Identifying News Shocks from Forecasts

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- How can we identify news vs. surprise shocks in macroeconomic data?
  - Even cleanly identified shocks mix surprises with news about the future
- Challenging when there is news about **multiple** shocks!

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  - Coordinated monetary-fiscal policy reduces inflation (output) variance by an extra 10 (30) percent over uncoordinated.

Why Can Forecasts Help? A Simple Example

- To build intuition, consider the simple NK model:

New Keynesian Phillips curve:	$\pi_t = \beta \mathbb{E}_t[\pi_{t+1}] + \kappa y_t + x_t$
Euler equation:	$0 = \mathbb{E}_t[z_t + \gamma(y_t - y_{t+1}) + i_t - \pi_{t+1}]$
Taylor rule:	$i_t = \phi_\pi \pi_t + h_t$

where x_t and z_t are iid shocks, and h_t is the exogenous policy residual

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$$h_t = \rho h_{t-1} + u_t + v_{t-1}$$

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  u_t is monetary policy *surprise* and v_{t-1} is monetary policy *news*
- u_t and v_{t-1} are individually known to agents in the model, but *not the econometrician*!

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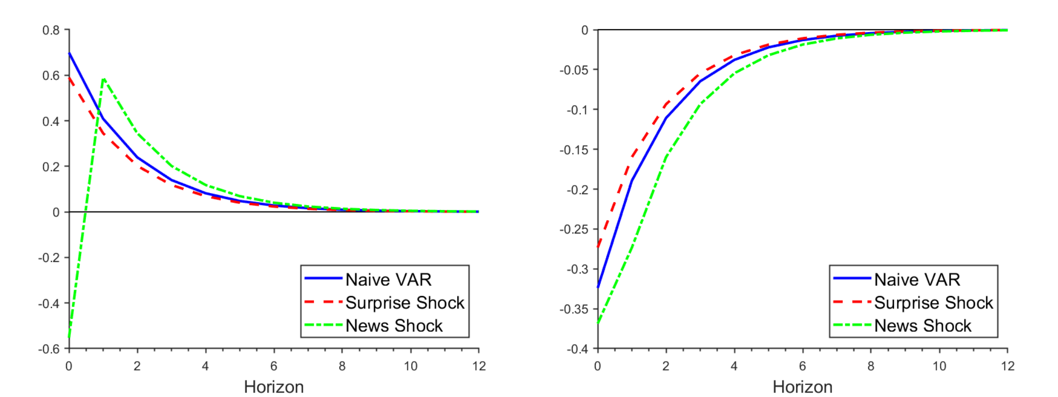

(a) Interest Rate IRFs

(b) Inflation IRFs

Figure 1: Impulse Response Functions in the Simple Example

"Naive VAR" identifies by causal ordering, and consistently estimates IRFs w/o news.

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- In this example, only one news shock, so only need one forecast: $f_t^\pi \equiv \mathbb{E}_t[\pi_{t+1}]$
- Intuition for identification: news today cause forecasts today and outcomes tomorrow to move together; surprises cause today's outcomes to depart from yesterday's forecasts.

Identification with Forecasts the Simple Example

- Model solution is:

$$\pi_t = b_h^\pi h_t + b_v^\pi v_t + b_x^\pi x_t + b_z^\pi z_t$$

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$$f^\pi_t = \mathbb{E}_t[\pi_{t+1}]$$
$$= \mathbb{E}_t[b^\pi_h h_{t+1}] = b^\pi_h \rho h_t + b^\pi_h v_t$$

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- Using forecasts, we can separately identify surprise shocks ($u_t = h_t - \frac{1}{b_h^\pi} f_{t-1}^\pi$) from news shocks ($v_t = \rho h_t - \frac{1}{b_h^\pi} f_t^\pi$)!

What's in the paper

- General Case with Multiple News Shocks
  - Set up
  - Identification: Conditions and implementation ▸ Identification
  - Verification via Monte Carlo simulation
- Application to the US
  - Data
  - Constructing forecasts ▸ Forecast cleaning ▸ See the data
  - Impulse responses and shock labeling
  - Shock validation ▸ Shock Validation
  - News versus surprise IRFs ▸ News vs. Surprise IRFs
  - Accounting for sources of macro fluctuations
- Counterfactual policies without a structural model
  - Impulse responses under active policies ▸ IRFs: Stabilization policies
  - Assessing the benefits of policy coordination
  - Impulse responses under passive policies ▸ IRFs: Passive policies

General SVAR Representation

- $n \times 1$ vector x_t determined by lags, structural shocks ϵ_t, and news v_t:

$$x_t = \sum_{j=1}^{m} B_j x_{t-j} + A\epsilon_t + Cv_t$$

- $n \times 1$ structural shocks have news and surprise components:

$$\epsilon_t = u_t + v_{t-1}$$

- **Theorem 1**: Equilibrium in a large class of models has this form
- Normalize the orthogonal structural shocks $Var(\epsilon_t) = I$
- Assume news/surprise also orthogonal (i.e. ϵ_t dimensions are *independent*) so diagonal variances satisfy:

$$Var(u_t) = D_u^2 \qquad Var(v_t) = D_v^2 \qquad \implies D_u^2 + D_v^2 = I$$

General SVAR Identification

- **Theorem 2**: If we have unbiased forecasts f_t for all entries of x_t, we can identify A, C, D_u^2, D_v^2 and $\{B_j\}_{j=1}^m$
- Intuition: rational forecasts imply "enough" restrictions

$$x_t = \sum_{j=1}^{m} B_j x_{t-j} + A\epsilon_t + Cv_t$$

$$\implies f_t = \mathbb{E}_t[x_{t+1}] = \sum_{j=1}^{m} B_j x_{t+1-j} + Av_t$$

- Approach: stack and estimate a VAR for $\begin{pmatrix} f_t \\ x_t \end{pmatrix}$ with linear restrictions

▸ Identification

Application to Fiscal and Monetary Policy

- Quarterly US data from 1968:IV - 2016:IV
- Baseline model with 6 time series and associated forecasts, deseasonalized and detrended
- Clean the forecasts using additional time series and forecasts, selecting variables by machine learning
- Lag length determined by AIC
- Bootstrapped standard errors

▸ Forecast cleaning

Data

Variable	Date range	Forecast Source
Baseline Specification		
Real GDP	1968:IV - 2022:II	SPF
Federal tax receipts	1968:IV - 2016:IV	Fed Greenbooks
Real government spending	1968:IV - 2022:II	Fed Greenbooks for 1968:IV - 1981:II
		SPF for 1981:III - 2022:II
GDP deflator	1968:IV - 2022:II	SPF
3-month Treasury rate	1968:IV - 2022:II	Yield curve
Housing starts	1968:IV - 2022:II	SPF
Additional Variables		
Unemployment Rate	1968:IV - 2022:II	SPF
Industrial production	1968:IV - 2022:II	SPF
Federal budget surpluses	1968:IV - 2016:IV	Fed Greenbooks
USD/CAD exchange rate	1968:IV - 2022:II	Futures contracts
Real oil price	1983:I - 2022:II	Futures contracts
1, 2, 3, 4, and 5-year Treasury rates	1968:IV - 2022:II	Yield curve

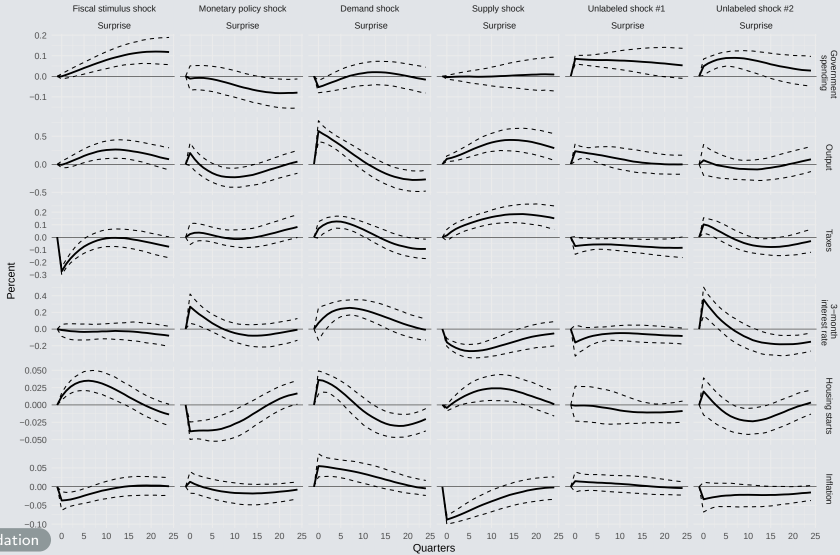
Table 1: List of Variables

See the data

Shock Labeling

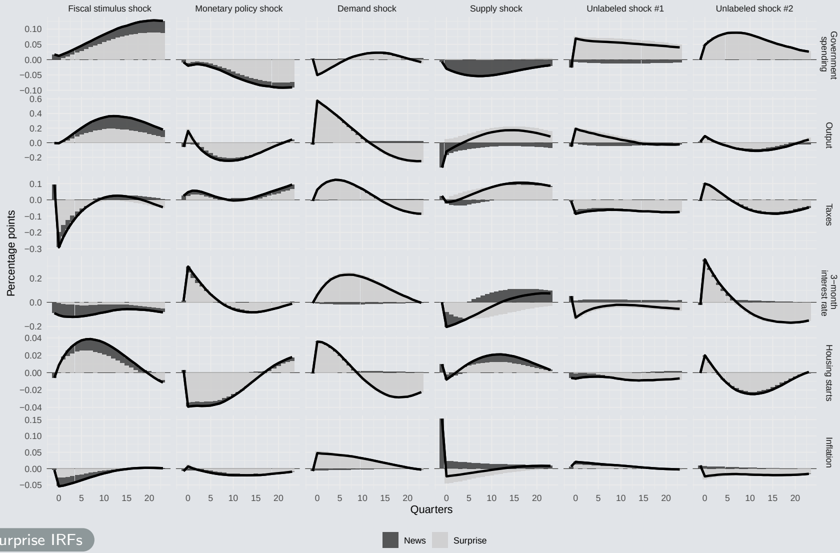
- SVARs require a scheme for labeling shocks
- We label based on responses to the surprise structural shocks u_t over the medium run. For example:
  - a "Fiscal Stimulus Shock" increases government spending, decreases taxes, and increases real activity.
  - a "Monetary Policy Shock" increases interest rates, decreases real activity and inflation
  - a "Demand Shock" increases interest rates, real activity and inflation.
  - a "Supply Shock" increases real activity, and decreases interest rates and inflation
- When bootstraping standard errors, we label shocks to minimize the error with our baseline estimates (satisfying Lewis (2021) theorem)

Structural Shock IRFs to 1 s.d. Surprise Shocks



▸ Shock Validation

Structural Shock IRFs Decomposed



▸ News vs. Surprise IRFs

Long-Run Variance Decomposition

Variable	Type	Fiscal stimulus	Mon. policy	Demand	Supply	Unlabeled #1	Unlabeled #2	Total
Gov. spending	News	4.5	3.6	1.6	5.6	2.2	1.1	24.3
	Surprise	20.4	10.0	3.8	2.3	14.8	12.3	75.7
	Total	25.6	15.8	6.4	9.7	18.5	14.5	100.0
Output	News	7.0	2.2	3.7	4.3	2.1	2.3	26.3
	Surprise	8.0	6.7	19.5	23.9	4.6	4.3	73.7
	Total	15.9	9.9	24.4	28.3	8.3	7.7	100.0
Taxes	News	4.9	3.3	1.9	1.7	1.8	2.3	19.4
	Surprise	12.5	4.7	11.6	30.3	7.6	7.4	80.6
	Total	18.2	8.6	14.5	32.1	10.1	10.9	100.0
3-month interest rate	News	5.6	2.2	3.7	5.8	2.1	2.3	25.9
	Surprise	2.8	8.0	16.9	18.1	4.9	17.4	74.1
	Total	9.2	11.2	22.5	24.8	8.1	20.0	100.0
Housing starts	News	5.1	2.4	2.2	2.0	1.8	1.8	19.0
	Surprise	13.8	18.4	17.7	8.3	6.0	9.6	81.0
	Total	19.3	21.7	20.8	11.4	8.3	12.2	100.0
Inflation	News	4.1	1.9	4.3	17.0	1.5	2.9	37.8
	Surprise	5.2	4.0	12.6	21.9	2.4	7.0	62.2
	Total	10.0	7.4	19.6	40.4	4.8	11.8	100.0
Unweighted average	News	5.2	2.6	2.9	6.1	1.9	2.1	25.5
	Surprise	10.5	8.6	13.7	17.5	6.7	9.7	74.5
	Total	16.4	12.4	18.0	24.5	9.7	12.8	100.0

Policy Rule Counterfactuals: McKay and Wolf (2023) method

- Require identified IRFs to policy news/surprises

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  - In many models, IRFs do not depend on shock covariance
  - ... so choose counterfactual shock covariances!

▸ Implementation

Policy Counterfactuals: Tradeoffs and policy coordination

Target:	Inflation			Output			Dual Mandate		
Policy used	*Fisc.*	*Mon.*	*Joint*	*Fisc.*	*Mon.*	*Joint*	*Fisc.*	*Mon.*	*Joint*
Inflation	**0.19**	**0.09**	**0.00**	0.46	1.41	0.80	**0.43**	**0.44**	**0.34**
Output	1.03	1.45	1.56	**0.30**	**0.33**	**0.01**	**0.56**	**0.58**	**0.37**
Government spending	3.28	2.73	1.24	2.77	1.08	2.47	2.49	1.22	1.32
Taxes	4.56	2.22	3.06	5.15	2.09	3.91	6.02	1.43	1.72
3-month interest rate	1.22	0.84	2.02	1.06	1.15	2.12	1.69	0.82	0.43
Housing starts	1.85	1.09	1.09	0.92	1.06	0.89	0.80	0.68	0.25

Table 2: Variance relative to baseline

▸ IRFs: Stabilization policies ▸ IRFs: Passive policies

Conclusion

- Including forecasts in VARs can identify news and surprise components of structural shocks
- We estimate realistic effects of fiscal and monetary shocks in US data
- News is a notable driver of business cycles
- News/surprise identification is particularly useful for estimating policy counterfactuals
- More work to do!

Identification Proof

- Constructive proof – we derive an analytical estimator for A and C given Σ and B_1
- Assumptions: structural shocks have linearly independent effects, and each shock has a news component
- Simple to implement – a few lines of matrix operations
- Only identified up to sign and column order (typical) – when calculating, ambiguity is due to non-uniqueness of the singular value decomposition

▸ Back ▸ Derivation

Deriving the Estimator (1/2)

- Subdivide the matrix $\Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{21}' \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}$ into $n \times n$ blocks:

$$\begin{pmatrix} \Sigma_{11} & \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} = \begin{pmatrix} (B_1 C + A) D_v^2 (B_1 C + A)' + B_1 A D_u^2 A' B_1' & \\ C D_v^2 (B_1 C + A)' + A D_u^2 A' B_1' & C D_v^2 C' + A D_u^2 A' \end{pmatrix}$$

- Define the $n \times n$ matrices ϕ and ψ by

$$\phi \equiv \Sigma_{11} - B_1 \Sigma_{21} - \Sigma_{21}' B_1' + B_1 \Sigma_{22} B_1'$$

$$= A D_v^2 A'$$

$$\psi \equiv \Sigma_{22} - (\Sigma_{21} - \Sigma_{22} B_1') \phi^{-1} (\Sigma_{21} - \Sigma_{22} B_1')'$$

$$= A D_u^2 A'$$

Deriving the Estimator (2/2)

- The variance restriction implies:

$$\phi + \psi = AA'$$

- SVD of $\phi + \psi$ gives unitary matrix U and diagonal matrix Λ^2 such that for some unitary V

$$\phi + \psi = U\Lambda^2 U' \qquad A = U\Lambda V'$$

- SVD of $\Lambda^{-1}U'\phi U\Lambda^{-1}$ gives the matrices V and D_v^2 from

$$\Lambda^{-1}U'\phi U\Lambda^{-1} = V'D_v^2 V$$

- This gives the matrices $A = U\Lambda V'$ and $D_u^2 = I - D_v^2$. Then the final matrix C is found from

$$C = (\Sigma_{21} - \Sigma_{22}B_1')(D_v^2 A')^{-1}$$

Back

General SVAR: Include Forecasts

- $n \times 1$ vector of forecasts $f_t = \mathbb{E}\left[x_{t+1} \middle| \{x_{t-j}\}_{j=0}^{m-1}, \epsilon_t, v_t\right]$:

$$f_t = \sum_{j=1}^{m} B_j x_{t+1-j} + A v_t$$

- Stack the expectations and time series into a single VAR$(m-1)$:

$$\begin{pmatrix} f_t \\ x_t \end{pmatrix} = \sum_{j=1}^{m-1} \mathbf{B}_j \begin{pmatrix} f_{t-j} \\ x_{t-j} \end{pmatrix} + \mathbf{A} \begin{pmatrix} v_t \\ u_t \end{pmatrix} \tag{1}$$

- With matrices:

$$\mathbf{B}_j \equiv \begin{cases} \begin{pmatrix} B_1 & B_2 \\ I & 0 \end{pmatrix} & j = 1 \\ \begin{pmatrix} 0 & B_{j+1} \\ 0 & 0 \end{pmatrix} & j > 1 \end{cases} \qquad \mathbf{A} \equiv \begin{pmatrix} B_1 C + A & B_1 A \\ C & A \end{pmatrix}$$

Back

Identifying Restrictions

$$x_t = \sum_{j=1}^{m} B_j x_{t-j} + A\epsilon_t + Cv_t$$

- B_j matrices identified from $\mathbf{B}_j$ matrices in stacked VAR
- A and C? Classic SVAR problem:
  - Observe $2n \times 1$ innovation $w_t = \mathbf{A} \begin{pmatrix} v_t \\ u_t \end{pmatrix}$ with $Var(w_t) \equiv \Sigma$
  - $\Sigma = \mathbf{A}\, Var \begin{pmatrix} v_t \\ u_t \end{pmatrix} \mathbf{A}'$ is symmetric: only $2n^2 + n$ unique entries
  - $\mathbf{A} = \begin{pmatrix} B_1 C + A & B_1 A \\ C & A \end{pmatrix}$ has $2n^2$ unknowns (A and C)
  - Shock variances: $D_u^2 + D_v^2 = I$ adds $2n$ unknowns and n restrictions

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Policy Rule Counterfactuals: Implementation (1/2)

- Policymaker controls shock g. Consider policy rules linear in other shocks:

$$\underbrace{\begin{bmatrix} u_t^g \\ v_t^g \end{bmatrix}}_{\text{policy shocks}} = \overbrace{\alpha}^{\text{to be found}} \underbrace{\begin{bmatrix} u_t^{-g} \\ v_t^{-g} \end{bmatrix}}_{\text{other shocks}}$$

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- The counterfactual impulse responses *to other shocks* $\psi_u(h)$ and $\psi_v(h)$ are:

$$\begin{bmatrix} \psi_u(h) & \psi_v(h) \end{bmatrix} = \begin{bmatrix} \phi_u^{-g}(h) & \phi_v^{-g}(h) \end{bmatrix} + \begin{bmatrix} \phi_u^{g}(h) & \phi_v^{g}(h) \end{bmatrix} \alpha$$

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Policy Rule Counterfactuals: Implementation (2/2)

- To estimate the counterfactual, find α to minimize some loss function for a matrix F:

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Policy Rule Counterfactuals: Implementation (2/2)

- To estimate the counterfactual, find α to minimize some loss function for a matrix F:

$$\min ||Fx_t||$$

- F may encode a policy objective (e.g. output stabilization) or a specific policy rule (e.g. a Taylor rule)
- Choose α to minimize the loss measured in IRFs over all h's:

$$\min \left|\left|F \left[\begin{array}{cc} \psi_u(h) & \psi_v(h) \end{array}\right]\right|\right| = \min \left|\left|F \left[\begin{array}{cc} \phi_u^{-g}(h) & \phi_v^{-g}(h) \end{array}\right] + F \left[\begin{array}{cc} \phi_u^{g}(h) & \phi_v^{g}(h) \end{array}\right] \alpha\right|\right|$$

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Forecast Cleaning (1/2)

- Identification requires f_t to be unbiased *in sample*

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- Therefore we must *clean* the forecasts
  - Constructing an in-sample rational expectation
  - Removes biases and small sample correlations

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Forecast Cleaning (2/2)

- To construct the rational expectation f_t from empirical expectations $\tilde{f}_t$, run the VAR(k) with $k \geq m$:

$$\begin{pmatrix} \tilde{f}_t \\ z_t \\ x_t \end{pmatrix} = \sum_{j=1}^{k} \mathbf{G}_j \begin{pmatrix} \tilde{f}_{t-j} \\ z_{t-j} \\ x_{t-j} \end{pmatrix} + \upsilon_t$$

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- Let $\mathbf{G}_{x,j}$ denote the final n rows of $\mathbf{G}_j$:

$$f_t = \sum_{j=1}^{k} \mathbf{G}_{x,j} \begin{pmatrix} \tilde{f}_{t+1-j} \\ z_{t+1-j} \\ x_{t+1-j} \end{pmatrix}$$

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- Cleaned forecast f_t is best linear forecast of x_{t+1} given $\tilde{f}_t$, x_t, and other regressors z_t. Baseline: Construct z_t as a machine-learning predictor for x_t using a large set of other variables (include lots of information without over-fitting).

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- Are the shocks that we label "fiscal stimulus" and "monetary policy" realistic?

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  - Compare the *cumulative output multipliers* to values from the literature
  - The stimulus shock conflates the spending multiplier ($\approx 1 - 1.5$ over 20Q) with the tax multiplier ($\approx 2 - 3$):

$$\mu_G^h = \frac{\sum_{s=0}^h \mathbb{E}_t \Delta Y_{t+s}}{\sum_{s=0}^h \mathbb{E}_t \Delta G_{t+s}} \qquad \mu_T^h = \frac{\sum_{s=0}^h \mathbb{E}_t \Delta Y_{t+s}}{\sum_{s=0}^h \mathbb{E}_t \Delta T_{t+s}}$$

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- Monetary policy shocks
  - Compare with shocks from the literature
- Appear reasonable, and robust to alternative specifications

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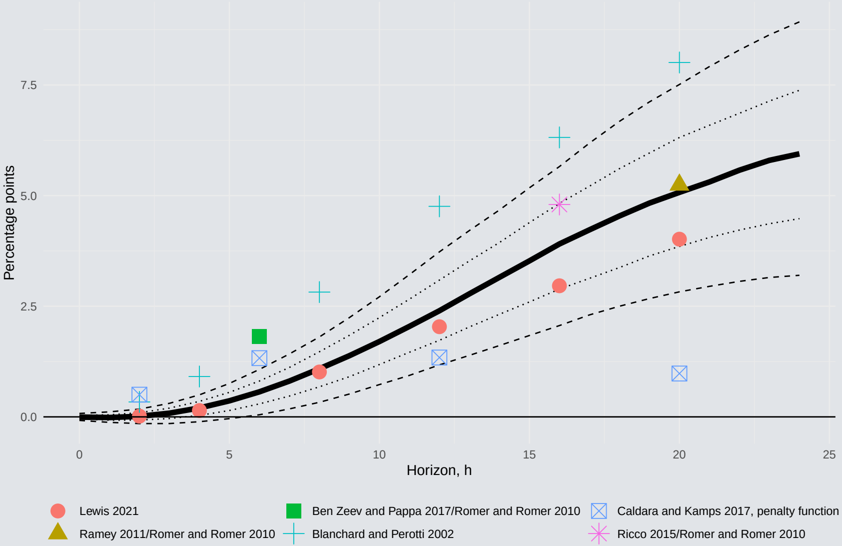
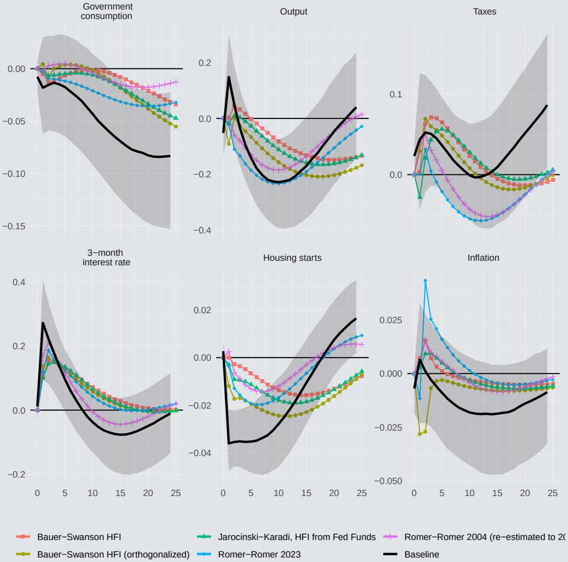
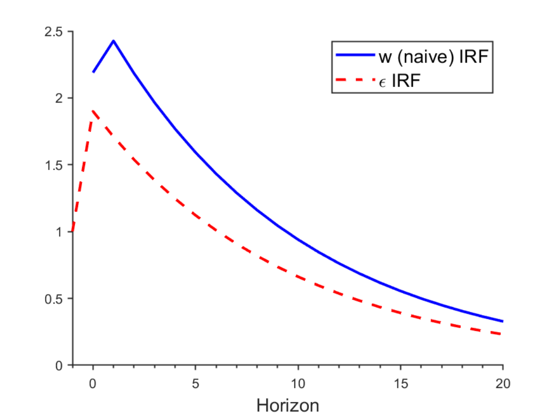
Fiscal Stimulus Cumulative Multipliers



Monetary Policy IRFs



IRFs in the Simple Example



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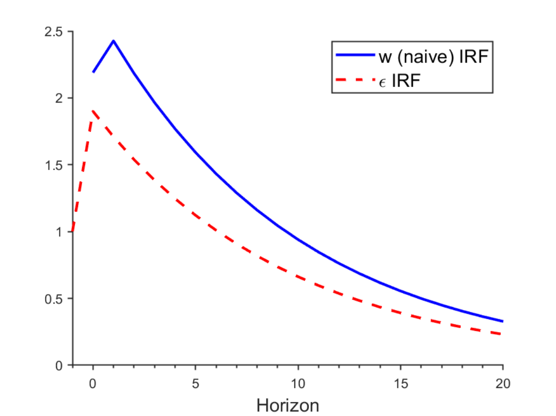
- Estimating x_t ARMA(1,1) IRF without forecasts

IRFs in the Simple Example



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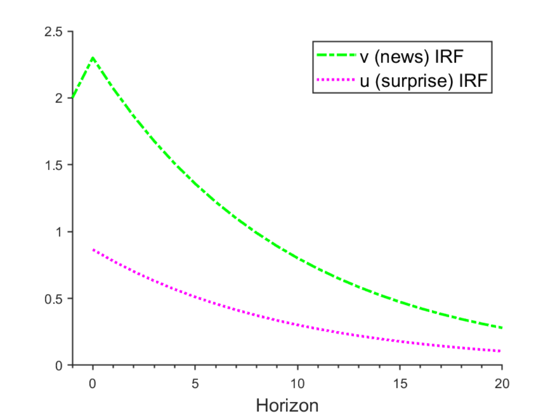

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- Estimating x_t ARMA(1,1) IRF without forecasts
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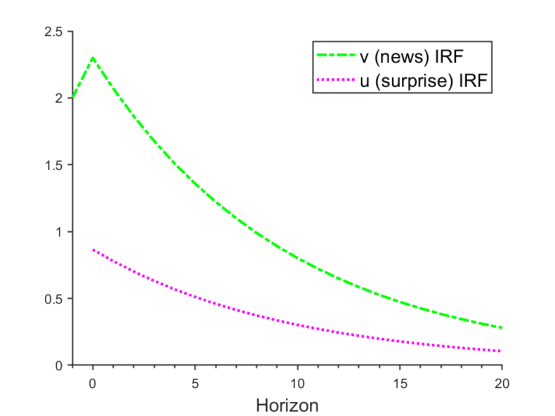
IRFs in the Simple Example



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- Estimating x_t ARMA(1,1) IRF without forecasts
- ... does not recover true (average) IRF to ϵ_t shock
- Including forecasts identifies news and surprise IRFs independently
- ... linear combination recovers the ϵ_t IRF

Baseline Series and Forecasts

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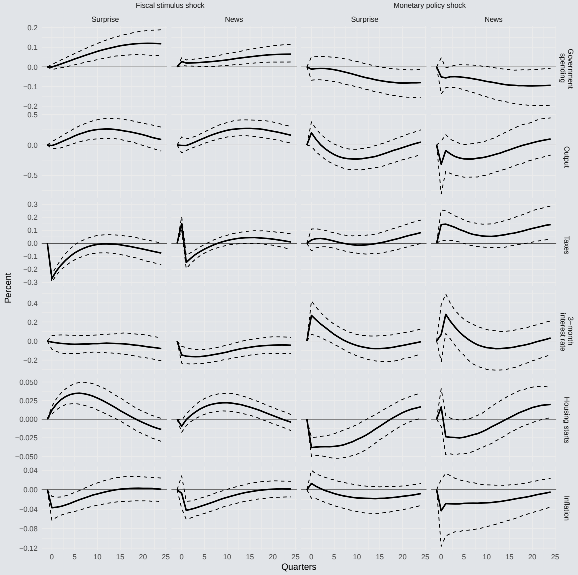
Policy Shock IRFs Decomposed



- News shock is scaled to be as if a unit SD surprise is expected in period 1.

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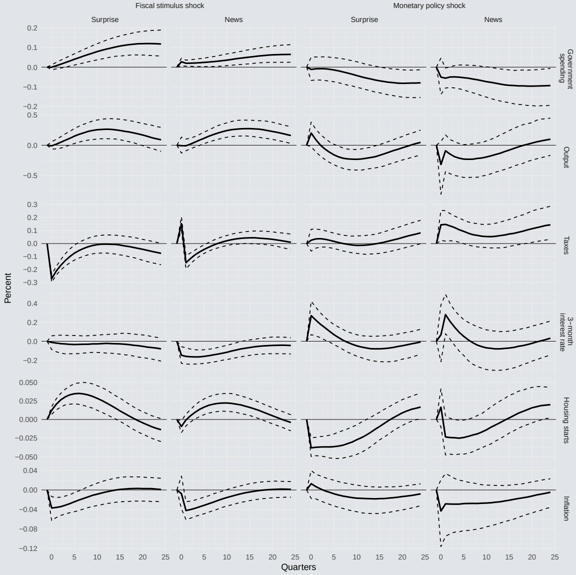

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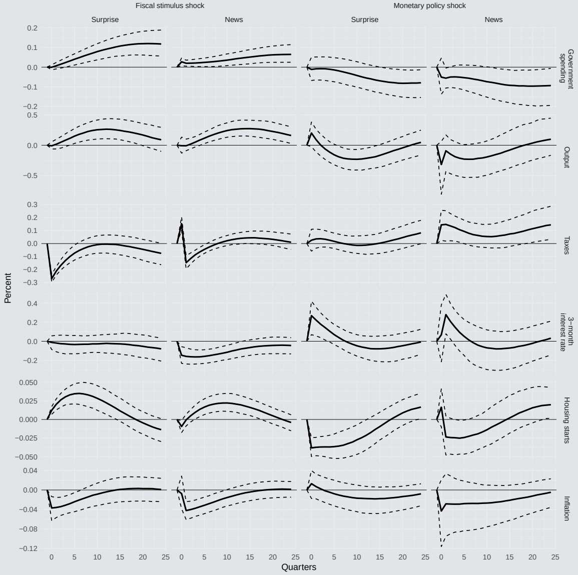

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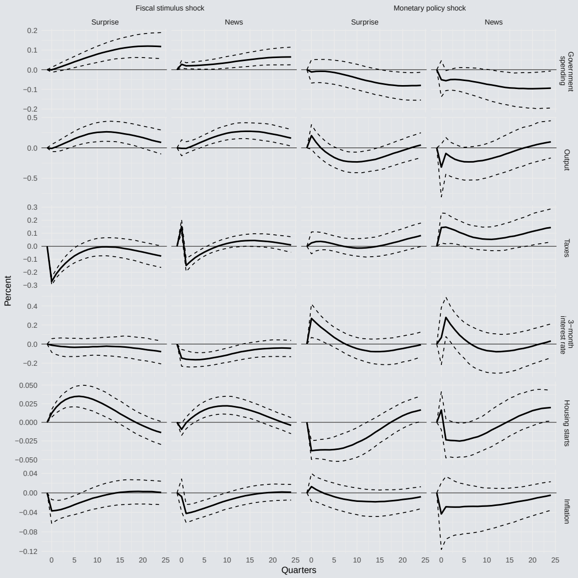

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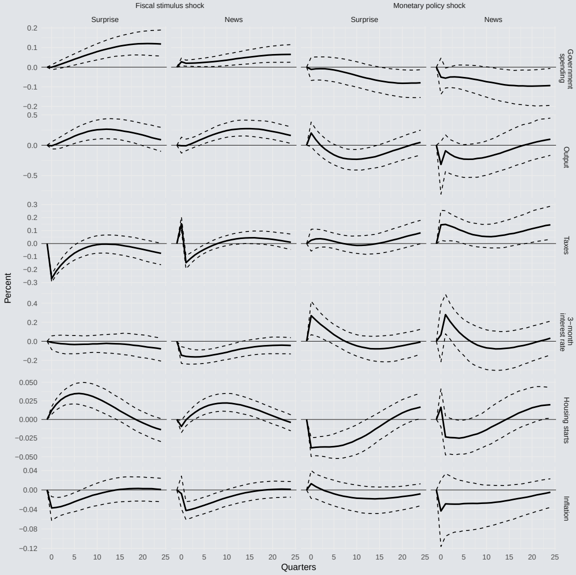

- News shock is scaled to be as if a unit SD surprise is expected in period 1.
- In the long run, responses look similar (sense check)
- Anticipation effects are non-negligible
  - Anticipated fiscal expansion (partly) pre-funded by taxes.
  - Monetary policy: no liquidity effect.

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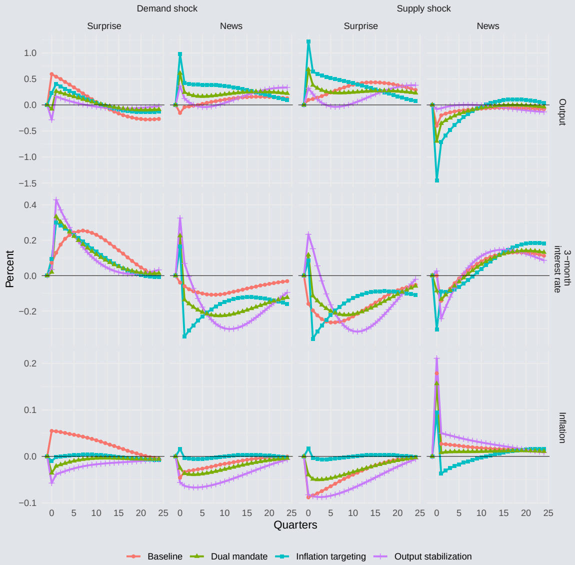
Monetary Policy Counterfactual: Business cycle stabilization



- Minimize one of three quadratic objective functions: weight on either inflation, output, or equally on both.
- Single objectives successfully implemented (not pre-baked).
- Demand surprises: raise rates to stabilize both output and inflation. (Demand news is tiny)
- Supply shocks: Cut (raise) interest rates to stabilize inflation (output).

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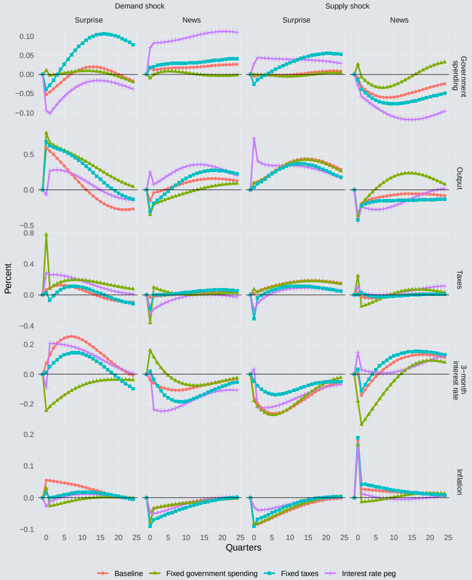
Passive Policy Counterfactual



- What if government spending was acyclical?
- Much harder to implement.
- Substantially more output volatility Inflation depends on the nature of the shock
- Current government spending behavior moderates business cycles?

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