation between money growth and inflation/stable correlation at cycles far beyond policy horizon.
  - Updated results of wavelet analysis for euro area.
- Evolution of monetary analysis into **monetary and financial analysis**
  - **Broadly based**: many financial and monetary indicators.
  - Analysis of **monetary policy transmission** through financial system.
  - Analysis of the effects of **financial shocks**.

Example: Money in a macro-financial BVAR analysis

- Analysis of **joint dynamics** of money and other macroeconomic and financial variables through the lens of a structural Bayesian vector autoregressive model (BVAR).
  - ➢ Applications to euro area (and Germany)
- Model places money into **context** with other variables.
  - – Interpretation of monetary dynamics.
  - – Use money growth for identification of (some) structural shocks.
- Looks more at information content at business cycle frequencies, i.e. closer to policy horizon.

Euro area BVAR model – data

- Estimation period:1999Q1 – 2025Q4
- 10 variables:

RGDP:	real GDP
HICP:	Harmonized index of consumer prices
Loans:	loans to non-financial corporations
LRate:	lending rate to non-financial corporations
Rate5Y_{DE}:	5y sovereign bond yield (DE)
MPRate:	EONIA/€STR, shadow short rate
M3:	monetary aggregate M3
Rate5Y_{US}:	U.S. 5y treasury bond yield
PStock:	Stock price index
PEnrg:	Energy price (oil or natural gas)

- 5 lags
- All variables in log-levels, except for interest rates.
- Outlier correction for Covid-Pandemic following Cascaldi-Garcia (2022).

Identification via sign-restrictions

Variables \ Shocks	AD	AS	MP	LS	MD
RGDP	+	-	-	+	-
HICP	+	+	-		-
LOANS	+		-	+	
LRATE	+		+	-	
$RATE5Y_{DE}$					+
MPRATE	+	+	+	+	-
M3	+		-	+	+
$RATE5Y_{US}$					
PSTOCK			-		-
PENRG					

Sign restrictions imposed on impact. Algorithm of Chan et al. (2025).
AD: aggregate demand shock, AS: aggregate supply shock, MP: monetary policy shock,
LS: loan supply shock, MD: money demand shock, UNC: uncertainty shock, ERG: energy price shock.

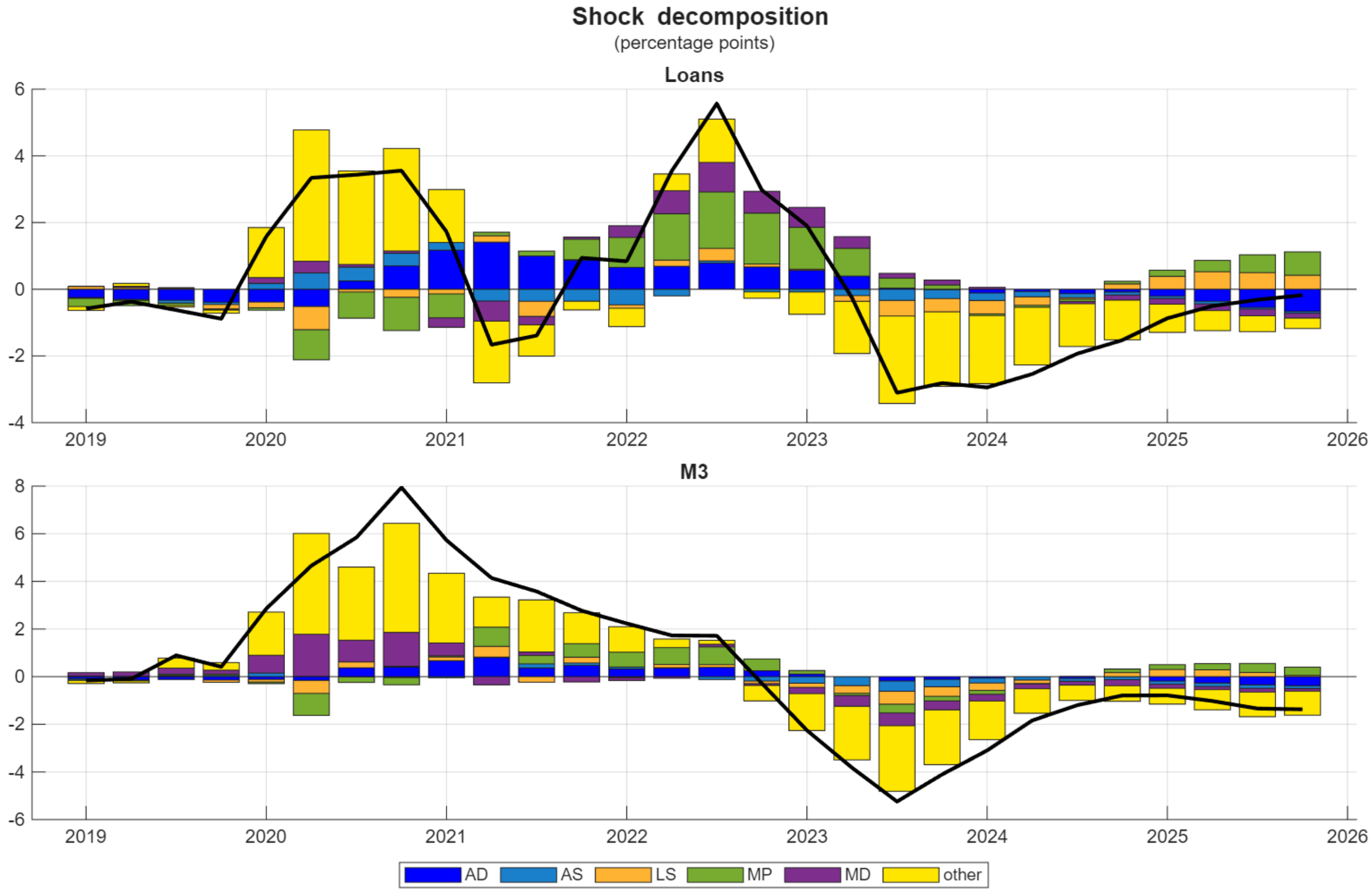
Impulse responses

How to treat pandemic in the shock decomposition?

- Pandemic priors approach (Cascaldi-Garcia, 2022), introduces dummies for outliers during pandemic.
- Bayesian estimation with prior with zero mean on coefficients on dummy variables.
- T**hree alternatives** for treating **dummies in shock decomposition** and they have **different economic interpretations**:

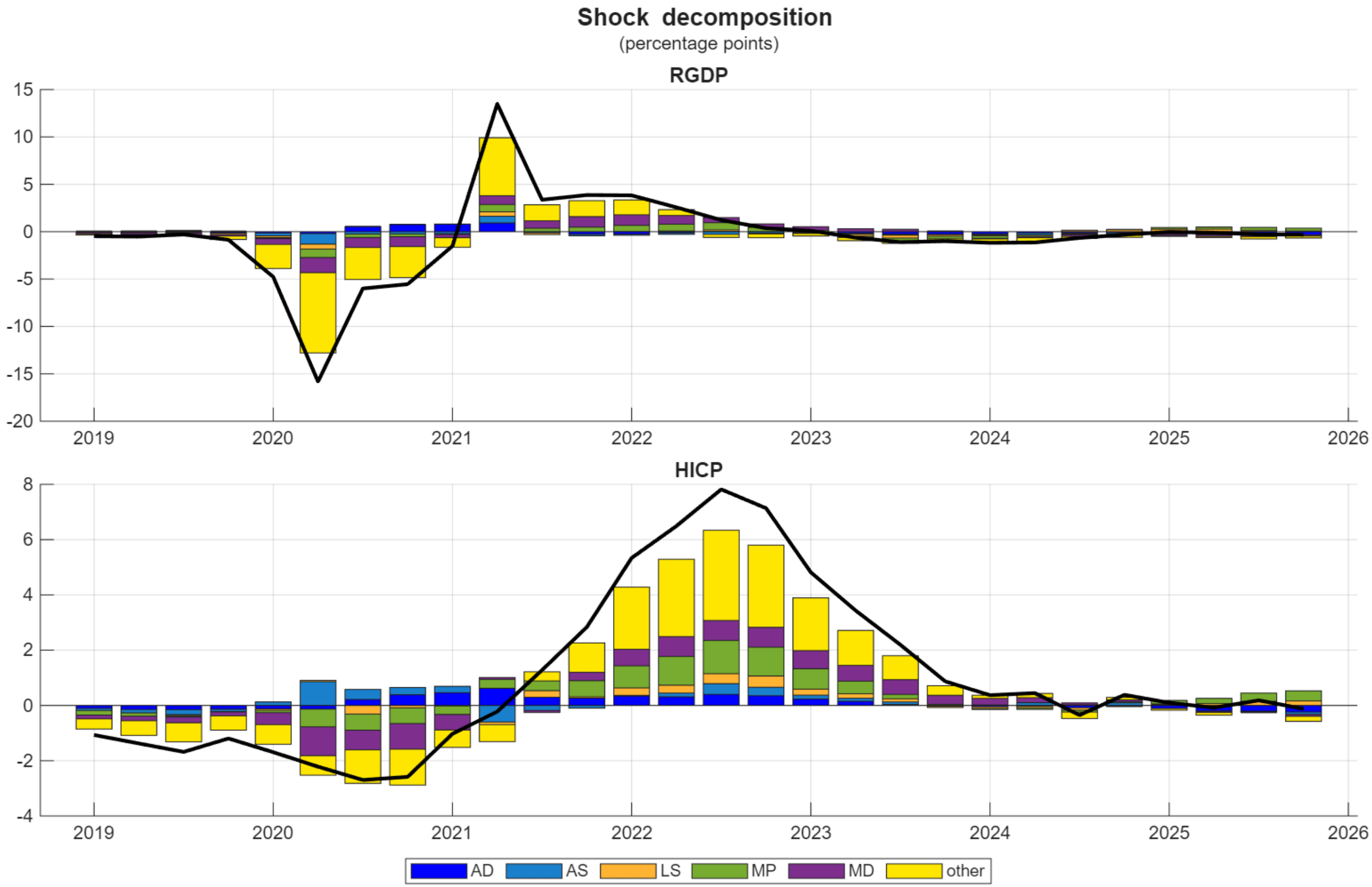
1. As in the estimation, dummy variables are included in the **deterministic part** of the model,
2. Treat pandemic as a sequence of “**pandemic shocks**” with initial effects represented by coefficients on dummy variables.
3. Treat pandemic as a **linear combination of the “normal” structural shocks**.

Shock decomposition (2019Q1-2025Q4)
- annual growth rates of Loans and M3



Estimates from Bayesian VAR. Median contributions of identified shocks to deviation from unconditional forecast (AD: aggregate demand shock, AS: aggregate supply shock, LS: loan supply shock, MP: monetary policy shock, MD: money demand shock, yellow bars denote contributions of unidentified shocks.

Shock decomposition (2019Q1-2025Q4) - annual growth rates of RGDP and HICP



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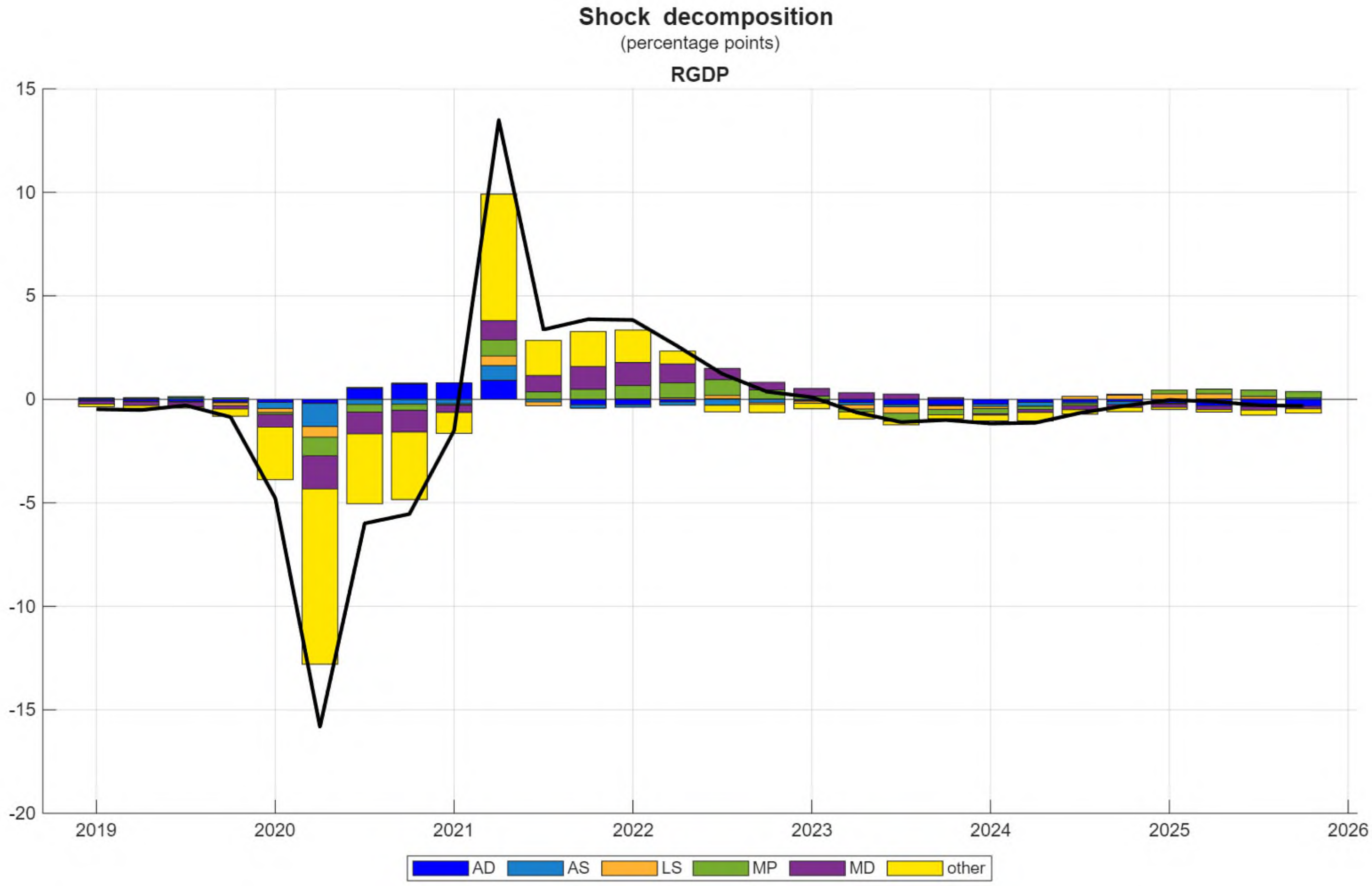
Shock decomposition (2019Q1-2025Q4) - annual growth rates of RGDP



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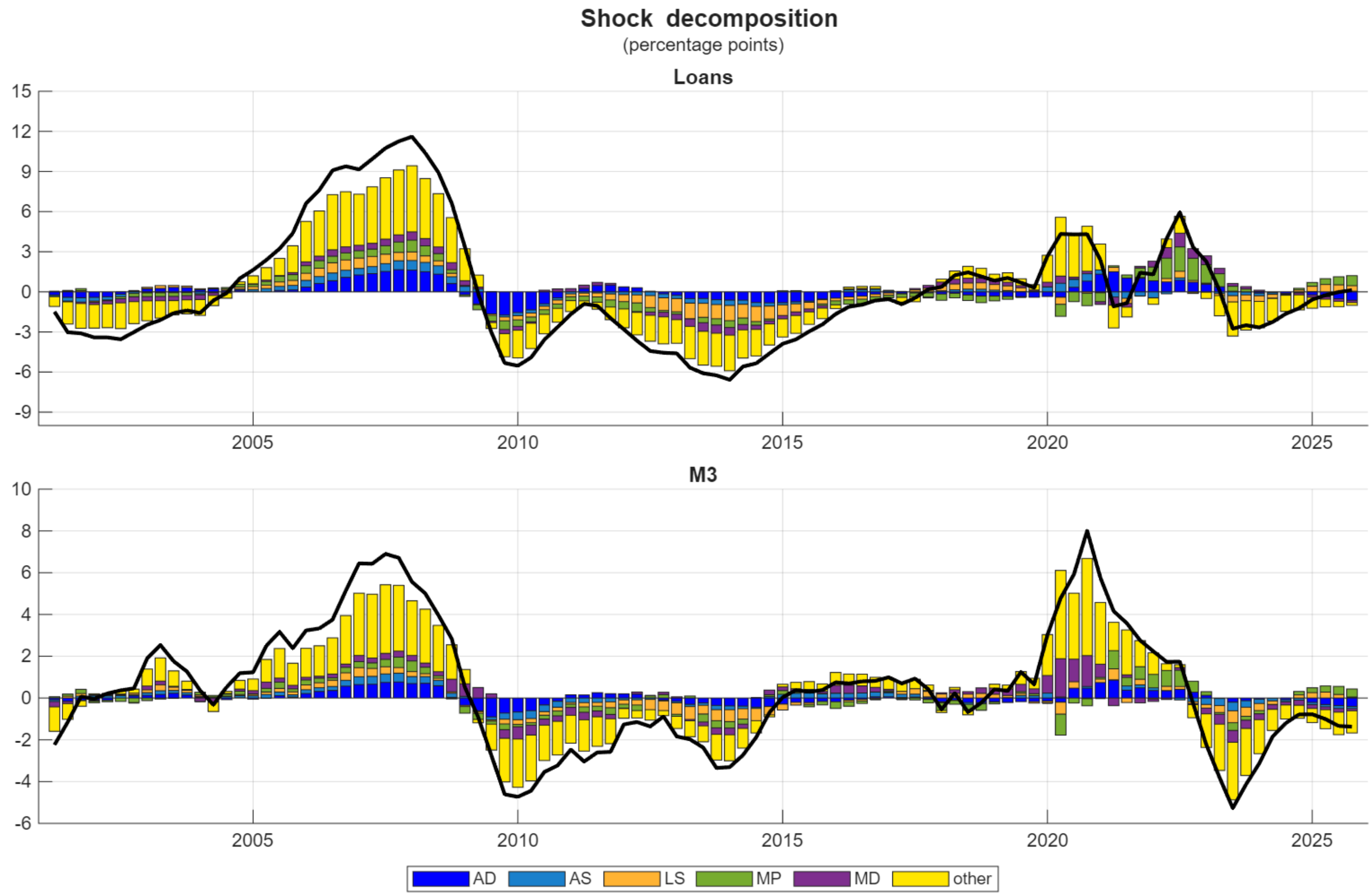
Shock decomposition (2001Q2-2025Q4) - annual growth rates of Loans and M3



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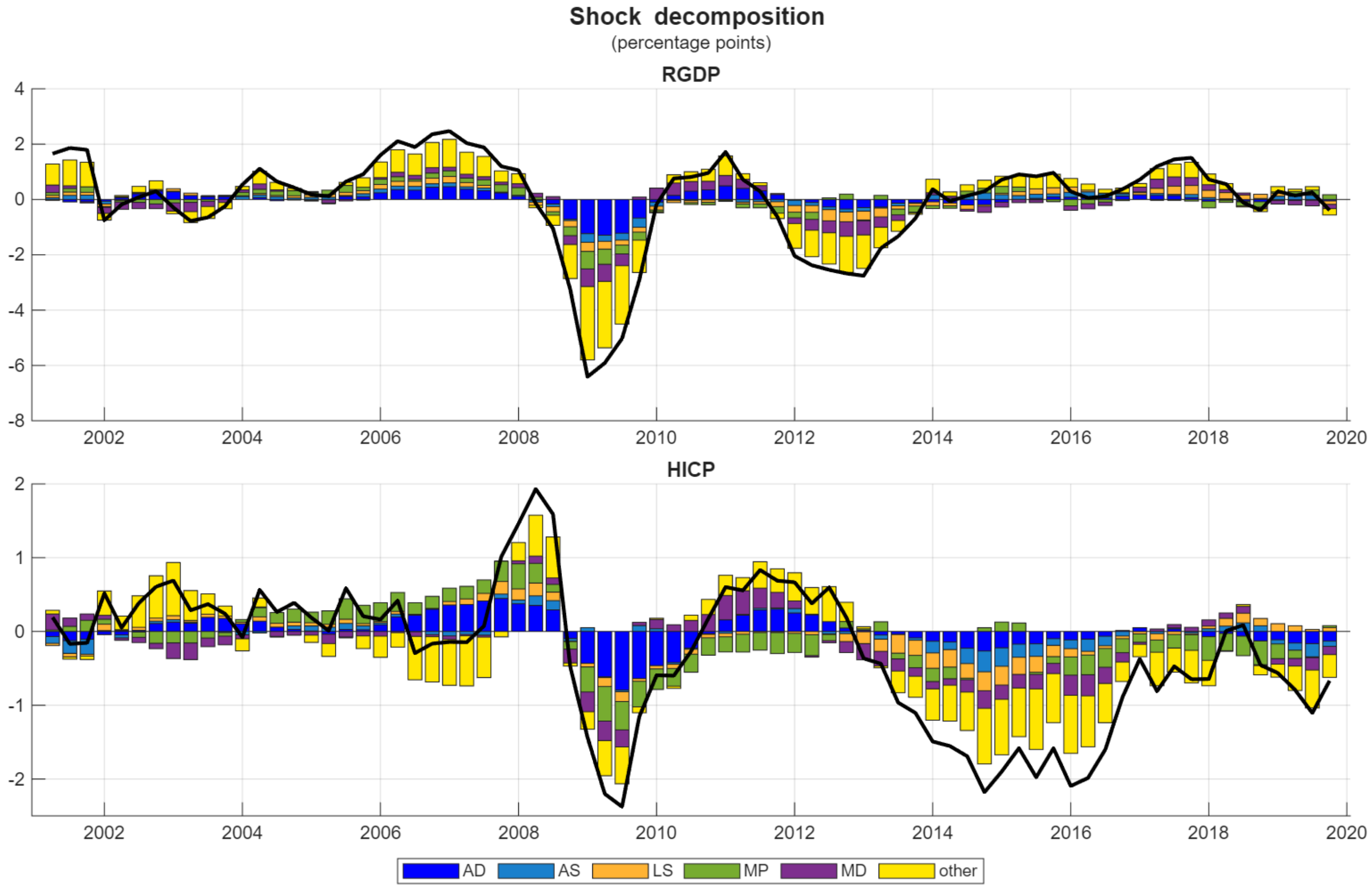
Shock decomposition (2001Q2-2019Q4) - annual growth rates of RGDP and HICP



Estimates from Bayesian VAR. Median contributions of identified shocks to deviation from unconditional forecast (AD: aggregate demand shock, AS: aggregate supply shock, LS: loan supply shock, MP: monetary policy shock, MD: money demand shock, yellow bars denote contributions of unidentified shocks.

More results

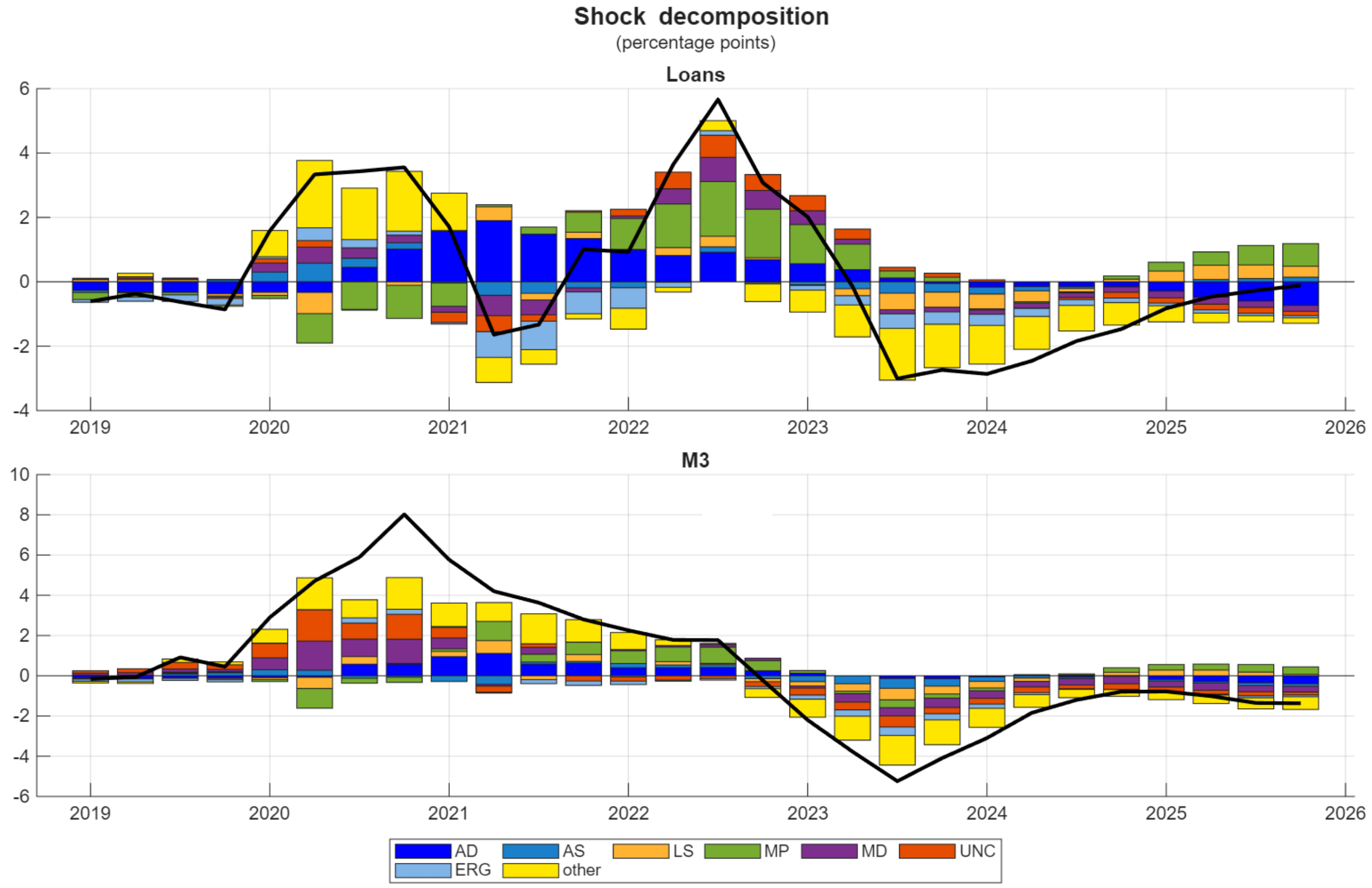
Extended model identification via sign-restrictions

Shocks Variables	AD	AS	MP	LS	MD	UNC	ERG
RGDP	+	-	-	+	-	-	-
HICP	+	+	-		-	-	+
LOANS	+		-	+			
LRATE	+		+	-		*)	
RATE5Y					+	-	
MPOLRATE	+	+	+	+	-	-	+
M3	+		-	+	+	+	
$\text{RATE5Y}_{\text{US}}$							
PSTOCK			-		-	-	-
PENRG		-					+

Sign restrictions imposed on impact. Algorithm of Chan et al. (2025) and Mandler and Scharnagl (2026).
AD: aggregate demand shock, AS: aggregate supply shock, MP: monetary policy shock,
LS: loan supply shock, MD: money demand shock, UNC: uncertainty shock, ERG: energy price shock.
*) spread between NFC and policy rate increases.

Impulse responses

Shock decomposition (2019Q1-2025Q4) - annual growth rates of Loans and M3



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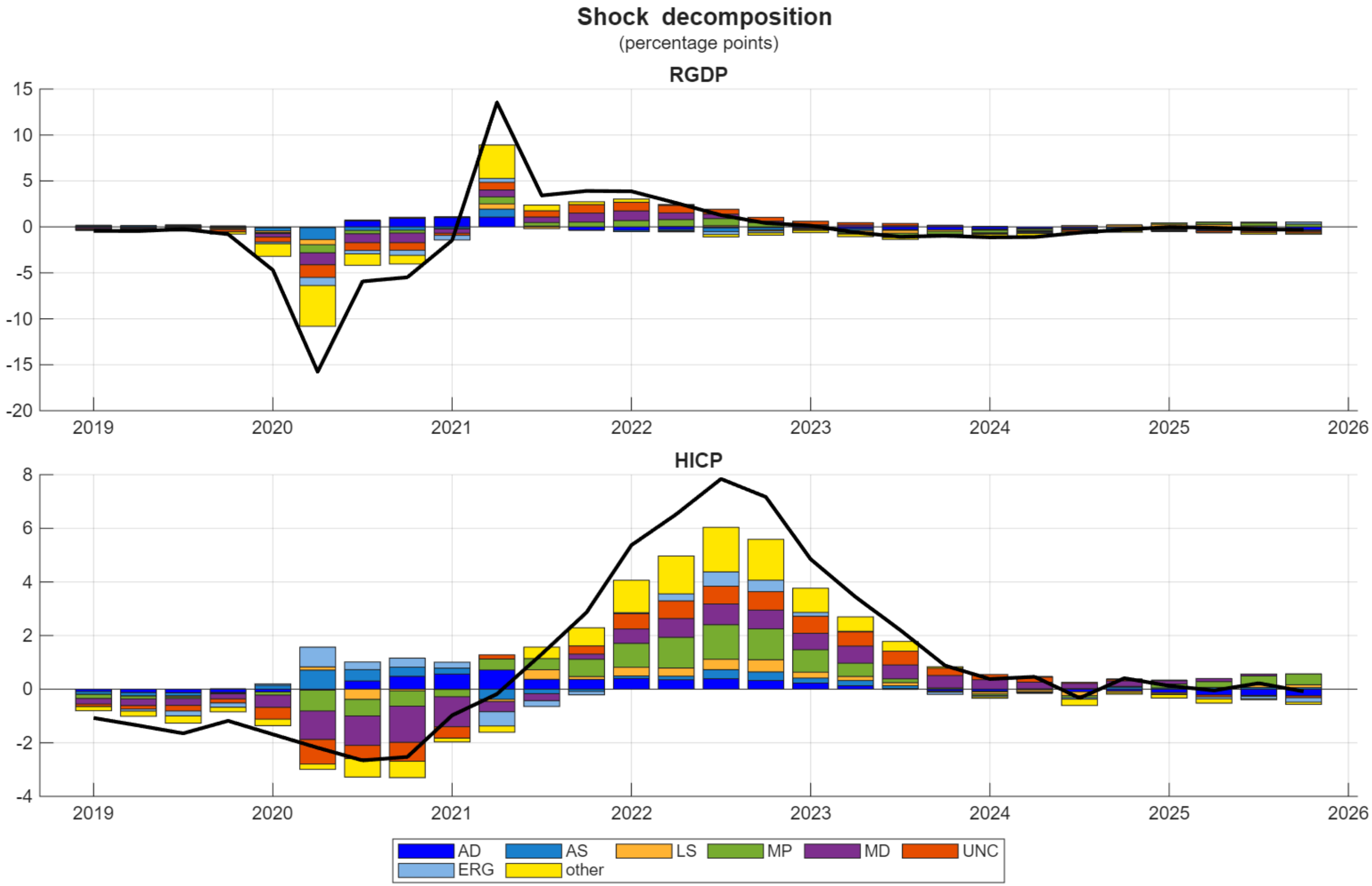
Shock decomposition (2019Q1-2025Q4) - annual growth rates of RGDP and HICP



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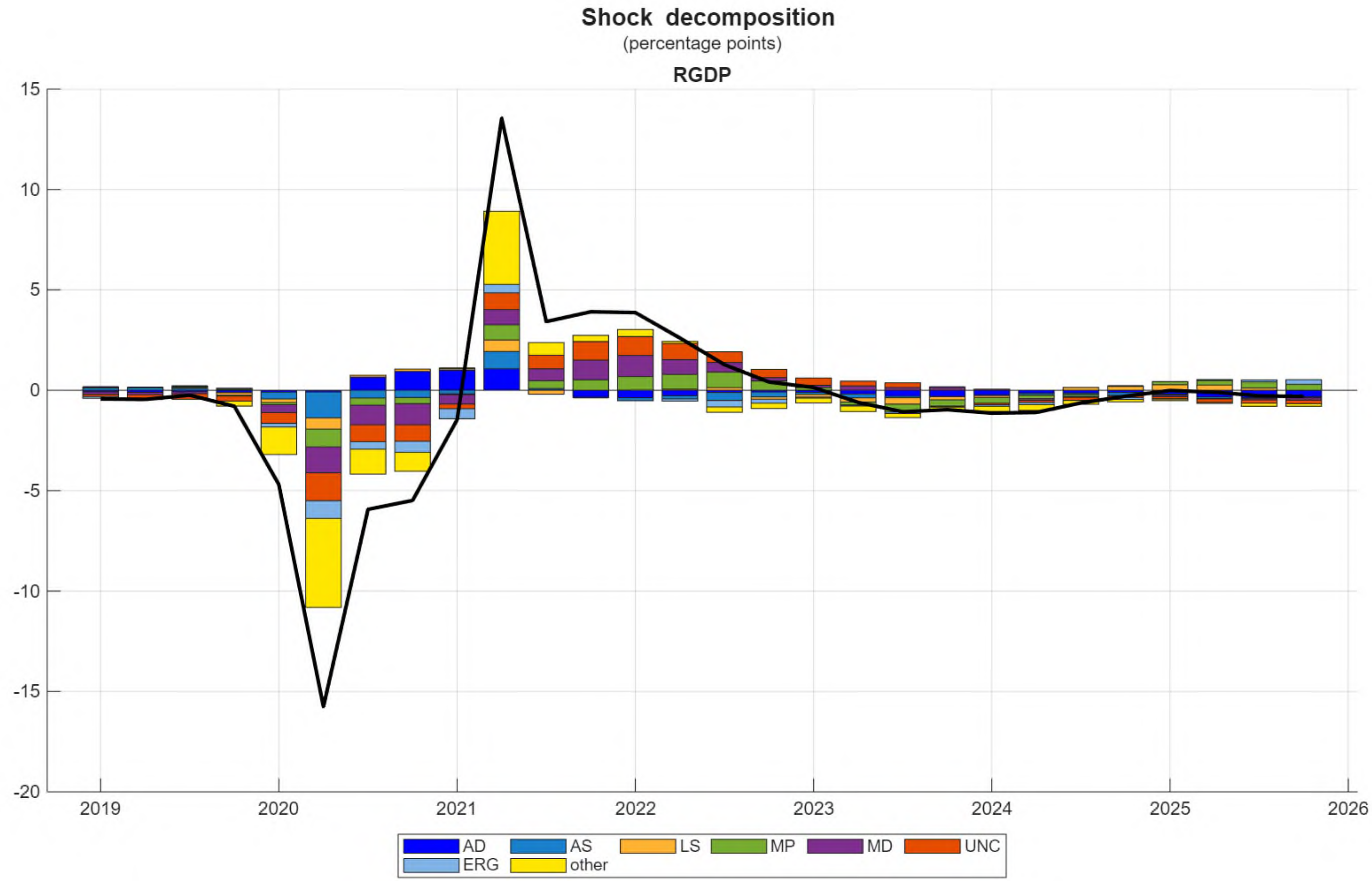
Shock decomposition (2019Q1-2025Q4) - annual growth rates of RGDP



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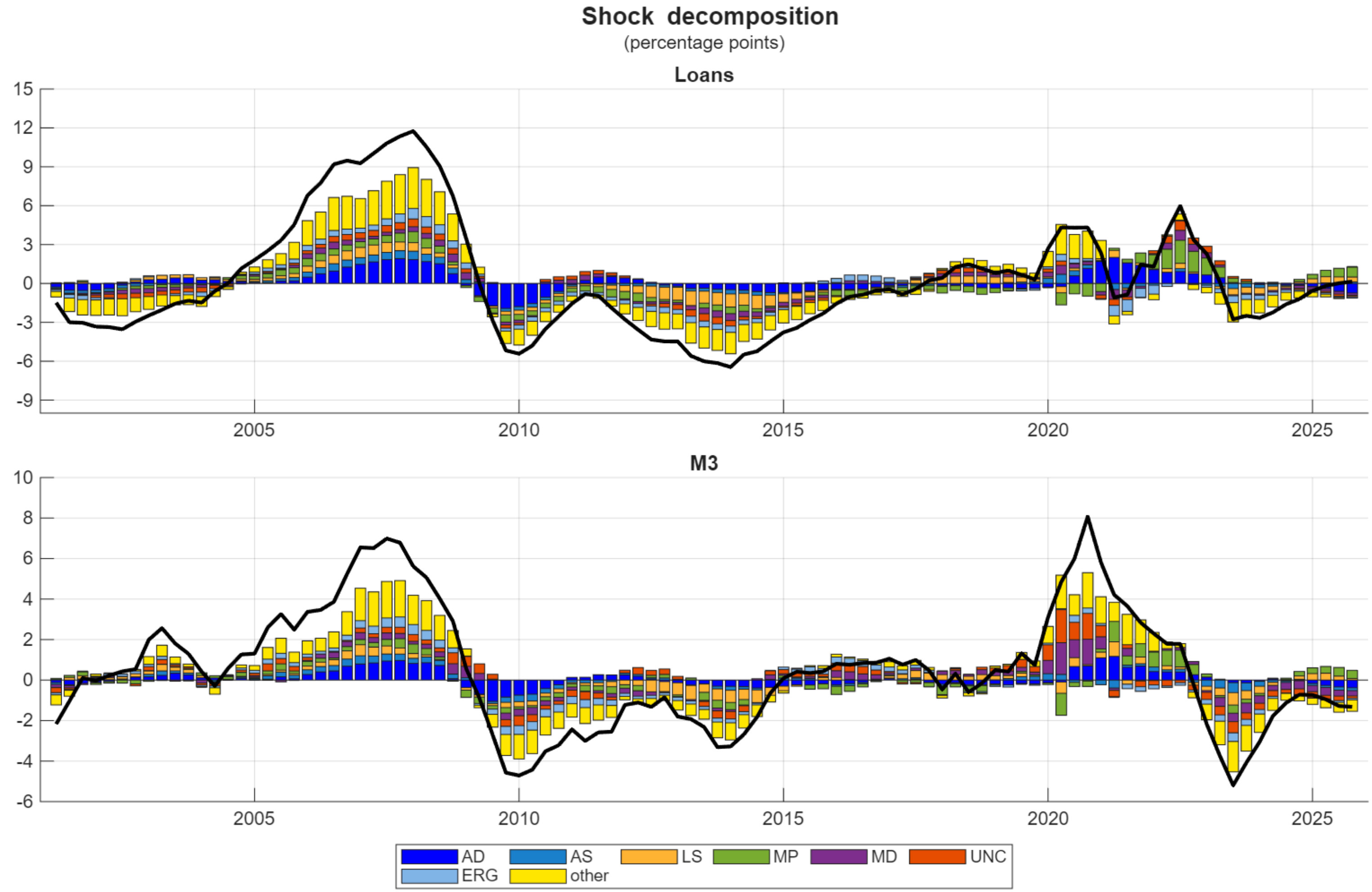

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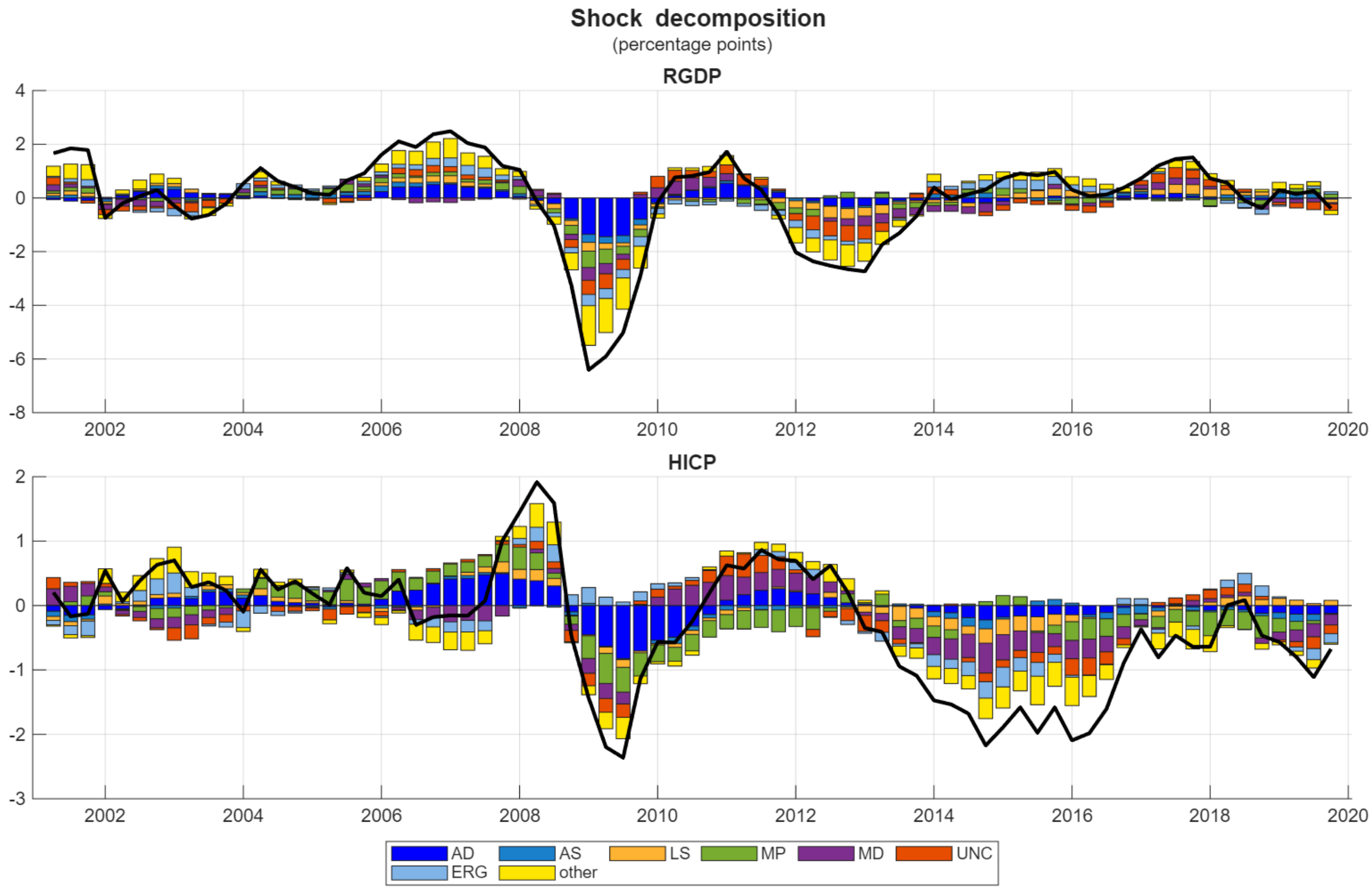
Shock decomposition (2001Q2-2019Q4) - annual growth rates of RGDP and HICP



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More results

Extending the model to Germany

- Replace euro area output, price level, loans and lending rate by **German variables**.
- Add real GDP and HICP for euro area **excluding** Germany as variables to fit monetary policy reaction function (Mandler and Scharnagl, 2020)
- Split aggregate demand and supply shock each **into symmetric and asymmetric shocks**.

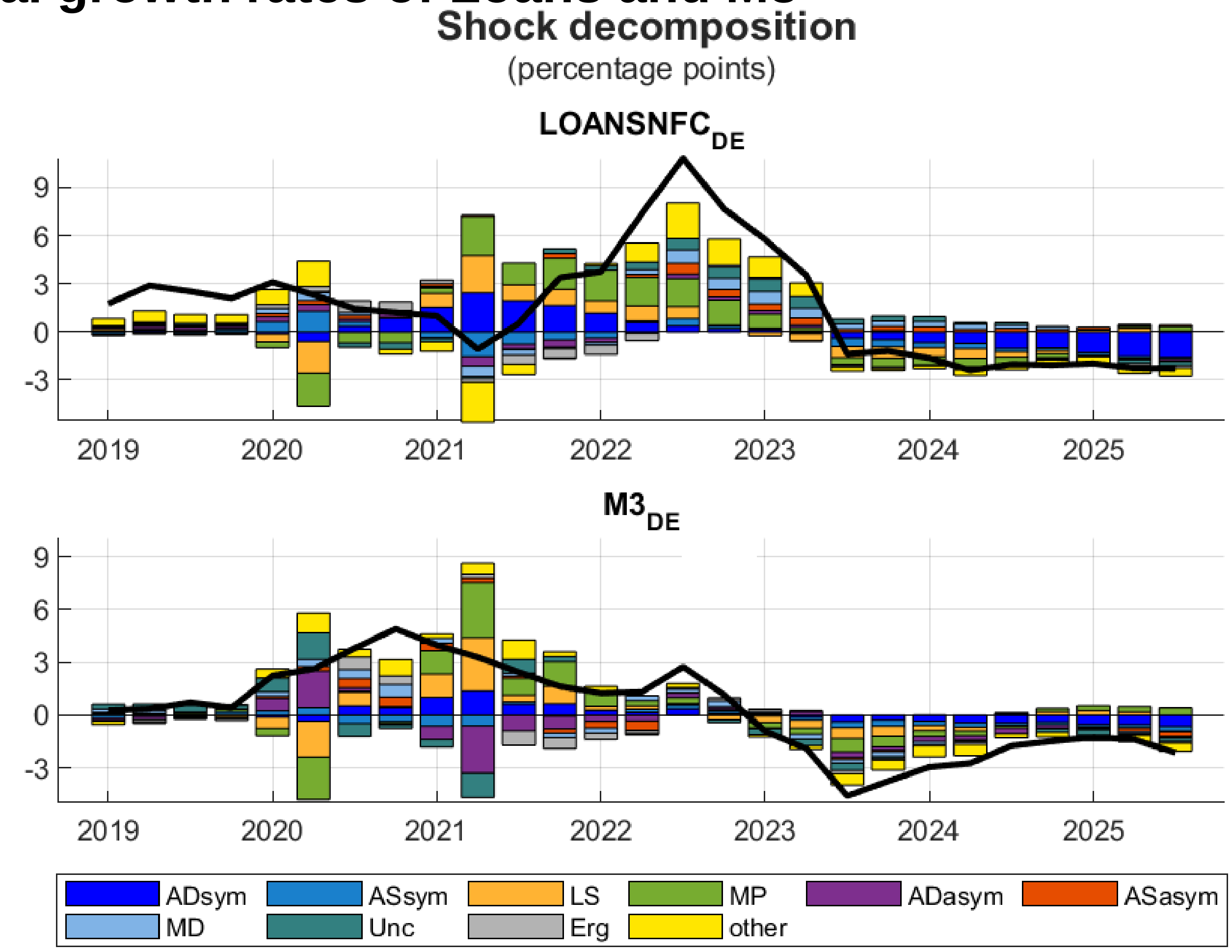
Extending the model to Germany - data

- Estimation period:1999Q1 – 2025Q3
- 10 variables:

$RGDP_{DE}$:	real GDP
$HICP_{DE}$:	Harmonized index of consumer prices
$LoansNFC_{DE}$:	loans to non-financial corporations
$NFCRate_{DE}$:	lending rate to non-financial corporations
$Rate5Y_{DE}$:	5y sovereign bond yield (DE)
MPRate:	EONIA/€STR, shadow short rate
$M3_{DE}$:	monetary aggregate M3
$Rate5Y_{US}$:	U.S. 5y treasury bond yield
$RGDP_{EAEX}$:	euro area real GDP excluding Germany
$HICP_{EAEX}$:	euro area HICP excluding Germany
PStock:	Stock price index
PEnrg:	Energy price (oil or natural gas)

- 5 lags
- All variables in log-levels, except for interest rates.
- Outlier correction for Covid-Pandemic following Cascaldi-Garcia (2022).

Shock decomposition (2019Q1-2025Q3) - annual growth rates of Loans and M3



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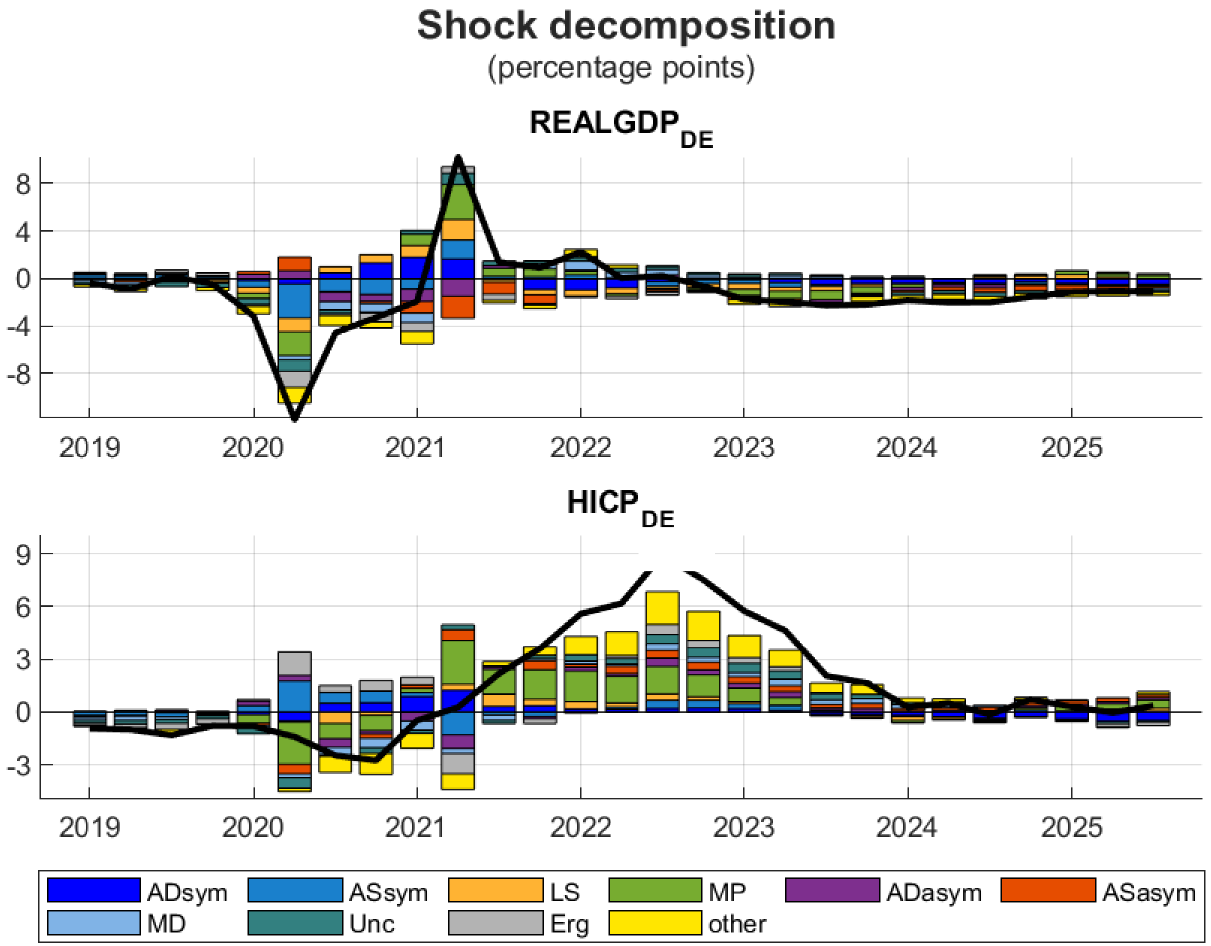
Shock decomposition (2019Q1-2025Q3)
- annual growth rates of RGDP and HICP



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More results

Summary

- Model analyses monetary dynamics within the **broader context** of other macroeconomic and financial variables.
- Money can be useful for **identification** of some types of structural macroeconomic shocks.
- Shows money demand shocks to have played a role during **global financial crises** and **pandemic** and their aftermath.
- Model offers an interpretation of **perceived correlation of money growth and inflation** during the final stages of the pandemic and the inflation surge.

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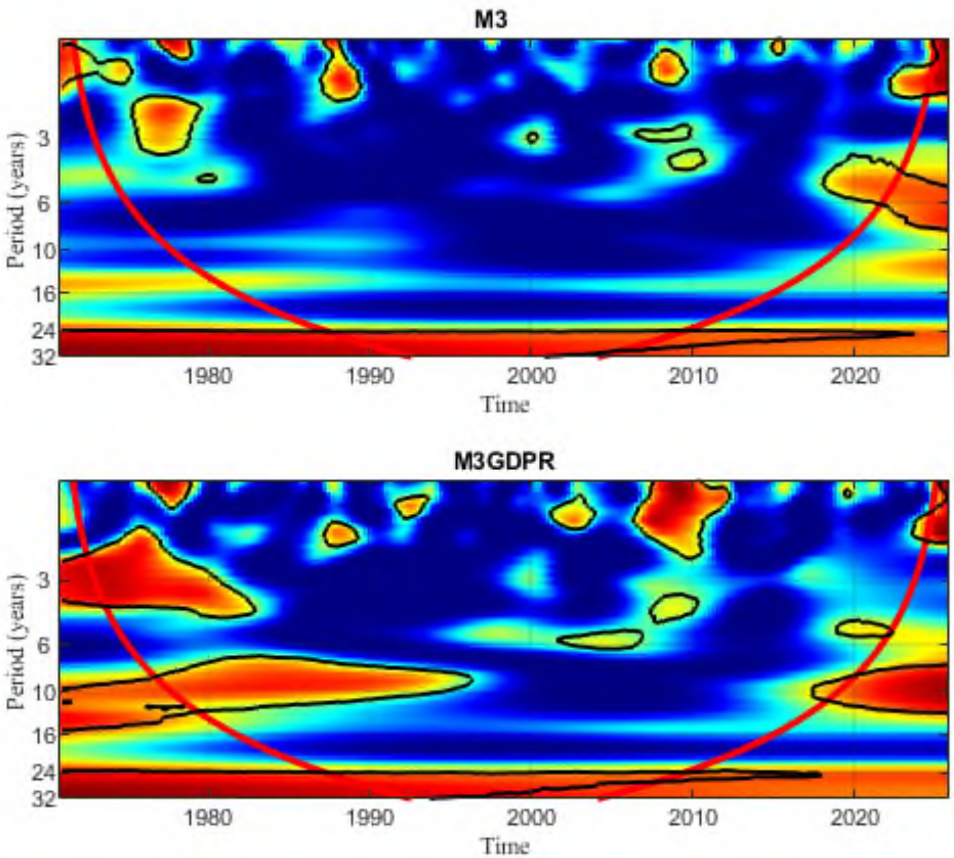
Supplementary material

1. Updated results from wavelet analysis

Wavelet coherency of money growth and inflation in the euro area

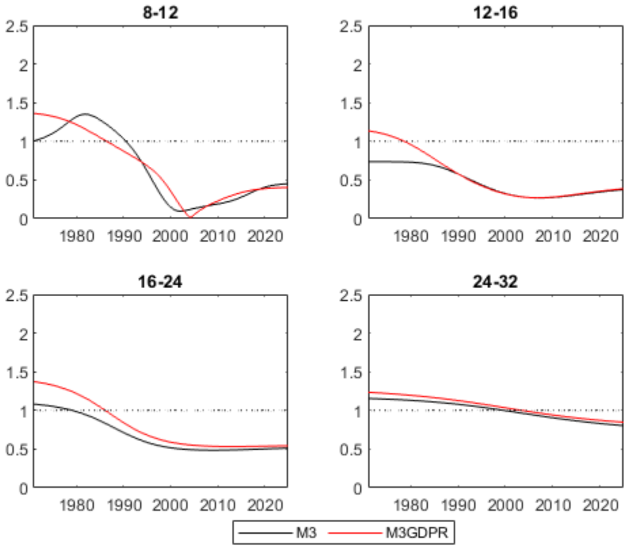


Note: Estimated wavelet coherency from zero (dark blue) to one (dark red). Curved red lines denote the cone of influence.
Black lines surround time-frequency combinations with coherency different from zero at the 5% significance level

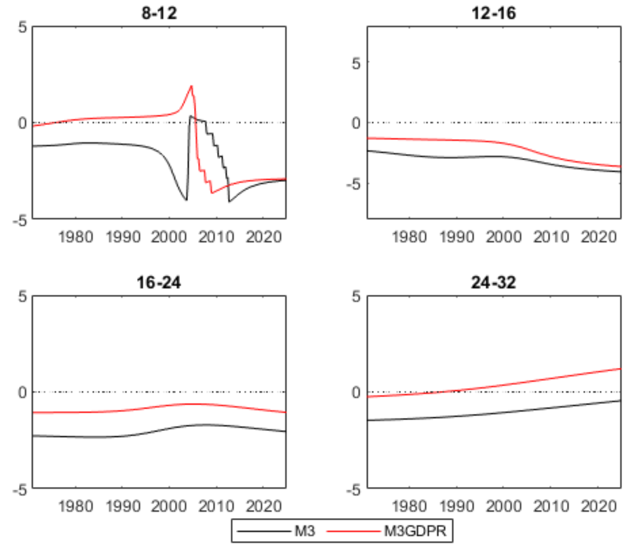
Updated results for Mandler and Scharnagl (2023).

Cross-spectral gain and time difference for money growth and inflation

gain



time difference

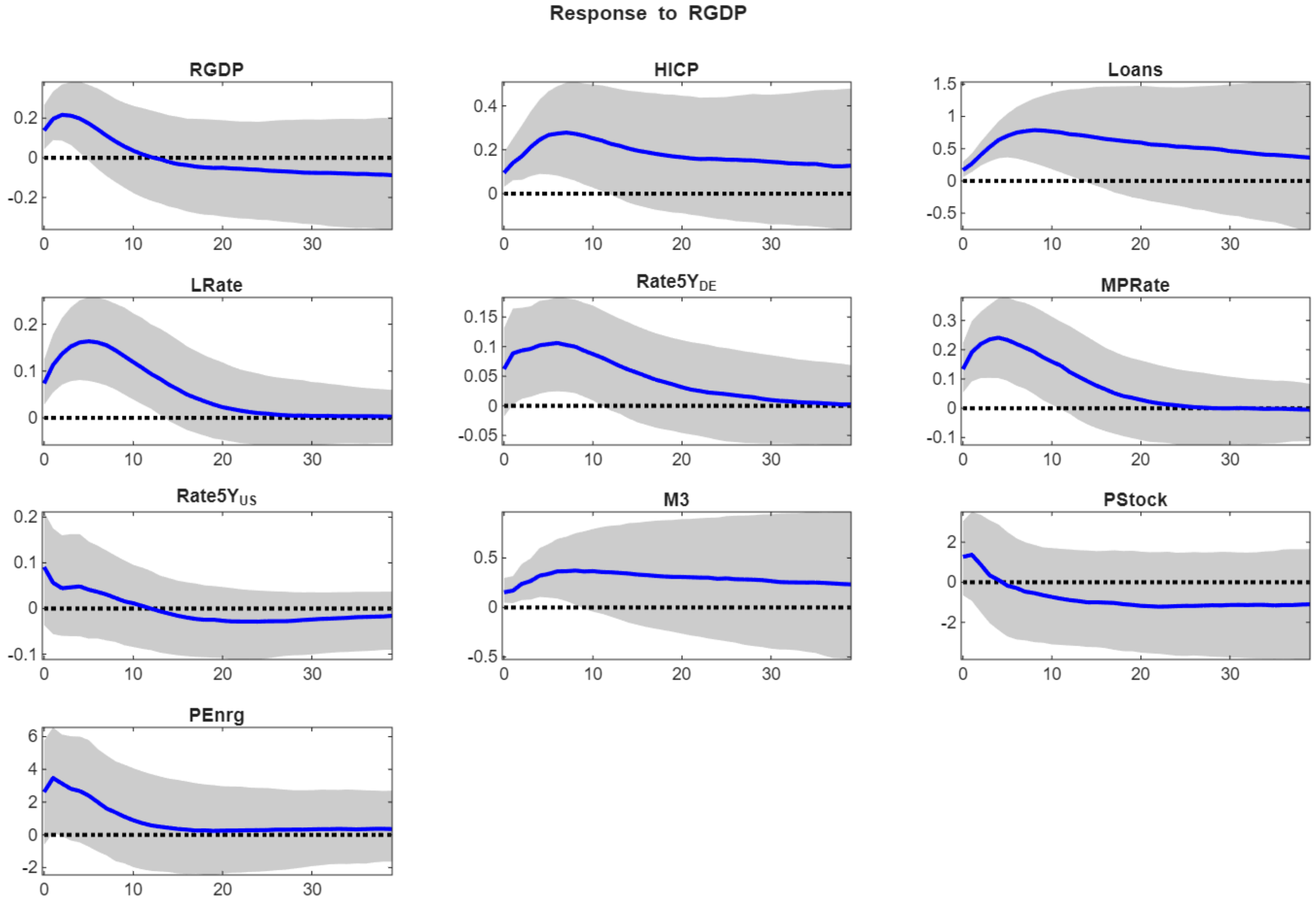


Updated results for Mandler and Scharnagl (2023).

back

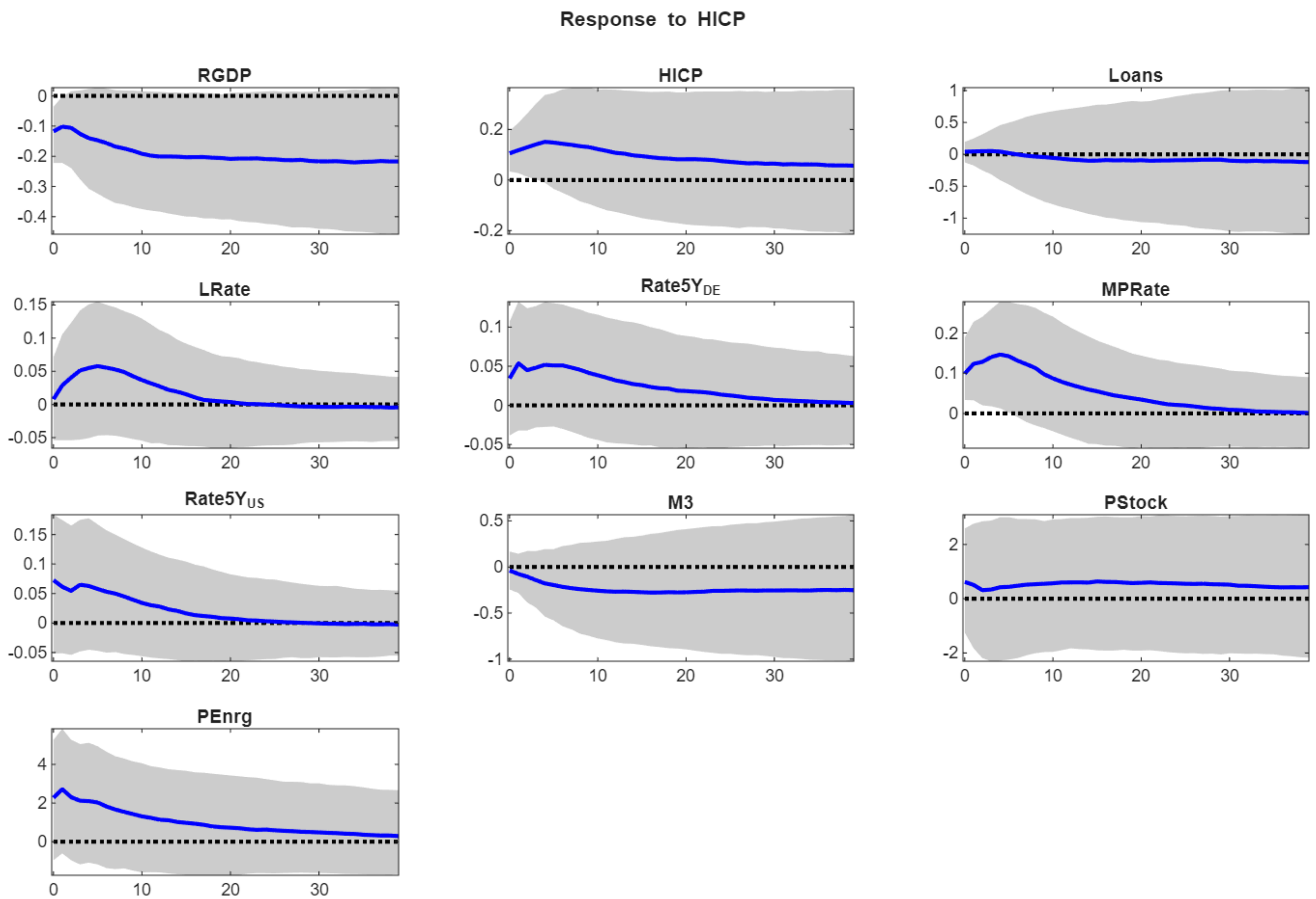
1. Impulse responses (euro area model)

Impulse responses to aggregate demand shock



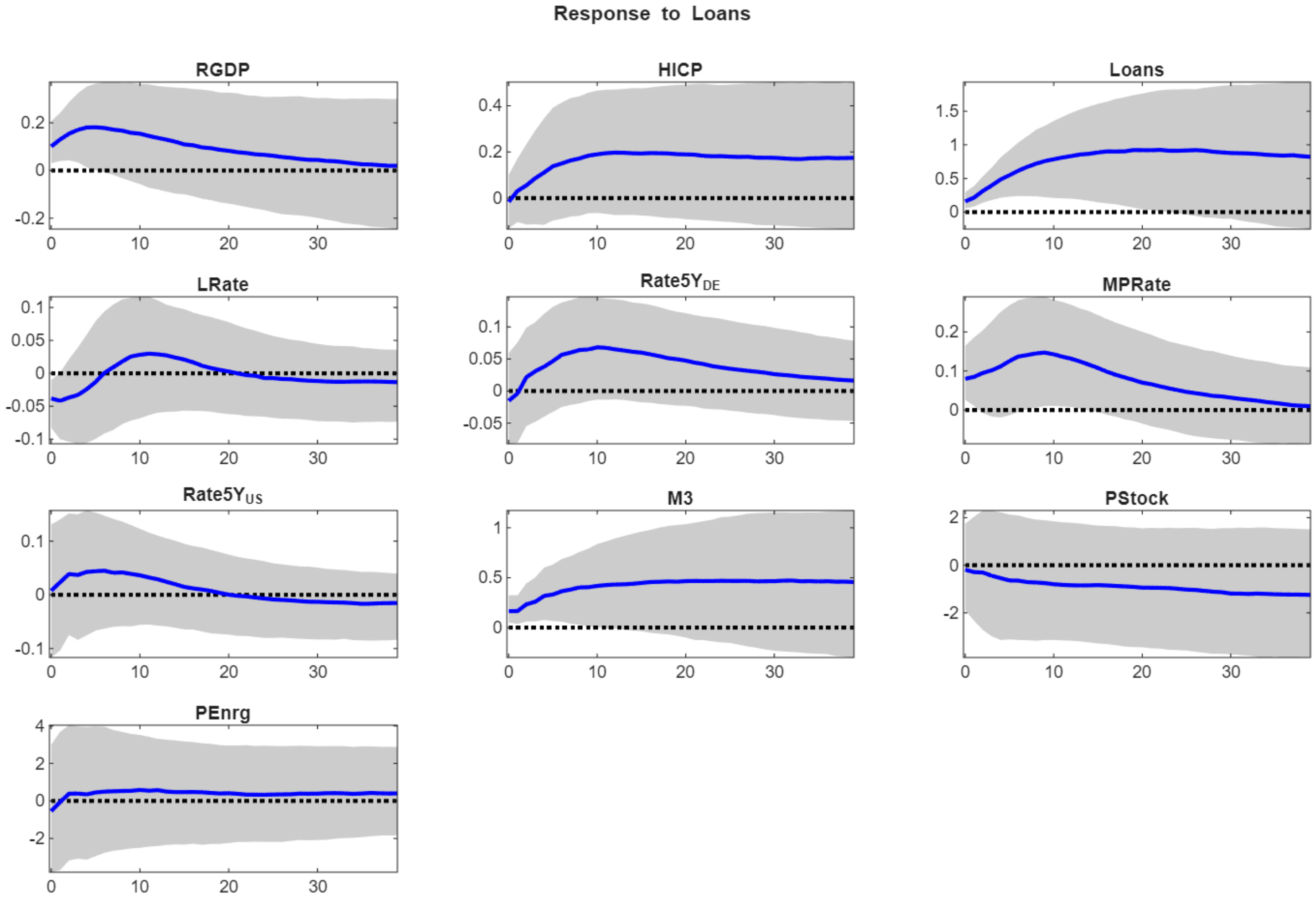
Estimates from Bayesian VAR. Deviations from steady state in percent. Median (blue) and area between 16th and 84th percentiles.

Impulse responses to aggregate supply shock



Estimates from Bayesian VAR. Deviations from steady state in percent. Median (blue) and area between 16th and 84th percentiles.

Impulse responses to loan supply shock



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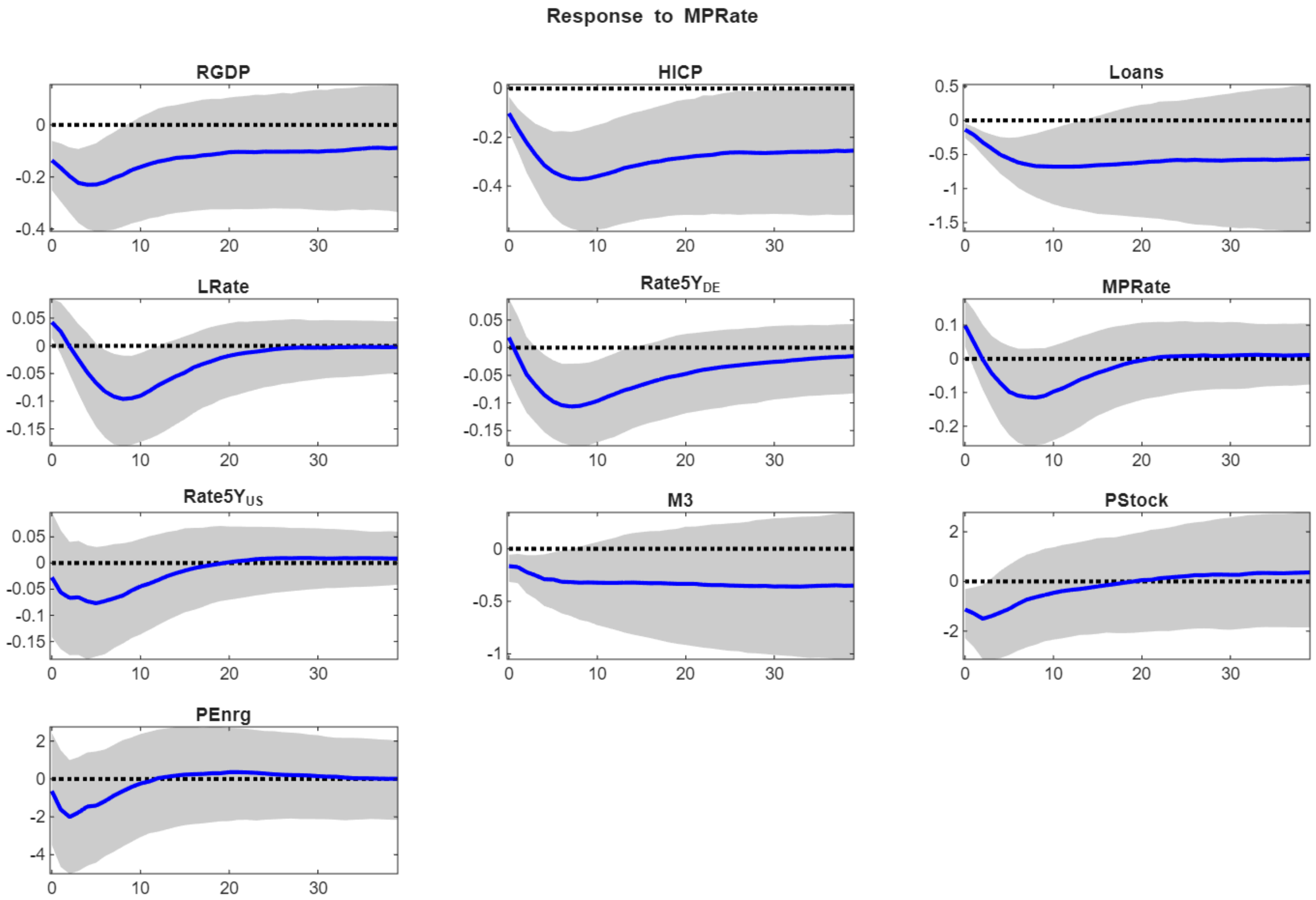
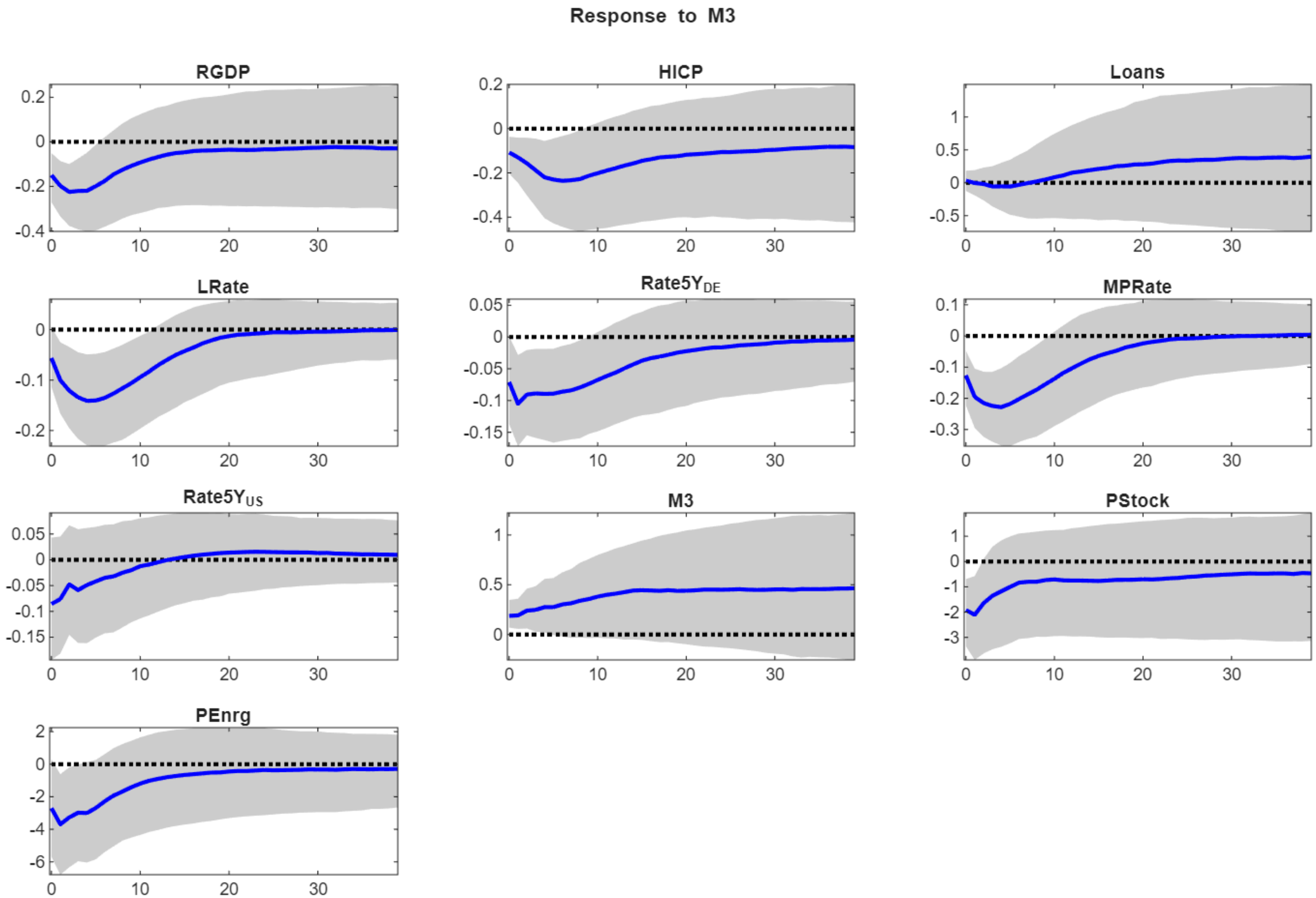
Impulse responses to monetary policy shock



Estimates from Bayesian VAR. Deviations from steady state in percent. Median (blue) and area between 16th and 84th percentiles.

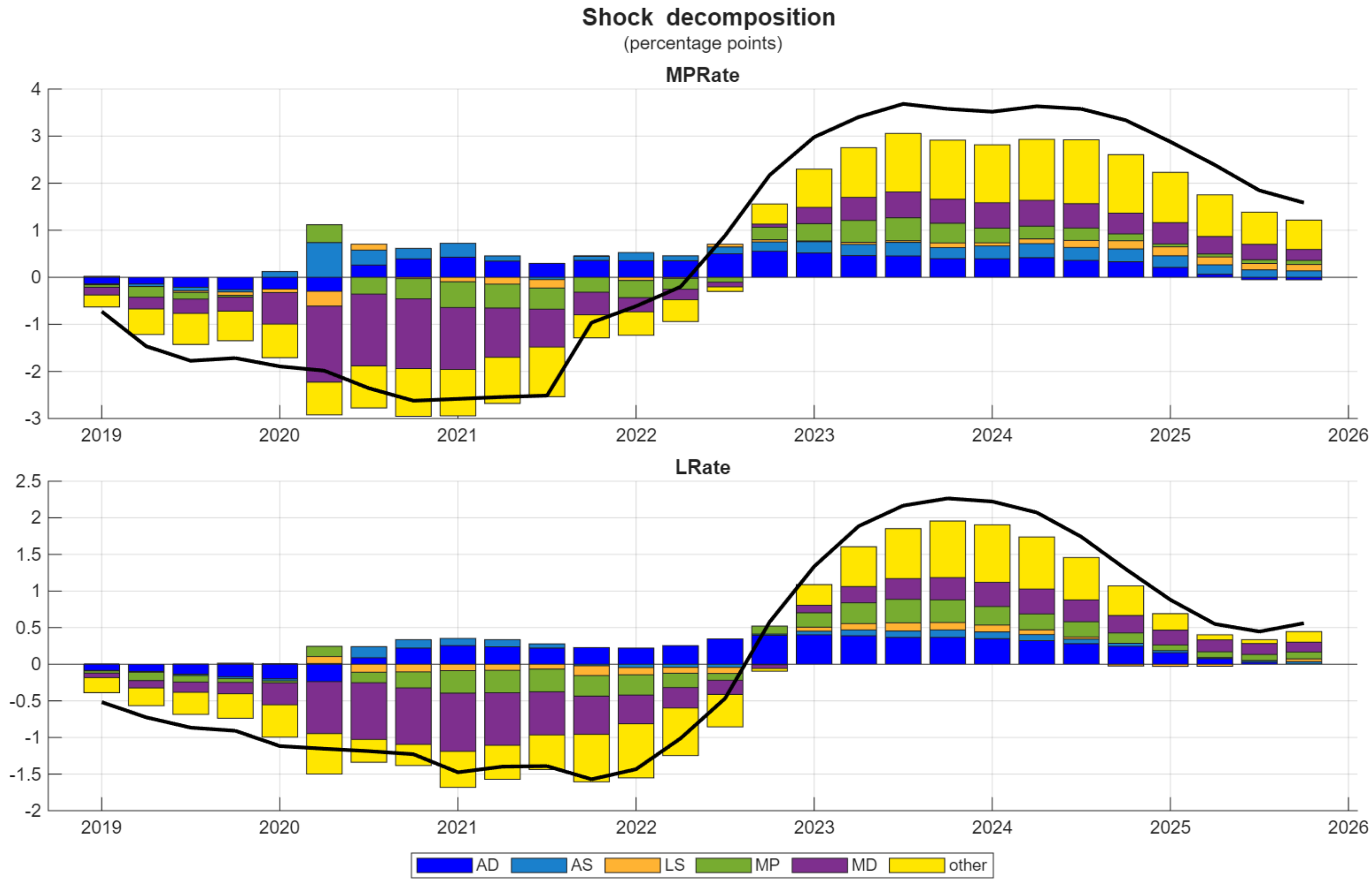
Impulse responses to money demand shock



Estimates from Bayesian VAR. Deviations from steady state in percent. Median (blue) and area between 16th and 84th percentiles.

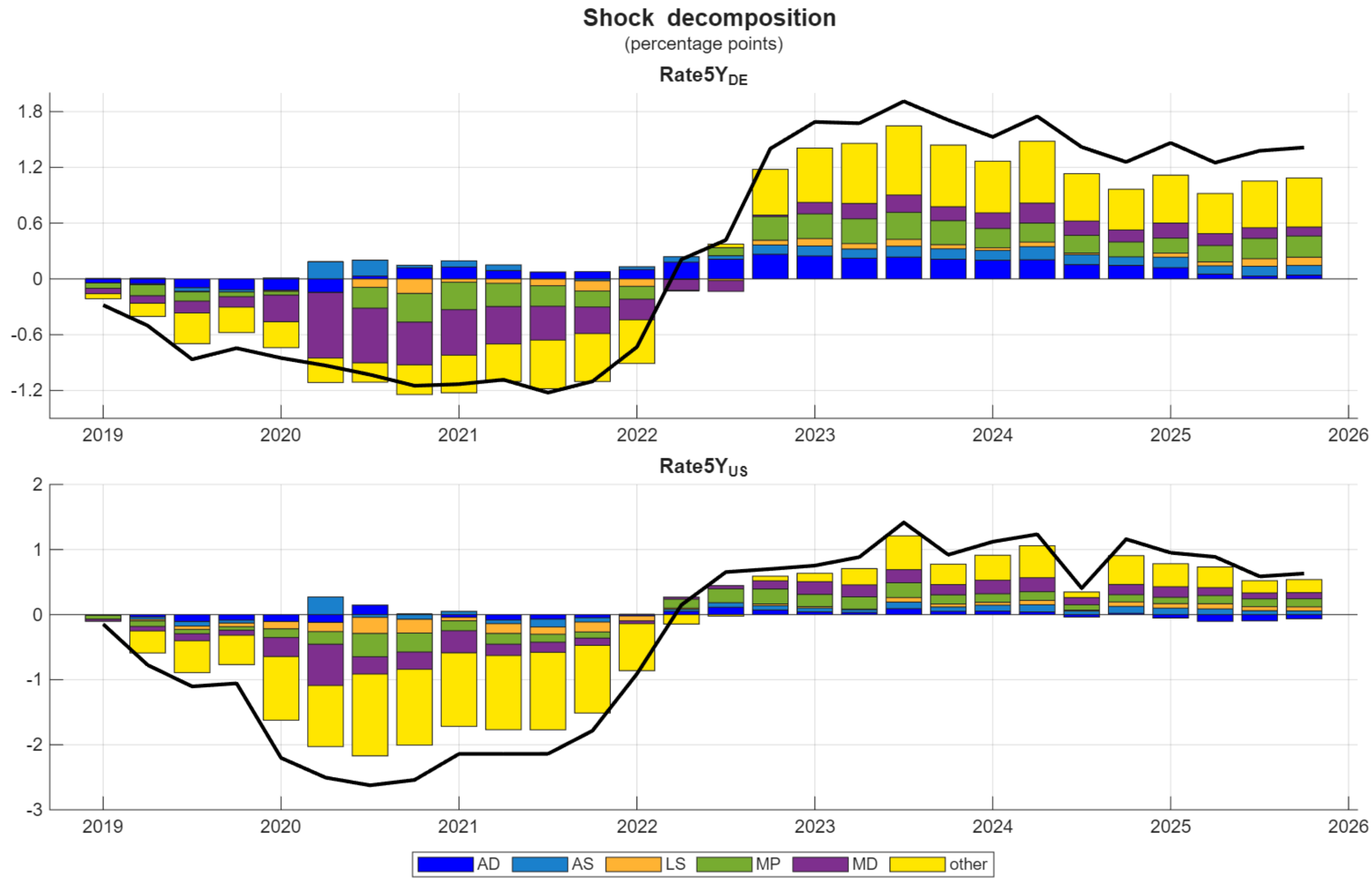
2. Further shock decompositions

Shock decomposition (2019Q1-2025Q4)
- Policy rate and bank lending rate



Estimates from Bayesian VAR. Median contributions of identified shocks to deviation from unconditional forecast (AD: aggregate demand shock, AS: aggregate supply shock, LS: loan supply shock, MP: monetary policy shock, MD: money demand shock, yellow bars denote contributions of unidentified shocks.

Shock decomposition (2019Q1-2025Q4) - bond yields



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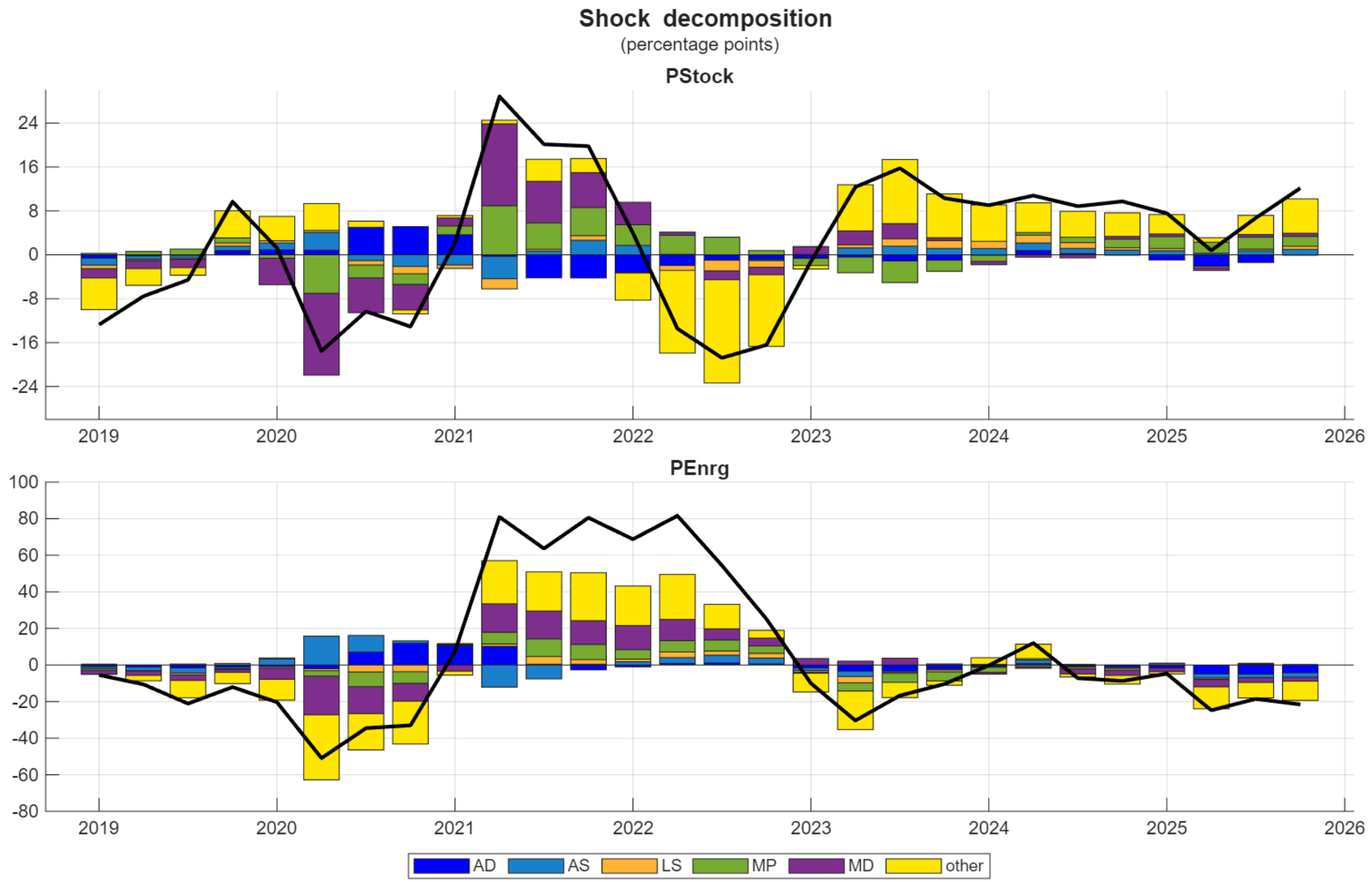
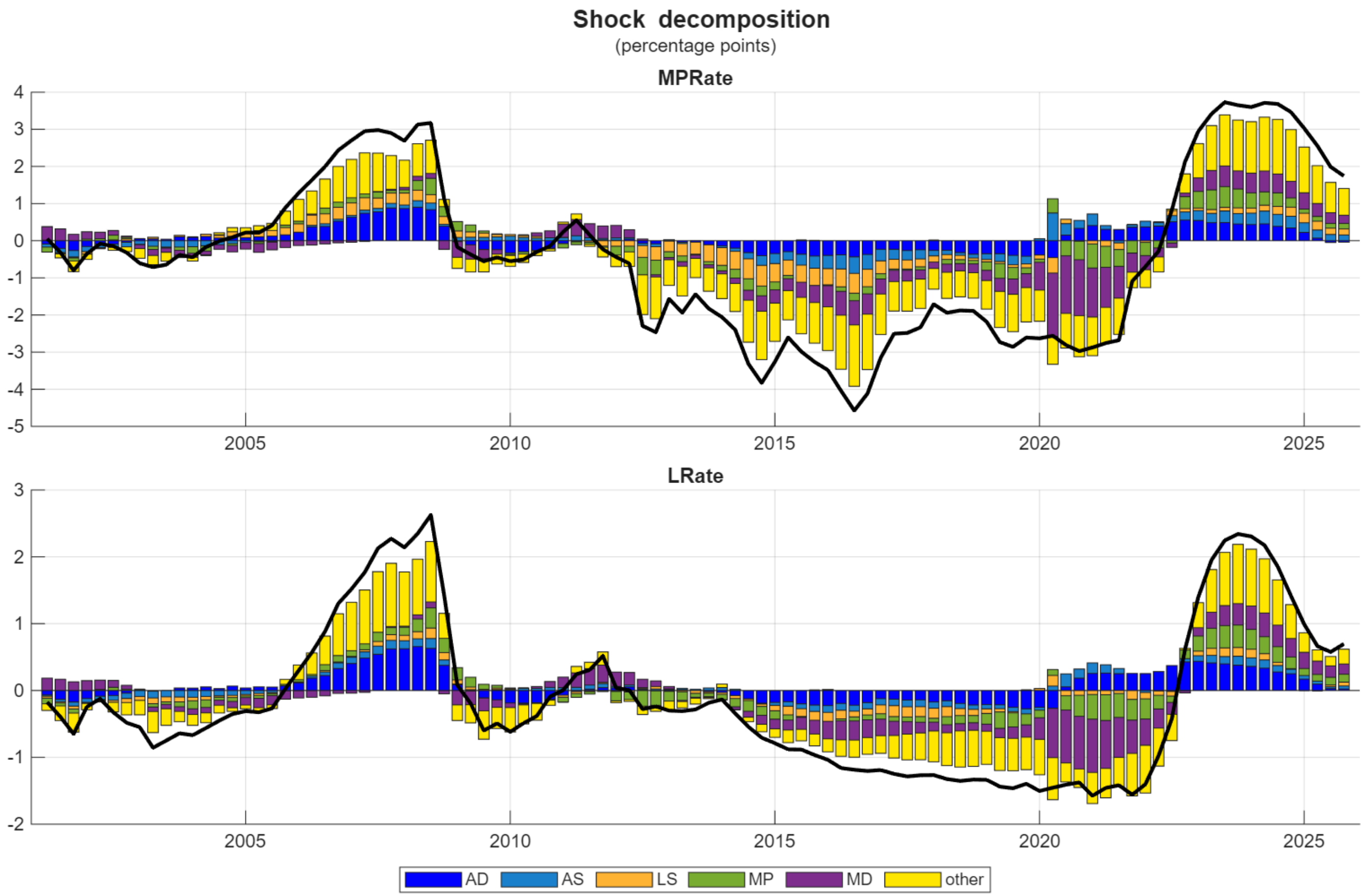
Shock decomposition (2019Q1-2025Q4)
- annual growth rates of stock price index and energy prices



Estimates from Bayesian VAR. Median contributions of identified shocks to deviation from unconditional forecast (AD: aggregate demand shock, AS: aggregate supply shock, LS: loan supply shock, MP: monetary policy shock, MD: money demand shock, yellow bars denote contributions of unidentified shocks.

Shock decomposition (2001Q2-2025Q4)
- Policy rate and bank lending rate



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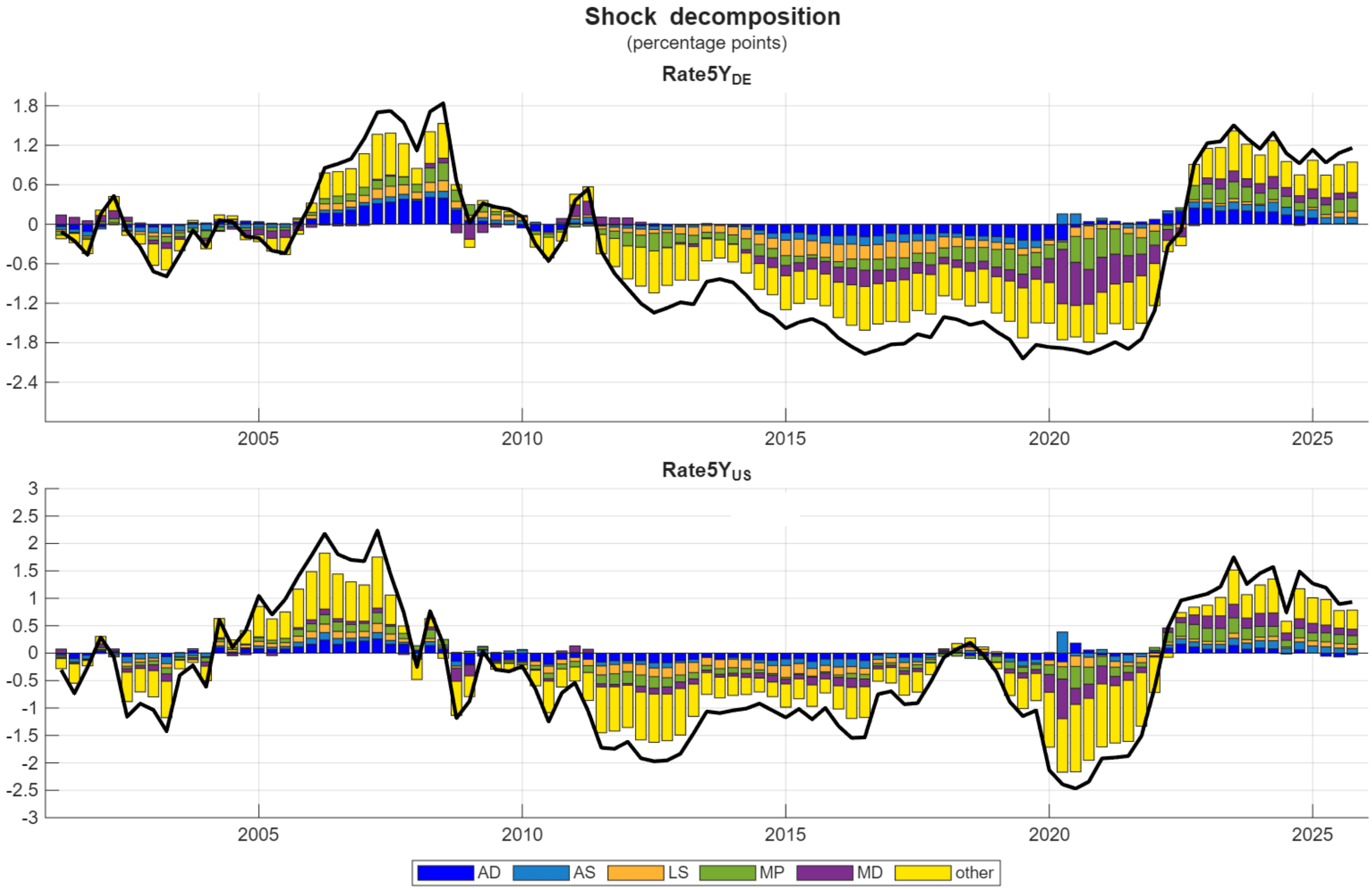
Shock decomposition (2001Q2-2025Q4) - bond yields



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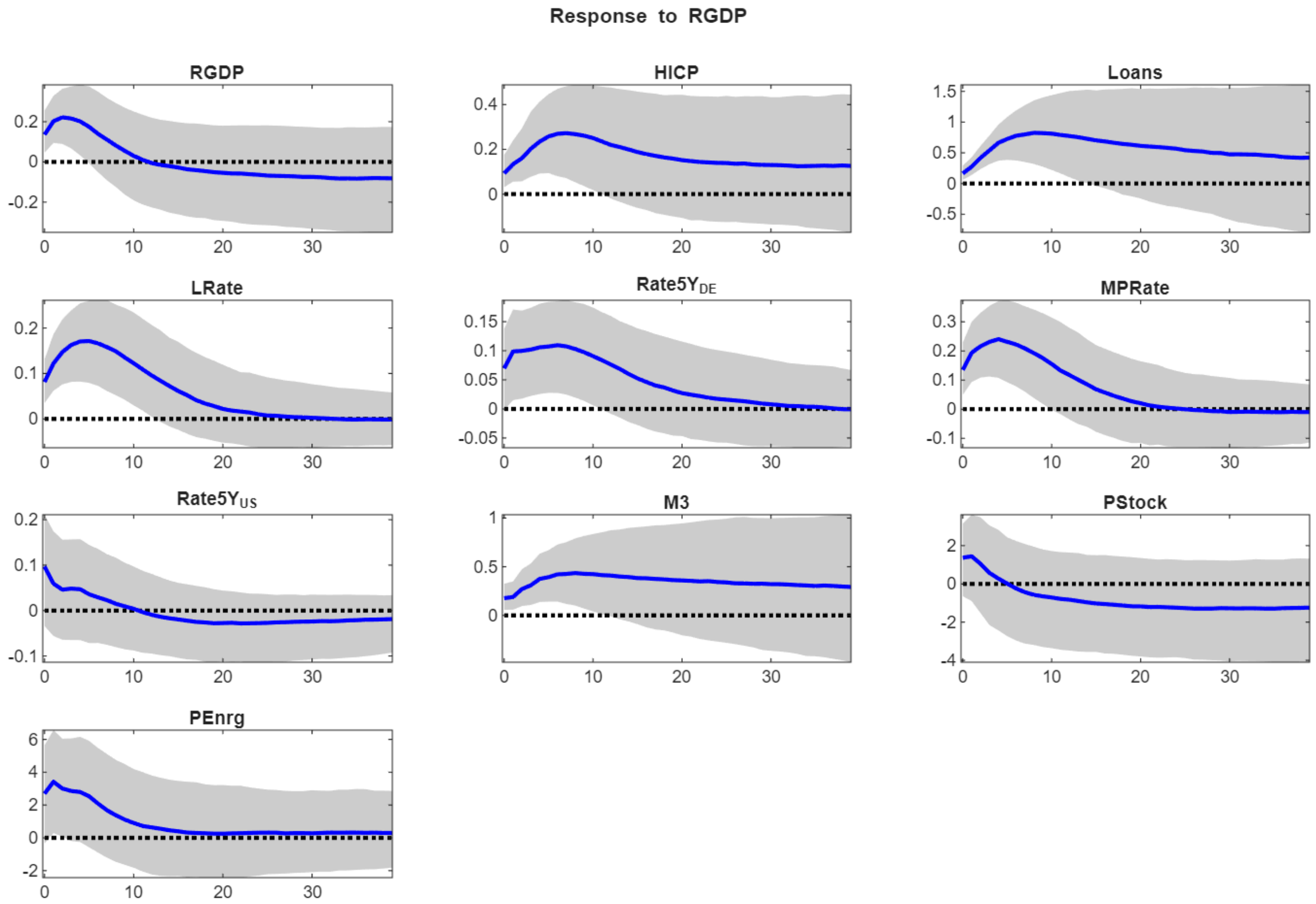
back

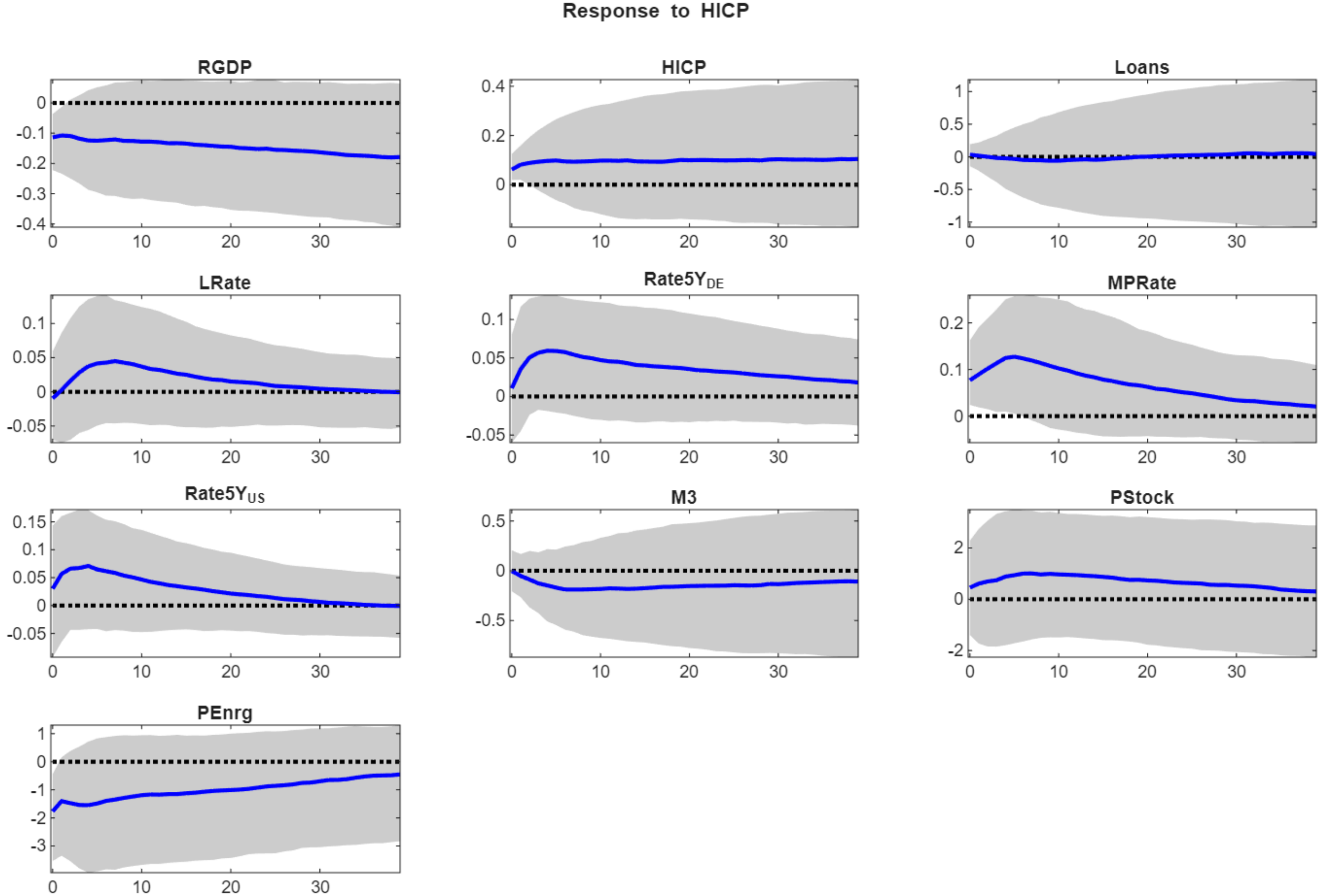
3. Impulse responses (extended euro area model)

Impulse responses to aggregate demand shock



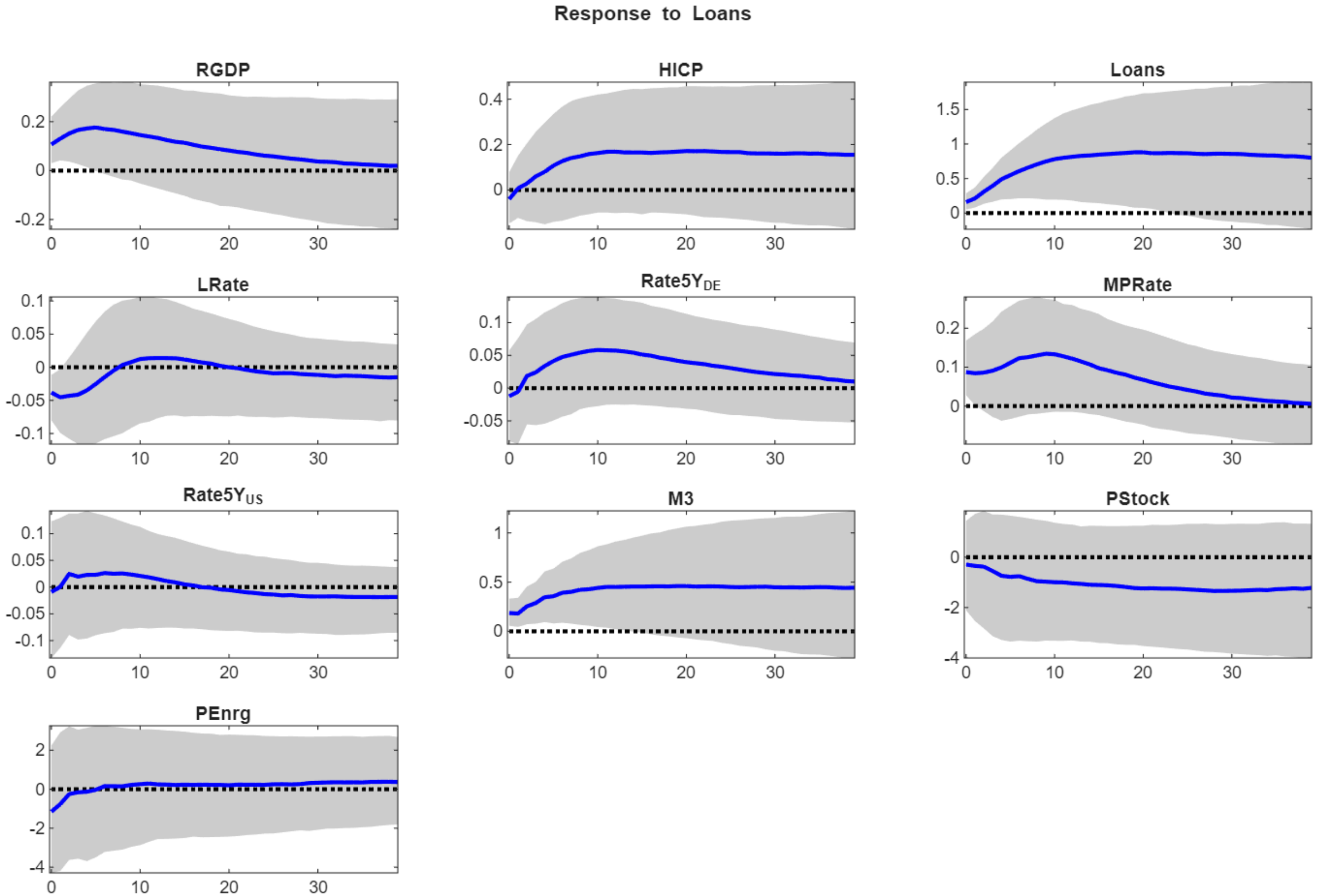
Estimates from Bayesian VAR. Deviations from steady state in percent. Median (blue) and area between 16th and 84th percentiles.

Impulse responses to aggregate supply shock



Estimates from Bayesian VAR. Deviations from steady state in percent. Median (blue) and area between 16th and 84th percentiles.

Impulse responses to loan supply shock



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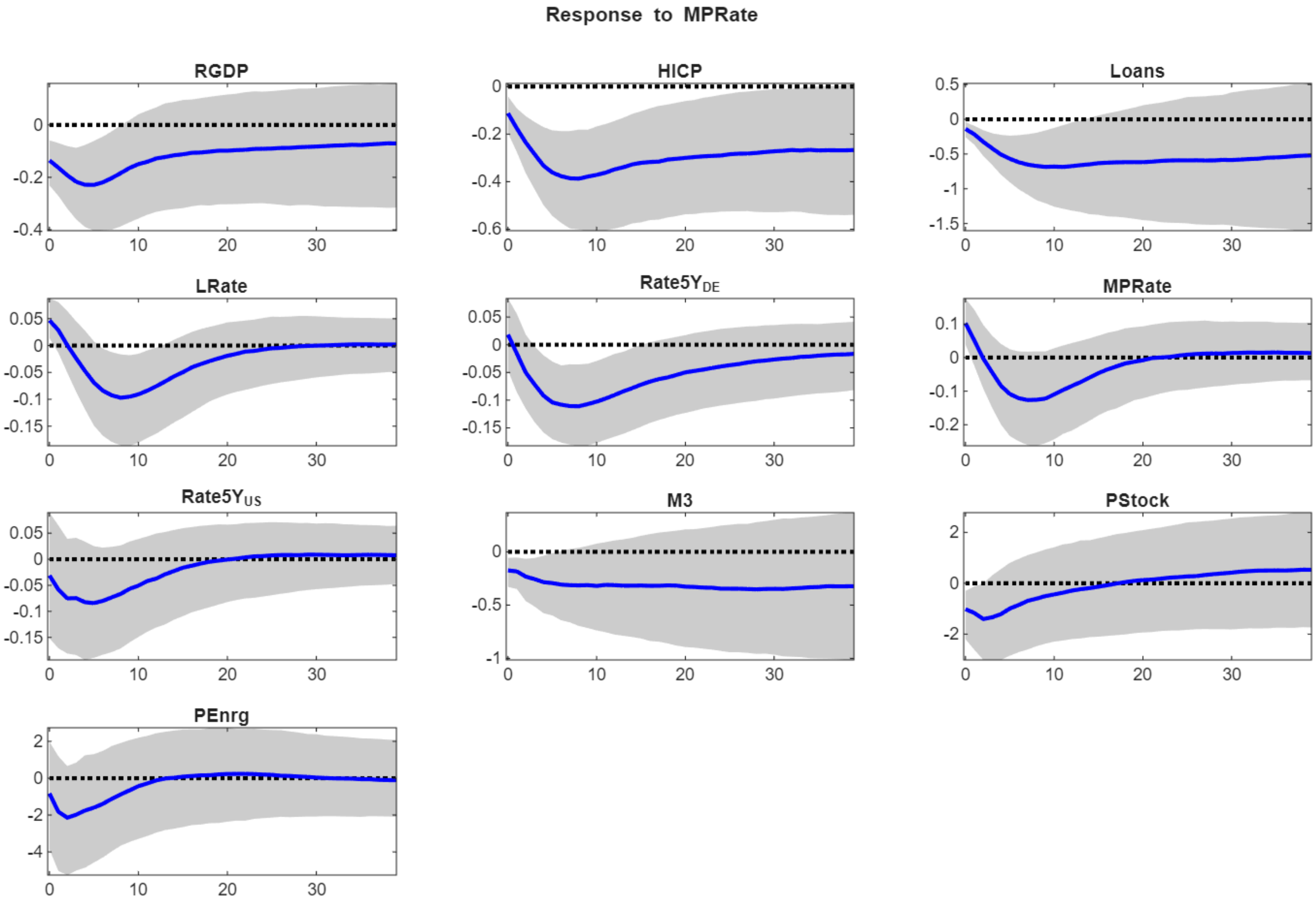
Impulse responses to monetary policy shock



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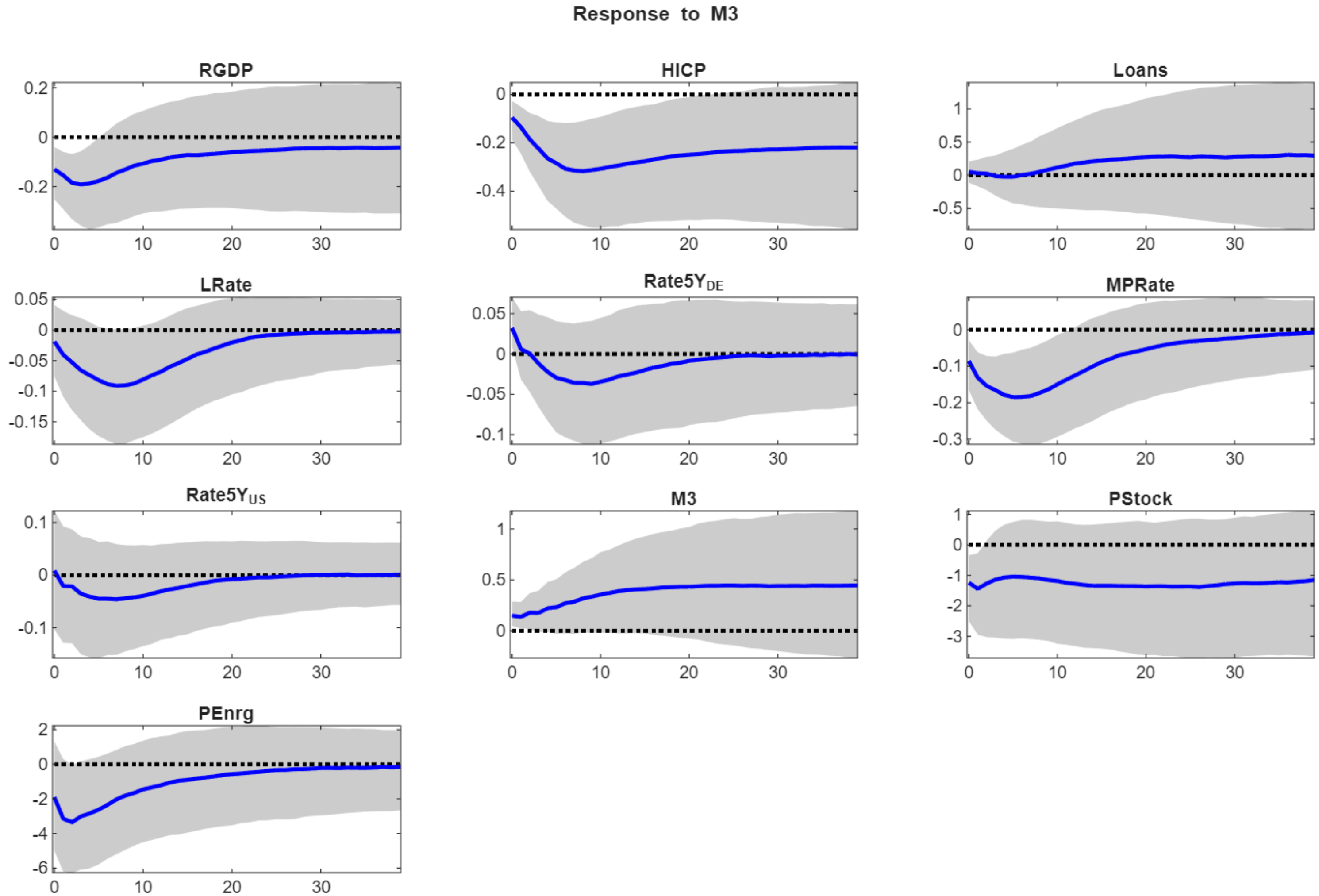
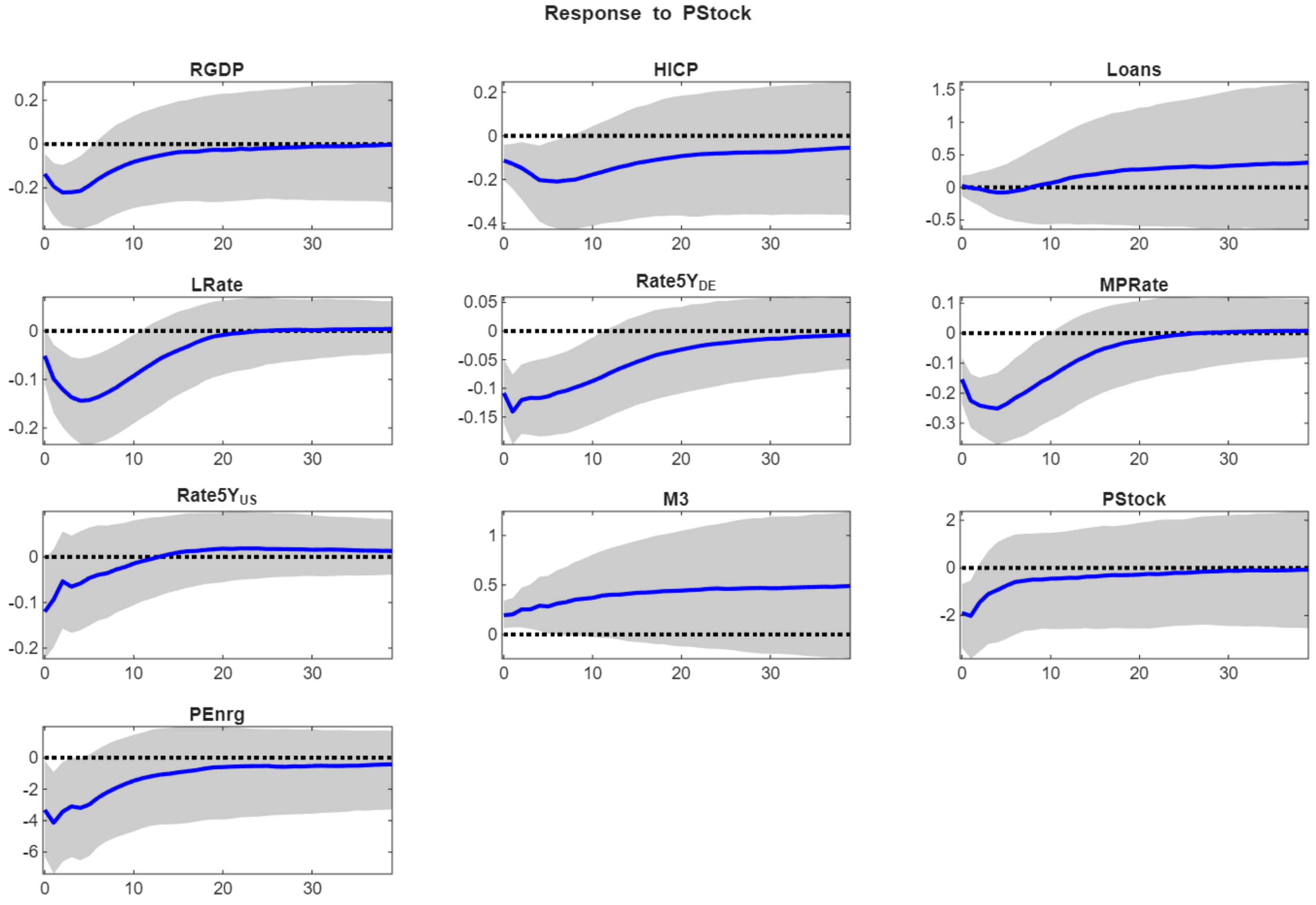
Impulse responses to money demand shock



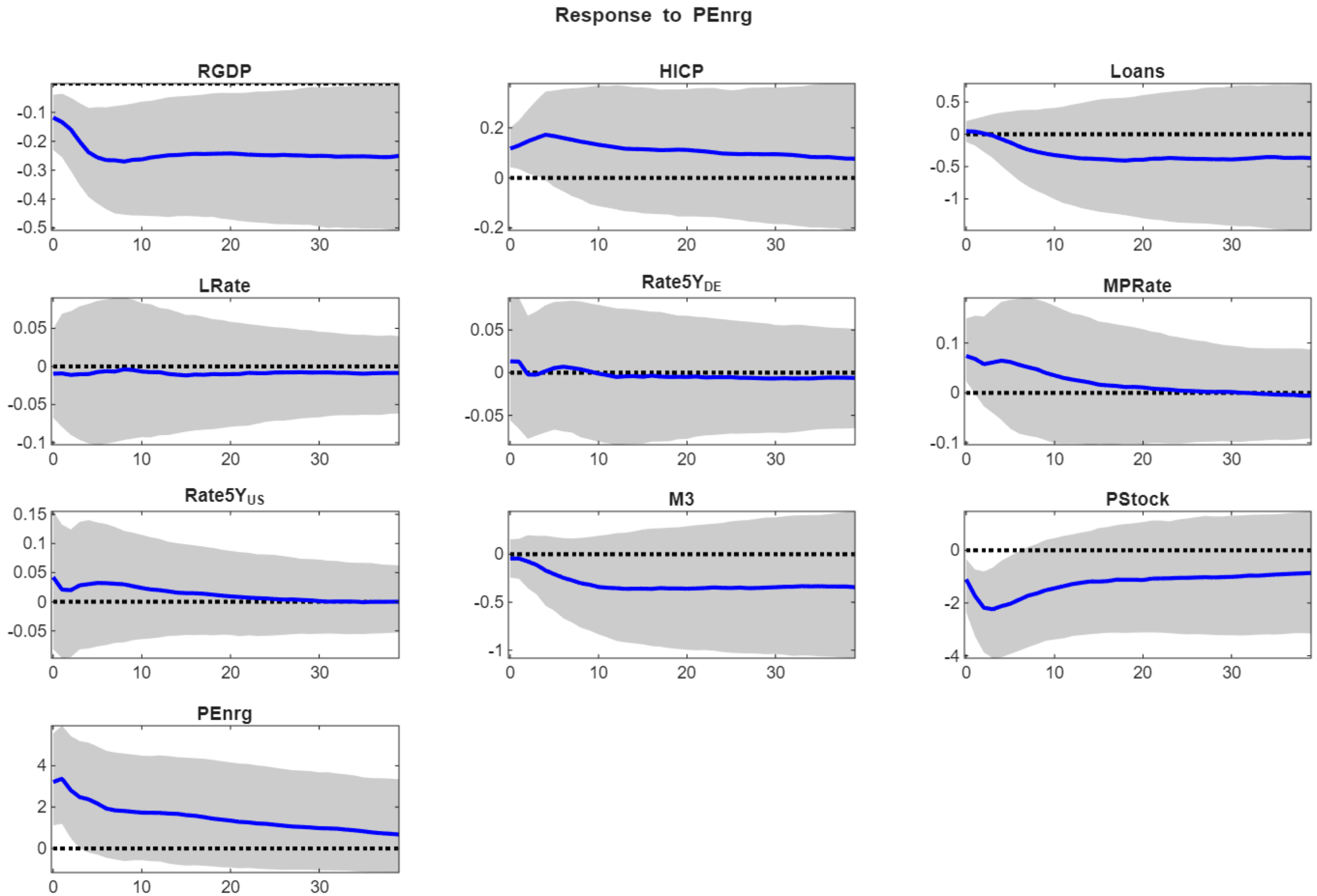
Estimates from Bayesian VAR. Deviations from steady state in percent. Median (blue) and area between 16th and 84th percentiles.

Impulse responses to uncertainty



Estimates from Bayesian VAR. Deviations from steady state in percent. Median (blue) and area between 16th and 84th percentiles.

Impulse responses to energy price shock

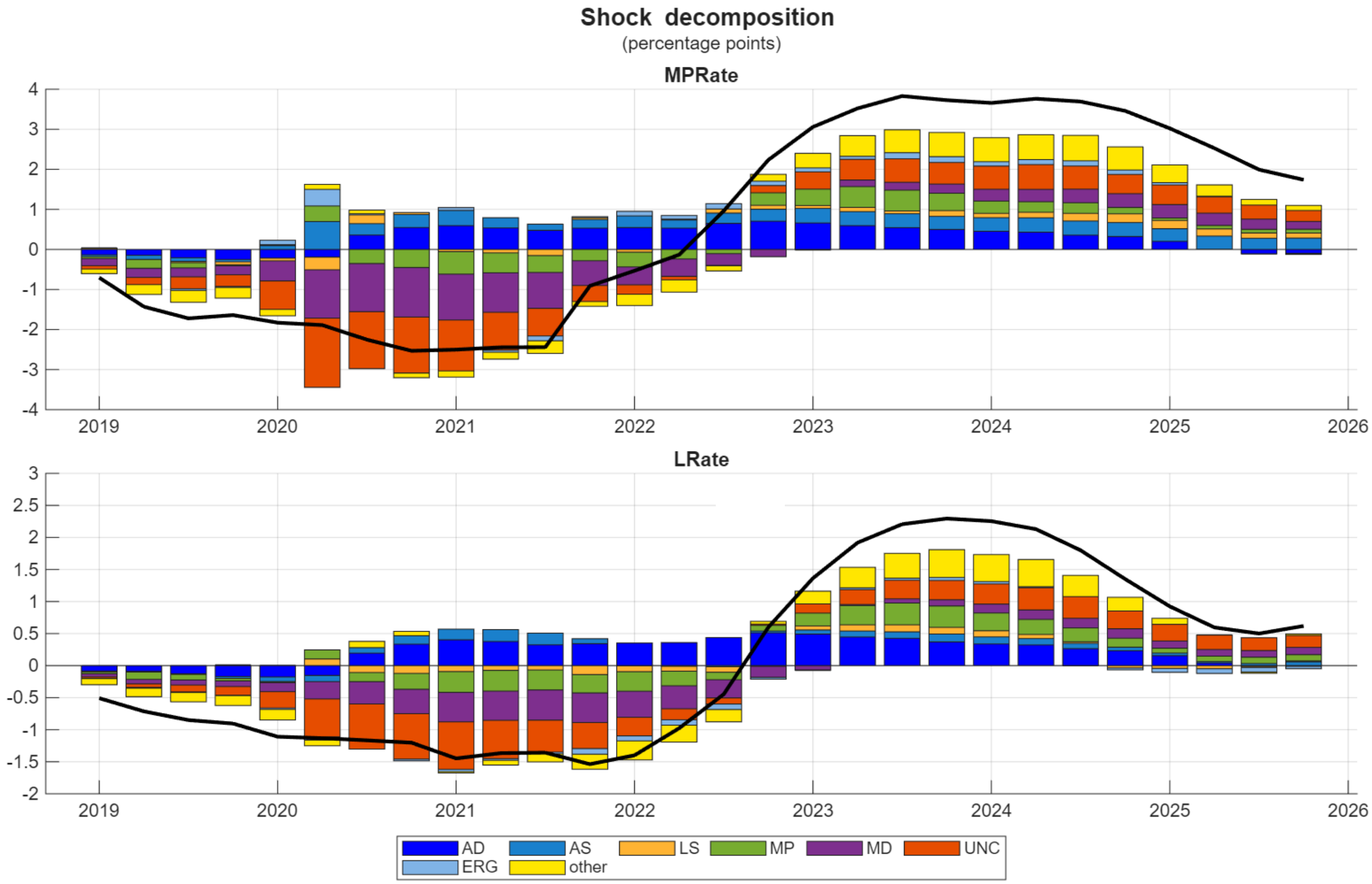


Estimates from Bayesian VAR. Deviations from steady state in percent. Median (blue) and area between 16th and 84th percentiles.

back

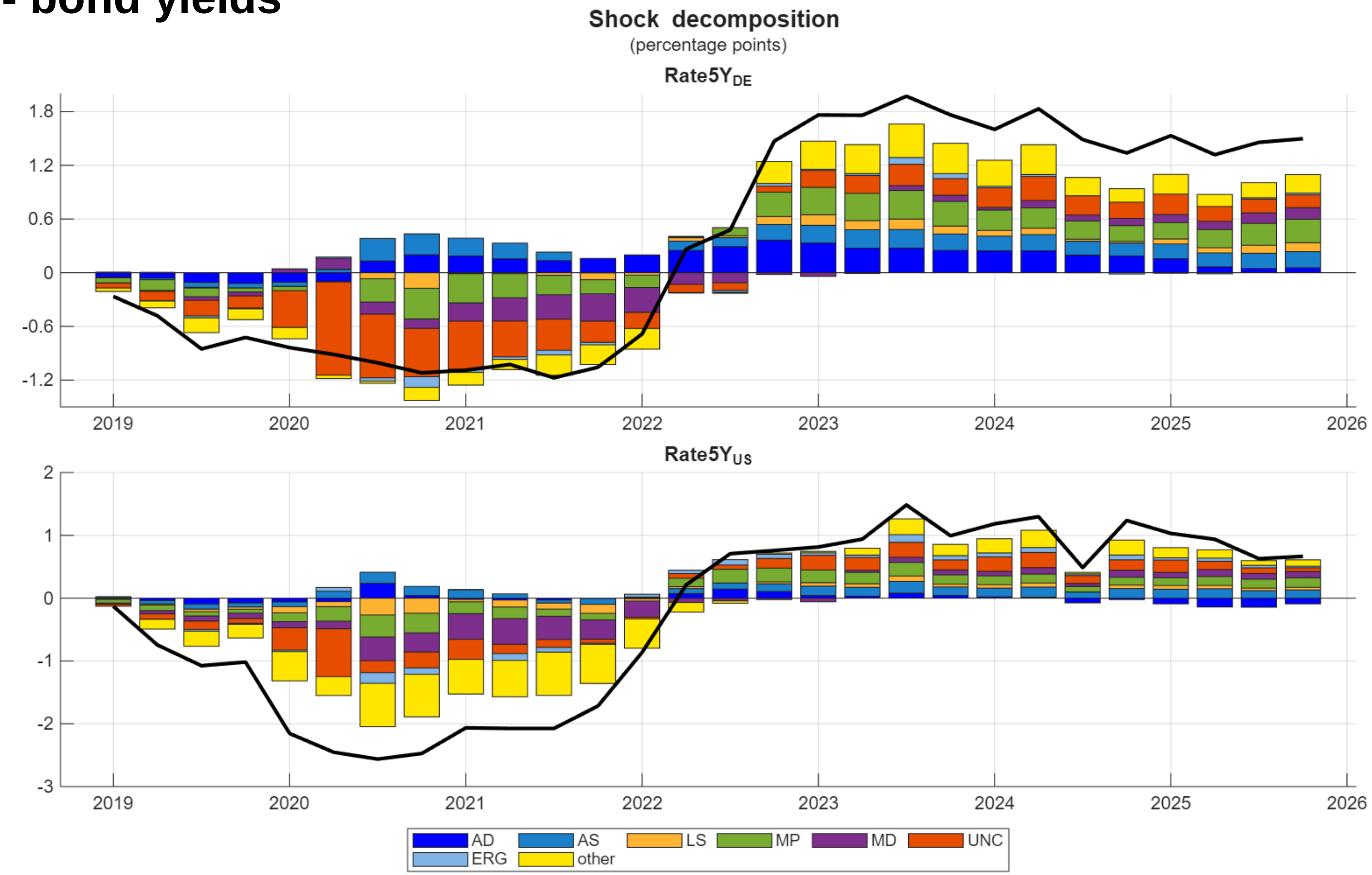
4. Further shock decompositions (extended euro area model)

Shock decomposition (2019Q1-2025Q4)
- Policy rate and bank lending rate



Estimates from Bayesian VAR. Median contributions of identified shocks to deviation from unconditional forecast (AD: aggregate demand shock, AS: aggregate supply shock, LS: loan supply shock, MP: monetary policy shock, MD: money demand shock, UNC: uncertainty shock; ERG: energy price shock; yellow bars denote contributions of unidentified shocks.

Shock decomposition (2019Q1-2025Q4) - bond yields



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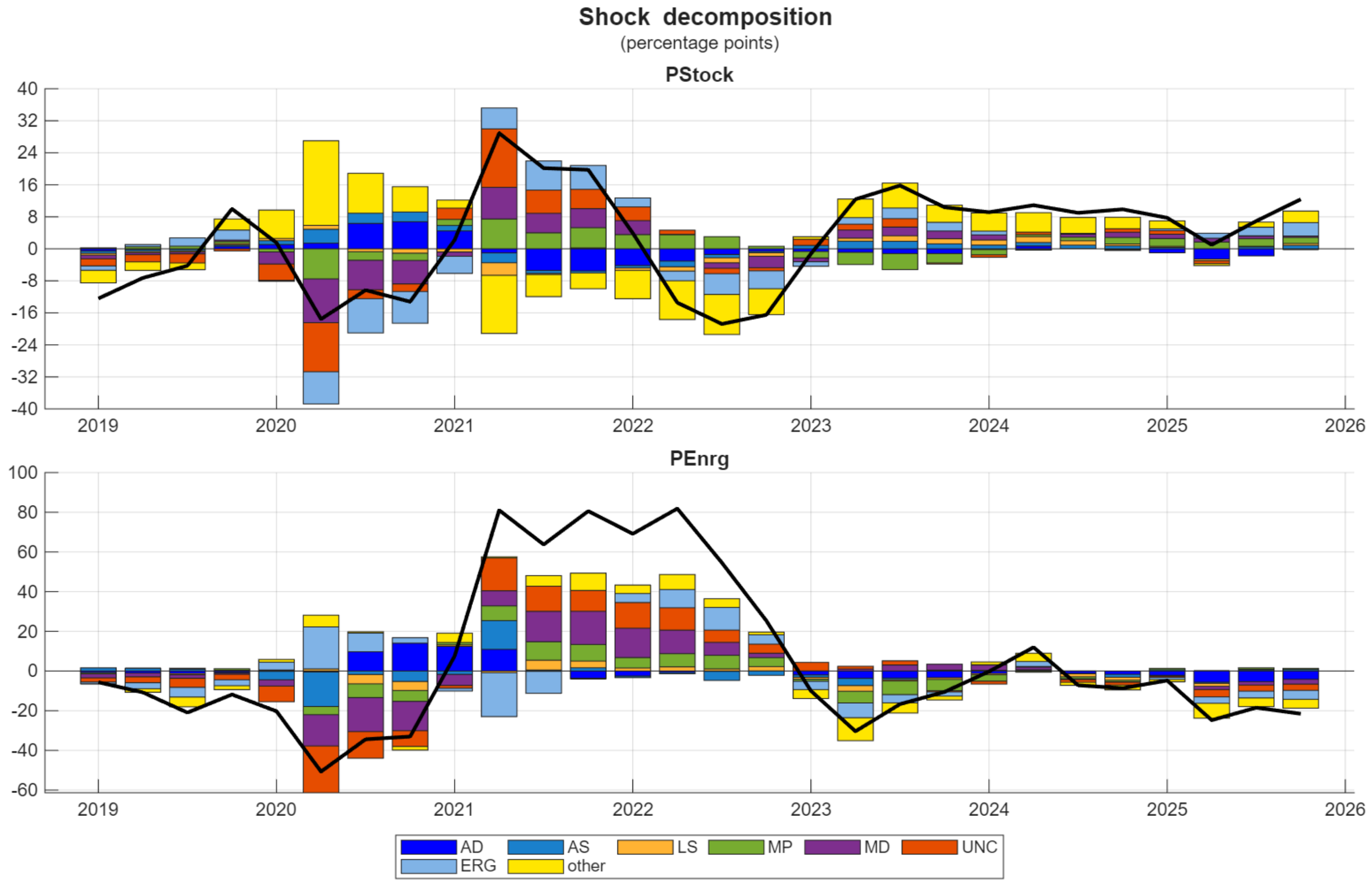
Shock decomposition (2019Q1-2025Q4)
- annual growth rates of stock price index and energy prices



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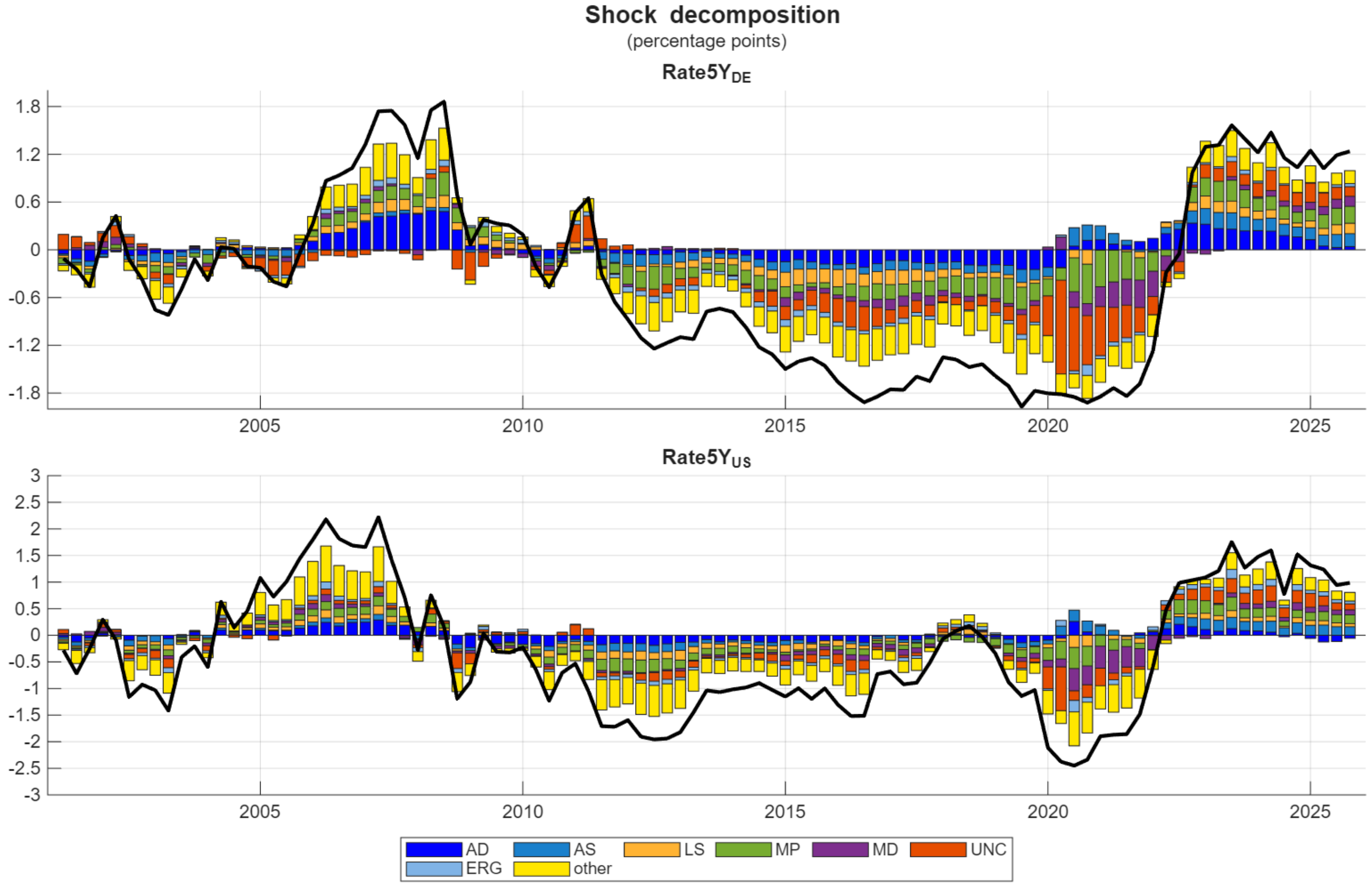
Shock decomposition (2019Q1-2025Q4) - bond yields



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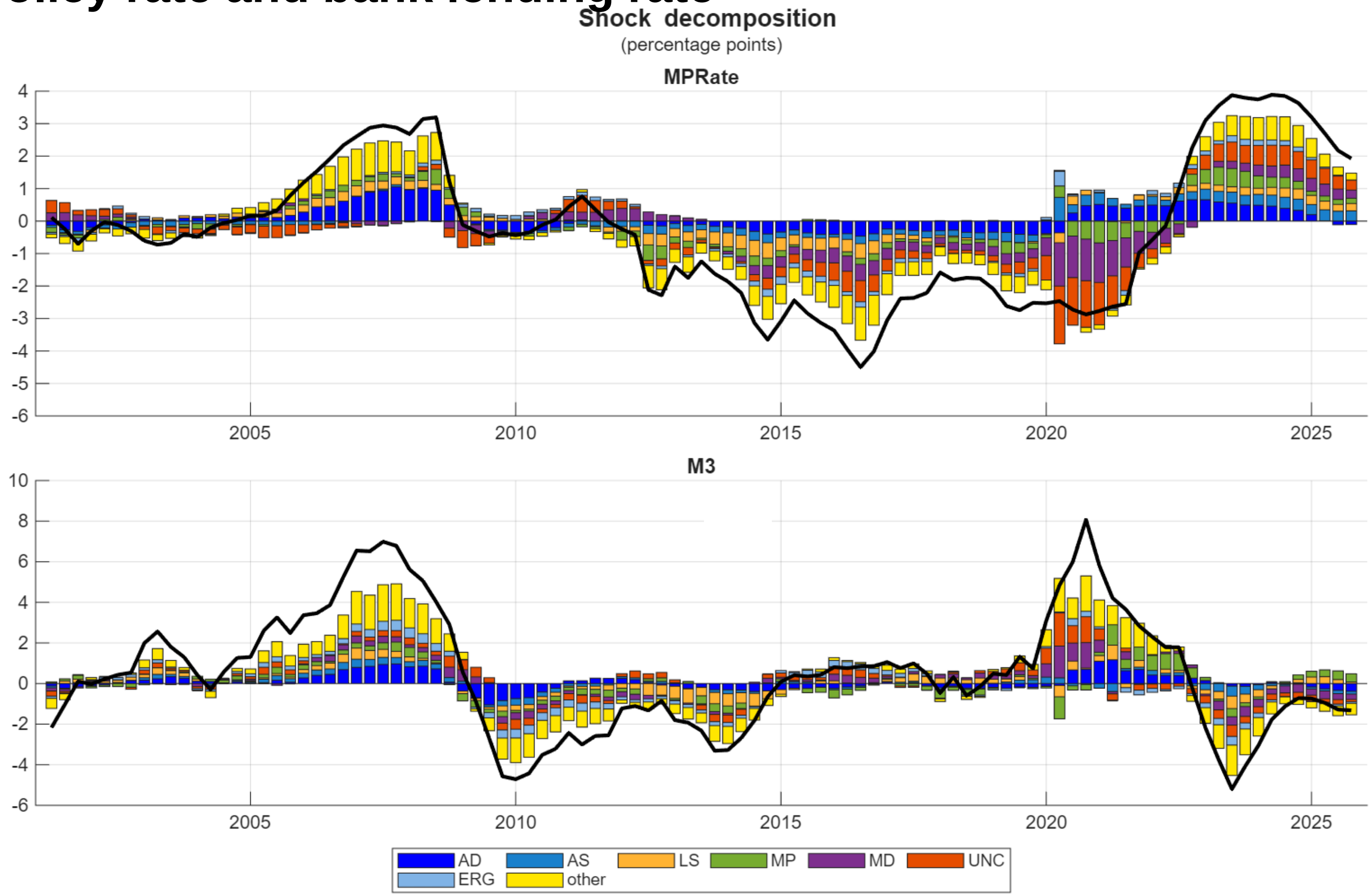
Shock decomposition (2001Q2-2025Q4)
- Policy rate and bank lending rate



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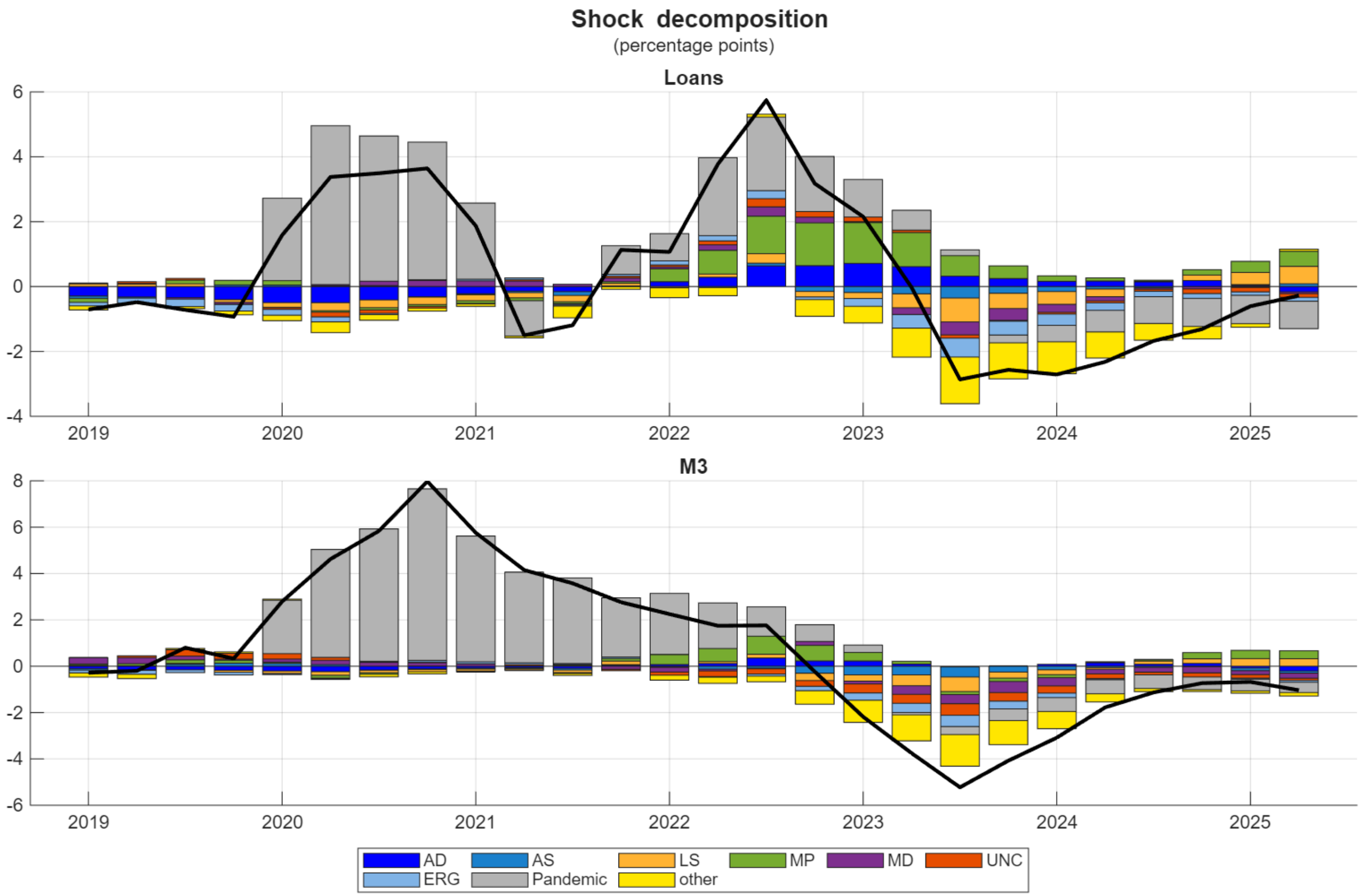
back

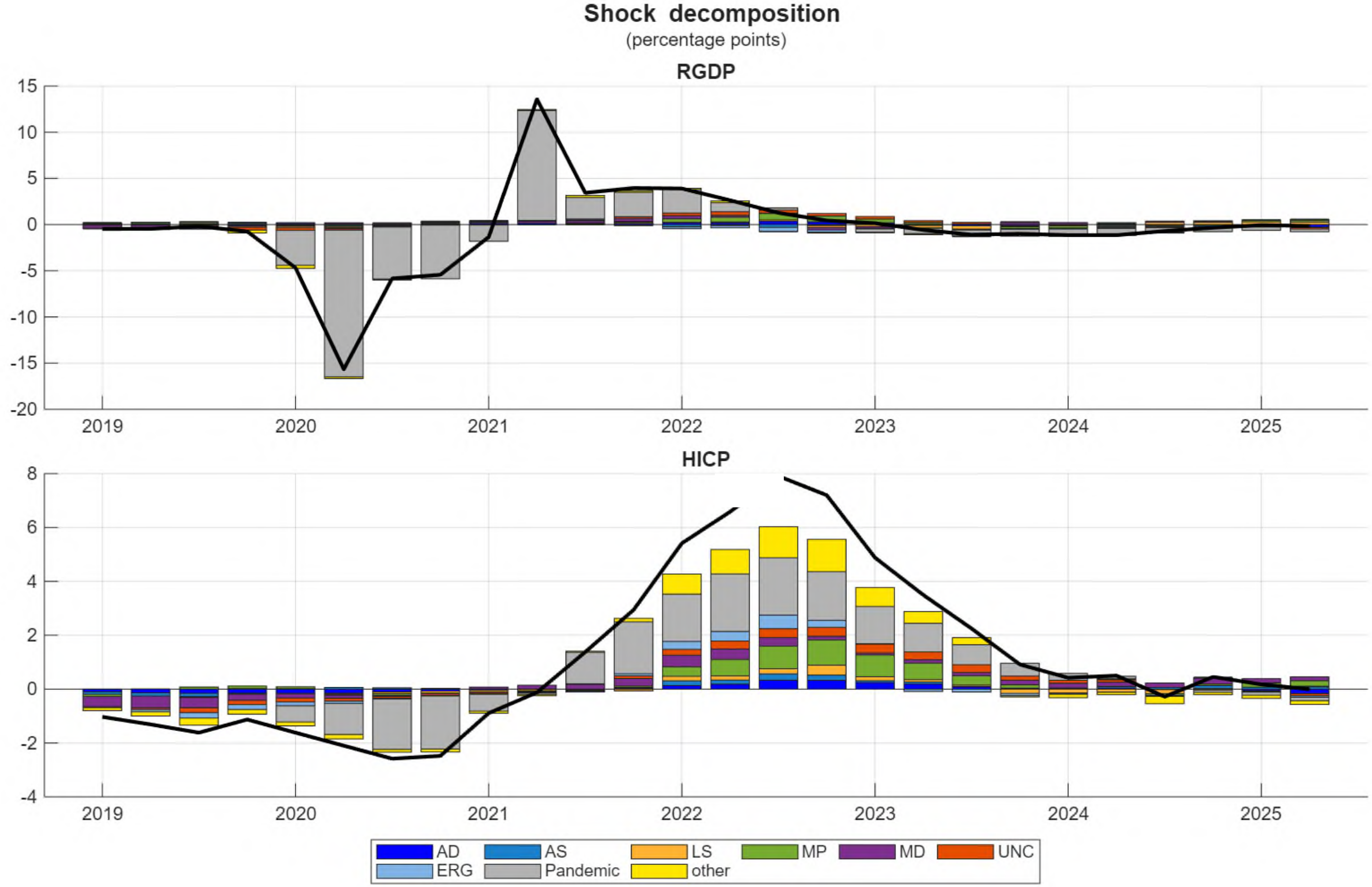
5. Shock decompositions with „pandemic shocks“

Shock decomposition (2019Q1-2025Q4) - annual growth rates of Loans and M3



Estimates from Bayesian VAR. Median contributions of identified shocks to deviation from unconditional forecast (AD: aggregate demand shock, AS: aggregate supply shock, LS: loan supply shock, MP: monetary policy shock, MD: money demand shock, UNC: uncertainty shock; ERG: energy price shock; yellow bars denote contributions of unidentified shocks.

Shock decomposition (2019Q1-2025Q4) - annual growth rates of RGDP and HICP



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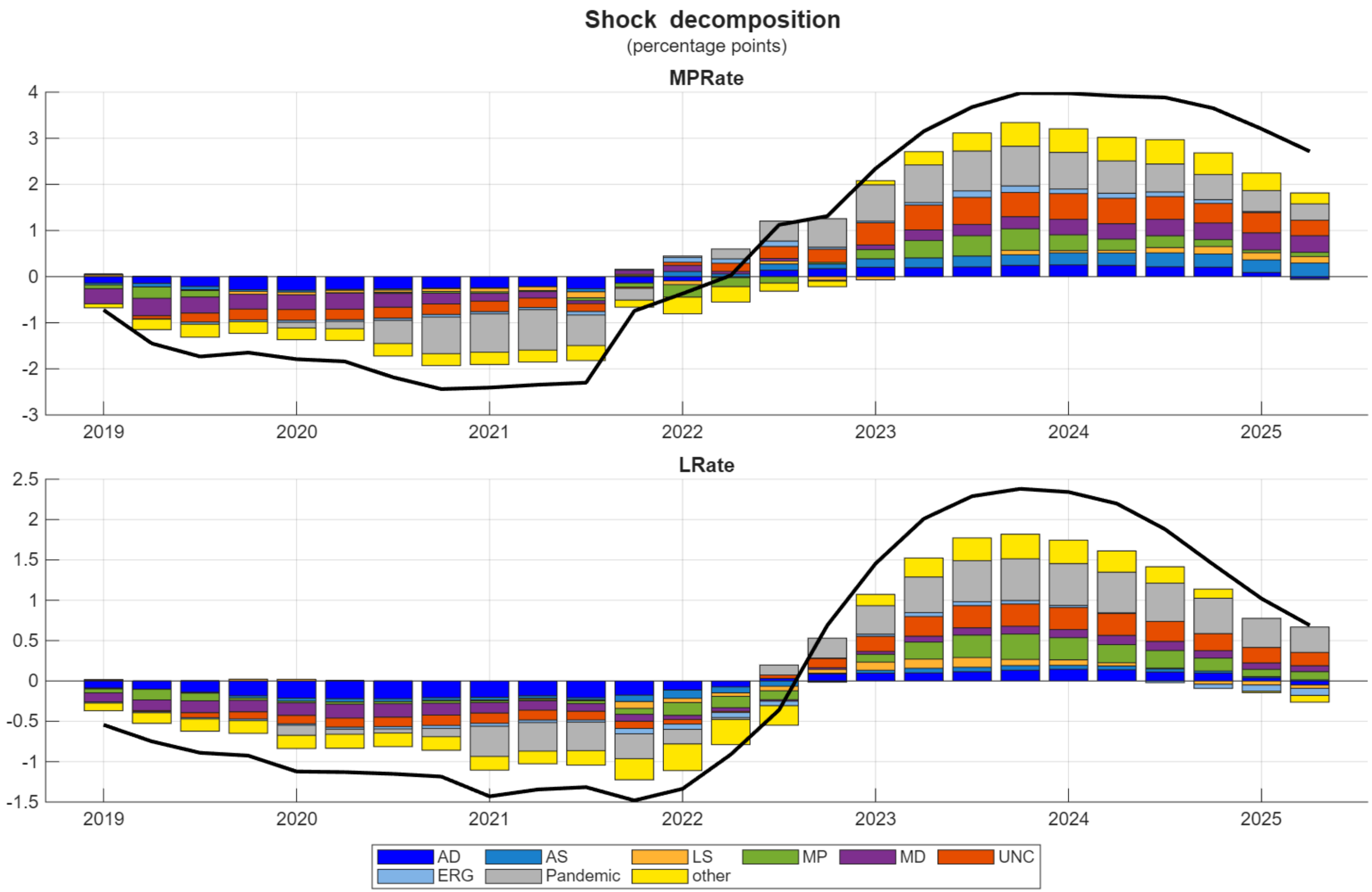
Shock decomposition (2019Q1-2025Q4) - Policy rate and bank lending rate



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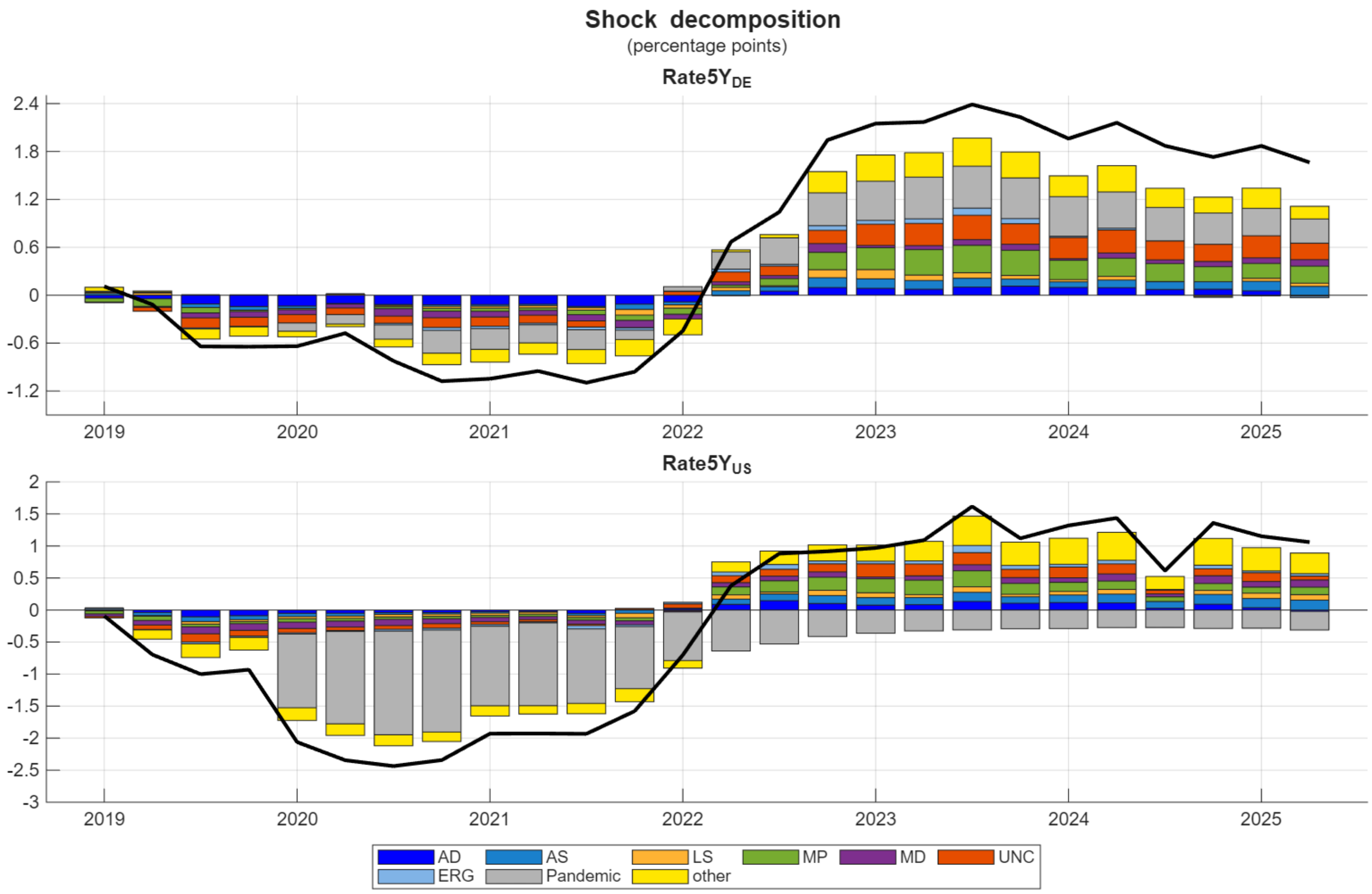
Shock decomposition (2019Q1-2025Q4) - bond yields



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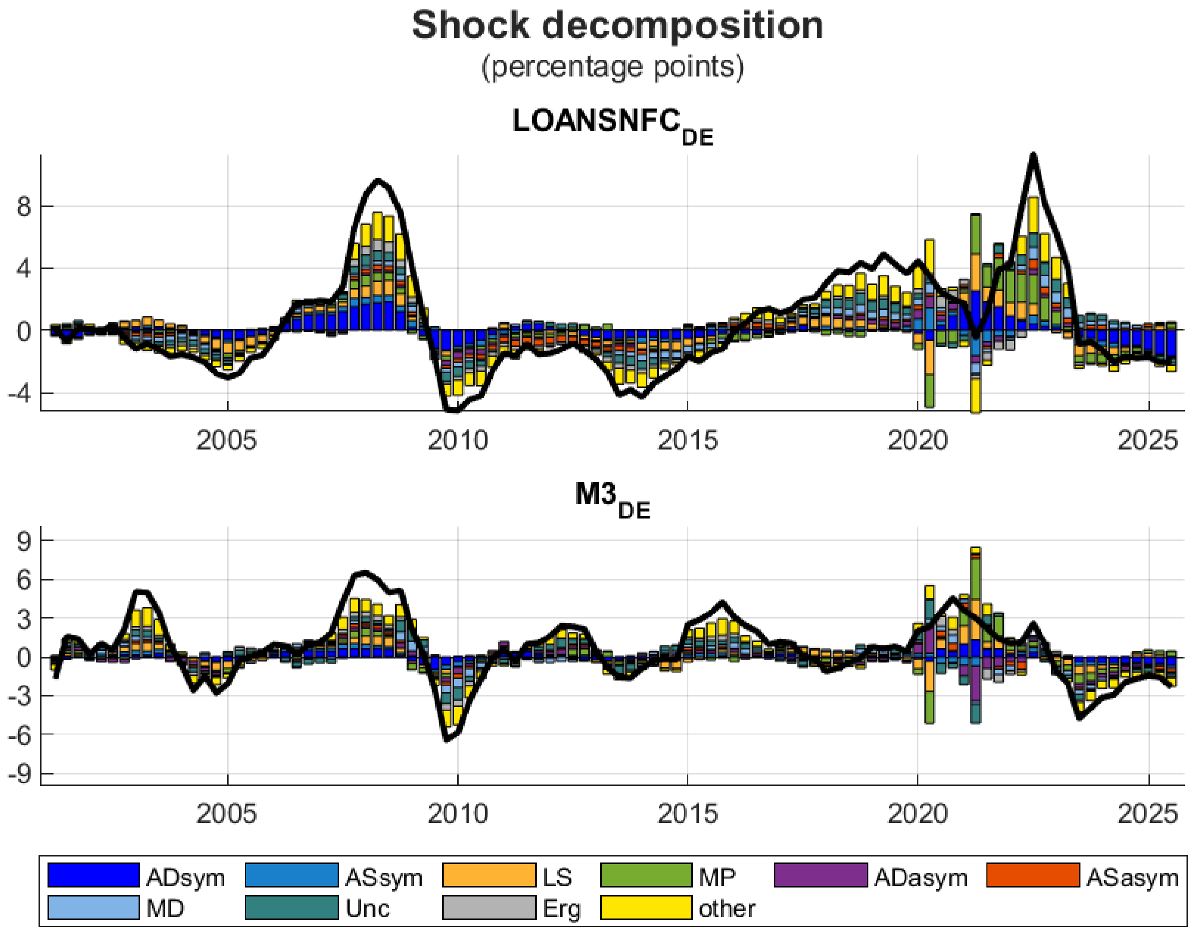
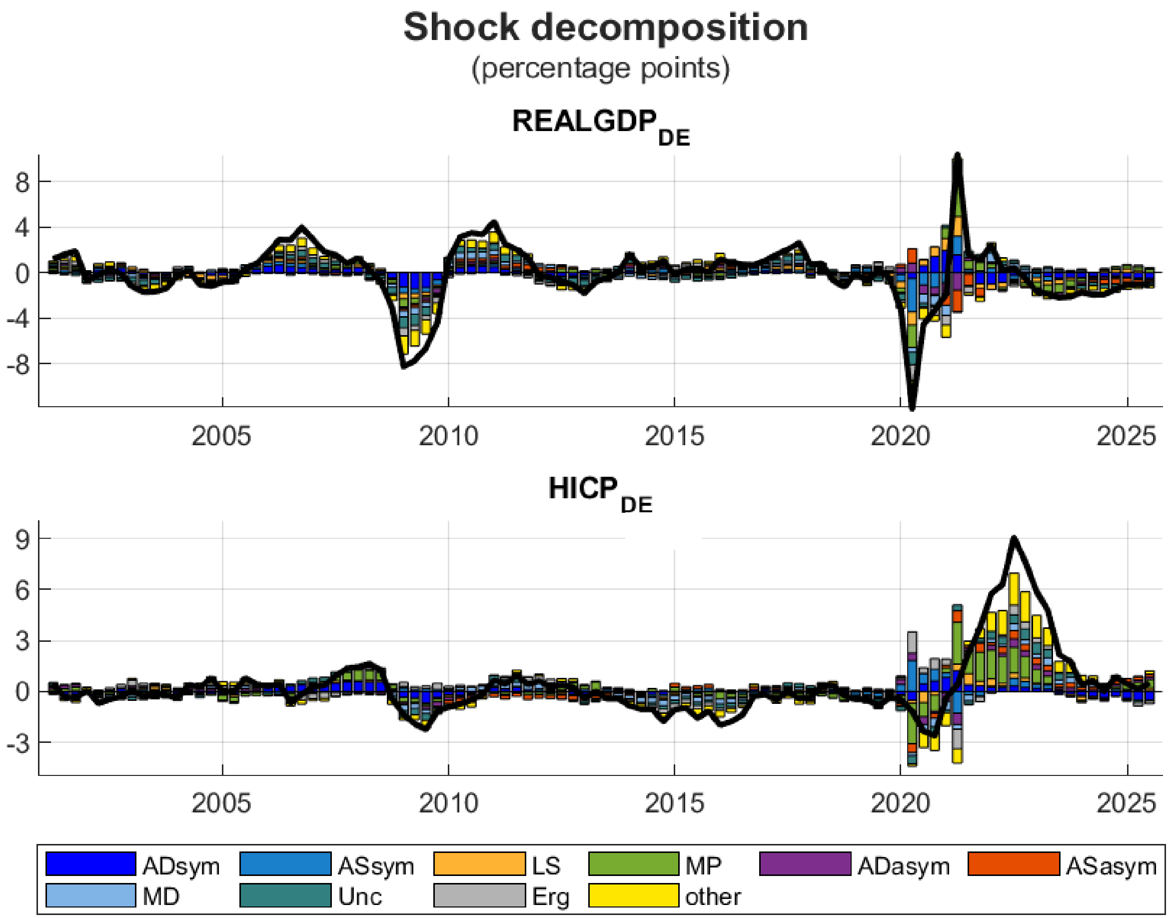
6. Further shock decompositions for DE + euro area model

Historical decomposition (2001Q2-2025Q3) - annual growth rates of loans to NFCs and of M3



Estimates from Bayesian VAR. Median contributions of identified shocks to deviation from unconditional forecast (AD: aggregate demand shock, AS: aggregate supply shock, LS: loan supply shock, MP: monetary policy shock, MD: money demand shock, UNC: uncertainty shock, ERG: energy price shock), yellow bars denote contributions of unidentified shocks. “sym” and “asym” denote symmetric and asymmetric shocks.

Historical decomposition (2001Q2-2025Q3) - annual growth rates of real GDP and HICP



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back

Identifying Monetary Policy Shocks with Divisia Money in the United Kingdom

Jane Binner, University of Birmingham

Rakesh Bissoondeeal, Aston University

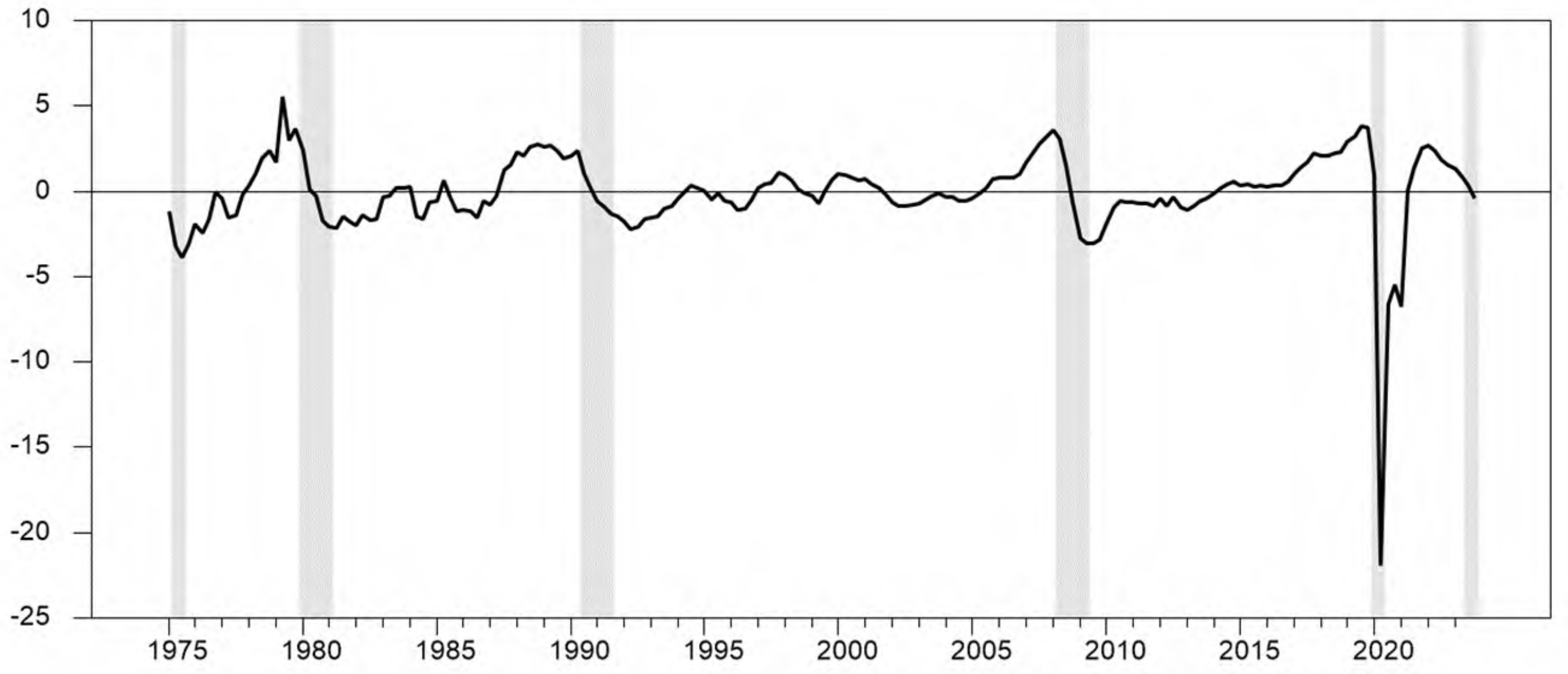
Barry Jones, Binghamton University (SUNY)

Victor Valcarcel, University of Texas at Dallas

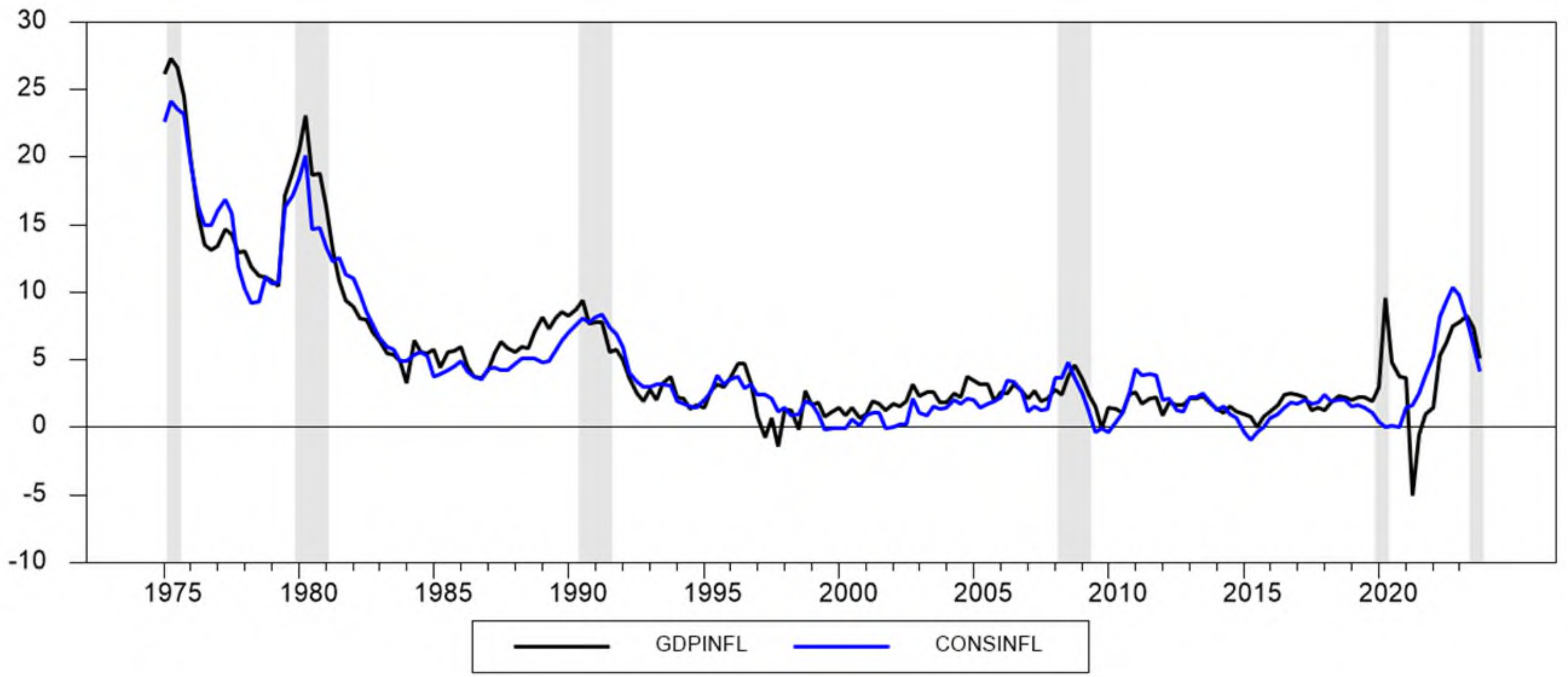
March 2026

Presentation for the Bank of England Spring Workshop

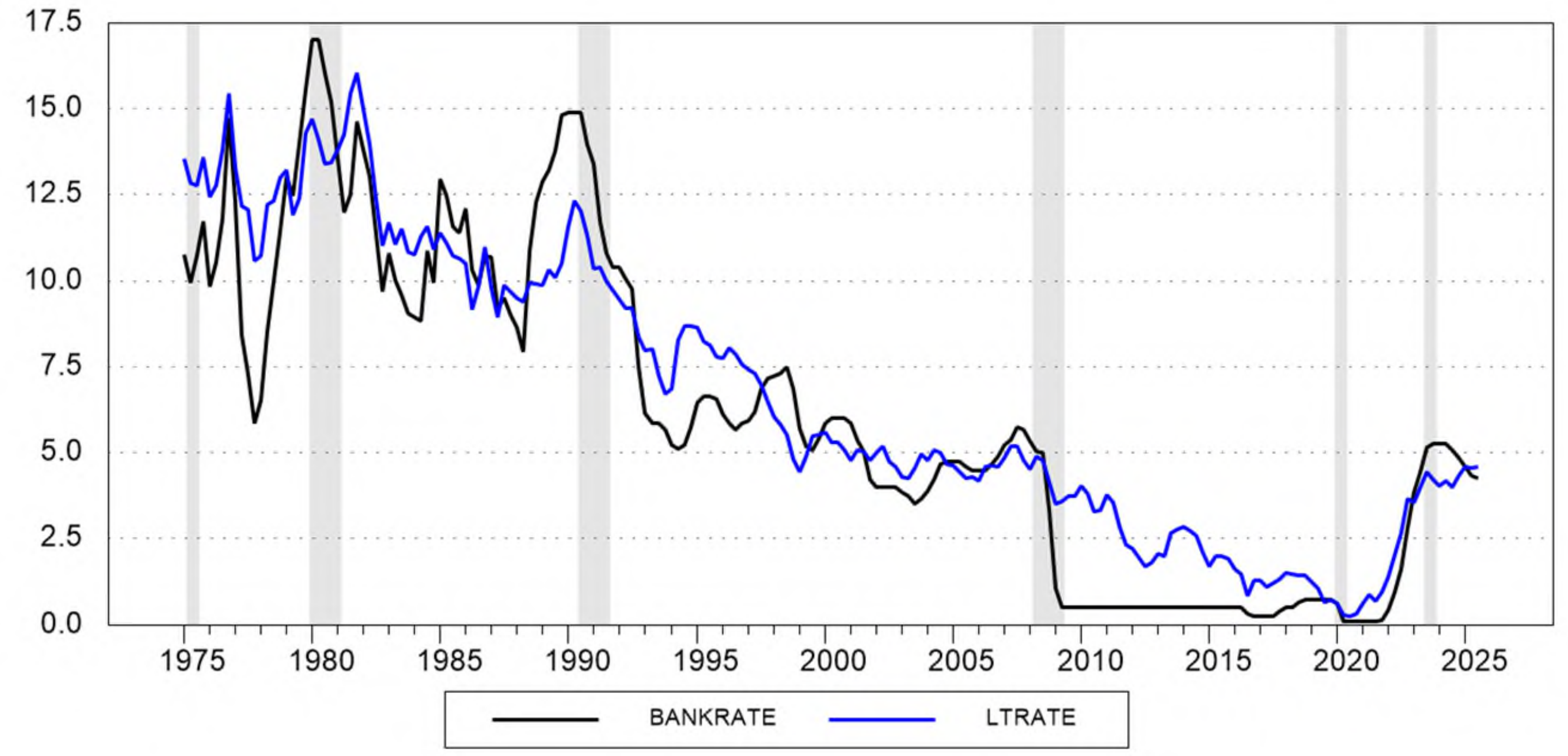
Detrended Real GDP, United Kingdom, 1975 to present



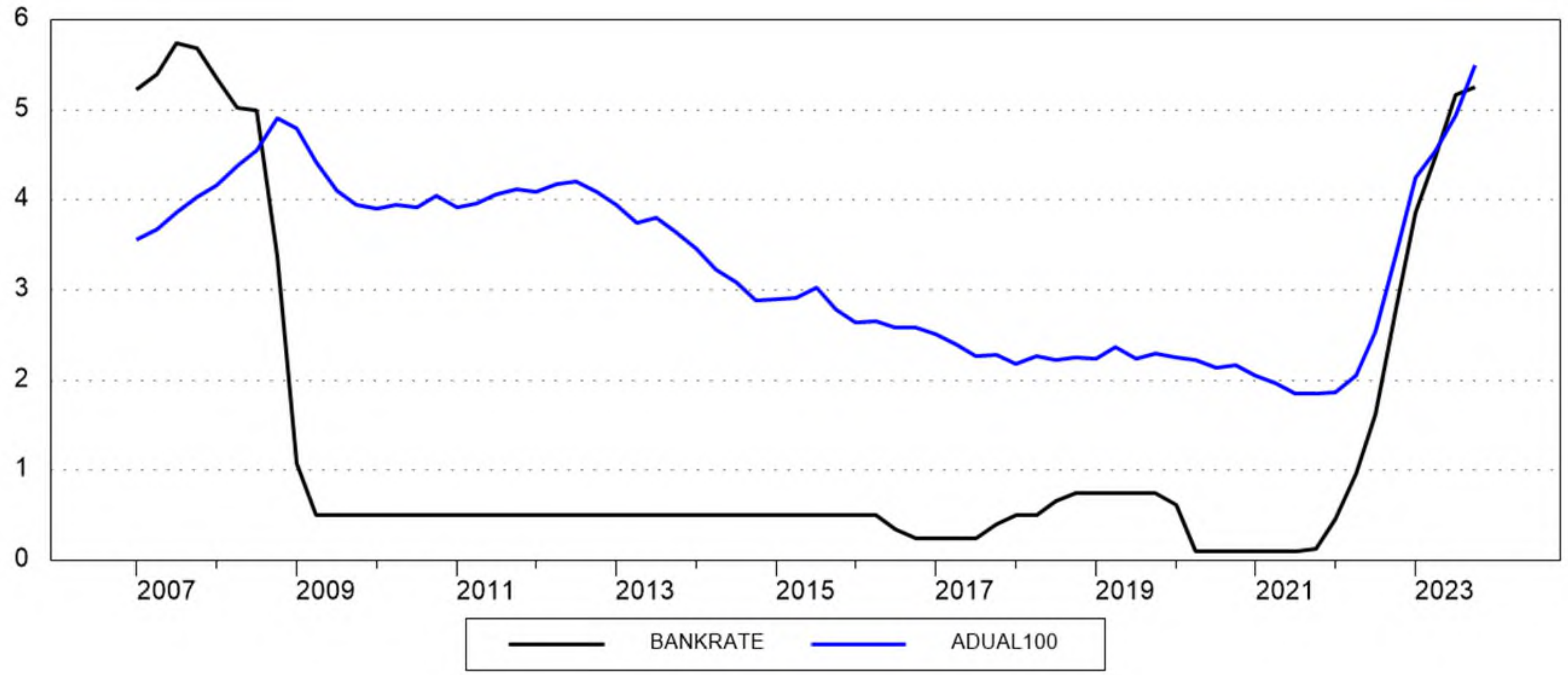
Annual Inflation Measures, United Kingdom, 1975 to present



Interest Rates: Bank Rate vs. Long-bond Rate, UK, 1975 to 2025

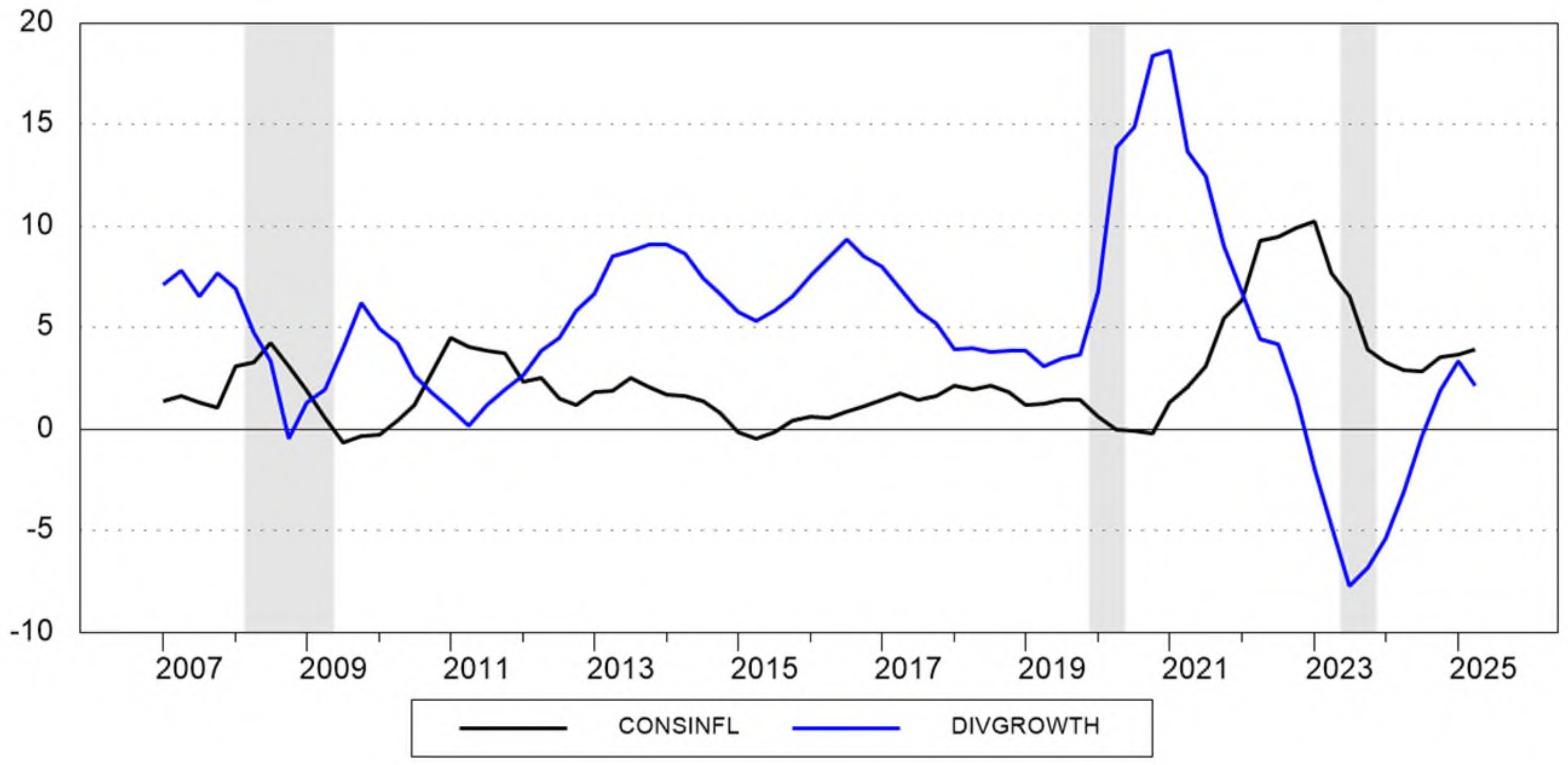


Monetary Policy and the ZLB, GFC to present



Money Growth and Inflation:

A role for money - Aggregate Divisia growth spikes during pandemic, leading subsequent inflation (CPI)



Money Measurement Matters

The focus in the literature has mainly been on

1) The composition of the M's:
    - Narrow Money
    - Broader Aggregates
    - Risk-bearing Assets
2) The method of aggregation:
    - Conventional measures
    - Empirically weighted measures
    - Aggregation-Theoretic Measures

Divisia measures are preferable, because monetary assets are poor substitutes for each other:

For example, Bissoondeeal et al. (2010) "Household Sector Money Demand for the UK"

Key Contributions of our Paper

- Construct Divisia indexes for household-sector and for households and PNFCs (aggregate Divisia) from 1977 to 2023 by extending Fleissig and Jones's approach to PNFCs.
- Construct corresponding dual user cost (price) indexes for the Divisia quantity indexes
- Components are treated consistently throughout the sample period and across sectors.
- Estimate SVAR models comparing Divisia money measures to various interest rates (Bank Rate, long-term government bond yield, shadow rate) as monetary policy indicators.

Key Contributions of our Paper, continued…

- Develop novel non-recursive identification with Divisia as the indicator that cleanly separates money demand from policy shocks.
- Recursive and non-recursive structures for the UK of the types advanced by Belongia and Ireland (2016, 2018) and Keating et al. (2019) for the U.S., reveal severe price puzzles when considering an interest rate as the indicator of monetary policy.
- When Divisia is considered as an indicator of monetary policy, it provides a resolution of the price puzzle across multiple specifications and samples.
- Results are robust to the pandemic and to the sectoral identification of Divisia.

User Costs

- Opportunity cost is based on an interest rate spread:

$$\pi_{i,t} = \frac{R_t - r_{i,t}}{1 + R_t}$$

where Rt is the benchmark rate

Proxies:

- Long-term interest rate
- Upper envelope
- Upper envelope plus a liquidity premium

Bank of England view (1993)

Fisher et al. (1993, pp. 246):

“[a] number of problems arise when using a maximum-rate benchmark. In principle the benchmark asset should not provide monetary services and, as such, an asset that is included as money in a previous time period should not later be used as the benchmark.”

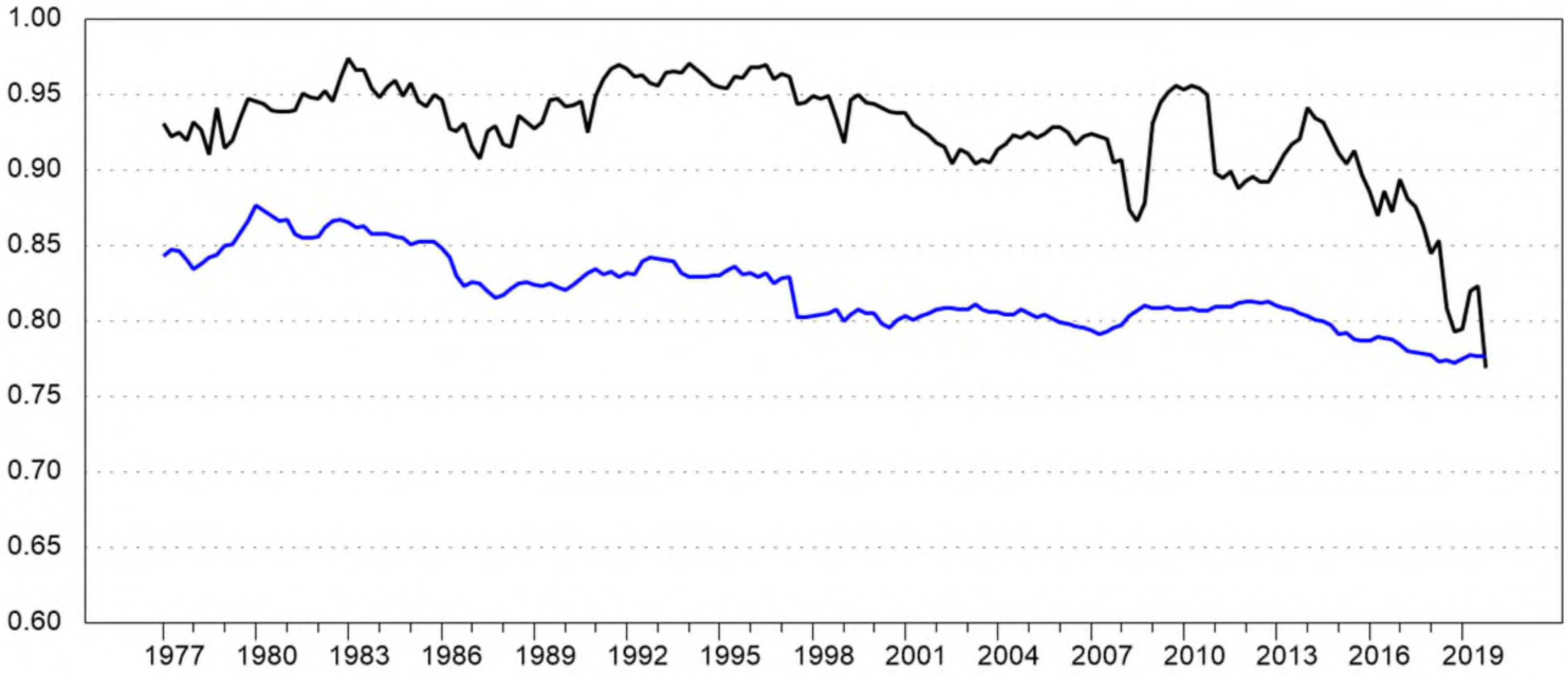
Bank of England Divisia

- Divisia monetary aggregates have been published by the Bank of England since the early 1990’s.
- Divisia measures are updated and improved to reflect changes in the underlying data.
- Sectoral composition is important (Households, PNFCs, OFCs) , especially in the 1990s (banks versus mutuals)
- Recent empirical evidence suggests that UK monetary assets are inelastic substitutes in response to Bank Rate changes (Fleissig and Jones, Economic Modelling, 2023, Macroeconomic Dynamics, 2024)

UK Divisia Measures

- Only available beginning in 1977.
- Use of break-adjusted flows is critical.
- After 2013, deposits at banks and mutually owned MFIs can’t be separated and OFCs no longer included.
- The Bank of England does not publish dual user cost (price) indexes for its Divisia quantity indexes.
- Envelope approach leads to inconsistent treatment of components over time and across sectors.

Households are overweighted (PNFCs are underweighted) in Divisia relative to Simple Sum



Black is Divisia share weight, Blue is simple sum weight

Our Approach:

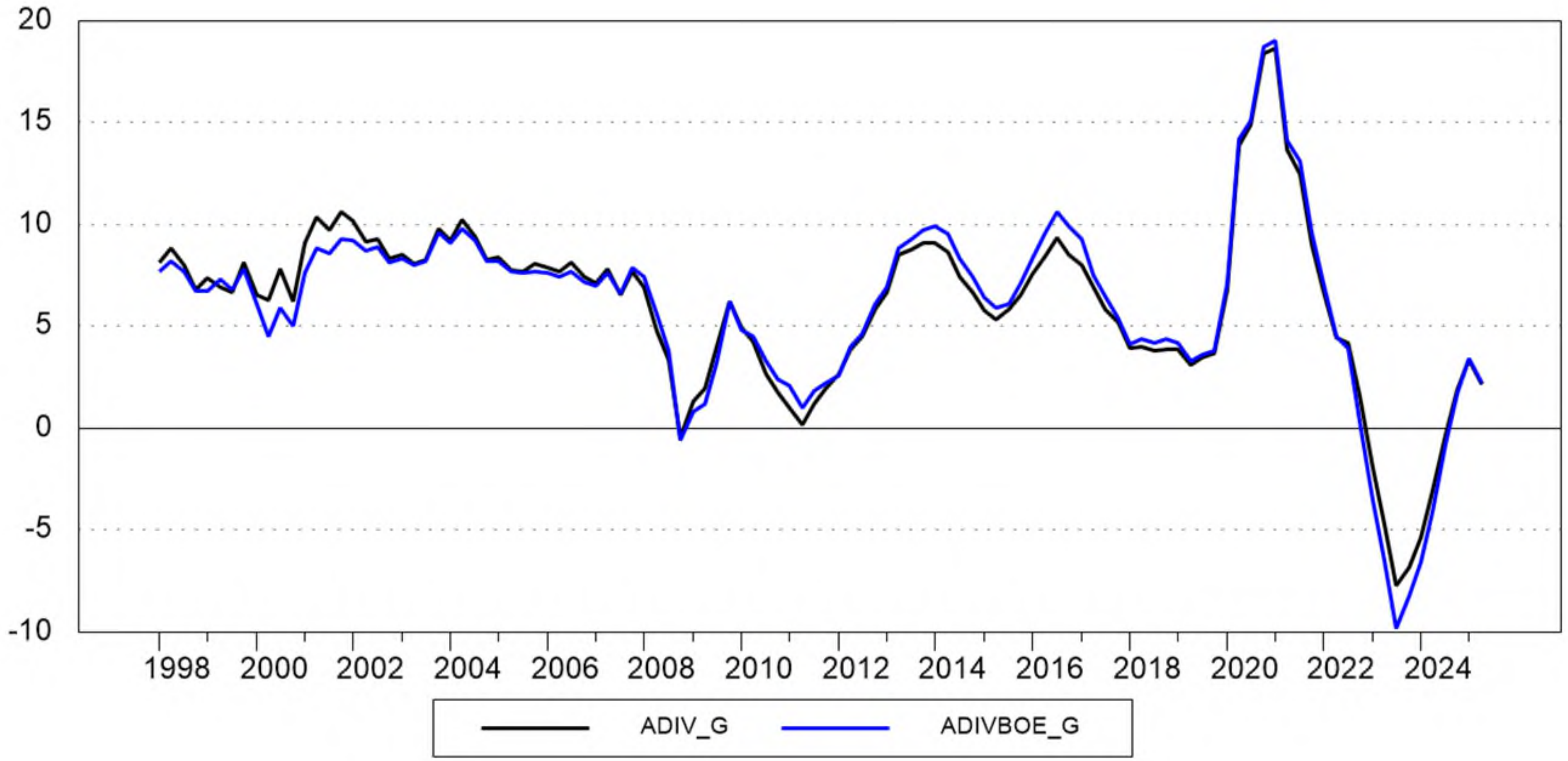
We construct an aggregate Divisia index (including households and PNFCs) and also extend Fleissig and Jones's household-sector index.

The benchmark rate for each sector is the upper envelope of tax-adjusted rates plus a small liquidity premium.

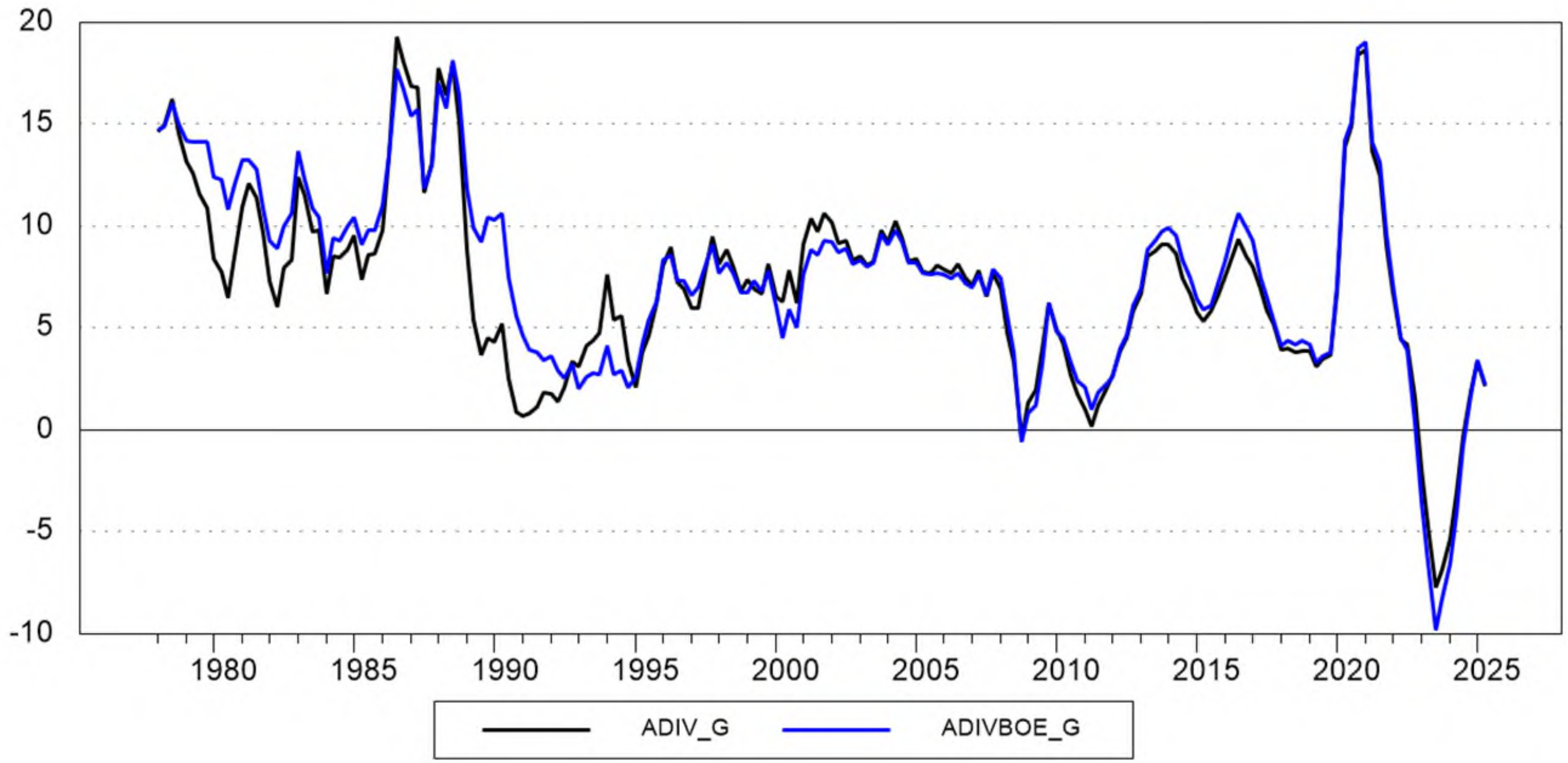
All components receive positive weights for both sectors throughout the entire sample period.

This allows us to construct corresponding dual user cost indexes for Divisia.

Our aggregate quantity index is very similar to the published index since 1997

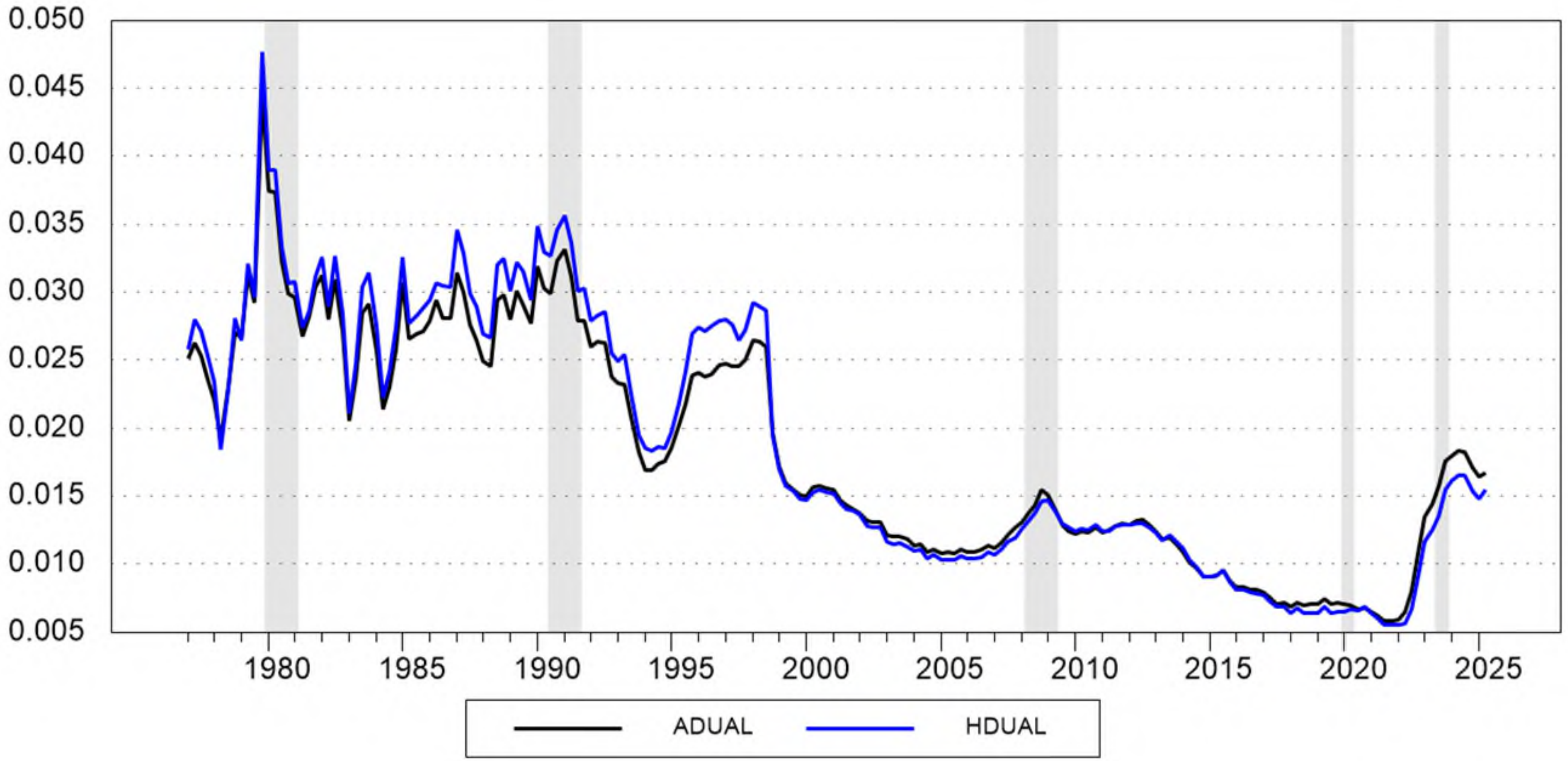


There are larger differences in early 1990s

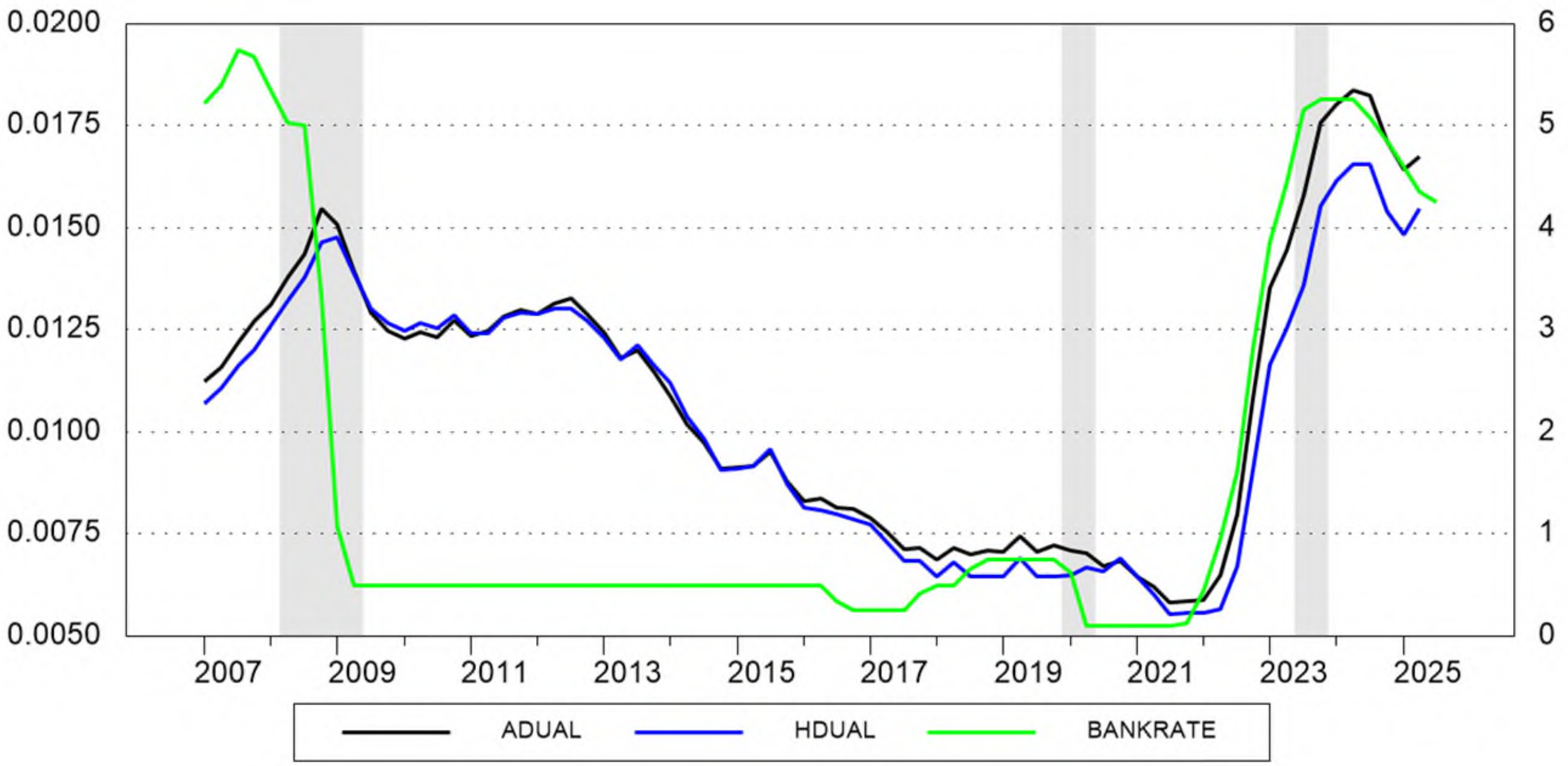


Reflects the use of the LG bonds rate before 1991.

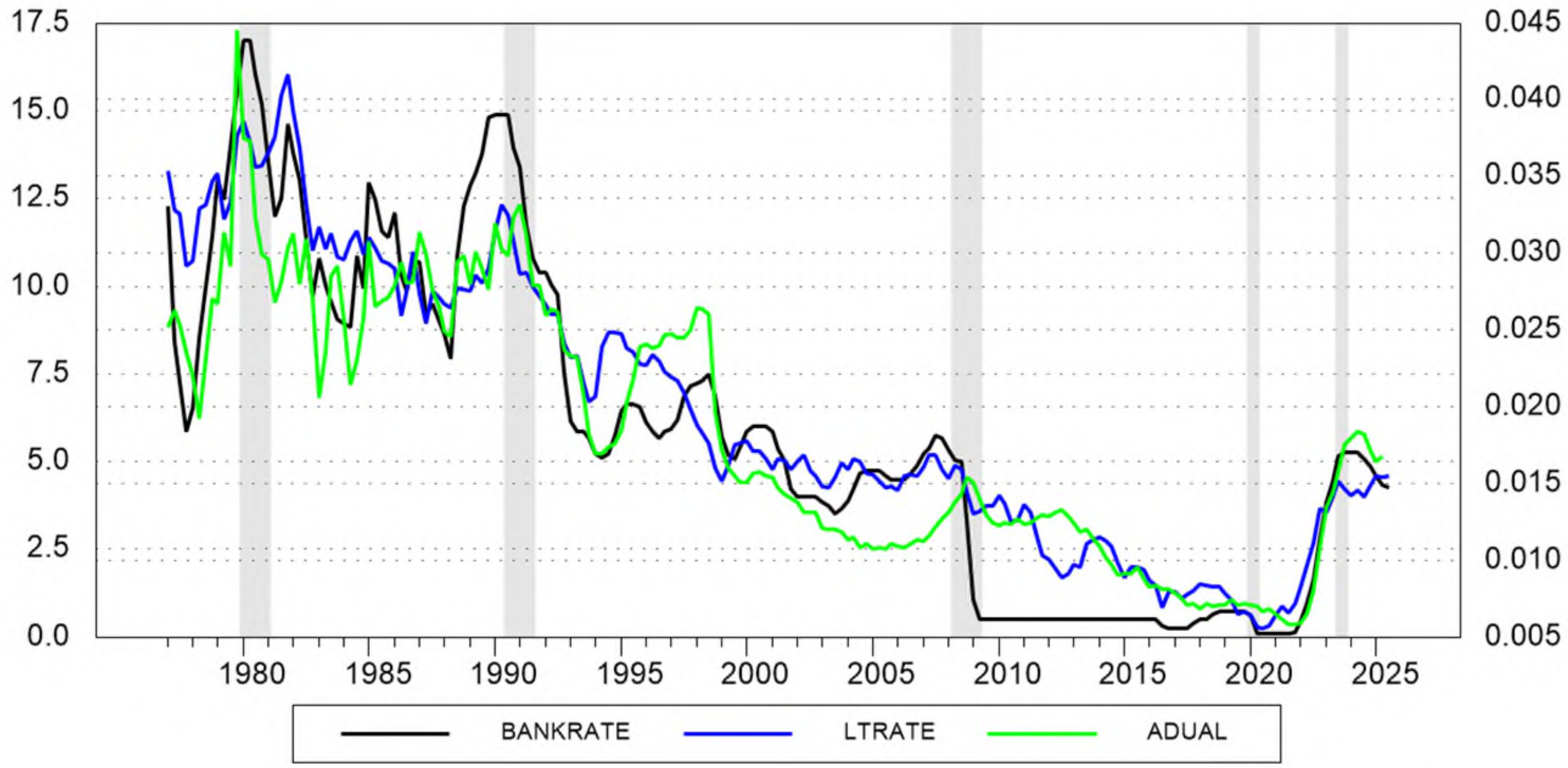
Dual Indices: Household-sector and Aggregate from 1977 - 2025



Duals decline slowly post-GFC: post-Covid increases in Bank Rate are strongly correlated with the dual indexes



Full sample: Aggregate Dual Index versus Bank Rate and Long-term Rate



Pre-1990: Fisher et al (1993, p 250) …

"As the price dual is based on interest differentials it is not surprising that its historical behaviour bears little resemblance to the level of the base rate."

Previous Literature

Direct Effects

- Elger *et al.* (2008), Binner *et al.* (2009), Bissoondeeal *et al.* (2019), Fleissig and Jones (2023)

Structural Models

- Keating *et al.* (2014), Keating *et al.* (2019)
- Belongia and Ireland (2015, 2016, 2018)
- Binner *et al.* (2018), Ezer (2019)
- Ellington *et al.* (2022)
- Fleissig and Jones (2023)

SVAR Models

Reduced form VAR:

$$z_t = B_1 z_{t-1} + \cdots + B_q z_{t-1} + u_t$$

Structural model:

$$A_0 z_t = A_1 z_{t-1} + \cdots + A_q z_{t-1} + \Sigma \varepsilon_t$$
$$E[\varepsilon_t {\varepsilon_t}^T] = I_n$$

Mapping the covariance matrices gives

$${A_0}^{-1} \Sigma \Sigma^T \left({A_0}^{-1}\right)^T = E[u_t {u_t}^T] = V$$

Σ is assumed to be diagonal and the main diagonal of A_0 is normalized to 1.

Identification is achieved by making $n(n-1)/2$ additional restrictions.

SVAR Model

Sample period is 1977 to 2019. Results are qualitatively robust for 1977 to 2023.

We consider six variables in our SVAR models:

$z=(P,Y,R,DM,UC,CP)^T$

Where;

P= GDP deflator

Y= Real GDP

R= Interest rate variable (Bank Rate, Shadow Rate, Bond yield)

DM= Divisia index (Aggregate, Household-sector)

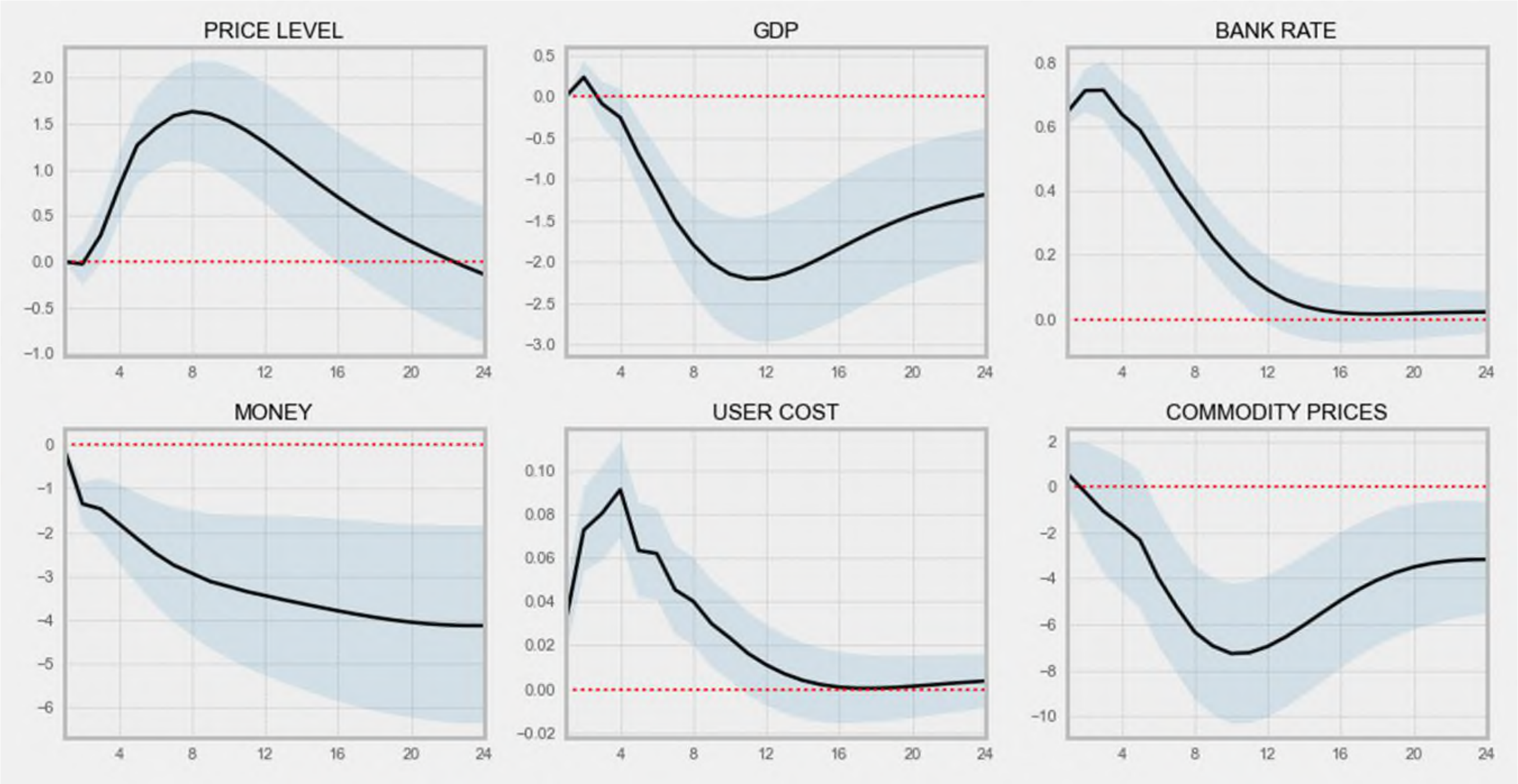
UC = Dual user cost index

CP= Commodity price index

Partially recursive identification

- Specifically, the monetary policy indicator variable has no contemporaneous impact on output, prices, or commodity prices.
- The indicator is influenced by contemporaneous values of output, prices, and commodity prices.
- The remaining “informational” variables respond immediately to all other variables but only affect them with a lag.

Impulse Responses to an interest rate shock



IRFs for output, money, and user cost look reasonable, but price puzzle lasts over 20 quarters

SVAR Model

Sample period is 1977 to 2019. Results are qualitatively robust for 1977 to 2023.

We consider six variables in our SVAR models:

$z = (P, Y, R, DM, UC, CP)^T$

Where;

P= GDP deflator

Y= Real GDP

DM= Divisia index (Aggregate, Household-sector)

R= Interest rate variable (Bank Rate, Shadow Rate, Bond yield)

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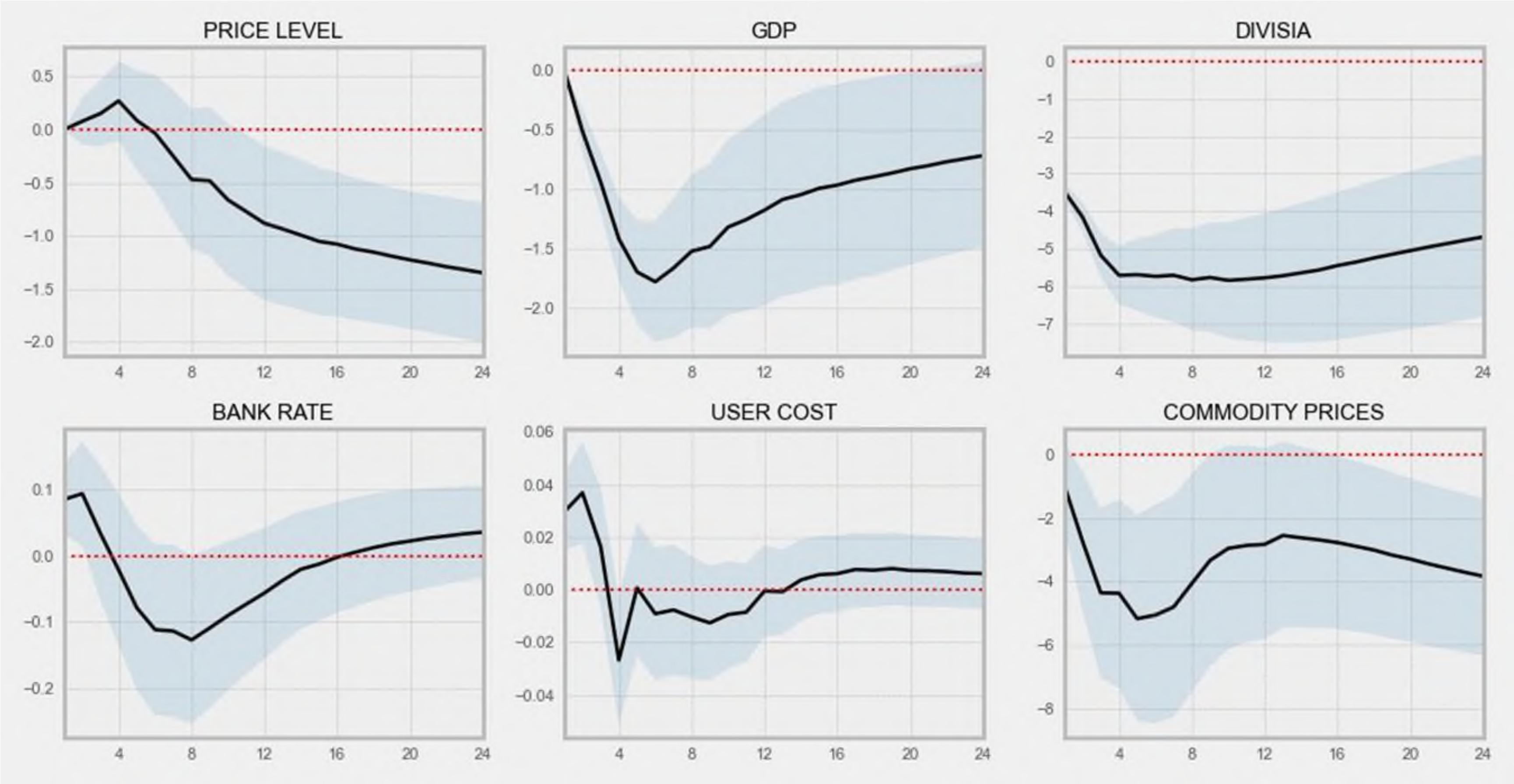
Impulse Responses to an aggregate Divisia shock (no price puzzle)

Change the order of DM and R to get a version with Divisia as the indicator:

$a_{31}P_t + a_{32}Y_t + DM_t + a_{36}CP_t = \sigma_{33}\varepsilon_t^{MP}$



Impulse responses to Divisia Shock

- Output responses peak at 6-8 quarters
- Price response is significant starting from 10-12 quarters
- Price and output responses are highly persistent
- No price puzzle
- Interest rates and the dual increase in response to a monetary contraction, although the effect is short-lived
- Results are very robust to the interest rate: Bank Rate, Shadow Rate, Long-term government bond yield
- Similar results for household-sector Divisia measures, but slight price puzzle at very short time horizon
- Responses are similar to those for partial identification
- Very consistent with recent evidence from the Euro area (Fleissig, Jones & Darvas 2022)

Conclusions

- Recent empirical evidence for the UK and Euro Area shows that money measures provide more information about real output and prices than interest rates (short-term, long-term, shadow rates).
- Monetary assets are inelastic substitutes suggesting that Divisia aggregates provide a better gauge of monetary conditions than conventional aggregates.
- Divisia quantity and dual user cost indexes are both needed to establish money demand relationships.
- Jointly constructing Divisia quantity indexes and dual user cost (price) indexes in a consistent manner is important and should be explored further.

Broad Divisia Money, Supply Chain Disruptions, & Inflation Following the COVID-19 Recession*

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Rutgers, NBER, Hoover Institution, and Stanford

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Oberlin College and
Emeritus Economist, Federal Reserve Bank of Dallas

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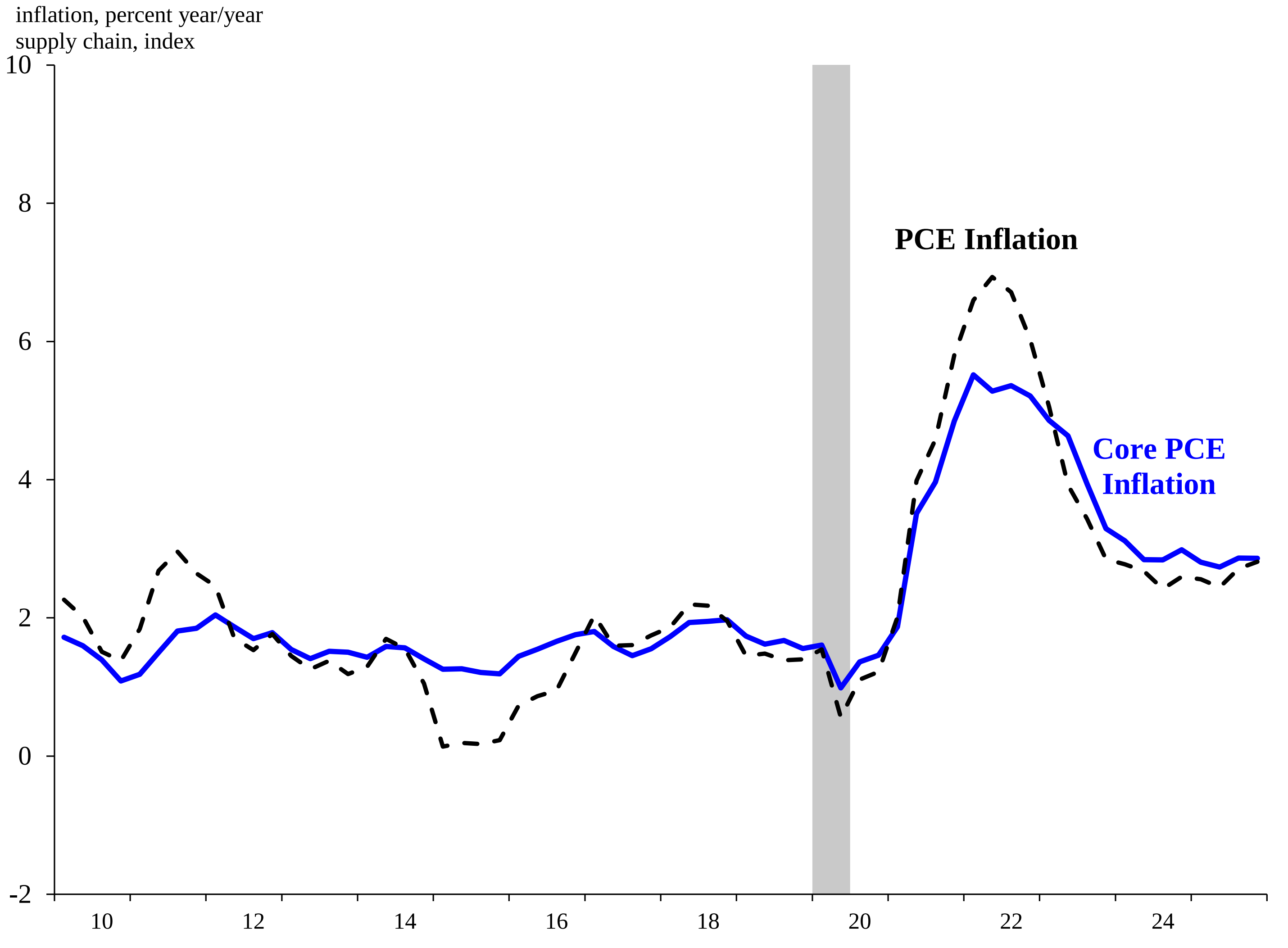
March 2026

*The views expressed are those of the authors and are not necessarily those of the Federal Reserve Bank of Dallas or of the Federal Reserve System.

Introduction

Controversy over how much the rise and ebbing of inflation owed to shifts in aggregate demand growth or supply chain disruptions.



Core and Total PCE Inflation Rises and Mostly Ebbs Since the COVID Recession

(Sources: BEA and authors' calculations. Shaded areas are NBER recessions.)

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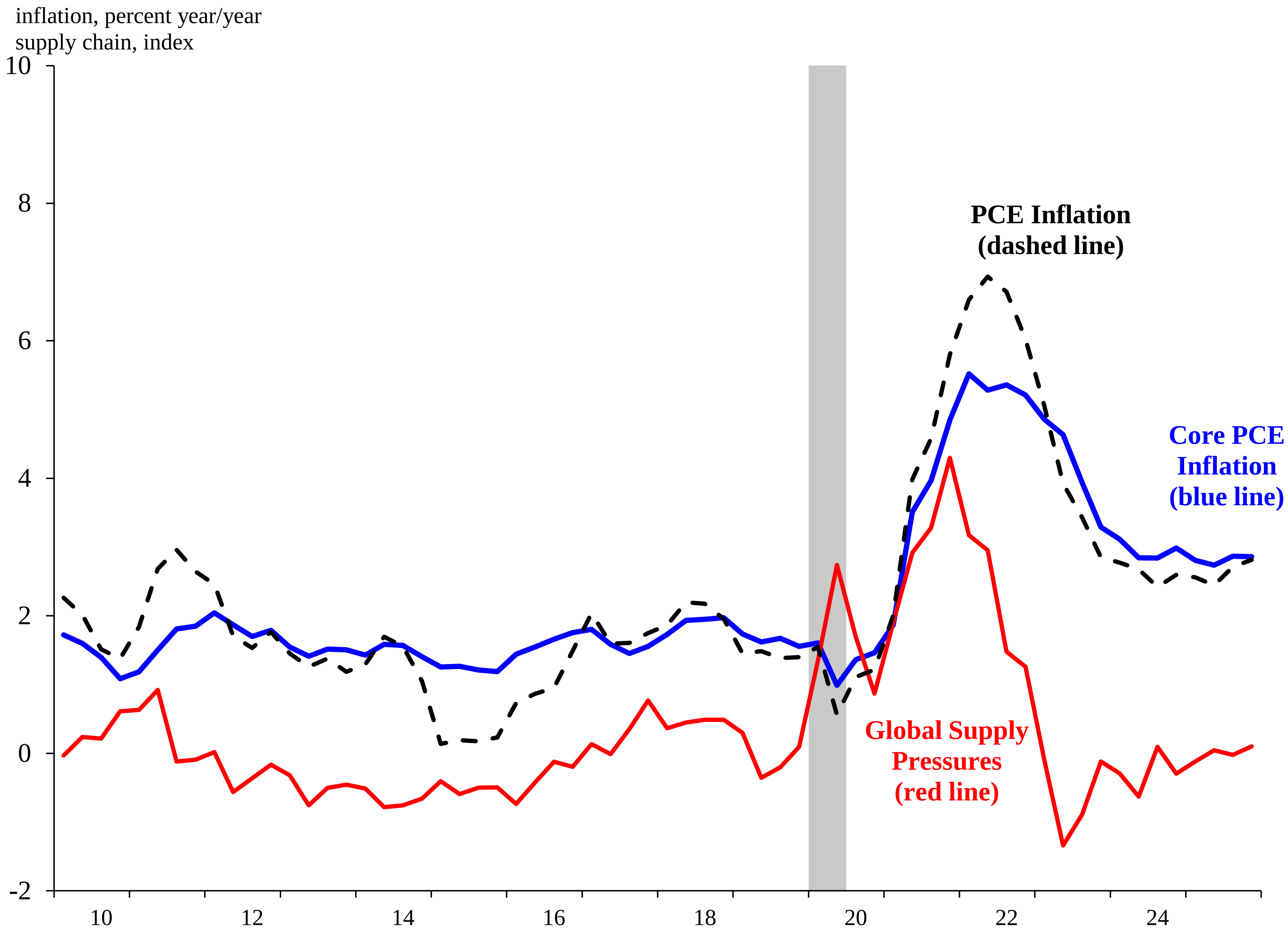
Controversy over how much the rise and ebbing of inflation owes to shifts in aggregate demand growth or supply chain disruptions.

Supply chain pressures rise & retreat => unless accommodated by aggregate demand, should have reversed & returned to a 2% path.



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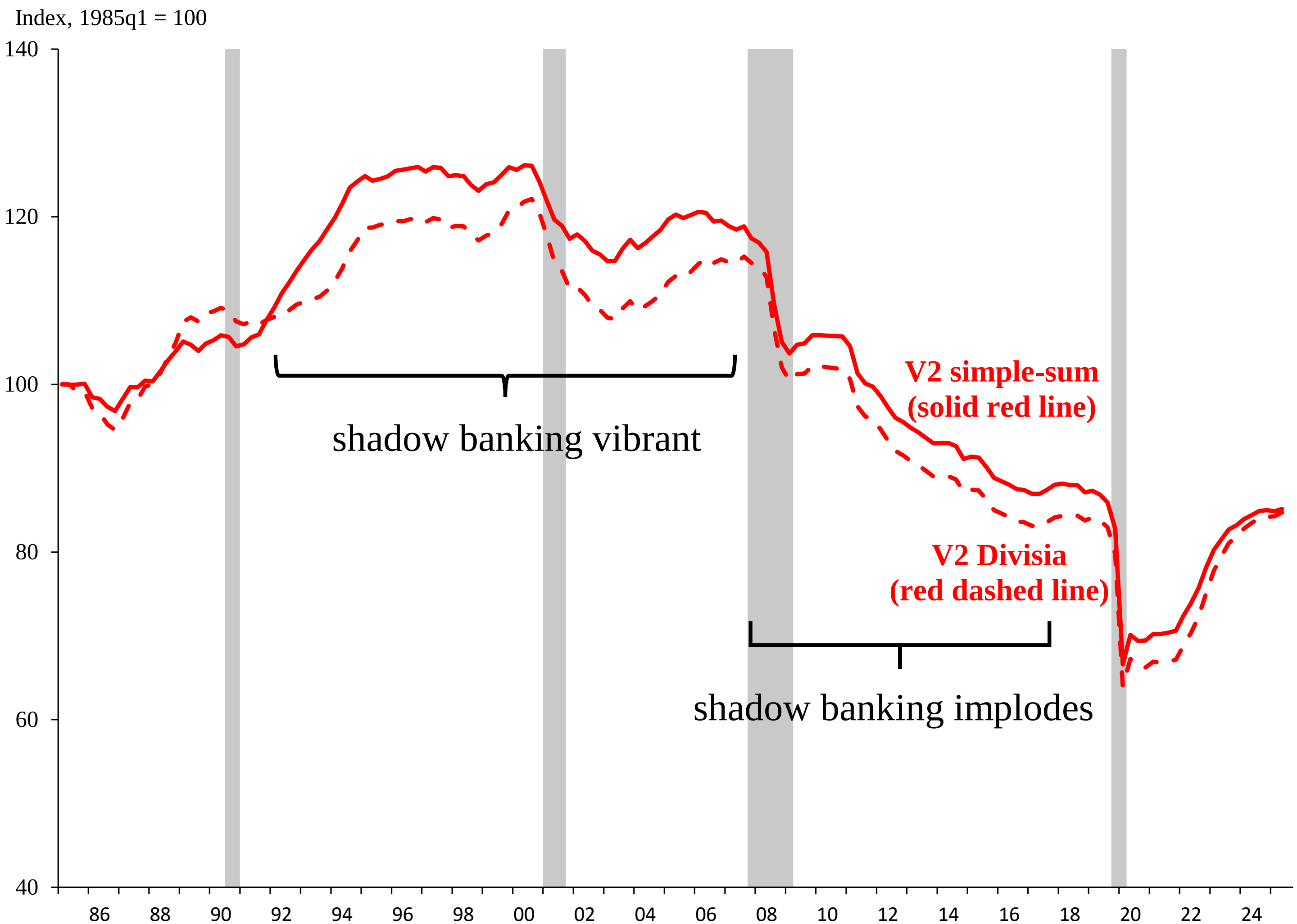
Supply chain pressures rise & retreat => unless accommodated by aggregate demand, should have reversed w/ return 2% path.

Strong US nominal GDP growth in 2021-22 coincided with inflation rising above 2% => role for demand, not just supply.

We use a modified P-Star Model to assess these competing roles.

Original P-Star model relied on a stable demand for simple-sum M2. MV = PY, if V stable in long-run, M growth linked to inflation. But V2 unstable, likely related to a recent rise & fall of shadow banking.



Since early 1990s, the Velocity of M2 <u>And</u> Divisia M2 Very Unstable

(Sources: CFS, Federal Reserve, Bordo & Duca, 2023, and authors' calculations.)

Introduction

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Many ignore money but surprised by inflation in COVID recovery.

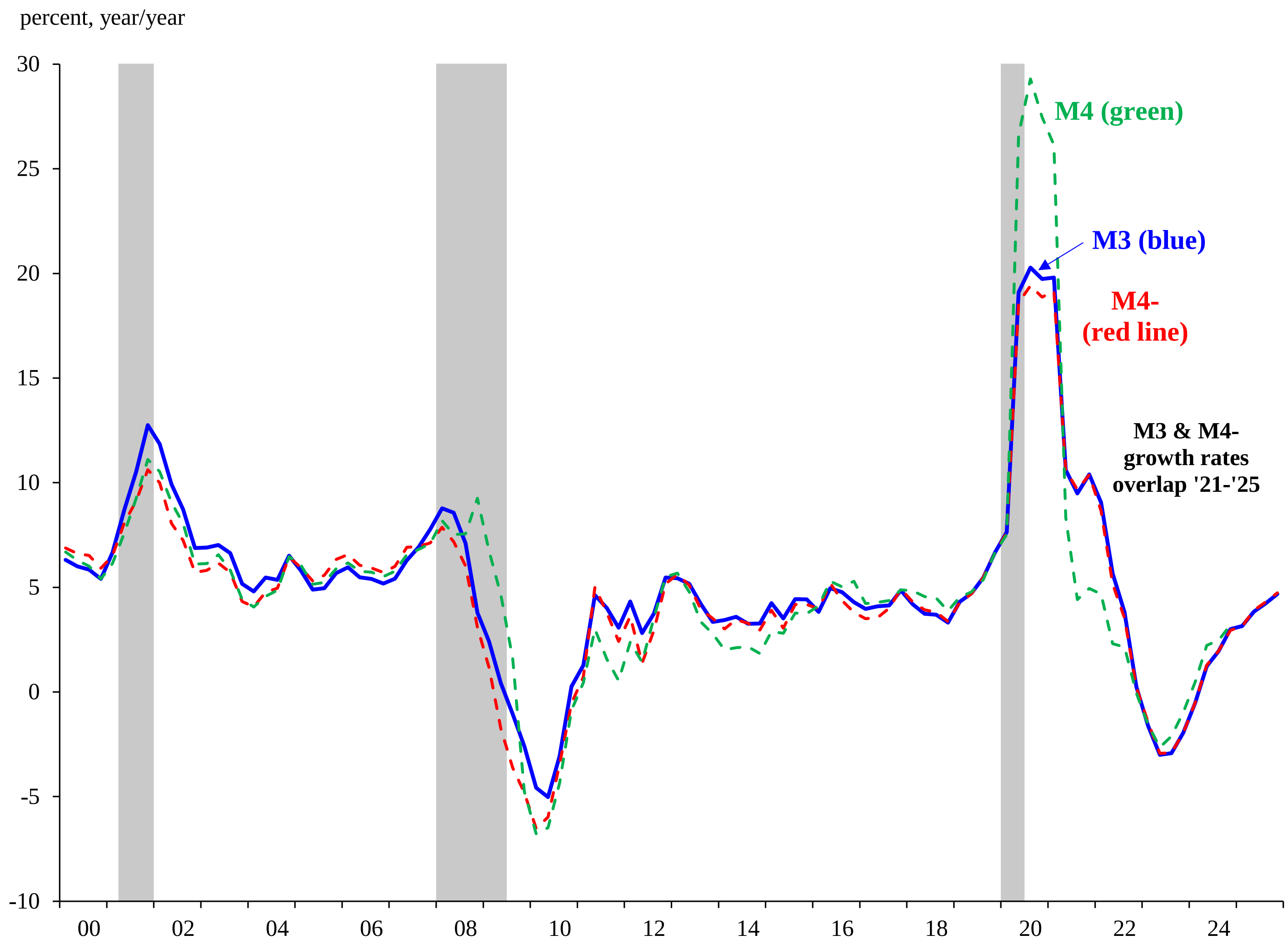
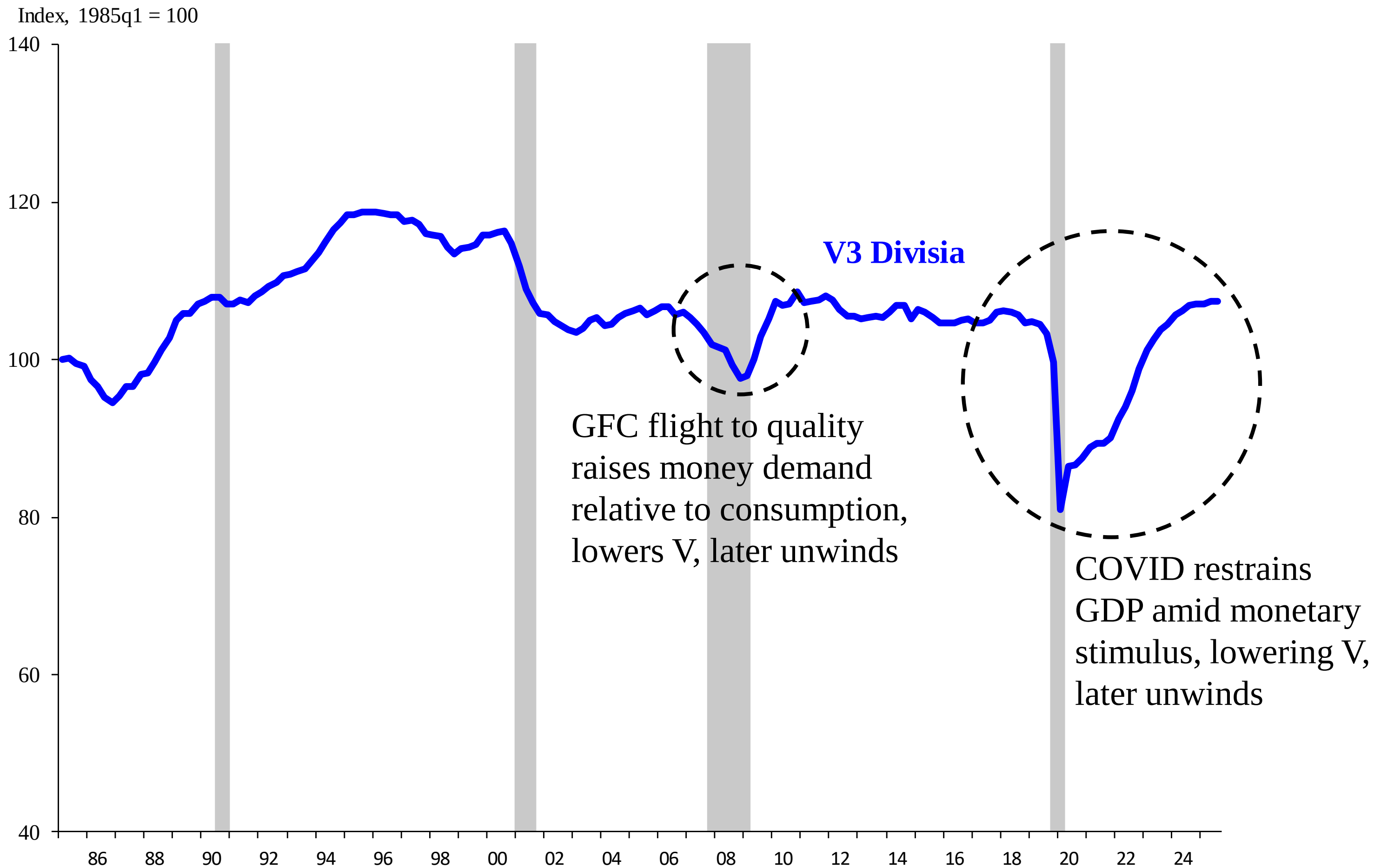


Figure 2: U.S. Broad Divisia Money Growth Surges in the COVID-19 Recession in Sharp Contrast to the Great Recession

(Sources: Center for Financial Stability and authors' calculations.)

Introduction (cont'd)

In contrast, Divisia M3 has a stable long-run velocity.

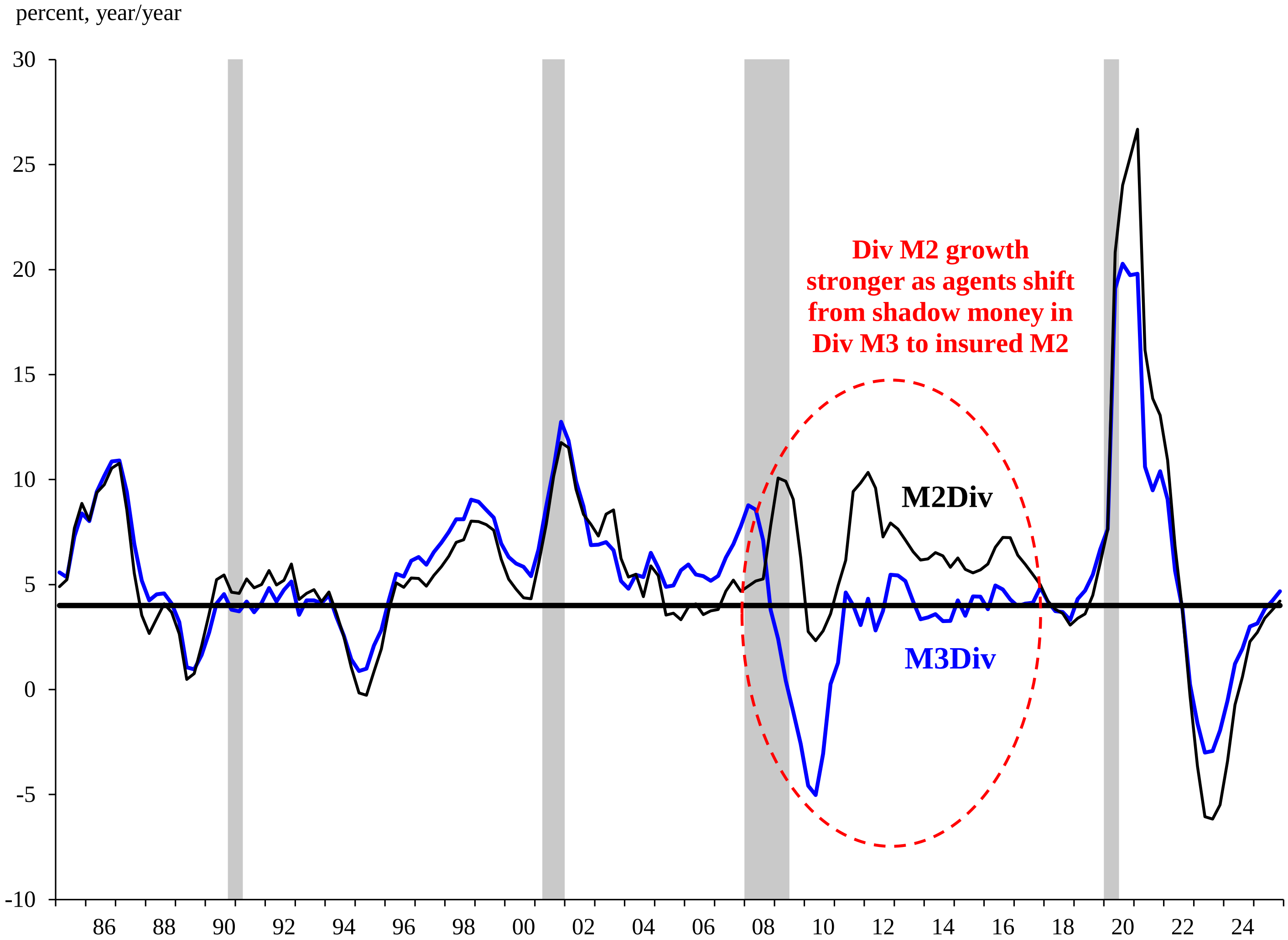


Since early 1990s, the Velocity of Divisia M3 Stable in Long-Run

(Sources: CFS, Federal Reserve, Bordo & Duca, 2023, and authors' calculations.)

Introduction (cont’d)

In contrast, Divisia M3 has a stable long-run velocity. M3 internalizes shifts between money created by commercial banks & shadow banking (a point emphasized by Tim Congdon, 2025).



Divisia M2 Stronger Than Div. M3 When Shadow Banking Shrank in the Subprime Bust

(Sources: Center for Financial Stability, Federal Reserve, and authors' calculations.)

Introduction (cont'd)

In contrast, Divisia M3 has a stable long-run velocity. M3 internalizes shifts between money created by commercial banks & shadow banking (a point emphasized by Tim Congdon, 2025).

We model Divisia M3 velocity. In GFC, V3 fell and rose with uncertainty. In pandemic V3 fell on govt restrictions, then recovered

We view DivM3 as indicator of aggregate demand reflecting fiscal & monetary policy, plus swings in risk aversion & gov't restrictions.

Inflation mainly owed to aggregate demand, limited effect of supply pressures. P-Star reflects monetary policy has long & variable lags.

Summary

1) Layout velocity framework and results
2) Layout P-Star model, folding in long-run velocity model
3) Review P-Star model results

Modeling the Demand for—and Velocity of Broad Divisia M3

- Quick Background on Divisia Money.
- Key Factors Affecting the Velocity of Divisia M3

An Overview of Divisia

- Idea: agents equate the marginal utility of monetary services provided by different assets divided by their user costs.
- User cost of asset *i*, $\pi_{it} = P_t(R_t - r_{it}) / (1 + R_t)$, prices monetary services as the lost (lower) interest from holding asset i.
- R_t = price of the benchmark asset that provides no services
- Divisia uses chained Törnqvist-Theil quantity index to weigh growth rates of money components by their share of total expenditures on liquidity services. Total sums each type of money balances x user cost. For a given composition of asset holdings, more liquid components have a higher weight (share of liquidity expenditures) on their growth. Simple-sum M aggregates have equal weights (empirically rejected).

Overview of Divisia Monetary Aggregates (indexes)

Data from CFS Divisia measures are okay after deposit deregulation:

DivM2: liquidity services from M2 balances (currency, bank checking, savings, and small time deposits plus household money market funds)

DivM3 adds services from LTDs, institutional money funds, RPs

DivM4- further adds services of non-intermediated commercial paper

DivM4 further adds services of T-bills

Stable broad Divisia velocity in deregulated deposit era.

Divisia tracks the evolving liquidity of monetary components.

Divisia M3 tracks liabilities of financial intermediaries: includes bank large-time deposits & nonbank money created by institutional money funds which bought s-run debt financing much subprime MBS that fell in the subprime bust.

Divisia M3 velocity falls in crises, but later recovers=> long & variable lags in the effects of swings associated with money growth.

Bordo & Duca '25 (and Serletis) find Div M3 more stable D than Div M4-, Div M4 that add **non-**liquidity transformed assets (commercial paper + T-bills)

Modeling Divisia M3 Velocity (C/M)

If inc./consumption elasticity (α_1) =1, / by M, simplify to:

Long-Run:

$$\ln V^{*}_{t} = \alpha_0 + \alpha_1 \underbrace{\ln \mathit{SLoad}_t}_{(-)} + \alpha_3 \underbrace{\mathit{CFMA}_t}_{(-)}$$

changing liquidity non Div M assets

Reg ↑ creation of shadow money

Short-Run:

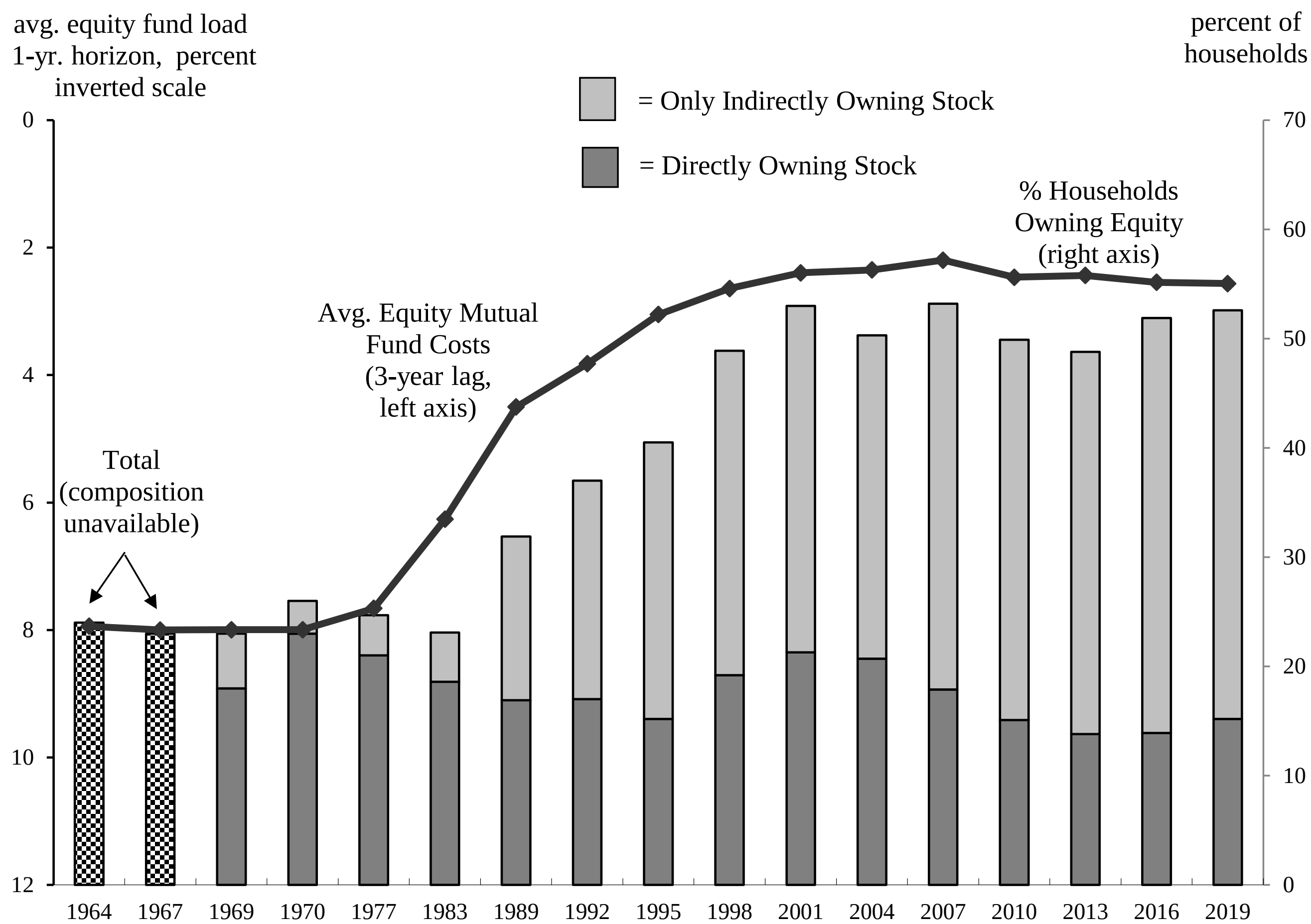
$$\Delta ln^{*}_{t} = \lambda_0 + \lambda_1(EC)_{t-1} + \beta_i \Delta(\ln V)_{t-i} + \theta_i \Delta(\ln \mathit{SLoad})_{t-i}$$
$$+ \varphi_i \Delta(\mathit{CFMA})_{t-i} + \delta \mathit{S\text{-}runVar}_t + \varepsilon_t$$

$EC_{t-1} \equiv \ln V_{t-1} - \ln V^{*}_{t-1}$, $\lambda_1 < 0$ => equilibrium correction

$|\lambda|$ = quarterly speed of adjustment

*Note tried adding user costs, that were insignificant and dropped.

Inverted Stock Mutual Fund Costs *SLoad* Correlated with Stock Ownership Rates (Duca & Walker, 2022)



Sources: Various Surveys of Consumer Finances reported in *Federal Reserve Bulletin* articles and authors' calculations.

Divisia M, Velocity, *CFMA*, and Derivatives

- Commodity Futures Modernization Act *CFMA* made derivatives legally enforceable, gave bankruptcy priority over most debt (Bolton & Oehmke, 2015). Derivatives (e.g., CDS) enhance liquidity of shadow bank liabilities funding risky investments.
- CDS credit enhancements spurred use of short-term debt of shadow banks (e.g., Lehman) bought by institutional & retail money market funds and RPs to fund long-run asset positions. Boosted M3 balances as a funding source => lowered velocity.
- As this regime shift is discrete, we use broken trend techniques of Johansen, Rosconi, Nielson, 2000. Results similar using a shift dummy, but valid significance tests on for cointegration only available for the broken trend (Giles & Godwin, 2012).

Controlling for COVID Effects

- Medium-run effects from unusual constraints on spending from pandemic: gov’t restrictions, uncertainty, vaccines. Parallels to temporary fall in V in WWII: goods rationing restricted spending and M policy pegged interest rates.
- Incorporate with some partial or sluggish adjustment.
- Impact of gov’t restrictions but also vaccine lessens uncertainty and fear of infection that deterred spending
- Fall in V akin to build up of excess saving as liquid savings
- Added 3 short-run impact dummies for 20q2, 20q3, 20q4.

Modeling Divisia M3 Velocity

Use broken constant cointegration technique for CFMA effects =>

$$\ln V^*_t = \alpha_0 \text{ (pre-CFMA) or } \alpha_0 \text{ (post-CFMA)} + \alpha_1 \ln SLoad_t$$

<u>Pre-2013 Sample (1985q3 to 2012q4)</u> EC: -.119, t-stat 4.17**

Pre-CFMA: $\ln V^*_t = 2.630 - 0.302 \ln SLoad_t$

Post-CFMA: $\ln V^*_t = 2.530 - 0.302 \ln SLoad_t$

<u>Pre-COVID Sample (1985q3 to 2019q4)</u> EC: -.115, t-stat 4.33**

Pre-CFMA: $\ln V^*_t = 2.631 - 0.304 \ln SLoad_t$

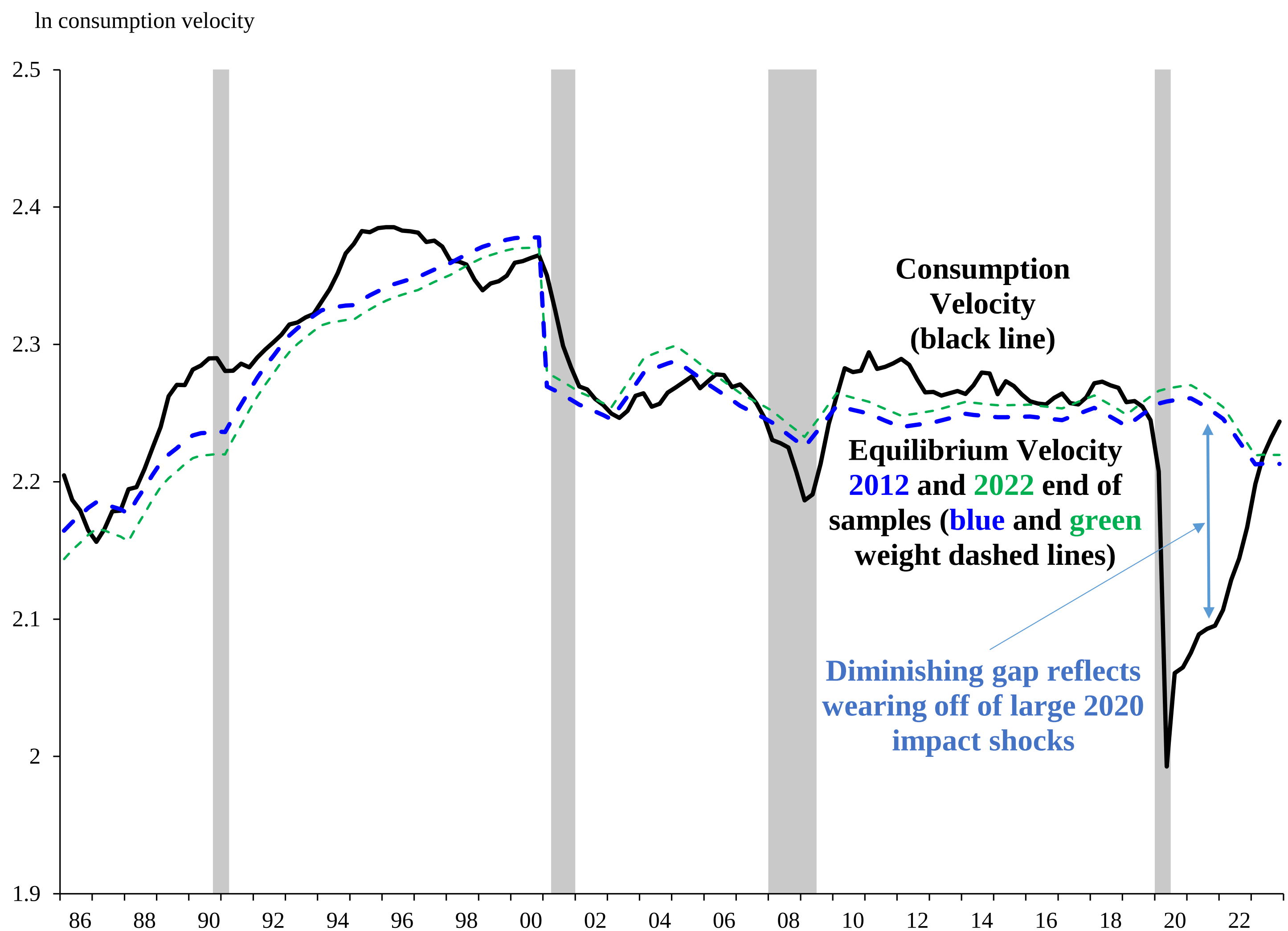
Post-CFMA: $\ln V^*_t = 2.535 - 0.304 \ln SLoad_t$

<u>Full Sample (1985q3 to 2022q4), 20q2-q4 dummies)</u> EC: -.090, t-stat 5.63**

Pre-CFMA: $\ln V^*_t = 2.638 - 0.321 \ln SLoad_t$

Post-CFMA: $\ln V^*_t = 2.547 - 0.321 \ln SLoad_t$

Similar long-run coefficients using a pre-GFC sample (1985q3-2005q4)
Unique and significant (99% confidence) cointegrating vectors.
In s-run models of ΔV get plausible 9-12% quarterly speeds of adjustment
Velocity lower post-CFMA, as more shadow M afterward, *ceteris paribus*.
Estimated equilibrium tracks actual trends in velocity well.
<u>Consistent with income elasticity ~ 1 implied by the Qty Theory of Money</u>



Long-Run Velocity Well Tracked Through 2019q4, Model Estimated Pre-COVID

(Sources: BEA, Federal Reserve, CFS, Oxford's Blavatnik Center, and authors' calculations)

P-Star in Inflation, not Δ Inflation

- $P_t Y_t = M_t V_t$ => in logs: $p_t + y_t = m_t + v_t$ => $p_t = m_t + v_t - y_t$
- In equilibrium, $p^*_t = m_t + v^*_t - y^*_t$
- If Δp is I(0) stationary, then allowing for partial adjustment:

  $$\Delta p_t = \alpha + \beta_1 \Delta p_{t-1} + .. + \beta_j \Delta p_{t-j} + \lambda(p^*_{t-1} - p_{t-1}) \qquad (1)$$

  partial adjustment => 0 < λ < 0
- Original P-Star model sample spanned 1960s-1980s when inflation Δp was **not** stationary while $\Delta^2 p$ was.
- Divisia M biased by deposit deregulation. Consistent since 1984. After lags, model inflation 1985q3-2024q3. Inflation stationary over **this** sample: Use inflation not $\Delta^2 p$ version.
- Denoting $\pi \equiv \Delta p$ rewrite (1) as:

$$\pi_t = \alpha + \beta_1 \pi_{t-1} + \ldots + \beta_1 \pi_{t-i} + \gamma(p^*_{t-1} - p_{t-1}) + \varepsilon_t \qquad (2)$$

P-Star in Inflation, not Δ Inflation

- One can decompose price gap as:

$$p_t^* - p_t = (m_t + v_t^* - y_t^*) - (m_t + v_t - y_t) = (v_t^* - v_t) - (y_t^* - y_t)$$

- Implying that eq. (2) can be re-expressed as:

$$\pi_t = \alpha + \beta_1 \pi_{t-1} \ldots + \beta_1 \pi_{t-i} + \gamma(v_{t-1}^* - v_{t-1}) - \gamma(y_{t-1}^* - y_{t-1}) + \varepsilon_t \qquad (3)$$

where v^* *is* equilibrium v and y^* is potential output.

- For consumer inflation, use PCE deflator replace *y* with *c*:

$$\pi_t = \alpha + \beta_1 \pi_{t-1} \ldots + \beta_1 \pi_{t-i} + \gamma\underbrace{(v_{t-1}^* - v_{t-1})}_{vgap} - \gamma\underbrace{(c_{t-1}^* - c_{t-1})}_{cgap} + \varepsilon_t \qquad (4)$$

c^* is tracked using a 1-sided HP filter, ảla Ireland (2024).

Can replace *vgap* & *cgap* with *pgap* = *vgap* - *cgap*

P-Star Model Regressions

- v^* for *vgap* = v^*- v, coefficients estimated with broken constant, evolves using actual, slowly evolving *LSLoad*. post-CFMA:

  85q3-12q4: $\ln V^*_t = 2.530 - 0.302 \ln SLoad_t$ EC: -.119, t-stat 4.17**

  Very similar to:

  85q3-19q4: $\ln V^*_t = 2.535 - 0.304 \ln SLoad_t$ EC: -.115, t-stat 4.33

- P-Star models estimated 2013q1-2024q3 and include the controls
  - *DPEnergy* = 1 for plunges (10% or greater) in real PCE price of energy
  - Separate COVID impact dummies for 2020q2, 2020q3, and 2020q4
- 3 sets of models:
  - Models 1 & 2: omit any supply control
  - Models 3 & 4: add t-1 level FRBNY Global Supply Pressures index
  - Models 5 & 6: add t-1 Δ FRBNY Global Supply Pressures index
- Odd num. models separate *vgap*, *cgap*; even: *pgap* = *vgap* – *cgap*. HP-filter miss-measures c^*. Also, *vgap* & -*cgap* may be collinear.
- Model core & total quarterly inflation, SAAR. 5 lags of inflation.

Table 5: Quarterly P-Star Models of U.S. Core PCE (Consumer) Inflation, 2013Q1-2024Q3

$$\pi_t = \alpha + \beta_1 \pi_{t-1} + \ldots + \beta_5 \pi_{t-5} + \gamma_v vgap_{t-1} + \gamma_c cgap_{t-1} + \Omega_1(\Delta)SupPress_{t-1} + \Omega_2 DPEnergy_t + \varepsilon_t$$

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
vgap t-1	0.138**		0.116**		0.135**	
	(7.43)		(5.62)		(7.79)	
cgap t-1	-0.087		-0.087		-0.009	
	(0.69)		(0.72)		(0.07)	
pgap t-1		0.136**		0.115**		0.130**
(*vgap-cgap*)		(7.73)		(5.88)		(7.80)
$DPEnergy_t$	-0.822	-0.892+	-0.783	-0.822+	-0.714	-0.886*
	(1.66)	(1.95)	(1.65)	(1.88)	(1.55)	(2.07)
$SupPress_{t-1}$ 3,4			0.247*	0.250*	0.369*	0.337*
$\Delta SupPress_{t-1}$ 5,6			(2.09)	(2.14)	(2.64)	(2.47)
$D2020Q2_t$	-3.194**	-3.066**	-3.435**	-3.365**	-3.780**	-3.432**
	(5.65)	(6.70)	(6.22)	(7.34)	(6.66)	(7.57)
$D2020Q3_t$	-0.877	-0.377	-1.138	-0.858	-1.957	-0.700
	(0.61)	(0.55)	(0.82)	(1.25)	(1.40)	(1.07)
$D2020Q4_t$	-3.872**	-3.746**	-3.834**	-3.764**	-3.397**	-3.149**
	(5.04)	(5.43)	(5.22)	(5.72)	(4.64)	(4.57)
Adjusted R^2	.906	.909	.915	.917	.920	.920
S.E.	0.450	0.445	0.430	0.424	0.416	0.416
LM(1)	0.27	0.12	0.01	0.01	0.46	0.14
LM(4)	10.97*	9.19+	6.08	6.05	8.05+	6.67

vgap sign. and +

cgap insign. and -

Notes: +,*,** denote 90%, 95% & 99% significance. v^* uses coefficients from Model 2, Table 3, estimated over 1985Q3-2012Q4. *cgap*, is formed from real PCE and an estimate of trend real PCE from a one-sided HP filter.

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Sign., similar coefficients

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LM(4)	10.97*	9.19^{+}	6.08	6.05	8.05^{+}	6.67

Significant coefficients

Notes: $^{+}$,*,** denote 90%, 95% & 99% significance. v^* uses coefficients from Model 2, Table 3, estimated over 1985Q3-2012Q4. *cgap*, is formed from real PCE and an estimate of trend real PCE from a one-sided HP filter.

Table 5: Quarterly P-Star Models of U.S. Core PCE (Consumer) Inflation, 2013Q1-2024Q3

$$\pi_t = \alpha + \beta_1 \pi_{t-1} + \ldots + \beta_5 \pi_{t-5} + \gamma_v vgap_{t-1} + \gamma_c cgap_{t-1} + \Omega_1(\Delta)SupPress_{t-1} + \Omega_2 DPEnergy_t + \varepsilon_t$$

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$vgap_{t-1}$	0.138**		0.116**		0.135**	
	(7.43)		(5.62)		(7.79)	
$cgap_{t-1}$	-0.087		-0.087		-0.009	
	(0.69)		(0.72)		(0.07)	
$pgap_{t-1}$		0.136**		0.115**		0.130**
(vgap-cgap)		(7.73)		(5.88)		(7.80)
$DPEnergy_t$	-0.822	-0.892+	-0.783	-0.822+	-0.714	-0.886*
	(1.66)	(1.95)	(1.65)	(1.88)	(1.55)	(2.07)
$SupPress_{t-1}$ 3,4			0.247*	0.250*	0.369*	0.337*
$\Delta SupPress_{t-1}$ 5,6			(2.09)	(2.14)	(2.64)	(2.47)
$D2020Q2_t$	-3.194**	-3.066**	-3.435**	-3.365**	-3.780**	-3.432**
	(5.65)	(6.70)	(6.22)	(7.34)	(6.66)	(7.57)
$D2020Q3_t$	-0.877	-0.377	-1.138	-0.858	-1.957	-0.700
	(0.61)	(0.55)	(0.82)	(1.25)	(1.40)	(1.07)
$D2020Q4_t$	-3.872**	-3.746**	-3.834**	-3.764**	-3.397**	-3.149**
	(5.04)	(5.43)	(5.22)	(5.72)	(4.64)	(4.57)
Adjusted R^2	.906	.909	.915	.917	.920	.920
S.E.	0.450	0.445	0.430	0.424	0.416	0.416
LM(1)	0.27	0.12	0.01	0.01	0.46	0.14
LM(4)	10.97*	9.19+	6.08	6.05	8.05+	6.67

Models 4 & 6 fit well with clean residuals

Notes: +,*,** denote 90%, 95% & 99% significance. v^* uses coefficients from Model 2, Table 3, estimated over 1985Q3-2012Q4. *cgap*, is formed from real PCE and an estimate of trend real PCE from a one-sided HP filter.

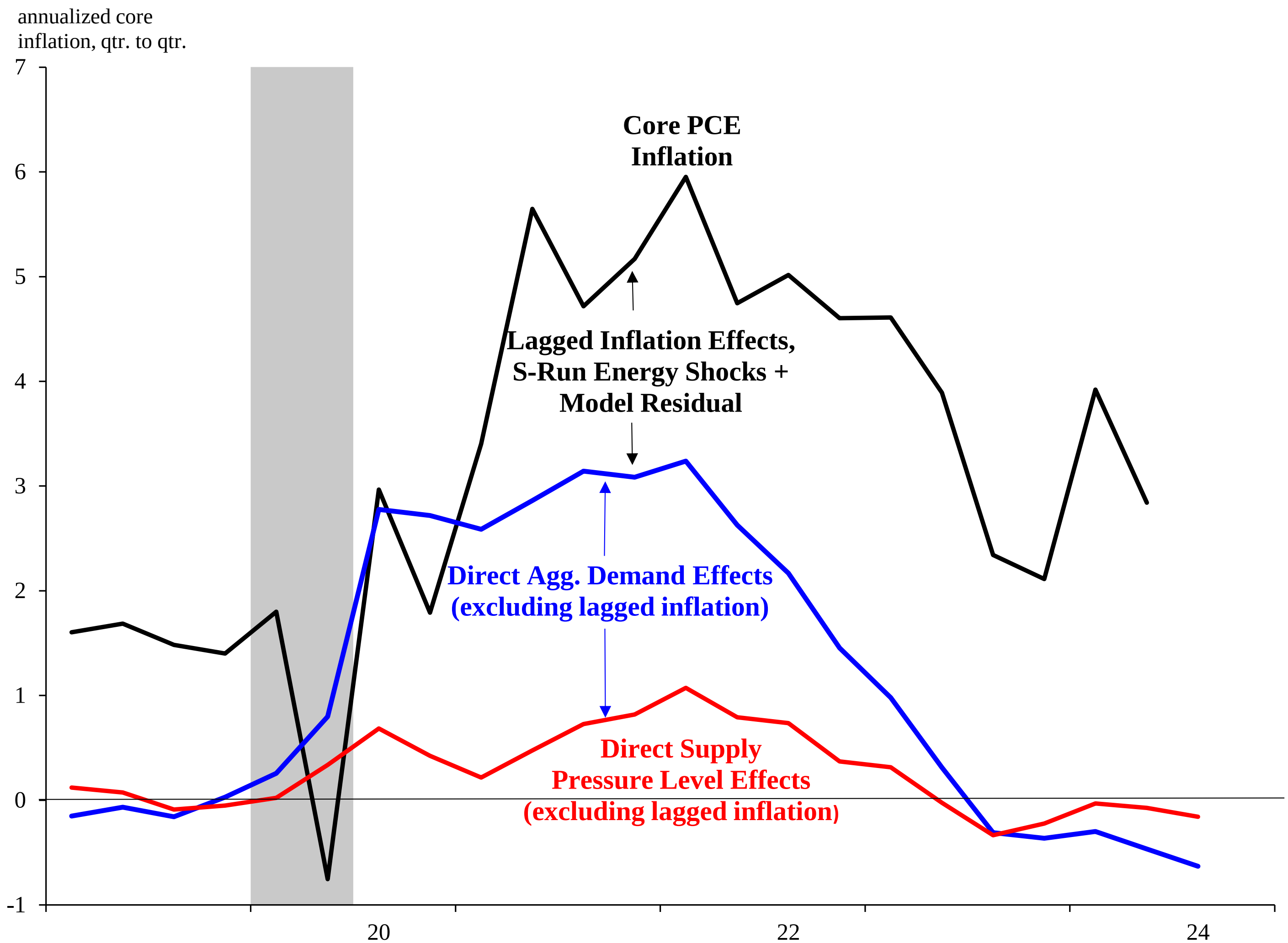


Figure 6: Effects of the Price Gap and Supply Chain (Level) Pressures on Core PCE Inflation

(Sources: BEA, FRBNY, and authors' calculations)

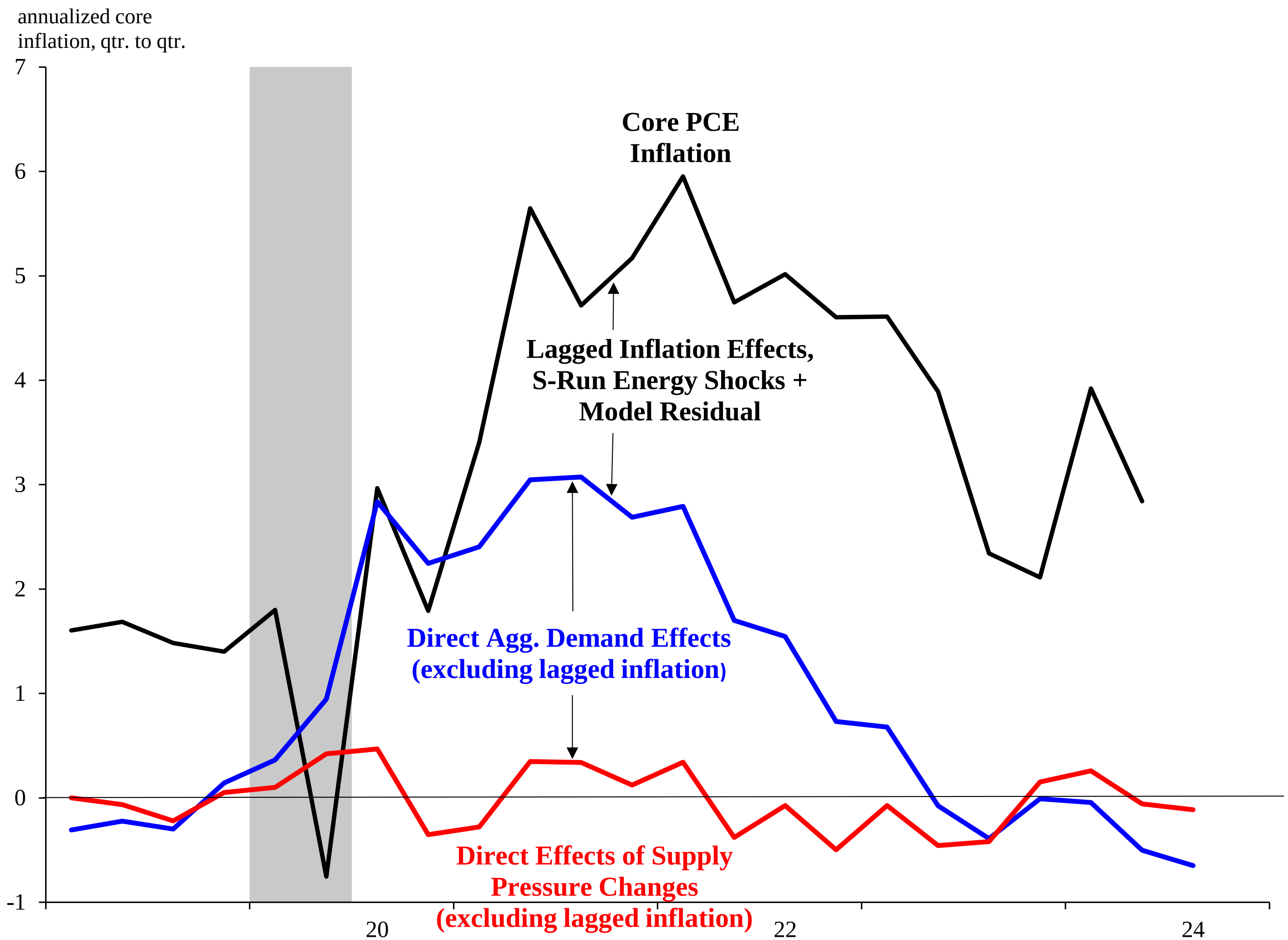


Figure 7: Effects of the Price Gap and Supply Chain (Changes) Pressures on Core PCE Inflation

(Sources: BEA, FRBNY, and authors' calculations)

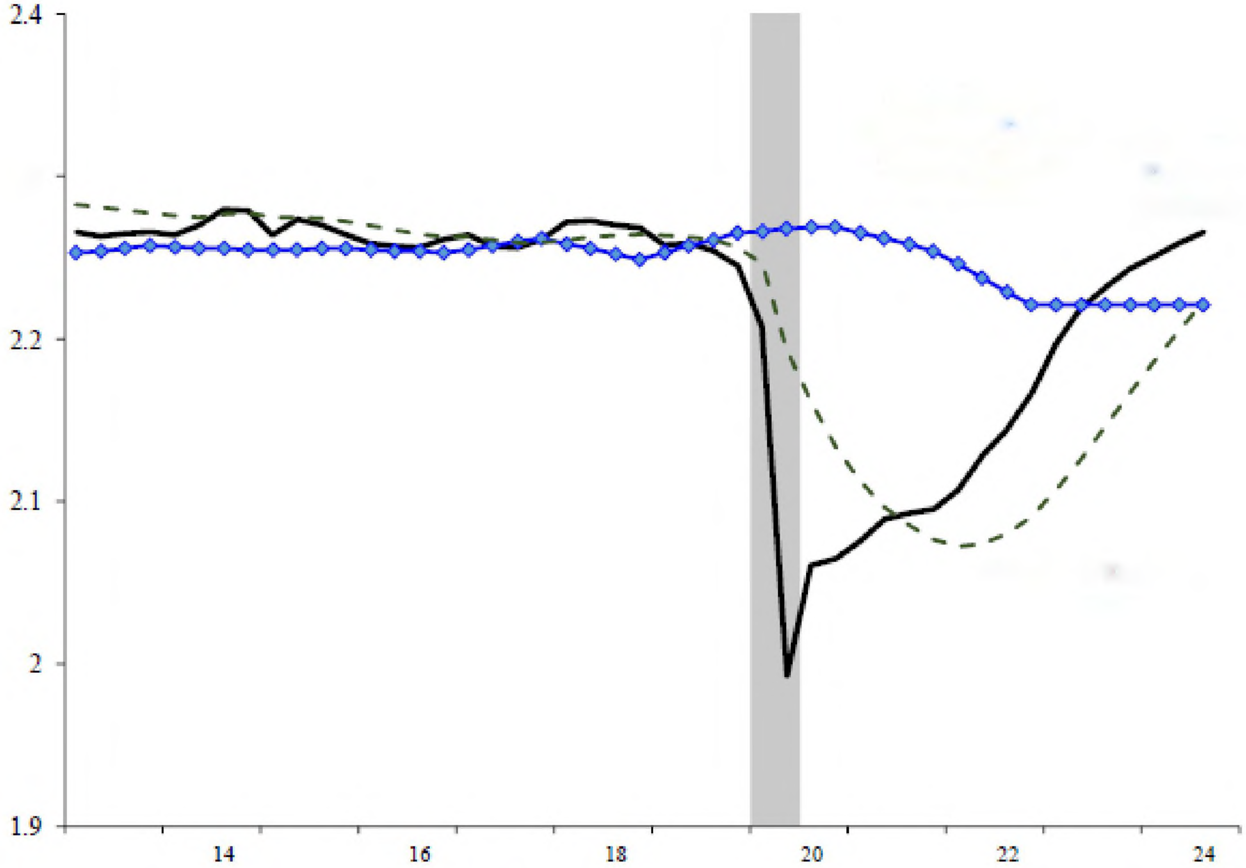
P* Model Using Our Long-Run V Improves Upon an HP Filter of V (ảla Ireland, 2024)

- Alternative V* uses one-sided HP. But fit is worse:

Model Fits of Inflation: BDJ V* (in-sample 85Q3-12Q4) Versus One-Sided HP V*

	No Supply Chain		Supply Chain Level		Δ Supply Chain lags	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Total PCE Inflation 2013-2024Q3					
BordoDucaJones V:*						
Adjusted R^2	.832	.834	.842	.843	.871	.856
*One-Sided HP of V**						
Adjusted R^2	.687	.690	.748	.751	.683	.691
	Core PCE Inflation 2013-2024Q3					
BordoDucaJones V:*						
Adjusted R^2	.906	.909	.915	.917	.920	.920
*One-Sided HP of V**						
Adjusted R^2	.811	.816	.843	.846	.845	.844

- Why? Our model better tracks V* and velocity gaps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2.2
2.1
2
1.9
14
16
18
20
22
24

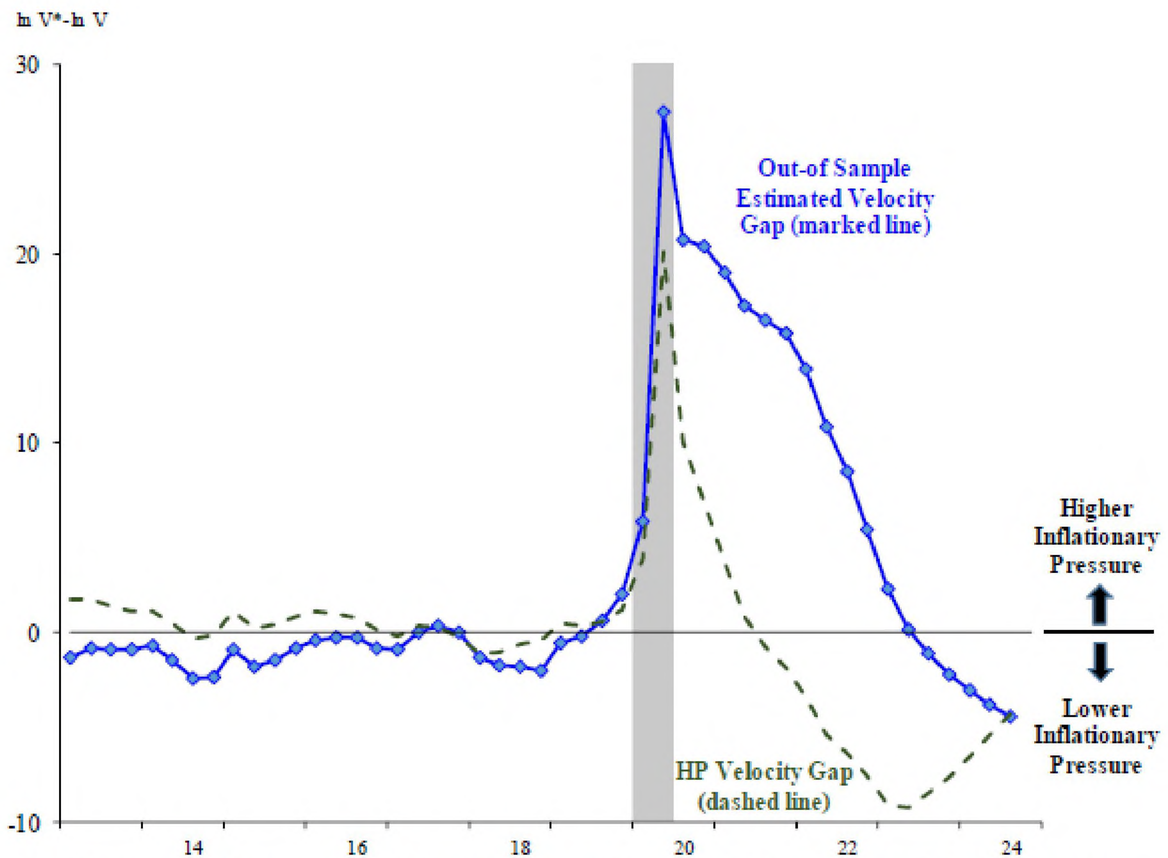


Figure 8: Estimated Velocity Gap Implies More Plausible Swings in U.S. Inflationary Pressures Than an HP Filter-Based Measure

(Sources: CFS, Federal Reserve, BEA, and author's calculations)

Concluding Comments

- Quantity theory: “too much money chasing too few goods” was ignored because of instability in velocity) of simple-sum M2.
- We develop a stable money demand/velocity function for Div. M3, which provides useful information a P-Star model of inflation.
- Recent swings in inflation mainly driven by aggregate demand reflected in Div. M3 with some effects from supply pressures.
- Lagged adjustment of Div. M3 velocity reflects lagged effects of policy & other shocks => lagged effects of Fed’s tightening cycle.
- Div. M3 reflects fiscal & monetary policy and shocks (COVID restrictions, risk). Div. M3 more an aggregate demand indicator worth monitoring than a directly controllable monetary aggregate.

Some Related Publications

- Barnett, William A. 1980. "Economic Monetary Aggregates: An Application of Index Number and Aggregation Theory." *Journal of Econometrics* 14(1): 11–48.
- Bordo, Michael D. and John V. Duca. 2022. “How New Fed Corporate Bond Programs Cushioned the Covid-19 Recession,” *Journal of Banking and Finance* 136: 1-22.
- Bordo, Michael D. and John V. Duca. 2021. “An Overview of The Fed’s New Credit Policy Tools and Their Cushioning Effect on the COVID-19 Recession.” *J. of Government Economics* 3: 1-10.
- Bordo, Michael D. and John V. Duca. 2025. "Money Matters: Broad Divisia Money and the Recovery of the U.S. Nominal GDP From the COVID-19 Recession." *J. Forecasting* 44(4):1071-96.
- Bordo, Michael D., John V. Duca, & Barry E. Jones. 2025. "Broad Divisia Money, Supply Pressures, and U.S. Inflation Following the COVID-19 Recession." *Macroeconomic Dynamics* 29: 1-35.
- Congdon, Tim. 2025. *Money and Inflation at the Time of Covid*. Edgar Elger: Cheltenham, UK and Northampton, MA U.S.A.
- Duca, John V. 2000. “Financial Technology Shocks and the Case of the Missing M2.” *Journal of Money, Credit, and Banking* 32 (4, Part 1): 820-39.
- Fleissig, Adrian and Barry Jones. 2015. “U.K. Household-Sector Money Demand during Brexit and the Pandemic.” *Economic Modelling* 123(c).
- Ireland, Peter 2024. “Money Growth and Inflation in the Euro Area, UK, and USA: Measurement Issues and Recent Results.” *Macroeconomic Dynamics*: 1-28.
- Jadidzadeh, Ali and Apostolos Serletis. 2019. “The Demand for Assets and Optimal Monetary Aggregation.” *Journal of Money, Credit, and Banking* 51(4): 929-52.
- Stoneman, David and John V. Duca. 2024. "Using Deep (Machine) Learning to Forecast US Inflation in the COVID-19 Era." *Journal of Forecasting* 43(4): 894–902.

Bank of England workshop

'Analysing the Information Content of Money:
Central Bank Practice and Recent Academic Research'

4 March 2026, London

Sectoral money and prices

Juan Castañeda (University of Buckingham), Jose Luis Cendejas (Universidad Francisco de Vitoria),
Florian Horber (Swiss National Bank), Samuel Reynard (Swiss National Bank)

Motivation and background

- Post Covid-19 inflationary episode: renewed interest in the study of the relation between (broad) money and CPI inflation

  - Broad money - inflation: Castañeda and Congdon (2020), Congdon (2021), Greenwood and Hanke (2021), King (2022), Neely (2023), Borio et al. (2023), Reynard (2024).
  - Broad money - money velocity – inflation: Castañeda and Cendejas (2024)
  - Divisia (broad) money – inflation: Ireland (2023) and Bordo et al. (2025).

Motivation and background

- Relation between sectoral money balances and prices:
  - UK:
    - Thomas (1997; part 1 and 2): effects of changes in M4 households' money holdings and private consumption (CPI inflation implied)
    - Cloyne et al. (2015): model to explain how financial institutions' responses to monetary policy shocks drive asset price volatility (with much more stable household and non-financial corporate money holdings).
    - Congdon (2004): correlation between volatility in financial institutions' (broad) money balances and volatility is shares prices during boom-and-bust cycles
    - Congdon (2021, 2024):
      - 'money-equity transmission channel'

  - Eurozone:
    - Ferrero et al. (2007, 2011): relationship between sectoral M3 growth and excess liquidity by households and and CPI inflation.

Theoretical framework

- ‘Portfolio-adjustment mechanism’ or ‘Money-Equity transmission channel’

Excess in the amount of money

→

Excess in liquidity in financial institutions’ portfolios

→

Increased demand of alternative assets

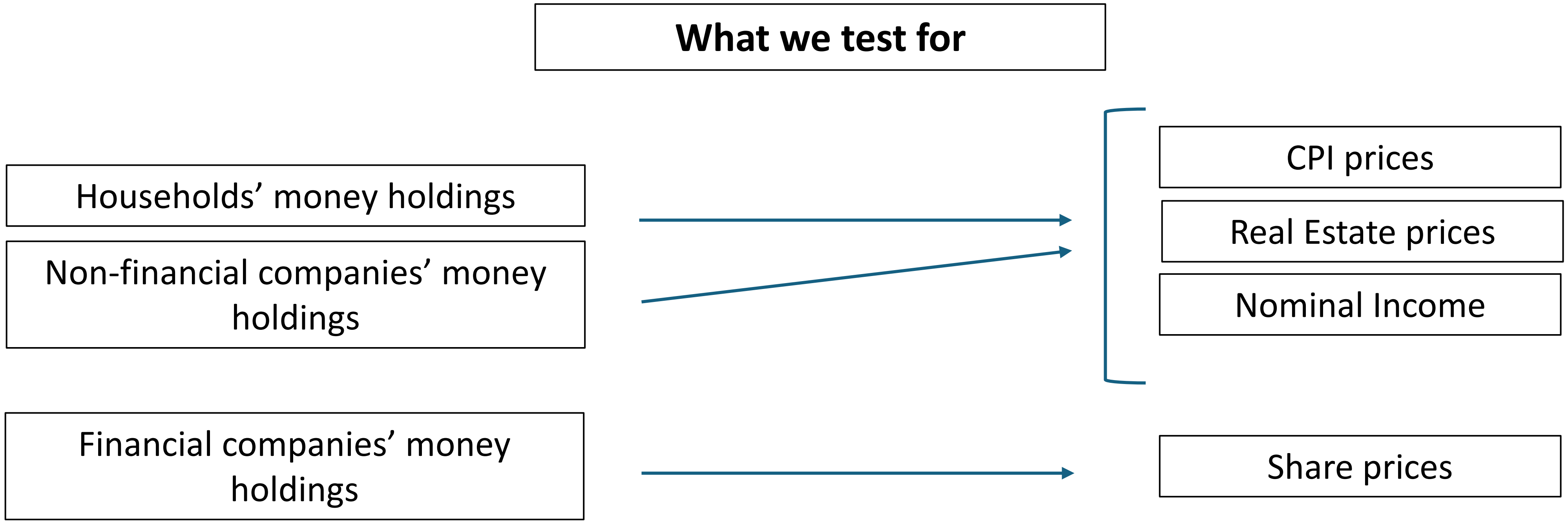
→

Asset price inflation

- The process/mechanism continues until the desired cash/asset ratio is restored

Our focus

We assess whether changes in households, financial companies and non-financial companies' (broad) money holdings have an effect on nominal income and CPI <u>and asset prices</u>, in the UK and in the USA:



Dataset: financial sector money holdings

	Series	Include Banks	Include Insurance Companies	Include Pension Funds
USA	Domestic Financial Sector	Yes	Yes	Yes
UK	Amounts outstanding of monetary financial institutions' sterling M4 liabilities to other financial corporations (in sterling millions) seasonally adjusted	No	Yes	Yes
Eurozone	Deposits in M3 from euro area financial corporations other than MFIs and ICPFs reported by MFIs, central gov. and POGIs, Stocks	No	No	No

Sources: US Fed, Bank of England and the European Central Bank

Methods (1/2)

- VAR Granger Causality and Block Exogeneity Tests

$$\mathbf{z}_t = \mathbf{c} + \sum_{i=1}^{p} \mathbf{A}_i \mathbf{z}_{t-i} + \mathbf{u}_t,$$

  - where $z_t = (x_t, y_t)'$
  - p is the lag length selected using the Akaike information criterion (AIC)
    - Possible values: {1,..,8}

  - Granger causality is assessed via **Block Exogeneity Wald Tests**

Methods (2/2)

- Impulse Response Functions (IRFs)

$$\mathbf{z}_t = \mathbf{c} + \sum_{i=1}^{p} \mathbf{A}_i \mathbf{z}_{t-i} + \mathbf{u}_t,$$

  - Based on the estimated VARs, we compute IRFs to:
    - trace the time path of each variable following **a one-standard-deviation shock** to sectoral M3/M4

  - The IRFs are orthogonalised using a **Cholesky decomposition**

Preliminary results: UK (1963-2024)

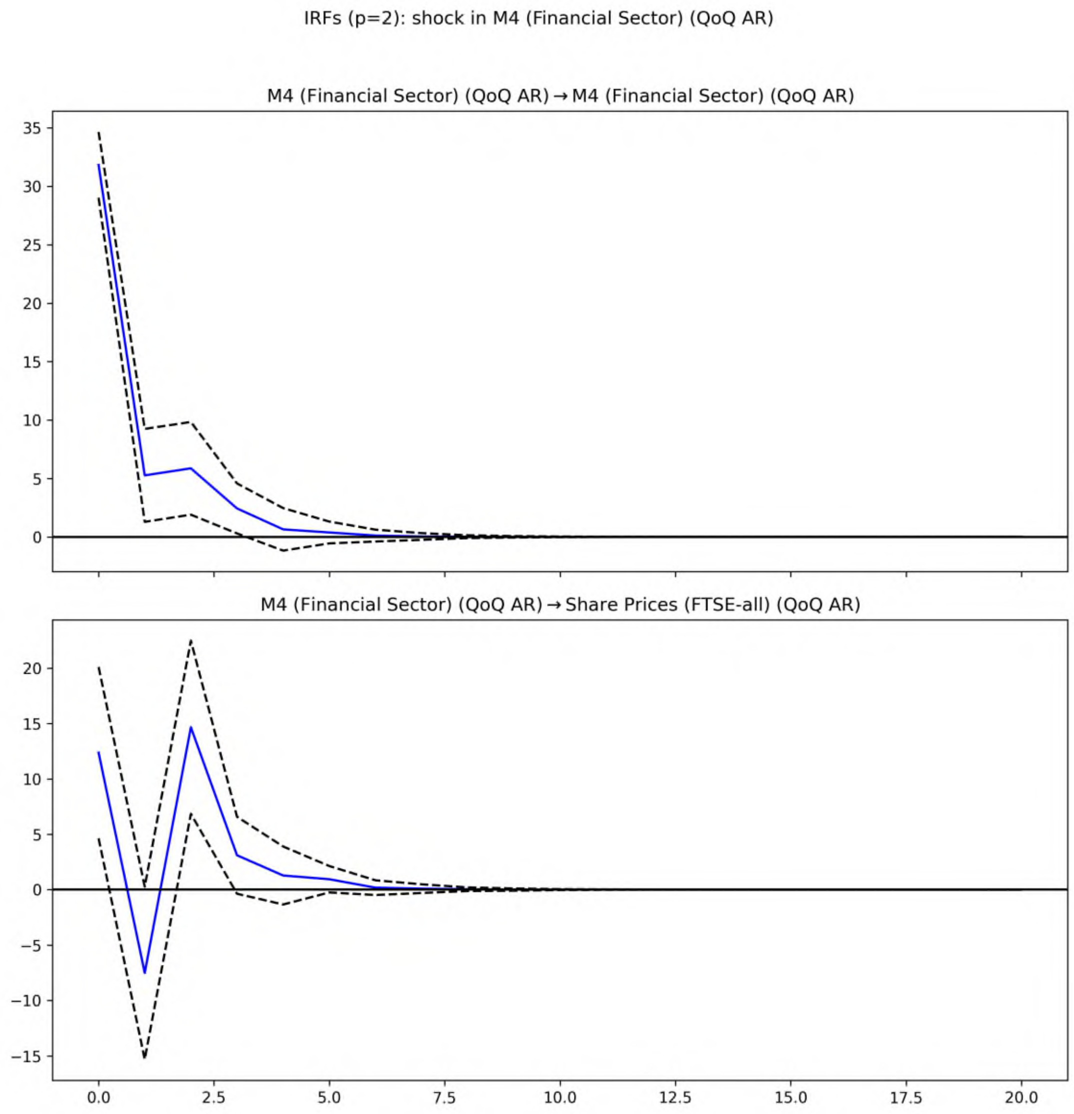
UK: VAR Granger causality test (quarter on quarter, annual rate)

	M4 (Financial Sector)	M4 (Households)	M4 (Non-financial sector)	M4 (Total)
CPI	+	+*	+	+***
Share Prices (FTSE-all)	+***	+	+**	+
House Prices	+*	+**	+*	+***
GDP	+	+***	+**	+***

Significance levels: * 10%, ** 5%, *** 1%.

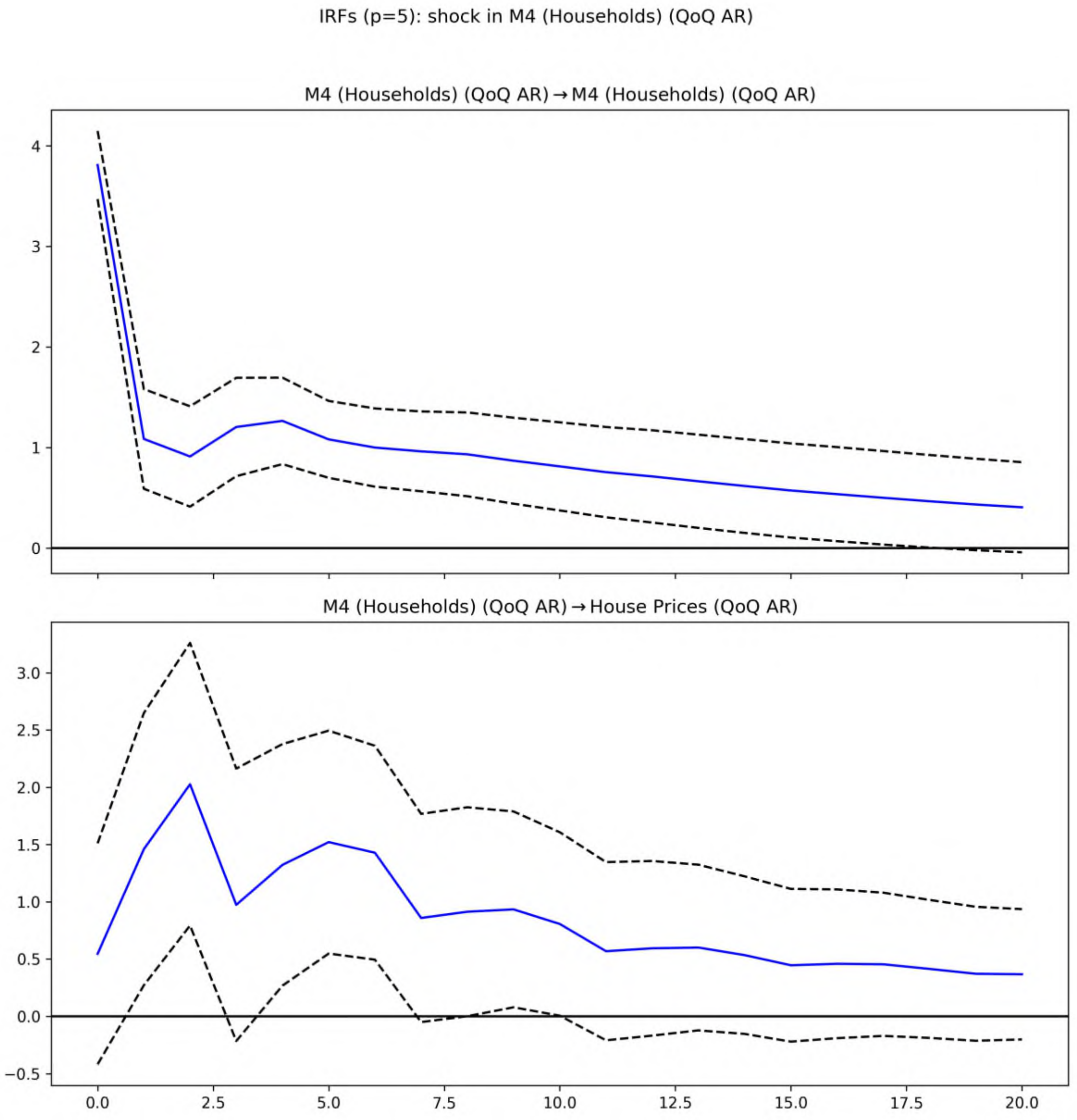
UK: M4 (financial corporations) on share prices

Impulse response functions
(‘p’ optimal lag)



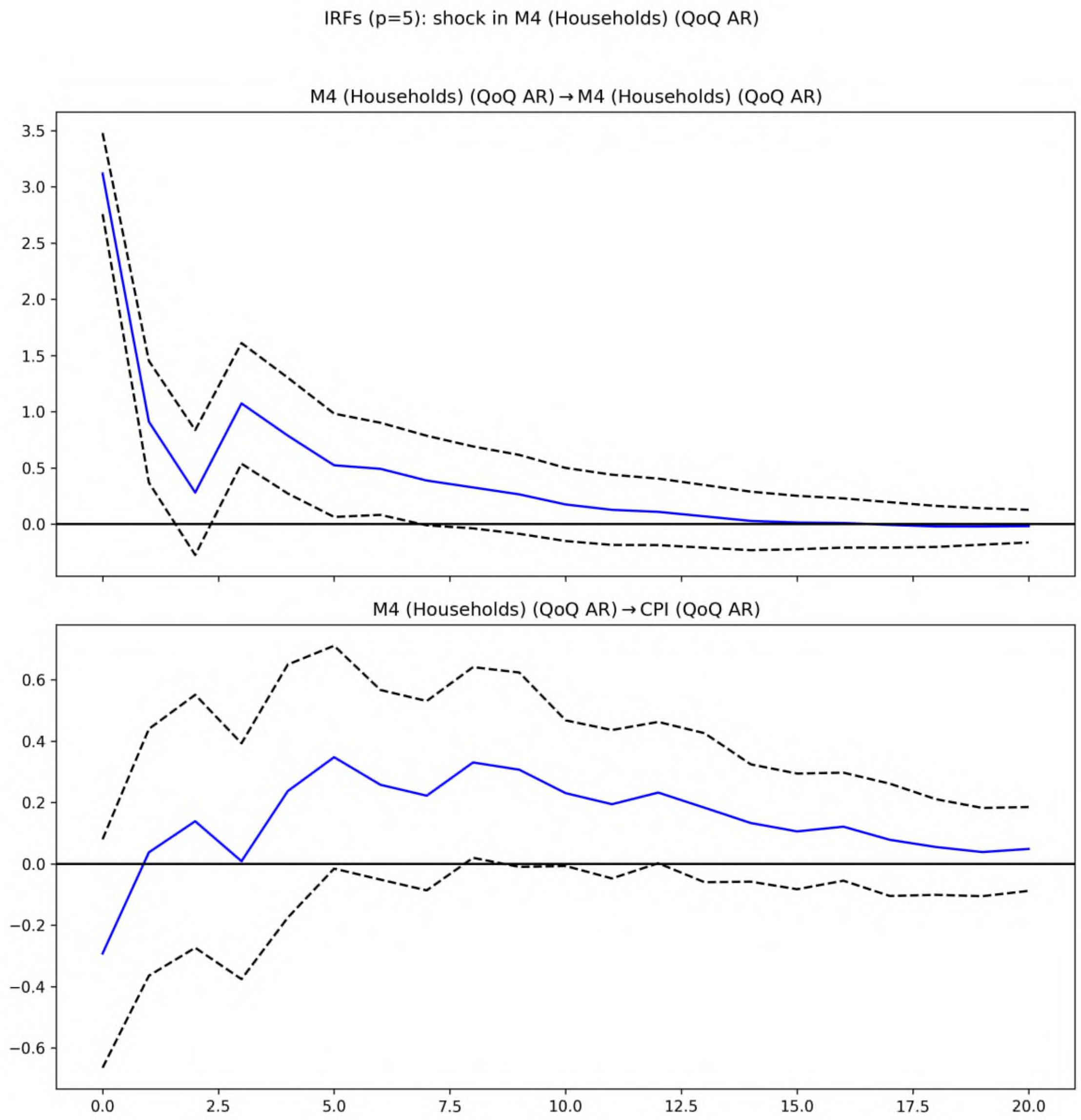
UK: M4 (households) on house prices

Impulse response functions
('p' optimal lag)



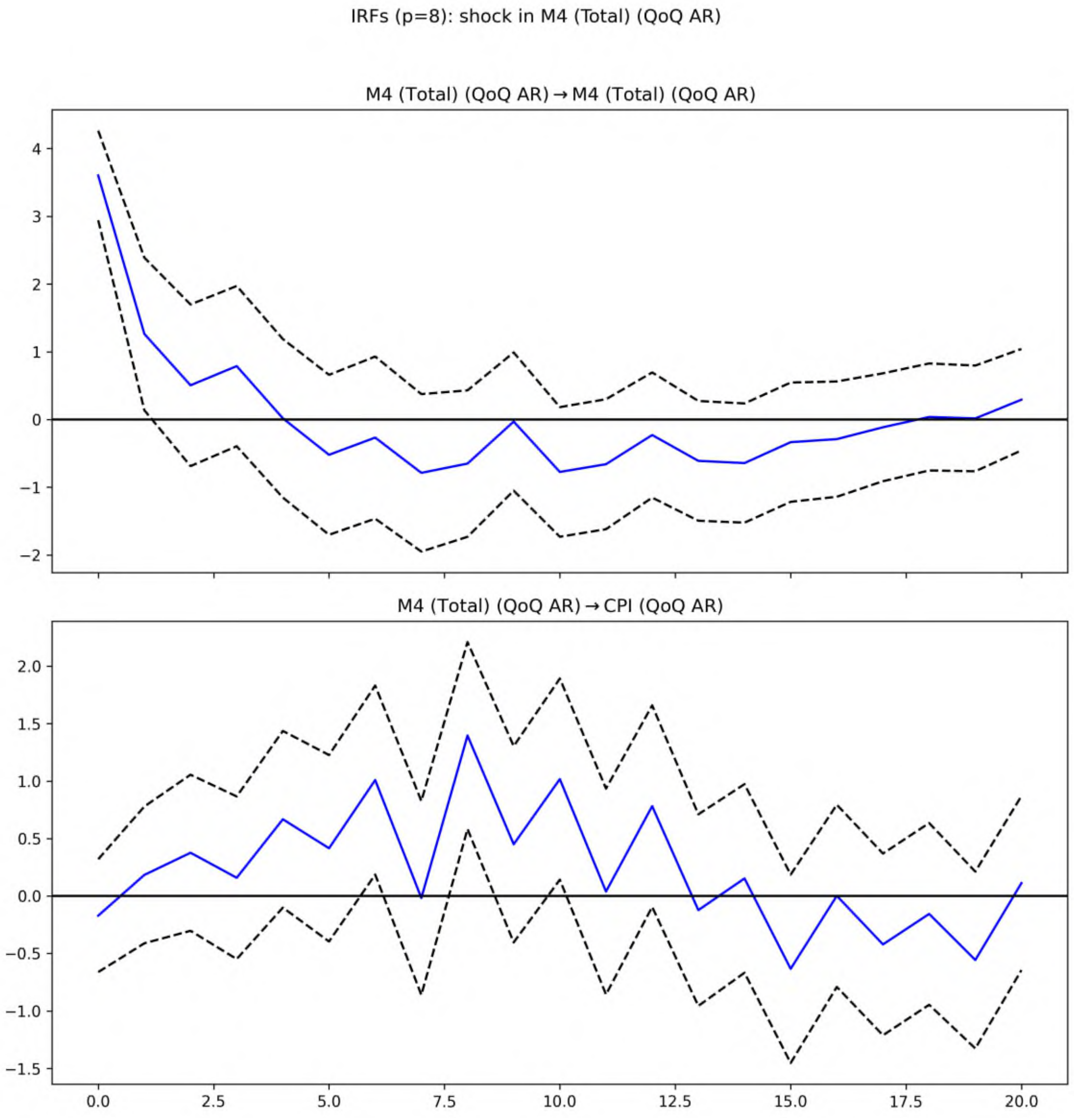
UK: M4 (households) on CPI prices

Impulse response functions
(p optimal lag)



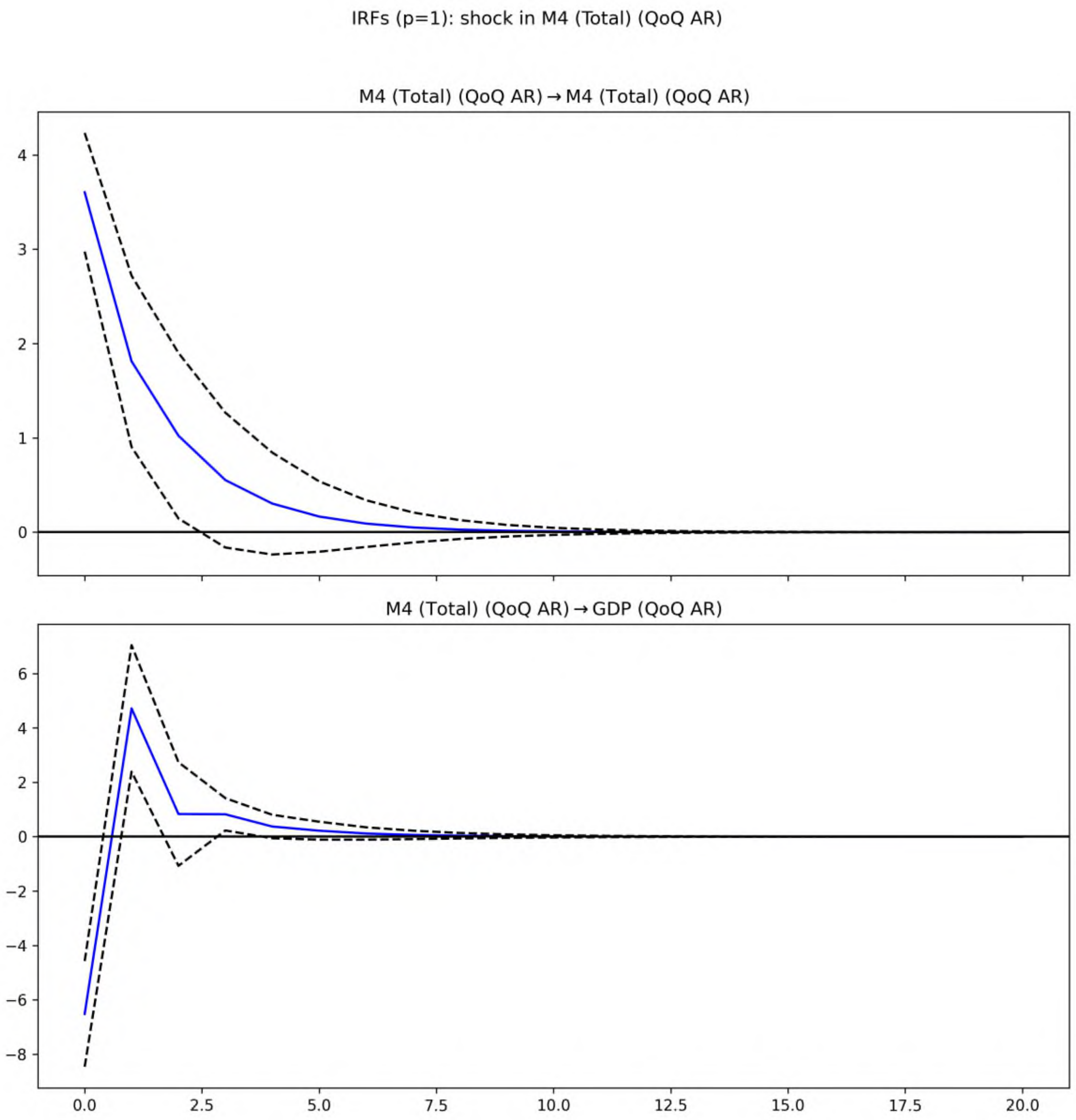
UK: M4 (total) on CPI prices

Impulse response functions
(p optimal lag)



UK: M4 (total) on nominal GDP

Impulse response functions
(p optimal lag)



Empirical analysis: USA (1951-2024)

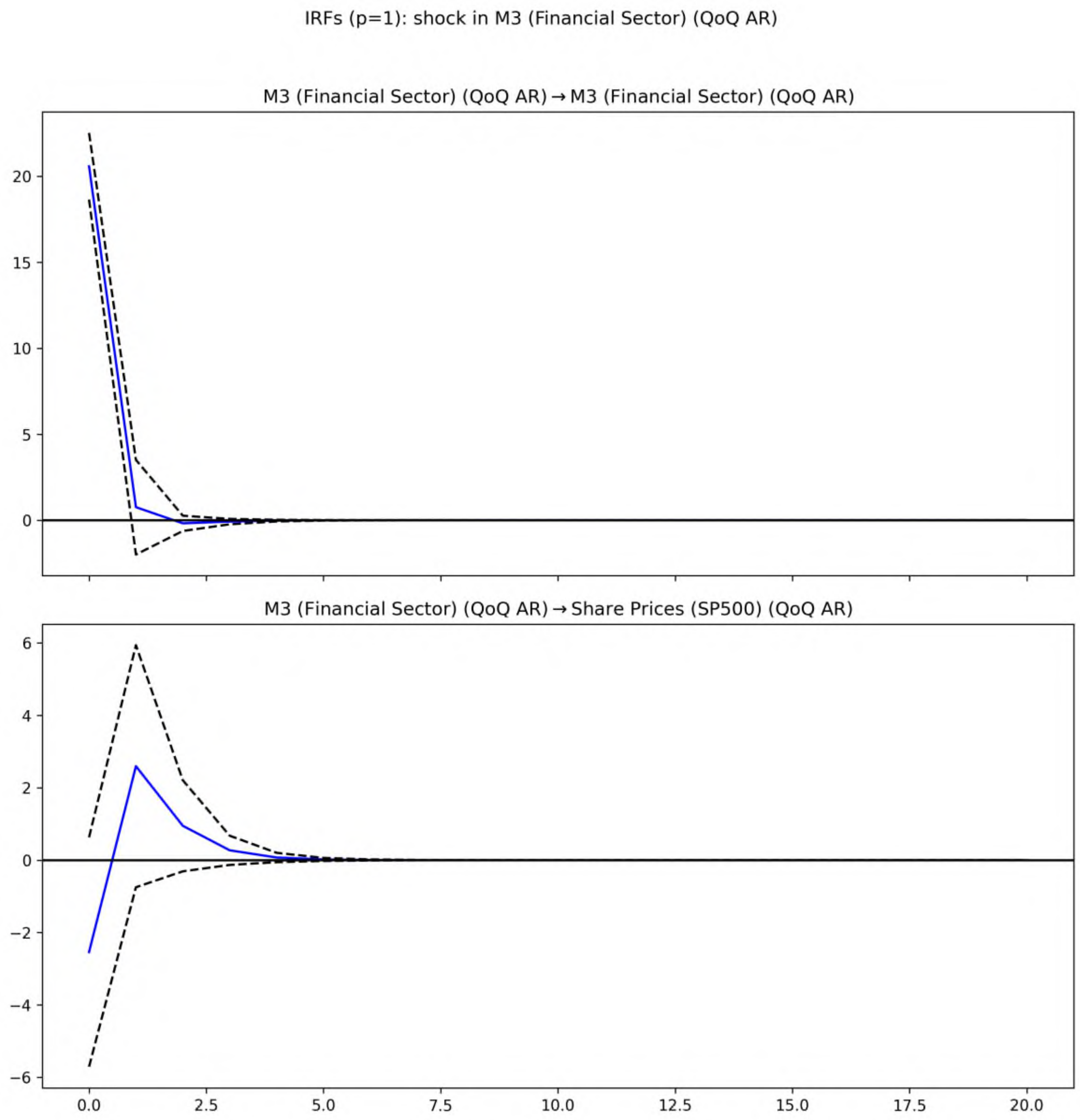
USA: VAR Granger causality test (quarter on quarter, annual rate)

	M3 (Financial sector)	M3 (Households)	M3 (Non-financial sector)	M3 (Total)
CPI	+	+	+*	+**
Share Prices (SP500)	+**	-	+	-
House Prices	+	+	+	+***
GDP	+***	+***	+***	+***

Significance levels: * 10%, ** 5%, *** 1%.

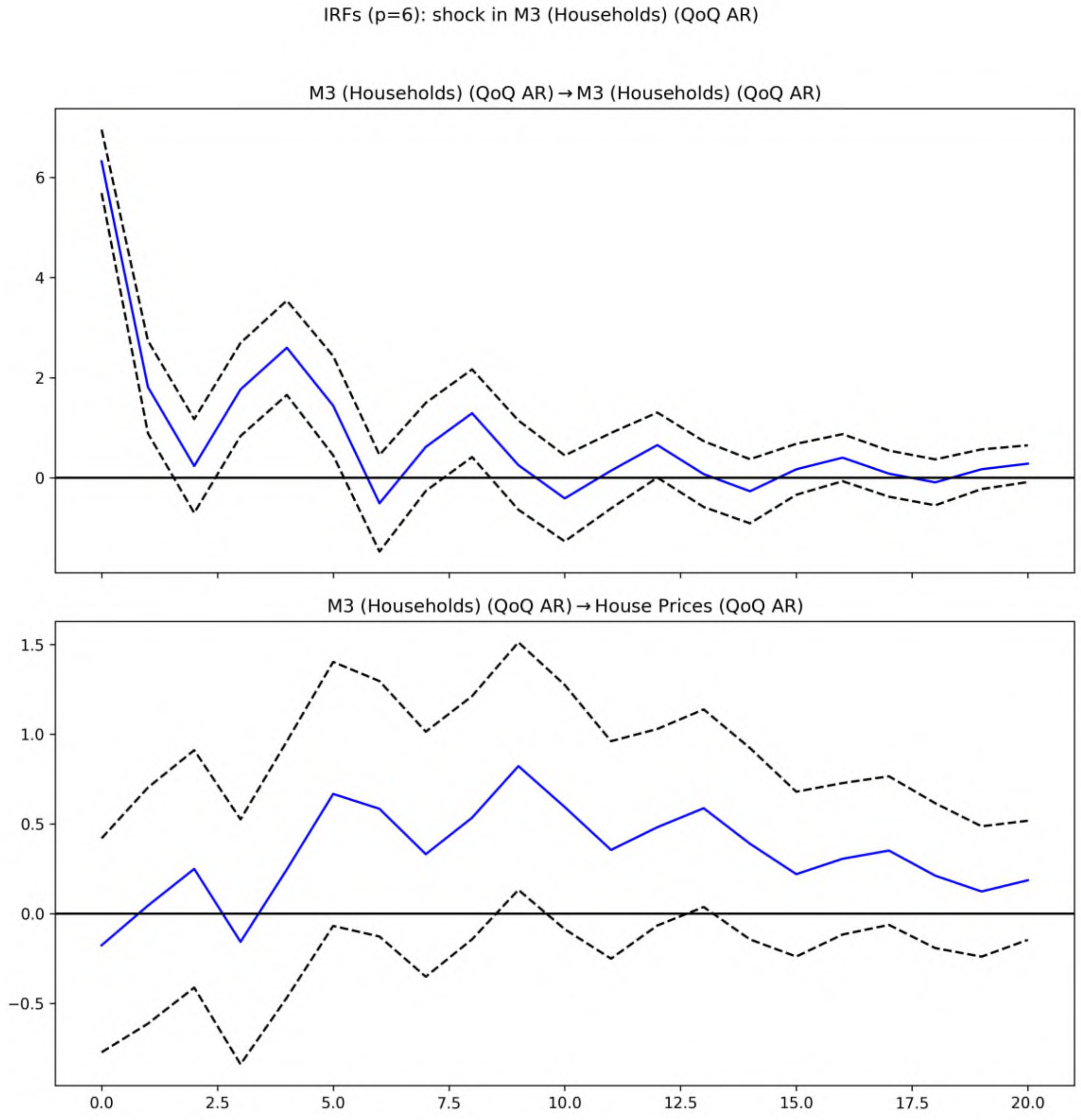
USA: M3 (financial corporations) on share prices

Impulse response functions
('p' optimal lag)



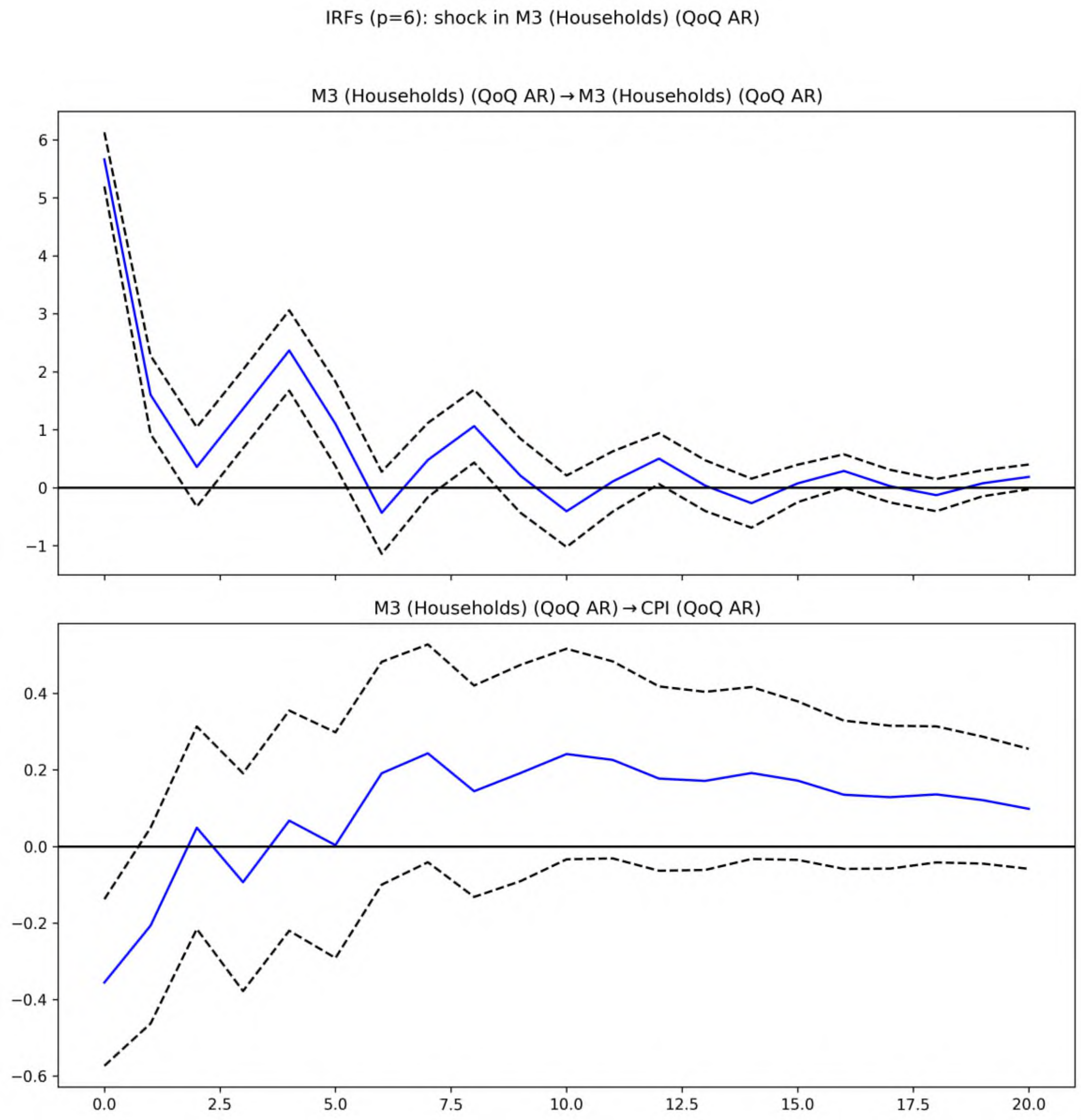
USA: M3 (households) on real estate prices

Impulse response functions
(p optimal lag)



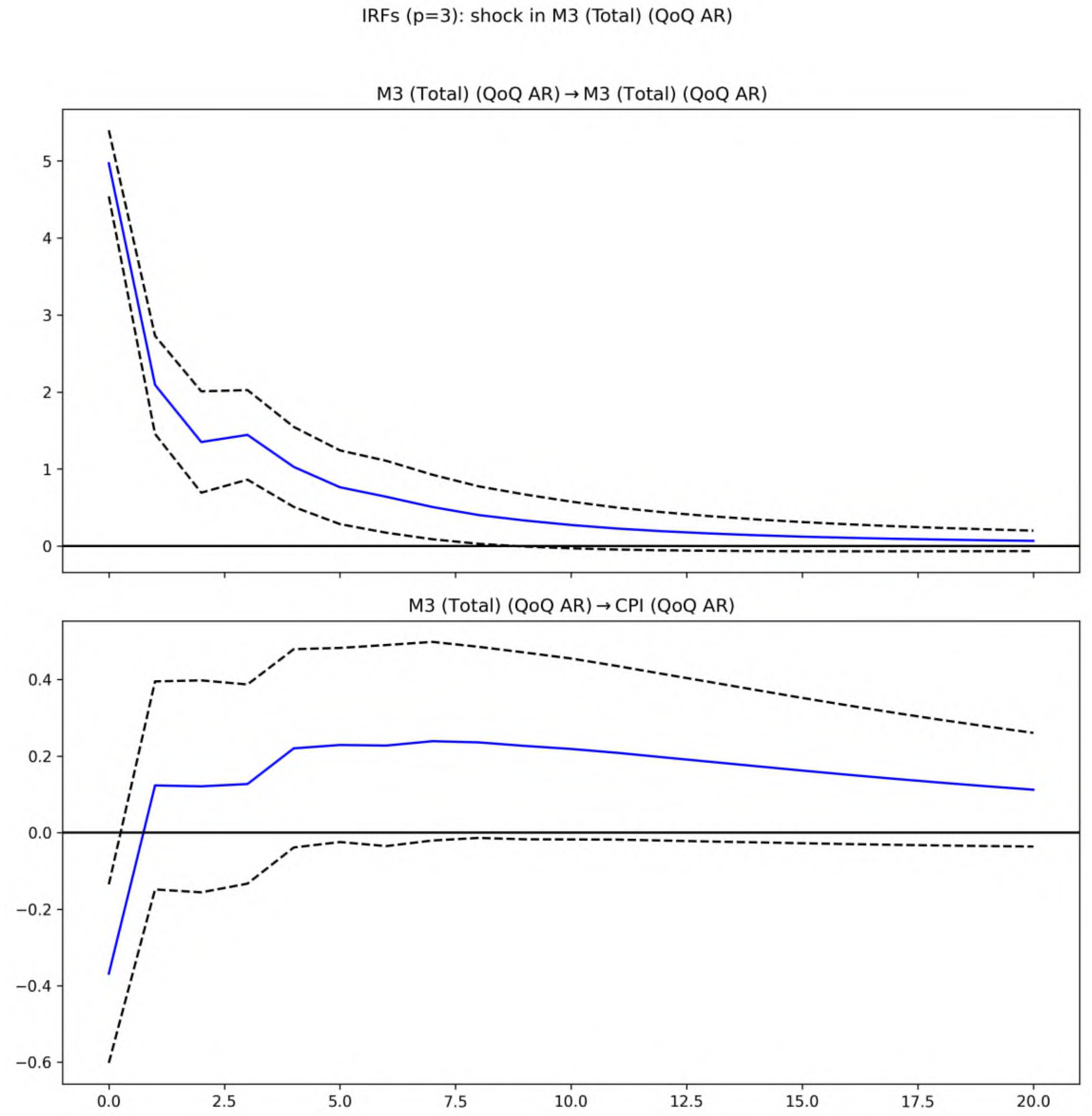
USA: M3 (households) on CPI prices

Impulse response functions
(p optimal lag)



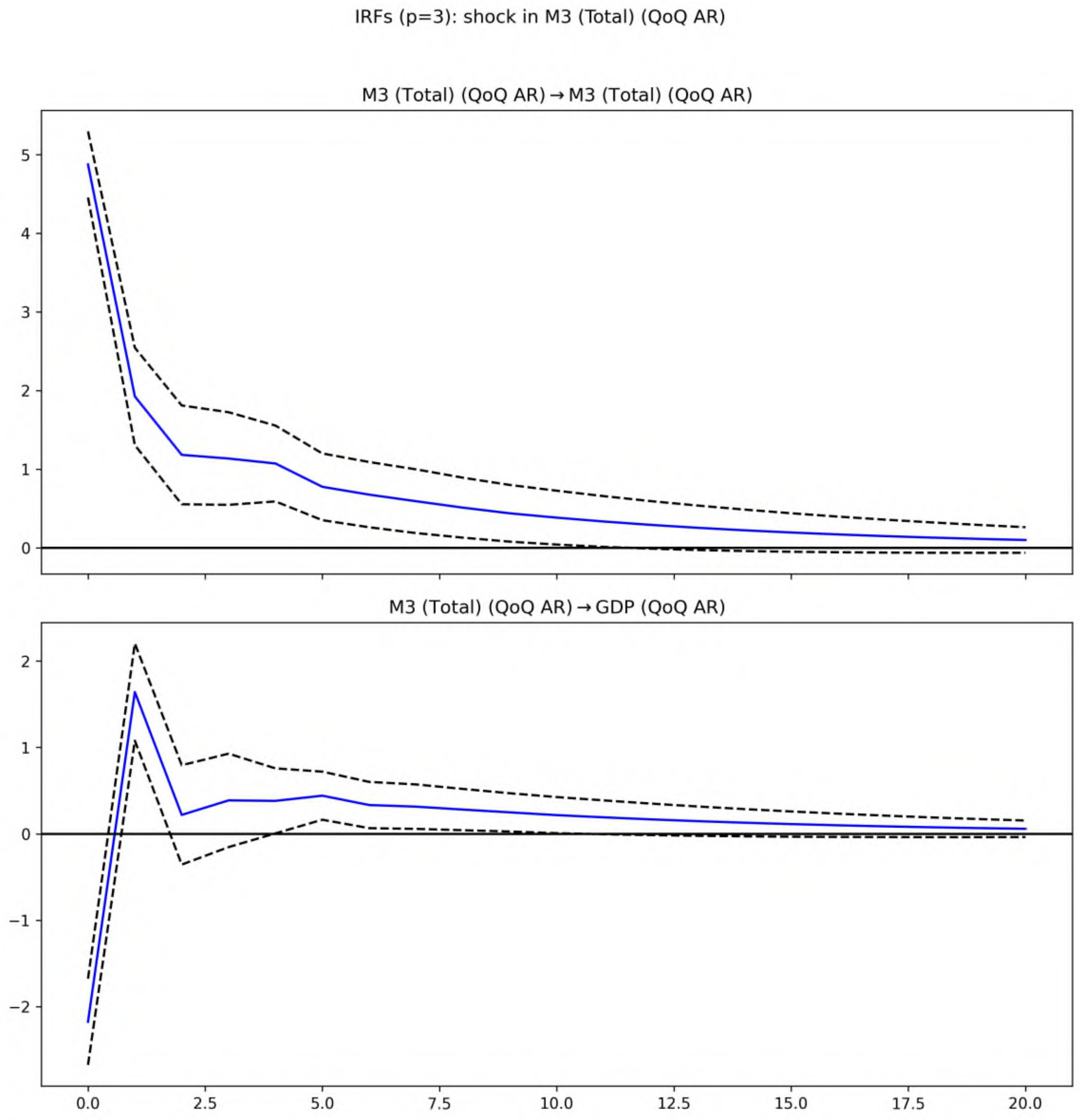
USA: M3 (total) on CPI prices

Impulse response functions
(p optimal lag)



USA: M3 (total) on nominal GDP

Impulse response functions
(p optimal lag)



Results: summary

- An excess in financial sectoral broad money balances has a positive impact on share prices in the very short term (1-3 quarters).

- An excess in households' sectoral broad money balances has positive impact on real estate prices that lasts over 3 - 4 years.

- An excess in households' sectoral broad money balances has a positive impact on CPI prices that lasts over 3 - 4 years.

- An excess in M3/M4 (total) money holdings has a positive impact on CPI prices over 3-4 years and a shorter effect on nominal GDP.

Ongoing research

- To model the relation between sectoral money holdings and (CPI and asset) prices:

  - To model sectoral money velocity

Appendix: sectoral money holdings dataset

- UK (M4):

- Households: quarterly data from June 1963. Monthly data from September 1997 to September 2024
- Financial Corporations ('Other Financial Corporations'): from June 2009 to September 2024, both quarterly and monthly
- Non-financial corporations ('Private non-financial corporations'): quarterly series from June 1963. Monthly series from September 1997 to September 2024.

- USA (M3/M2):
- Households: annual data from September 1945, quarterly data from September 1951 to March 2024.
- Financial Sector: annual data from September 1945, quarterly data from September 1951 to March 2024.
- Non-financial corporate business: annual data from September 1945, quarterly from September 1951 to March 2024.

- Eurozone (M3):

- Households: Monthly (end of period), from January 2003 to October 2024
- Financial corporations: Monthly (end of period), from January 2003 to October 2024
- Non-financial corporations: Monthly (end of period), from January 2003 to October 2024

How should central banks assess and communicate risks around money growth?

Lawrence Goodman

President – Center for Financial Stability (CFS)

Bank of England
Central Bank Practice and Recent Academic Research Workshop

London, England
March 4, 2026

With thanks to William A. Barnett, Jeff van den Noort, and Liting Su.

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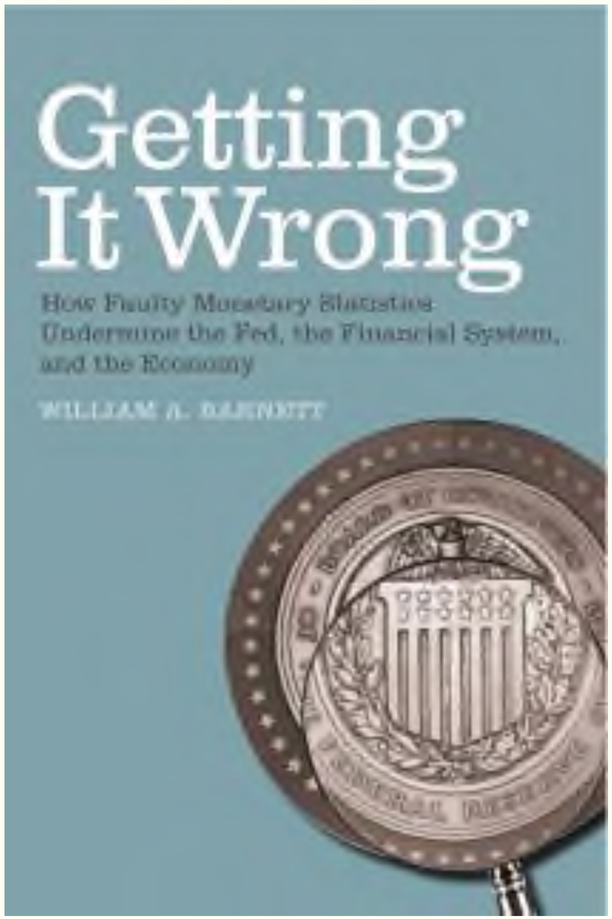
Figure 1. Advances in Monetary and Financial Measurement



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NEWS RELEASE

EMBARGOED UNTIL RELEASE AT 9:00 A.M. ET, MONDAY, MARCH 2, 2026.

CFS DIVISIA MONETARY DATA FOR THE UNITED STATES:[1]

JANUARY 2026

On February 23, 2021, the Federal Reserve Board enacted major changes to their H.6 Statistical Release which have impacted how the CFS Divisia Monetary Aggregates are calculated as well as our upcoming release schedule. See page 2 for more details.

The CFS Featured Broad Divisia Monetary Aggregates in January 2026

- CFS Divisia M4, including Treasuries (DM4) – the broadest and most important measure of money calculated by the Center for Financial Stability – grew by 5.0% in January 2026, on a year-over-year basis. In contrast, CFS Divisia M4 increased by 3.2% in January 2025 over the preceding year.
- The narrower version of the CFS Divisia M4, excluding Treasuries, (DM4-), grew by 5.1% in January 2026 over the year, relative to a year-over-year gain of 3.0% in January 2025.
- CFS Divisia M3 (DM3) advanced by 5.0% year-over-year, relative to an increase of 3.0% in January 2025.

The Narrow Divisia Monetary Aggregates in January 2026[2]

- CFS Divisia M2 (DM2) advanced by 4.4% year-over-year, relative to an increase of 2.6% in January 2025 over the preceding year.
- CFS Divisia M1 (DM1) advanced by 4.7% year-over-year, relative to an increase of 2.8% in January 2025 over the preceding year. Note that the composition of M1 changed in May 2020. See more below.

Most Significant Factors Influencing CFS Divisia M4 in January 2026

Positive Contributors to CFS Divisia M4 Growth

- The largest positive contributor to CFS Divisia M4 growth was demand deposits, contributing an increase of 5.3% in the last 12 months ending January 2026. Their growth-rate weight was 25.8%. Unweighted, they increased 21.8% in the last 12 months. This component is included in all of the aggregates.
- The second largest positive contributor to growth was repurchase agreements, contributing an increase of 0.4% in the last 12 months ending January 2026. Their growth-rate weight was 1.8%. Unweighted, they increased 29.0% in the last 12 months. This component is included in DM3, DM4-, and DM4, but not in the narrower aggregates (DM1 and DM2).
- The third largest positive contributor to growth was currency, contributing an increase of 0.3% in the last 12 months ending January 2026. Its growth-rate weight was 10.3%. Unweighted, it increased 3.3% in the last 12 months. This component is included in all of the aggregates.

[1] The CFS Divisia indexes in this release were constructed under the direction of Professor William A. Barnett. Dr. Barnett is the originator of the Divisia monetary aggregates, which he has been developing and refining for decades, in accordance with modern advances in economic aggregation and index-number theory.

[2] The narrow aggregates are similar to the Monetary Services Index supplied by the St. Louis Federal Reserve until 2013. See page 15 for the relationship between the CFS narrow aggregates and MSI. No other source currently exists for broad Divisia monetary aggregates, DM3, DM4-, and DM4 which are available only from the CFS.

Source: MIT Press and the Center for Financial Stability.

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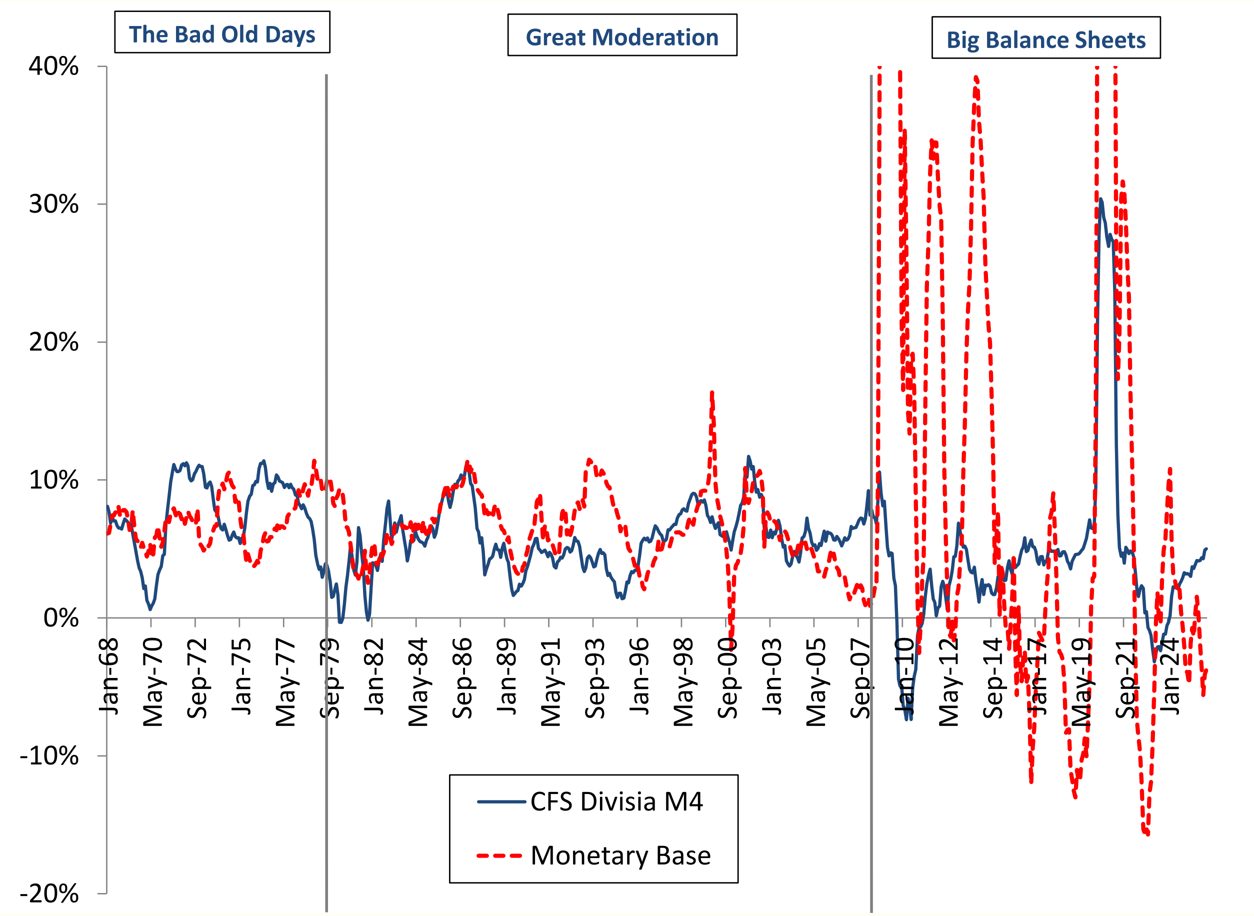
Figure 2. Policy Shift based on Lessons Learned in “Real-Time” and over Years

Money growth and other monetary measures offer central banks the opportunity to better incorporate the activities of financial institutions, markets, and innovation into its policy calculus. Hence, money should:

- Play a vital role in the formulation and communication of policy.
- Provide a complimentary analytic approach to traditional central bank assessment methods or a cross check on present strategies that are effective, yet have faltered over the last 25 years.
- Advise financial policy committees and / or regulatory and supervisor functions on a range of emerging financial stability risks – beyond simply a red early warning inflation hot button.

Figure 3. Assessment of the Role of Money in the Era of Big Balance Sheets



Source: Federal Reserve Board and Center for Financial Stability.

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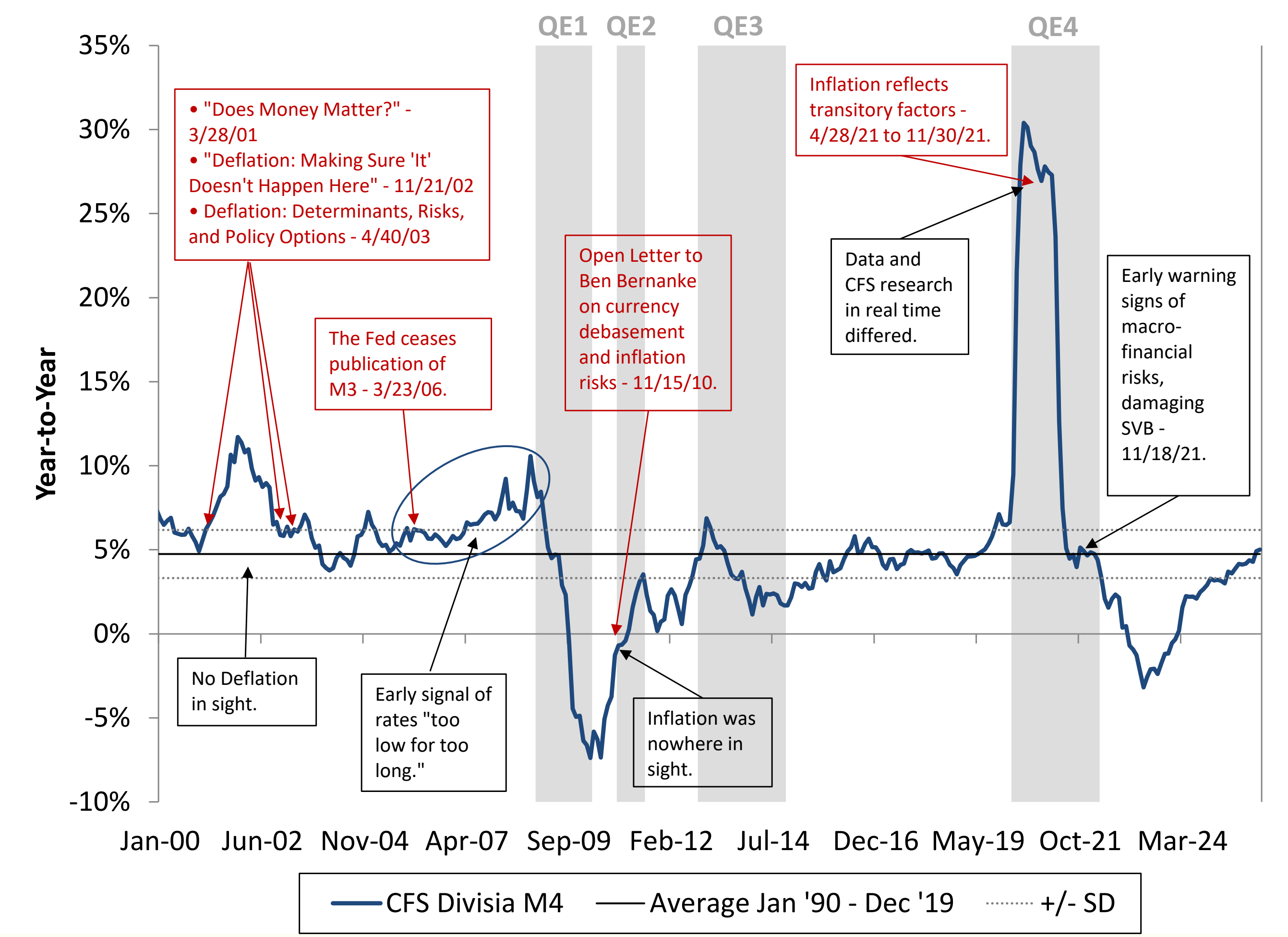
Figure 4. Assessment of CFS Divisia M4 Signals versus Conventional Wisdom



Source: Center for Financial Stability.

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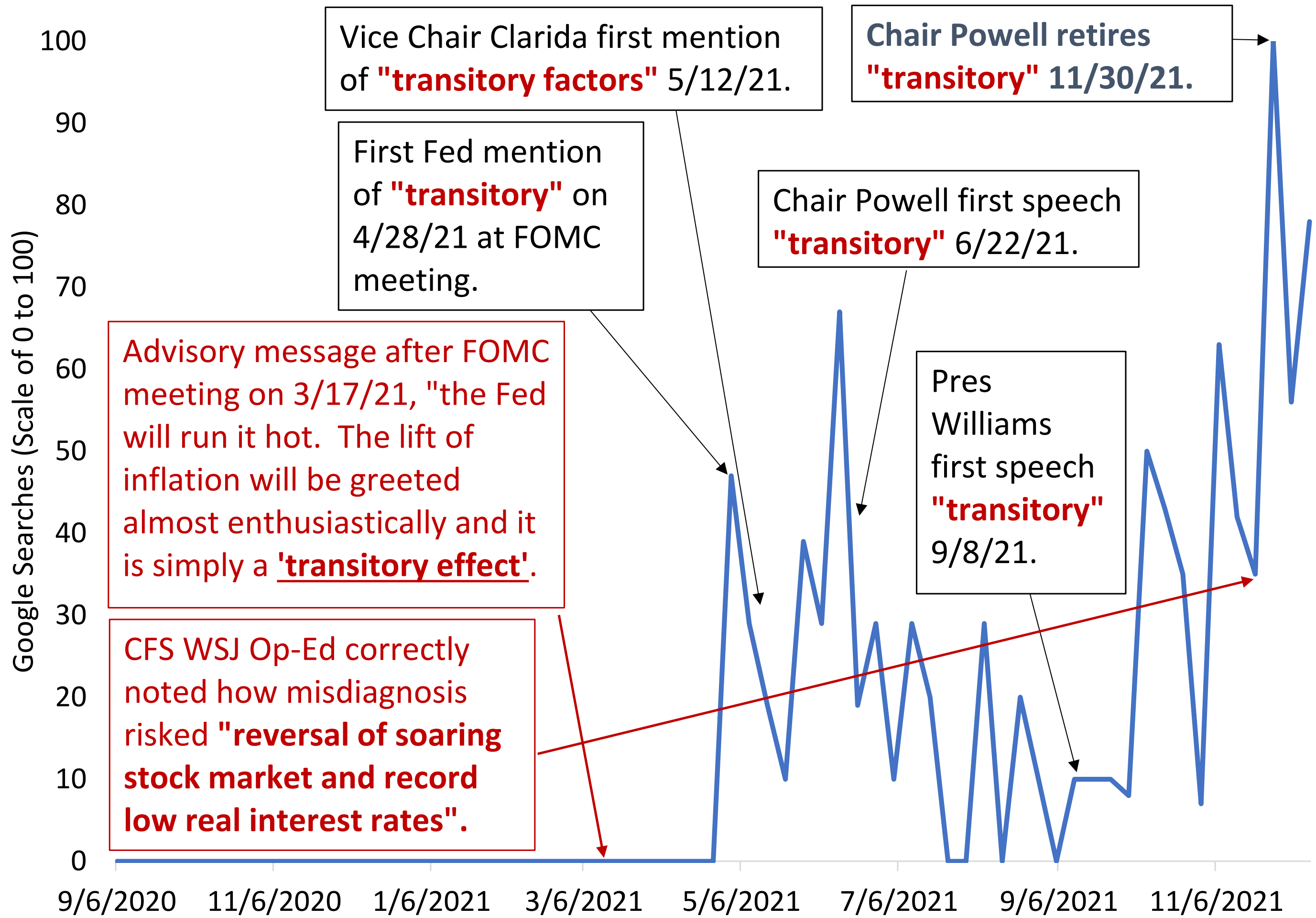
Figure 5. Communication of "Transitory" Despite Data Suggesting Otherwise



Source: Google Analytics, Federal Reserve Board and Center for Financial Stability.

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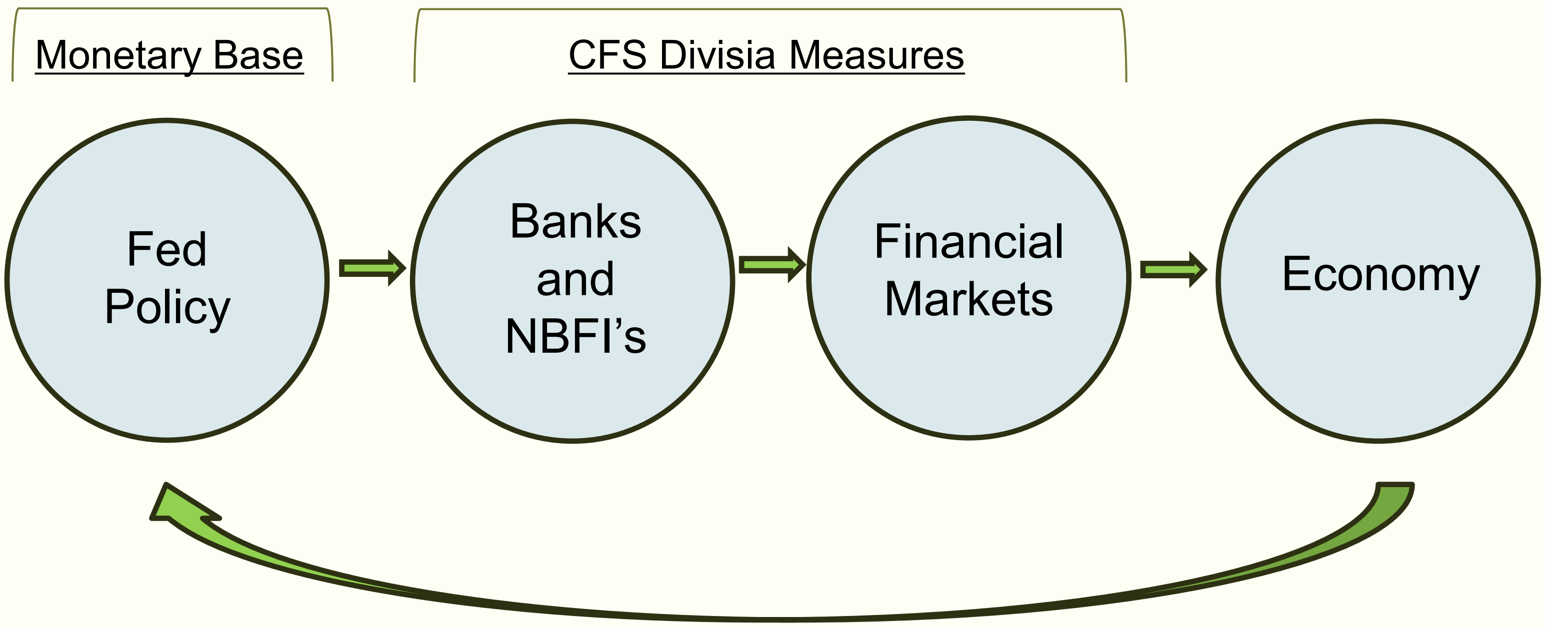
Figure 6. Communication and Assessment: What is missing from the policy framework?

Financial Institutions, Markets, and Innovations



Source: Center for Financial Stability.

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