The Transmission of Monetary Policy Shocks

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Seventh BIS Research Network meeting
Basel - March 9, 2018

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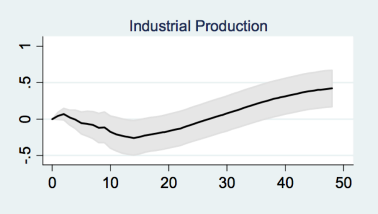
Ramey (2017)



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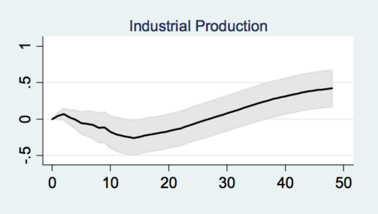

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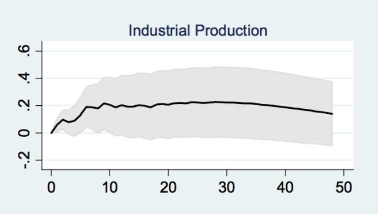

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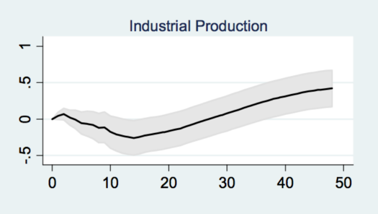

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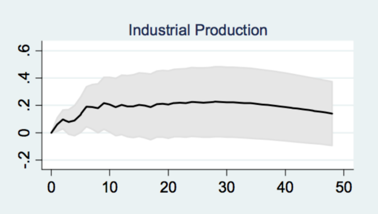

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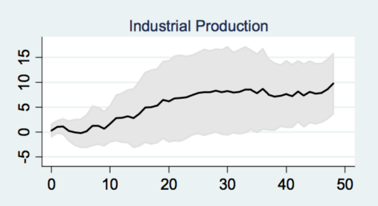

(c) GK Proxy LP 90-12

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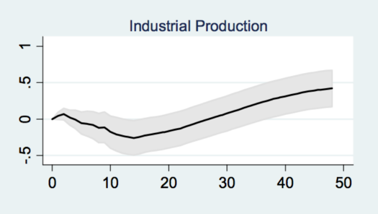

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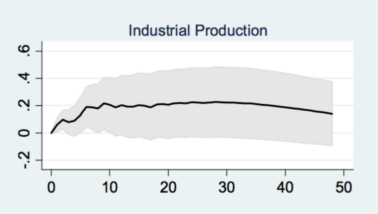

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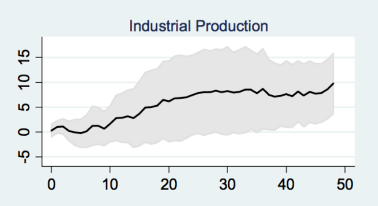

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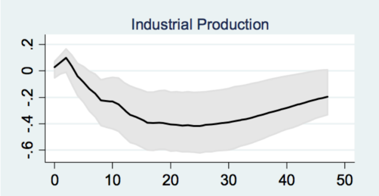

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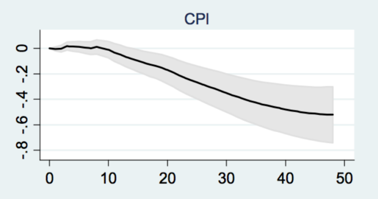

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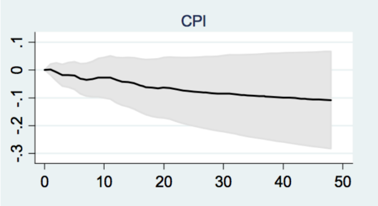

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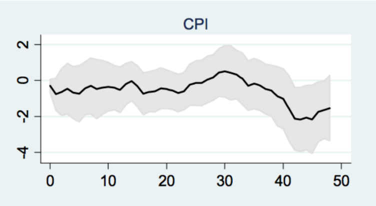

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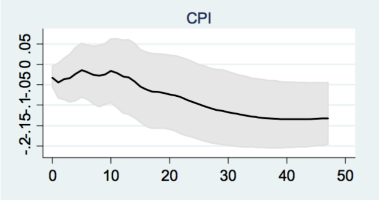

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1. Evidence of **information frictions** in leading MP instruments

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Following a Contractionary Monetary Policy Shock
economic activity and prices contract: **no puzzles**

The Identification Problem

- **Interest rate hike** to informationally constrained agents
  1. **MP shock**
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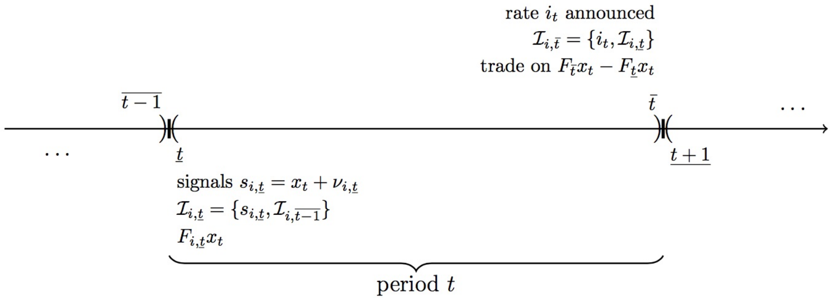
- Market surprises blend MP shocks with current and past macro shocks!
  $\Longrightarrow$ **price and output puzzles**

The HF Identification



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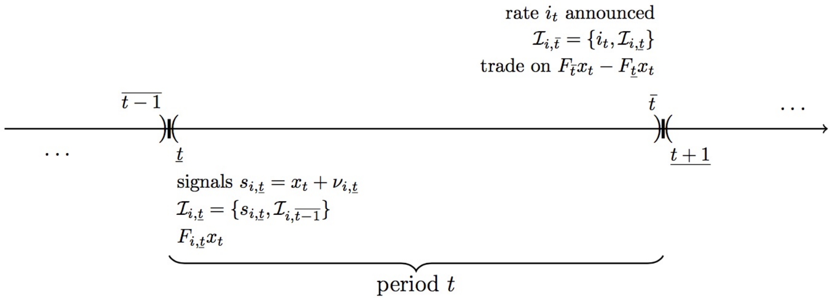

Expectation Revision

$$\underbrace{F_{\bar{t}} x_t - F_{\underline{t}} x_t}_{\text{Exp. Revision at } t} = \underbrace{\kappa_x \left(F_{\overline{t-1}} x_t - F_{\underline{t-1}} x_t \right)}_{\text{Exp. Revision at } t-1}$$

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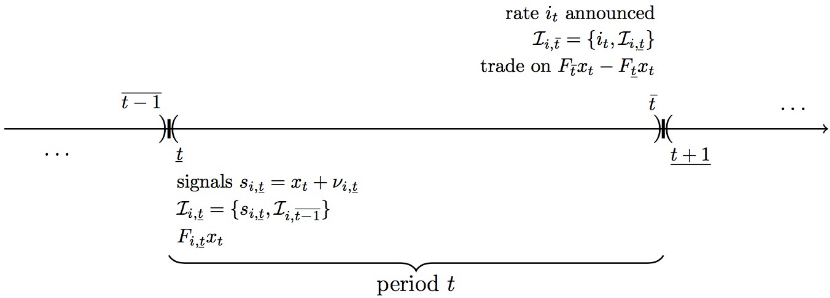

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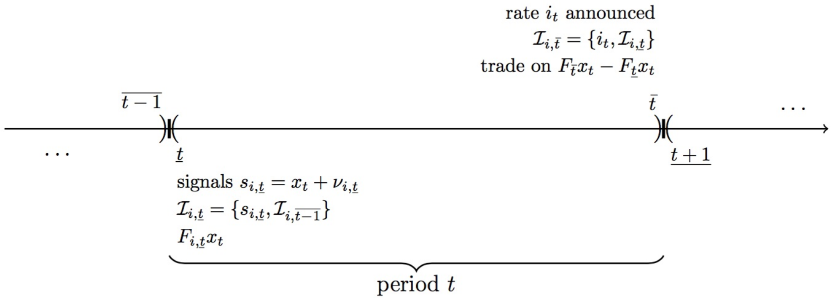

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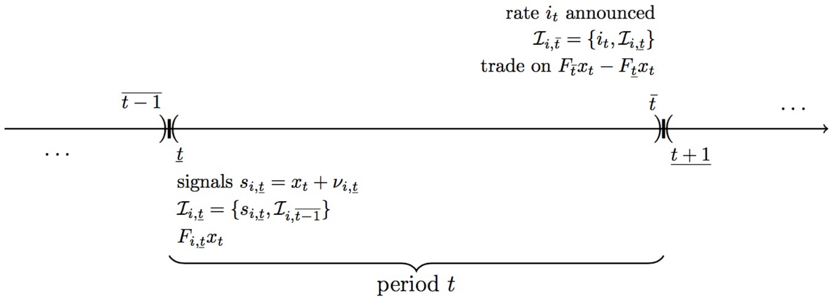

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	$\mathbf{FF4_t}$			$\mathbf{FF4_t^{GK}}$			$\mathbf{MPN_t}$		
AR(4)	2.219 [0.272]*			10.480 [0.000]***			16.989 [0.000]***		
Greenbook Forecast		2.287 [0.011]**			3.377 [0.000]***			–	
Greenbook Revision			2.702 [0.007]***			3.719 [0.000]***			–
R^2	0.021	0.080	0.129	0.142	0.068	0.100	0.237	–	–
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	$\mathbf{FF4_t}$		$\mathbf{FF4_t^{GK}}$		$\mathbf{MPN_t}$	
$f_{1,t-1}$	-0.012	[-1.97]*	-0.011	[-2.74]***	-0.103	[-4.13]***
$f_{2,t-1}$	0.001	[0.38]	0.004	[1.79]*	-0.005	[-0.45]
$f_{3,t-1}$	0.002	[0.41]	-0.001	[-0.23]	-0.035	[-2.21]**
$f_{4,t-1}$	0.015	[2.09]**	0.008	[1.92]*	0.068	[2.71]***
$f_{5,t-1}$	0.002	[0.26]	0.001	[0.12]	0.017	[0.61]
$f_{6,t-1}$	-0.011	[-2.19]**	-0.007	[-2.58]**	0.008	[0.57]
$f_{7,t-1}$	-0.010	[-1.69]*	-0.006	[-1.40]	-0.053	[-2.85]***
$f_{8,t-1}$	-0.001	[-0.35]	0.001	[0.32]	-0.042	[-2.38]**
$f_{9,t-1}$	-0.002	[-0.59]	-0.002	[-0.53]	-0.037	[-1.65]
$f_{10,t-1}$	0.004	[0.75]	0.000	[-0.03]	-0.030	[-2.54]**
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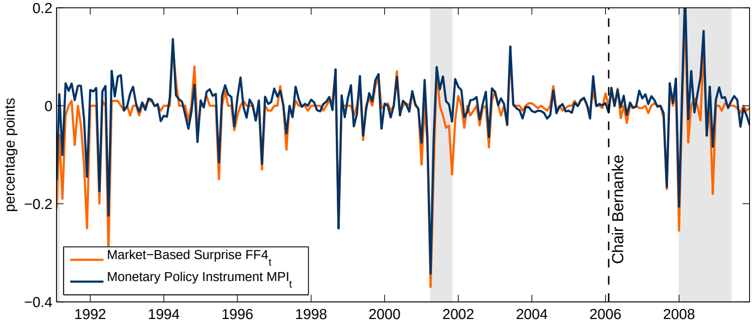
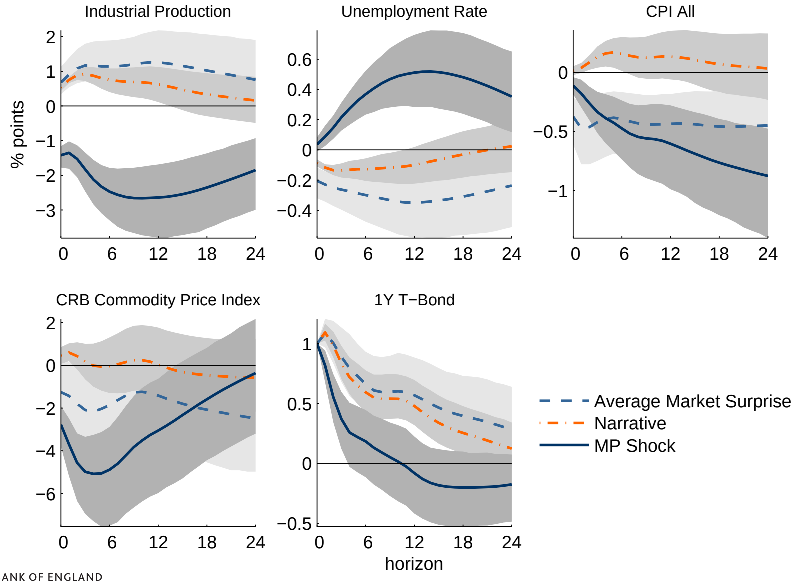
Monetary Policy Instrument



$$mps_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i mps_{t-i} + \varrho F_t^{cb} u_{q+0} + \sum_{j=-1}^{3} \rho_j F_t^{cb} x_{q+j} + \sum_{j=-1}^{2} \theta_j \left[F_t^{cb} x_{q+j} - F_{t-1}^{cb} x_{q+j} \right] + MPI_t$$

Puzzles #1: Identification



VAR-IRFS

$$y_{t+1} = By_t + u_{t+1}$$

$$\text{IRF}_h^{VAR} = B^h A_0^{-1}$$

- optimal and consistent only if the VAR captures the DGP

The Bias-Variance Tradeoff

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LP-IRFS

$$y_{t+h} = \widetilde{B}^{(h)} y_t + v_{t+h}$$

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- robust to misspecification but high estimation uncertainty

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- Selecting between the two methods: empirical problem choosing between **bias** and **estimation variance**...
  (Schorfheide, 2005)

↓

standard tradeoff in Bayesian estimation!

BLP: Intuition

- Discipline LP with VAR prior on pre-sample

BLP POSTERIOR MEAN

$$B_{BLP}^{(h)} \propto \left(X'X + \left[\Omega_0^{(h)}(\lambda^{(h)})\right]^{-1}\right)^{-1} \left((X'X)B_{LP}^{(h)} + \left[\Omega_0^{(h)}(\lambda^{(h)})\right]^{-1} B_{VAR}^{h}\right)$$

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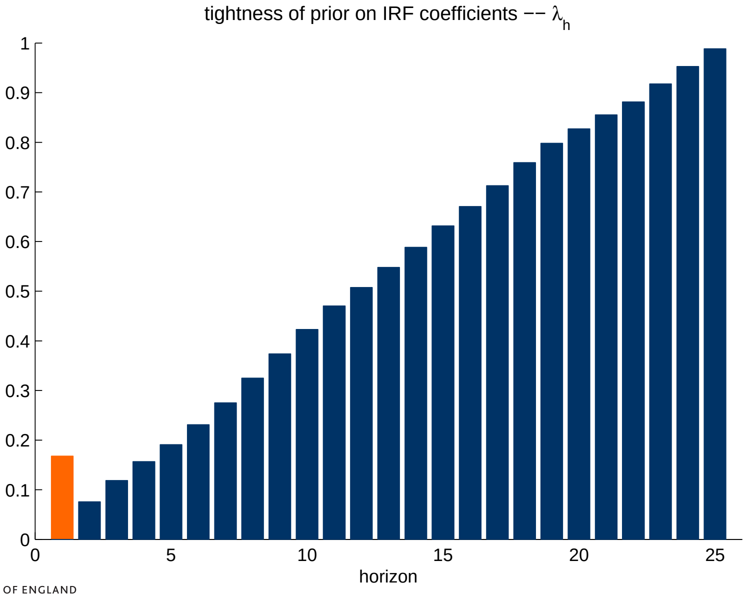
- $\lambda^{(h)}$ optimally spans between VAR and LP
(Giannone, Lenza, and Primiceri, 2015)

1. $\lambda^{(h)} \to 0 \quad \Longrightarrow \quad B_{BLP}^{(h)} \to B_{VAR}^{h}$
2. $\lambda^{(h)} \to \infty \quad \Longrightarrow \quad B_{BLP}^{(h)} = B_{LP}^{(h)}$

Optimal Shrinkage



BLP: Priors

BLP PRIOR

$$\Sigma_v^{(h)}|\gamma^{(h)} \sim IW\left(\Psi_0^{(h)}, d_0\right)$$

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- Macro variables' behaviour is **approximately linear** and described by a VAR(p)
- Conjugate priors centred around iterated VAR(p) (pre-sample)

$$\beta_0^{(h)} = \beta_{T_0}^{(0,h)} = \text{vec}\left(b_{T_0}^{(0,h)}\right)$$

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- Macro variables' behaviour is **approximately linear** and described by a VAR(p)
- Tightness of prior regulated by $\lambda^{(h)}$

$$\lambda^{(h)} \sim \Gamma\left(k^{(h)}, \theta^{(h)}\right)$$

BLP: Posterior

BLP POSTERIOR

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Misspecified parametric model:

- Likelihood is asymptotically Gaussian and centred at the MLE
- Posterior variance-covariance is underestimated

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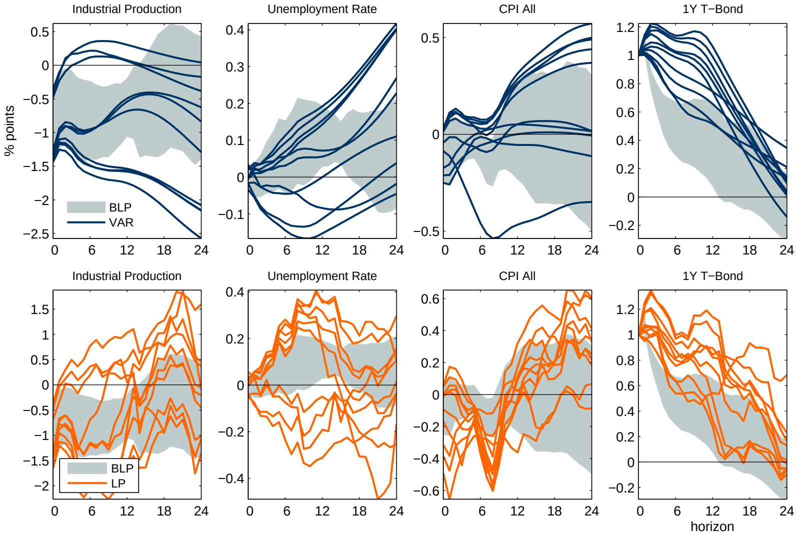
Misspecified parametric model:

- ▷ Likelihood is asymptotically Gaussian and centred at the MLE
- ▷ Posterior variance-covariance is underestimated

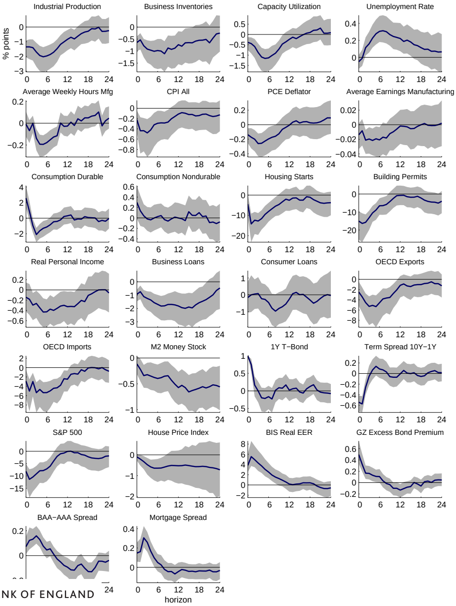
- ▷ Inference based on an **'artificial' Gaussian posterior** centred at the MLE with HAC covariance matrix (Müller, 2013)

Puzzles #2: Specifications

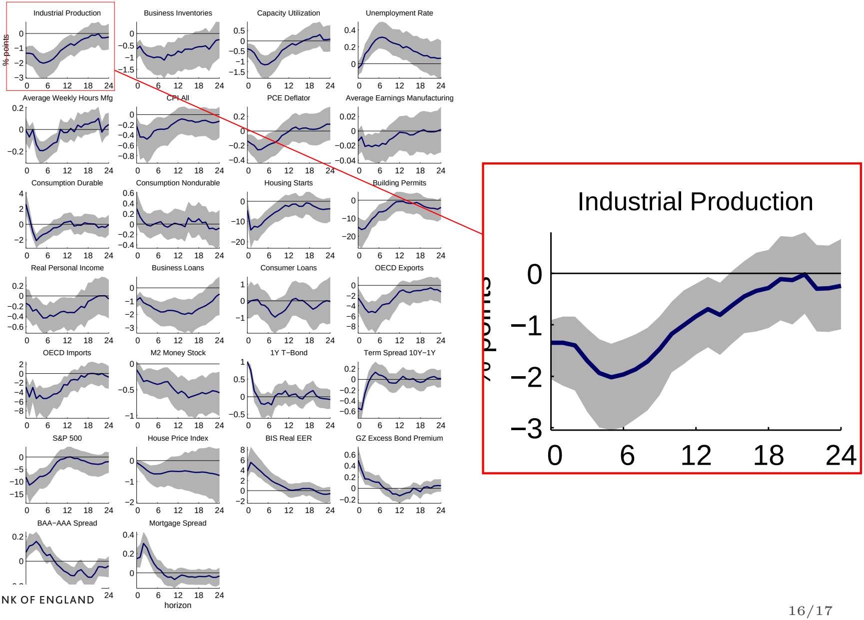


Rolling 20-year subsamples

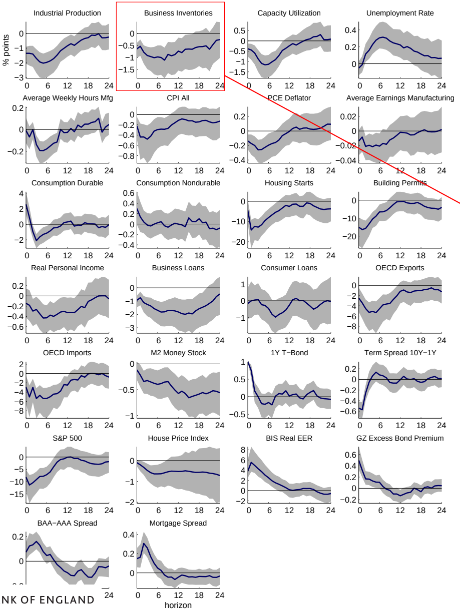
Large(r) Information Set:

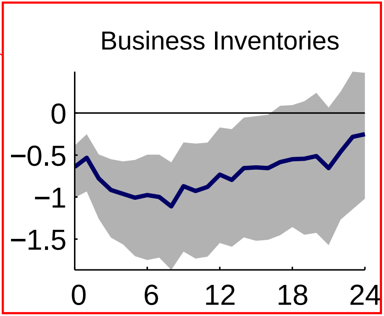


Large(r) Information Set: Real Activity

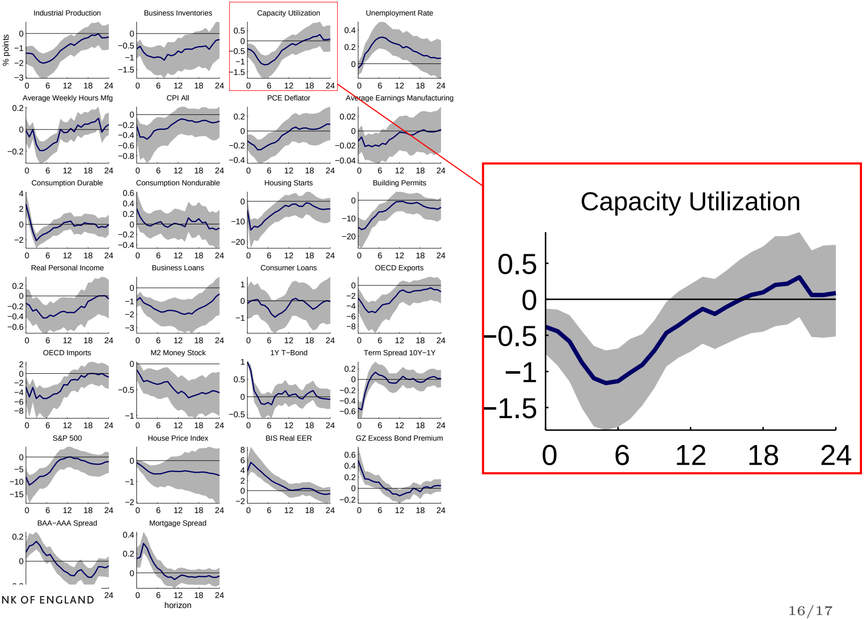


Large(r) Information Set: Real Activity

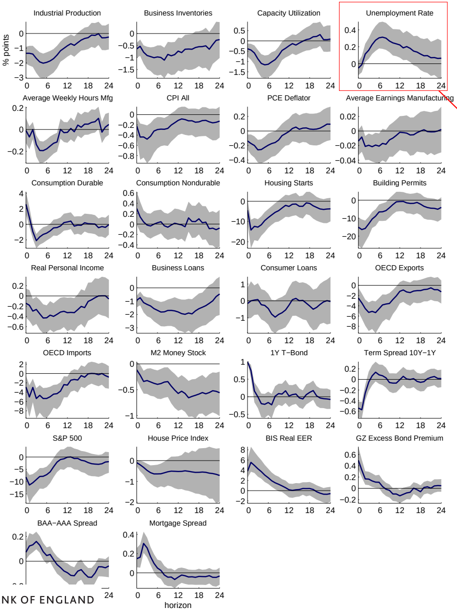


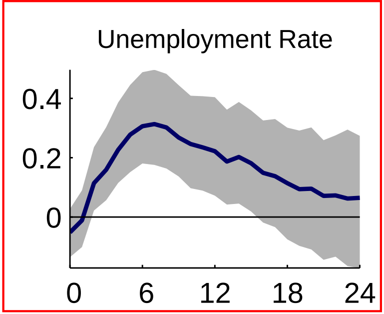


Large(r) Information Set: Real Activity

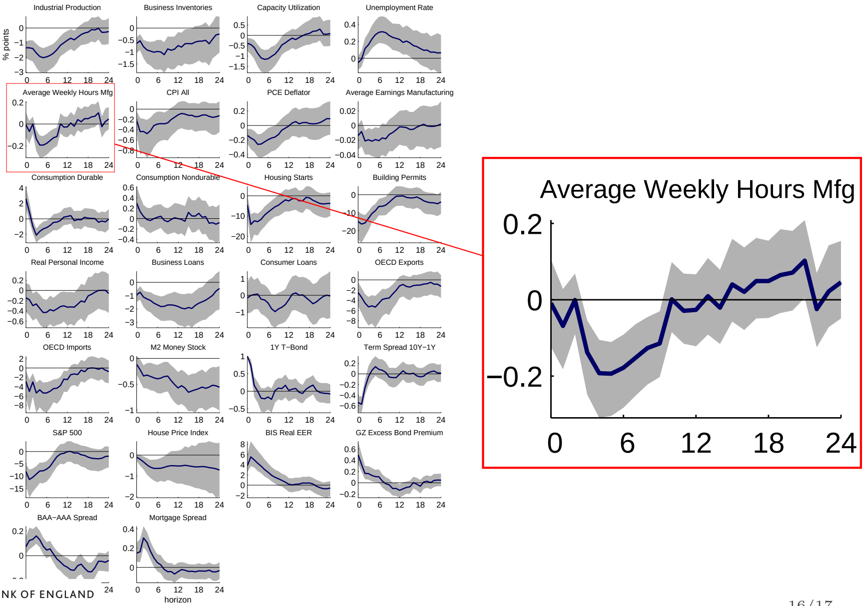


Large(r) Information Set: Real Activity

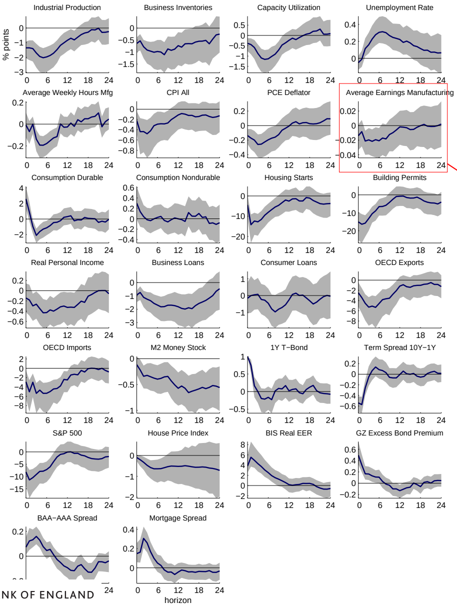


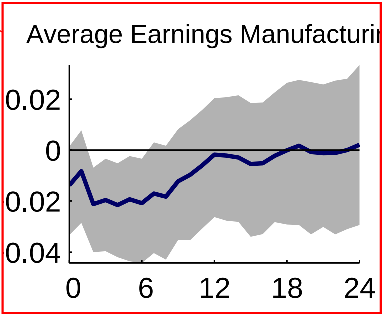


Large(r) Information Set: Real Activity

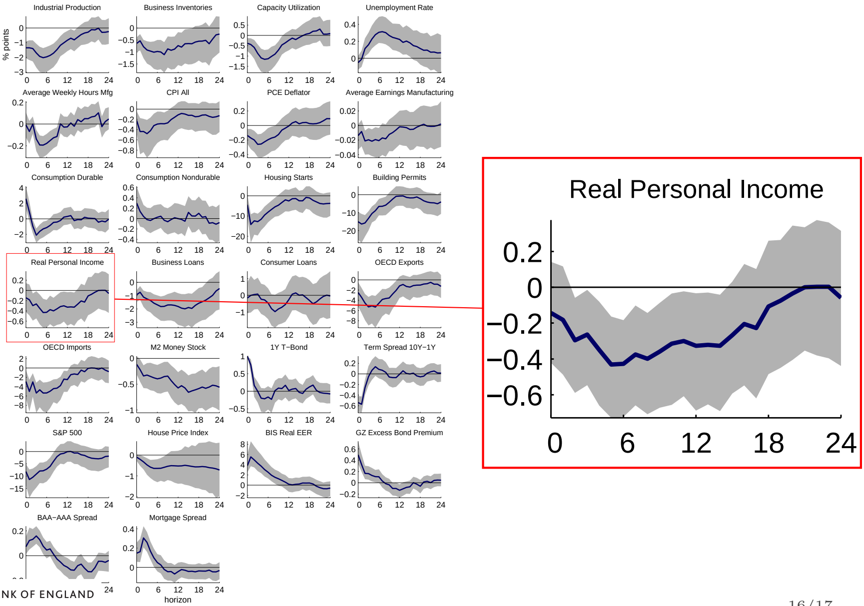


Large(r) Information Set: Real Activity

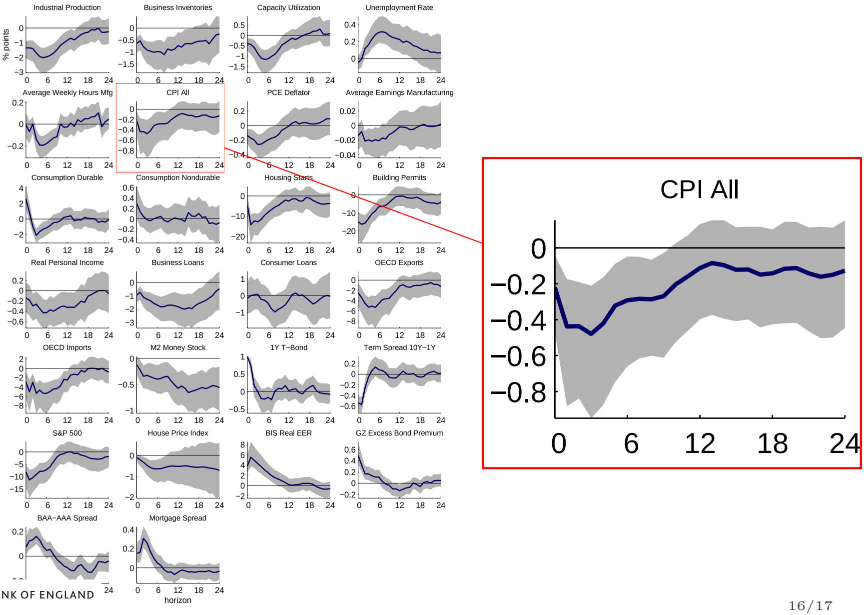




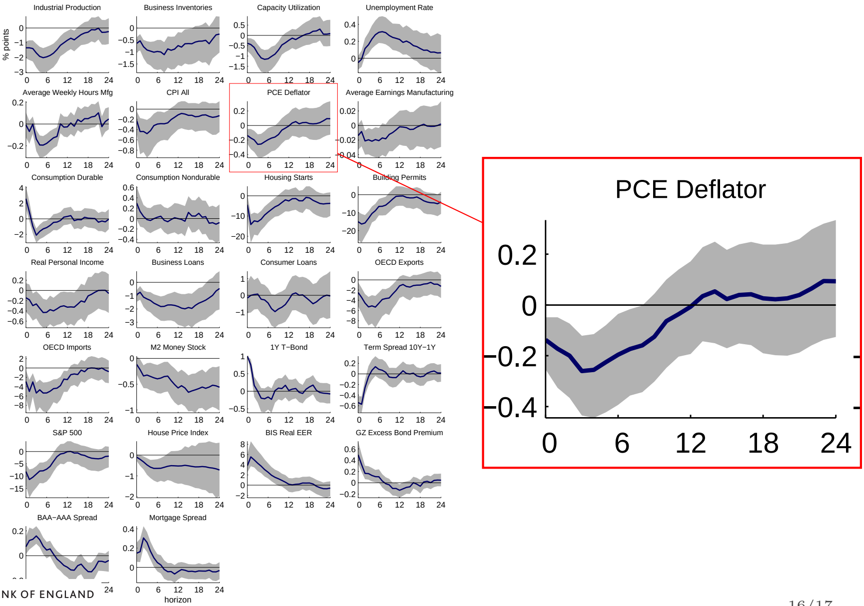
Large(r) Information Set: Real Activity



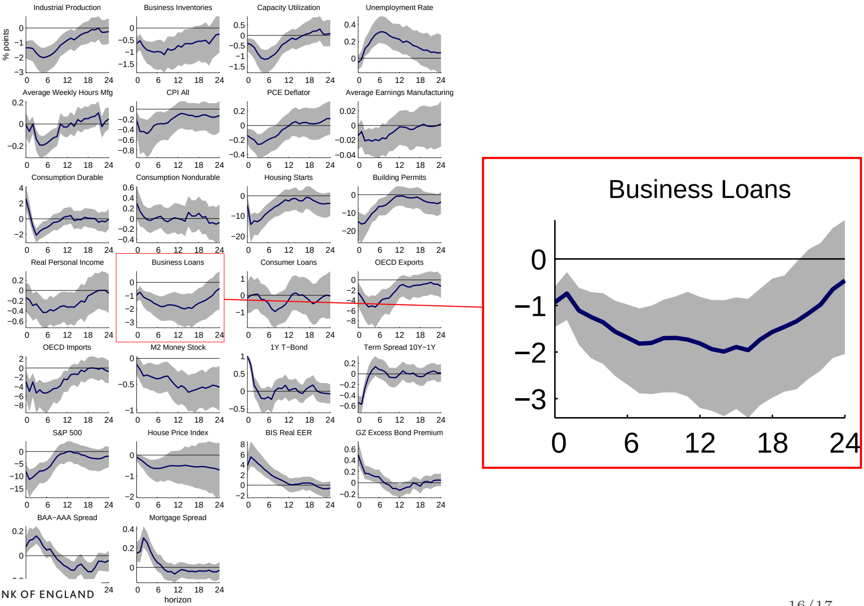
Large(r) Information Set: Prices



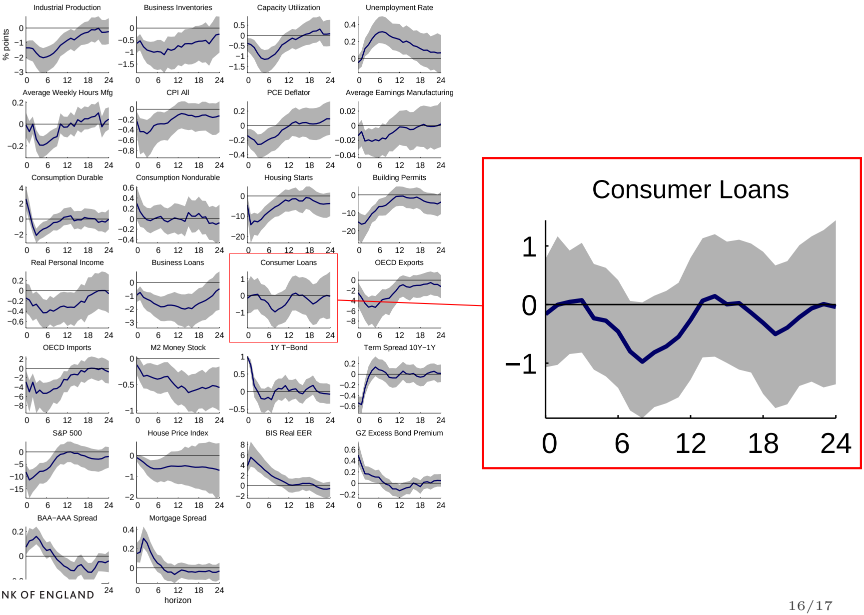
Large(r) Information Set: Prices



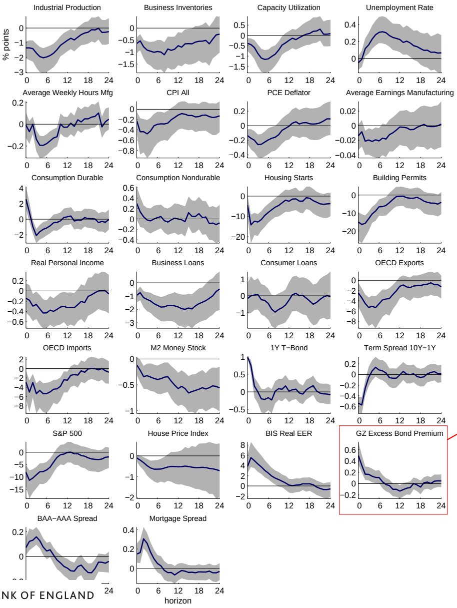
Large(r) Information Set: Credit

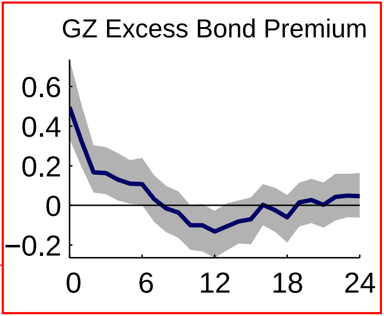


Large(r) Information Set: Credit



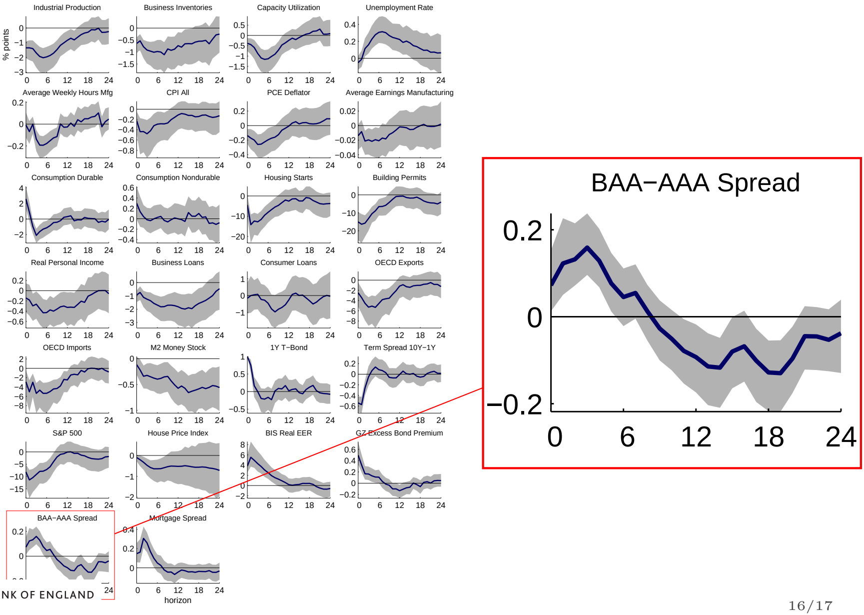
Large(r) Information Set: Credit





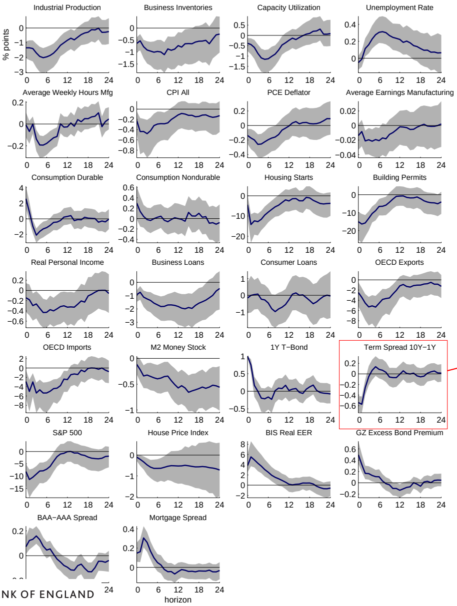
BANK OF ENGLAND

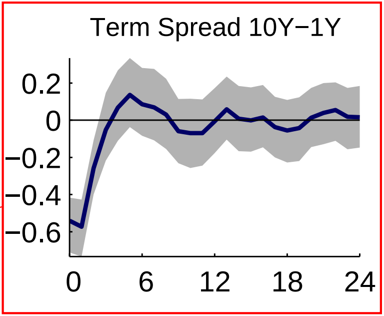
Large(r) Information Set: Credit



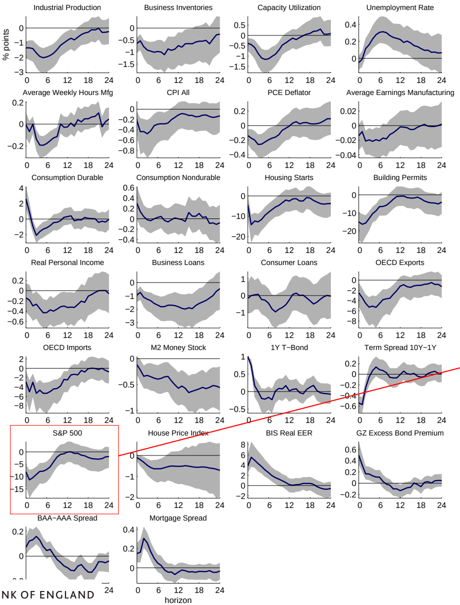
BANK OF ENGLAND

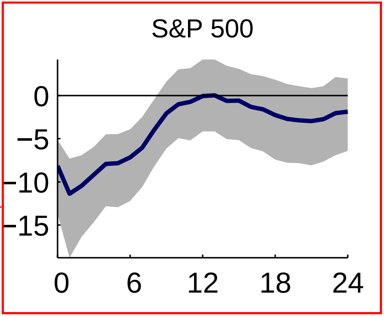
Large(r) Information Set: Credit



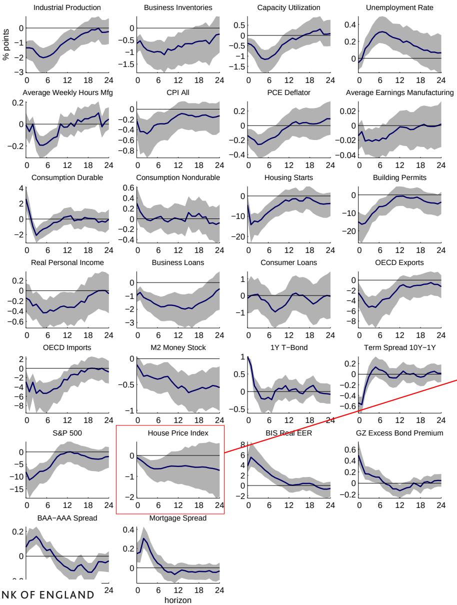


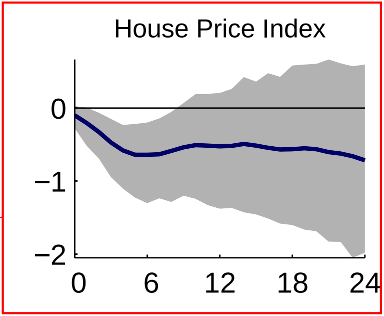
Large(r) Information Set: Other Assets





Large(r) Information Set: Other Assets





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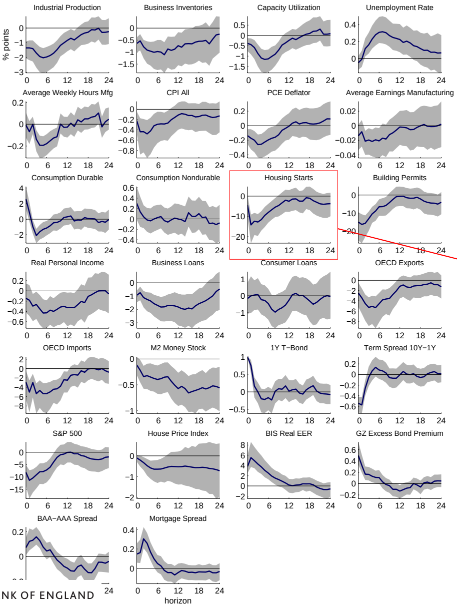

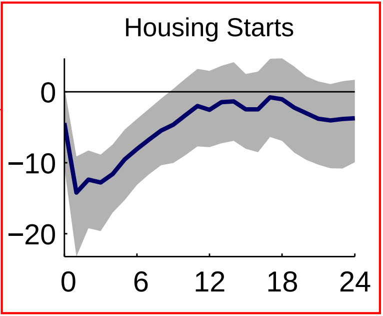

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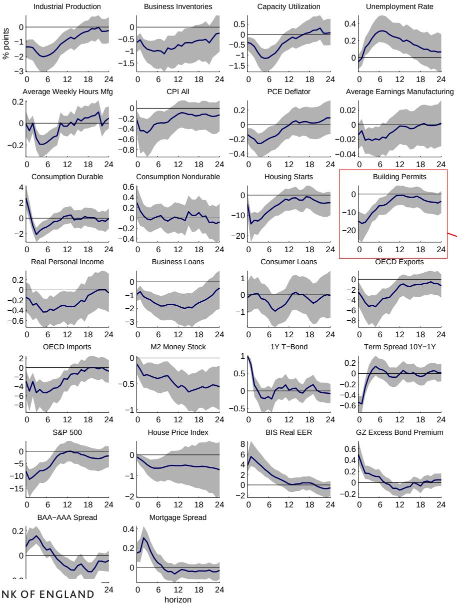
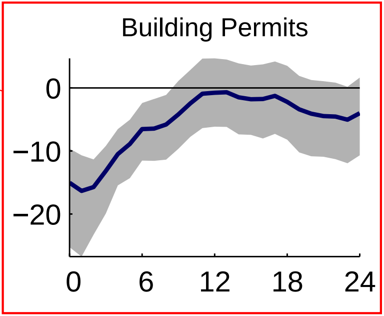
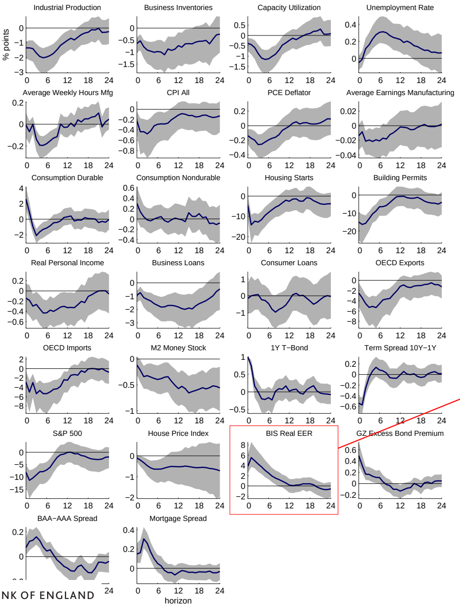
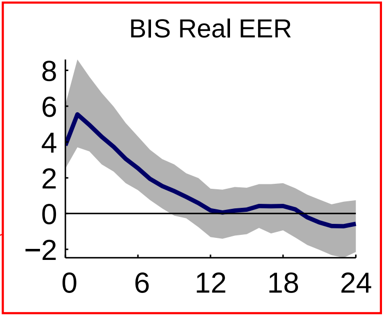


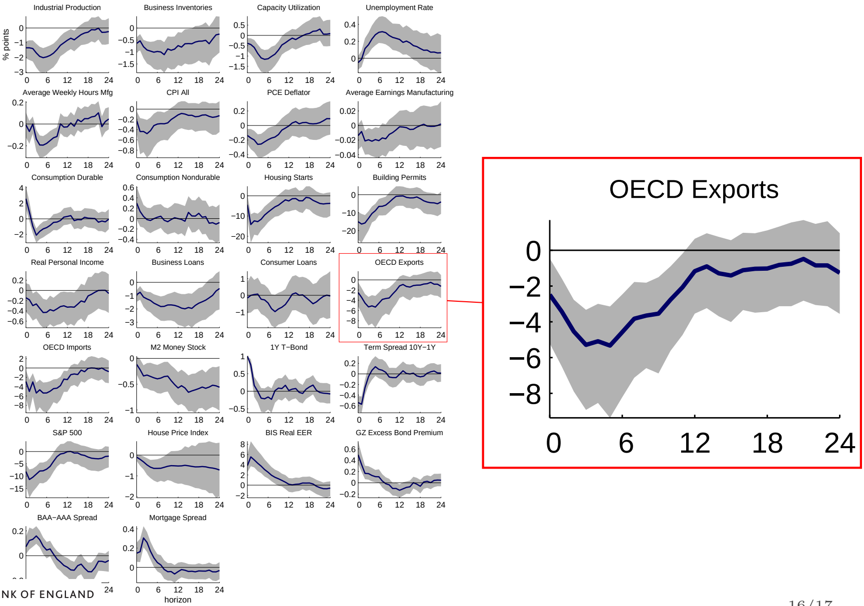


Large(r) Information Set: International Trade

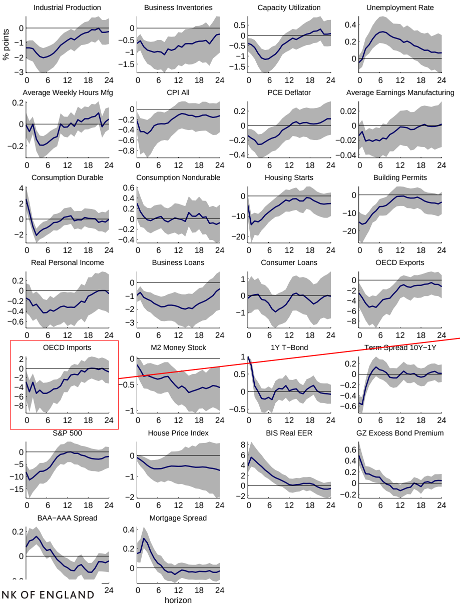


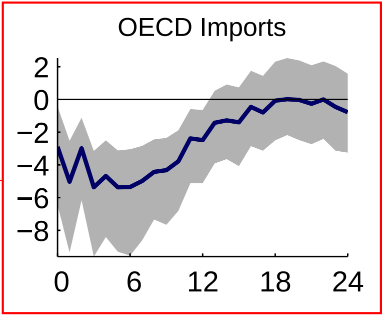


Large(r) Information Set: International Trade



Large(r) Information Set: International Trade





What are the Effects of Monetary Policy?

- We contribute to the debate with
  1. a **novel flexible econometric method** that optimally bridges between VARs with LPs
  2. an **identification strategy** that is coherent with imperfect/asymmetric information

- We find that following a monetary tightening:
  1. **economic activity and prices contract** – no puzzles
  2. firms and households **lending cools down**, borrowing costs rise and so do corporate spreads
  3. **expectations** move in line **with fundamentals**
  4. the slope of the **yield curve flattens**, and equity prices fall
  5. finally, the **currency appreciates**

Additional Slides

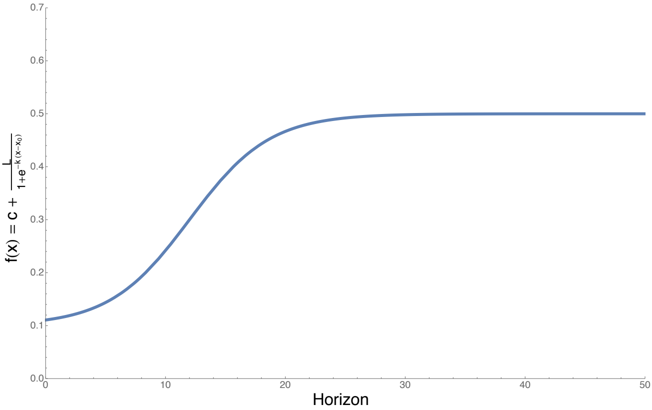
Testing for Information Frictions #2

	$\mathbf{FF4_t}$	$\mathbf{FF4_t^{GK}}$	$\mathbf{MPN_t}$	$\mathbf{MPI_t}$
$f_{1,t-1}$	-0.012 [-1.97]*	-0.011 [-2.74]***	-0.103 [-4.13]***	0.006 [0.98]
$f_{2,t-1}$	0.001 [0.38]	0.004 [1.79]*	-0.005 [-0.45]	0.005 [1.56]
$f_{3,t-1}$	0.002 [0.41]	-0.001 [-0.23]	-0.035 [-2.21]**	0.001 [0.29]
$f_{4,t-1}$	0.015 [2.09]**	0.008 [1.92]*	0.068 [2.71]***	0.005 [0.70]
$f_{5,t-1}$	0.002 [0.26]	0.001 [0.12]	0.017 [0.61]	0.008 [1.18]
$f_{6,t-1}$	-0.011 [-2.19]**	-0.007 [-2.58]**	0.008 [0.57]	-0.008 [-1.63]
$f_{7,t-1}$	-0.010 [-1.69]*	-0.006 [-1.40]	-0.053 [-2.85]***	-0.004 [-0.54]
$f_{8,t-1}$	-0.001 [-0.35]	0.001 [0.32]	-0.042 [-2.38]**	-0.001 [-0.15]
$f_{9,t-1}$	-0.002 [-0.59]	-0.002 [-0.53]	-0.037 [-1.65]	0.000 [0.07]
$f_{10,t-1}$	0.004 [0.75]	0.000 [-0.03]	-0.030 [-2.54]**	-0.003 [-0.70]
R^2	0.073	0.140	0.202	0.033

BLP: Hyperprior

$$\lambda^{(h)} \sim \Gamma\left(k^{(h)}, \theta^{(h)}\right)$$

- mode $= 0.4$
- standard deviation $=$ logistic function over h



BLP: Hyperprior

$$\lambda^{(h)} \sim \Gamma\left(k^{(h)}, \theta^{(h)}\right)$$

- mode $= 0.4$
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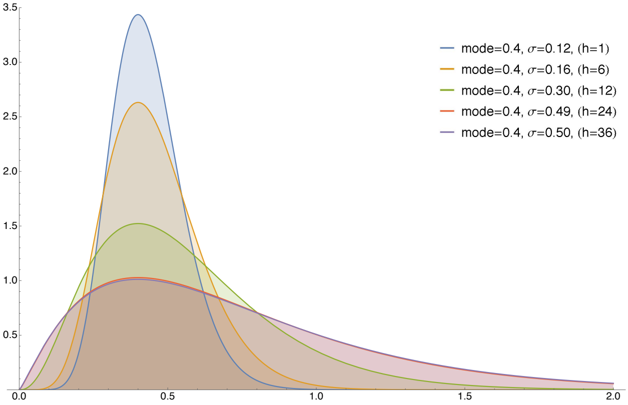
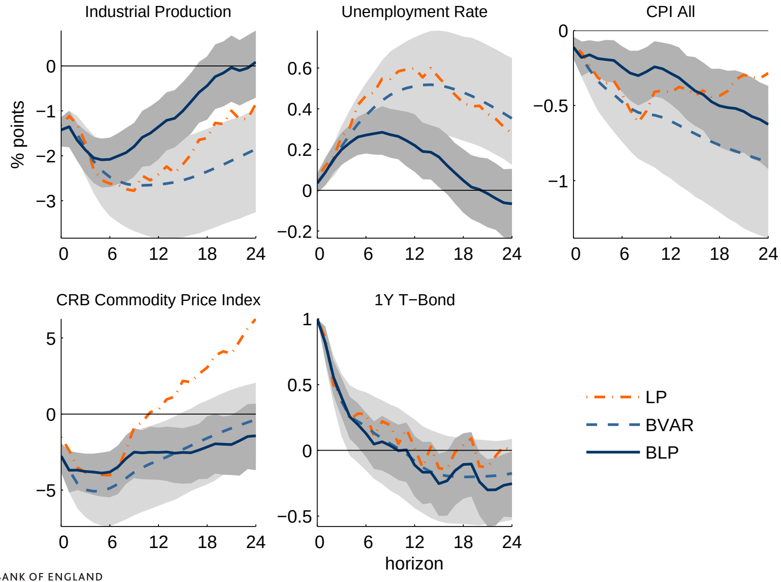
Out[34]=

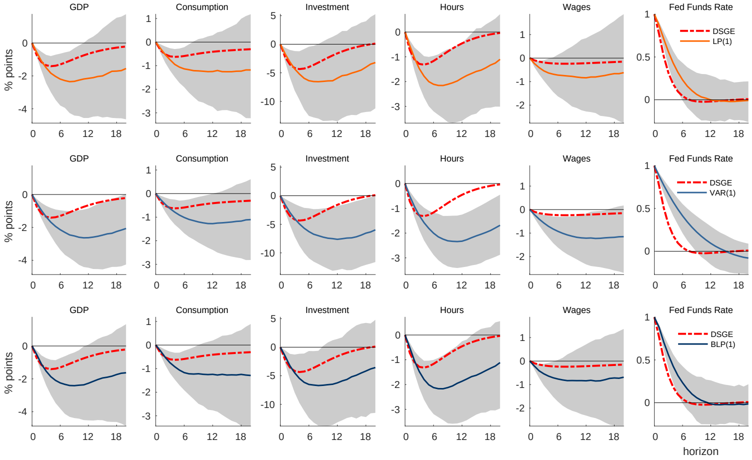


MP SHOCKS – 1979 TO 2014



VAR, LP, BLP on Simulated Data from JPT (2010)

- True model: $n = 7$, $p = 5$. Estimated models: $n = 6$, $p = 1$



VAR, LP, BLP on Simulated Data from JPT (2010)

- True model: $n = 7$, $p = 5$. Estimated models: $n = 3$, $p = 1$