Did the global financial crisis break the U.S. Phillips Curve?

Stefan Laseen and Marzie Taheri Sanjani

Sveriges Riksbank

International Monetary Fund

Understanding inflation: lessons from the past, lessons for the future?

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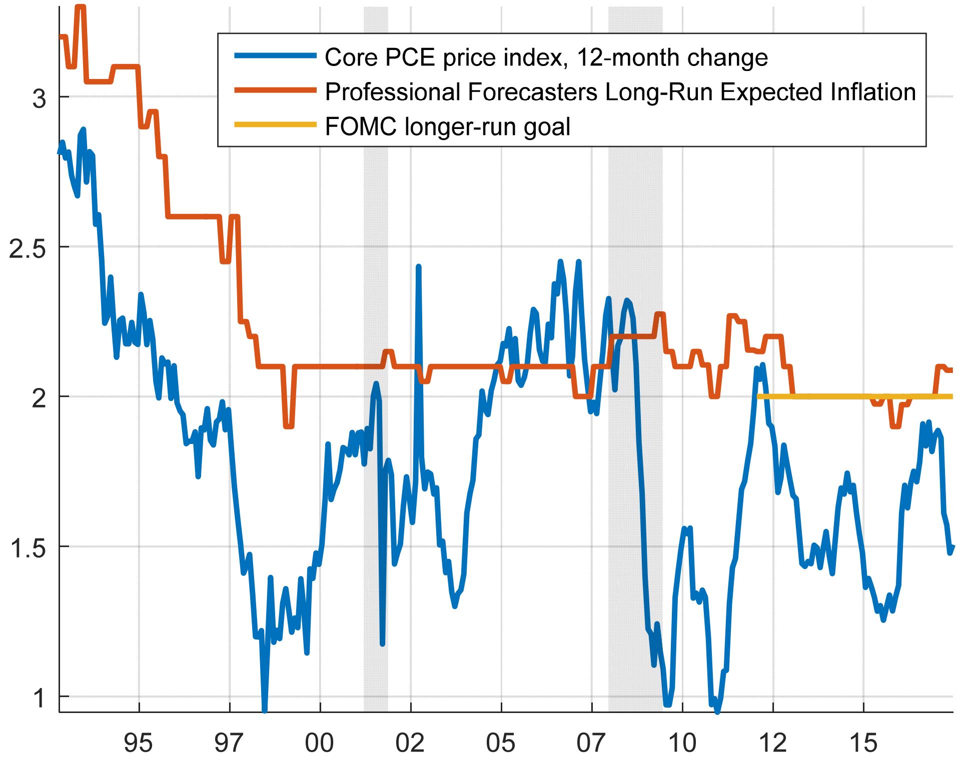
What we do and what we find

- The Puzzles.. and the question..
  - Since the Global Financial Crisis (GFC) of 2008-2009, unemployment and inflation dynamics have been puzzling. The Phillips curve predicts that a lower level of unemployment causes inflation to increase over time. This prediction does, however, not seem to have been present recently.
  - So.. Did the GFC break the Phillips curve? -> Inflation Dynamics… is it constant or changing?
- The methodology
  - We use a multivariate possibly non-linear approach to address multiple sources of possible explanations. Our approach is in the spirit of the literature on the “good luck” vs “good policy” hypothesis of the great moderation.
- What do we find?

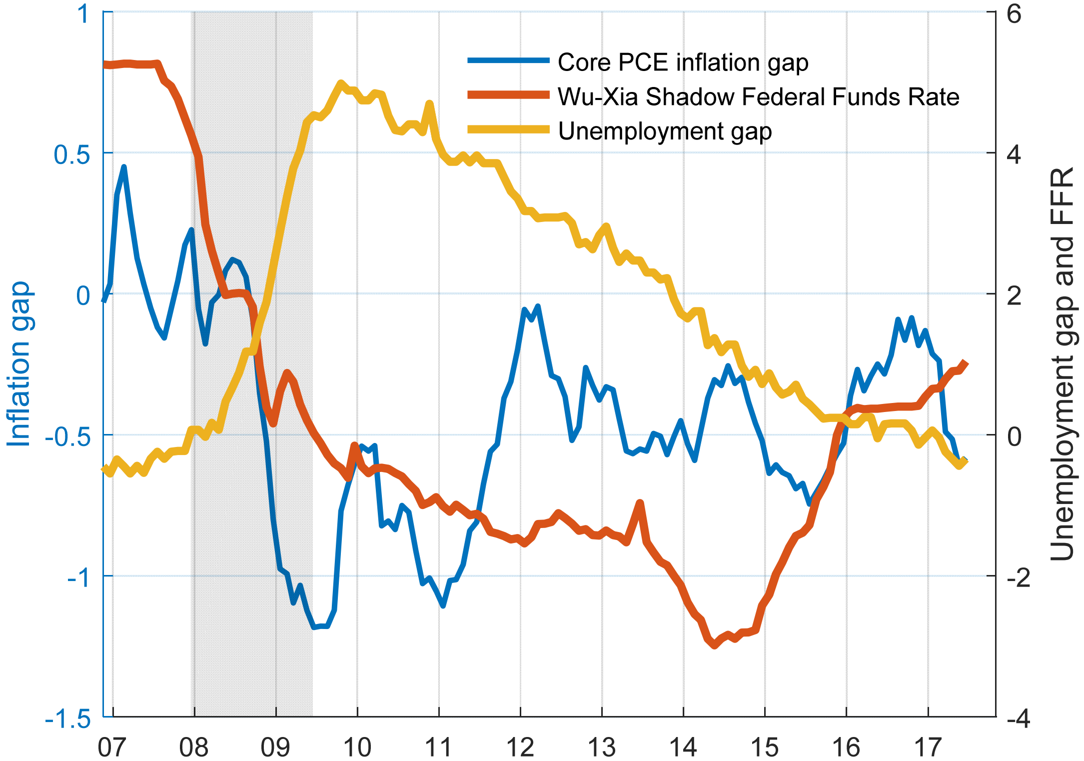
1. Changes in shock variances are a more salient feature of the data than changes in coefficients
   → Hence, our finding suggests that the GFC did <u>not</u> break the Phillips curve.
1. We find some changes in propagation though: .. But only for the dynamics of policy interest rates (monetary policy has been constrained by the ZLB). This implies shifts in reduced form correlations.
2. Conditional forecasts reveal useful information in external and financial variables.

U.S. PCE core inflation has been running below the FOMC target …



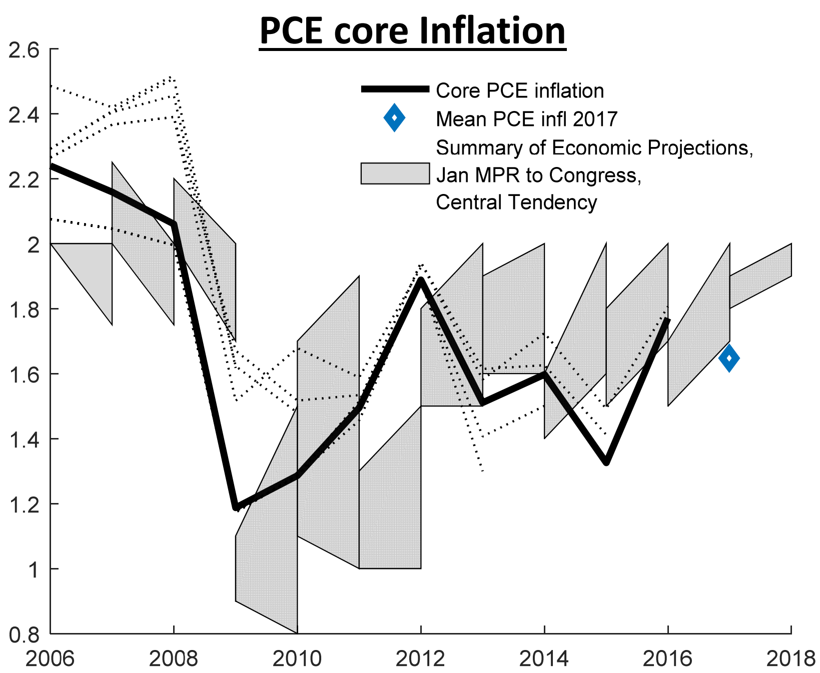
Note: The data are monthly. PCE is personal consumption expenditures. FOMC is Federal Open Market Committee. Inflation expectations is proxied using the median forecasts of long-run PCE or CPI inflation reported in the Survey of Professional Forecasters, with a constant adjustment of 40 basis points prior to 2007 to put the CPI forecasts on a PCE basis.
Source: U.S. Department of Commerce, Bureau of Economic Analysis and Board of Governors of the Federal Reserve System.

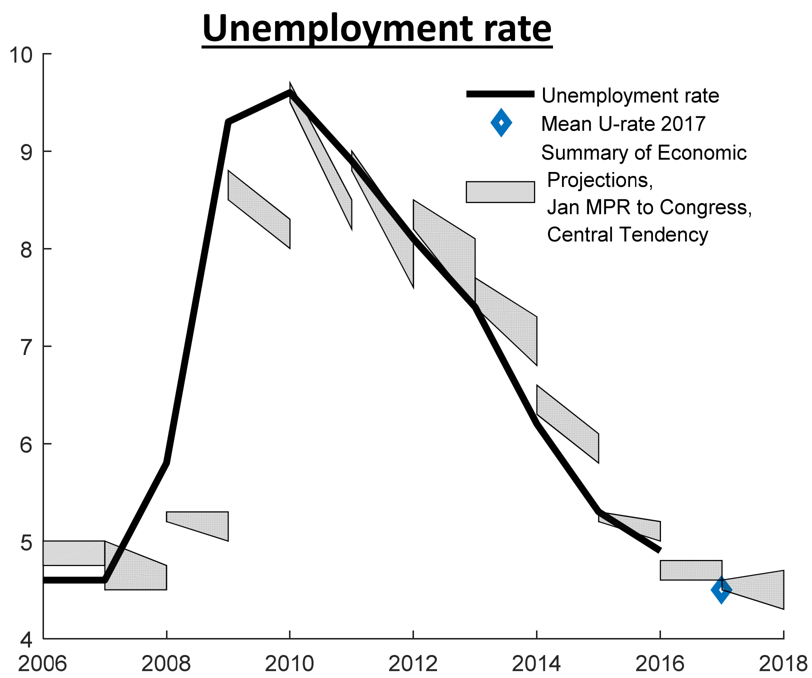
… despite reduced slack and an expansionary monetary policy



Note: Monthly data. The inflation gap is measured as PCE is personal consumption expenditures less the median forecasts of long-run PCE or CPI inflation reported in the Survey of Professional Forecasters, with a constant adjustment of 40 basis points prior to 2007 to put the CPI forecasts on a PCE basis. The unemployment gap is the unemployment rate less the CBO's estimates of the historical path of the long-run natural rate.
Source: U.S. Department of Commerce, Bureau of Economic Analysis and Board of Governors of the Federal Reserve System, Federal Reserve Bank of Atlanta.

Surprising dynamics also for policymakers in real time..



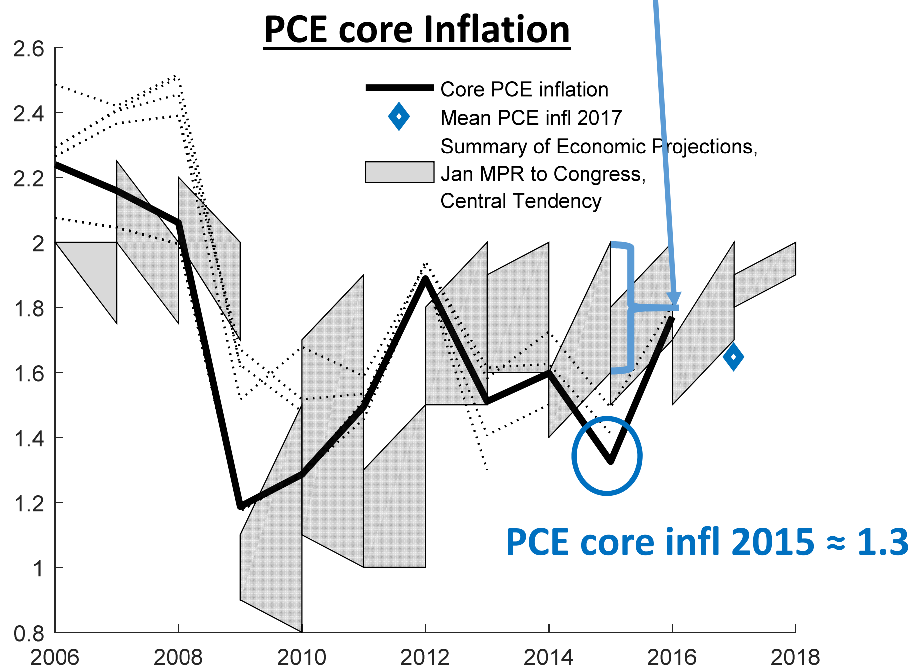


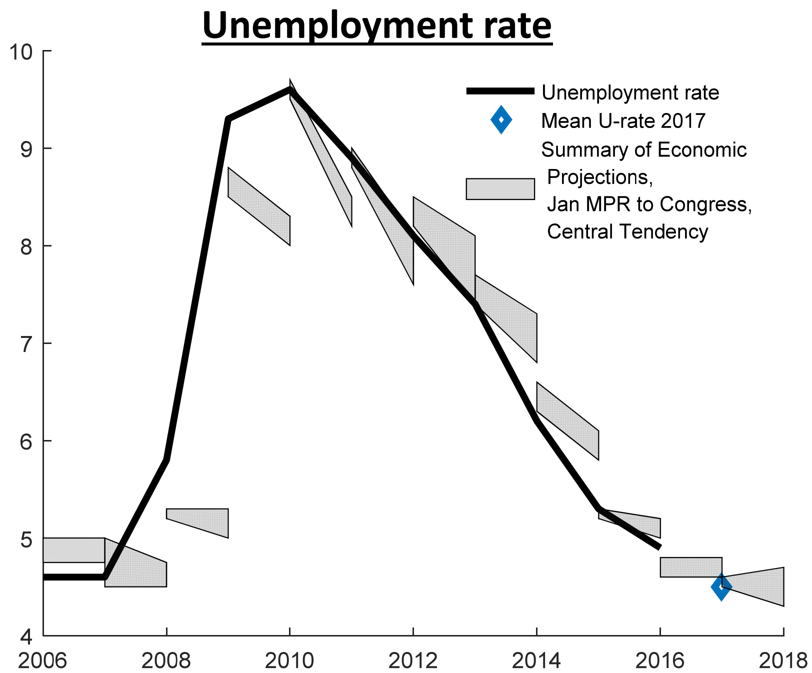
Note: Dashed lines are vintages of Core PCE inflation
Dec 2007- Dec 2016

The central tendency excludes the three highest and three lowest projections for each variable in each year.

An example on how to understand the chart..

In **December 2013**, the central tendency of PCE core inflation for **2015** was **1.6-2.0%** in the economic projections of Federal Reserve Board members and Federal Reserve Bank presidents (from Table 1 of the Febr 2014 MPR)…





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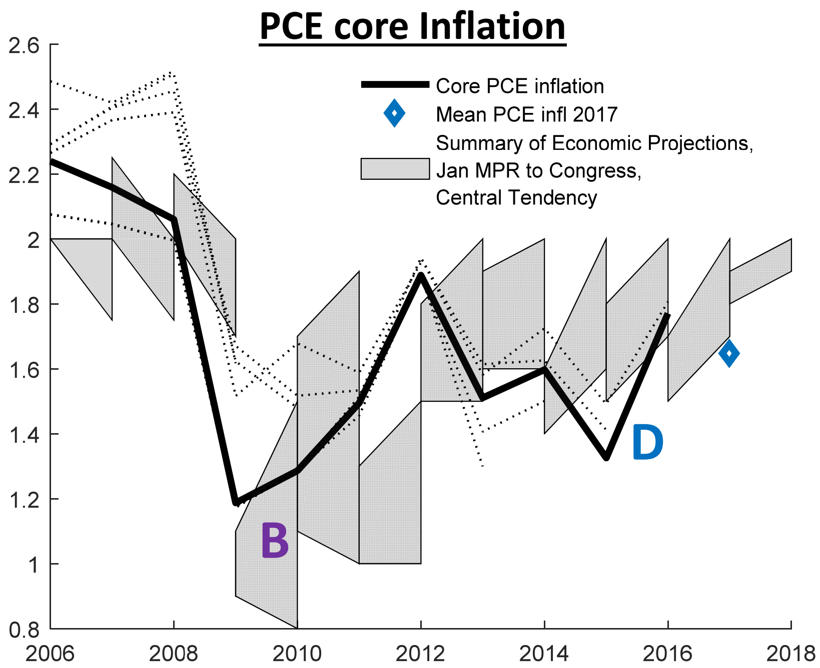
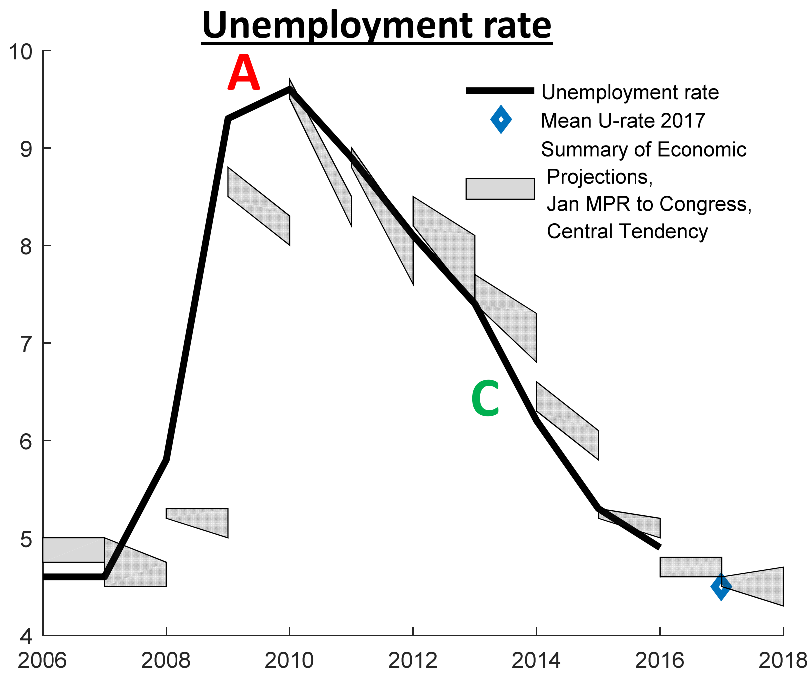
Dec 2007- Dec 2016

The central tendency excludes the three highest and three lowest projections for each variable in each year.

Surprising dynamics also for policymakers in real time..

A. Unemployment surprisingly **high** B. yet inflation unexpectedly **high**
C. Unemployment surprisingly **low** D. yet inflation unexpectedly **low**





Note: Dashed lines are vintages of Core PCE inflation Dec 2007- Dec 2016

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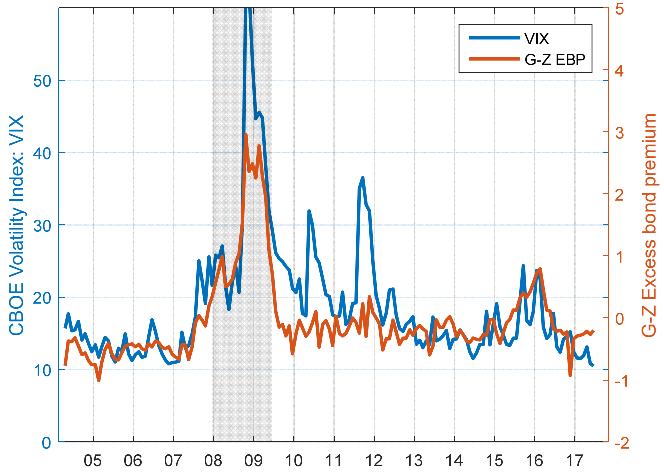
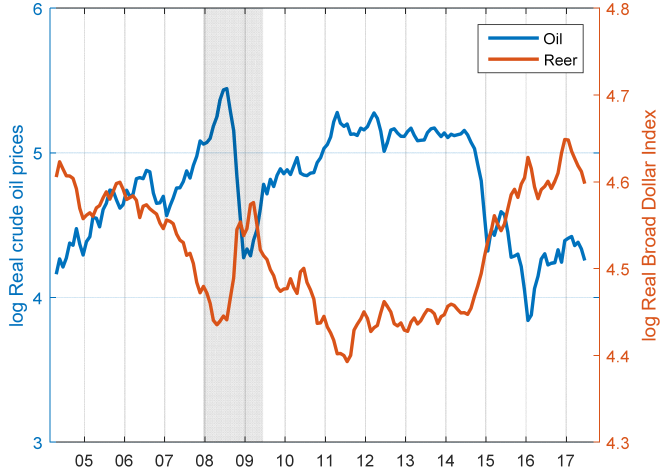
Lots of possible confounding factors at play during and after the GFC..

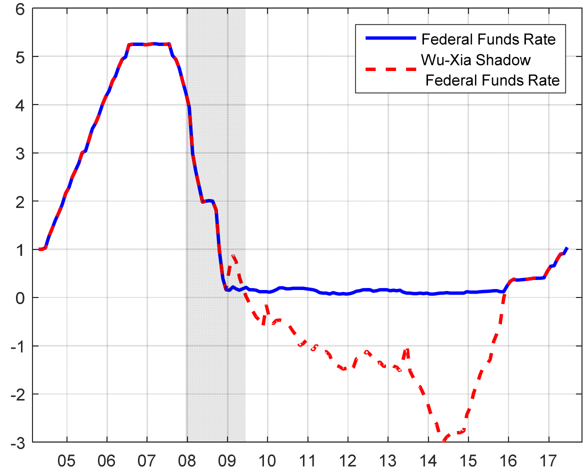
Financial frictions and shocks…



…large energy price and FX movements..



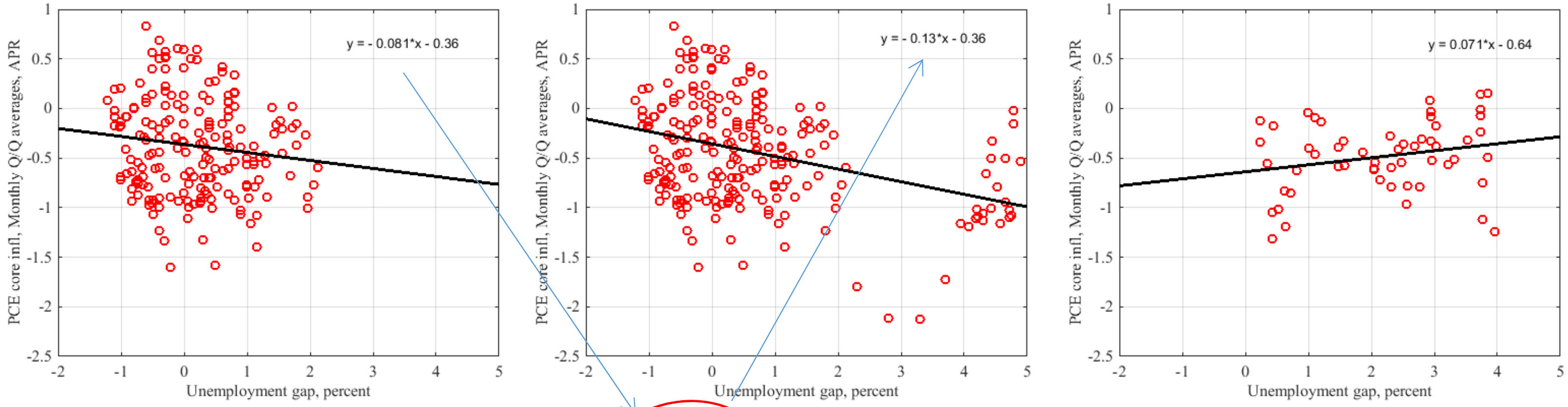
… and constraints on policy..



...make it challenging to estimate the slope of the PC in a univarate context

A large literature has indeed shown that estimates of the slope depends on the estimation time period, or choice of measure of slack, and inflation indicator used, or on type of inflation expectations...

1992M3-2007M12 **1992M3-2010M12** **2011M1-2015M6**



Flat Phillips Curve Steeper Phillips Curve Flat Phillips Curve

Unemployment and Inflation: Before, including and after the GFC

…first.. elicit your Phillips curve priors..

- Views on (the slope of the) PC have surely been influenced by a series of papers:
  - IMF (2013), Ball and Mazumder (2011), Blanchard (2016) etc.
  - + an enormous literature on every possible aspect on the topic..

- What do these papers find:
  - The US Phillips curve is alive and well (or at least as well as it has been in the past).
  - The slope of the Phillips curve, i.e., the effect of the unemployment rate on inflation given expected inflation, has substantially declined.
  - But the decline dates back to the end of the 1980s rather than to the crisis. There is no further evidence of a decline during the crisis.

Our methodology

- The literature (all papers on previous slide e.g.) focus on estimating univariate Phillips curves to study the possibly changing nature of the inflation process – without controlling for changes or switches in variances.
  - Brunnermeier, Palia and Sims (2014): "Tightly constrained dynamics in variance regime switches may make nonlinearity and coefficient regime switches pick up explanatory power, and vice versa."
- We instead take a flexible multivariate approach by using large-cross-section Bayesian Vector Auto Regression (BVAR's), dynamic factor models (DFM's) as well as Markov switching MS-BVARs to provide some answers.
- The benefit of a multivariate approach:

1. We can control and account for various factors, forces and omitted variables which may be more difficult in a univariate context.
2. Our approach provides a formal framework to statistically *test* for the presence of nonlinearities
3. We can distinguish between variance switching as the source of time variation and coefficient switching that alters the transmission of shocks to the real economy.

We also investigate the information content in data pertaining to three hypothesis on why inflation is currently low:

1. Financial frictions, and shocks could imply slow recoveries and persistently low inflation. (Christiano, Eichenbaum, and Trabandt (2015), and Gilchrist and Zakrajsek (2015)).
2. Globalization has increased the role of international factors and decreased the role of domestic factors in the inflation process in industrial economies. Mixed evidence (Ihrig et al. 2010, Bianchi and Civelli 2015).
3. Inability of stabilization policy – due to the effective lower bound on policy rates – to lower real interest rates enough to bring the economy back to long-run sustainable levels and to achieve long-run inflation goals (Constâncio 2014).

Our Empirical Framework: More formally …

- The general (Sims and Zha 2006) framework is described by nonlinear stochastic dynamic simultaneous equations of the form:

$$\begin{aligned} A_0'\left(s_t^c\right) y_t &= C\left(s_t^c\right) x_t + \Xi_m^{-1}\left(s_t^v\right) \epsilon_t, \\ x_t &= A_+'\left(s_t^c\right) x_{t-1} + \Xi_s^{-1}\left(s_t^v\right) \varepsilon_t, \end{aligned}$$

$$p\left(s_t^{c,v} = i | s_{t-1}^{c,v} = k\right) = p_{ik}^{c,k}, \qquad i, k = 1, 2, .., h$$

- y_t an nx1 vector of endogenous, and observable, variables and contains PCE inflation and unemployment,
- $s_t^{c,v}$ are latent state variables for coefficients and variances respectively.
- x_t is an m-dimensional vector of potentially unobserved state variables.

Our Empirical Framework: A simple special case

- Phillips curve (with time-varying coefficients and variance):

$$\alpha_{\pi|\boldsymbol{s_t^c}}\pi_t = \alpha_{\pi_1|\boldsymbol{s_t^c}}\pi_{t-1} + \alpha_{\pi_2|\boldsymbol{s_t^c}}\pi_{t-2} + \alpha_{y|\boldsymbol{s_t^c}}y_t + \sigma^{\pi}_{t|\boldsymbol{s_t^v}}\varepsilon^{\pi}_t$$

- IS curve:

$$\beta_{y_0}y_t = \beta_{y_1}y_{t-1} + \beta_{y_2}y_{t-2} - \beta_r(i_t - \pi_t) + \sigma_y\varepsilon^y_t$$

- Taylor rule:

$$\gamma_{i_0}i_t = \gamma_{i_1}i_{t-1} + \gamma_y y_t + \gamma_\pi\pi_t + \sigma_i\varepsilon^i_t$$

- The two Markov processes $\boldsymbol{s_t^c}$and $\boldsymbol{s_t^v}$ are independent. We consider several cases:
  - $\boldsymbol{s_t^c}$ has 1 or 2 regimes, $\boldsymbol{s_t^v}$ has 1, 2 or 3 regimes
  - $\boldsymbol{s_t^c}$ governs coefficients in all or only some equations (like above example)

Our Empirical Framework: A simple special case

- The general framework is then given by

$$\begin{bmatrix} \alpha_{\pi|\boldsymbol{s_t^c}} & \alpha_{y|\boldsymbol{s_t^c}} & 0 \\ -\beta_r & \beta_{y_0} & \beta_r \\ -\gamma_\pi & -\gamma_y & \gamma_{i_0} \end{bmatrix} \begin{bmatrix} \pi_t \\ y_t \\ i_t \end{bmatrix} =$$

$$\begin{bmatrix} \alpha_{\pi_1|\boldsymbol{s_t^c}} & 0 & 0 & \alpha_{\pi_2|\boldsymbol{s_t^c}} & 0 & 0 \\ 0 & \beta_{y_1} & 0 & 0 & \beta_{y_2} & 0 \\ 0 & 0 & \gamma_{i_1} & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ y_{t-1} \\ i_{t-1} \\ \pi_{t-2} \\ y_{t-2} \\ i_{t-2} \end{bmatrix} + \begin{bmatrix} \sigma^{\pi}_{t|\boldsymbol{s_t^v}} & 0 & 0 \\ 0 & \sigma_{\mathrm{y}} & 0 \\ 0 & 0 & \sigma_i \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\pi} \\ \varepsilon_t^{y} \\ \varepsilon_t^{i} \end{bmatrix}$$

PART 1: Large Bayesian VARs and Factor Models

$$p\left(s_t^{c,v} = i | s_{t-1}^{c,v} = k\right) = 0$$

&

y_t = "Large"

Shocks or Propagation? Conditional Forecast and the Role of Information

- We first perform counterfactual exercises to assess the role of shocks versus propagation.
- The models are estimated separately in the two subsamples:

  - $A'_0(pre08Q1)y_t = A'_+(pre08Q1)x_t + \Xi^{-1}(pre08Q1)\varepsilon_t$

  - $A'_0(pre15Q2)y_t = A'_+(pre15Q2)x_t + \Xi^{-1}(pre15Q2)\varepsilon_t$

Large and Rich Information Set

Block #	Position	Mnemonic	Description	Transformation
			US Data -1987Q1-2015Q2	
Real Activities	1	world RGDP	YOY (pct change) World RGDP	level/100
Real Activities	2	rgdp	US Real GDP (SAAR, Bil.Chn.2009$)	log level x 4
Real Activities	3	ip	US Industrial Production Index (SA, 2012=100)	log level x 4
Real Activities	4	c	US Real Personal Consumption Expenditures (SAAR, Bil.Chn.2009$)	log level x 4
Real Activities	5	g	US Real Government Consumption Expenditures & Gross Investment(SAAR, Bil.Chn.2009$)	log level x 4
Real Activities	6	i	US Real Gross Private Domestic Investment (SAAR, Bil.Chn.2009$)	log level x 4
Real Activities	7	x	US Real Exports of Goods & Services (SAAR, Bil.Chn.2009$)	log level x 4
Real Activities	8	m	US Real Imports of Goods & Services (SAAR, Bil.Chn.2009$)	log level x 4
Real Activities	9	emp	US All Employees: Total Nonfarm Payrolls (SA, Thous)	log level x 4
Real Activities	10	u	US Unemployment Rate: 16 Years + (SA, %)	level / 100
Real Activities	11	nairu	US Natural Rate of Unemployment [CBO] (%)	level / 100
Real Activities	12	cap ut	US Capacity Utilization: Industry (SA, Percent of Capacity)	level / 100
Real Activities	13	util	Utilization of capital and labor	log level x 4
Real Activities	14	u_invest	Utilization in producing investment	log level x 4
Real Activities	15	u_consumption	Utilization in producing non-investment business output ("consumption")	log level x 4
Real Activities	16	c conf	US University of Michigan: Consumer Sentiment (NSA, Q1-66=100)	level / 100
TFP	17	tfp_util	Utilization-adjusted TFP	log level x 4
TFP	18	tfp_I_util	Utilization-adjusted TFP in producing equipment and consumer durables	log level x 4
TFP	19	tfp_C_util	Utilization-adjusted TFP in producing non-equipment output	log level x 4
Prices	20	oil	Spot Price Idx of UK Brt Lt/Dubai Med/Alaska NS heavy (2010=100)	log level x 4
Prices	21	non oil	Non-fuel Primary Commodities Index (2010=100)	log level x 4
Prices	22	cpi shelter	US CPI-U: Shelter (SA, 1982-84=100)	log level x 4
Prices	23	cpi core	US CPI-U: All Items Less Food & Energy (SA, 1982-84=100)	log level x 4
Prices	24	pce core	US PCE less Food & Energy: Chain Price Index (SA, 2009=100)	log level x 4
Prices	25	ppi	US PPI: Finished Goods (SA, 1982=100)	log level x 4
Prices	26	gdp def	US GDP Implicit Price Deflator (SA, 2009=100)	log level x 4
Prices	27	mxrmd	US Imports Deflator (excluding raw materials)	log level x 4
Prices	28	w	US Avg Hourly Earnings: Prod & Nonsupervisory: Total Private Industries(SA, $/Hour)	log level x 4
Monetary	29	euro-stn	Euro Area 11-19: 3-Month EURIBOR (%)	level / 100
Monetary	30	libor us	3-Month London Interbank Offer Rate: Based on US$ (%)	level / 100
Monetary	31	ust3m	3-Month Treasury Bills, Secondary Market (% p.a.)	level / 100
Monetary	32	ust10	10-Year Treasury Note Yield at Constant Maturity (% p.a.)	level / 100
Monetary	33	m1	Money Stock: M1 (SA, Bil.$)	log level x 4
Monetary	34	m2	Money Stock: M2 (SA, Bil.$)	log level x 4
Financial	35	loan hh	US: Household & Nonprofit Outstanding Debt (SA, Bil.US$)	log level x 4
Financial	36	loan corp	US: Nonfinancial Corporations Outstanding Debt (SA, Bil.US$)	log level x 4
Financial	37	reer	Real Broad Trade-Weighted Exchange Value of the US$ (Mar-73=100)	log level x 4
Financial	38	sp500	Stock Price Index: Standard & Poor's 500 Composite (1941-43=10)	log level x 4
Financial	39	corp Aaa	Moody's Seasoned Aaa Corporate Bond Yield (% p.a.)	level / 100
Financial	40	corp Baa	Moody's Seasoned Baa Corporate Bond Yield (% p.a.)	level / 100
Financial	41	pol uncert	Policy-related Economic Uncertainty	level / 100
Financial	42	ebp_oa	Excess Bond Premium	level
Financial	43	gz_spr	Gilchrist and Zaktajšek default risk spread	level

Shocks or Propagation? Conditional Forecast and the Role of Information

1. *First counterfactual exercise:* How much of the dynamics of inflation since the GFC can be explained by a change in the *propagation*? Do conditional forecasting 2008Q1-2015Q2 and compute RMSFE using:

$$A'_0(pre15Q1)y_t = A'_+(pre15Q1)x_t + \Xi^{-1}(pre08Q1)\varepsilon_t$$

2. *Second counterfactual exercise*: How much of the dynamics of inflation since the GFC can be explained by a change in the *shock variances*? Do conditional forecasting 2008Q1-2015Q2 and compute RMSFE using:

$$A'_0(pre08Q1)y_t = A'_+(pre08Q1)x_t + \Xi^{-1}(pre15Q1)\varepsilon_t$$

- We use conditional forecasts analysis – following Giannone et al. (2012a,2012b) and Stock and Watson (2012).
- Conditional forecasts are projections of a set of variables of interest on future paths of some other variables. We compare the actual evolution of unemployment, inflation with forecasts conditional on the path of actual outcomes for blocks of variables.
- The knowledge of the future evolution of some economic variables may carry information for the outlook of other variables – like inflation and unemployment. Significant differences between expected and observed developments may signal that either historically unusual shocks have occurred or the relationships among variables have changed during the crisis

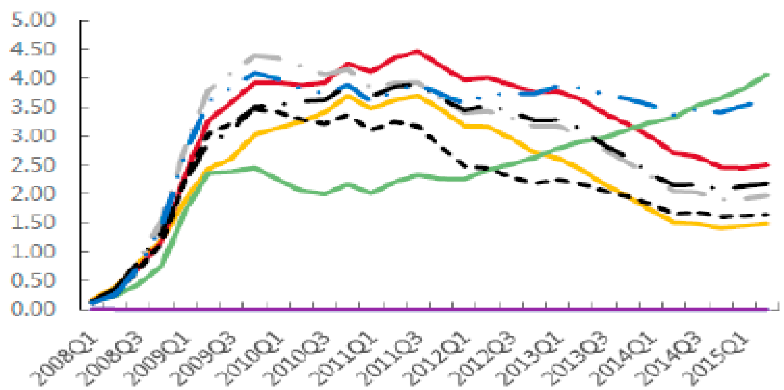
Conditioning variables

Scenario		Observables
1	External Factors	World GDP Growth Real Exports of Goods & Services Real Imports of Goods & Services Real Broad Trade-Weighted Exchange Value of the US (Mar-73=100) 3-Month EURIBOR Imports Deflator (excluding raw materials)
2	Commodities	Oil Price Index (Brent/Dubai/WTI) Non-fuel Primary Commodities Index
3	Labor Factors	Unemployment Rate Total Nonfarm Payrolls Natural Rate of Unemployment Avg Hourly Earnings: Total Private Industries
4	Interest Rates	3-Month LIBOR USD 3-Month Treasury Bill Yield 10-Year Treasury Note Yield
5	Credit	Nonfinancial Corporations Outstanding Debt Household & Nonprofit Outstanding Debt
6	Financial Risk	Aaa Corporate Bond Yield Baa Corporate Bond Yield Policy-related Economic Uncertainty Excess Bond Premium Gilchrist and Zaktajsek default risk spread
7	TFP	Utilization-adjusted TFP Utilization-adjusted TFP in producing equipment and consumer durables Utilization-adjusted TFP in producing non-equipment output

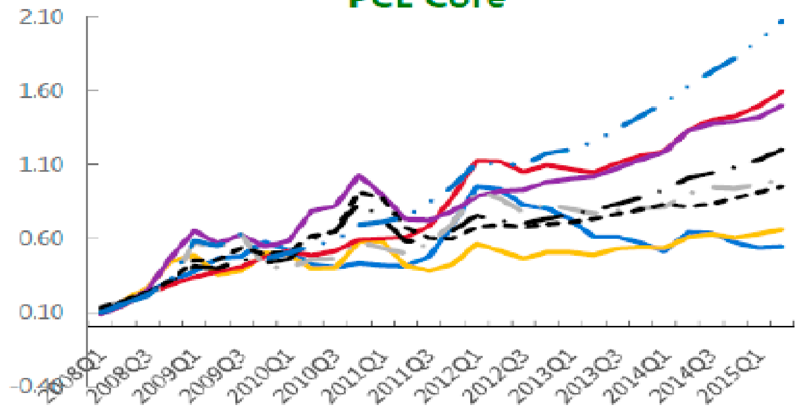
RMSFE - Hybrid Conditional Forecast Scenarios – Structural coefficient (estimated up to 2015Q2), Shock variances (estimated up to 2007Q4)

First counter-factual exercise

Unemployment



PCE Core



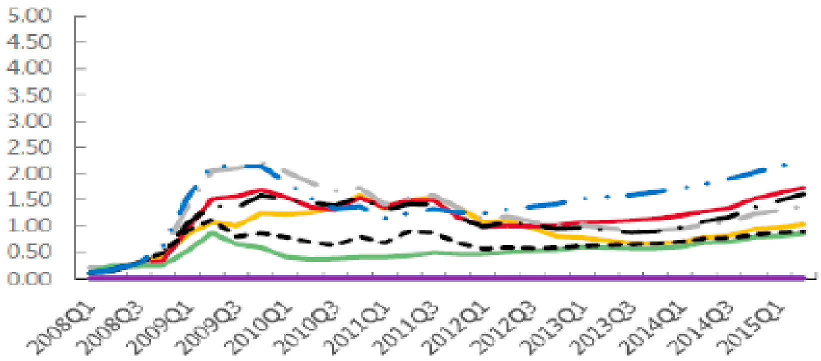
All | External Factors | Commodity Factors | Labor Market Factors | Interest Rates
Credit | Financial Risk | TFP | Unconditional Forcast

Change in propagation does not explain inflation or unemployment post-crisis and gives much higher RMSFE than…

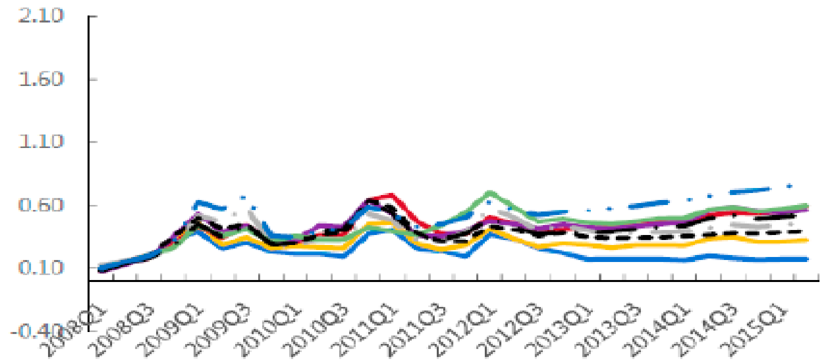
RMSFE - Hybrid Conditional Forecast Scenarios – Structural coefficient (estimated up to 2007Q4), Shock variances (estimated up to 2015Q2)

Second counter-factual exercise

Unemployment



PCE Core



…. allowing for change in shock variances.

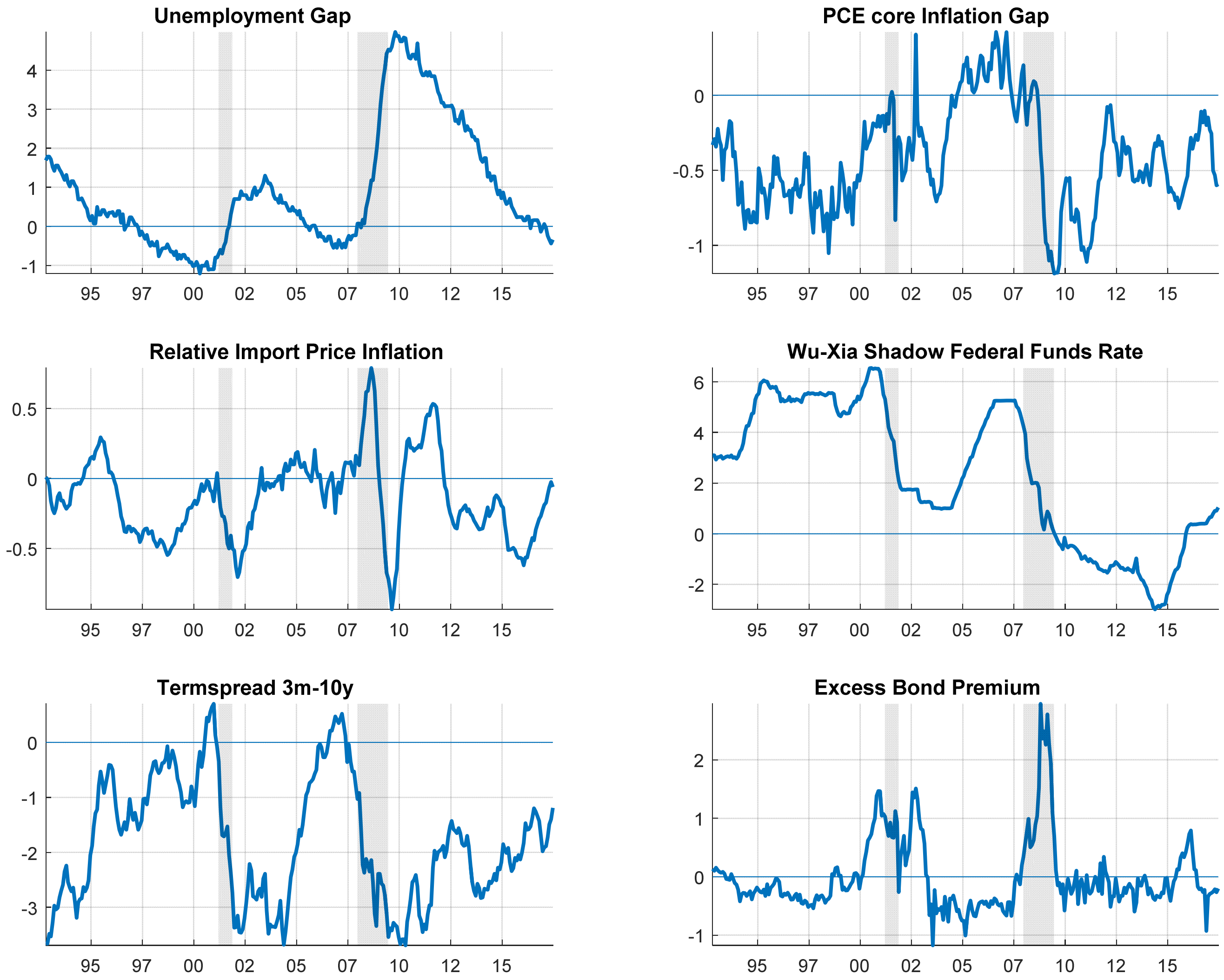
PART 2: Smaller Markov-Switching Bayesian VARs

$$p\left(s_t^{c,v} = i | s_{t-1}^{c,v} = k\right) = p_{ik}^{c,k},$$

&

y_t = "Small"

Data



Unemployment Gap
4
3
2
1
0
-1
95 97 00 02 05 07 10 12 15
PCE core Inflation Gap
0
-0.5
-1
95 97 00 02 05 07 10 12 15
Relative Import Price Inflation
0.5
0
-0.5
95 97 00 02 05 07 10 12 15
Wu-Xia Shadow Federal Funds Rate
6
4
2
0
-2
95 97 00 02 05 07 10 12 15
Termspread 3m-10y
0
-1
-2
-3
95 97 00 02 05 07 10 12 15
Excess Bond Premium
2
1
0
-1
95 97 00 02 05 07 10 12 15

Results: Did the Phillips Curve Change?

Log Marginal Data Densities $p\left(Y|\mathcal{M}_i\right) = \int p\left(Y|\theta,\mathcal{M}_i\right) p\left(\theta\right) d\theta$ (likelihood function integrated over the model parameters*)

Table 3.MS − VAR estimation results

Model	$s^v = 1$	$s^v = 2$	$s^v = 3$
$s^c = 1$	**685.5**	**764.3**	**781.4**
Diff. from best	-138.9	-60.1	-43
$s^c = 2$	**765.5**	**784.8**	**812.1**
Diff. from best	-58.9	-39.6	-12.3

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$s^c = 2$ *in PC*	**701.7**	**783.9**	**791.3**
Diff. from best	-122.7	-40.5	-33.1
$s^c = 2$ *in MP − Rule*		**789.2**	**824.4**
Diff. from best		-35.2	0

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Constant coefficient/variance BVAR

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Constant coefficient/variance BVAR

Regime switches / time variation in variances or coefficients in ALL EQ is clearly preferred by the data (relative to no change)

Results: Did the Phillips Curve Change?

Log Marginal Data Densities $p\left(Y|\mathcal{M}_i\right) = \int p\left(Y|\theta, \mathcal{M}_i\right) p\left(\theta\right) d\theta$ (likelihood function integrated over the model parameters*)

Table 3.MS – VAR estimation results

Model	$s^v = 1$	$s^v = 2$	$s^v = 3$
$s^c = 1$	**685.5**	**764.3**	**781.4**
Diff. from best	-138.9	-60.1	-43
$s^c = 2$	**765.5**	**784.8**	**812.1**
Diff. from best	-58.9	-39.6	-12.3

Model	$s^v = 1$	$s^v = 2$	$s^v = 3$
$s^c = 1$	**685.5**	**764.3**	**781.4**
Diff. from best	-138.9	-60.1	-43
$s^c = 2$ *in PC*	**701.7**	**783.9**	**791.3**
Diff. from best	-122.7	-40.5	-33.1
$s^c = 2$ *in MP – Rule*		**789.2**	**824.4**
Diff. from best		-35.2	0

Constant coefficient/variance BVAR

Regime switches / time variation in variances or coefficients in ALL EQ is clearly preferred by the data (relative to no change)

Regime switches / time variation in coefficients in PC EQ is clearly also preferred by the data (relative to no change)

Results: Did the Phillips Curve Change?

Log Marginal Data Densities $p(Y|\mathcal{M}_i) = \int p(Y|\theta, \mathcal{M}_i)\, p(\theta)\, d\theta$ (likelihood function integrated over the model parameters*)

$Table\ 3. MS - VAR\ estimation\ results$

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Constant coefficient/variance BVAR

Regime switches / time variation in variances or coefficients in ALL EQ is clearly preferred by the data (relative to no change)

Regime switches / time variation in coefficients in PC EQ AND variances (independently) is superior (relative to only coeff)

Results: Did the Phillips Curve Change?

Log Marginal Data Densities $p(Y|\mathcal{M}_i) = \int p(Y|\theta, \mathcal{M}_i)\, p(\theta)\, d\theta$ (likelihood function integrated over the model parameters*)

Table 3. MS − VAR estimation results

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$s^c = 2$ *in MP − Rule*		**789.2**	**824.4**
Diff. from best		-35.2	0

Constant coefficient/variance BVAR

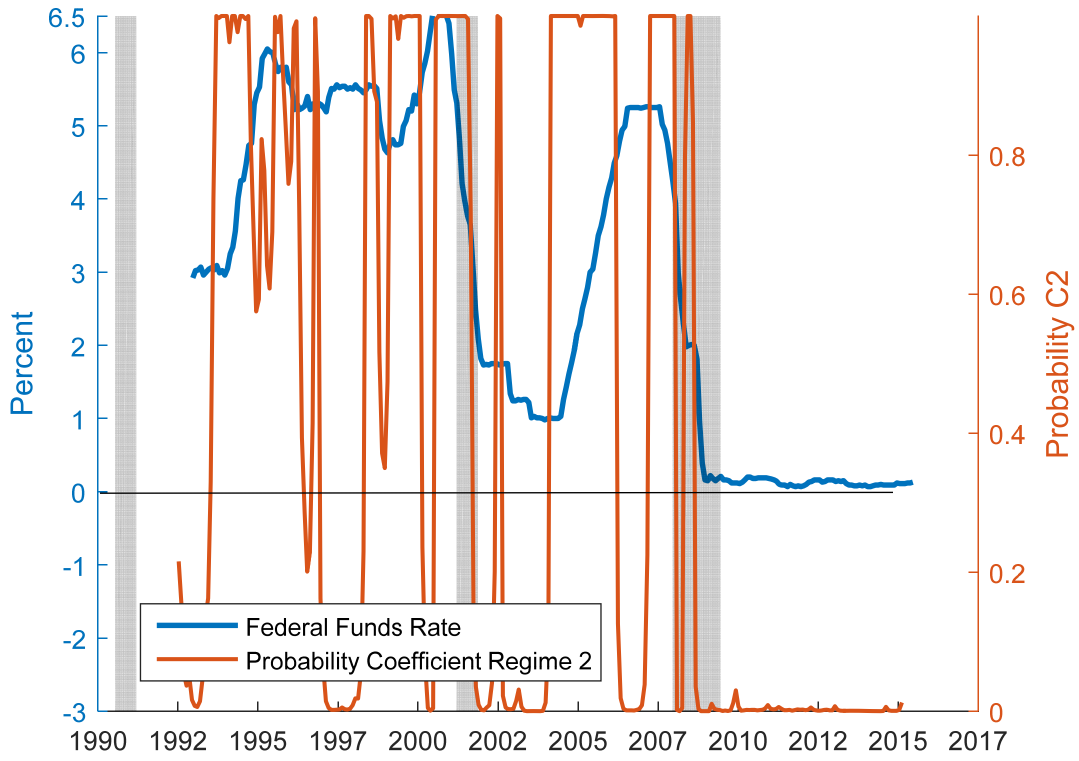
Regime switches / time variation in variances or coefficients in ALL EQ is clearly preferred by the data (relative to no change)

Regime switches / time variation in coefficients ONLY in Interest equation AND variances (independently) is superior (relative to all alternatives)

Coefficient Regime Posterior Probabilities

Regimes seem to capture a active monetary policy

MS-BVAR using Federal Funds Rate

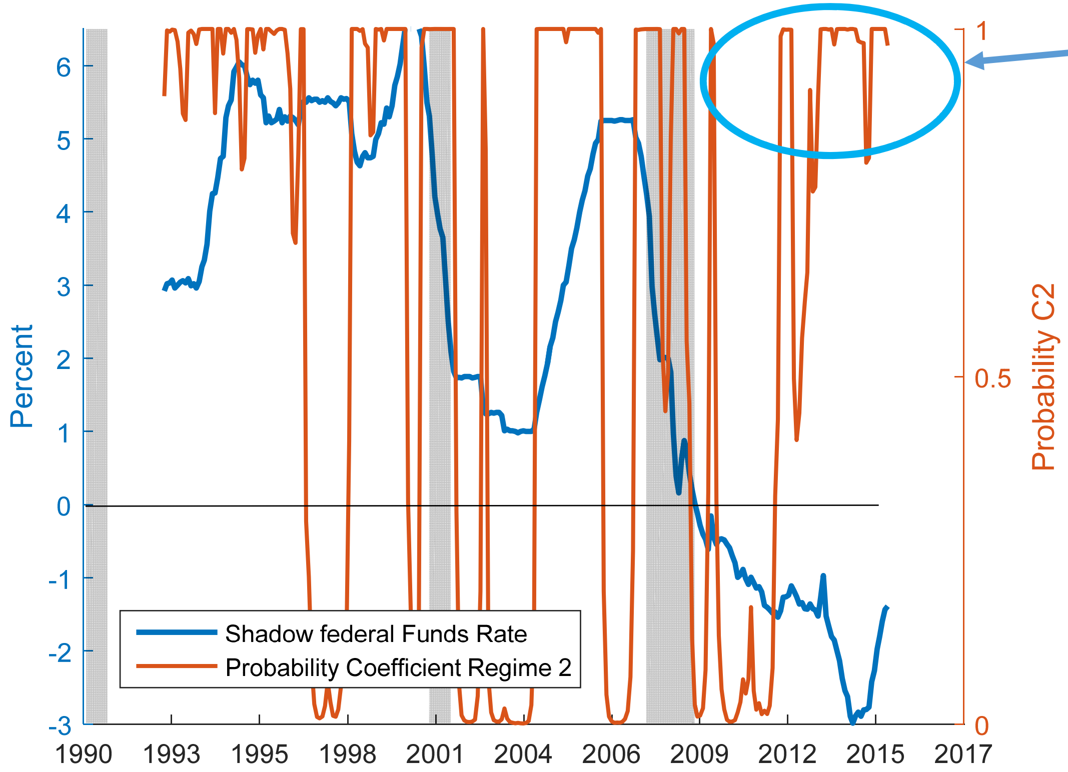


… clear that regimes are governed by changes in the interest rate when using the actual effective federal funds rate....

Coefficient Regime Posterior Probabilities

Regimes seem to capture a active monetary policy

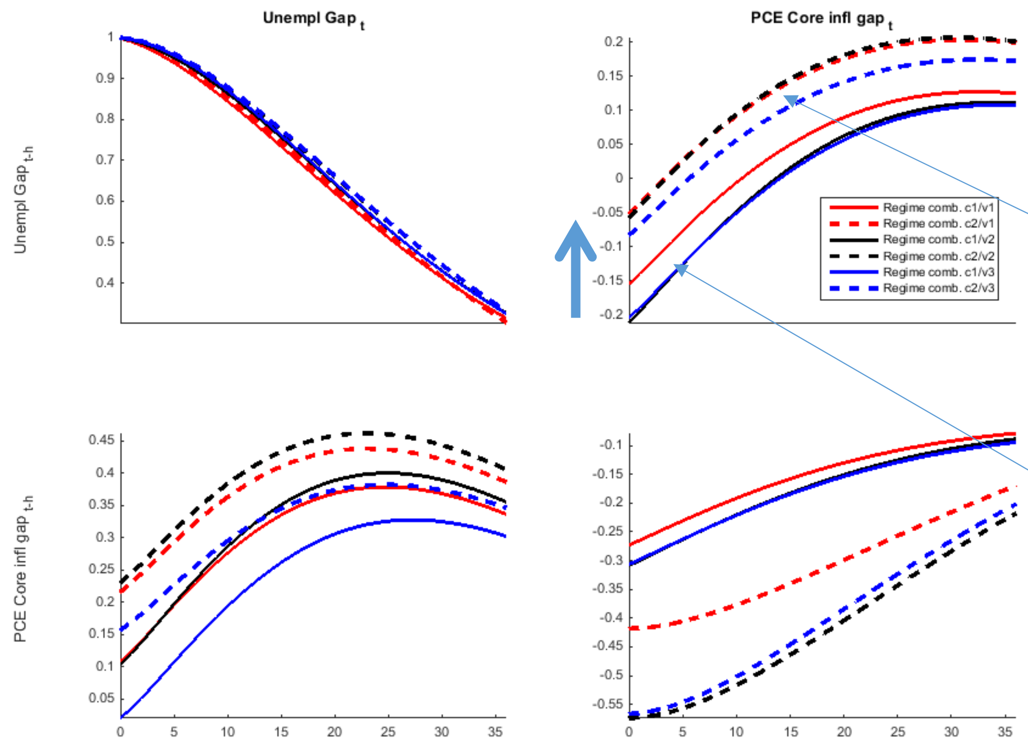
MS-BVAR using W-X Shadow Federal Funds Rate



… policy has been less constrained during the last years due to unconventional policies which pushed shadow rates below zero….

What are the implications for the Phillips Curve Correlation?

Compare cross-correlation functions (CCF) from the MSBVAR **for different regimes**…



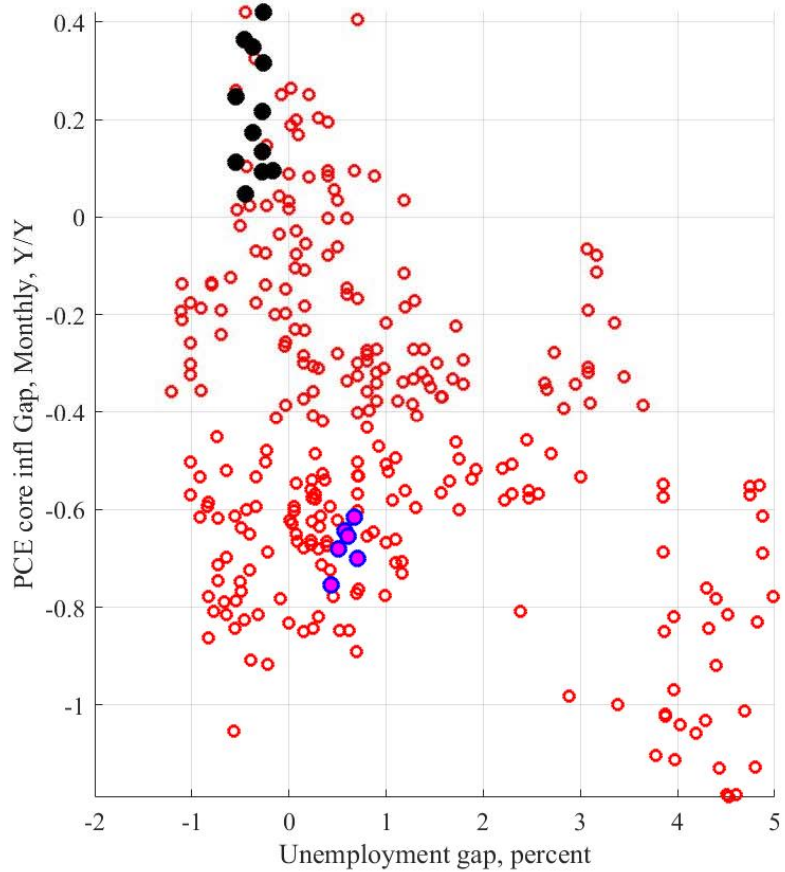
Single equation regressions *without* regime changes will likely find changes in the slope …

Inflation/Unempl reduced form cross-correlation: monetary policy **in regime 2**

Inflation/Unempl reduced form cross-correlation: monetary policy **in regime 1**

X-axis shows: corr(PCE core in period t , Unempl Gap in period t,t-1,…t-30)

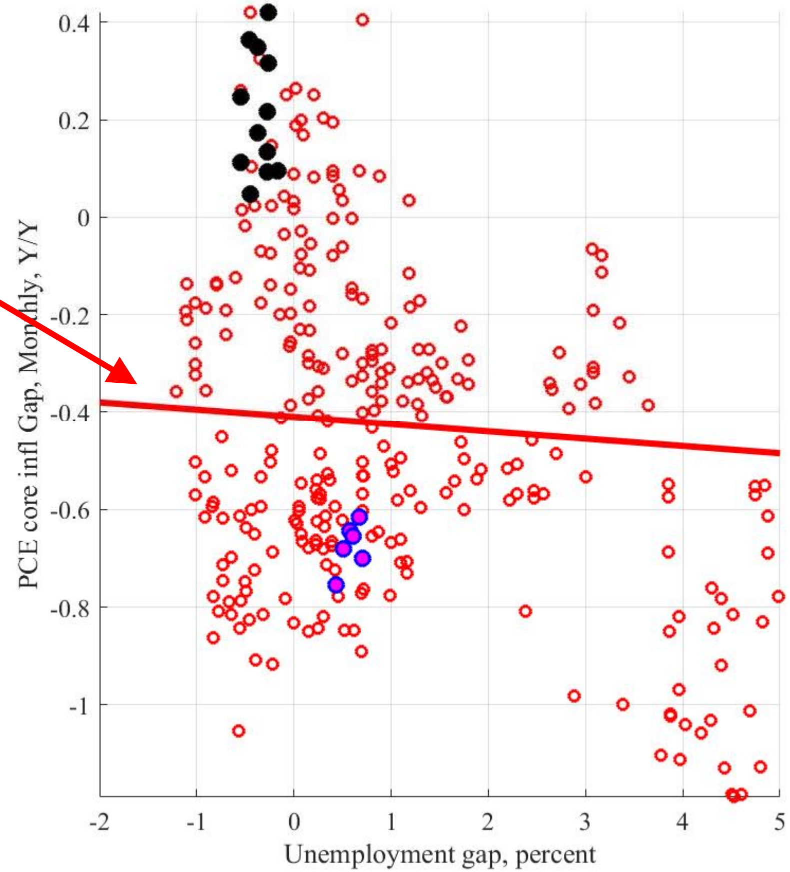
The structural short run PC is stable but the reduced form changes with the coeff states of monetary policy…



The structural short run PC is stable but the reduced form changes with the coeff states of monetary policy…

Structural short run Phillips Curve when all variables except unemployment and inflation are at their mean values

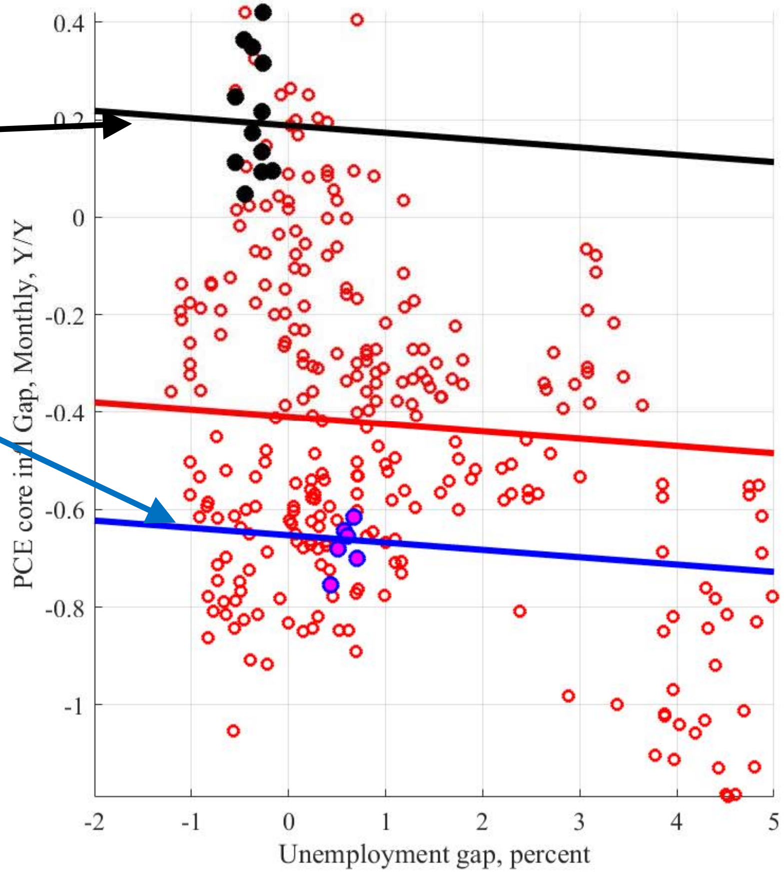
$$\alpha(L)\pi_t = {\color{red}\beta(L)}\hat{u}_t + \gamma(L)\bar{Z}_t$$



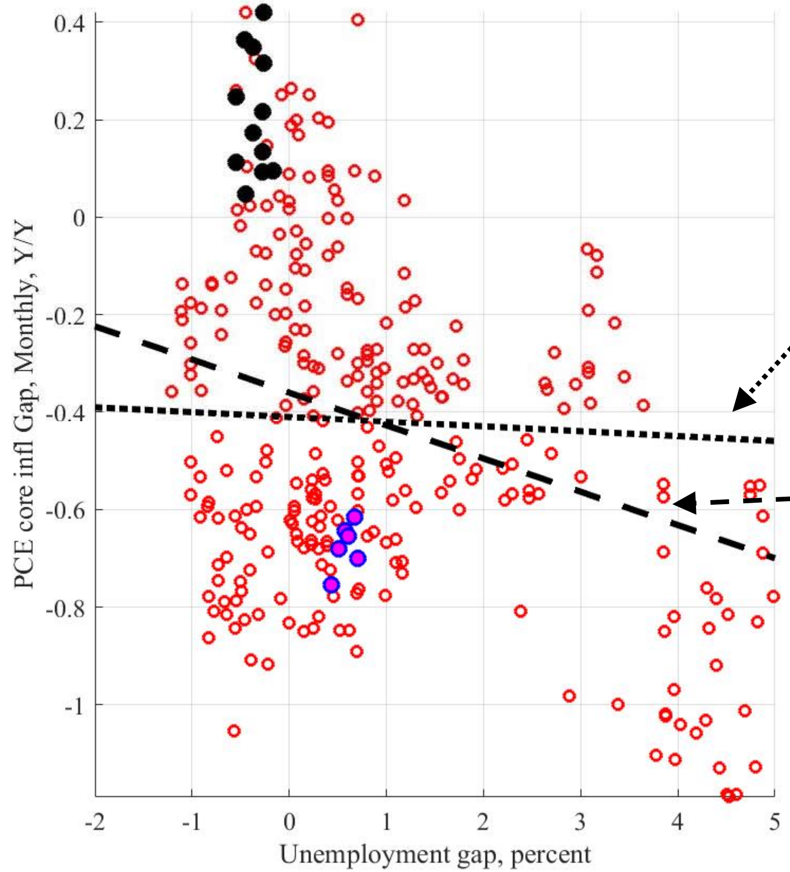
The structural short run PC is stable but the reduced form changes with the coeff states of monetary policy…

Structural short run Phillips Curve when all variables except unemployment and inflation are at their 2006 and 2015 values

$$\alpha(L)\pi_t = \beta(L)\hat{u}_t + \gamma(L)Z_t^{15}$$



The structural short run PC is stable but the reduced form changes with the coeff states of monetary policy…

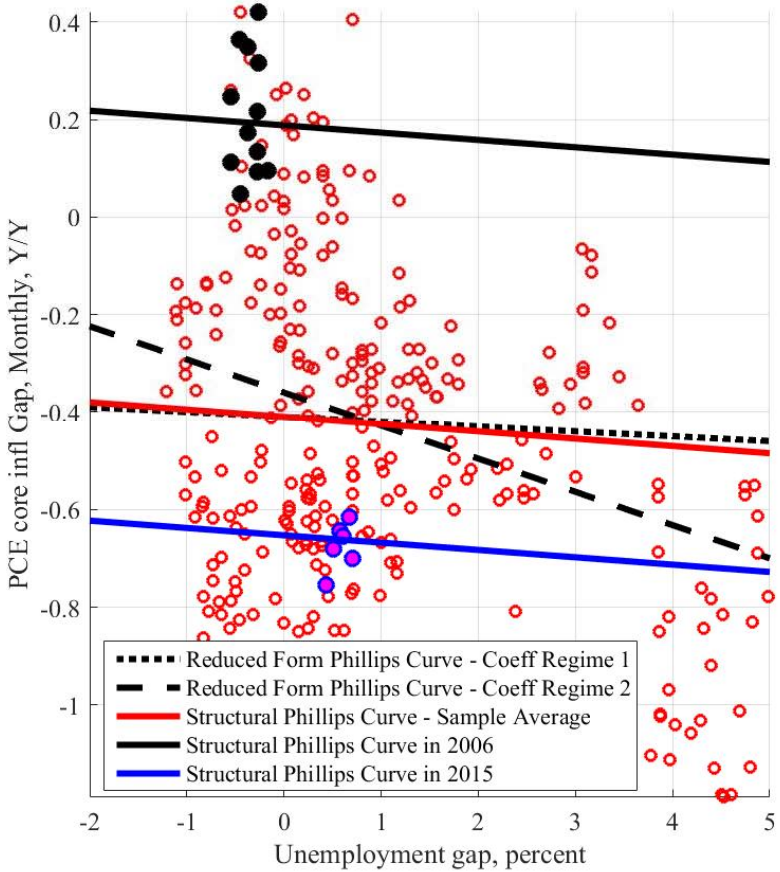


Inflation/Unempl reduced form relation with monetary policy **<u>in regime 2</u>**

Inflation/Unempl reduced form relation with monetary policy **<u>in regime 1</u>**

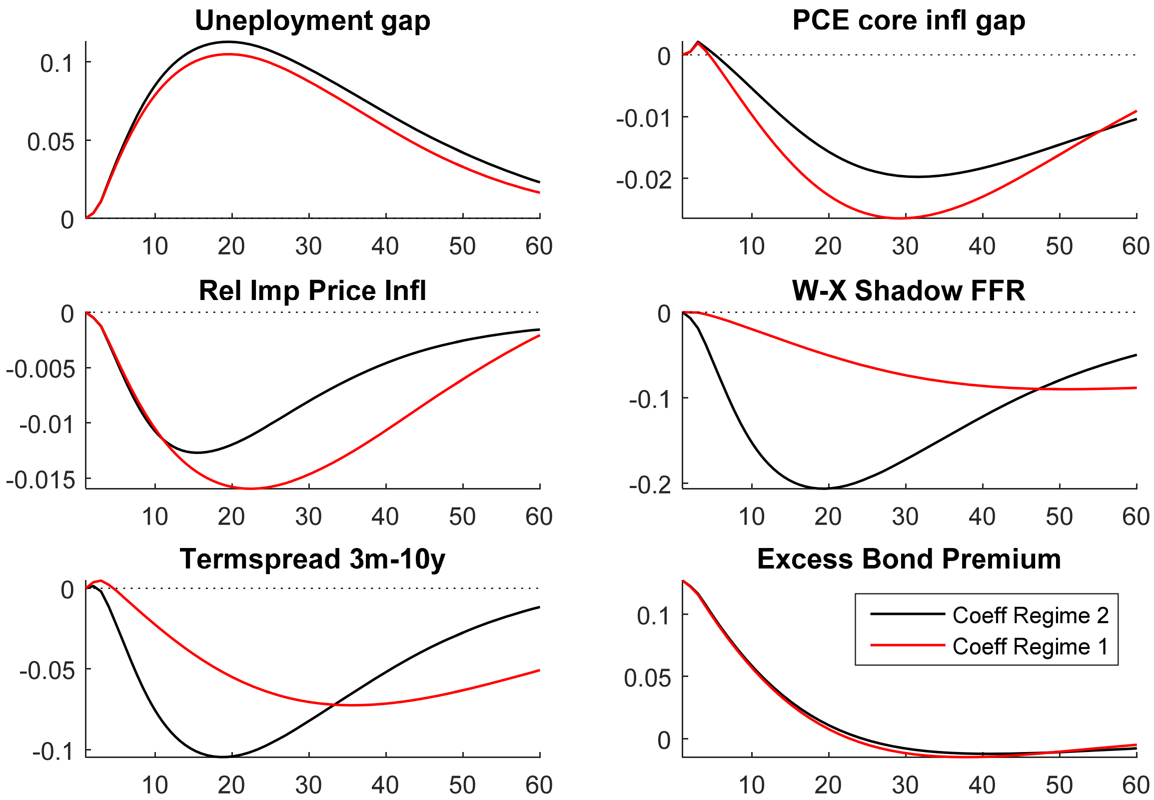
(Restrictions on policy means that inflation will not be stabilized as effectively and the PC corr will be steeper)

The structural short run PC is stable but the reduced form changes with the coeff states of monetary policy…



Monetary policy in Coeff Regime 1 is stabilizing inflation (Relative Imported and PCE Core) less well following a financial shock…

Impulse-response functions



…which gives rise to a steeper reduced form Phillips Curve.

Conclusions

1. Drivers of unemployment and inflation are complex but external and financial data offer the lowest RMSE's
2. Knowing the data (conditioning on actual outcomes) is not enough..
   - Variance/co-variances change over time
3. Some evidence that monetary policy changes between passive and active reaction to shocks
4. The short run Phillips Curve appears to be stable but shocks change in nature making the PC seemingly unstable.

5. Extensions and further work:
   1. We are currently working on including a broader set of measures of short run inflation expectations in our framework.
   2. Further research on possible structural changes of labor markets that examines whether the most recent recession was fundamentally different from previous recessions would be valuable.
   3. Modeling monetary policy since the Great Recession, to capture the effects of the effective lower bound, extended forward guidance from central banks, and government bond purchases is needed.

Policy implications

- #1. A linear Phillips curve warrants a symmetric monetary policy response with respect to business cycle conditions.

- #2. A nonlinear Phillips curve may imply preemptive measures are needed to counter inflation when the economy is closer to potential.

- #3. If, on the other hand, the Phillips curve is very flat monetary policy should react more strongly to unemployment, relative to inflation.
  - See e.g. discussion in Blanchard (2016).

- Note! Monetary policy is not powerless if the PC is flat since it does not only affect inflation through unemployment! The impact of financial shocks differ e.g. markedly between coefficient regime 1 and 2.

Extra slides

MS-BVAR Robustness

- The result of changes in only the monetary policy equation is robust to both changes in lag length, priors and changes in data

- y_t = [U , ln(PCE), ln(REER), R, ln(M), GZ].

Table 4: MS-VAR in levels estimation results

$Model \longrightarrow$	$3v2c$	$3v\ all\ eq\ 2c\ eq4$
(a) log MDD	3766.25	3797.00
$Diff.\ from\ best$	-30.75	0

MS-BVAR Robustness: A Markov-Switching Version of the New-Keynesian Model (slide 14)

Table A1.MS − VAR estimation results : A Version of the New-Keynesian Model

Model $\longrightarrow$	$1v1c$	$2v1c$	$3v1c$
(a) *General Models*	2158.6	2258.6	2267.9
Diff. from best	-128.2	-28.2	-18.9
	$1v2c$	$2v2c$	$3v2c$
	2241.9	2269.7	2274.4
	-44.9	-17.1	-12.4

Model $\longrightarrow$	$3v(PC\ Eq)2c$	$3v(IS\ Eq)2c$	$3v(Mon\ Pol\ Eq)2c$
(b) *Restricted Models*	2262.1	2254.6	2286.8
All equations 3 states	-24.7	-32.2	0
variance switching			