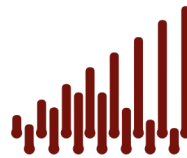




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Beyond Point Forecasting: Macroeconomic Scenario Evaluation Using Multi-Recurrent Networks

Jon Tepper, Huw Dixon and Jane Binner

1. MASCET
Motivations

2. Research
Objectives

3. Why Multi-
recurrent Networks
(MRNs)?

4. Data &
Methodology

5. Scenario
Evaluation
Experiments

6. Impulse
Responses: Key
Findings

7. Conclusions

1. MASCET Motivations

Three crises, one lesson

2008 · 2020 · 2022: the relationships that held in normal times stopped holding.

A point forecast answers one question

"What is the most likely path IF the past continues to hold?"

Crises are when it doesn't through **nonlinearity, interaction, feedback** and **state dependence**.

Bernanke Review, 2024

"Significant shortcomings" — and a call for alternative scenarios, not a single central path.

MASCET

An EPSRC-funded tool for forecasting *and* scenario evaluation: macroeconomic expertise plus a nonlinear architecture.

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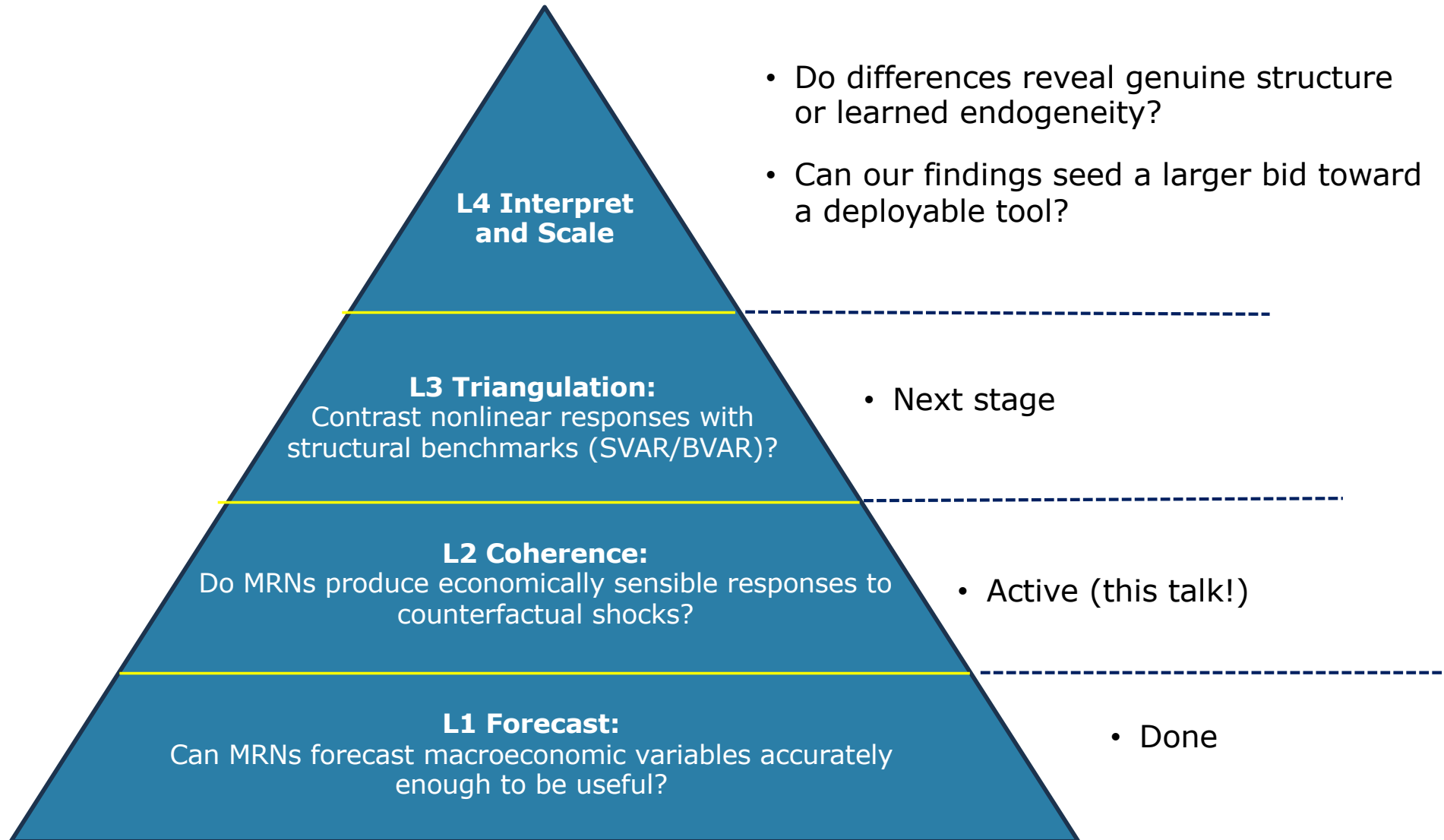
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Methodology

5. Scenario
Evaluation
Experiments

6. Impulse
Responses: Key
Findings

7. Conclusions

2. Research Objectives



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2. Research
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3. Why Multi-
recurrent
Networks (MRNs)?

4. Data &
Methodology

5. Scenario
Evaluation
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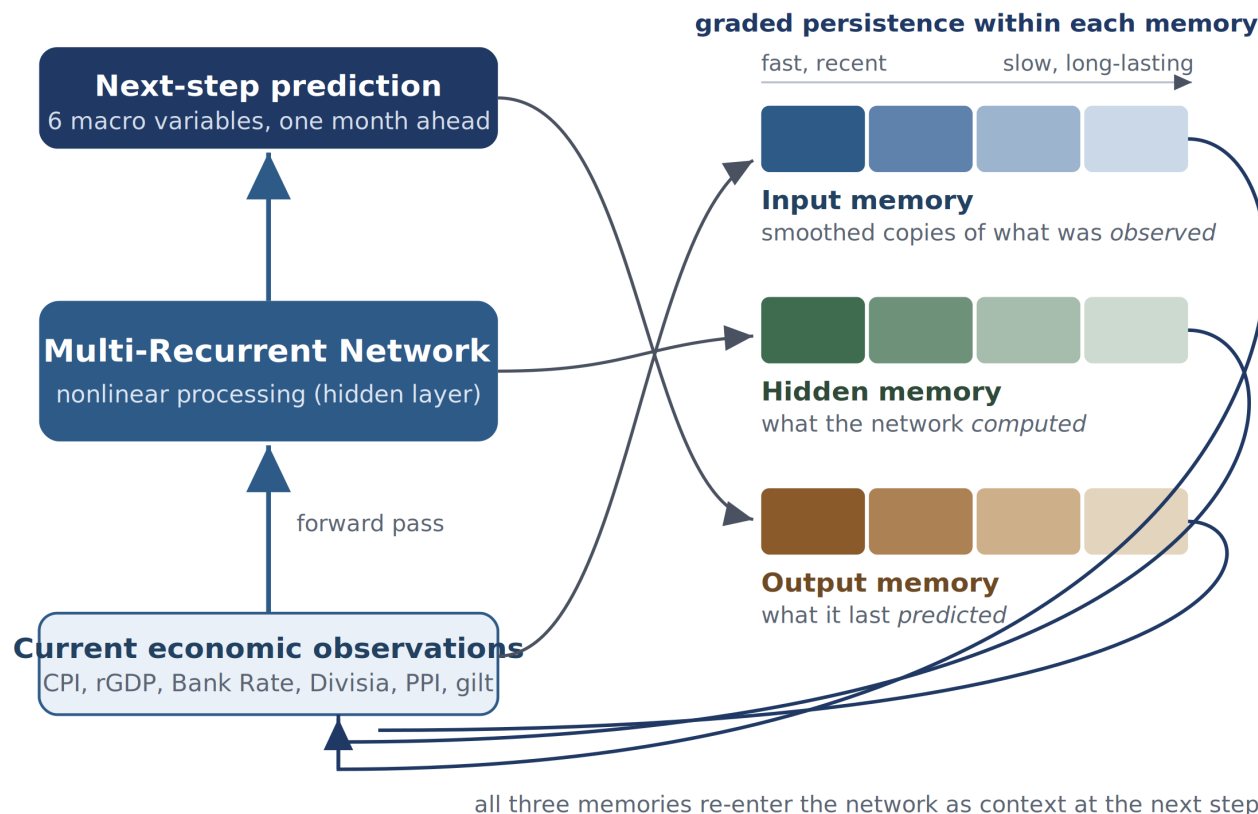
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3. Why Multi-recurrent Networks (MRNs)?

The MRN keeps three kinds of memory, each at several persistences

what was observed, what was computed, what was predicted — the network learns which horizons to lean on



Conceptual schematic — MASCET / MRN. Persistence is a property of the memory-bank design and is learned in use, not a preset horizon.

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2. Research
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recurrent
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Methodology

5. Scenario
Evaluation
Experiments

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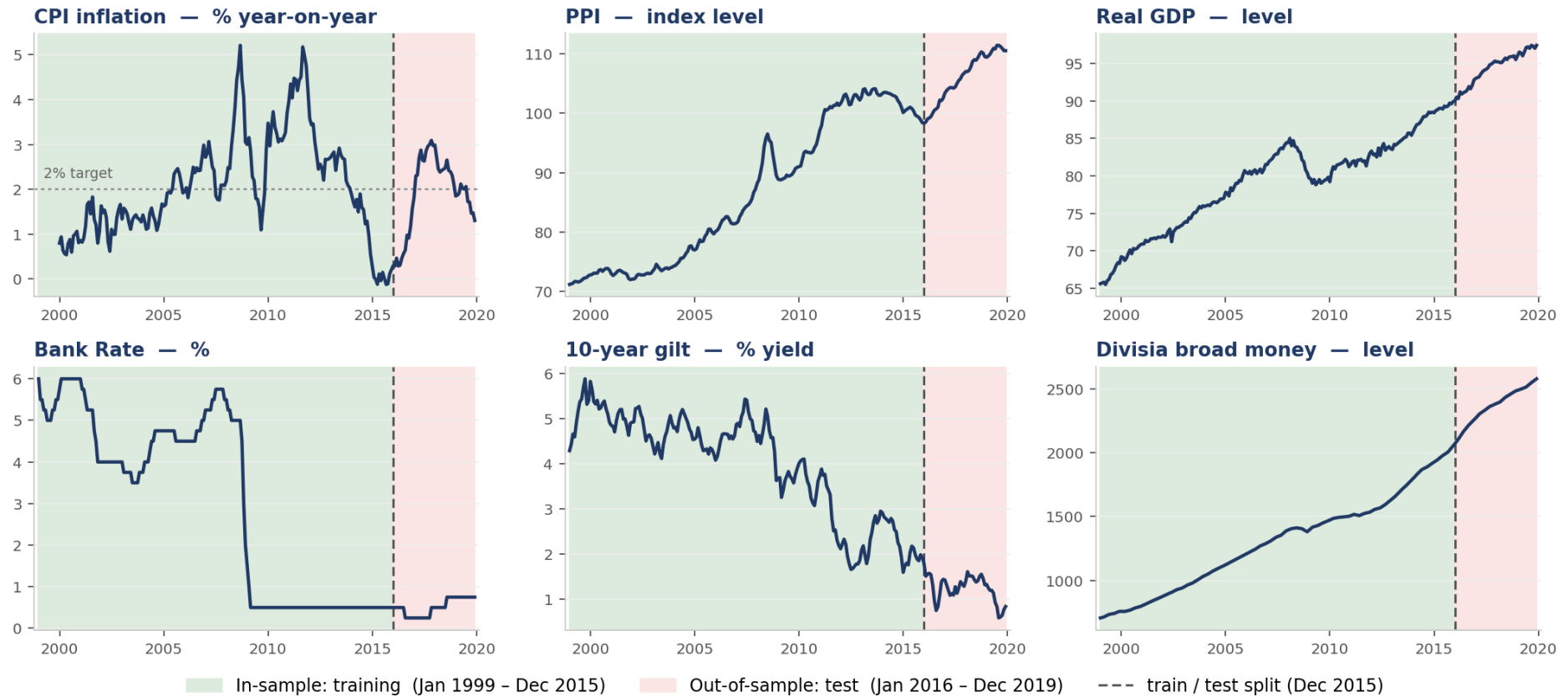
7. Conclusions

Why not simply use an LSTM? Most do!

- **For small, noisy macro data sets, flexibility is a liability, not a virtue!**
 - *only a few hundred monthly observations, an LSTM's learned gating risks fitting noise; the danger is an over-flexible model, not an under-powered one*
- **The MRN's memory is built in, not learned**
 - *it fixes the multi-timescale structure as a deliberate prior and spends its parameters on the mapping, so it needs far less data to pin down*
- **Competitive-or-better at a fraction of the cost**
 - *The MRN matched or beat the LSTM using $\sim 2,000$ vs $\sim 800,000$ trainable parameters (Orojo et al., 2019), and remained competitive across four forecasting domains at far lower complexity (Orojo et al., 2023).*
- **More recently, state-based models have started to independently converge on the same principle**
 - *S4 (Structured State Space Sequence model) for long sequence learning by Gu, Goel & Re (2021) from Stanford Uni*
 - *Mamba (Gu & Dao, 2023) extended the S4 line to compete with Transformers, independently converging on the same principle as the MRN: multi-timescale memory dynamics with a learned readout*

4. Data & Methodology

The six macroeconomic series, Jan 1999 - Dec 2019



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2. Research
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Two macroeconomic regimes

the same six series — but a crisis economy and a recovery economy behave very differently



Crisis regime

2008

- Banking crisis
- Deep recession
- Quantitative easing
- Collapsing credit & liquidity

amplifying loops switched on — the economy near a cliff-edge

Post-crisis regime

2015

- Steady recovery
- Low interest rates
- Inflation returning
- Brexit uncertainty

calmer starting point — the same shock has far less to amplify

NOTE

Through most of 2015–2019, UK CPI sat below the 2% target (dipped to ~0% in 2015); rose only after the 2016 sterling depreciation — inflation returns late in the period.

In-sample crisis experiments originate in Dec 2008 (green); out-of-sample post-crisis experiments originate in Dec 2015 (pink).

The same network, used two ways

forecasting reads in new data each month; scenario mode feeds predictions back to propagate a shock

Forecasting mode

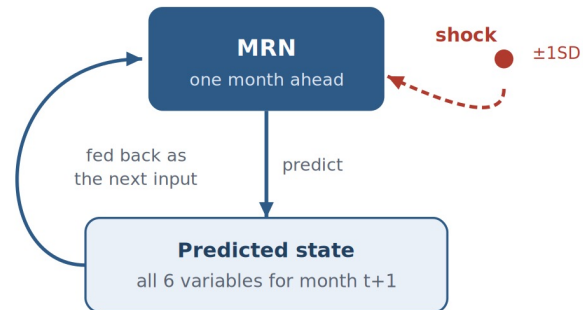
new real observations in → forecast out



Each month a fresh real observation enters the network — no feedback loop.

Scenario mode

a shock is injected, then the model runs on its own output

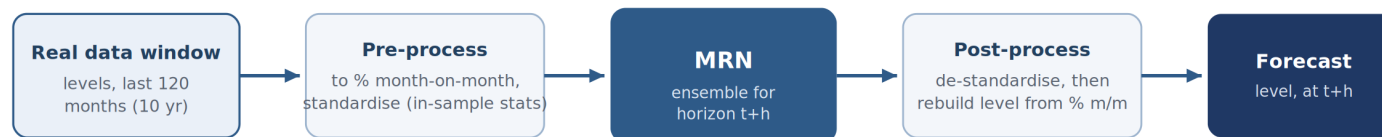


The loop propagates the shock forward in time; the gap from an unshocked run is the impulse response.

Conceptual schematic — MASCET / MRN.

Forecasting mode — direct horizon forecast

new real data enters each month; a dedicated MRN ensemble per horizon, t+1 ... t+16



Why forecast the % change, not the level?

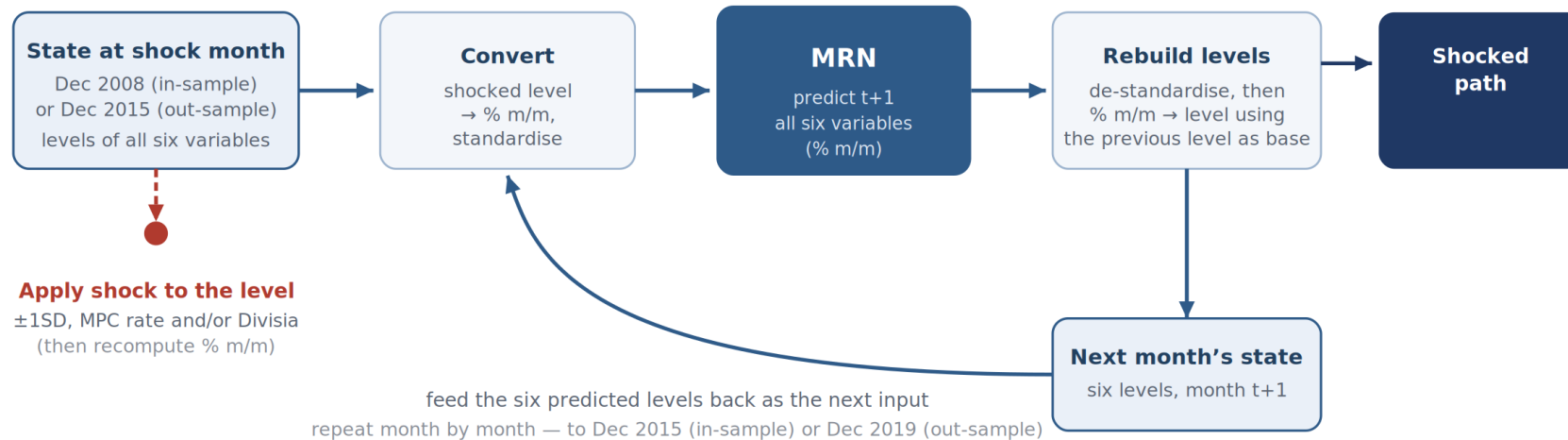
The series trend upward, so out-of-sample levels leave the range the model was trained on. Training on the month-on-month % change keeps inputs in range; levels are rebuilt afterwards.

NOTE: MRN module = ensemble of five independently trained MRNs, whose final post-processed outputs are averaged

Conceptual schematic — MASCET / MRN. Trained on Jan 1999 – Dec 2015; each new real observation slides the window forward.

Scenario mode — shock, then simulate on the model's own output

run twice — once shocked, once not; the gap between the two paths is the impulse response



No-shock baseline: the identical loop with no shock applied — the counterfactual “what the model expected anyway.”

Impulse response = shocked path – baseline path, per variable, over the horizon.

NOTE: MRN module = ensemble of five independently trained MRNs are tested and post-processed outputs averaged

5. Scenario Evaluation Experiments

Shock	Scenario description
Single-variable shocks	
+1SD MPC	Conventional monetary tightening ie BoE MPC policy rate is raised
-1SD MPC	Conventional monetary easing ie BoE MPC policy rate is cut
+1SD Divisia	Broad money / liquidity strengthens ie a QE-style liquidity repair
-1SD Divisia	Broad money / liquidity contracts ie a credit crunch
Joint shocks – same direction (economically offsetting)	
+1SD MPC & Divisia	Rate tightening and strong liquidity (pulling against each other)
-1SD MPC & Divisia	Rate easing whilst broad money contracts (easing that only 'cushions')
Joint shocks – opposite direction (economically aligned)	
+1SD MPC, -1SD Divisia	Coordinated tightening ie higher rates AND weaker liquidity (a policy-error / credit squeeze stress test)
-1SD MPC, +1SD Divisia	Coordinated easing ie rate cut reinforced by liquidity support (what we saw in Aug 2016 after Brexit referendum with Term Funding Scheme and expanded QE)

Session focus: We will review a curated subset chosen for the richest economic insight

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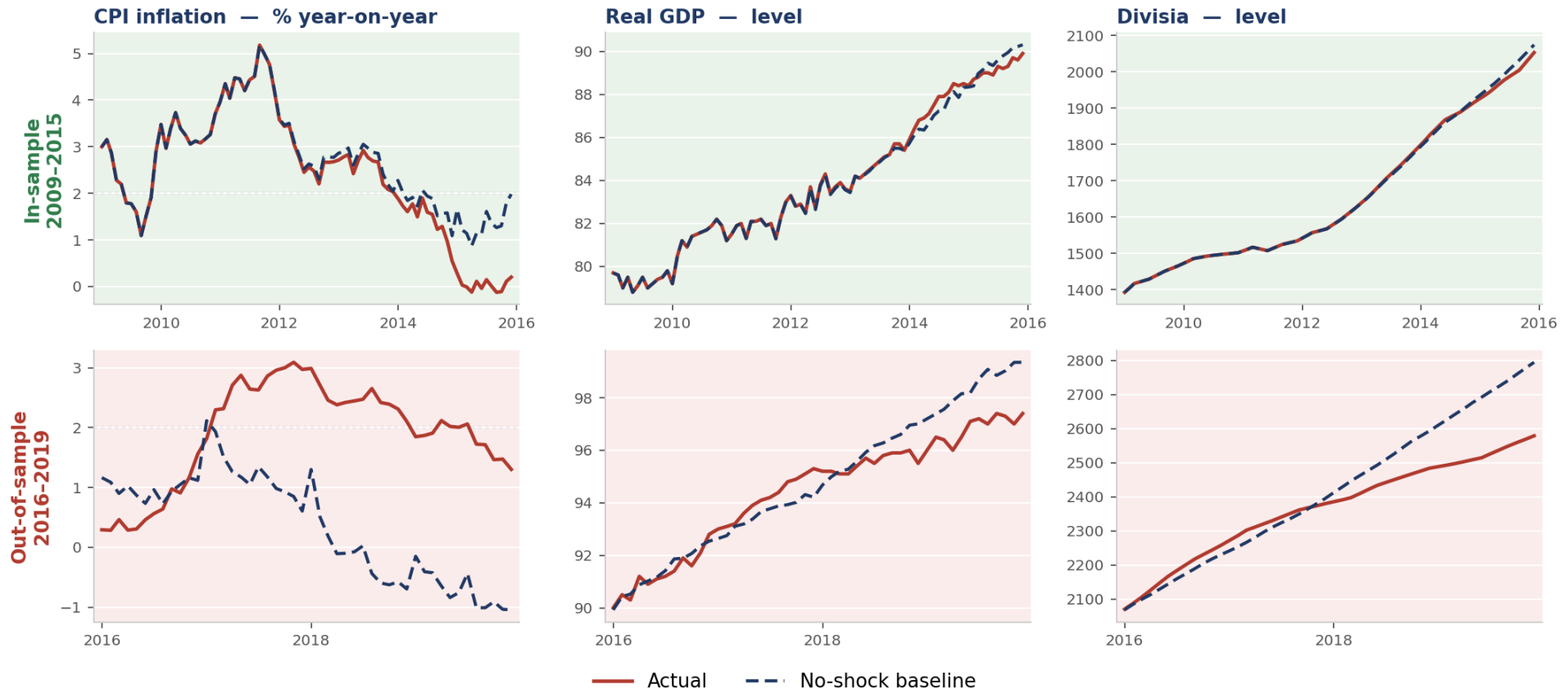
6. Impulse Responses: Key Findings

First, establish 'no shock' dynamic simulation is a legitimate counterfactual

The no-shock baseline reproduces the realised economy — the counterfactual we shock against

In-sample: the baseline tracks realised inflation, GDP and broad money closely.

Out-of-sample: GDP holds; inflation is under-predicted — the post-referendum sterling depreciation the model never saw.



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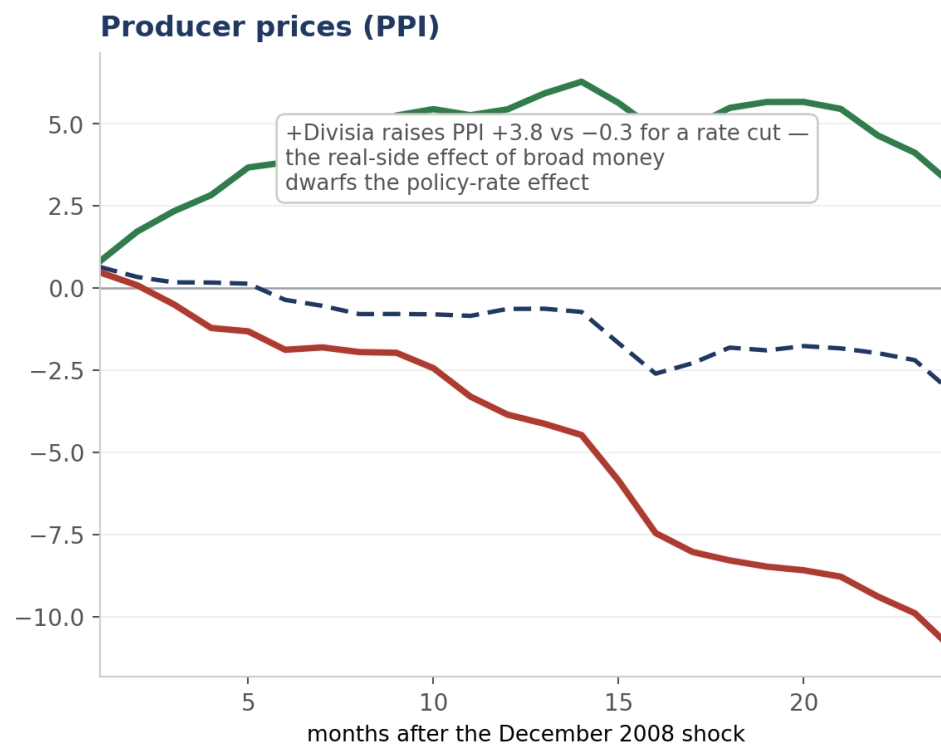
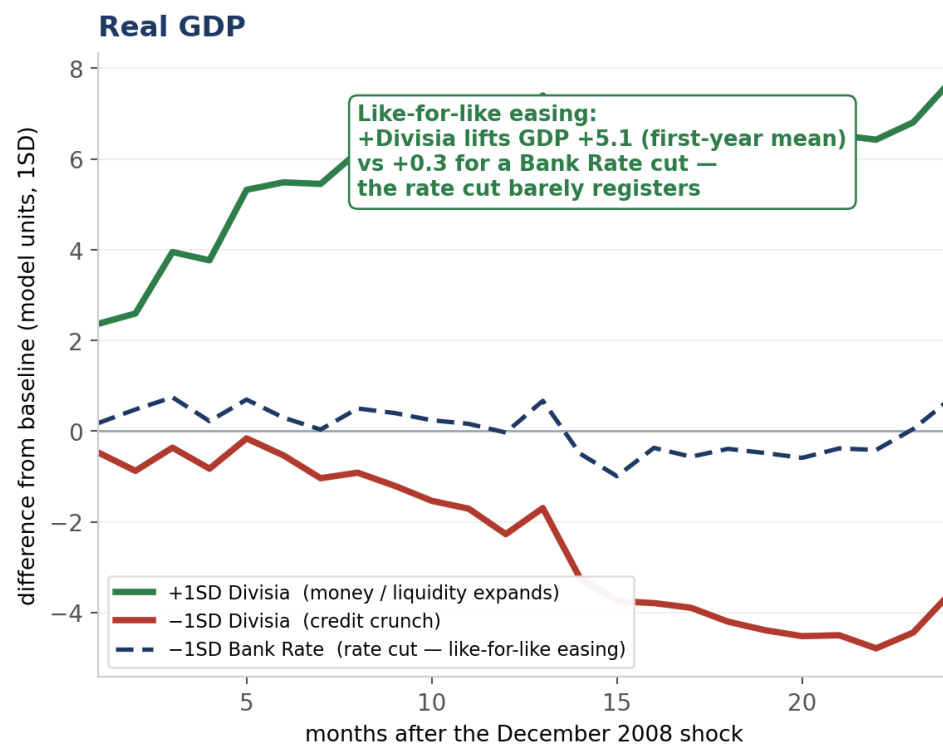
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Finding 1: Broad monetary conditions carry the real-side signal (Dec 2008)

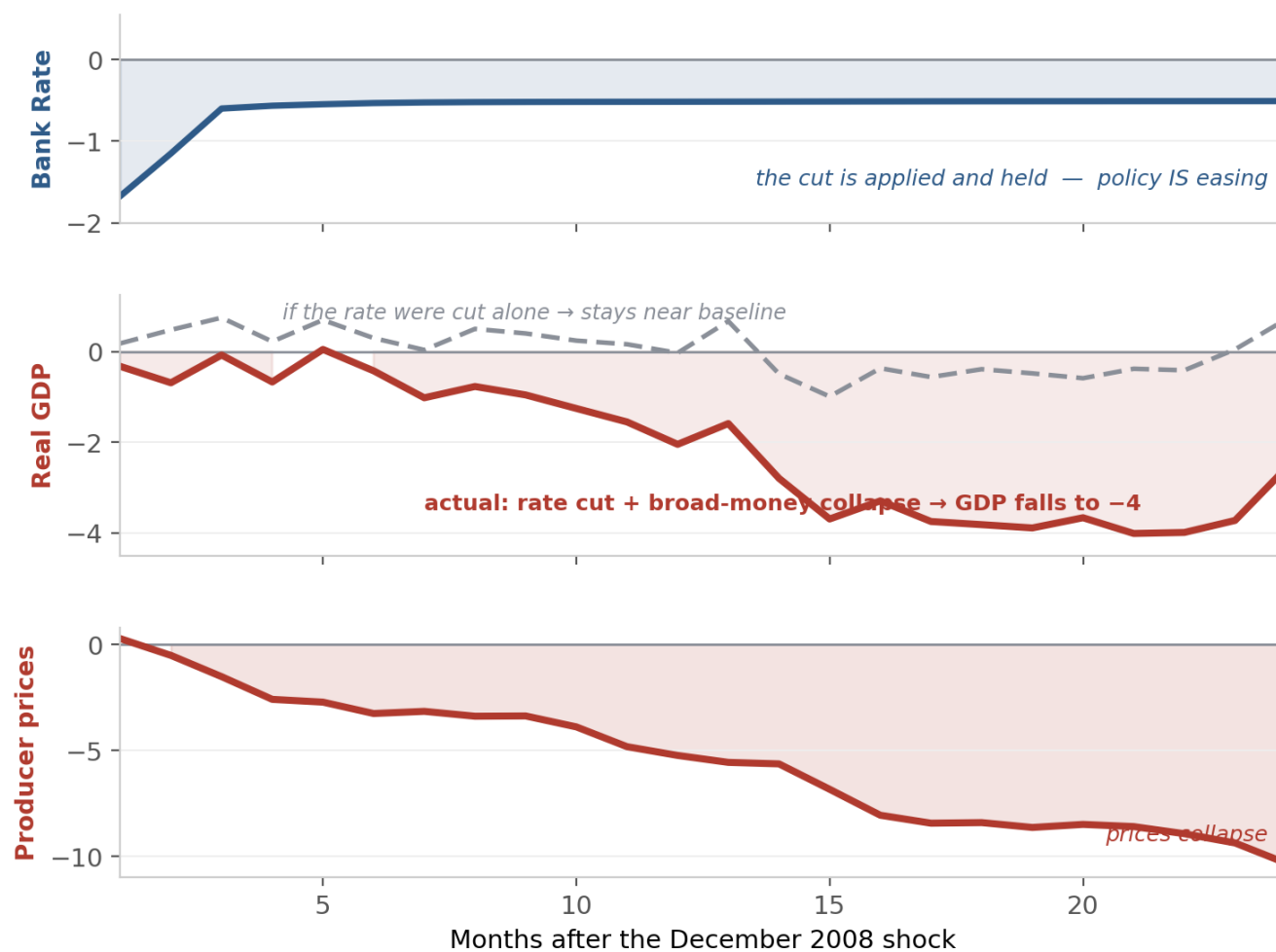


MASCET MRN • in-sample, difference from no-shock baseline • all shocks are 1SD; the Bank Rate cut is the like-for-like easing comparator

Finding 2: The stance of policy is multidimensional

The rate cut that couldn't save the economy (Dec 2008)

A 1SD Bank Rate cut delivered into a 1SD collapse in broad money (Divisia): easing the price of money is overwhelmed by the collapse in its quantity.



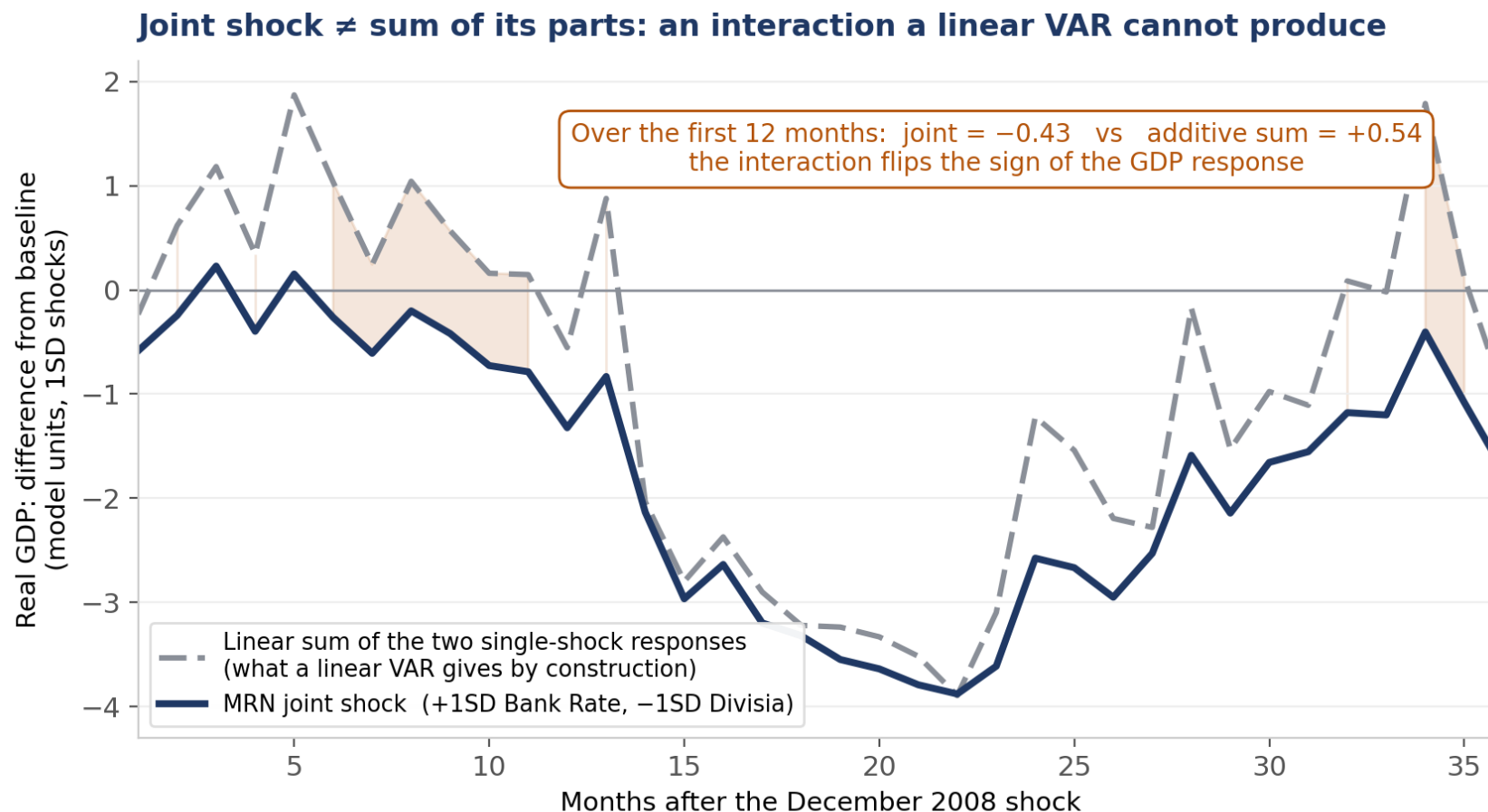
Akin to pressing the accelerator when there is no fuel in the tank....car wont move!

MASCET MRN • -1SD Bank Rate + -1SD Divisia, in-sample (Dec 2008) • source: MRNVAR_InsampleImpulseResponses summary

It's important to look at the instrument AND the monetary conditions it's operating through.

The actual 2009 response combined the rate cut with QE and balance-sheet repair, because easing the rate alone was not enough.

Finding 3: Interaction – the joint effect is not simply the sum of the parts!



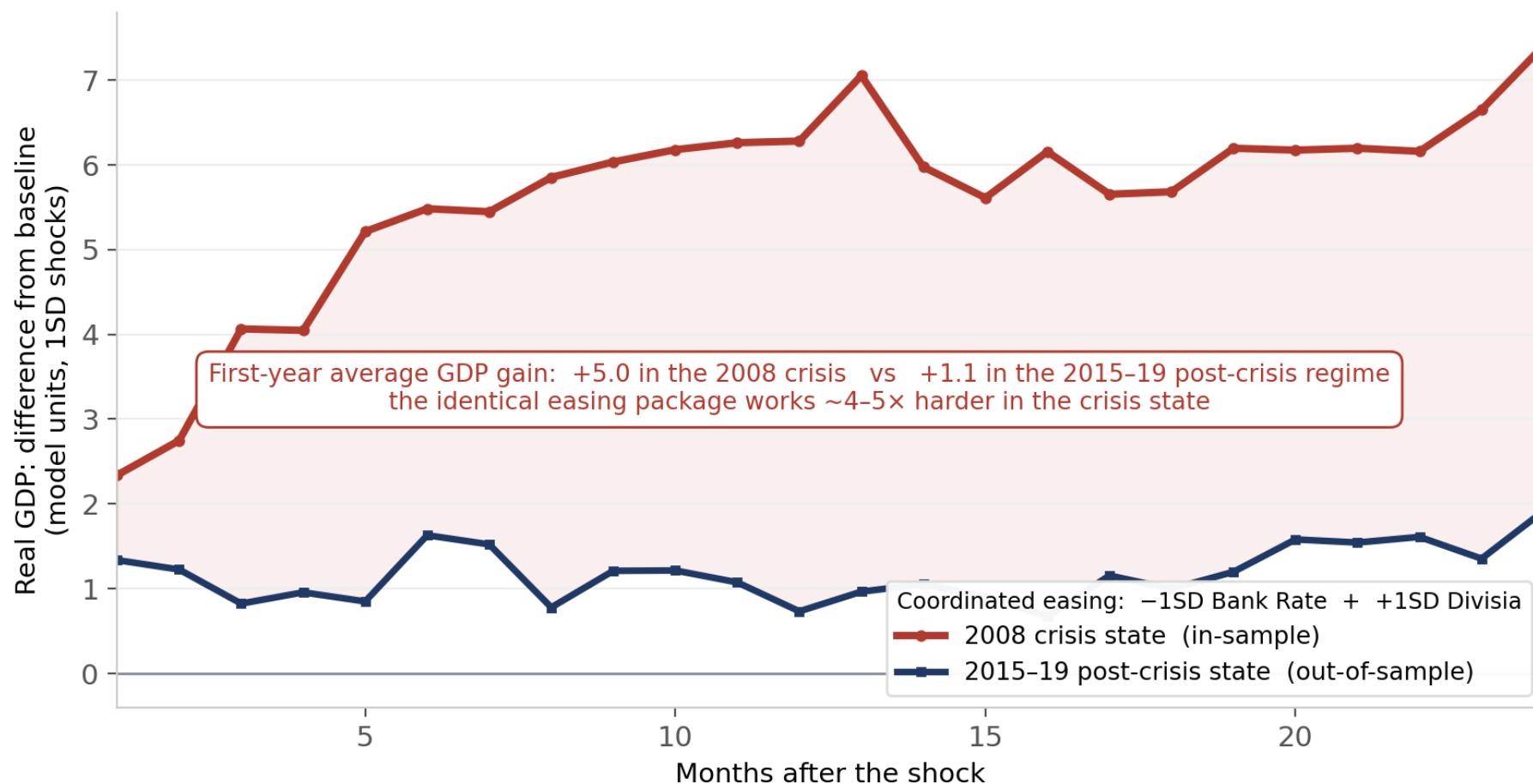
MASCET MRN • in-sample (Dec 2008 state) • source: MRNVAR_InsampleImpulseResponses summary

Akin to two medicines working well when taken separately, but when taken together we experience unexpected consequences!

Shaded regions show months with opposite signs

Finding 4: State dependence

Same policy, different economy: a coordinated easing works far harder in a crisis



MASCET MRN • GDP response to –1SD Bank Rate + +1SD Divisia • source: MRNVAR in-sample (2008) & out-of-sample (2015) summaries

Effect depends on state of the economy and in 2008 the financial system was broken and rGDP climbed strongly; 2015-19 saw the calmer post-crisis regime and less to amplify

7. Conclusions

- Policymakers need scenario evaluation - forecasting alone is not enough
- The economy reacts differently to the same inputs during different macroeconomic states (state dependence)
- Broad monetary/liquidity conditions matter, especially under stress
- AI reveals these nonlinear, state-dependent relationships
 - NOT claiming MRN is a structurally identified causal model per se
 - MRN's recurrent memory provides a mechanism by which identical external perturbations can generate different trajectories depending the internal memory state
- **Next step:** benchmark against SVAR/BVAR to distinguish genuine structural insight from learned policy-reaction patterns.

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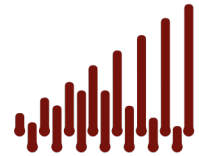
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Evaluation
Experiments

6. Impulse
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Thank You!

Any Questions?

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Objectives

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recurrent Networks
(MRNs)?

4. Data &
Methodology

5. Scenario
Evaluation
Experiments

6. Impulse
Responses: Key
Findings

7. Conclusions

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