Exchange Rate Disconnect Revisited

Ryan Chahrour
Cornell University & NBER

Vito Cormun
Santa Clara University

Pierre De Leo
U. of Maryland - College Park

Pablo Guerrón-Quintana
Boston College

Rosen Valchev
Boston College & NBER

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Exchange Rate Disconnect

Real exchange rate and macro fundamentals don't move together like they *should*.

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1. Determination Puzzle (Meese & Rogoff 83)

$$\text{corr}(\Delta q_t, \Delta f_t) \approx 0 \qquad \text{corr}(\Delta q_{t+1}, \Delta f_t) \approx 0$$

2. Uncovered Interest Parity (UIP) Puzzle (Fama 84)

$$\text{corr}(\Delta q_{t+1}, r_t - r_t^\star) \lesssim 0$$

3. Risk-sharing Puzzle (Backus & Smith 93)

$$\text{corr}(\Delta q_t, \Delta(c_t - c_t^\star)) \lesssim 0$$

4. Excess volatility and persistence in q_t (Rogoff 96)

$$\frac{\sigma(\Delta q_t)}{\sigma(\Delta y_t)} \approx 6$$

Exchange Rate Disconnect

- ◦ Much research on resolving these puzzles, but...
- ◦ Focus has been on structural approaches resulting in
  - different answers depending on the set of shocks
  - different answers depending on the target moments
  - little model-agnostic empirical evidence

⋆ Our question: Can we say more with less structure?

Summary of Results

- Real exchange rates are connected w. macro fundamentals
  - link between current q and future f
- Noisy news about future TFP explains over half of q_t.
  - realized TFP $\Rightarrow$ low-frequency, anticipation $\neq$ realization
  - noise $\Rightarrow$ high frequency, excess volatility
  - conditional responses of q_t reproduce famous puzzles
- Model with incomplete asset markets can explain facts
  - emphasizes demand channel for TFP
  - UIP deviations play central role

Literature

Empirical: Meese & Rogoff 83, Fama 84, Backus & Smith 93, Eichenbaum & Evans 95, Rogoff 96, Obstfeld and Rogoff (2000), Chari, Kehoe & McGrattan 02, Cheung, Ching & Pascual 02, Engel & West 05, Gourinchas & Rey 07, Engel, Mark & West 08, Chen, Rogoff & Rossi 10, Sarno & Schmelling 14, Nam & Wang 15, Siena 17, Stavrakeva & Tang 20, Alessandria & Choi 21, Miyamoto et al. 21

Theoretical Puzzle Solutions:

1. **Currency Excess returns:**
    - **Consumption Risk:** Verdelhan 10, Bansal & Shaliastovich 12, Colacito & Croce 13, Farhi & Gabaix 16
    - **Segmented Markets Risk:** Alvarez, Atkeson & Kehoe 09, Adrian, Etula & Shin 15, Gabaix and Maggiori 15, Camacho, Hau & Rey 18
    - **Behavioral biases:** Gourinchas & Tornell 04, Bacchetta & van Wincoop 06, Burnside et al. 11, Candian & De Leo 21
    - **Liquidity premia:** Engel 16, Valchev 20, Engel & Wu 20, Bianchi, Bigio & Engel 21
2. **Disconnect:** Engel & West 05, Bacchetta & Van Wincoop 06, Obstfeld & Rogoff 00, Eichenbaum et al. 20, Itskhoki & Mukhin 21, Kekre & Lenel 24
3. **Backus-Smith Puzzle:** Kocherlakota & Pistaferri 07, Corsetti, Dedola & Leduc 08, Benigno & Thoenissen 08, Colacito & Croce 13, Karabarbounis 14, Itskhoki

Empirical Approach

Overview

Three semi-structural techniques

$\hookrightarrow$ from fewer assumptions to more assumptions

1. Bivariate forecasting regressions
2. Descriptive VAR using "max-share" approach
3. VAR identification, based on fundamental/noise distinction

Data

Baseline: US & G6 aggregates from 1976:Q1-2008:Q2

- longer sample results don't change

Main variables:

1.	Exchange rate	$\ln(S_t)$
2.	US utilization-adj. TFP	$\ln(TFP_t)$
3.	US consumption	$\ln(C_t)$
4.	G6 consumption	$\ln(C_t^*)$
5.	US investment	$\ln(I_t)$
6.	G6 investment	$\ln(I_t^*)$
7.	Nominal interest rate differential	$\ln(\frac{1+i_t}{1+i_t^*})$
8.	Relative price	$\ln(CPI_t/CPI_t^*)$

Bivariate forecasting regressions

What predicts changes in RER?

$$\Delta q_t = \alpha + \beta_0 \Delta f_t + \sum_{k=1}^{h} \beta_{-k}^{\text{lag}} (\Delta f_{t-k}) + \sum_{k=1}^{h} \beta_{k}^{\text{lead}} (\Delta f_{t+k}) + \varepsilon_t$$

Bivariate forecasting regressions

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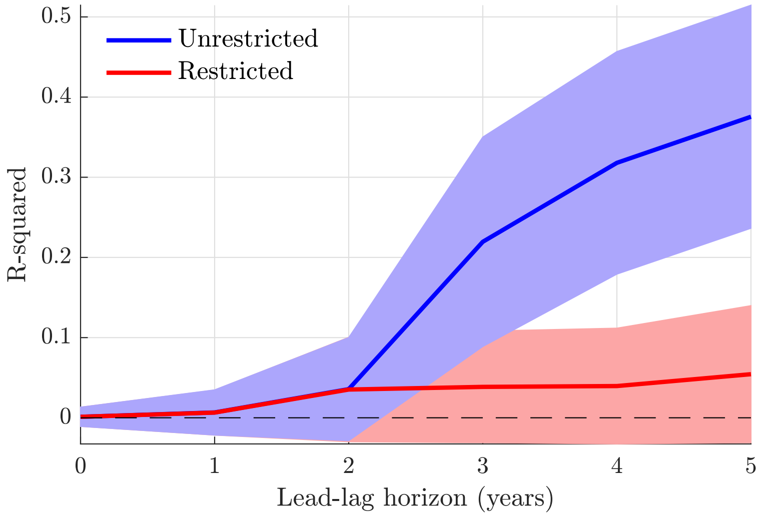
Similar to existing exercises, but...

1. two-sided
   $\hookrightarrow$ econometrician's super power!
2. longer horizons

Just going to show one of these...

Bivariate Forecasting Regression w. TFP



VAR: Max Share Approach

- Estimate a VAR

$$Y_t = B(L)Y_{t-1} + u_t$$

[Bayesian, 4 lags]

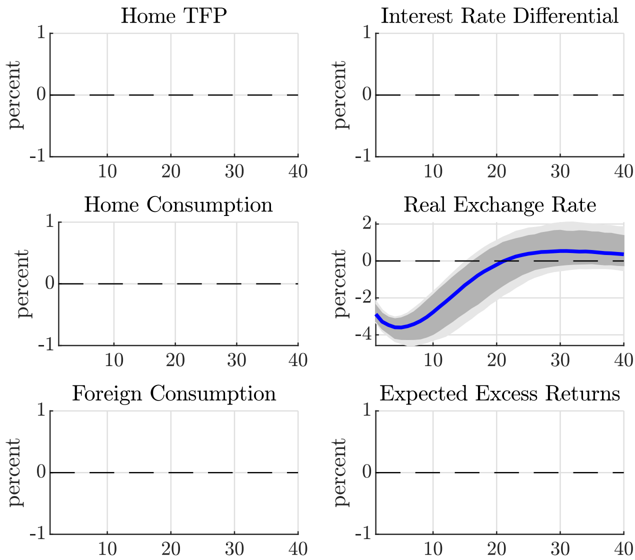
- Let

$$u_t = A\varepsilon_t, \qquad cov(\varepsilon_t) = I$$

⋆ Procedure: pick A s.t. $\varepsilon_{1,t}$ explains most of q_t

$$\begin{aligned} q_t &= \phi_q Y_t \\ &= \phi_q (I - B(L))^{-1} u_t \\ &= \phi_q (I - B(L))^{-1} A\varepsilon_t \end{aligned}$$

Conditional Dynamics – Max-Share (ε_1)



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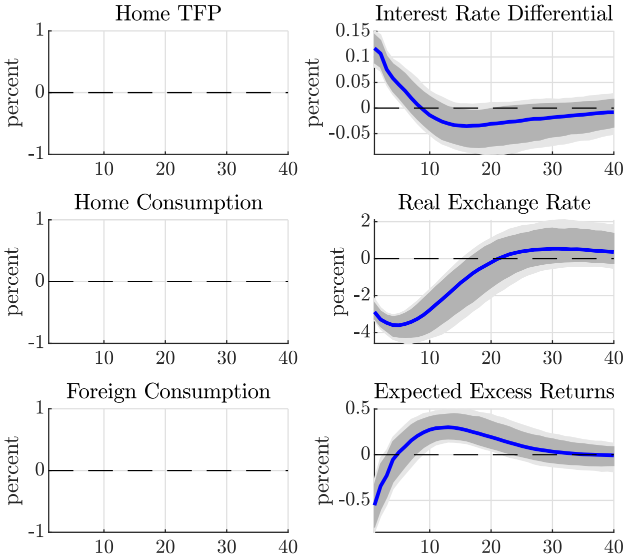

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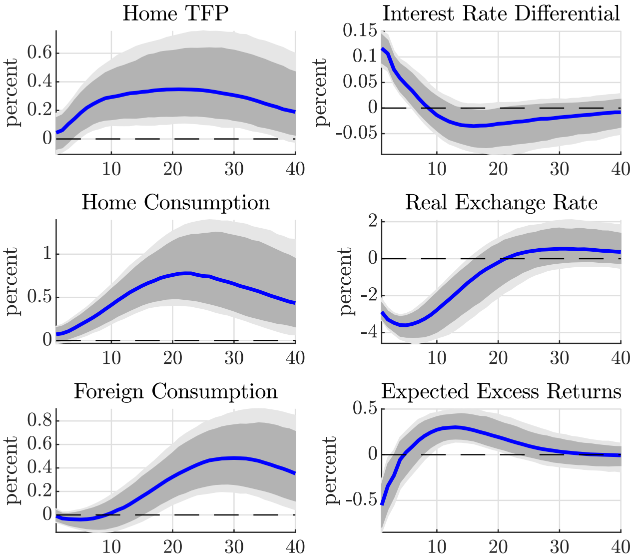

First Conclusions

- Strong link between current q and future f

Forecast Error Variance Decomposition

	Q1 Δ	Q4 Δ	Q12 Δ	Q24 Δ	Q40 Δ	Q100 Δ
Home TFP	0.03	0.06	0.20	**0.37**	**0.45**	**0.43**
Home Consumption	0.02	0.04	0.21	**0.47**	**0.51**	**0.40**
Foreign Consumption	0.01	0.04	0.06	**0.21**	**0.36**	**0.30**
Home Investment	**0.29**	**0.34**	**0.32**	**0.40**	**0.42**	**0.41**
Foreign Investment	0.06	0.08	0.15	0.22	0.34	0.33
Interest Rate Differential	0.40	0.39	0.30	0.34	0.35	0.39
Real Exchange Rate	**0.50**	**0.69**	**0.82**	**0.73**	**0.70**	**0.68**
Expected Excess Returns	0.47	0.33	0.34	0.44	0.45	0.47

- Specifically, a link to future TFP

$\Rightarrow$ **Next:** identify disturbances to TFP and TFP expectations

Identifying Expectations Channels

Identifying Expectations

Objective: Identify technological & expectational disturbances

Basic idea: Agents observe a_t & noisy signal about future a:

$$a_t = \sum_{k=0}^{\infty} \alpha_k \varepsilon^a_{t-k} \qquad \eta_t = \sum_{k=1}^{\infty} \zeta_k a_{t+k} + v_t \qquad v_t = \sum_{k=0}^{\infty} \nu_k \varepsilon^v_{t-k}$$

Goal: separately identify ε^a_t and ε^v_t

Identifying Expectations

Problem:

- Common view: "VAR methods not applicable"
- Noise information structures non-causal and non-invertible
- *Barsky & Sims 2012; Blanchard et al, 2013; etc.*

Solution: Chahrour & Jurado (RESTUD, 21)

- Focus on "recoverability"
- Relaxes invertibility
  - Past and future symmetric to econometrician
- Expand the scope of VAR methods to...cases exactly like this

Identifying Expectations

Assumptions:

0. Variables in the VAR span agents' information
1. Technological disturbances (ε_t^a) explain 100% of TFP
2. Expectational disturbances (ε_t^v) orthogonal to TFP at all leads & lags

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MA representation:

$$\begin{bmatrix} a_t \\ \eta_t \end{bmatrix} = \cdots + \begin{bmatrix} 0 & 0 \\ * & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_{t+1}^a \\ \varepsilon_{t+1}^v \end{bmatrix} + \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon_t^a \\ \varepsilon_t^v \end{bmatrix} + \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon_{t-1}^a \\ \varepsilon_{t-1}^v \end{bmatrix} + \cdots$$

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Compare to Cholesky:

$$\begin{bmatrix} a_t \\ \eta_t \end{bmatrix} = \cdots + \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_{t+1}^a \\ \varepsilon_{t+1}^v \end{bmatrix} + \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon_t^a \\ \varepsilon_t^v \end{bmatrix} + \begin{bmatrix} * & * \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon_{t-1}^a \\ \varepsilon_{t-1}^v \end{bmatrix} + \cdots$$

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No more (or less) restrictive than traditional VAR

Identifying Expectations

Do not need to observe agents' actual signals η_t or beliefs

Macro variables & asset prices forward looking:

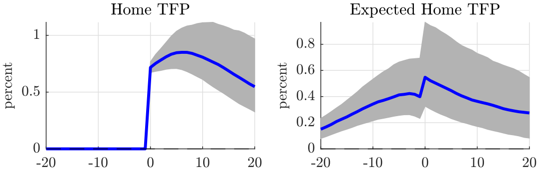
$$y_t = \chi E_t(a_{t+1}) + \dots$$

$\Rightarrow$ VAR captures agents' expectations of future TFP, $E_t(a_{t+k})$

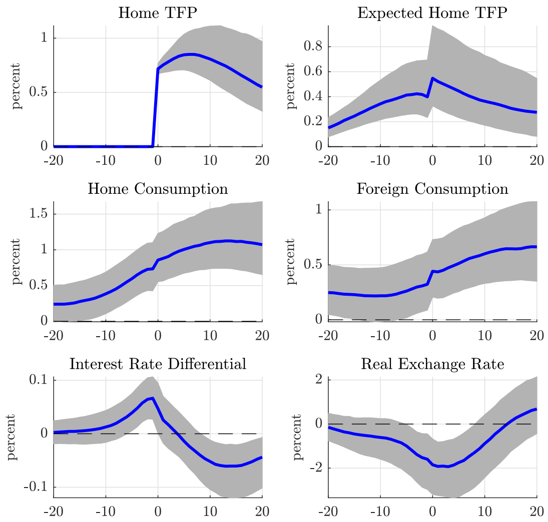
Decompose expectation into

a. Component that realizes $\rightarrow$ portion of $E_t(a_{t+k})$ related to ε^a_{t+k}
b. Component that doesn't $\rightarrow$ portion of $E_t(a_{t+k})$ driven by ε^v_{t+k}

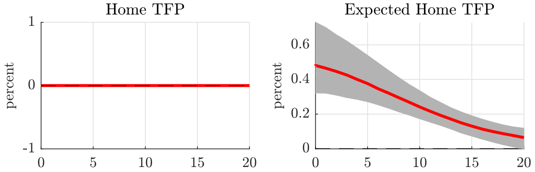
TFP Disturbances Are Partially Anticipated



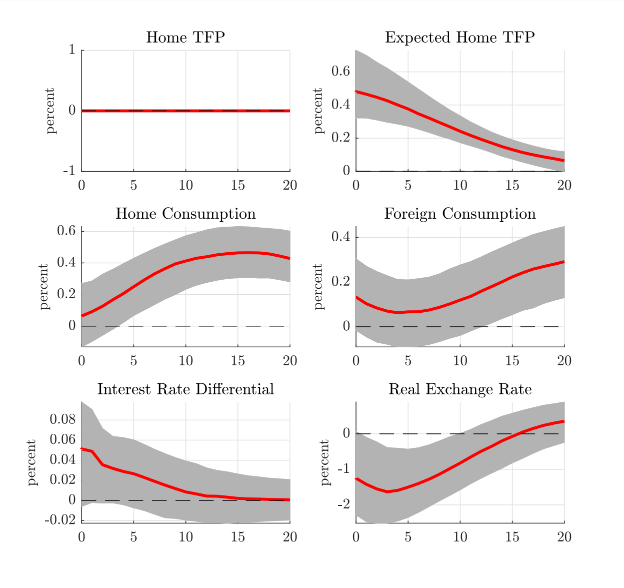
TFP Disturbances Lead to Hump-Shaped RER Appreciation



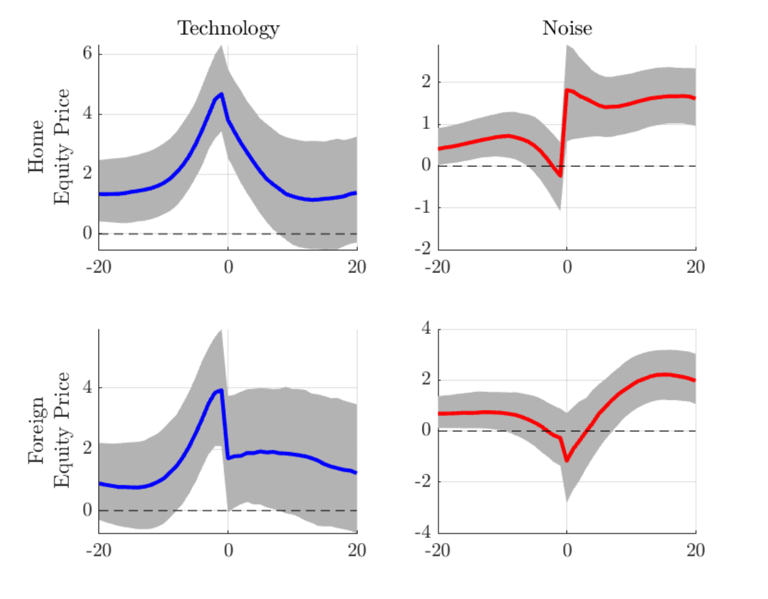
Noise Disturbances Affect Expectations But Not Future TFP



Noise Disturbances Have Demand-Like Effects



Equity price responses



Variance Decomposition

Not disconnected: shocks drive *both* FX and international bus. cycles

Variance Decomposition (2-100Q frequency)

	Both	Technology	Exp. Noise
Home TFP	1.00		
Home Consumption	**0.70**		
Foreign Consumption	**0.63**		
Home Investment	0.62		
Foreign Investment	0.68		
Interest Rate Differential	0.57		
Real Exchange Rate	**0.64**		
Expected Excess Returns	0.50		

Variance Decomposition

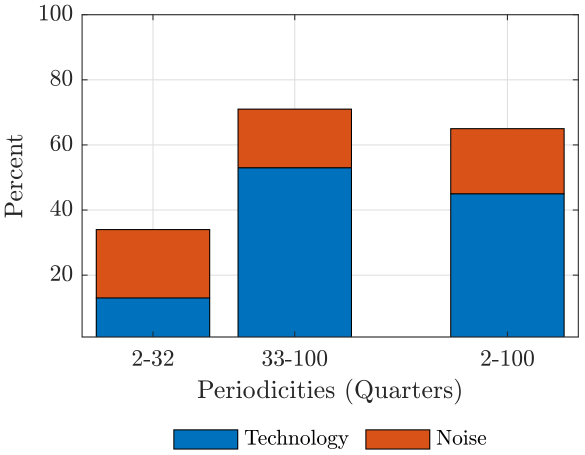
Variance Decomposition (2-100Q frequency)

	Both	Technology	Exp. Noise
Home TFP	1.00	1.00	0.00
Home Consumption	**0.70**	**0.54**	**0.16**
Foreign Consumption	**0.63**	**0.49**	**0.14**
Home Investment	0.62	0.46	0.15
Foreign Investment	0.68	0.43	0.25
Interest Rate Differential	0.57	0.46	0.11
Real Exchange Rate	**0.64**	**0.45**	**0.20**
Expected Excess Returns	0.50	0.35	0.15

More on Role of Expectations

Noise Matters More at Higher Frequencies

Variance Decomposition of Real Exchange Rate



Conditional responses exhibit RER puzzles

Define excess currency return as

$$\lambda_{t+1} \equiv q_{t+1} - q_t + r_t^* - r_t$$

Traditional **UIP regressions:**

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Define excess currency return as

$$\lambda_{t+1} \equiv q_{t+1} - q_t + r_t^* - r_t$$

Traditional **UIP regressions:**

$$\lambda_{t+1} = \alpha_{UIP} + \beta_{\mathbf{UIP}}(r_t - r_t^*) + \varepsilon_{t+1}$$

	Unconditional	Both	Technology	Noise
β_{UIP}	**-2.43**	**-2.20**	**-2.07**	**-2.96**

Conditional responses exhibit RER puzzles

Define excess currency return as

$$\lambda_{t+1} \equiv q_{t+1} - q_t + r_t^* - r_t$$

Traditional **UIP regressions:**

$$\sum_{k=0}^{\infty} \mathbb{E}_t(\lambda_{t+k+1}) = \alpha_\Lambda + \beta_{\boldsymbol{\Lambda}}(r_t - r_t^*) + \varepsilon_t$$

	Unconditional	Both	Technology	Noise
β_{UIP}	-2.43	-2.20	-2.07	-2.96
β_Λ	**2.56**	**2.50**	**2.17**	**1.72**

Conditional responses exhibit RER puzzles

Backus-Smith correlation:

$$\text{corr}(\Delta q_t, \Delta(c_t - c_t^\star))$$

	Unconditional	Both	Technology	Noise
β_{UIP}	-2.43	-2.20	-2.07	-2.96
β_Λ	2.56	2.50	2.17	1.72
corr$(\Delta q_t, \Delta(c_t - c_t^\star))$	**-0.27**	**-0.35**	**-0.31**	**-0.38**

Conditional responses exhibit RER puzzles

Excess Volatility and Persistence:

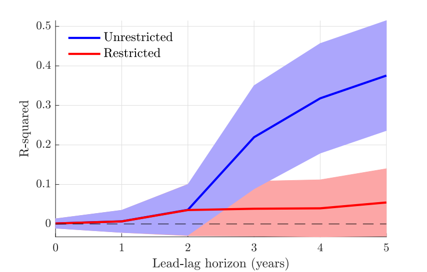
$$\sigma(\Delta q_t)/\sigma(\Delta c_t), \quad \text{autocorr}(\Delta q_t)$$

	Unconditional	Both	Technology	Noise
β_{UIP}	-2.43	-2.20	-2.07	-2.96
β_{Λ}	2.56	2.50	2.17	1.72
$\text{corr}(\Delta q_t, \Delta(c_t - c_t^{\star}))$	-0.27	-0.35	-0.31	-0.38
$\sigma(\Delta q_t)/\sigma(\Delta c_t)$	**6.04**	**5.65**	**3.99**	**8.14**
autocorr(Δq_t)	**0.29**	**0.58**	**0.90**	**0.33**

Granger Causality

In practice, TFP is virtually a random walk $\rightarrow$ can interpret first reduced-form exercise as local projection...

$$\Delta q_t = \alpha + \beta_0 \Delta TFP_t + \sum_{k=1}^{h} \beta_{-k}^{lag} (\Delta TFP_{t-k}) + \sum_{k=1}^{h} \beta_k^{lead} (\Delta TFP_{t+k}) + \varepsilon_t$$



...but this is not the usual direction of Granger causality tests.

Granger Causality Test

H_0 : Δq does not Granger Cause ΔTFP

P-values from a Wald test excluding future TFP up to h years

	CAN	FRA	DEU	ITA	JPN	UK	G7
$h = 1$	0.92	0.78	0.61	0.97	0.65	0.64	0.95
$h = 2$	0.11	0.86	0.57	0.67	0.80	0.80	0.99
$h = 3$	0.20	0.04**	0.09*	0.00***	0.17	0.00***	0.09*
$h = 4$	0.17	0.05**	0.10*	0.02**	0.09*	0.04**	0.21
$h = 5$	0.11	0.00***	0.00***	0.03**	0.00***	0.04**	0.00***

- RER Granger-causes future TFP at long horizons (3–5 years)
- Previous studies examine $h = 1$ (e.g. Engel & West 05)
- Does not mean that Δq Granger causes any f

$\Delta TFP_t \rightarrow \Delta q_{t+h}$

Robustness and Other Results

- Results in extended sample (1976-2018) Extended Sample
- Results across G7 countries CAN FRA DEU ITA JPN UK
- Results using VECM (assumes q and $r - r^{\star}$ are stationary) VECM
- Responses of other variables Trade Balance Stock Prices
- R&D Expenditures R&D
- Correlation with monetary shocks Monetary shocks
- Results without FX in VAR No FX
- Responses to TFP surprises TFP shock

Implications for Theory

What does noisy news do in theory?

Approach

- Noisy info structure that matches the dynamics of $\mathbb{E}_t(a_{t+k})$
- Two-country endowment economies

Markets	**Preferences**	**Examples**
Complete	CRRA	Backus-Kehoe-Kydland 94
Complete	Epstein-Zin	Colacito-Croce 11, 13
Incomplete	CRRA	Itskhoki-Mukhin 21, Kekre-Lenel 24
Incomplete	CRRA +	variable home-bias, Bodenstein-al 2025

⋆ **Question:** Do these models match our empirical results?

Summary of Models

1. Complete markets
   - CRRA preferences over aggregate consumption
   - exogenous endowment of home good
   - CES preferences between *home* & *foreign* goods
   - home bias parameter $\varsigma > 0.5$
2. Recursive utility
   - Epstein-Zin preferences over aggregate consumption
3. Incomplete markets
   - CRRA preferences over aggregate consumption
   - trade only one risk-free bond
   - interest rate depends on NFA position (elasticity $= \phi$)
4. Incomplete markets +
   - home bias parameter ς related to TFP

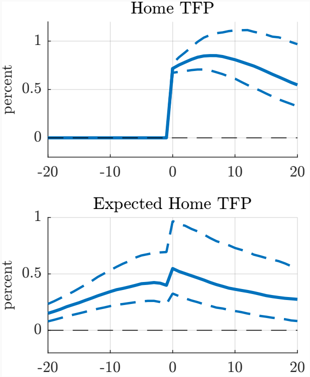
$$\varsigma_t = \varsigma \left(\frac{A_t}{\frac{1}{2}A_t + \frac{1}{2}A_t^\star} \right)^\vartheta, \qquad \varsigma_t^\star = \varsigma \left(\frac{A_t^\star}{\frac{1}{2}A_t + \frac{1}{2}A_t^\star} \right)^\vartheta$$

Parameterization

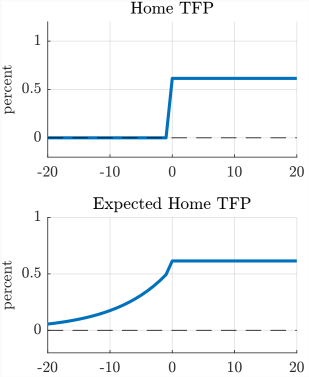
Parameter	Description	Complete Markets		Incomplete Markets	
		CRRA	EZ	CRRA	CRRA +
Preferences					
β	Subjective Discount Factor	0.99	0.99	0.99	0.99
γ	Relative Risk Aversion	5	5	5	5
ψ	Elas. of Intertemporal Subs.	$1/\gamma$	1.5	$1/\gamma$	$1/\gamma$
ς	Home Bias	0.95	0.95	0.95	0.95
σ	Trade Elasticity	1	1	1	1
ϕ	Elas. of Interest Rate Prem.	-	-	0.01	0.01
ϑ	Time-varying Home Bias	-	-	-	0.35

Notes: Models are parameterized to quarterly frequency. All other parameters are set to standard values. The parameter φ is estimated through impulse response matching.

- “Noise representation” of Blanchard et al, 2012
  ↪ 3 free parameters



Fundamental - Data



Fundamental - Theory

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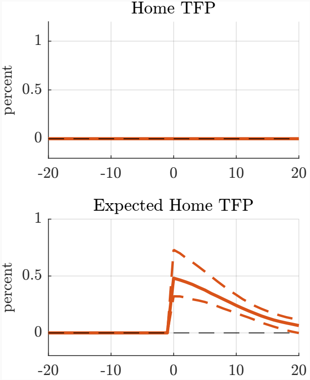
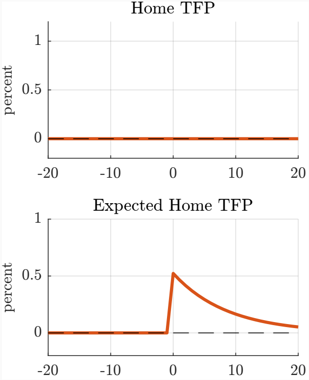
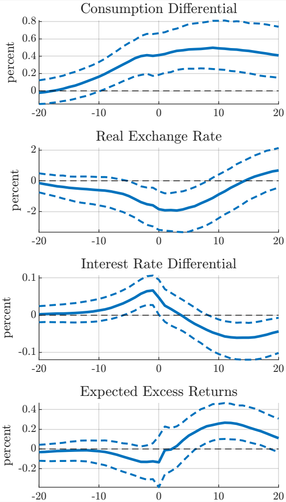


Noise - Data

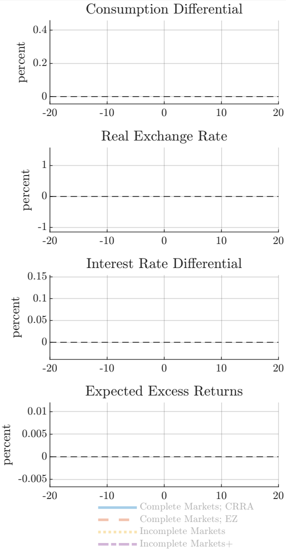


Noise - Theory

Model Comparison - Realized Productivity

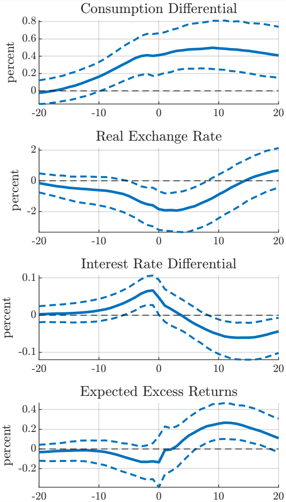


Data

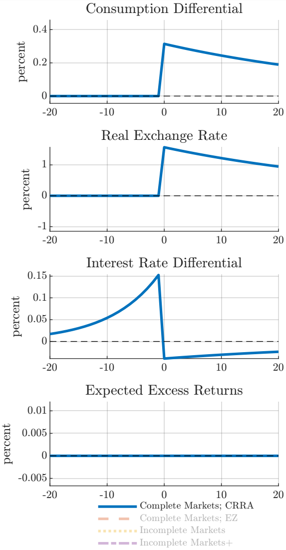


Theory

Model Comparison - Realized Productivity

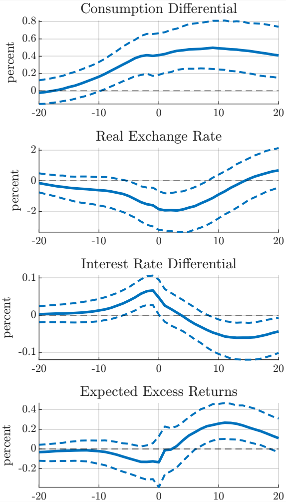


Data



Theory

Model Comparison - Realized Productivity



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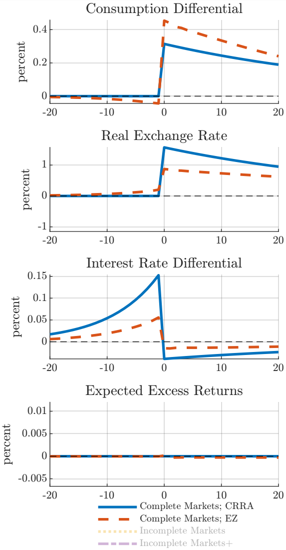
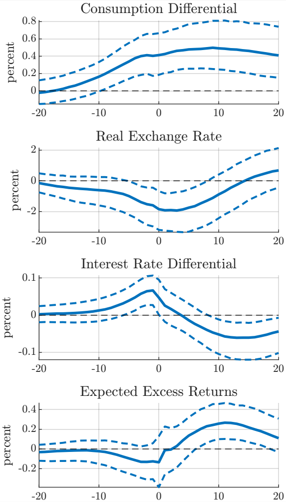


Theory

Model Comparison - Realized Productivity



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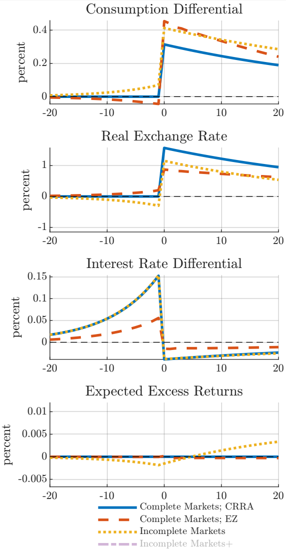
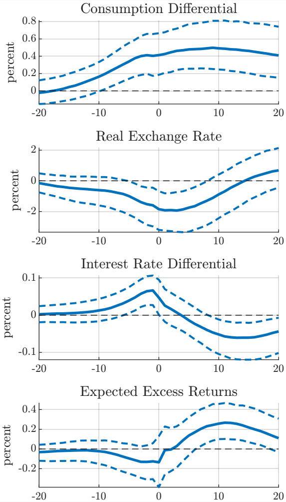
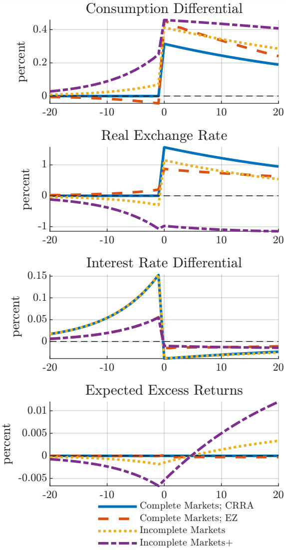


Theory

Model Comparison - Realized Productivity



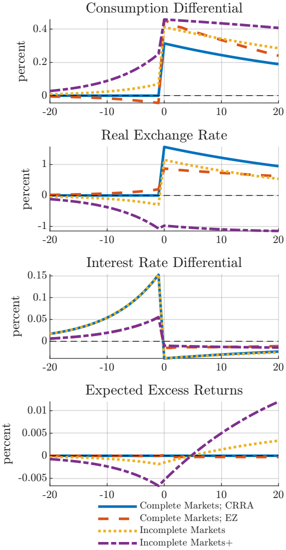
Data



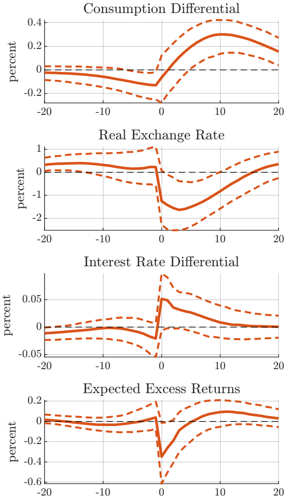
Theory

Model Comparison - Realized Productivity

$$q_t = \gamma(c_t - c_t^*) - \phi \sum_{j=1}^{\infty} E_t b^{\star}_{t+j}$$



Model Comparison - Expectational Noise



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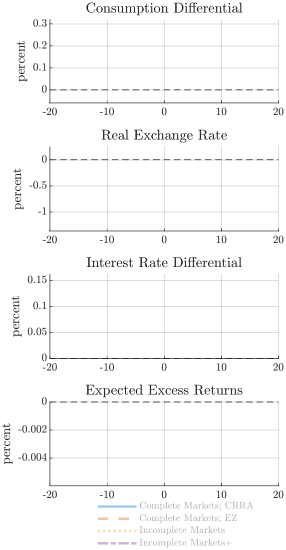
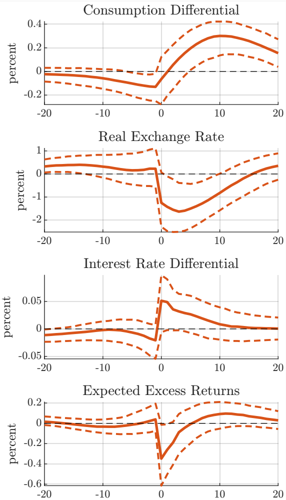


Theory

Model Comparison - Expectational Noise



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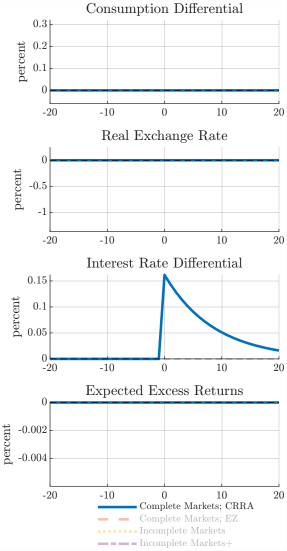
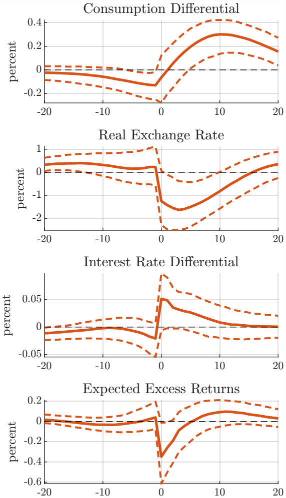


Theory

Model Comparison - Expectational Noise



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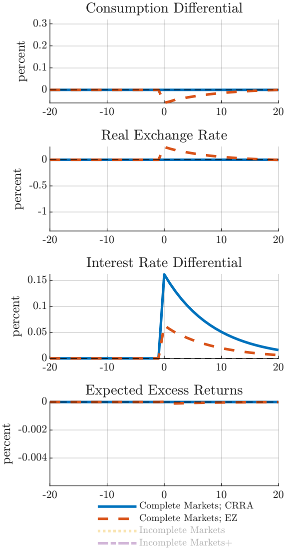
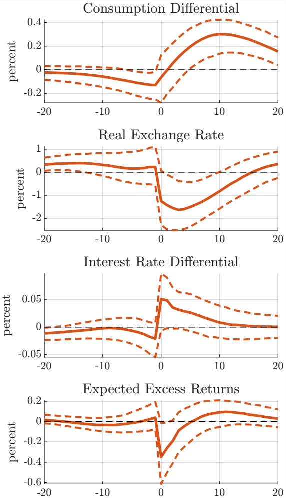
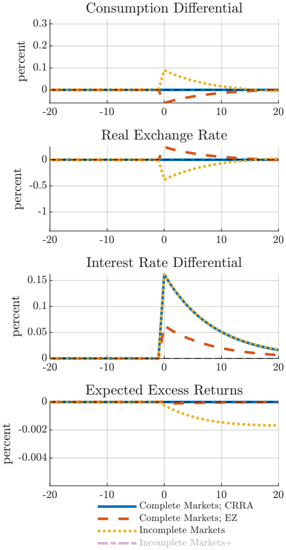


Theory

Model Comparison - Expectational Noise

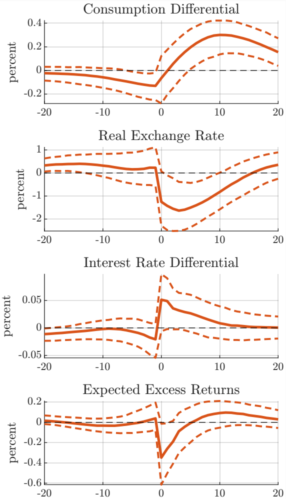


Data

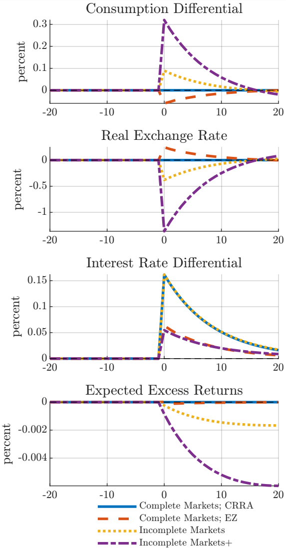


Theory

Model Comparison - Expectational Noise



Data



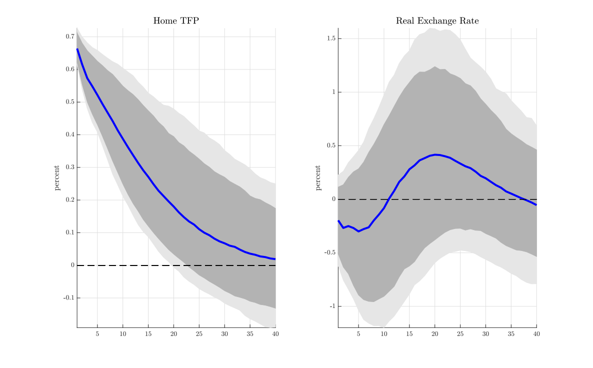
Theory

Conclusion

- Exchange rates are connected to macro fundamentals!
  - Productivity expectations drive both q_t & macro aggregates (incl. stock prices)
  - RER puzzles have a common fundamental origin
  - Expectational noise important for shorter-run flucs.

- Implications for theory
  - Fundamental theories of exchange rates still relevant
  - Incomplete markets + demand channel improve model match
  - *Endogenous* UIP wedge important (Itskhoki & Mukhin 22)

Cholesky TFP

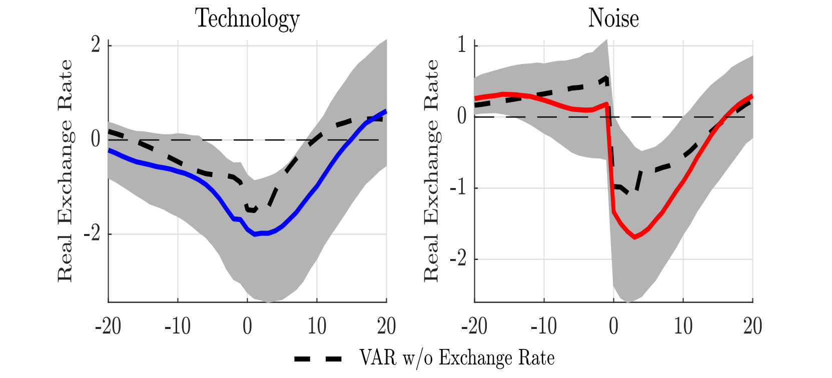


- Cholesky-identified TFP shock assumed ε_t^a is complete surprise
  - Surprise-TFP shocks have no impact on q_t

Return

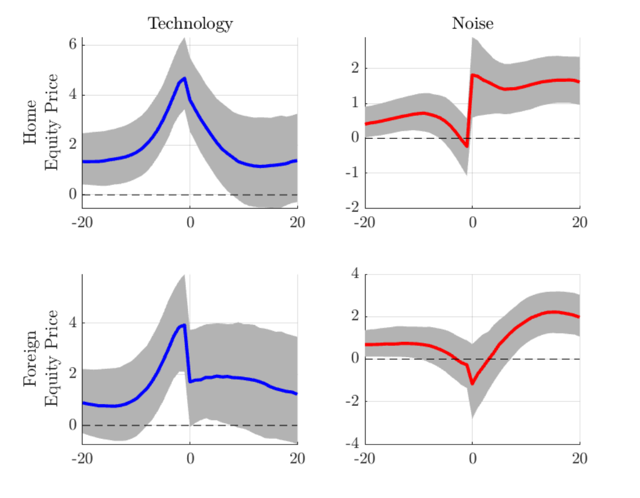
VAR without FX

- We redo our analysis dropping q_t from the VAR set
  - Extracted shocks correlation is 0.99



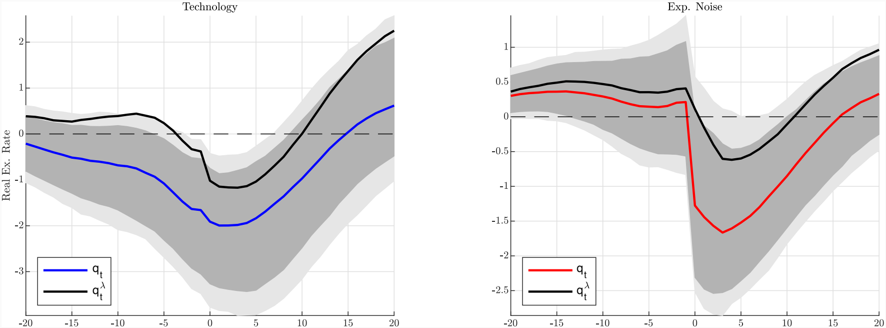
Return

Response of stock prices



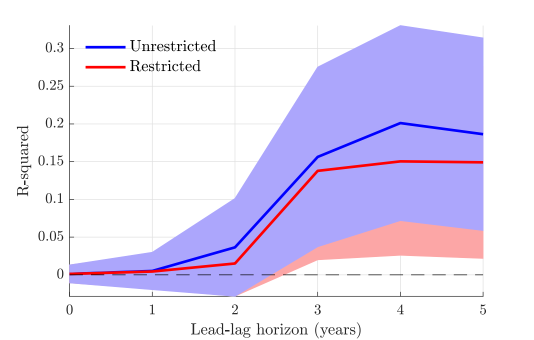
Return

Impulse responses: q_t^{UIP} vs q_t^{λ}



Return

$$\Delta TFP_t = \alpha + \beta_0 \Delta q_t + \sum_{k=1}^{h} \beta_{-k}^{lag} (\Delta q_{t-k}) + \sum_{k=1}^{h} \beta_{k}^{lead} (\Delta q_{t+k}) + \varepsilon_t$$



More on Granger Causality

H_0 : ΔTFP does not Granger Cause Δq

P-values from a Wald test excluding future q up to h years

	CAN	FRA	DEU	ITA	JPN	UK	G7
h = 1	0.67	0.76	0.82	0.89	0.99	0.96	0.90
h = 2	0.39	0.80	0.76	0.63	0.99	0.20	0.75
h = 3	0.39	1.00	1.00	0.85	0.81	0.75	0.95
h = 4	0.07*	0.62	0.71	0.44	0.82	0.83	0.44
h = 5	0.00***	0.83	0.88	0.49	0.70	0.97	0.76

Return

Variance Decomposition (Reduced-form Approach)

	Q1 Δ	Q4 Δ	Q12 Δ	Q24 Δ	Q40 Δ	Q100 Δ
Home TFP	0.03	0.06	0.20	0.37	0.45	0.43
Home Consumption	0.02	0.04	0.21	0.47	0.51	0.40
Foreign Consumption	0.01	0.04	0.06	0.21	0.36	0.30
Home Investment	0.29	0.34	0.32	0.40	0.42	0.41
Foreign Investment	0.06	0.08	0.15	0.22	0.34	0.33
Interest Rate Differential	0.40	0.39	0.30	0.34	0.35	0.39
Real Exchange Rate	0.50	0.69	0.82	0.73	0.70	0.68
Expected Excess Returns	0.47	0.33	0.34	0.44	0.45	0.47
Real Exchange Rate Changes	0.50	0.49	0.47	0.49	0.49	0.51

Share of forecast error variance explained by the Main FX shock (ε_1)

Return

FX Decomposition

Using the definition of expected excess returns:

$$E_t \lambda_{t+1} = E_t(q_{t+1}) - q_t - (r_t - r_t^\star)$$

We can rearrange:

$$q_t = E(q_{t+1}) - (r_t - r_t^\star) - E_t \lambda_{t+1}$$

And solve forward:

$$q_t = \underbrace{-\sum_{k=0}^{\infty} E_t(r_{t+k} - r_{t+k}^\star)}_{=q_t^{UIP}} \underbrace{-\sum_{k=0}^{\infty} E_t \lambda_{t+k+1}}_{=q_t^{\lambda}}$$

Anticipated vs surprise in fundamentals

- Our empirical procedure allows us to identify the following representation of the exchange rate

$$q_t|\{\varepsilon_t^a, \varepsilon_t^v\} = \sum_{k=-\infty}^{\infty} \zeta_k^q \varepsilon_{t+k}^a + \sum_{k=0}^{\infty} \zeta_k^v \varepsilon_{t-k}^v$$

$$= \underbrace{\sum_{k=1}^{\infty} \zeta_k^q \varepsilon_{t+k}^a + \sum_{k=0}^{\infty} \zeta_k^v \varepsilon_{t-k}^v}_{\text{Forward-looking/expectational comp}} + \sum_{k=0}^{\infty} \zeta_k^q \varepsilon_{t-k}^a$$

Var Decomposition: Forward-looking vs backward-looking components

	Fwd-looking	Bkwd-looking
q_t	0.29	0.71
Δq_t	0.69	0.31

Return

Identifying Expectations

Problem:

- Noise information structures are generically non-causal and non-invertible
- Common view: "VAR methods not applicable"
- Barsky & Sims 2012; Blanchard et al, 2013; etc.

Solution: Chahrour & Jurado (RESTUD, 21)

- Relax these assumptions
  - Past and future symmetric to econometrician
- Focus on "recoverability"
- Expand the scope of VAR methods to...exactly cases like this

Return

MA Representation

MA representation:

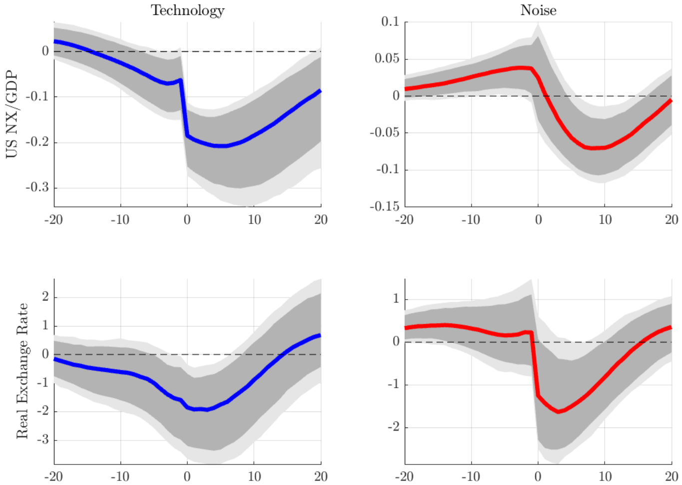
$$\begin{bmatrix} a_t \\ \eta_t \end{bmatrix} = \cdots + \begin{bmatrix} 0 & 0 \\ * & 0 \end{bmatrix} \begin{bmatrix} \varepsilon^a_{t+1} \\ \varepsilon^v_{t+1} \end{bmatrix} + \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon^a_{t} \\ \varepsilon^v_{t} \end{bmatrix} + \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon^a_{t-1} \\ \varepsilon^v_{t-1} \end{bmatrix} + \cdots$$

Compare to Cholesky:

$$\begin{bmatrix} a_t \\ \eta_t \end{bmatrix} = \cdots + \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon^a_{t+1} \\ \varepsilon^v_{t+1} \end{bmatrix} + \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon^a_{t} \\ \varepsilon^v_{t} \end{bmatrix} + \begin{bmatrix} * & * \\ * & * \end{bmatrix} \begin{bmatrix} \varepsilon^a_{t-1} \\ \varepsilon^v_{t-1} \end{bmatrix} + \cdots$$

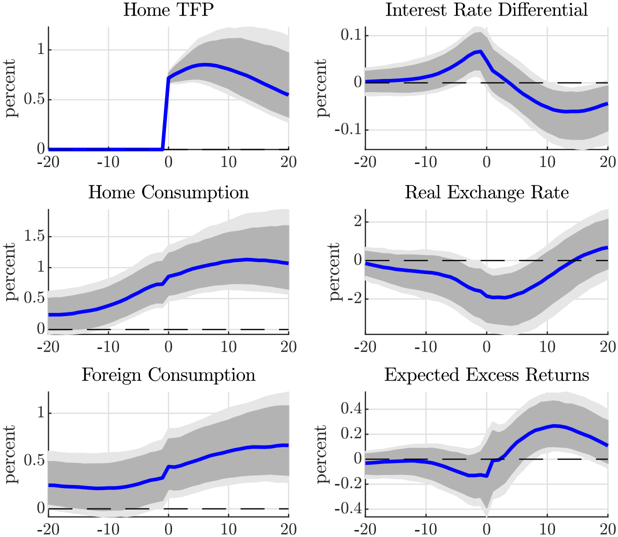
Return

Trade Balance and Exchange Rate

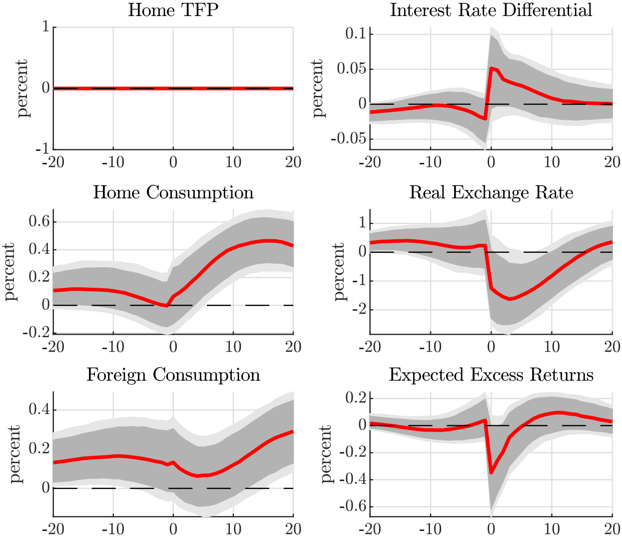


Return

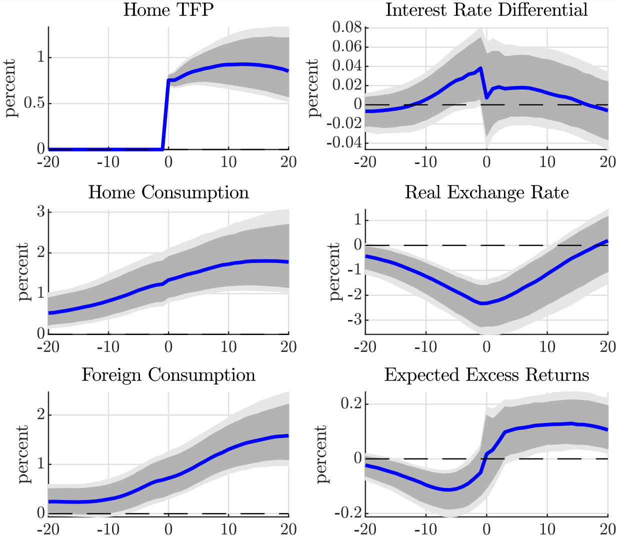
Conditional Dynamics – Technology (ε^a) – Extended Sample



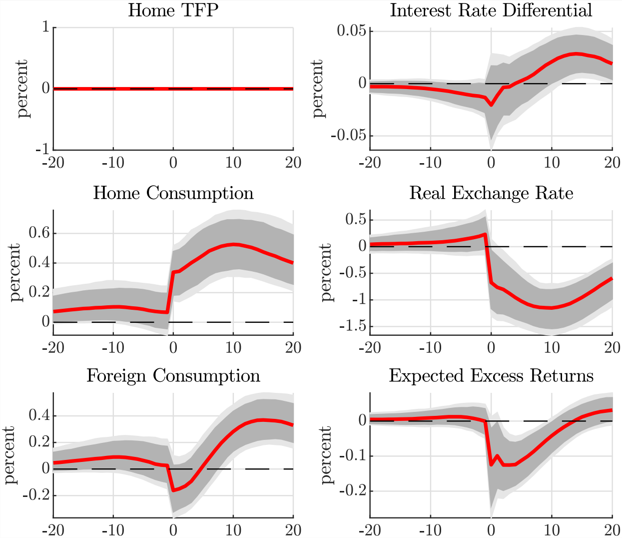
Conditional Dynamics – Expectational noise (ε^v)– Extended Sample



Conditional Dynamics – Technology (ε^a) – Canada

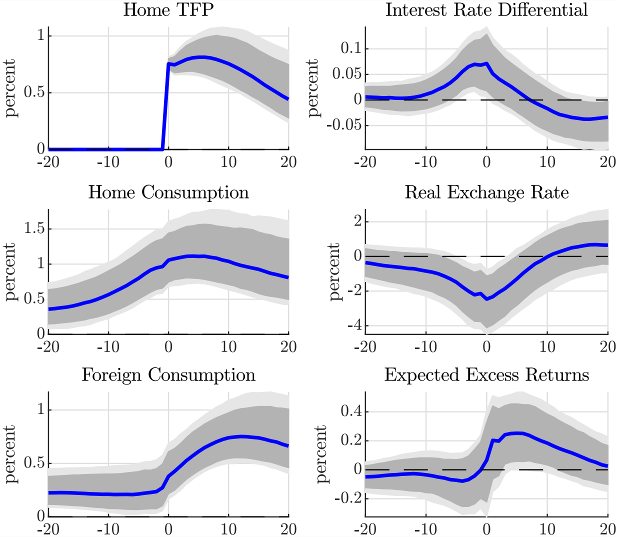


Conditional Dynamics – Expectational noise (ε^{v})– Canada

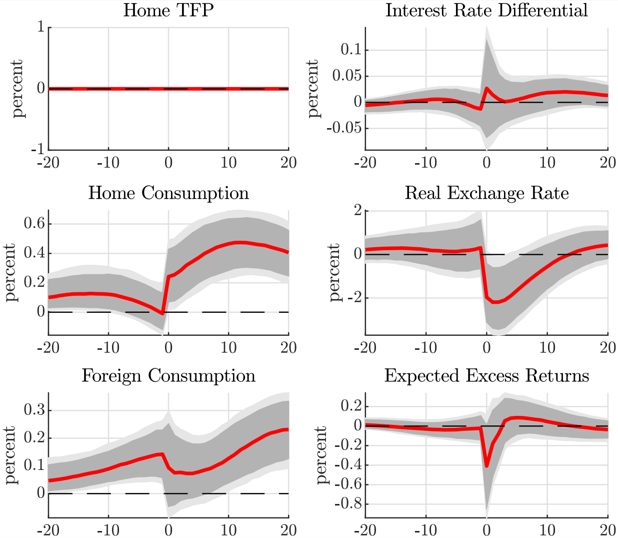


Return

Conditional Dynamics – Technology (ε^a) – France

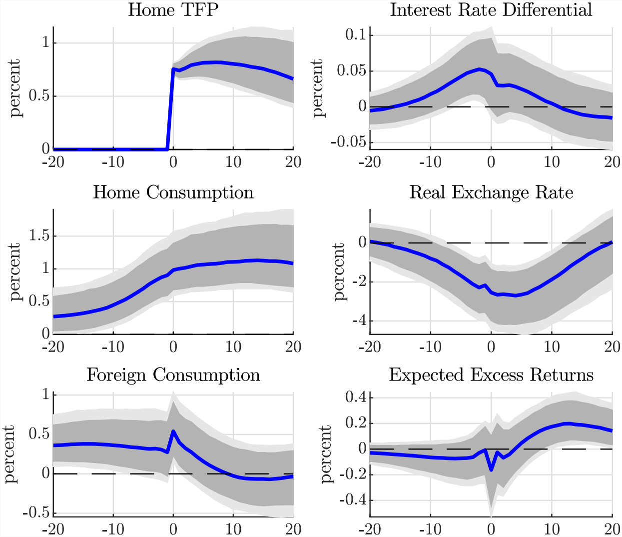


Conditional Dynamics – Expectational noise (ε^v)– France

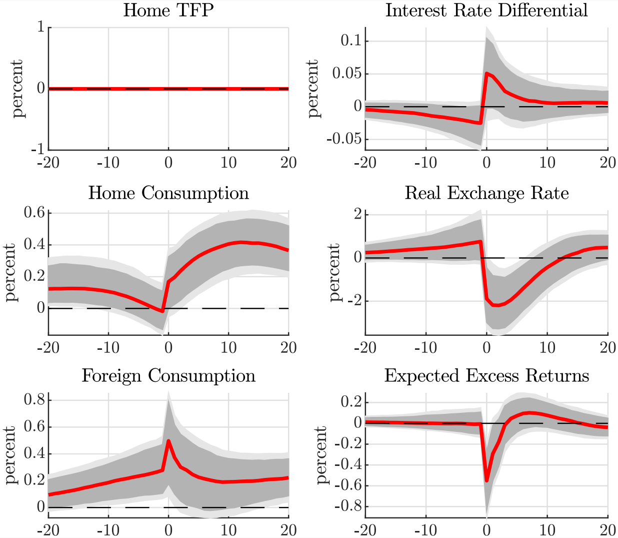


Return

Conditional Dynamics – Technology (ε^a) – Germany

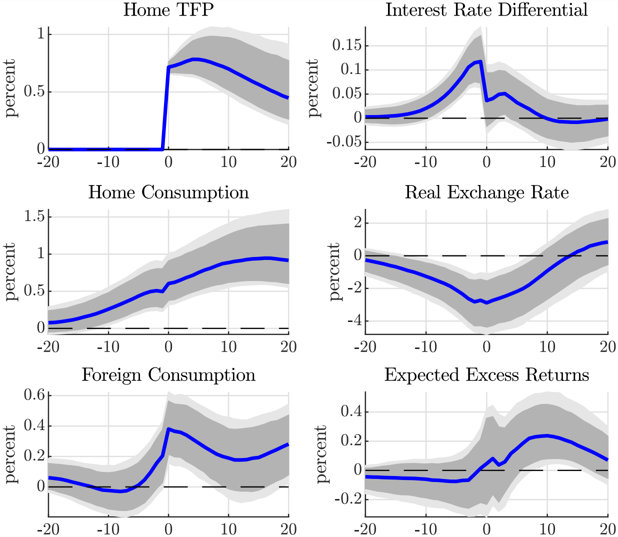


Conditional Dynamics – Expectational noise (ε^v)– Germany

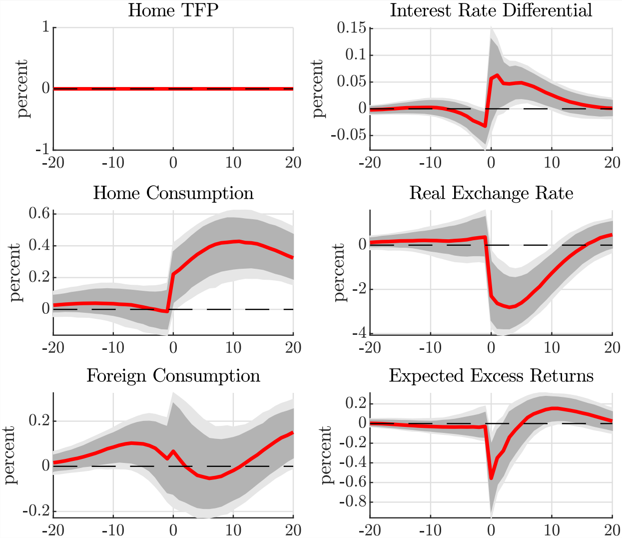


Return

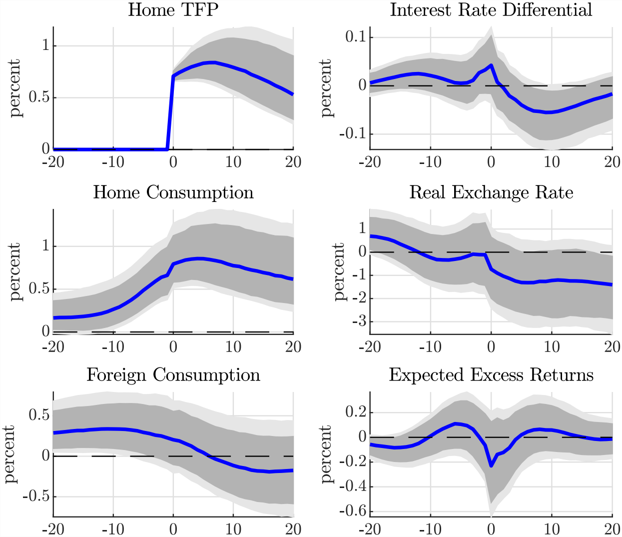
Conditional Dynamics – Technology (ε^a) – Italy



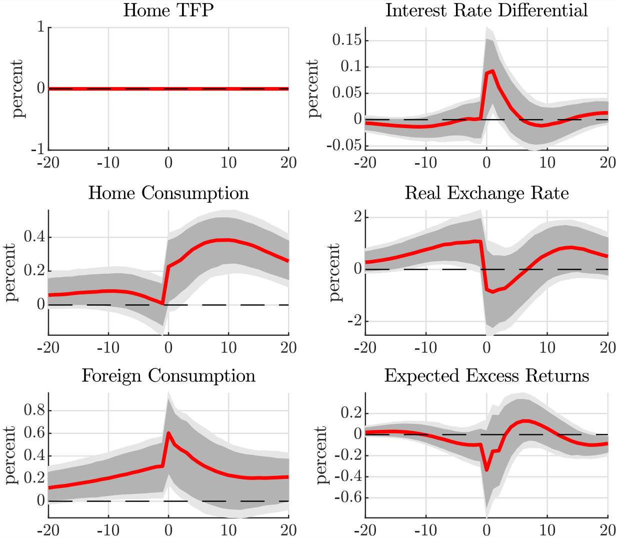
Conditional Dynamics – Expectational noise (ε^v)– Italy



Conditional Dynamics – Technology (ε^a) – Japan

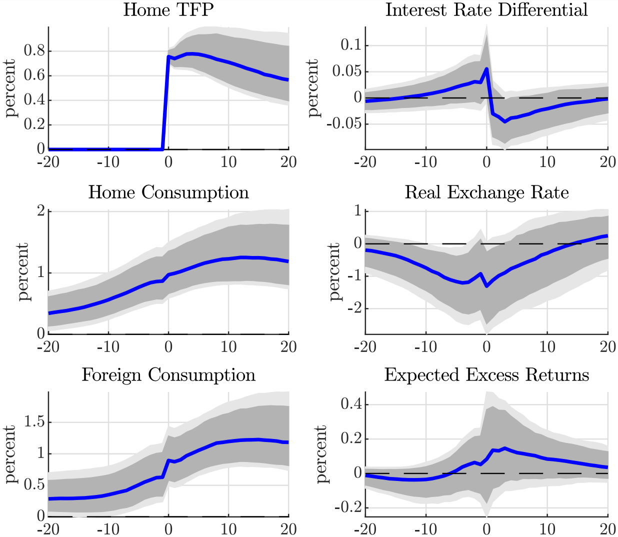


Conditional Dynamics – Expectational noise (ε^v)– Japan

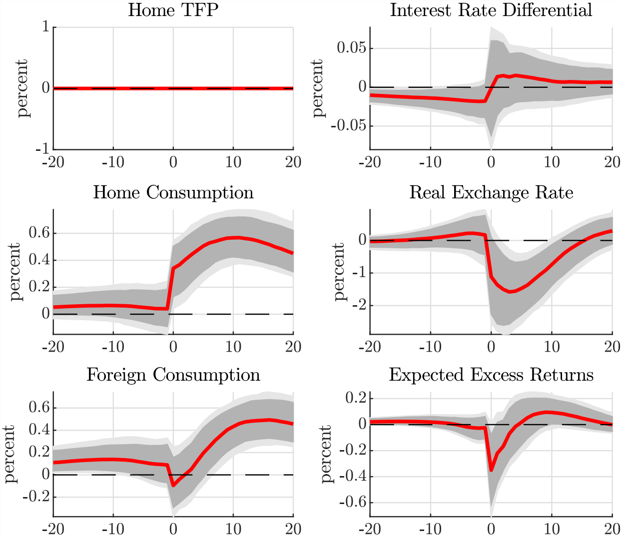


Return

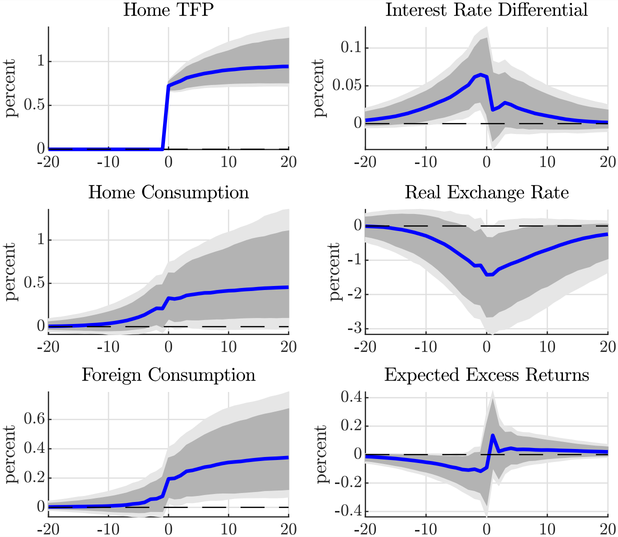
Conditional Dynamics – Technology (ε^a) – United Kingdom



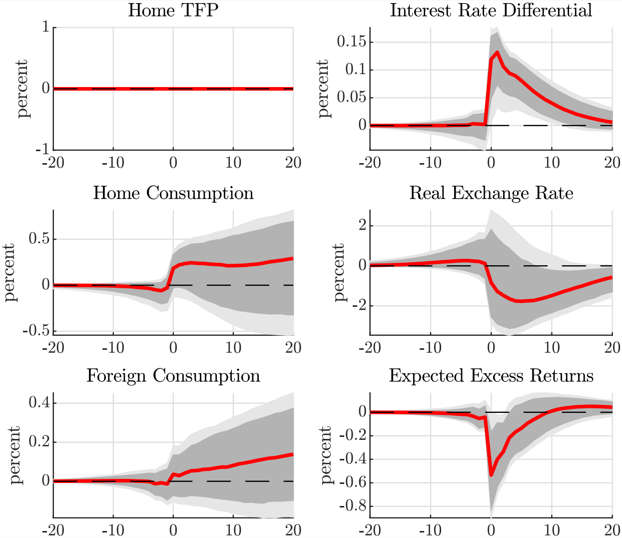
Conditional Dynamics – Expectational noise (ε^v)– United Kingdom



Conditional Dynamics – Technology (ε^a) – VECM

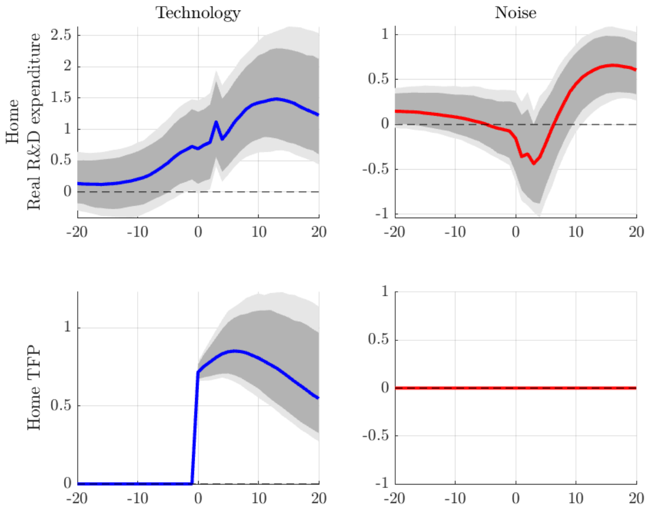


Conditional Dynamics – Expectational noise (ε^v)– VECM



Return

Conditional Dynamics – R&D Expenditure



Return

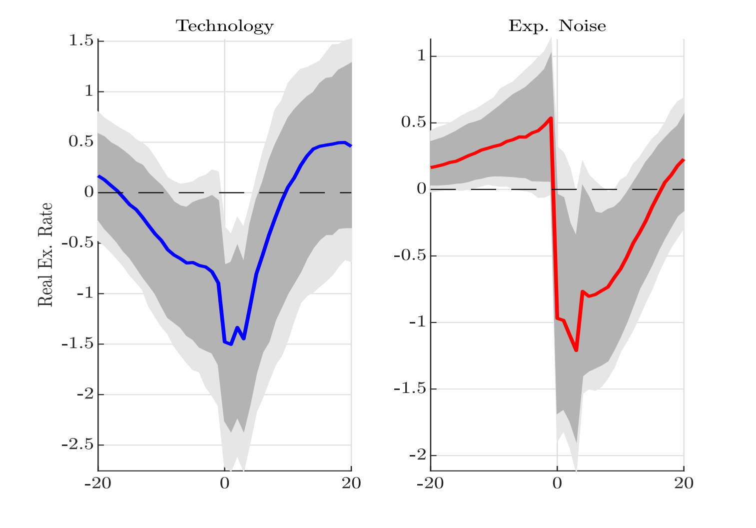
Correlation with monetary policy shocks

Correlation between Technology, Noise and Other Economic Shocks

	Technology	Exp. Noise
U.S. Monetary Policy Shocks	0.09	0.06
	p-value $= 0.46$	*p-value* $= 0.62$

Return

Conditional Dynamics – no FX in VAR



Return