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

by Stefan Laseen and Marzie Taheri Sanjani

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Did the global financial crisis break the US Phillips Curve?

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Abstract

Inflation dynamics, as well as its interaction with unemployment, have been puzzling since the Global Financial Crisis (GFC). In this empirical paper, we use multivariate, possibly time-varying, time-series models and show that changes in shocks are a more salient feature of the data than changes in coefficients. Hence, the GFC did not break the Phillips curve. By estimating variations of a regime-switching model, we show that allowing for regime switching solely in coefficients of the policy rule would maximize the fit. Additionally, using a data-rich reduced-form model we compute conditional forecast scenarios. We show that financial and external variables have the highest forecasting power for inflation and unemployment, post-GFC.

Keywords: Phillips curve, Inflation, Unemployment, Financial Frictions, Conditional Forecast, Regime Switching and Bayesian Estimation.

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I. Introduction

How does unemployment affect inflation? This question is a central topic in macroeconomics, and the Phillips curve of textbooks say that a higher level of unemployment causes inflation to decrease over time. Since the Great Financial Crisis (GFC) of $2008-2009$, while inflation has declined, it has fallen less than was anticipated (an outcome referred to as the "missing disinflation"). More recently the currently low unemployment rates should have pushed the inflation rate closer to the Federal Open Market Committee's longer-run inflation goal, but inflation has been running below the 2 percent target for an extended period (see Figure 1 and 2).[1] This has lead leading researchers to revisit the relation between inflation and activity.[2]

Clearly, if confirmed, a changing or non-linear, relation between inflation and unemployment would have significant implications for monetary policy. While a linear Phillips curve warrants a symmetric monetary policy response with respect to business cycle conditions, a nonlinear Phillips curve, where inflation increases rapidly when unemployment rate declines below the natural rate may imply pre-emptive measures are needed to counter inflation when the economy is closer to potential. If, on the other hand, the Phillips curve is very flat monetary policy should react more strongly to unemployment movements, relative to inflation.

In this paper, we shed light on the forces and, possibly changing, dynamics between inflation and activity since the GFC. In other words, did the GFC break the U.S. Phillips curve? Moreover, we investigate three hypotheses which have recently been put forward as factors which could explain why inflation is currently low: (a) Financial frictions, and shocks could imply slow recoveries and persistently low inflation. Several recent papers, including Christiano, Eichenbaum, and Trabandt (2015), and Gilchrist and Zakrajsek (2015) have e.g. shown that financial frictions play an important role in shaping the dynamics of prices after the GFC; (b) Globalization has increased the role of international factors and decreased the role of domestic factors in the inflation process in industrial economies. These hypotheses originated from the concerns of some monetary policymakers of an increasing disconnect between monetary policy on one side and domestic inflation and long-term interest rates on the other. The evidence of the importance of global factors is however mixed (Ihrig et al. 2010, Bianchi and Civelli 2015); (c) the last hypothesis pertains to the 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.[3] Policymakers have emphasized how persistently low inflation poses substantial risks if monetary policy is constrained by the zero bound, and could derail the economic recovery (e.g. Constâncio 2014).

The literature has to a large extent focused on estimating univariate Phillips curves to study the possibly changing nature of the inflation process. We instead take a flexible multivariate approach

[1] See e.g. Kiley (2015) for a summary of recent research of low inflation in the United States.

[2] Before the GFC policy institutions such as the International Monetary Fund (IMF) and the Federal Reserve started to emphasize a long decline in the slope of the Phillips curve, i.e. the coefficient of economic slack (IMF 2006 and Roberts 2006). This decline has been challenged by other researchers as being too dependent on the Phillips curve specification (see e.g. Gordon 2007 and 2013). Coibion and Gorodnichenko (2015) demonstrates that evidence of slope decline is mixed for the United States. Stock and Watson (2010) find that there is some evidence that the slope parameter might be smaller at low levels of inflation, but statistical tests do not confirm these findings robustly.

[3] Arias, Erceg and Trabandt (2016) investigate the macroeconomic risks posed by low inflation, and specifically, highlight how a persistent decline in inflation can have very costly implications for output when the zero lower bound is binding.

by using Large Bayesian Vector AutoRegression (BVAR's), dynamic factor models (DFM's) as well as time-varying (Markov-switching) MS-BVARs to provide some answers. There is a rich literature in VAR emphasizing the importance of using large information set in addressing non-fundamentalness (Giannone and Reichlin 2006), also using a rich dataset allows for a comprehensive analysis of which set of data (e.g. macro, financial, external, TFP, among others) is informative for shaping the dynamics of inflation and unemployment. We use conditional forecast analysis (similar to the analysis proposed by Giannone, Lenza, and Reichlin (2008) to explain the great moderation) by mixing in-sample and out-of-sample forecasts to distinguish between variance changes and structural parameter variations in the data post-GFC. Note that conditional forecasts are projections of a set of variables that are of interest assuming we know the future paths of some other variables. We follow seminal work of Banbura, Giannone, and Lenza (2015) to compute conditional forecasts.We can also control for changes in, or restrictions on, monetary policy, such as the effective lower bound on interest rates. Our approach provides a formal framework to investigate the presence of nonlinearities, and it can distinguish between variance switching as the source of time variation and coefficient switching that alters the transmission of shocks to the real economy.

Our most important empirical finding is that the Phillips curve is, not broken by the GFC.[4] Both, the large VAR and smaller regime switching, models explain differences in the behavior of the economy between periods, before and after GFC, as reflecting variation in the sources of economic disturbances not as variation in the dynamics of the Phillips curve to a given disturbance in the economy. Moreover, we estimate variations of the regime switching model, with regimes being either on the coefficients or variances of the equations. We then compute marginal data density to compare the fit of these models. Our results show that the version of our models that fits best is one that shows a change in coefficients only of the monetary policy rule not of the Phillips curve. What changes across "regimes" is most importantly the variances of structural disturbances.[5] Additionally, using large VAR and DFM, we compute conditional forecasts scenarios to compare the forecasting power of various sets of observables, conditioning variables, for the dynamic of inflation and unemployment. We illustrate that the external and financial risk variables[6] contain valuable information in forecasting inflation and unemployment post recent financial crisis. Furthermore, our finding confirms the rich amount of information that is contained in excess bond premium (EBP), reflecting credit supply shocks as an important driver of macroeconomic dynamics, as argued by e.g. Gilchrist and Zakrajsek (2010). Gilchrist, Sims, Schoenle and Zakrajsek (2015) goes further and looks at differences in the firms' price-setting behavior, in the context of financial frictions. They explain why firms with limited internal liquidity significantly increased prices in 2008, while their liquidity unconstrained counterparts slashed prices.

The paper is organized as follows: In section 2 we describe our methodology; in section 3 we present the empirical evaluation by first assessing how the large cross-sections BVAR's and DFM's identify the effects of various shocks and structural changes in explaining the dynamics of unemployment and inflation. In this section, we also investigate which conditioning information sets are informative for inflation and unemployment developments since the GFC. In section 4 we conclude.

[4]This is in line with Blanchard, Cerutti, and Summers 2015 and Blanchard 2016 who found that, while the slope coefficient of the Phillips curve declined from the mid-1970s to the early 1990s, it has not further declined after the global financial crisis.

[5]In this sense our results are in line with Canova (2009) who show that changes in the parameters of the policy rule and the covariance matrix of the shocks are the most important in accounting for the changes in the volatility of output and inflation during the great moderation.

[6]Table 1 lists the variable within each category.

II. Models

The general framework is described by a (possibly) nonlinear vector stochastic dynamic process of the following form:

$$A_0'(s_t^c)\,y_t = C(s_t^c)\,x_t + \Xi_m^{-1}(s_t^v)\,\epsilon_t, \tag{1}$$
$$x_t = A_+'(s_t^c)\,x_{t-1} + \Xi_s^{-1}(s_t^v)\,\varepsilon_t, \tag{2}$$

where y_t is an $n \times 1$ vector of endogenous, and observable, variables, s^c and s^v are latent state variables for coefficients and variances respectively. x_t is an m-dimensional vector of potentially unobserved state variables. A_0 is an $n \times n$ matrix of parameters describing contemporaneous relationships among the endogenous variables in y_t, and A_+ is an $m \times n$ matrix of parameters. T is the sample size. The structural disturbances are assumed to have the distribution

$$\pi\left(\varepsilon_t | Y^t, s_t^m, A_0, A_+\right) \sim N\left(0_{n\times 1}, I_n\right),$$

where Y^t denotes the vector y stacked in the time dimension, $Y^t = \{y_0, y_1, y_2, ..., y_t\}$, and where $N(0_{n\times 1}, I_n)$ refers to the normal pdf with mean 0 and covariance matrix I, where I is an $n \times n$ identity matrix. The values of s^c and s^v are elements of $\{1, 2, ..., h^m\}$ and evolve according to a first order Markov process

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

Following Sims and Zha (2006) we impose no restrictions on the transition matrix. In the empirical analysis we consider four different specifications of eqs. (1)–(2). The first three are large cross-section dynamic factor models and vector autoregressive models and the last one is a markov-switching structural VAR model.

III. Empirical Evaluation

A. Large Cross-Sections VAR's and DFM's

In this section, we use a rich information set to compute conditional forecast scenarios, to identify the effect of various shocks and structural changes in explaining the dynamic of the unemployment rate and inflation. The use of large database allows for a comprehensive analysis of different channels through which various factors would affect the dynamics of inflation minimizing the possibility of the non-fundamentalness problem of smaller scale models. The choice of variables in the model is motivated by findings of the literature on inflation dynamic and the hypothesis that we are testing. Hence, we mainly focus on the role labor, financial, external, commodity and total factor productivity (TFP) factors.

A.1. The Large Scale Quarterly Data

Our dataset contains 45 quarterly variables.[7] In general, we have the most relevant real activity variables for United States and also a set of variables that indicates the global macroeconomic conditions (world GDP, US GDP and expenditure components, industrial production index, consumer sentiment, labor market data and total factor productivity), price variables (commodity price, CPI, producer price index, GDP deflator and imports deflator), monetary variables (short-term and long-term interest rates, money supply), financial variables (credit to households and corporations, stock price, real effective exchange rate, Moodys *Aaa* and *Baa* corporate bond yield, number of housing units started and economic uncertainty). The data feeds the models in annualized log-levels, except those variables which are defined in terms of annualized rates, such as interest rates, corporate bond yields, and TFP, among others, which are taken in levels.

Our sample covers the period from $1987Q1$ to $2015Q2$. Table 1 below provides details of variables definition, and the transformation applied to them before estimation.

A.2. Model 1: The Bayesian Dynamic Factor Model

The general representation of the linear dynamic factor model,

$$\begin{aligned}\Delta y_t &= z_t + \Lambda F_t + \Xi^{-1}\epsilon_t, \qquad t = 1, 2, .., T, & (3)\\ F_t &= \Phi_1 F_{t-1} + .. + \Phi_s F_{t-s} + \Xi_s^{-1}\varepsilon_t, & (4)\end{aligned}$$

can be cast in the representation in Eqs. (1)–(2) by imposing that $p\left(s_t^{c,v} = i | s_{t-1}^{c,v} = k\right) = 0$, $y_t = \Delta y_t$, $A_0' = I_n$, $C = (\Lambda, 0_{n\times r(s-1)}, I_n)$ and

$$\begin{aligned} x_t' &= \left[F_t, F_{t-1}, ..., F_{t-s+1}, z_t\right], \\ A_+' &= \begin{bmatrix} \Phi_1 & \Phi_2 & \dots & \Phi_s & 0_{r\times n} \\ I_r & 0_r & \dots & 0_r & \vdots \\ \vdots & \ddots & \dots & \vdots & \vdots \\ 0_r & \dots & I_r & 0_r & 0_{r\times n} \\ 0_{n\times r} & \dots & \dots & 0_{n\times r} & I_n \end{bmatrix}. \end{aligned}$$

F_t is is an r-dimensional vector of common factors, with r typically being much smaller than n, and Λ is an $n \times r$ matrix of factor loadings. z_t is a matrix of exogenous variables or constants. The residual ϵ_t is the idiosyncratic component.

[7] Our data come from various sources; most of them can be found in Bureau of Economic Analysis, Federal Reserve Board, Bureau of Labor Statistics, Congressional Budget Office, Census Bureau, and IMF database. All these variables can be accessed through Haver Analytics. All TFP data is provided the Federal Reserve Bank of San Francisco (http://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/). Three months EURIBOR data can be found in Area Wide Model database (Fagan, Henry, & Mestre, 2005). Economic uncertainty data is constructed using Nick Bloom's methodology and can be download from the Economic Policy Uncertainty homepage.

Table 1: Data Description and Transformation

Block #	Position	Mnemonic	Description	Source	Transformation
	1	world RGDP	YOY (pct change) World RGDP	level/100	
	2	rgdp	US Real GDP (SAAR, Bil.Chn.2009)	log level x 4	
	3	ip	US Industrial Production Index (SA, 2012=100)	log level x 4	
	4	c	US Real Personal Consumption Expenditures (SAAR, Bil.Chn.2009)	log level x 4	
	5	g	US Real Government Consumption Expenditures & Gross Investment(SAAR, Bil.Chn.2009)	log level x 4	
	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	
	8	m	US Real Imports of Goods & Services (SAAR, Bil.Chn.2009)	log level x 4	
	9	emp	US All Employees: Total Nonfarm Payrolls (SA, Thous)	log level x 4	
	10	u	US Unemployment Rate: 16 Years + (SA, %)	level / 100	
	11	nairu	US Natural Rate of Unemployment [CBO] (%)	level / 100	
	12	cap ut	US Capacity Utilization: Industry (SA, Percent of Capacity)	level / 100	
	13	util	Utilization of capital and labor	log level x 4	
	14	util-invest	Utilization in producing investment	log level x 4	
	15	util-consumption	Utilization in producing non-investment business output ("consumption")	log level x 4	
	16	c conf	US University of Michigan: Consumer Sentiment (NSA, Q1-66=100)	level / 100	
	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	
	19	tfp-C-util	Utilization-adjusted TFP in producing non-equipment output	log level x 4	
	20	oil	Spot Price Idx of UK Brt Lt/Dubai Med/Alaska NS heavy (2010=100)	log level x 4	
	21	non oil	Non-fuel Primary Commodities Index (2010=100)	log level x 4	
	22	cpi shelter	US CPI-U: Shelter (SA, 1982-84=100)	log level x 4	
	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	
	25	ppi	US PPI: Finished Goods (SA, 1982=100)	log level x 4	
	26	gdp def	US GDP Implicit Price Deflator (SA, 2009=100)	log level x 4	
	27	mxrmd	US Imports Deflator (excluding raw materials)	log level x 4	
	28	wages	US Avg Hourly Earnings: Prod & Nonsupervisory: Total Private Industries(SA, /Hour)	log level x 4	
	29	euro-stn	Euro Area 11-19: 3-Month EURIBOR (%)	level / 100	
	30	libor us	3-Month London Interbank Offer Rate: Based on US (%)	level / 100	
	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	
	33	m1	Money Stock: M1 (SA, Bil.)	log level x 4	
	34	m2	Money Stock: M2 (SA, Bil.)	log level x 4	
	35	loan hh	US: Household & Nonprofit Outstanding Debt (SA, Bil.US)	log level x 4	
	36	loan corp	US: Nonfinancial Corporations Outstanding Debt (SA, Bil.US)	log level x 4	
	37	reer	Real Broad Trade-Weighted Exchange Value of the US (Mar-73=100)	log level x 4	
	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	
	40	corp Baa	Moody's Seasoned Baa Corporate Bond Yield (% p.a.)	level / 100	
	41	pol uncert	Policy-related Economic Uncertainty	level / 100	
	42	ebp-oa	Excess Bond Premium	level	
	43	gz-spr	Gilchrist and Zakrajsek default risk spread	level	

A.3. Model 2 and 3: The Large Cross-Section Bayesian Vector Autoregressive Models

The general representation of the linear large Cross-Section VAR models are given by

$$y_t = z_t + A_1 y_{t-1} + ... + A_p y_{t-p} + \Xi^{-1}\varepsilon_t, \qquad t = 1, 2, .., T, \tag{5}$$

for the VAR in levels and

$$\Delta y_t = z_t + B_1 \Delta y_{t-1} + ... + B_p \Delta y_{t-p} + \Xi^{-1}\varepsilon_t, \qquad t = 1, 2, .., T, \tag{6}$$

for the VAR in differences. These VAR models can be cast in the representation in Eqs. (1)–(2) by imposing that $p\left(s_t^{c,v} = i | s_{t-1}^{c,v} = k\right) = 0$, $y_t = \Delta y_t$ (for the VAR in differences), $A_0' = I_n$, $C = (I_n, 0_{n\times np})$, $\Xi_m^{-1} = 0$ and

$$\begin{aligned} x_t' &= \left[y_t, y_{t-1}, ..., y_{t-s+1}, z_t\right], \\ A_+' &= \begin{bmatrix} A_1 & A_2 & \dots & A_p & I_n \\ I_n & 0_n & \dots & 0_n & 0_n \\ \vdots & \ddots & \dots & \vdots & \vdots \\ 0_n & \dots & I_n & 0_n & 0_{r\times n} \\ 0_n & \dots & \dots & 0_n & I_n \end{bmatrix}. \end{aligned}$$

A.4. Shocks or Propagation? Conditional Forecast and the Role of Information

Large VAR model is a useful tool for studying the complex dynamic interrelations in data. In a time-series model, determining the split between shocks and propagation depends on the conditioning information set.[8] This is due to the possibility that economic agents might have additional information that is not known to the econometrician. Hence, agents' forecasts are not the conditional expectations obtained from the econometrician's model for the data. Lutkepohl (2012), and others have pointed out that this, so called, non-fundamentalness problem is quite likely to arise in the presence of news shocks, i.e. in a situation where agents actions reflect news regarding future events. Two alternative approaches have been proposed to cope with it. One solution is to increase the information set, that is, the number of variables included in the set of variables under study. This solution has also been used to promote factor augmented VAR and large BVAR models, which can deal with large data sets. The second and the more technical solution is to allow for MA representations for which the determinant has roots inside the complex unit circle and thereby open up for non-fundamental shocks.

Hence, the advantage of the models we use in the first part of our analysis, where we make use of models that can process large datasets, is that they are less likely to be affected by the non-fundamentalness problem (Forni et al. 2009). The intuition is that these models include a large amount of information (virtually all available macroeconomic series) so that insufficient information is unlikely. Furthermore, this suggests that models which use a small data set, and that attribute a large part of the dynamics of inflation post the GFC to shocks *might* not have included enough information and could, therefore, be misspecified. Therefore, when evaluating the role of shocks or propagation in post-GFC inflation dynamics, we should study models of different size.

[8] See Giannone, Lenza and Reichlin (2008) for a discussion.

We follow Giannone, Lenza and Reichlin (2010) and perform counterfactual exercises to assess the role of shocks versus propagation in explaining the dynamics if inflation since the GFC. This approach has also been extensively used in the literature (Stock and Watson 2002, 2003; Ahmed, Levin and Wilson 2004; Justiniano and Primiceri 2006; Giannone, Lenza and Reichlin 2008). We differ however in one important respect. We use conditional forecasts analysis to investigate our questions whereas Giannone, Lenza and Reichlin and others simulate their models to study the variance of the variables of interest such as Gross Domestic Product.

Conditional forecasts are projections of a set of variables that are of interest assuming we know the future paths of some other variables. Related to that, scenario analysis is a conditional forecast exercise to assess the impact of the future specific event on a set of observed variables.[9] For example, by designing a financial variables scenario for inflation, we mean we are forecasting the post-crisis path of inflation conditional on knowing the post-crisis path of selected financial observables. We benchmark our forecast with the unconditional forecasts, where no knowledge of the future paths of any variables is assumed. For recent examples of conditional forecasts, see Bloor and Matheson (2011), Giannone et al. (2014), Jarocinski and Smets (2008), and Stock and Watson (2012*a*). But why do we use a large BVAR models to compute conditional forecast? The computational burden of the conventional algorithm, developed by Waggoner and Zha (1999), means that it can easily become impractical or unfeasible for high dimensional data and long forecast horizons. Hence, we follow Bańbura, Giannone and Lenza (2015) and use their algorithm, which is based on Kalman filtering methods, and is computationally viable for large models that can be cast in a linear state space representation.[10]

Our baseline model is a BVAR performed on level variables. However, as a robustness check, to show that our results don't depend on the choice of model or assumptions on pre-treatment of the data we also perform the same exercise using dynamic factor models (DFMs) and BVAR in first difference. In the main text of the paper we only focus on the results of VAR in level; however as robustness check Figure A1 to A4 in appendix A presents the results for the three models. The Large BVARs and DFM are estimated separately in the two samples:

$$\begin{aligned}(A) &\ :\ x_t = A'_+\left(pre08Q1\right)x_{t-1} + \Xi^{-1}\left(pre08Q1\right)\varepsilon_t,\\ (B) &\ :\ x_t = A'_+\left(pre15Q3\right)x_{t-1} + \Xi^{-1}\left(pre15Q3\right)\varepsilon_t.\end{aligned}$$

First counterfactual exercise: How much of the dynamics of inflation since the GFC can be explained by a change in the propagation? In this exercise we run counterfactual scenarios on shocks assuming that their covariance matrix has remained unchanged at the level of the pre-2008 sample estimates, $\Xi^{-1}\left(pre08Q1\right)$, and feed them through the propagation mechanism estimated for the post-2007$Q4$ sample $A'_+\left(pre2015Q3\right)$. To be more specific, we consider the following counterfactual process:

$$x_t = A'_+\left(pre15Q3\right)x_{t-1} + \Xi^{-1}\left(pre08Q1\right)\varepsilon_t.$$

If the counterfactual inflation dynamics is the same as actual inflation outcomes observed in the post-2007$Q4$ sample - yielding a low root mean square forecast error (RMSFE), then this should indicate

[9]For the estimation and computation of conditional forecast, please see the appendix in Bańbura, Giannone, and Lenza (2015). Our technical appendix can be provided upon request.

[10]For technical discussion on simulation smoothers, see Carter and Kohn, 1994; de Jong and Shephard, 1995; Durbin and Koopman, 2002.

that the change of propagation mechanisms explains the dynamics of inflation since the GFC. The change in shocks plays a role if, instead, the counterfactual RMSE is large. We denote this scenario exercise $C2015V2007$ in the charts.

Second counterfactual exercise: How much of the dynamics of inflation since the GFC can be explained by a change in the shocks? In this exercise we run the opposite counterfactual to the one above. Hence, we consider the following counterfactual process:

$$x_t = A'_+ \left(pre08Q1\right) x_{t-1} + \Xi^{-1} \left(pre15Q3\right) \varepsilon_t.$$

We denote this scenario excercise $C2007V2015$ in the charts. By comparing the fit of two counterfactuals - as measured by RMSFE - we demonstrate the critical role of shocks post-crisis. Figure 3 shows RMSFE for these "hybrid" scenarios and depicts four charts namely the unemployment rate and PCE core inflation for $C2015V2007$ and $C2007V2015$. The bottom panel counterfactual ($C2007V2015$) provides a better fit for both unemployment and inflation than the top-panel counterfactual. Put it differently, knowing pre-crisis covariance structure is not sufficient to replicate the path of the inflation and unemployment post-crisis, even if we know a complete dynamic of model's structural coefficients.

What do these results imply about the shape of the Phillips curve? The data favor changes in the variance-covariance matrix and not changes in the propagation which indicates that the Phillips curve did not change during the sample period.

A.5. What Conditioning Information Set is Informative for Inflation and Unemployment Dynamics?

In the section above we studied the importance of changes in shocks or propagation for the dynamics of inflation and unemployment since the GFC. In this section, we go one step further and investigate the informativeness of conditioning on various blocks of observable variables related to the role labor, financial, external, commodity and total factor productivity (TFP) factors. The use of a rich information set allows for a comprehensive analysis of different channels through which various factors (macro/financial/external) affect the dynamics of inflation. We choose the variables in the model carefully so that it is motivated by findings of the literature on inflation dynamic and the hypothesis that we are testing. We use a wide variety of measures of macro/financial/external data for our conditioning information since we a priori don't know which matter most. The results of this section are also used to motivate the choice of variables in a small-scale regime switching VAR in the next step.

The table below shows different scenarios that we compute. Within each scenario, we use multiple indicators to capture fully the various aspect of the scenario. For example, the list of variables in external factor composed to capture both demand and price effects. When we assume the knowledge of all the variables in the model except the prices, we can produce a conditional forecast scenario called "All" and it will show the unidentified residual.

We generate forecasts from the BVAR in level model conditional on the realized paths of the variables in the scenario table 2. The conditional forecasts are generated over the post-crisis period $2008Q1$ to $2015Q2$ as was done in the section above. We use (A) above to generate out of sample forecasts (the parameters are estimated over the sample $1987Q1$ to $2007Q4$) and (B) for in-sample forecast (where we estimate the model using the whole data length namely $1987Q1$ to $2015Q2$). The

Table 2: Conditional Forecast Scenario Descriptions

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

conditional forecasts can be compared with the realized data in order to gauge how informative the specific conditioning information is for unemployment and inflation. By assessing the forecast error, we can evaluate if the conditioning variables is informative in capturing the salient features of the variables in our model.

Figure 4 and 5 presents two panels; each consists of four charts namely unemployment rate, CPI shelter, CPI Core and PCE core. CPI shelter has the biggest weight in the CPI basket. Food and energy are excluded from core indicators. Figure 4 presents the point-wise RMSFE and Figure 5 the forecasts. The unemployment rate is presented in level, and the prices are in annual growth rate. The top panel shows the in-sample forecasts, and the bottom panel shows the out-of-sample forecasts. Each colored curve shows the conditional forecasts from each scenario. The relative position of the curves from the unconditional forecasts, dashed blue line, shows the direction of the imposed force on the forecast. For example, in the recent episode, commodity prices are pushing PCE core inflation down, as oppose to financial risk insert slight upward pressure. The relative accuracy of the forecasts can be assessed by comparing Root Mean Square Forecast Error (RMSFE). Figure 6 shows the average RMSFE over the recession period (2008Q1 to 2009Q2) and post-recession (2009Q3 to 2015Q2).

In-sample forecasts have better fits than their out-of-sample parallels, as we expected. However, the sizable inaccuracy in out-of-sample unemployment rate forecast shows that the dynamic of this variable undergone substantial changes post-crisis. In reading the scenario charts, one needs to focus on 2008Q1- 2009Q3, the unemployment rate was going up, and inflation was going down. During this episode, most of the conditional scenarios imply a lower PCE core inflation than the unconditional (naive) scenarios. The persistence and inherent dynamic of PCE core prices by inserting upward pressure on the dynamic resulted in a naive forecast which is higher than realized value. The RMSFE figures 4 and 6 shows that external data, financial risk, interest rate and TFP are the most important conditioning information of inflation respectively. Credit seems to be an important conditional variable for the unemployment dynamic and CPI shelter. These are in line with the findings of Rabanal and Taheri Sanjani (2015) in the context of Euro Area and Taheri Sanjani (2014) in the context of U.S. The scenario called "All" condition on knowing all the information in the model except the prices. This scenario along with the unconditional scenario provides us with an upper limit and a lower limit RMSFEs to benchmark other scenarios.

We observe that while commodity scenarios (red curves) from 2014 onward put downward pressure on inflation, the forecast has a wide confidence band; hence, the RMSFEs of this forecast scenarios are large. This is true across different models. We conclude that while financial variables (credit and risk) are important to explain the dynamic of unemployment rate while external factors and financial risks are relevant conditional variables for price inflation. To test how much each set of observables, or conditioning set, has forecasting power for our unobservable variables of interest, we have done some robustness check using smaller dataset for BVAR in level[11]. Figure A5 in appendix B presents the results.

[11] For every scenario described in table 2, we estimate a smaller BVAR model in which the dataset only includes the four variables of interest (unemployment, cpi shelter, cpi core and pce core) in addition to the observables (as described in table 2); for example to test the forecasting power of external variables in isolation from the rest of the variables in the big dataset, we estimate a BVAR with 10 variables; we call this scenario external factor. Using the estimated small model for each scenario, we can condition on subset of observables and compute RMSFEs. The findings on importance of external and financial variables are still hold

B. Markov-switching Structural Bayesian VAR

In this section, the fourth model, i.e. the multivariate regime-switching model is confronted with U.S. data.

B.1. Model 4: The Markov-switching Structural Bayesian VAR.

Following Sims and Zha (2006), and Sims, Waggoner, and Zha (2008), and Hubrich and Tetlow (2015) we employ a Markov-switching structural VAR model of the following form:

$$A_0'\left(s_t^c\right) y_t = A_+'\left(s_t^c\right) x_t + \Xi_s^{-1}\left(s_t^v\right) \varepsilon_t, \qquad t = 1, ..., T, \tag{7}$$

This Markov-switching structural VAR model can be cast in the representation in Eqs. (1)–(2) by imposing $C = (I_n, 0_{n\times np})$, $\Xi_s^{-1} = 0$ and

$$\begin{aligned} x_t' &= \left[y_{t-1}, y_{t-2}, ..., y_{t-s+1}, z_t\right], \\ A_+'\left(s_t^c\right) &= \begin{bmatrix} A_1\left(s_t^c\right) & A_2\left(s_t^c\right) & \dots & A_p\left(s_t^c\right) & C\left(s_t^c\right) \\ I_n & 0_n & \dots & 0_n & 0_n \\ \vdots & \ddots & \dots & \vdots & \vdots \\ 0_n & \dots & I_n & 0_n & 0_{r\times n} \\ 0_n & \dots & \dots & 0_n & I_n \end{bmatrix}. \end{aligned}$$

The reduced form is given by:

$$y_t = B\left(s_t^c\right) x_t + u_t\left(s_t^v, s_t^c\right), \qquad t = 1, ..., T, \tag{8}$$

with

$$\begin{aligned} B\left(s_t^c\right) &= A_0'\left(s_t^c\right)^{-1} A_+'\left(s_t^c\right), \\ u_t\left(s_t^v, s_t^c\right) &= A_0'\left(s_t^c\right)^{-1} \Xi_s^{-1}\left(s_t^v\right) \varepsilon_t, \\ E\left(u_t u_t'\right) &= \left(A_0\left(s_t^c\right) \Xi_s^2\left(s_t^v\right) A_0'\left(s_t^c\right)\right)^{-1}. \end{aligned}$$

Notice also that switching in the coefficients, s_t^c, impose switching in the reduced-form residuals. Allowing for only switching in variances, on the other hand, does not impose switching in the reduced-form coefficients which are fixed. Furthermore, the more s^v accounts for variability in the data, the smaller is the role of s^c to explain the variability in the data.

We follow Hubrich and Tetlow (2015) and introduce some useful notation to facilitate the presentation of the results. Let us define $\#v$, $\# = 1, 2, 3$ to indicate the number of independent Markov states governing variance switching, and $\#c$ to indicate the number of states governing coefficient switching. Moreover, when shifts in structural parameters are constrained to a specific equation(s), the restriction is indicated by prefixing - in parenthesis - the letter of the variable, $(Eq\#)$, $\# = 1:6$. So, for example, an MS-VAR with two Markov states in the variances and two in coefficients with the latter restricted to the last equation would be denoted $2v(Eq6)2c$. In the baseline case we will allow for switches in all equations, and then this would be denoted $2v2c$.

Three questions are of primary interest: first, whether there are periods for example, of high financial stress or constraints on monetary policy (zero lower bound), and if those periods are characterized by different inflation-unemployment dynamics than more regular times; second, if there is evidence of regime switching, whether it is confined to variance switching, as Sims and Zha (2006) find in a different context, or whether differences in economic behavior, as captured by coefficient switching, as Hubrich and Tetlow (2015) find, better explain inflation and data dynamics; and third, whether any regime switching is confined to specific equations—such as the monetary policy equation alone, or the inflation response to stress—as opposed to applying to all equations.

B.2. The Monthly Database

The focus of the second exercise is a subset of the variables described in part 1 above. Based on the results in the previous section we concentrate on a six-variable MS-VAR identified using the well-known Cholesky decomposition. In particular, let $y_t = [\hat{U}_t \ \hat{\pi}_t^{PCE} \ \pi_t^{RPIM} \ R_t \ TS_t \ EBP_t]$ where $\hat{U}_t$ is the monthly seasonally adjusted civilian unemployment rate less the Congressional Budget Office (CBO) historical series for the long-run natural rate; $\hat{\pi}_t^{PCE}$ is PCE inflation, excluding food and energy prices less expected long-run inflation expectations which is proxied using the median forecast of long-run PCE or CPI inflation reported in the Survey of Professional Forecasters, with a constant adjustment of 40 basis point before 2007; following e.g. Yellen (2015) we define π_t^{RPIM} as the annualized growth rate of the price index for core imported goods (defined to exclude petroleum), less the lagged four-quarter change in core PCE inflation, all multiplied by the share of nominal core imported goods in nominal GDP.; R_t is the Wu-Xia (2016) shadow nominal federal funds rate; TS_t is 3-Month Treasury Constant Maturity Minus 10-Year Treasury Constant Maturity; and EBP_t represent the excess bond premium. All variables are monthly and expressed at annual rates. The sample run from 1991 : 10 to 2015 : 6.

We choose the excess bond premium as the financial indicator in the excessive for two reasons. First, as was found in part 1, the financial variables are an important factor explaining both unemployment and inflation dynamics since the GFC. Second, as Gilchrist and Zakrajsek (2012) show, the excess bond premium has a strong forecasting ability for economic activity, outperforming every other financial indicator. Accordingly, this variable may provide a convenient summary of much of the information from variables left out of the MS-VAR that may be relevant to the economic activity. Faust et al. (2013) confirm that the excess bond premium have considerable marginal predictive power for economic activity.

B.3. The Zero Lower Bound

In December 2008, the Federal Reserve lowered the federal funds rate to the zero lower bound (ZLB) where it remained until December 2015. Like Hubrich and Tetlow (2015) explains the MS-BVAR model handles the ZLB bound in two ways. First, the ZLB can be thought of as another regime which the model can pick out if this is preferred by the data. Specifically, once the ZLB, or a negative Shadow Funds rate, is obtained, the perception, if applicable, that the funds rate reacts differently e.g. can fall no further, would be captured by switching in coefficients plus switching in shock variances such that adverse shocks to the Shadow funds rate are obtained. Second, there could be a change in the relationship between the federal funds rate and the term spread either directly because of the negative Shadow rates, or because of nonstandard monetary policy measures that stand in for conventional monetary policy. This is the main reason why the term spread is included as a variable in the model. Thus, the model can, in principle, pick out new states to capture the ZLB period.

C. Regime Switching Analysis

We follow Hubrich and Tetlow (2015) and Sims and Zha (2006) in the estimation and evaluation of the model. Two sets of priors are applicable for the model, one for the VAR parameters, the other for the state transition matrix. The standard Minnesota prior is used for the VAR parameters. For the state transition matrix, the Dirichlet prior is used. The key prior here is the prior probability of remaining in the same state in the next period as in the current period. A prior that is reasonable for the problem under study is one that does not promote, a priori, a finding of more switching in one part of the model over switching in another.

To evaluate models regarding goodness of fit, consistent with accepted practice, the marginal data densities (MDDs) of candidate specifications are compared. Note that the table displays the MDD's on a log-likelihood scale, so that differences of 1 or 2 in absolute value mean little, while differences of 10 or more imply extreme odds ratios for the higher-marginal-data-density model.

The results are summarized in Table 3 panel(a) shows outcomes for "general models", in which switching is entertained in all equations but could be in either variance switching alone or in variances and coefficients. The first line of the panel shows the MDDs. The second line reports the difference in MDD for the applicable model from that of the best fitting model in the same table. Like many other papers in the literature, we find that a model with constant coefficients and constant shock variances, the $1v1c$ model, is not favored by the data. Adding a second state in variances or coefficients improve the fit substantially. The best model shown in panel(a) is the $3v2c$ model. This is also the model Hubrich and Tetlow (2015) found fitted their data best.

Next, we investigate models where variance and coefficient switching are restricted to certain equations. These results are summarized in Panels (b) and (c). Panel (b) shows results for allowing switching in variances and coefficients whereas panel (c) allows for variance switching in all equations but restricts coefficient switching in single equations, or in a the combination of equations. The period between 1990 and 2015 could be associated with different inflation dynamics, but with macro and policy responses unchanged, or it could be mostly associated with restrictions on the behavior of monetary policy, but the real side of the economy responds normally.

The focus here is on restrictions of coefficient switching to the inflation equation, either alone, $3v(Eq2)2c$, or in combination with the real economy, $3v(Eq1-3)2c$ & $3v(Eq1-4)2c$ etc.; or in combination with monetary policy, $3v(Eq2\&4)2c$. Panel (c) shows that the data favor variance switching in all equations, but only coefficient switching in the interest rate equation. This indicates that the dynamics of monetary policy have differed over recent monetary history. One can also note that coefficient switching in the inflation equation alone, $3v(Eq2)2c$, is not favored by the data implying that the Phillips curve did not change significantly since the beginning of 1990's.These results are also in line with the results of section 1 where changes in shock variances were shown to be the most important factor behind changes in inflation and unemployment dynamics. Moreover, the results are also in line with Stock and Watson (2012a) and Sims and Zha (2006) who find that changes in shocks are a more

Table 3: MS-VAR estimation results.

Model $\longrightarrow$	$1v1c$	$2v1c$	$3v1c$	
(a) General Models	685.45	764.27	781.36	
Diff. from best	-138.94	-60.12	-43.03	
	$1v2c$	$2v2c$	$3v2c$	
	765.48	784.84	812.11	
	-58.91	-39.55	-12.28	
Model $\longrightarrow$	$(Eq6)3v2c$	$(Eq5-6)3v2c$	$(Eq4-6)3v2c$	$(Eq3-6)3v2c$
(b) Restricted Models	715.19	716.51	777.78	783.61
Diff. from best	-109.20	-107.88	-46.61	-40.78
	$(Eq2-6)3v2c$	$(Eq1,3-5)3v2c$	$(Eq4-5)3v2c$	
	809.76	790.06	738.00	
	-14.63	-34.33	-86.39	
Model $\longrightarrow$	$3v(Eq4\&5)2c$	$3v(Eq1-3\&6)2c$	$3v(Eq1-3)2c$	$3v(eq4-6)2c$
(c) Restricted Models	812.72	816.76	808.76	791.25
All equations 3 states	-11.67	-7.63	-15.63	-33.14
variance switching				
	$3v(Eq1-4)2c$	$3v(Eq4)2c$	$3v(Eq2\&4)2c$	$3v(Eq2)2c$
	813.41	**824.39**	816.08	791.25
	-10.98	0	-8.31	-33.14

		$Eq1; \hat{U}_t, Eq2 : P\hat{C}E_t, Eq3 : RPIM_t, Eq4 : R_t, Eq5 : TS_t, Eq6 : EBP_t$
$1v1c$	:	A constant parameter BVAR.
$3v2c$	:	Three independent Markov states governing variance switching and two governing coeff. switching.
$3v(Eq4)2c$	:	Three independent Markov states governing variance switching in all equations and two governing coeff. switching in equation 4, i.e. the monetary policy equation.

salient feature of the data than changes in coefficients. The results in Sims and Zha are interesting and also similar to the findings here since they find that their model with time-varying coefficients in the policy rule fit substantially better than all other models that allow the change in coefficients.[12]

[12] As was discussed by Sims and Zha (2006), the model with time variation in all equations might be expected to fit best if there were policy regime changes were important. In this case changes in expectations and the private sector forecasting behavior would observe changes not only in the policy rule but also in the private sector dynamics. However, even if the public believes that policy is time-varying and tries to adjust its expectation formation accordingly, its behavior could be well approximated as non-time-varying and linear. It is, in this case, an empirical matter whether the linear approximation is adequate for a particular sample. The story that emerges is very similar to Boivin and Giannoni (2006) namely that to explain the dynamics of inflation, policy rates, and unemployment/output, it is important for the policy rule to have changed the way it has, along with the shocks. Hence, it is not an all-shocks or an all-policy story but a

The result of changes in only the monetary policy equation is robust to both changes in lag length, priors and changes in data.[13] Table 4 below shows e.g. the marginal data densities for changes in all equations compared with changes in only the monetary policy equation for a data set in levels with the log of the M2 Money Stock used instead of the term spread and the real exchange rate used instead of the relative price of import price inflation, and the Gilchrist and Zakrajsek raw spread instead of their measure of the excess bond premium and finally the Unemployment rate instead of the unemployment gap, i.e. $y_t = [U_t \ln P_t^{PCE} \ln REER_t\ R_t \ln M_t\ GZ_t]$.

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

See also the appendix for an analysis where we use a small empirical model of the U.S. economy to examine the sensitivity of the results to changes in identifying assumptions and the sample size. The results confirm the main result from the MS-BVAR estimated on monthly data since the $1990's$. Changes in shocks is a more salient feature of the data than changes in coefficients and a model with time-varying coefficients in the policy rule fits better than all other models that allow a change in coefficients. The model with coefficient switching in the simple instrument rule with variance switching in all equations attains the highest marginal data density.

Figures $7-8$ show the (two-sided) estimated state probabilities for the preferred $3v(Eq4)2c$ specification. As can be seen from figure 7, coefficient state 1 prevails in times when the policy rate is changing, i.e. In tightening or loosening phases. Coefficient regime 2 prevails in passive or constrained phases, such as during the zero lower bound period. This is also evident when estimating the MS-BVAR with the actual Federal funds rate instead of the shadow rate. Figure 8 shows that regimes are clearly determined by the dynamics of the funds rate. The three variances states are shown in Figure 9 and do not simply scale up and down across all structural equations. Some states affect a group of structural shocks jointly, as can be seen from the probabilities for variance regime two which is associated with a low monetary policy shock variance and a high import price variance. At the end of the sample in June, 2015 the U.S. economy is estimated to be in variance state 2 and coefficient state 1. Monetary policy is active in this regime with a relatively high import price variance and a low monetary policy shock variance.

What do these results imply about the shape of the Phillips curve? The data favor variance switching in all equations, but only coefficient switching in the interest rate equation which implies that the Phillips curve did not change during the sample period. Comparing vector cross-correlation functions (Figure 10) from the MS-BVAR for two different coefficient regimes and for three different variance regimes shows that simple correlations also change depending on which regime is generating the data. The sub-graphs below the diagonal display the cross-correlation between the column variable and the lag of the row variable. The opposite order applies to the upper diagonal graphs.

The sub-graph in the first row and the second column shows the cross correlation function between

mixed one.

[13]Changes in ordering do not affect the results. However, if the excess bond premium (EBP_t) is ordered before the policy rate (R_t) the models $2v3c$ and $3v(Eq4)2v$, are difficult to separate from the data. The MDD's for this specification are however lower than the baseline specifications.

core PCE inflation and the unemployment gap. Variance regime 2 is dominated by import price shocks which act like cost-push shocks which in turn imply a positive correlation between inflation and contemporaneous and lagged unemployment. In variance regime 1, which is dominated by demand disturbances, e.g. through changes in unemployment, the correlation is negative. Changes in the responsiveness also affect the strength of the correlation making it challenging to estimate univariate Phillips curve equations to investigate changes in the slope of the curve. Hence, allowing for variance switching is important to avoid biasing results toward the erroneous finding of coefficient switching. Figure 11 shows the same implications as Figure 10 but in a scatter plot of inflation and unemployment. When monetary policy is constrained, or passive, it does not stabilize shocks to inflation as well as when it is unconstrained. The implication is that the Phillips curve is seemingly steeper in the passive state than in the active monetary policy state.

IV. Conclusion

We use large BVAR's, DFM's and MS-VAR models to investigate the possibility of non-linearity in the recent post-crisis dynamic of inflation and unemployment rate in U.S. data. In other words, did the GFC break the U.S. Phillips curve? We also study what conditioning information set is informative for inflation and unemployment. We find that changes in shocks is a more salient feature of the data than changes in coefficients and a model with time-varying coefficients in the policy rule fits better than all other models that allow a change in coefficients. The model with coefficient switching in the simple instrument rule with variance switching in all equations attain the highest marginal data density. Moreover, conditional forecasts which condition on external variables and financial risk variables seems to come closest to describing the dynamics of inflation while credit variables are the most important conditioning variables of the post-GFC unemployment rate.

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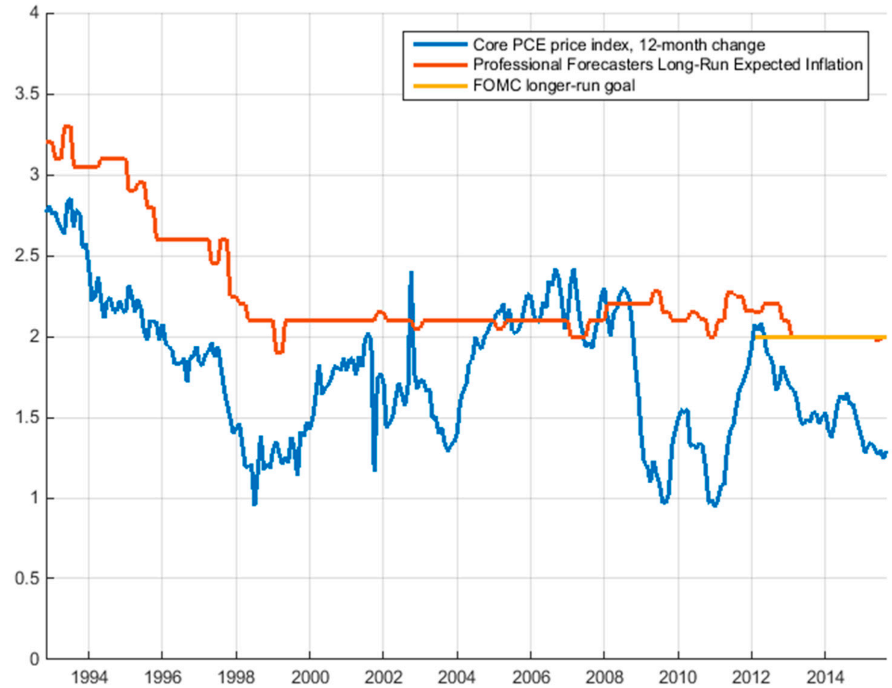
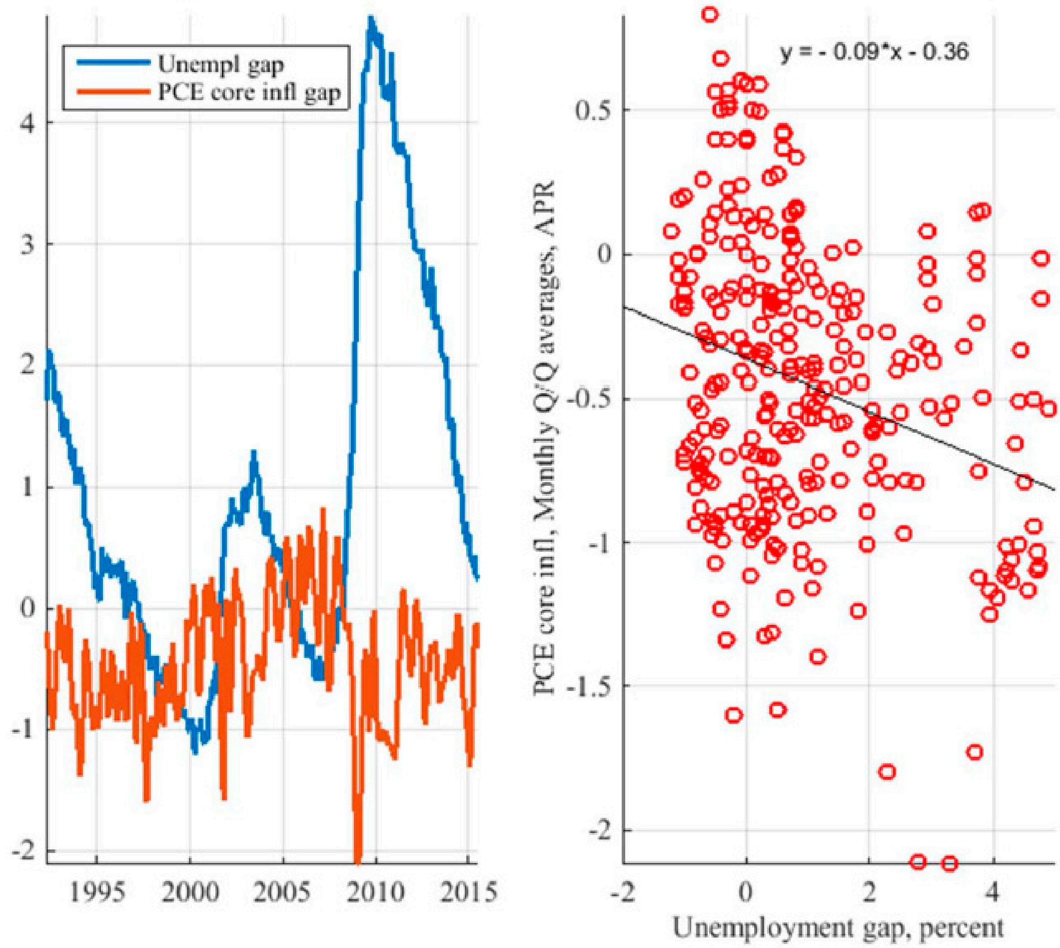
[49] Yellen, J. (2015), "Inflation Dynamics and Monetary Policy," The Philip Gamble Memorial Lecture, University of Massachusetts, Amherst, September 24, 2015.

Figure 1. U.S. Inflation since the 1990s.



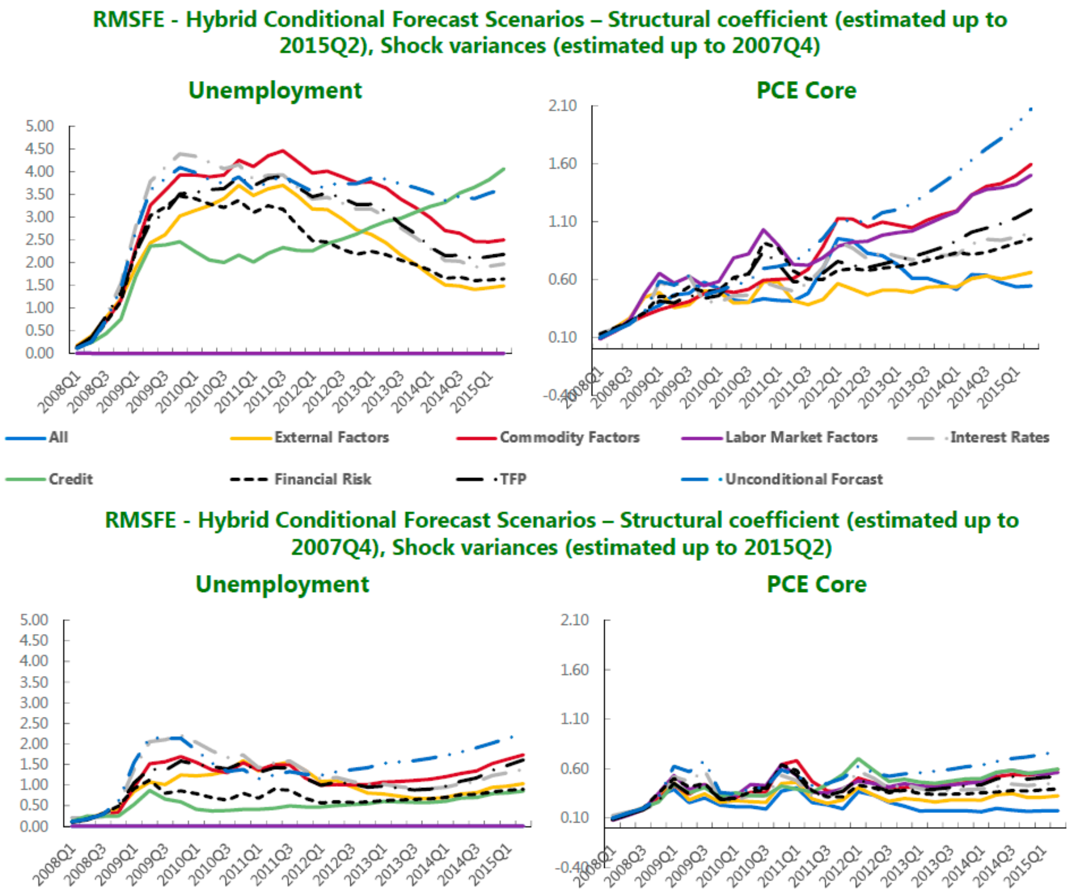
Note: The data are monthly. PCE is personal consumption expenditures. FOMC is Federal Open Market Committee. Inflation expectations is proxied using the median forecasts of long-run PCE or CPI inflation reported in the Survey of Professional Forecasters, with a constant adjustment of 40 basis points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

Figure 2. U.S. Unemployment and Inflation since 1990s.



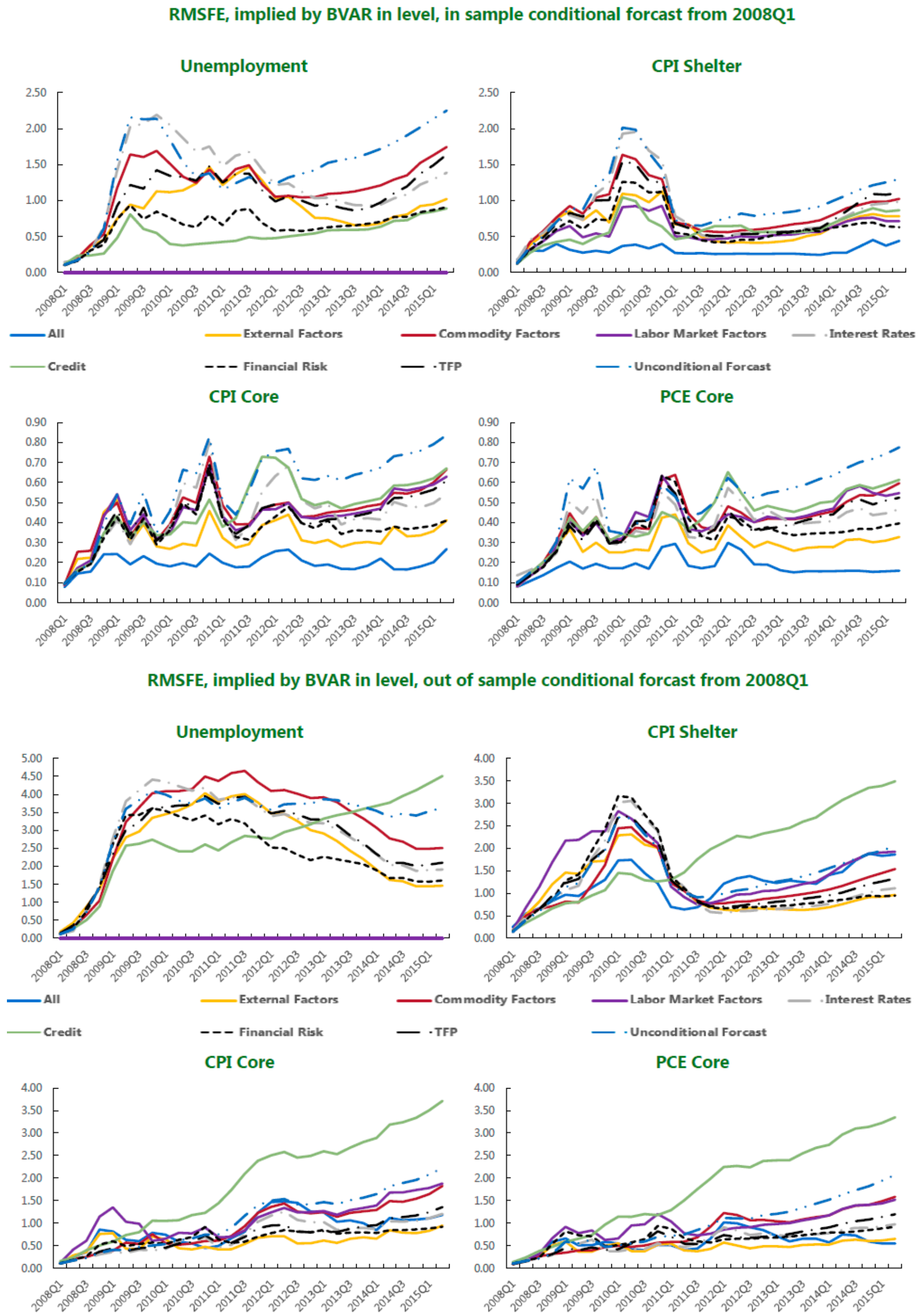
Note: The data are monthly, March 1992-June 2015. The inflation gap is measured as PCE is personal consumption expenditures less the median forecasts of long-run PCE or CPI inflation reported in the Survey of Professional Forecasters, with a constant adjustment of 40 basis points prior to 2007 to put 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, the Federal Reserve Bank of Philadelphia and US. Congressional Budget Office.

Figure 3. Root Mean Square Forecast Errors Using Alternative Conditioning Information and Parameter Estimates.



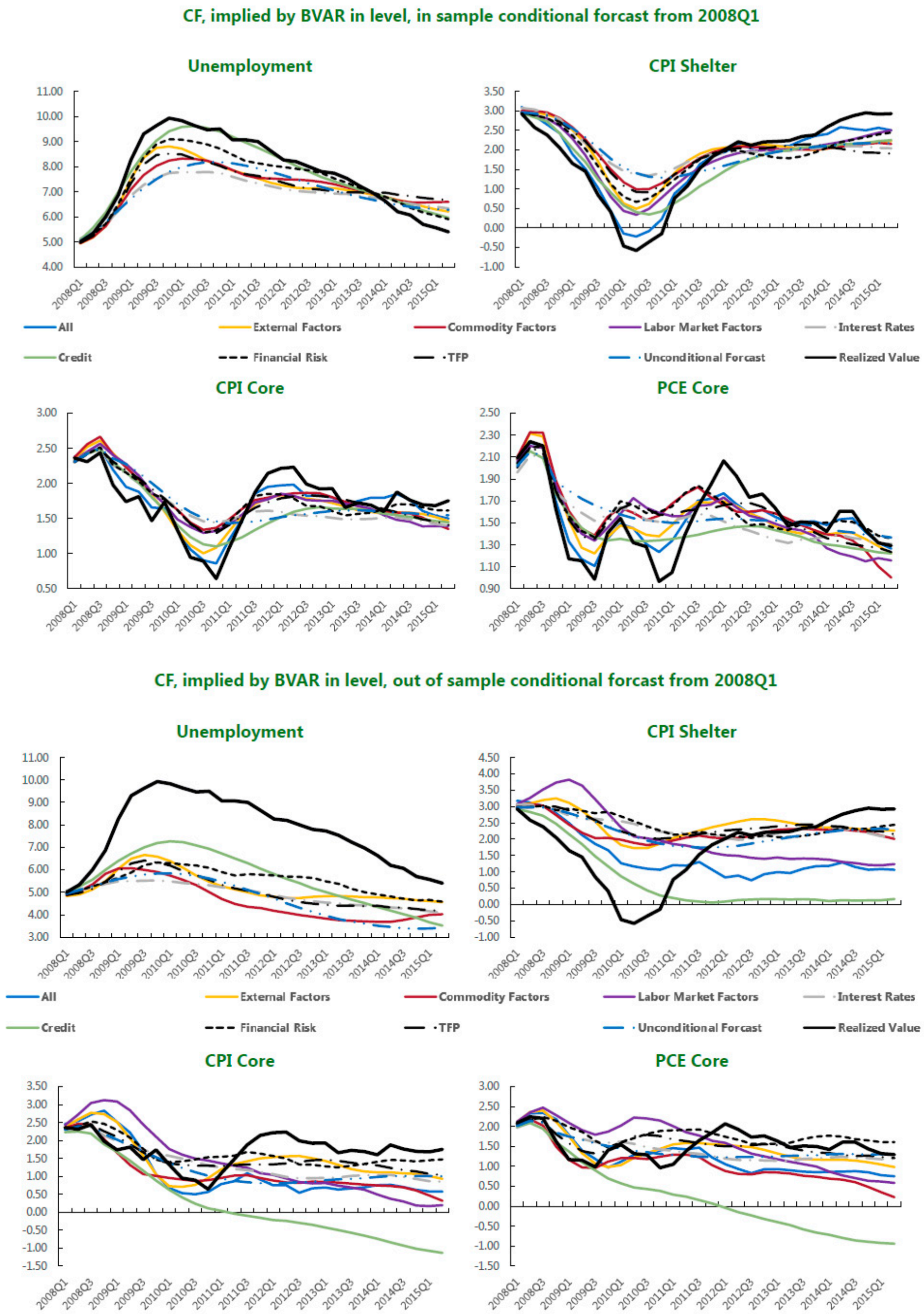
Note: Horizontal axis shows the year. Prices are presented in percentage annual growth rates, while unemployment is presented the level.

Figure 4. In-sample and Out of Sample Root Mean Square Forecast Errors Using Alternative Conditioning Information Sets.



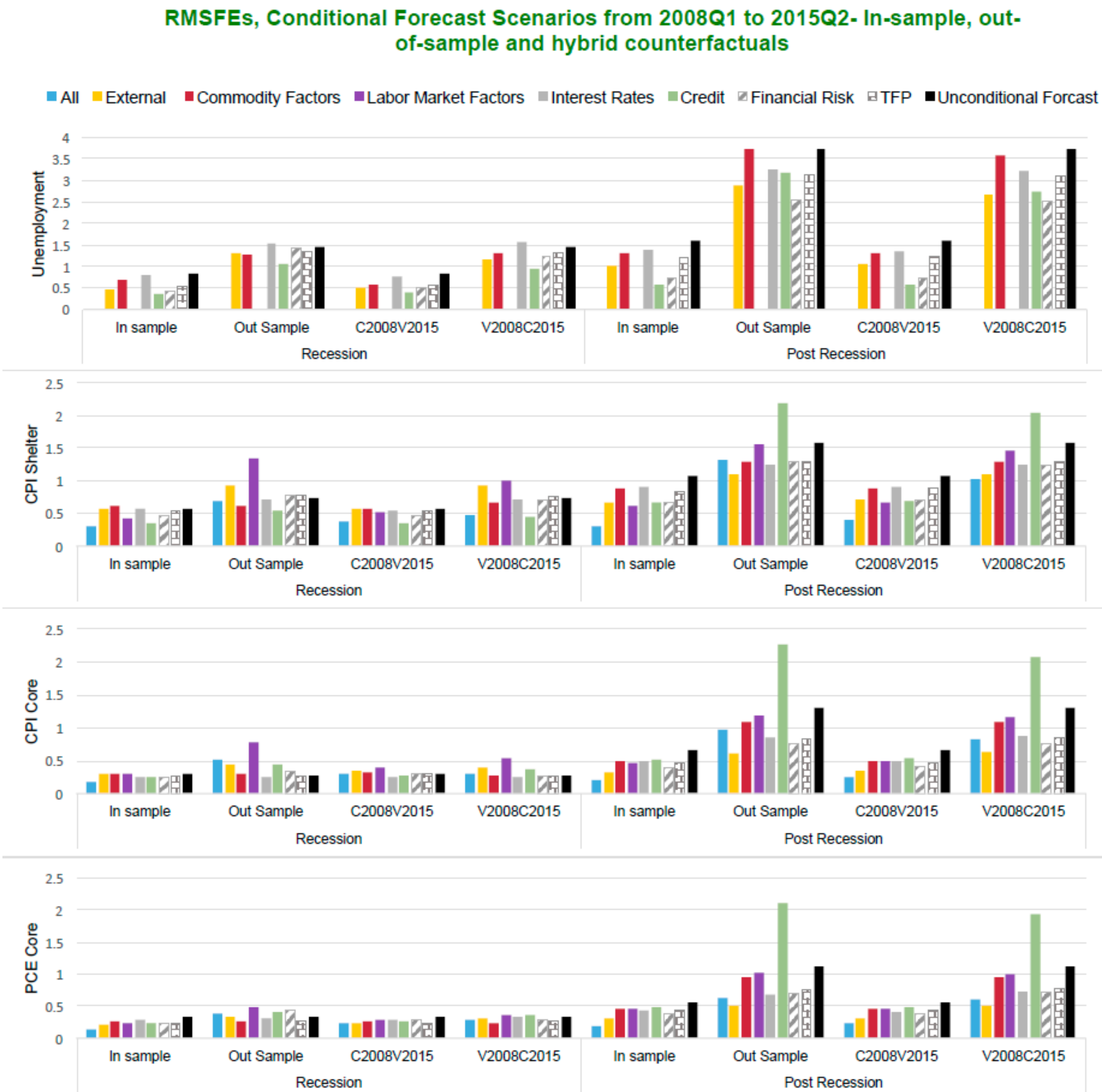
Note: Horizontal axis shows the year. Prices are in percentage annual growth rates, while unemployment is in level.

Figure 5. In-sample and Out of Sample Forecasts Using Alternative Conditioning Information Sets.



Note: Horizontal axis shows the year. Prices are in percentage annual growth rates, while unemployment is in level.

Figure 6. In-sample and Out of Sample Root Mean Square Forecast Errors Using Alternative Conditioning Information Sets.



Note: Prices are in percentage annual growth rates, while unemployment is in level. Recession period covers 2008Q1 to 2009Q2 and post-recession covers 2009Q3 to 2015Q2.

Figure 7. Probabilities of coefficient state, smoothed estimates, 3v(Mon Pol Eq)2c model specification using the Wu-Xia (2016) Shadow Federal Funds Rate.

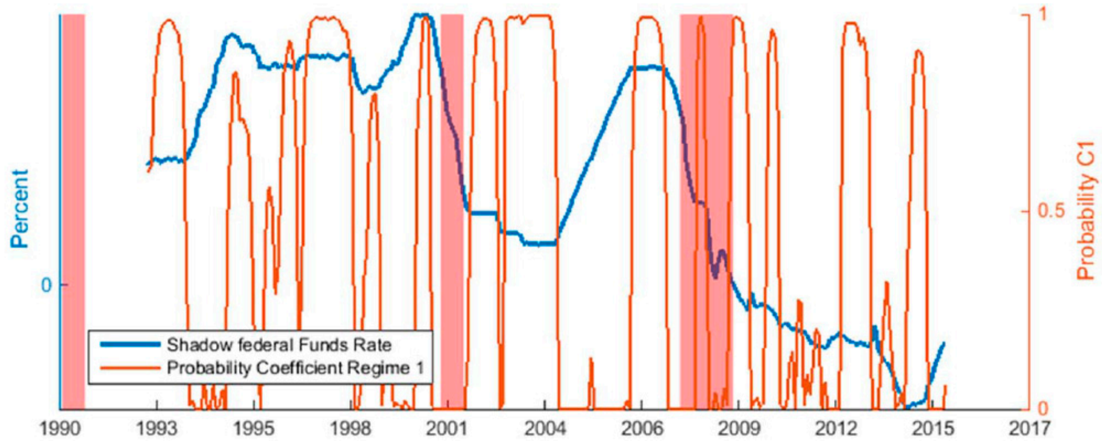


Figure 8. Probabilities of coefficient state, smoothed estimates, 3v(Mon Pol Eq)2c model specification using the Effective Federal Funds Rate.

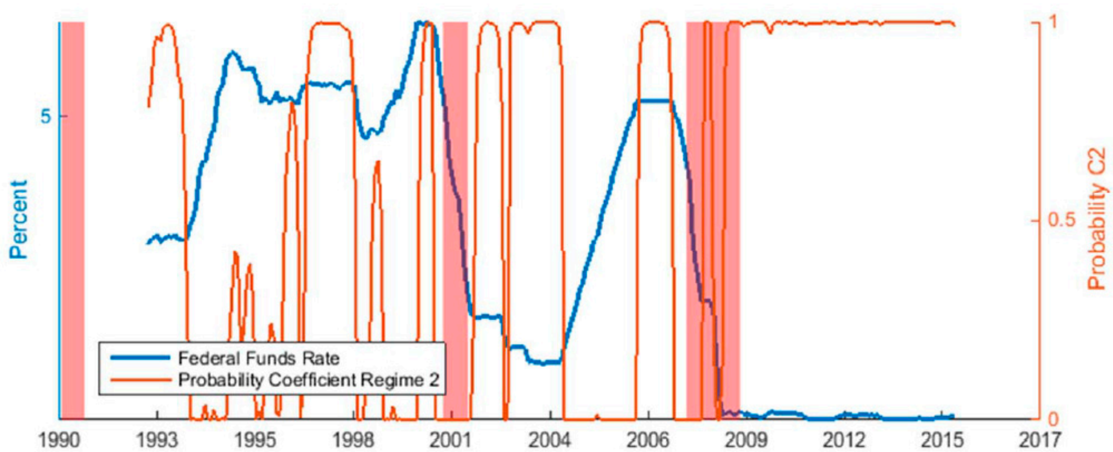


Figure 9. Probabilities of Shock Variance states, smoothed estimates, 3v(Mon Pol Eq)2c model specification using the Wu-Xia (2016) Shadow Federal Funds Rate.

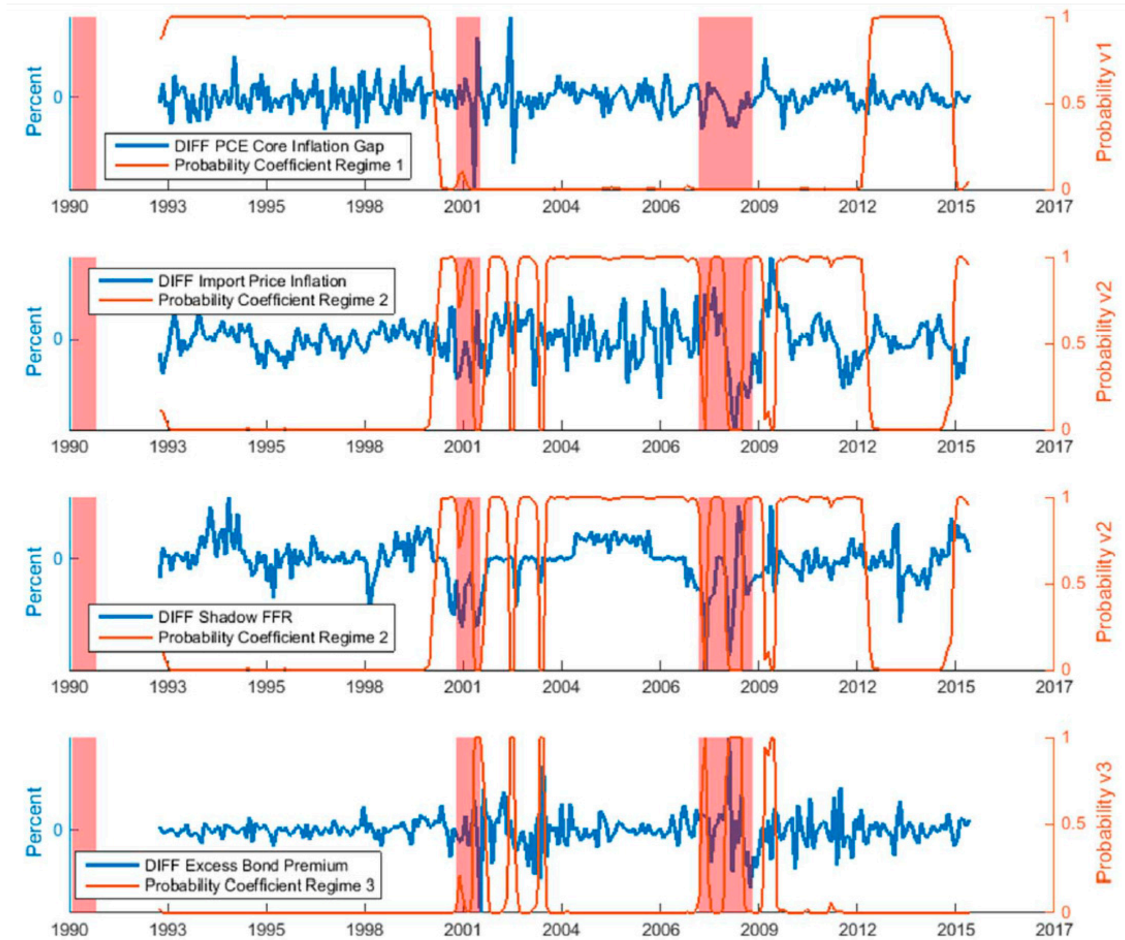


Figure 10. Variance Cross Correlation Functions Conditional on Coefficient and Variance Regimes.

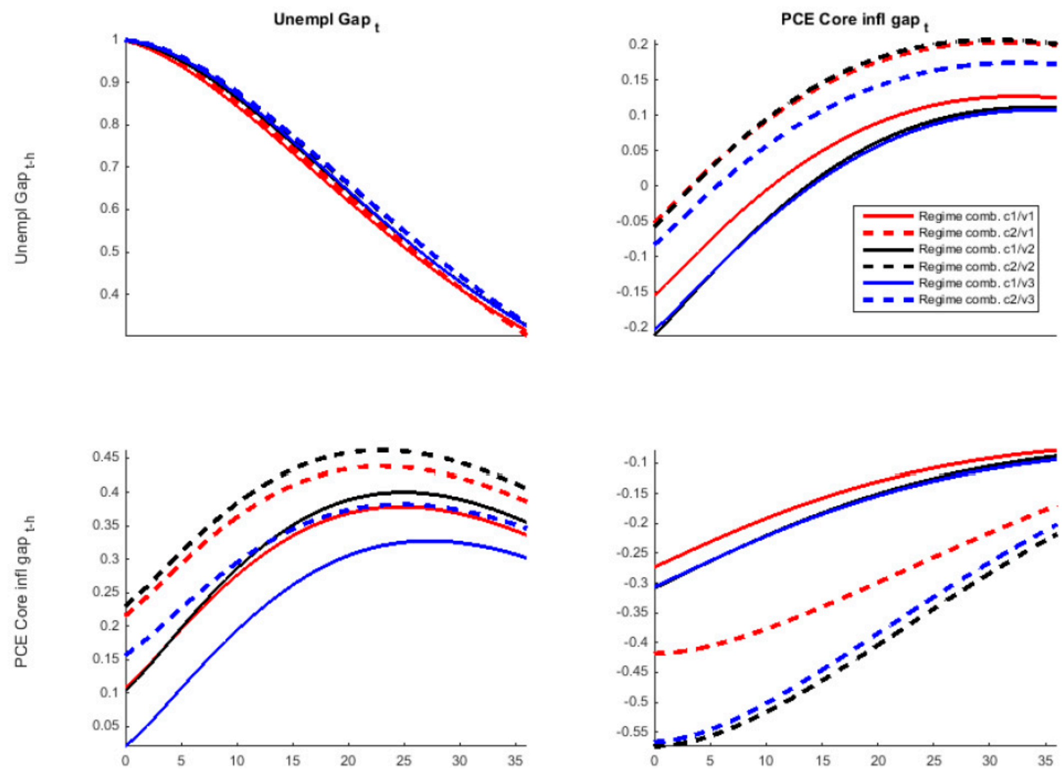
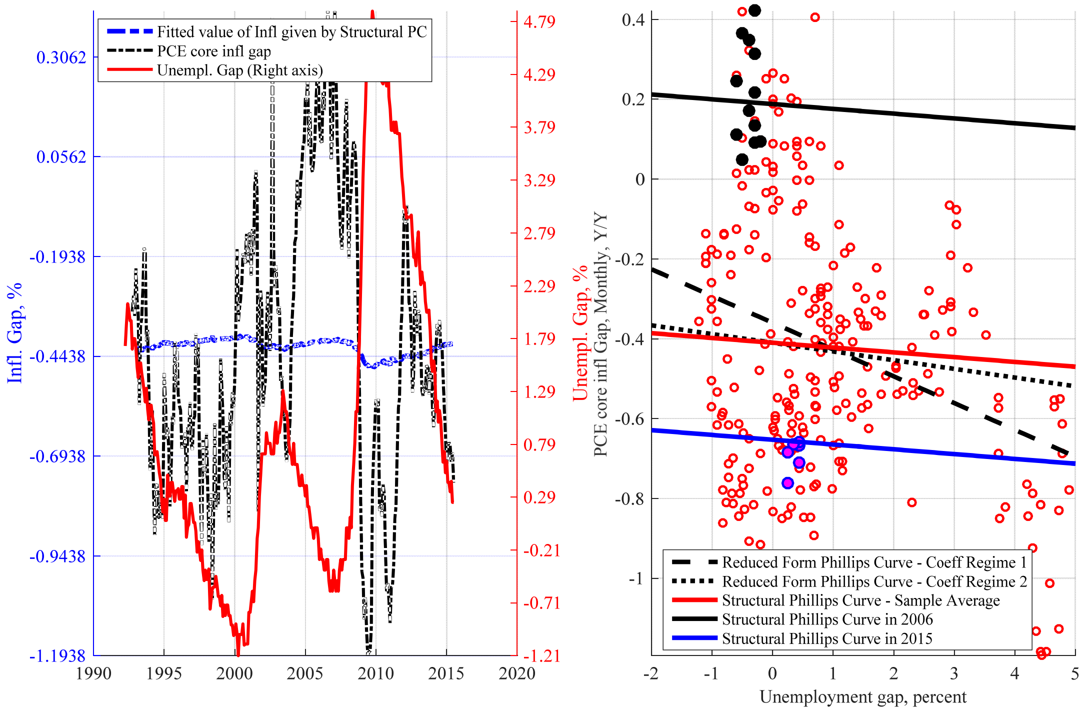


Figure 11. Structural and Reduced Form Linear Regressions Conditional on Coefficient and Variance Regimes Implied by the MS-BVAR.



Note: The structural Phillips curve is computed as the fitted value of inflation in the MS-BVAR given by only the unemployment gap holding all other variables at their sample mean values (or values indicated in the figure). Note that the slope of this curve is invariant to policy/regime changes. The reduced form linear regressions are computed by generating data from the reduced form MS-VAR conditional on being in either coefficient regime 1 (constrained/passive monetary policy) or coefficient regime 2 (unconstrained/active monetary policy). Hence, the constant in the structural Phillips curve is changing and traces out the reduced form linear regression. In coefficient regime 1, where monetary policy is constrained, shocks to e.g. the excess bond premium are not stabilized as well as in coefficient regime 2. Greater variability of inflation and unemployment through the other variables and shocks in the MS-BVAR implies that the structural Phillips curve shifts which in turn traces out a steeper reduced form linear regression between inflation and unemployment. See Figure 2 for data description.

A Appendix - A Markov-Switching Version of the New-Keynesian Model

In this section, we use a small empirical model of the U.S. economy to examine the sensitivity of the results to changes in identifying assumptions and the sample size. More specifically, our choice of an empirical model of output and inflation is motivated by two simple considerations. First, we choose a simple model, so that our analysis will be tractable and our results transparent. The model consists of an aggregate supply equation (or "Phillips curve") that relates inflation to an output gap and an aggregate demand equation (or "IS curve") that relates output to a short-term interest rate. Second, our model captures the same features as many practical policy-oriented macroeconometric models. See Rudebusch and Svensson (1999) for a fuller description of the model and, in particular, the choice of a Phillips curve with adaptive or autoregressive expectations. The two equations of our model are

$$\begin{aligned} \alpha_\pi \pi_t &= c_\pi + \alpha_{\pi_1}\pi_{t-1} + \alpha_{\pi_2}\pi_{t-2} + \alpha_y \hat{y}_t + \sigma_\pi \varepsilon_t^\pi, \\ \beta_y \hat{y}_t &= c_y + \beta_{y_1}\hat{y}_{t-1} + \beta_{y_2}\hat{y}_{t-2} + \beta_r (i_t - \pi_t) + \sigma_y \varepsilon_t^y, \end{aligned}$$

where π_t is quarterly inflation in the GDP chain-weighted price index (p_t) at an annual rate, that is, $\pi_t = 4(p_t/p_{t-1} - 1)$; i_t is the quarterly average federal funds rate in percent at an annual rate; $\hat{y}_t$, is the percentage gap between actual real GDP (q_t) and potential GDP[14] (q_t^*), that is, $\hat{y}_t = (\ln q_t - \ln q_t^*)$. The first equation relates inflation to a lagged output gap and to lags of inflation. The lags of inflation are an autoregressive or adaptive representation of inflation expectations. The second equation relates the output gap to its own lags and to the difference between the federal funds rate and inflation - an approximate ex post real rate. Monetary policy is described by a simple instrument rule:

$$\gamma_{i_1} i_t = c_i + \gamma_{i_2} i_{t-1} + \gamma_y y_t + \gamma_\pi \pi_t + \sigma_i \varepsilon_t^i.$$

The contemporaneous matrix A_0, and the matrices A_1 and A_2 in the general framework are in this case given by

$$A_0 = \begin{bmatrix} \alpha_\pi & \beta_r & \gamma_{i_1} \\ \alpha_y & \beta_y & \gamma_y \\ 0 & -\beta_r & \gamma_\pi \end{bmatrix}, \; A_1 = \begin{bmatrix} \alpha_\pi & 0 & 0 \\ 0 & \beta_{y_1} & 0 \\ 0 & 0 & \gamma_{i_2} \end{bmatrix}, \; A_2 = \begin{bmatrix} \alpha_{\pi_2} & 0 & 0 \\ 0 & \beta_{y_2} & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

The sample used is from $1960Q1$ to $2015Q2$.[15] The results are summarized in Table $A1$. Panel (a) shows outcomes for "general models", in which switching is entertained in all equations but could be in either variance switching alone or in variances and coefficients. Panel (b) shows results for models

[14] Real potential GDP is the CBO's estimate.

[15] One can show, using the theorem of Rubio-Ramirez, Waggoner, & Zha (2010), that the model is globally identified.

where variance and coefficient switching are restricted to certain equations.

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			

The results confirm the main result from the MS-BVAR estimated on monthly data since the $1990's$. Changes in shocks is a more salient feature of the data than changes in coefficients and a model with time-varying coefficients in the policy rule fits better than all other models that allow change in coefficients. The model with coefficient switching in the simple instrument rule with variance switching in all equations attain the highest marginal data density.

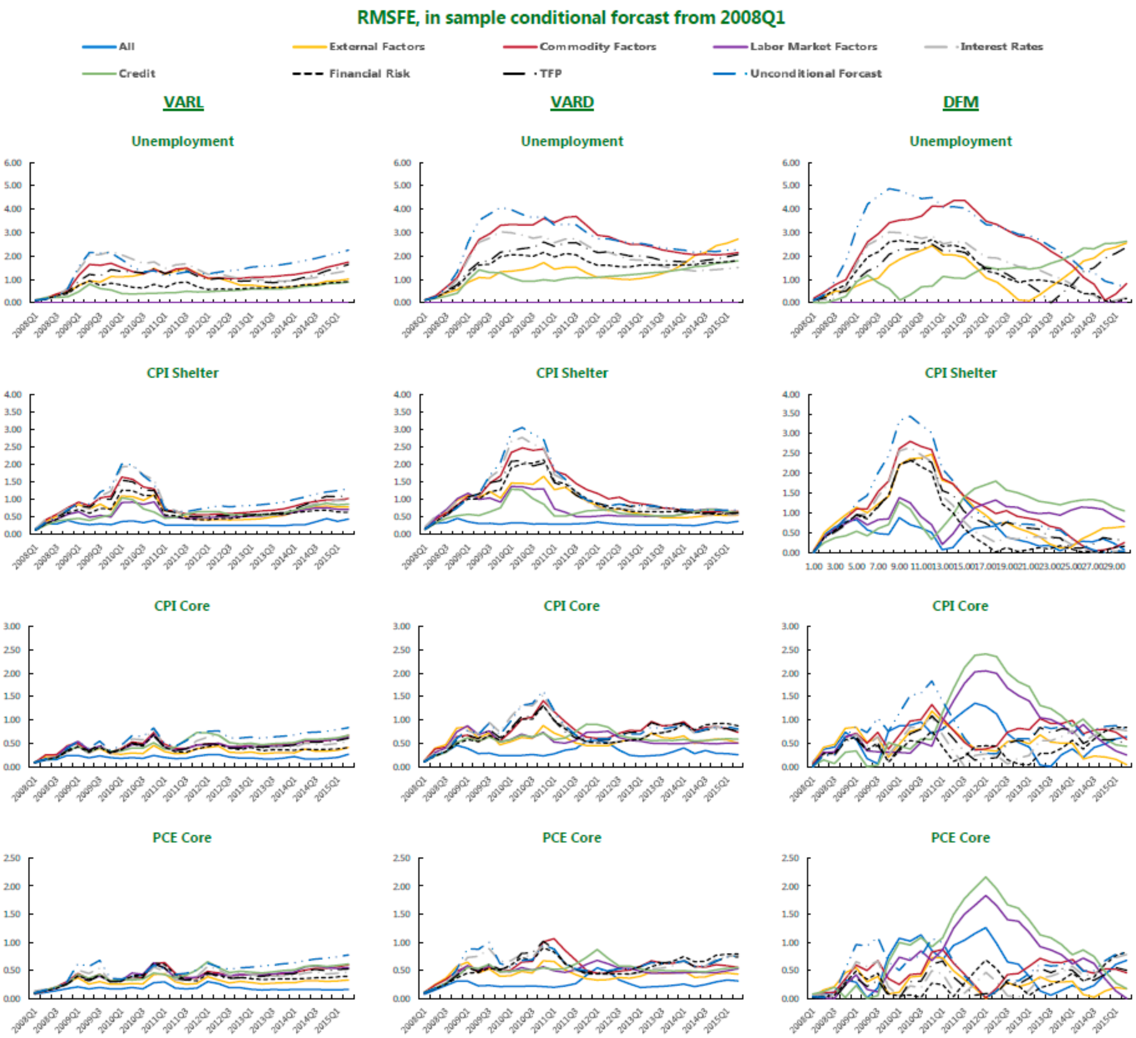
Figure $A5$ shows the implied state-probabilities over time produced by the $3v(Mon\ Pol\ Eq)2c$ model. We can see that state 1 prevails when the Fed is lowering the federal funds rate. This state is independent of who was chair of the Federal Reserve. The light green color shows Greenspan's time as chair whereas the red light shows when Burns was chair. Coefficient states 1 and 2 seems - like in the case of the model estimated on monthly data since beginning of the 1990's - to capture tightening and loosening phases of monetary policy.

Note that our results differ slightly from Sims and Zha (2006). While our results point in the same overall direction to those in Sims and Zha our estimates of when changes in monetary policy took place differ. Sims and Zha found e.g. one dominating regime and three less frequent regimes. The dominating regime was named the Greenspan regime since it prevailed during much of Greenspans time as chair. One should, however, bear in mind that this regime was also dominating much of the 1960s and 1970s. We also find a change between chairs, but this mostly occurs after 1987 when we find a clearer pattern of changes in regimes pertaining to time periods when the federal funds rate was lowered, i.e. when the fed loosened the monetary policy stance. One reason for the differences might be due to the inclusion of $M2$ in the Sims and Zha dataset which seems to be an important change in coefficients in their VAR model but which is not included in our data set. In two of four regimes the contemporaneous coefficient on $M2$ is e.g. much larger.

Our focus here is however mainly to investigate if the main results of coefficient switching in for monetary policy only - and not in the Phillips curve - is a robust result to a longer data sample and a different identification of the structural VAR with a well-defined and identified Phillips curve. Here we clearly see that this is in fact the case.

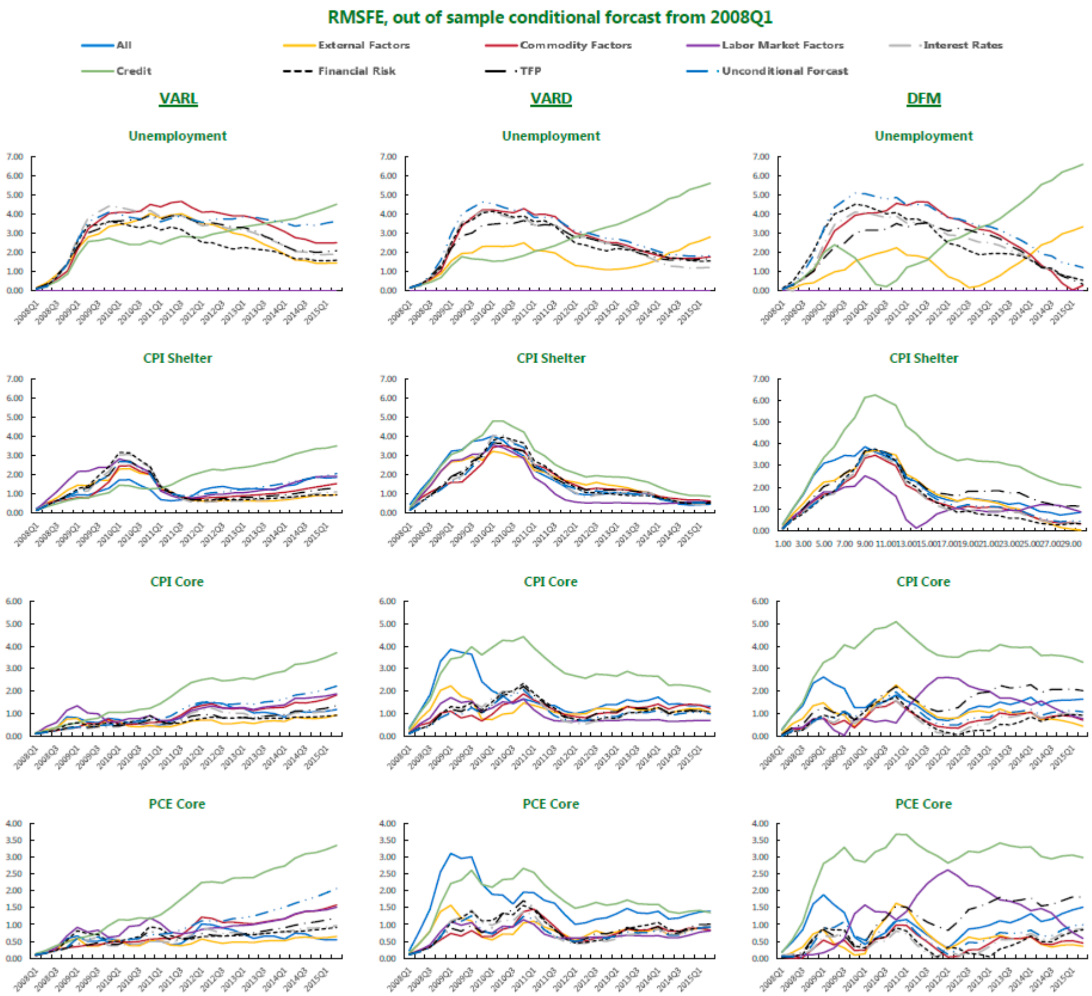
B Appendix - Robustness Check

Figure A1. In-Sample Root Mean Square Forecast Errors Using Alternative Conditioning Information Sets – All Models.



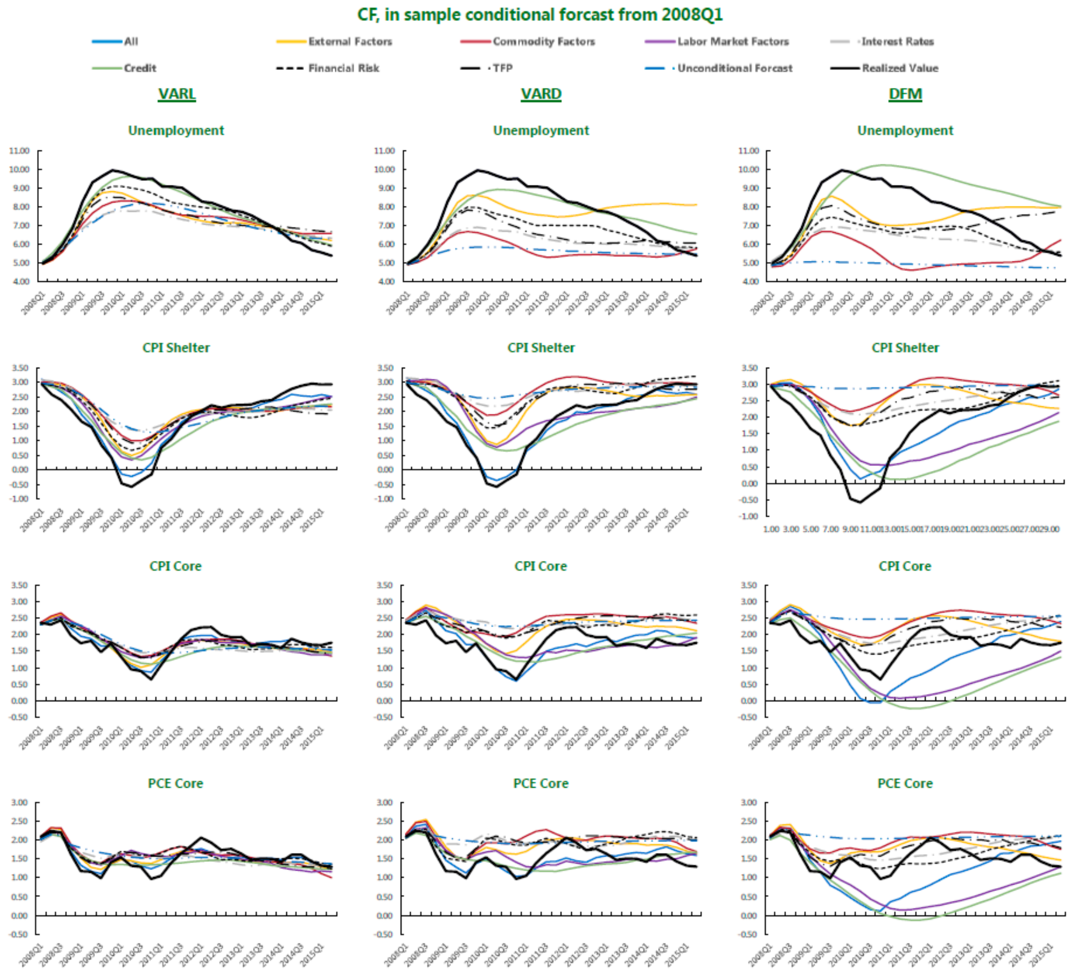
Note: Horizontal axis shows the year. Prices are in percentage annual growth rates, while unemployment is in level.

Figure A2. Out of Sample Root Mean Square Forecast Errors Using Alternative Conditioning Information Sets – All Models.



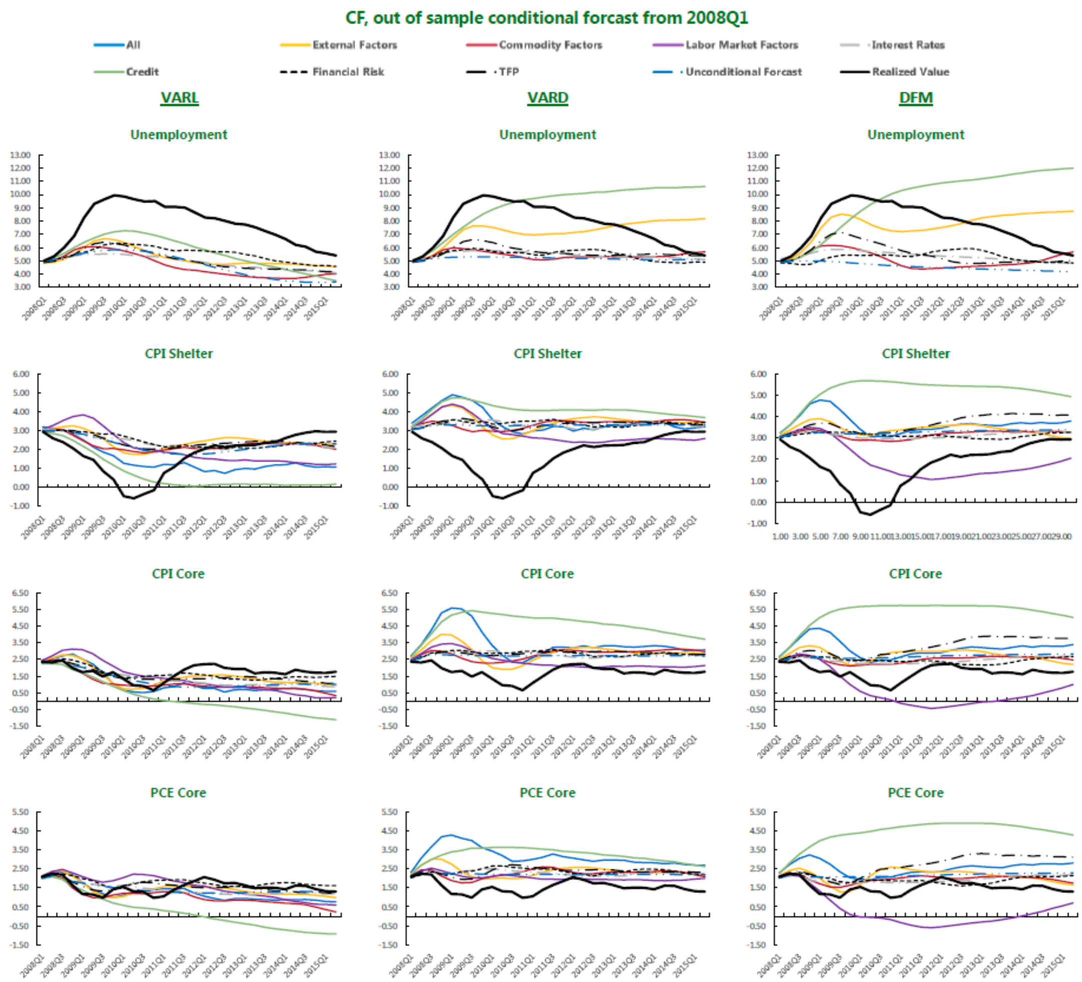
Note: Horizontal axis shows the year. Prices are in percentage annual growth rates, while unemployment is in level.

Figure A3. In-Sample Conditional Forecasts Using Alternative Conditioning Information Sets – All Models.



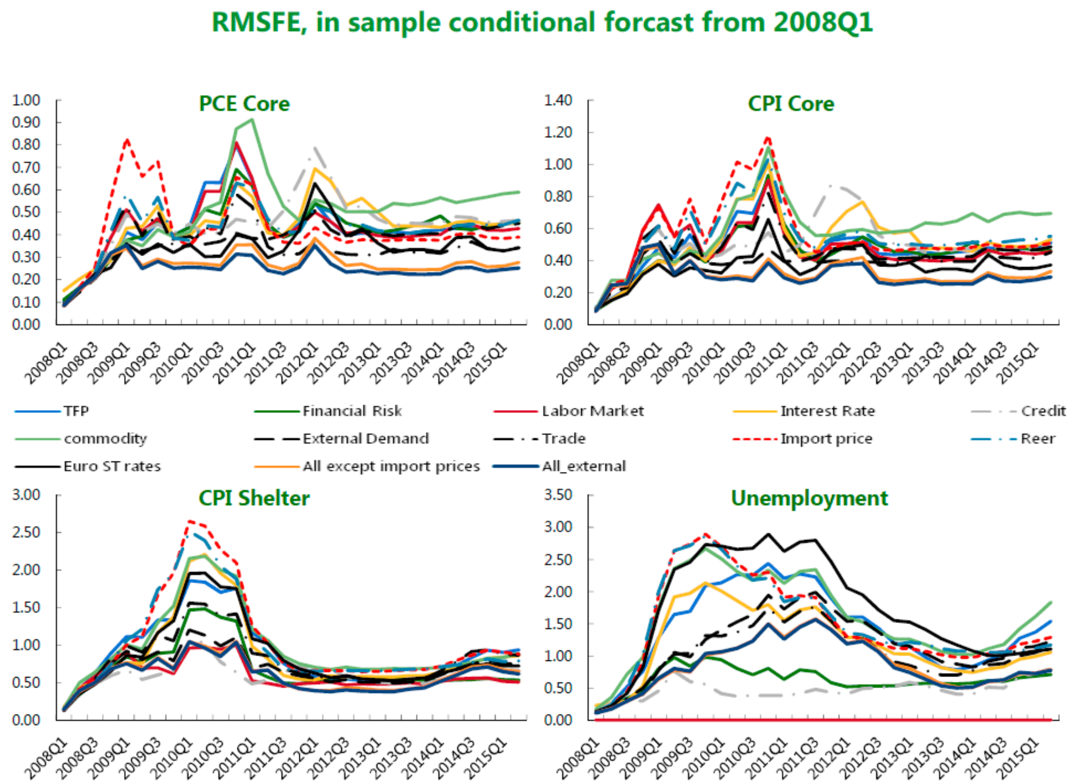
Note: Horizontal axis shows the year. Prices are in percentage annual growth rates, while unemployment is in level.

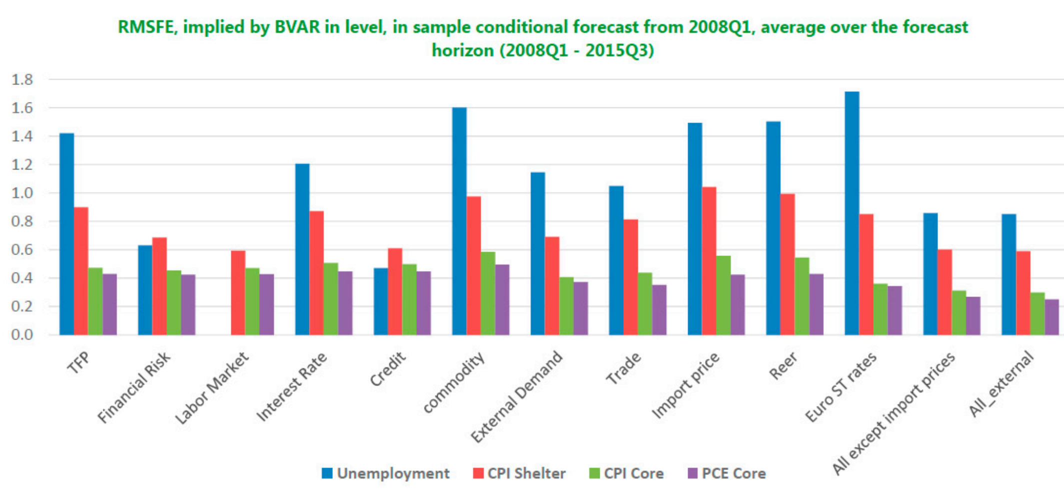
Figure A4. Out of Sample Conditional Forecasts Using Alternative Conditioning Information Sets – All Models.



Note: Horizontal axis shows the year. Prices are in percentage annual growth rates, while unemployment is in level.

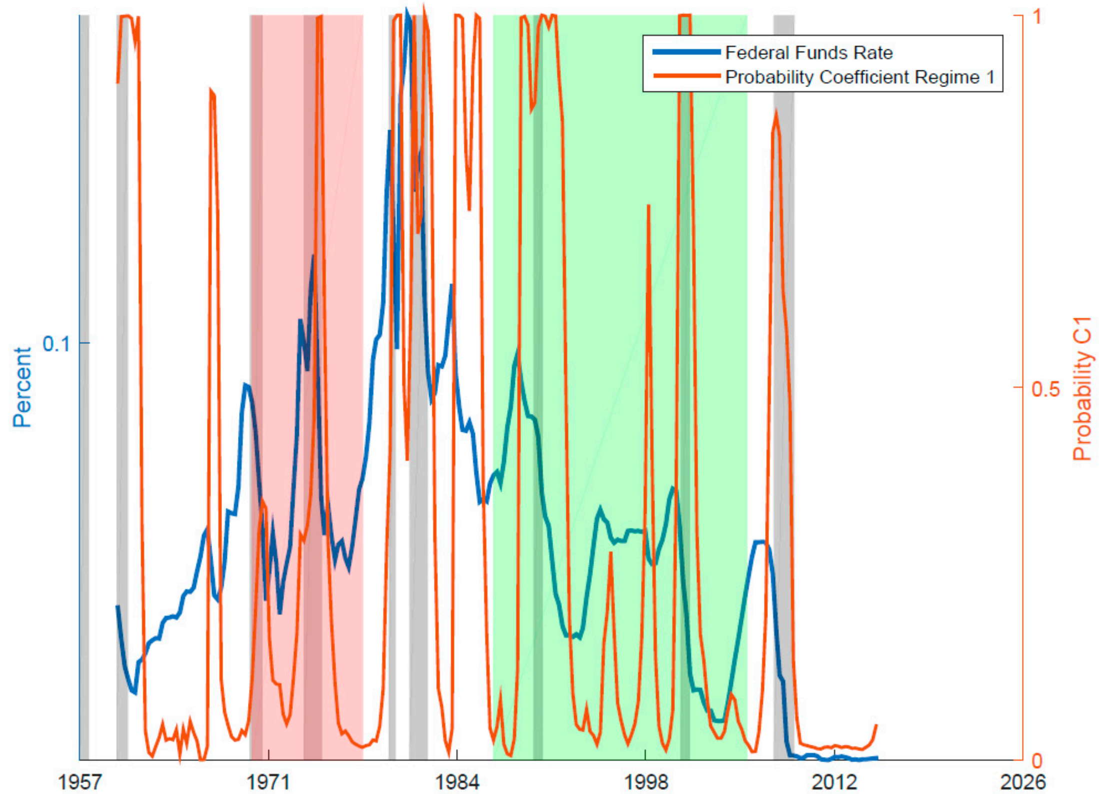
Figure A5. Robustness check using smaller database for conditional forecast. The top panel shows the Timeseries of Root Mean Square Forecast Error and the bottom panel shows the average of RMSFEs over the forecast horizon (2008Q1-2015Q3).





Note: Horizontal axis, in the top panel shows the year and in the bottom panel shows alternative scenarios. Prices are in percentage annual growth rates, while unemployment is in level.

Figure A6. Probabilities of coefficient state, smoothed estimates, 3v (Mon Pol Eq) 2c model specification.



C Appendix - Data

1. WORLD REAL GROSS DOMESTIC PRODUCT, YEAR-OVER-YEAR PERCENT CHANGE (SA)
2. US REAL GROSS DOMESTIC PRODUCT (SAAR, BIL.CHN.2009)
3. US INDUSTRIAL PRODUCTION INDEX (SA, 2012=100)
4. US REAL PERSONAL CONSUMPTION EXPENDITURES (SAAR, BIL.CHN.2009)
5. US REAL GOVERNMENT CONSUMPTION EXPENDITURES & GROSS INVESTMENT(SAAR, BIL.CHN.2009)
6. US REAL GROSS PRIVATE DOMESTIC INVESTMENT (SAAR, BIL.CHN.2009)
7. US REAL EXPORTS OF GOODS & SERVICES (SAAR, BIL.CHN.2009)
8. US REAL IMPORTS OF GOODS & SERVICES (SAAR, BIL.CHN.2009)
9. US ALL EMPLOYEES: TOTAL NONFARM PAYROLLS (SA, THOUS)
10. US UNEMPLOYMENT RATE: 16 YEARS + (SA,
11. US NATURAL RATE OF UNEMPLOYMENT [CBO] (
12. US CAPACITY UTILIZATION: INDUSTRY (SA, PERCENT OF CAPACITY)
13. US UNIVERSITY OF MICHIGAN: CONSUMER SENTIMENT (NSA, Q1-66=100)
14. BUSINESS SECTOR TFP
15. UTILIZATION OF CAPITAL AND LABOR
16. UTILIZATION-ADJUSTED TFP
17. TFP IN EQUIP AND CONSUMER DURABLES
18. TFP IN NON-EQUIPMENT BUSINESS OUTPUT ("CONSUMPTION")
19. UTILIZATION IN PRODUCING INVESTMENT
20. UTILIZATION IN PRODUCING NON-INVESTMENT BUSINESS OUTPUT ("CONSUMPTION")
21. UTILIZATION-ADJUSTED TFP IN PRODUCING EQUIPMENT AND CONSUMER DURABLES
22. UTILIZATION-ADJUSTED TFP IN PRODUCING NON-EQUIPMENT OUTPUT
23. SPOT PRICE IDX OF UK BRT LT/DUBAI MED/ALASKA NS HEAVY (2010=100)
24. NON-FUEL PRIMARY COMMODITIES INDEX (2010=100)
25. US CPI-U: SHELTER (SA, 1982-84=100)
26. US CPI-U: ALL ITEMS LESS FOOD & ENERGY (SA, 1982-84=100)
27. US PCE LESS FOOD & ENERGY: CHAIN PRICE INDEX (SA, 2009=100)

28. US PPI: FINISHED GOODS (SA, 1982=100)
29. US GDP IMPLICIT PRICE DEFLATOR (SA, 2009=100)
30. US IMPORTS DEFLATOR (EXCLUDING RAW MATERIALS)
31. US AVG HOURLY EARNINGS: PROD & NONSUPERVISORY: TOTAL PRIVATE INDUSTRIES(SA, /HOUR)
32. EURO AREA 11-19: 3-MONTH EURIBOR (%)
33. 3-MONTH LONDON INTERBANK OFFER RATE: BASED ON US (%)
34. 3-MONTH TREASURY BILLS, SECONDARY MARKET (% P.A.)
35. 10-YEAR TREASURY NOTE YIELD AT CONSTANT MATURITY (% P.A.)
36. MONEY STOCK: M1 (SA, BIL.)
37. MONEY STOCK: M2 (SA, BIL.)
38. US: HOUSEHOLD & NONPROFIT OUTSTANDING DEBT (SA, BIL.US)
39. US: NONFINANCIAL CORPORATIONS OUTSTANDING DEBT (SA, BIL.US)
40. HOUSING STARTS (SAAR, THOUS.UNITS)
41. REAL BROAD TRADE-WEIGHTED EXCHANGE VALUE OF THE US (MAR-73=100)
42. STOCK PRICE INDEX: STANDARD & POOR'S 500 COMPOSITE (1941-43=10)
43. MOODY'S SEASONED AAA CORPORATE BOND YIELD (% P.A.)
44. MOODY'S SEASONED BAA CORPORATE BOND YIELD (% P.A.)
45. POLICY-RELATED ECONOMIC UNCERTAINTY