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EVOLUTION OF MONETARY POLICY IN PERU: AN EMPIRICAL APPLICATION USING A MIXTURE INNOVATION TVP-VAR-SV MODEL

Jhonatan Portilla Goicochea
y Gabriel Rodríguez

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Abstract

This paper discusses the evolution of monetary policy (MP) in Peru in 1996Q1-2016Q4 using a mixture innovation time-varying parameter vector autoregressive model with stochastic volatility (TVP-VAR-SV) as proposed by Koop et al. (2009). The main empirical results are: (i) the VAR coefficients and volatilities change more gradually than the covariance errors over time; (ii) the volatility of MP shocks was higher under the pre-Inflation Targeting (IT) regime; (iii) a surprise increase in the interest rate produces GDP growth falls and reduces inflation in the long run; (iv) the interest rate reacts more quickly to aggregate supply (AS) shocks than to aggregate demand (AD) shocks; (v) MP shocks explain a high percentage of domestic variable behavior under the pre-IT regime but their contribution decreases under the IT regime.

JEL Classification: C11, C32, E52.

Keywords: Monetary Policy, TVP-VAR-SV, Bayesian Estimation, Mixture Innovation Model, Peruvian Economy.

Resumen

Este artículo discute la evolución de la política monetaria (MP) en Perú en el periodo 1996Q1-2016Q4 utilizando un modelo VAR de mezcla de innovaciones que admite parámetros cambiantes y volatilidad estocástica (TVP-VAR-SV) propuesto por Koop et al. (2009). Los principales resultados empíricos son: (i) los coeficientes VAR y las volatilidades cambian más gradualmente que las covarianzas en el tiempo; (ii) la volatilidad de los shocks de MP ha sido mayor bajo el régimen anterior a la adopción de metas de inflación (IT); (iii) un aumento inesperado en la tasa de interés produce caídas en el crecimiento del PBI y reduce la inflación a largo plazo; (iv) la tasa de interés reacciona más rápidamente a los choques de oferta agregada (AS) que a los shocks de demanda agregada (AD); (v) las perturbaciones de MP explican un alto porcentaje del comportamiento de las variables domésticas bajo el régimen anterior a IT, pero su contribución disminuye bajo el régimen de IT.

Clasificacion JEL: C11, C32, E52.

Palabras Claves: Poítica Monetaria, TVP-VAR-SV, Estimación Bayesiana, Modelo de Mezcla de Innovaciones, Economía Peruana.

Evolution of Monetary Policy in Peru: An Empirical Application Using a Mixture Innovation TVP-VAR-SV Model[1]

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1 Introduction

Deep structural reforms have been implemented in Peru since the 1990s. The deep economic reforms carried out in the 1990s across a number of areas (mainly eliminating price and capital controls, as well as quantitative trade restrictions; unifying the exchange rate and allowing it to float freely; and liberalizing the financial market) marked a transition to a free market economy. The government opened private sector participation in industries previously controlled by the public sector. Crucially, the institutional framework and autonomy of the Central Reserve Bank of Peru (BCRP) and the Superintendency of Banking, Insurance, and Pensions Funds (SBS) were constitutionally mandated. These reforms ushered in a long period of macroeconomic stability and sustainable growth; see Rossini and Santos (2015).

Regarding the monetary regime, the BCRP set out to fulfill its mandate to achieve low inflation in the wake of the 1980s hyperinflation episode. The arrangement used in the transition to single-digit inflation was control of monetary aggregates, with the monetary base as nominal anchor (1995-2001). In 2002 the BCRP adopted an Inflation Targeting (IT) regime with a 1.5%-3.5% target band. Banks' current accounts with the BCRP were used as operating target, but were replaced by the interbank interest rate in September 2003. In 2007 the target band was lowered to 1%-3%. At the same time, the BCRP uses alternative instruments, such as the reserve ratio or FX market intervention, to achieve its inflation objective and maintain the interbank market in balance while addressing Peru's financial dollarization; see Castillo et al. (2011). Therefore, the transmission mechanism and/or volatility may vary over time in response to structural reforms or changes in the monetary regime.

Understanding the behavior of the monetary transmission mechanism is a key objective of this paper. Starting with Sims' (1980) seminal work, VAR frameworks have become an important tool in this field, for example in Sims (1992), Bernanke and Blinder (1992), Gordon and Leeper (1994), Christiano et al. (1996), and Bernanke and Mihov (1998). Leeper et al. (1996) and Christiano et al. (1999) provide an extensive review of the literature on the monetary transmission mechanism in the U.S. Particularly, these papers show that, following a contractionary monetary shock, economic

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activity declines quickly in a hump-shaped manner but, in contrast, the negative price reaction is more delayed and persistent. Mojon and Peersman (2001) discuss the effects of monetary policy (MP) shocks in individual Eurozone countries; and find that an unexpected rise in the short-term interest rate leads to a decrease in output, with investment and exports falling more than consumption and prices decreasing gradually in all countries. Peersman and Smets (2001) study the monetary transmission mechanism for the Eurozone as a whole; and find that a temporary rise in the short-term interest rate leads to a real exchange rate appreciation, a temporary fall in output, and a significant fall in prices several quarters after the decrease in output.

All the above models are based on the assumption of constant VAR coefficients and a constant error variance-covariance matrix. However, it is better to use multivariate models when the transmission mechanism and the variance of the exogenous shocks can both change over time because the inter-relationships between the variables may also change over time; see Koop et al. (2009). Taking into account these considerations, time-varying components are incorporated into the VAR analysis. Cogley and Sargent (2001) analyze the inflation-unemployment dynamics in the U.S. in 1948Q1-2000Q4 using a Bayesian time-varying parameter (TVP) VAR model, but with the assumption of a constant variance matrix. They find that the mean and persistence of inflation show a strong positive correlation and that the degree of persistence in inflation has been drifting downward as inflation has come under control. However, the assumption of constant variances implies that the volatility of shocks hitting the economy does not evolve over time. Therefore, Cogley and Sargent (2005) extend Cogley and Sargent (2001) to incorporate stochastic volatility and then re-estimate for the same data, finding that inflation persistence increased during the 1970s and fell over the next decades; and that the innovation variances are larger for the late 1970s than for other periods.

However, in these models the simultaneous relationship among variables is time-invariant. This is a disadvantage because they cannot distinguish between changes in the typical size of exogenous innovations and changes in the transmission mechanism. Therefore, Primiceri (2005) develops a flexible TVP-VAR-SV model where the coefficients and the entire variance-covariance matrix for the shocks are allowed to vary over time[4] in order to assess the potential causes of the poor economic performance of the U.S. in the 1970s and early 1980s, and to what extent monetary policy played an important role in high unemployment and inflation episodes. Primiceri (2005) finds that both systematic and non-systematic monetary policy has changed during the last 40 years. The role played by exogenous non-policy shocks seems more important than interest rate policy in explaining the high inflation and unemployment episodes in recent U.S. economic history.

In the same line, Benati and Surico (2008) use a structural TVP-VAR-SV model and a dynamic stochastic general equilibrium (DSGE) model to prove that the persistence of the U.S inflation gap declined sharply around the time of the Volcker disinflation and that the predictability of U.S. inflation has fallen sharply over the post-1984 period due to the Fed's more aggressive stance against inflation. Based on a DSGE model, they find that a more aggressive stance to control inflation causes a fall in both the persistence and predictability of inflation, thus providing a possible interpretation of the evidence uncovered via the TVP-VAR-SV model.

Koop et al. (2009) develop a TVP-VAR-SV model similar to Primiceri (2005), but allow for more flexibility using a mixture innovation model that extends the class of TVP-VAR-SV models. The advantage of this extension is that it allows estimating whether, where, when, and how parameters

[4] See also del Negro and Primiceri (2015).

changes occur. The model is used to investigate if the U.S. monetary transmission mechanism has changed or if apparent changes are due to changes in the volatility of exogenous shocks. Moreover, the question of whether changes have been gradual or abrupt is also considered. We find that the transmission mechanism, the volatility of exogenous shocks, and the correlations between exogenous shocks are all changing gradually.

Concerning the evidence from other countries, Nakajima (2011) explores monetary policy transmission in Japan under zero interest rates by explicitly incorporating the zero lower bound (ZLB) for nominal interest rates. The author finds that the dynamic relationship between monetary policy and macroeconomic variables operates through changes in medium-term interest rates rather than policy interest rates under the ZLB. Franta et al. (2013) use a TVP-VAR-SV model to study the evolution of the monetary transmission mechanism in the Czech Republic. The results suggest that prices have become increasingly responsive to MP shocks and the exchange rate pass-through has largely remained stable over time. Bittencourt et al. (2016) use a TVP-VAR-SV model to evaluate how monetary transmission has changed over time since Malawi introduced financial reforms in the 1980s. We find that inflation and real output responses to monetary shocks changed over the period under study. Importantly, beginning mid-2000, the monetary transmission performed consistently with economic theory predictions partly due to stable macroeconomic conditions and positive structural changes in the economy.

Regarding the literature on monetary policy in Peru, most papers estimate a standard VAR model and its extensions with recursive or non-recursive identifying assumptions. Quispe (2000) analyzes Peru's monetary policy in 1980-1998 using three VAR models and concludes that shocks on the money base explain most of the variance in inflation. Quispe (2001) studies different topics of monetary policy in Peru. First, the paper documents that the inflation process in Peru is mostly driven by aggregate demand (AD) shocks, where MP shocks account for 30%-40% of inflation variance. Second, it seeks to identify the best indicator of monetary policy and finds that different studies for Peru on this topic show that money aggregates are the best indicators of monetary policy. Third, the paper presents a model to describe the BCRP's operating procedure, mainly its interaction with the banking system through the money market, considering the partial dollarization of the economy. The results suggest that the time horizon of the impact of an MP shock on inflation is between 8-16 sixteen months. Finally, it identifies the different transmission channels of monetary policy and finds that the money channel seems to be effective in Peru.

Castillo et al. (2011) extend the model proposed by Bernanke and Mihov (1998) for the case of a small partially dollarized economy to estimate the effects of monetary policy in Peru in 1995M1-2009M12. We find that, in the face of a contractionary MP shock, interest rates rise, monetary aggregates contract, the local currency appreciates, aggregate demand slows down, and inflation eventually falls. Additionally, exchange rate shocks turn out to be an important determinant of the money market. Their results show that the BCRP responds more strongly to demand-for-money shocks than to exchange rate shocks during the period following IT adoption.

Other studies relating to Peru's monetary policy are Winkelreid (2004), Bigio, and Salas (2006), Rossini and Vega (2007), Lahura (2010), and Pérez Forero (2015). Winkelreid (2004) estimates an error-correction model to analyze the consequences of structural shocks and the effects of monetary shocks on output and inflation; and the results show the presence of an interest rate channel. Bigio and Salas (2006) estimate a smooth transition VAR model to explore whether changes in the monetary stance and the real exchange rate generate nonlinear effects on output and inflation; and find evidence of nonlinearities in the face of MP shocks, which indicate the convexity of the aggregate supply curve. Rossini and Vega (2007) analyze the changes in the transmission mechanism of monetary policy in Peru using the BCRP Quarterly Forecasting Model; and find that the direct interest rate and expectations channels have become more important in recent years, especially since IT adoption. Lahura (2010) uses a Factor-Augmented VAR benchmark to analyze the effects of MP shocks. Pérez Forero (2015) estimates a Hierarchical Panel VAR to assess and compare the effects of MP shocks across Latin American IT countries (Brazil, Chile, Colombia, Mexico, and Peru); and finds a real short-run effect of monetary policy on output, a significant medium-run response of prices, and a hump-shaped response of the exchange rate. Moreover, Pérez Forero (2015) identifies some degree of heterogeneity on the impact and propagation of MP shocks across countries.

Finally, Castillo et al. (2016) estimate a TVP-VAR-SV model to analyze the causes underlying Peru's "Great Moderation"; i.e., the authors analyze the determinants of the reduction in growth and inflation volatility in 1981Q1-2014Q3. They find that monetary policy has contributed significantly to Peru's "Great Moderation" by reducing the volatility of its non-systematic component and changing its reaction function to AD and aggregate supply (AS) shocks. Moreover, the AS and MP shocks were the most important determinants of macroeconomic instability during the high-volatility period.

This paper analyzes the evolution of monetary policy (transmission mechanism and volatility of MP shocks) in Peru in 1996Q1-2016Q4. More specifically, the paper analyzes the response of domestic variables to MP shocks over time. The paper also studies the response of interest rates to foreign, AD, and AS shocks over time. Given the impact of monetary policy on the real side of the economy, it provides insights into Peru's monetary policy that may be important for its design and implementation. Moreover, it contributes to the extant literature on the changes in the monetary transmission mechanism and the volatility of exogenous shocks by providing new stylized facts. It uses a mixture innovation TVP model with stochastic volatility (TVP-VAR-SV), as proposed by Koop et al. (2009), which has the advantage of allowing estimation of whether, where, when, and how parameter changes occur.

Regarding the parameter evolution, our results suggest that the three blocks of parameters (VAR coefficients, the volatilities and error covariances) change over time. Concerning the volatility of exogenous shocks, we find two volatility peaks, 1998Q3 and 2009Q3, where the first is higher than the second. These peaks are related to two international crises: the Asian-Russian crises and the Great Financial Crisis (GFC), respectively. These results suggest a considerable influence of the international economic context on Peru's economy. In addition, the volatility of MP shocks was significantly higher under the pre-IT regime.

Concerning the impulse response functions (IRFs) to MP shocks, growth tends to fall after a surprise interest rate increase, with the greatest impact occurring after one year on average. Moreover, a contractionary monetary policy reduces inflation in the long run, with the desired effect occurring after two and a half years on average. The results also suggest that IRFs to MP shocks do not vary much over time. Regarding the interest rate IRFs, a foreign shock has a positive effect on interest rates, with a higher reaction after IT adoption. Additionally, the interest rate IRFs for AD shocks are hump-shaped, with a peak between the fourth and fifth quarters. Finally, the interest rate IRFs for AS shocks are hump-shaped, with a peak in the third quarter. The paper does not find any remarkable difference between IRFs for AD and AS shocks over time. In addition, the results suggest that the interest rate reacts more quickly to AS than AD shocks. This is consistent with the BCRP mandate to preserve monetary stability.

Moreover, the paper finds evidence that MP shocks play a considerable role in explaining the forecast error variance decomposition (FEVD) of domestic variables (growth, inflation, and interest rate), especially the interest rate in the pre-IT period. However, under IT the contribution of monetary shocks to domestic variables decreases over time. In the same line, the historical decomposition (HD) of domestic variables shows that MP shocks were more important under the pre-IT regime. Concerning the methodological implications of the results, the paper finds that a TVP-VAR with a constant-error variance-covariance matrix performs poorly in capturing the dynamics between variables compared with other models where variance errors can change. Therefore, the volatility of errors should be time-variant.

The paper is organized as follows. Section 2 presents the mixture innovation TVP-VAR-SV model by Koop et al. (2009). Section 3 discusses the empirical results, including a robustness analysis. Section 4 concludes.

2 Methodology

The econometric model is a mixture innovation TVP-VAR-SV model as proposed by Koop et al. (2009), where both the transmission mechanism and the error variance-covariance matrix can change over time. The three different blocks of parameters (the VAR coefficients, a block for the error variances, and another one for the error covariances) can evolve in completely different ways.

The literature shows two extreme ways of modeling parameter changes: models with very few (but usually large) breaks or with many (usually small) breaks. For estimating the number of breaks, Koop et al. (2009) nest the two extreme cases to estimate the frequency of changes in the parameters and establish whether the change is constant and gradual. The authors draw from the mixture innovation approach of Gerlach et al. (2000) and Giordani and Kohn (2008) as a way to keep the model more tightly parameterized in key dimensions. The advantage of the model is that it allows estimating whether, where, when, and how parameter changes occur, as opposed to assuming a particular model for a parameter change like in Primiceri (2005). The methodology of the mixture innovation TVP-VAR-SV model proposed by Koop et al. (2009) is described below.

The reduced form of the TVP-VAR-SV model in state-space form is:

$$y_t = X_t B_t + u_t, \qquad t = 1, 2, \dots, T, \tag{1}$$

$$B_{t+1} = B_t + v_t, \qquad t = 1, 2, \dots, T, \tag{2}$$

where y_t is an $n \times 1$ vector of observations on the dependent variables; B_t is an $m \times 1$ vector of states (the VAR coefficients); X_t is an $n \times m$ matrix of data on the explanatory variables (each row of X_t contains lags for all the dependent variables, an intercept, and other deterministic variables); u_t are independent $N(0, H_t)$ random vectors; and v_t are independent $N(0, Q_t)$ random vectors for $t = 1, 2, \dots, T$. The errors in the two equations, u_t and v_s, are independent of one another for all t and s. The algorithm of Carter and Kohn (1994) is used to draw the variables' states $B_t = (B_1, \dots, B_T)'$.

It is important to allow the error variance-covariance matrix in the measurement equation (H_t) to vary over time because many important aspects of the transmission mechanism are reflected in this matrix. A triangular reduction is used: $H_t = A_t^{-1} \Sigma_t \Sigma_t' (A_t^{-1})'$, where Σ_t is a diagonal matrix with diagonal elements $\sigma_{j,t}$ for $j = 1, \dots, n$ and A_t is the lower triangular matrix:

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \dots & . & 0 \\ 0 & \sigma_{2,t} & \dots & . & . \\ . & . & \dots & . & . \\ . & . & \dots & \sigma_{n-1,t} & 0 \\ 0 & . & \dots & 0 & \sigma_{n,t} \end{bmatrix}, A_t = \begin{bmatrix} 1 & 0 & \dots & . & 0 \\ \alpha_{21,t} & 1 & \dots & . & . \\ . & . & \dots & . & . \\ . & . & \dots & 1 & 0 \\ \alpha_{n1,t} & . & \dots & \alpha_{n(n-1),t} & 1 \end{bmatrix}.$$

The stochastic volatility framework is used for Σ_t. Starting from $\sigma_t = (\ \sigma_{1,t}, \dots, \sigma_{n,t})'$, then, $h_{i,t} = \ln(\sigma_{i,t})$ and $h_t = (h_{1,t}, \dots, h_{p,t})'$, which evolve according to $h_{t+1} = h_t + \eta_t$, where η_t is $N(0, W)$ and is independent of u_t and v_t over t. The algorithm of Kim et al. (1998) is used to draw the states h_t. Additionally, for A_t, Koop et al. (2009) stack the unrestricted elements by rows into a $\frac{n(n-1)}{2}$ vector as $\alpha_t = (\alpha_{21,t}, \alpha_{31,t}, \alpha_{32,t}, \dots, \alpha_{n(n-1),t})'$, which evolve according to $\alpha_{t+1} = \alpha_t + \varsigma_t$, where ς_t is $N(0, S)$ and is independent of u_t, v_t and η_t over t. Carter and Kohn's (1994) method is used to draw the states α_t.

Regarding the mixture innovation, the model allows some or all the states and parameters to be determined by a sequence of Markov random vectors $K = (K_1, \dots, K_T)'$ that control the structural breaks in the model. The model allows for breaks in the VAR coefficients (B_t) and in the error variance-covariance matrix H_t (Σ_t and A_t); and these breaks may occur at different times; i.e., $K_t = (K_{1t}, K_{2t}, K_{3t})'$ for $t = 1, \dots, T$, where $K_{1t} \in \{0, 1\}$ controls breaks in the VAR coefficients, $K_{2t} \in \{0, 1\}$ controls breaks in Σ_t, and $K_{3t} \in \{0, 1\}$ controls breaks in A_t. Therefore, the state equations of B_t, h_t and α_t are reformulated as follows:

$$B_{t+1} = B_t + K_{1t} v_t, \tag{3}$$
$$h_{t+1} = h_t + K_{2t} \eta_t, \tag{4}$$
$$\alpha_{t+1} = \alpha_t + K_{3t} \varsigma_t, \tag{5}$$

where a Bernoulli distribution is used for the hierarchical prior of K_{jt}; $p(K_{jt} = 1) = p_j$ for $j = 1, 2, 3$. The breaks occur independently in B_t, Σ_t, and A_t.

2.1 Posterior Computation

All posteriors described below are the full conditionals required to set up a valid Markov Chain Monte Carlo (MCMC) algorithm. Regarding the VAR coefficients (B_t), a Wishart prior is used for Q^{-1}: $Q^{-1} \sim W(\underline{v}_Q, \underline{Q}^{-1})$. The posterior for Q^{-1} (conditioned on the states and K) is also Wishart: $Q^{-1}|Data \sim W(\overline{v}_Q, \overline{Q}^{-1})$, where $\overline{v}_Q = \sum_{t=1}^{T} K_{1t} + \underline{v}_Q$ and $\overline{Q}^{-1} = (\underline{Q} + \sum_{t=1}^{T} (B_{t+1} - B_t)(B_{t+1} - B_t)')^{-1}$.

Concerning the volatilities (Σ_t), Koop et al. (2009) adapt the algorithm of Kim et al. (1998) as follows. The equation (1) is transformed as:

$$y_t^* = A_t(y_t - Z_t \alpha_t) = A_t u_t = A_t(A_t^{-1} \Sigma_t \epsilon_t) = \Sigma_t \epsilon_t, \tag{6}$$

where ϵ_t are independent $N(0, I_t)$. This is a system of nonlinear measurement equations but can be converted into a linear one by squaring and taking the logarithm of each element of (6)

$y_{i,t}^{**} = \log\left[(y_{i,t}^{*})^2 + \bar{c}\right]$, where $\bar{c}$ is an offset constant 0.001 used to ensure non-zero values. This leads to the following approximating state space form:

$$
\begin{aligned}
y_t^{**} &= 2h_t + e_t, \\
h_t &= h_{t-1} + \eta_t,
\end{aligned}
\tag{7}
$$

where $e_t = \ln(\epsilon_t^2)$. Note that e_t and η_t are not correlated and e_t is not normally distributed. Moreover, $e_t = (e_{1t}, \ldots, e_{nt})'$ are independent because $y_{i,t}^*$ and $y_{j,t}^*$ are independent for $i \neq j$. However, Kim et al. (1998) show how its distribution can be approximated with a high degree of accuracy by a mixture of seven Normals. If $C_{jt} \in \{1, 2, 3, \ldots, 7\}$ denotes which of the seven Normals e_{jt} is drawn from, it is possible to construct $C_j = (C_{j1} \ldots, C_{jT})'$ and $C = (C_1, \ldots, C_p)'$ as component indicators for all the elements of e_t. Following the approach suggested by Kim et al. (1998), it is possible to obtain a Normal linear state space model (conditioned on C and other parameters); and Carter and Kohn's (1994) algorithm can be used to draw h_t. Kim et al. (1998) draw the posterior of C conditioned to model parameters and states. Thus, q_i, m_i and ψ_i^2 for $i = 1, \ldots, 7$ are the component probability, mean, and variance of each of the components in the normal mixture, respectively. Then, $\Pr(C_{it} = j|Data, h_t) \propto q_j f_N(y_{i,t}^{**}|2h_{i,t} + m_j - 1.2704, \psi_j^2)$ for $j = 1, \ldots, 7$, $i = 1, \ldots, p$, and $t = 1, \ldots, T$. Finally, a Wishart prior is used for W^{-1} to complete the description of the MCMC algorithm for the volatilities (Σ_t): $W^{-1} \sim W(\underline{v}_w, \underline{W}^{-1})$. The posterior for W^{-1} (conditioned on the states and K) is also Wishart: $W^{-1}|Data \sim W(\overline{v}_w, \overline{W}^{-1})$ where $\overline{v}_w = \sum_{t=1}^{T} K_{2t} + \underline{v}_w$ and $\overline{W}^{-1} = (\underline{W} + \sum_{t=1}^{T}(h_{t+1} - h_t)(h_{t+1} - h_t)')^{-1}$.

Concerning the error covariances (A_t), Koop et al. (2009) transform the original measurement equation (1) so that Carter and Kohn's (1994) algorithm can be used to draw the states $A_t(y_t - X_t B_t) = A_t(\widehat{y}_t) = \Sigma_t \epsilon_t = \xi_t$, where ξ_t is $N(0, \Sigma_t \Sigma_t')$ and independent of ς_t. The structure of A_t is used to isolate $\widehat{y}_t$ on the left-hand side as follows:

$$
\widehat{y}_t = Z_t a_t + \xi_t,
\tag{8}
$$

where Z_t is detailed in Koops et al. (2009) and $\widehat{y}_{j,t}$ is the ith element of $\widehat{y}_t$. Thus, the state space form is (8) with $\alpha_{t+1} = \alpha_t + \varsigma_t$. A Wishart prior is used for S_j^{-1}: $S_j^{-1} \sim W(\underline{v}_{Sj}, \underline{S}_j^{-1})$. The posterior for S_j^{-1} (conditioned on the states and K) is also Wishart: $S_j^{-1}|Data \sim W(\overline{v}_{Sj}, \overline{S_j}^{-1})$, where $\overline{v}_{Sj} = \sum_{t=1}^{T} K_{3t} + \underline{v}_{Sj}$ and $\overline{S_j}^{-1} = (\underline{S}_j + \sum_{t=1}^{T}(\alpha_{t+1}^{(j)} - \alpha_t^{(j)})(\alpha_{t+1}^{(j)} - \alpha_t^{(j)})')^{-1}$ and $\alpha_t^{(j)}$ are the elements of α_t corresponding to S_j.

Finally, regarding the hierarchical prior of K_{jt}, which depends on the parameters p_j, a conjugate Beta prior is used for p_j: $p_j \sim B(\underline{\beta}_{1j}, \underline{\beta}_{2j})$. Thus, the conditional posterior for p_j is $p_j \sim B(\overline{\beta}_{1j}, \overline{\beta}_{2j})$, where $\overline{\beta}_{1j} = \underline{\beta}_{1j} + \sum_{t=1}^{T} K_{jt}$ and $\overline{\beta}_{2j} = \underline{\beta}_{2j} + T - \sum_{t=1}^{T} K_{jt}$. Regarding the methodology for drawing K_t, Gerlach et al. (2000) develop an algorithm that integrates the states analytically and draws from $p(K_t|Data, K_{(-t)})$, where $K_{(-t)}$ denotes all the elements of K except for K_t and $Data$. Concerning state space models, Gerlach et al. (2000) show that $p(K_t|Data, K_{(-t)}) \propto p(y^{t+1,T}|y^{1,t}, K)p(y_t|y^{1,t-1}, K^{1,t})p(K_t|K_{(-t)})$, where $p(K_t|K_{(-t)})$ is the hierarchical prior. The authors propose an efficient algorithm for drawing from the above terms. Koop et al. (2009) follow the approach of Giordani and Kohn (2008) to draw K_{1t}, K_{2t}, and K_{3t} separately. The authors combine the algorithm of Gerlach et al. (2000) with Carter and Kohn (1994) to draw from K_{1t} and B_t (conditioned on all other model parameters including K_{2t} and $K_{3,t}$). Moreover, the authors combine the algorithm of Gerlach et al. (2000) with their extension of Kim et al. (1998) to draw from K_{2t} and Σ_t (conditioned on all other model parameters including K_{1t} and $K_{3,t}$). Finally, the authors combine the algorithm of Gerlach et al. (2000) with Carter and Kohn (1994) to draw from K_{3t} and A_t (conditioned on all other parameters of the model including K_{2t} and $K_{3,t}$).

2.2 Values for the Priors

This paper uses a training sample consisting of the first 15 quarters (1992Q2-1995Q4) to choose the priors' hyper-parameters. Using the training sample, we estimate a standard (time-invariant) VAR to obtain the VAR coefficients, $\widehat{B}_{OLS}$; and the error variance-covariance matrix can be decomposed to produce $\widehat{A}_{OLS}$ and $\widehat{\sigma}_0$. We also obtain the variance-covariance matrices of $\widehat{B}_{OLS}$ and $\widehat{A}_{OLS}$, which are labeled $V(\ \widehat{B}_{OLS})$ and $V(\ \widehat{A}_{OLS})$, respectively. Using the above values, we set the following priors for the initial conditions in each state equation: $B_0 \sim N(\widehat{B}_{OLS}, 4V(\widehat{B}_{OLS}))$, $A_0 \sim N(\widehat{A}_{OLS}, 4V(\widehat{A}_{OLS}))$, and $\log(\widehat{\sigma}_0) \sim N\left(\log(\widehat{\sigma}_0), 4I_n\right)$. Next, the priors are set for the error variances in the state equation, allowing these priors to depend on the prior for the number of breaks that may occur. It is important to remember that the Beta prior used for p_j implies that: $E(p_j) = \frac{\underline{\beta}_{1j}}{\underline{\beta}_{1j}+\underline{\beta}_{2j}}$ where $\underline{\beta}_{1j} = 1, \underline{\beta}_{2j} = 1$. Therefore, the following prior is set for the error variances in the state equation: $\underline{v}_Q = 37, \underline{Q} = (k_Q)^2 V(\widehat{B}_{OLS})(1/E(p_1)), \underline{v}_w = 5, \underline{W} = 4(k_W)^2\left(I_3\right)\left(1/E(p_2)\right), \underline{v}_{Sj} = j+1$ and $\underline{S}_j = (j+1)(k_S)^2 V(\widehat{A}_{m,OLS})(1/E(p_3))$ for $j = 1, 2, 3$. It is also worth noticing that k_Q, k_W and k_S are prior values for the time variation; and $k_Q = 0.01, k_W = 0.01$, and $k_S = 0.1$ as in Primiceri (2005).

2.3 Evaluating Model Performance

Following Carlin and Louis (2000), this paper uses the expected value of the log-likelihood function as conventional information criterion (e.g., the Schwarz criterion). The advantage of this approach is that the expected value of the log-likelihood function will be less sensitive to the prior choice. To obtain the expected value of the log-likelihood function, let $\mathbf{Y}$ stack all the data on the dependent variables and $\boldsymbol{\lambda}$ denote all the parameters in the model except for K_1, K_2, and K_3 and the states themselves. Gerlach et al. (2000) describe how to calculate $p(\mathbf{Y}|K_t, \boldsymbol{\lambda})$. Therefore, the authors calculate $p(\mathbf{Y}|K_1, \boldsymbol{\lambda})$, $p(\mathbf{Y}|K_2, \boldsymbol{\lambda})$ and $p(\mathbf{Y}|K_3, \boldsymbol{\lambda})$ and obtain an average of these values.

3 Empirical Evidence

This section presents the data used in the estimation. Then it discusses the empirical results, which include the evidence on parameter evolution, the volatility of exogenous shocks, the IRFs related to monetary policy, the FEVD of variables, the HD, the robustness analysis, and a brief analysis of the reactions to other shocks.

3.1 Data

The model presented in this paper uses four variables: terms of trade growth (Figure 1a), real GDP growth (Figure 1b), and inflation (Figure 1c), representing the non-policy block; and the interest rate (Figure 1d), representing the policy block. The final sample is 1996Q1-2016Q4, with a training sample of 1992Q2-1995Q2. The data are obtained from the BCRP website. All the variables are expressed as year-on-year percent changes, except for the interest rate. The latter is a combination of the interbank interest rate (until 2003Q3) and the reference interest rate (from 2003Q4 until the end of the sample).

3.2 Empirical Results

The simulations are based on 70,000 iterations of the Gibbs Sampler, discarding the first 20,000 for convergence. This paper employs the following order for the variables in the y_t vector: terms of trade growth, real GDP growth, inflation, and the interest rate. Furthermore, we use two lags for the estimation. Regarding the identifying assumption, equation (1) is rewritten as $y_t = X_t B_t + \Upsilon_t \epsilon_t$, where $\Upsilon_t = A_t^{-1} \sum_t$, Υ_t imposes the identifying restrictions, and ϵ_t is assumed to be $N(0, I)$. Therefore, we assume that Υ_t is a lower triangular matrix. This implies that the MP shock has no immediate effect on the other variables. This standard assumption is used by many researchers like Primiceri (2005) and Koop et al. (2009), among others. Each structural shock is identified as follows: a foreign shock for the terms-of-trade equation; an AD shock for the GDP growth equation; an AS shock for the inflation equation; and an MP shock for the interest rate equation.

3.2.1 Evidence on Parameter Evolution

This paper shows some evidence on whether breaks have occurred in the three blocks of parameters: VAR coefficients (B_t), volatilities (Σ_t), and error covariances (A_t); and, if so, of what sort. It is necessary to analyze the variables that control the changes in the three sets of parameters, K_1, K_2, and K_3 and their associated transition probabilities, p_1, p_2, p_3, respectively. The advantage of the methodology proposed by Koop et. al. (2009) is that it allows obtaining different models of interest by imposing values on K_1, K_2, and K_3. We consider different restricted versions of the benchmark (i.e., the mixture innovation TVP-VAR-SV) used in the literature to establish which model is supported by the data. The models that can be considered are listed in Table 1. We consider Primiceri's (2005) model, which can be obtained assuming $K_{1t} = K_{2t} = K_{3t} = 1$ (i.e., the model assumes that the three blocks of parameters always change). This paper also considers a model that restricts the error covariances to be constant over time (i.e., a Benchmark A_t constant model) assuming $K_{3t} = 0$, similar to Cogley and Sargent (2005). Another model considered restricts the volatilities and error covariances to be constant over time (i.e., a Benchmark A_t and Σ_t constant model) assuming $K_{2t} = K_{3t} = 0$, similar to Cogley and Sargent (2001). Yet another model is used to restrict the VAR coefficients to be constant over time (i.e., a Benchmark B_t constant model) assuming $K_{1t} = 0$, motivated by Sims and Zha (2006), who find evidence for models with no changes in the VAR coefficients but with changes in the error variance-covariance matrix. Finally, we consider a time-invariant model (VAR) assuming $K_{1t} = K_{2t} = K_{3t} = 0$.

This paper uses Beta priors for p_j as benchmark. Therefore, $B(\underline{\beta}_{1j} = 1, \underline{\beta}_{2j} = 1)$ for $j = 1$, 2, 3. Based on the properties of the Beta distribution, $E(p_j) = 0.5$ with a standard deviation of 0.29. This benchmark prior implies, *a priori*, that there is a 50% probability that a break will occur in any period for the three blocks of parameters. Moreover, the standard deviation is very large, indicating a relatively non-informative prior. This benchmark prior is used for the other restrictive models depending on which parameter block changes.

The empirical results for the evidence on the existence of breaks in the three blocks of parameters and which type of model is supported by the data are summarized in Table 2. The expected value of the log-likelihood function, $E(\log L)$, is used to assess the performance of the models listed in Table 1. In the Benchmark model, the two expected transition probabilities $E(p_1|Data)$ and $E(p_2|Data)$ related to B_t and Σ_t are above 95%, indicating a high probability that the VAR coefficients and the volatilities change at any time in a gradual manner. Additionally, the expected transition probability $E(p_3|Data)$ related to A_t is 50%, indicating an expectation that a break may occur about twice a year. These results are evidence against the abrupt breaks in conventional structural break models (e.g., Pesaran et al., 2007). In conclusion, this paper obtains a more parsimonious model using the Benchmark model, compared with its restricted versions. The same results are maintained for the restricted models, depending on which parameter block changes.

The Benchmark model performs better because of a higher expected log-likelihood than its restricted versions. Among the latter, Primiceri's (2005) model and the Benchmark A_t constant model are the best performers. The Benchmark A_t and $\sum_t$constant model and the Benchmark B_t constant model receive little support. Finally, the constant and invariant VAR model is the least performer. Therefore, as a first conclusion, this paper finds evidence that parameter evolution is an important issue to be considered.

In sum, all three blocks of parameters change over time. These changes are more gradual for B_t and $\sum_t$ than for A_t. There is also strong evidence in favor of the Benchmark model. Nevertheless, these arguments are purely statistical. The following sections assess the implications of parameter evolution for monetary policy.

3.2.2 Volatility of Exogenous Shocks

The non-systematic monetary policy captures both "policy mistakes" and interest rate movements that are responses to variables other than inflation and growth; see Primiceri (2005). Therefore, a common and theoretically important measure of the non-systematic monetary policy is the volatility of MP shocks. It is important to highlight that in 1996-2001 the exogenous shock in the interest rate equation cannot be directly interpreted as an MP shock, because in that period the policy instrument was monetary base growth. Nevertheless, the interest rate can be used as proxy for the policy instrument,[5] as it became the policy instrument since IT adoption (2002-2016).

Figure 2 presents the posterior mean, the 16th and 84th percentiles of the time-varying standard deviation for the four shocks in the Benchmark model. First, there is a considerable volatility peak in 1998Q3 associated with the Asian-Russian crises for the four exogenous shocks. In addition, there is also a smaller peak in 2009Q3 associated with the GFC for the four exogenous shocks. These two international crises were associated with a strong global contraction in the prices of Peru's metal exports and a considerable fall in Peruvian banks' FX credit to firms and households. This adversely affected aggregate demand and price stability; see Dancourt (2015). These results suggest a significant influence of the international economic context on Peru's economy. The difference between both peaks may be explained by precautionary measures adopted before, and policies

[5] Winkelried (2004), Bigio, and Salas (2006) and Castillo et al. (2011) also use the interest rate as proxy for the policy instrument, although their samples cover the pre-IT regime.

implemented during, each crisis; see Dancourt (2015), Velarde (2015) and Rossini (2016). At the same time, since 1998Q3 the volatilities of the four exogenous shocks show a downward trend, indicating a period of low volatility in Peru's economy due to appropriate policies adopted in the wake of the Asian-Russian crises, such as IT adoption; see Velarde (2015) and Rossini (2016).

In this regard, Figure 2(d) shows that the volatility of MP shocks is higher on average under the pre-IT regime (1996Q1-2001Q4) than under IT (2002Q1-2016Q4).[6] Therefore, IT adoption may have played a key role in reducing MP volatility. This result is consistent with Velarde and Rodríguez (2001), Castillo et al. (2009), and Castillo et al. (2016). Velarde and Rodríguez (2001) argue that the high interest rate variability during the Asian-Russian crises is due to BCRP monetary policy. Likewise, Castillo et al. (2009) suggest that inflation, GDP, and interest rate volatility was higher in 1994-2001 than in 2002-2005. We also conclude that use of the interest rate as policy instrument induces a reduction in macroeconomic risk. Finally, Castillo et al. (2016) identify a significant decline in the volatility of AS, AD and MP shocks since the early 1990s. However, their results are not totally comparable with the ones obtained in this paper, because their monetary policy variable is monetary base growth and their sample is different (1981Q1-2014Q3).

Regarding the comparison between volatility magnitudes of exogenous shocks, Figure 3 shows the posterior mean of the time-varying standard deviation of the four exogenous shocks for the Benchmark model. Foreign shock volatility is the highest in the entire sample because Peru is a small, open, and mining export economy, and the terms of trade are influenced by the prices of mining commodities. Concerning the other exogenous shocks, the volatility of MP shocks is higher than that of AD shocks until 2002. Since 2002Q1, MP shock volatility ceases to be an important source of macroeconomic volatility in Peru's economy, compared with AD shock volatility. Another interesting feature is that AS shock volatility is the lowest over the entire sample.

Furthermore, this paper shows the volatility of exogenous shocks for the models where volatility (Σ_t) changes: Benchmark, Primiceri (2005), Benchmark A_t constant, and Benchmark B_t constant models. Figure 4 presents the posterior mean of the time-varying standard deviation in the four exogenous shocks for these four models. All of them capture the same broad patterns of volatility for all exogenous shocks. In Figure 4(a), the Benchmark A_t constant and Benchmark B_t constant models show a much smoother volatility pattern in the equation for terms-of-trade growth. For the other three equations (Figures 4(b), 4(c), and 4(d)) there are no noticeable differences between models.

In conclusion, the results suggest that MP shock volatility was higher on average under the pre-IT regime than under the IT regime. Additionally, MP shocks are no longer an important source of macroeconomic volatility in Peru since IT adoption. Finally, the benchmark model and its restricted versions capture the same broad patterns of volatility for all exogenous shocks.

3.2.3 Impulses Response Functions (IRFs)

This section analyzes the IRFs to MP shocks and the IRFs of the interest rate to foreign, AD, and AS shocks. The IRFs are normalized to unity for all t to describe the changes in the propagation of shocks. Furthermore, it shows the results for the four models listed in Table 1: Benchmark,

[6] The AD and AS shocks show the same features; see Figure 2(b) and Figure 2(c).

Primiceri (2005), Benchmark A_t constant, and Benchmark A_t and Σ_t constant models.[7]

Figure 5 shows the posterior medians of the IRFs to growth, inflation, and the interest rate to an MP shock for the models mentioned above. In theory, a surprise increase in the interest rate should make growth and inflation fall. This pattern is present over the entire sample for each model. Therefore, it can be concluded that the effect of an MP shock is robust to the model specification.

The IRFs of GDP growth, inflation, and the interest rate to an MP shock are then analyzed for each model in four representative time periods: 1998Q3, 2003Q4, 2009Q3, and 2016Q4. The volatility peaks in the sample (1998Q3 and 2009Q3); the period after IT adoption and before the GFC (2003Q3); and the period after the GFC (2016Q4) are selected. Figure 6 shows the posterior medians of the IRFs of growth, inflation, and the interest rate to an MP shock in each model at different time periods.

The results suggest that an MP shock has the greatest effect on growth between the fourth and fifth quarters. In addition, all models show the same broad pattern in all selected periods. However, the Benchmark A_t and Σ_t constant model overestimates the IRFs of GDP growth to an MP shock in all selected periods, indicating a poor performance. Regarding the effect of an MP shock on inflation, the results indicate that an MP shock has a long-term effect on inflation, with a strong impact between the eighth and tenth quarters. Additionally, the IRFs of inflation also show a small price puzzle, which is more noticeable in the IT periods. Regarding the differences between models, again the Benchmark A_t and Σ_t constant model overestimates the effect of an MP shock, indicating a poor performance, while the remaining models show almost the same pattern in each period. Finally, concerning the effect of an MP shock on the interest rate, only the Benchmark A_t and Σ_t constant model shows a significantly different pattern from the other models.

Furthermore, the paper analyzes the response of the interest rate to foreign, AD, and AS shocks. Figure 7 shows the posterior medians of the IRFs of the interest rate to foreign, AD, and AS shocks in the models mentioned above. The results suggest a poor performance of the Benchmark A_t and Σ_t constant model because it does not show the same pattern as the IRFs for the other models. Therefore, it is important that the volatility of errors should change over time to estimate the IRFs.

Concerning the IRFs to a foreign shock, the results suggest that the latter causes interest rate increases and its effect grows over time. Regarding the IRFs to AD shocks, the IRFs show a positive hump-shaped pattern and the interest rate reacts gradually, with the highest effect after one year. Finally, the IRFs to an AS shock show a quick positive interest rate response, with a higher effect after two quarters. Therefore, the responses to AS shocks are more immediate and stronger than the responses to AD shocks. This conclusion is consistent with the BCRP's mandate to preserve monetary stability and maintain inflation within its target band.

Figure 8 shows the posterior medians of the IRFs of the interest rate to foreign, AD, and AS shocks for each model in selected periods. The IRFs of the interest rate to a foreign shock show more interesting features. The interest rate response in 2016Q4 is stronger than for the other periods. The results confirm that the interest rate response grows over time and the BCRP reacts more aggressively to a foreign shock over time. Regarding the IRFs of the interest rate to AD shocks, the IRFs for the different time periods do not vary much. Finally, there are no remarkable

[7] This paper only considers these models because the IRFs to MP shocks change over time. Concerning the other models, in the case of the Benchmark B_t constant model, the IRFs for an MP shock do not change because the VAR coefficients are constant, a recursive identification is used, and the interest rate is treated as the most endogenous variable. Therefore, the IRFs to MP shocks in the Benchmark B_t constant model are the same over the period. Likewise, the reason for not considering a constant VAR model are obvious.

differences between IRFs of the interest rate to AS shocks. Therefore, it can be concluded that BCRP responses to AD and AS shocks are consistent over time.

Summarizing, the responses to MP shocks have not changed considerably over time, as no significant differences are identified between the selected periods. Additionally, the responses are robust to model specification. Moreover, the patterns of responses to MP shocks are consistent with Winkelried (2004), Bigio and Salas (2006), Lahura (2010), Castillo et al. (2011), and Pérez Forero (2015); and the interest rate response to a foreign shock increases over time, while the responses to AD and AS shocks do not change significantly over time. Finally, the interest rate responses to AS shocks are more immediate and stronger than to AD shocks.

3.2.4 Forecast Error Variance Decomposition (FEVD)

Another important monetary policy issue is the forecast error variance decomposition (FEVD) of variables in response to MP. The paper shows the FEVD of domestic variables in the short (second horizon), medium (eleventh horizon), and long term (twentieth horizon).[8] Figure 9 shows the time evolution of the FEVD for GDP growth in various models over different horizons. In the Benchmark model, MP shocks explain less than 4.5% in the short-term for all the periods in the sample. At the same time, MP shocks show a greater contribution and variation in the medium and long term. Under the pre-IT regime, MP shocks' long-term contribution was 8.1% in 1996Q1. Their contribution increases to its highest value (33.8%) in 1998Q3; then the trend changes and their contribution decreases in 2001Q4 (to 12.3%). Finally, under IT, the contribution of MP shocks continues to decrease (to 0.7%) until the end of the sample. Therefore, MP shocks are more important to explain the GDP growth's FEVD in the pre-IT period.

Figure 10 shows the time evolution of the inflation's FEVD for various models over different horizons. For the Benchmark model, MP shocks explain less than 2.04% in the short run. However, in the long run, the inflation's FEVD due to MP shocks is 5.8% in 1996Q1; then increases to its highest value of 25.5% in 1998Q3; and finally decreases to 6.3% in 2001Q4 under the pre-IT regime. In contrast, MP shocks under IT explain 4.3% in 2002Q1 and their contribution decreases to 0.3% in 2016Q4. Therefore, MP shocks become less important in explaining the inflation's FEVD under IT.

Finally, Figure 11 shows the time evolution of the interest rate's FEVD for various models over different horizons. For the Benchmark model, in the short run the interest rate's FEVD due to MP shocks is 43.2% in 1996Q1; then increases to 92.7% in 1998Q3; and finally decreases to 52.2% in 2001Q4 under the pre-IT regime. However, under IT, the contribution of MP shocks decreases to 10.6% in 2005Q3; then increases to 22.9% in 2009Q3; and finally decreases to 3.4% until the end of the sample. These percentages decrease to a maximum of 11% in the medium and long term. Thus, MP shocks explain a higher percentage of FEVD under the pre-IT regime compared to the IT regime. Another result is that MP shocks are more important than foreign shocks in explaining the interest rate FEVD under the pre-IT regime, while foreign shocks show the highest contribution to the interest rate's FEVD under the IT regime.

The above results are in line with Castillo et al. (2009), who argue that IT adoption reduced the volatility of domestic variables. Moreover, Armas and Grippa (2008) conclude that inflation fluctuations are explained by AS shocks and the international prices of Peru's imports since IT

[8] The medium- and long-term values of the FEVD are quite similar. Therefore, only the latter are described.

adoption. Additionally, Mendoza (2013) finds that greater trade openness since 2003 can explain the higher contribution of foreign shocks to the FEVD of domestic variables under IT.

Regarding the results for other models, the Primiceri (2005) model and the Benchmark A_t constant model yield very similar results. Nevertheless, the Benchmark A_t and Σ_t constant model does not capture the changes in shock participation over time.

In conclusion, under the pre-IT regime, MP shocks explain a significant percentage of the FEVD of domestic variables, especially the interest rate. Nonetheless, under the IT regime, the contribution of MP shocks to the FEVD of the domestic variables decreases over time.

3.2.5 Historical Decomposition (HD)

The last issue to analyze is the historical decomposition (HD) of domestic variables associated with MP shocks. Figure 12 describes the HD of GDP growth for different models. For the benchmark model, the contribution of MP shocks is important under the pre-IT regime, but decreases under the IT regime. In addition, their contribution is negative before IT and is positive after IT adoption.

Figure 13 presents the HD of inflation for different models. For the Benchmark model, MP shocks play an important role in inflation until 2004Q4. Then, the role of MP shocks is minor compared to others shocks. Moreover, most shocks are negative over time.

Finally, Figure 14 shows the HD of the interest rate for different models. For the Benchmark model, MP shocks are larger than the others shocks under the pre-IT regime. At the same time, under the IT regime their contribution to the interest rate decreases and foreign shocks become relevant in explaining the interest rate.

Summarizing, MP shocks play a relevant role in explaining domestic variables under the pre-IT regime, while their contribution decreases after IT adoption. It is an indicator of the monetary authority's good performance because MP shocks are no longer a source of uncertainty. Regarding the other models, the one proposed by Primiceri (2005) and the Benchmark A_t constant model yield quite similar results. Specifically, the Benchmark A_t and $\sum_t$ constant model overestimates or underestimates the contribution of shocks.

3.2.6 Robustness Analysis

Concerning the prior sensitivity analysis, this paper uses different priors to estimate the probabilities of change in the three blocks of parameters. Table 3 shows the posterior means for the transition probabilities that a break may occur at time t using two different priors for the mixture innovation TVP-VAR-SV: informative priors and few-breaks prior. For the informative priors, $B(\underline{\beta}_{1j} = \frac{\sqrt{T}}{2}, \underline{\beta}_{2j} = \frac{\sqrt{T}}{2})$ for $j = 1, 2, 3$ and $T = 84$. Based on the properties of the Beta distribution, $E(p_j) = 0.5$ with a 0.14 standard deviation. Compared with the Benchmark model, *a priori* they have the same probability (50%) of a break occurring at any period, but the standard deviation is smaller. For the few-breaks prior, following Koop et. al. (2009), $B(\underline{\beta}_{1j} = 0.01, \underline{\beta}_{2j} = 10)$ for $j = 1, 2, 3$. Therefore, $E(p_j) = 0.001$ with a standard deviation of 0.01. These results mean that, *a priori*, there is a 0.1% probability that a break may occur in any period for the three blocks of parameters. That is, the transition probabilities are close to zero.

For the informative priors, the posterior means for transition probabilities are above 90% in the VAR coefficients (B_t) and the volatilities ($\sum_t$). This result suggests that there is a high probability that the parameters change gradually in any period. Moreover, in the error covariances (A_t), the posterior mean for the transition probabilities is almost 50%. This result indicates that a break can be expected to occur about twice a year. At the same time, using the few-breaks prior, the posterior means for the transition probabilities are $E(p_1|Data) = 0.73$, $E(p_2|Data) = 0.72$ and $E(p_3|Data) = 0.01$. It should be noted that, while with the prior information of the transition probabilities is close to zero, a break may be expected to occur about three times per year in the VAR coefficients (B_t) and the volatilities (Σ_t). However, very few changes may be expected in the error covariances (A_t) over the period of analysis. In conclusion, it is still possible to find evidence of a gradual change in the parameters (at least in the VAR coefficients and the volatilities) in both alternative priors.

At the same time, uninformative values are used for the initial states: $\widehat{B}_0 = 0$, $\widehat{V(B_0)} = I_n$, $\widehat{A}_0 = 0$, $\widehat{V(A_0)} = I_n$ and $\log(\widehat{\sigma}_0) = 0$. Only the posterior mean for the transition probabilities of the error covariances (A_t) changes ($E(p_3|Data) = 0.03$). However, the pattern of IRFs for different shocks does not change. Moreover, if much flatter specifications for these priors are used, with variances ten or twenty times bigger, the results do not change.[9]

While the choice of the priors for the initial states is innocuous, the selection of k_Q, k_W and k_S turns out to be more important. Table 4 shows the posteriors of the transition probabilities that a break may occur at time t for different values of k_Q, k_W and k_S. It is worth noting that k_Q, k_W, and k_S do not parameterize the time variation, but prior beliefs about the magnitude of the time variation do. The first row shows $k_Q = 0.01$, $k_W = 0.01$ and $k_S = 0.1$ used in the Benchmark model and its results. In the second row, $k_W = 1$ and the other values are maintained. The posterior means for transition probabilities are the same results of the Benchmark model. In the third row, $k_S = 1$ and the other values are maintained. Only the posterior mean for the transition probabilities of the error covariances (A_t) changes ($E(p_3|Data) = 0.03$). Finally, in the fourth row, $k_Q = 1$ and the other values are maintained. The posterior mean for the transition probabilities of the volatilities (Σ_t) is the same as in the benchmark result. However, this value of k_Q affects $E(p_1|Data)$ with a lower value (0.23), but with a higher value (0.62) of $E(p_3|Data)$. It is worth noting that the election of different values for k_W does not affect any the posteriors of the transition probabilities.

Regarding the IRFs, only $k_Q = 1$ does not result in well-behaved IRFs. According to Primiceri (2005), $k_Q = 0.01$ is a value that does not particularly penalize the time variation in the coefficients. Therefore, the coefficients change considerably with time, but only to explain the outliers and to push the in-sample error to zero. Thus, with values of k_Q greater than 0.01 (e.g., $k_Q = 1$), the coefficients change very little and cannot explain the sample outliers. For these reasons, the results of transition probabilities relating to the VAR coefficients and the IRFs are not the best. In conclusion, $k_Q = 0.01$ is a good choice for the sample and is consistent with the literature: Cogley and Sargent (2001), Cogley and Sargent (2005), Primiceri (2005), and Koop et. al. (2009).

Finally, the estimation is performed with a different variable ordering to test the robustness of the results:[10] terms of trade growth, inflation, GDP growth, and interest rate. The posterior means for the transition probabilities do not change. Concerning the volatility of exogenous shocks, there is a volatility peak in 1998Q3 for the four shocks, as in the baseline model. However, the 2009Q3 peak is not clear as in the baseline model, but there is a period of increased volatility between 2006Q1 and 2010Q1. Regarding magnitudes, the volatility from foreign and AS shocks are the

[9] All results are available upon request.

[10] All results are available upon request.

largest and lowest over the period, respectively, as well as in the Benchmark model. However, the robustness results show that MP shocks are always larger than AD shocks and different from the baseline results. Concerning the IRFs for the robustness analysis, the patterns of the responses of variables to MP shocks are very similar in both estimations. Specifically, the pattern of the interest rate response to foreign and AS shocks are similar in both models. However, interest rate responses to AD shocks are negative in the first quarters, but positive in the remaining quarters as well as in the Benchmark model.

4 Other Shocks

The results asociated with foreign, AD, and AS shocks are presented, considering the same models employed before.[11] Concerning the effect of foreign shocks, the response of GDP growth changes over time; for the Benchmark model, the response of GDP growth is positive during most of the pre-IT regime, but negative under the IT regime. These results are similar for the others models, except for the Benchmark A_t and $\sum_t$ constant model. Additionally, the response of inflation is always negative over time and across the models. Regarding their contribution to the FEVD of domestic variables in the long run, a foreign shock explains at least 17%, 25%, and 7% of the FEVD of GDP growth, inflation, and the interest rate, respectively, under the pre-IT regime. Nonetheless, these results change under the IT regime, where foreign shocks have a contribution of at least 40% of the FEVD of each domestic variable. Finally, the contribution of foreign shocks to the HD of GDP growth does not change over the sample, while their contribution to the HD of inflation an the interest rate becomes more important under the IT regime.

Additionally, the response of inflation to AD shocks is positive over time, with a strong effect in the fourth quarter, and the results are similar across the models. Regarding their long-run contribution to the FEVD of GDP growth, AD shocks explain 48% in 2001Q4 (pre-IT regime) and their contribution decreases to 15% in 2016Q4 (IT regime). In addition, AD shocks explain less than 11% and 5% of the FEVD of inflation and interest rate, respectively. Finally, AD contribute significantly to the HD of GDP growth, while its contribution to the HDs of inflation and interest rate are lower compared to other shocks.

Finally, the response of GDP growth to AS shocks is negative over time, with a strong effect in the second quarter, and the results are similar across the models. AS shocks have a higher long-run contribution of the FEVD of inflation under the pre-IT regime (between 30% and 44%) compared with the IT regime (40% in 2002Q1 to 17% in 2016Q4). In addition, AS shocks explain less than 3% and 9% of the FEVD of GDP growth and interest rate, respectively. AS shocks contribute significantly to the HD of inflation; but their contributions to the HDs of GDP growth and interest rate are lower compared to other shocks.

5 Conclusions

This paper uses a mixture innovation TVP-VAR-SV model, proposed by Koop et al. (2009), to analyze the evolution of monetary policy in Peru in 1996Q1-2016Q4. The model allows estimating whether, where, when, and how parameter changes occur. We estimate a small quarterly model of the Peruvian economy with four variables: terms of trade growth, real GDP growth, inflation, and interest rate with recursive identifying assumptions.

[11] All Figures are available upon request.

The paper finds evidence that the three blocks of parameters (VAR coefficients, volatilities, and error covariances) change gradually. In addition, the transition probabilities of the VAR coefficients (B_t) and volatilities ($\sum_t$) are above 95%. This result is evidence that, in any period, there is a high probability that these blocks of parameters change gradually. Moreover, the transition probabilities of error covariances (A_t) is 50%; i.e., a break may be expected to occur about twice a year. An assessment is also made of the performance of the Benchmark model and its restricted versions, finding that the Benchmark model does better.

Regarding the volatility of exogenous shocks, the results suggest two high-volatility peaks (1998Q3 and 2009Q3) associated with international economic events: the Asian-Russian crises and the GFC. Moreover, the volatility of MP shocks is on average higher under the pre-IT regime compared with the IT regime. In addition, since 2002Q1, MP shock volatility has ceased to be an important source of macroeconomic volatility in Peru's economy.

There is also evidence that MP shocks explain a considerable percentage of the FEVD of domestic variables under the pre-IT regime, especially the interest rate's FEVD. However, this scenario changes under the IT regime; i.e., MP shocks become less important and foreign shocks explain al least 40% of the FEVD of domestic variables. In the same line, the participation of MP shocks in the HD of domestic variables decreased under the IT regime compared with the pre-IT regime.

Since IT adoption, MP shocks are no longer an important source of macroeconomic volatility, which is a good indicator of the BCRP's good performance. Therefore, policy-makers should focus on mitigating the influence of other shocks, especially foreign shocks. Likewise, monetary policy is an important tool to reduce the negative effects of these shocks. However, the biggest challenge is identifying what kind of shock the economy is facing and designing a monetary policy response to deal with it. An appropriate monetary policy will allow maintaining macroeconomic stability.

Finally, a future agenda includes a non-recursive identification or adding other variables to the model. Moreover, it is important to do further reasearch on aspects such as lending and the expectations channel of monetary transmission within the TVP-VAR-SV framework to gain a better understanding of monetary policy in Peru.

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Table1. Models and Priors

Model	Prior or modelling assumptions relating to		
	B_t	$\sum_t$	A_t
Benchmark	$\underline{\beta}_{11} = \underline{\beta}_{21} = 1$	$\underline{\beta}_{12} = \underline{\beta}_{22} = 1$	$\underline{\beta}_{13} = \underline{\beta}_{23} = 1$
Primiceri (2005)	$K_{1t} = 1 \; \forall \; t$	$K_{2t} = 1 \; \forall \; t$	$K_{3t} = 1 \; \forall \; t$
Benchmark A_t constant	$\underline{\beta}_{11} = \underline{\beta}_{21} = 1$	$\underline{\beta}_{11} = \underline{\beta}_{21} = 1$	$K_{3t} = 0 \; \forall \; t$
Benchmark A_t and $\sum t$ constant	$\underline{\beta}_{11} = \underline{\beta}_{21} = 1$	$K_{2t} = 0 \; \forall \; t$	$K_{3t} = 0 \; \forall \; t$
Benchmark with B_t constant	$K_{1t} = 0 \; \forall \; t$	$\underline{\beta}_{11} = \underline{\beta}_{21} = 1$	$\underline{\beta}_{11} = \underline{\beta}_{21} = 1$
VAR	$K_{1t} = 0 \; \forall \; t$	$K_{1t} = 0 \; \forall \; t$	$K_{3t} = 0 \; \forall \; t$

Note: B_t, $\sum_t$ and A_t are the parameters blocks of VAR coefficients, volatilities and error covariances, respectively. $\underline{\beta}_{1j}$ and $\underline{\beta}_{2j}$ are prior hyperparameters related to the prior probability that a break occurs in any period. K_t is a vector that controls the structural breaks in the model. If $K_{jt} = 1$, the break occurs; and if $K_{jt} = 0$, the break doesn't occur.

Table 2. Results using Benchmark Prior for Mixture Innovation TVP-VAR-SV and Restricted Versions of Benchmark

Model	$E(p_1\|Data)$	$E(p_2\|Data)$	$E(p_3\|Data)$	$E(\log L)$
Benchmark	0.98 (0.01)	0.98 (0.02)	0.50 (0.26)	−35.62
Primiceri	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)	−36.15
Benchmark A_t constant	0.98 (0.01)	0.98 (0.02)	0.00 (0.00)	−35.64
Benchmark A_t and $\sum_t$ constant	0.98 (0.02)	0.00 (0.00)	0.00 (0.00)	−36.88
Benchmark with B_t constant	0.00 (0.00)	0.98 (0.02)	0.47 (0.26)	−40.27
VAR	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	−42.91

Note: B_t, $\sum_t$ and A_t are the parameters blocks of VAR coefficients, volatilities and error covariances, respectively. $E(p_1|Data)$, $E(p_2|Data)$, $E(p_3|Data)$ are the posteriors means of transition that a break occurs at time t and are related to B_t, $\sum_t$ and A_t, respectively. Standard deviations are in parenthesis. $E(\log L)$ is the expected value of the log-likelihood function.

Table 3. Robustness Analysis: Results using Different Priors for Mixture Innovation TVP-VAR-SV

Model	Prior or modelling assumptions	$E(p_1\|Data)$	$E(p_2\|Data)$	$E(p_3\|Data)$
Benchmark	$\underline{\beta}_{1j} = \underline{\beta}_{2j} = 1$, for $j = 1, 2, 3$	0.98 (0.01)	0.98 (0.02)	0.50 (0.26)
Informative Prior	$\underline{\beta}_{1j} = \underline{\beta}_{2j} = \frac{(\sqrt{T})}{2}$, for $j = 1, 2, 3$	0.93 (0.03)	0.92 (0.03)	0.49 (0.15)
Few Breaks	$\underline{\beta}_{1j} = 0.01, \underline{\beta}_{2j} = 10$, for $j = 1, 2, 3$	0.73 (0.07)	0.72 (0.09)	0.01 (0.01)

Note: $\underline{\beta}_{1j}$ and $\underline{\beta}_{2j}$ are prior hyperparameters related to the prior probability that a break occurs in any period. $E(p_1|Data)$, $E(p_2|Data)$, $E(p_3|Data)$ are the posteriors means of transition that a break occurs at time t and are related to VAR coefficients, the volatilities and the error covariances, respectively. Standard deviations are in parenthesis.

Table 4. Robustness Analysis: Results using different prior beliefs about the amount of time variation

Values of k_Q, k_W and k_S	$E(p_1\|Data)$	$E(p_2\|Data)$	$E(p_3\|Data)$
$k_Q = 0.01$, $k_W = 0.01$, $k_S = 0.1$	0.98 (0.01)	0.98 (0.02)	0.50 (0.26)
$k_Q = 0.01$, $k_W = 1$, $k_S = 0.1$	0.98 (0.01)	0.97 (0.02)	0.50 (0.26)
$k_Q = 0.01$, $k_W = 0.01$, $k_S = 1$	0.98 (0.01)	0.98 (0.01)	0.03 (0.02)
$k_Q = 1$, $k_W = 0.01$, $k_S = 0.1$	0.23 (0.05)	0.98 (0.02)	0.62 (0.25)

Note: k_Q, k_W and k_S are prior beliefs about the amount of time variation. $E(p_1|Data)$, $E(p_2|Data)$, $E(p_3|Data)$ are the posteriors means of transition that a break occurs at time t and are related to VAR coefficients, the volatilities and the error covariances, respectively. Standard deviations are in parenthesis.

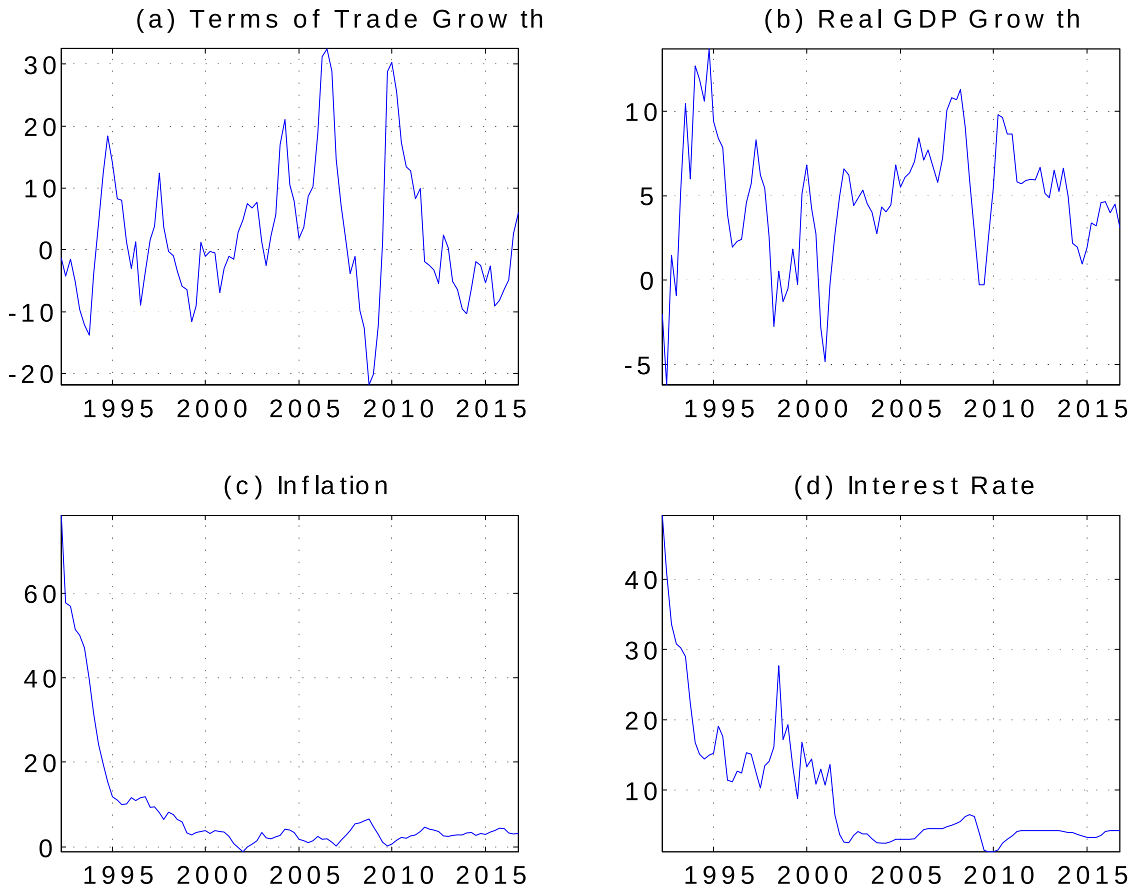

Figure 1. Time Series (1992Q2-2016Q4)

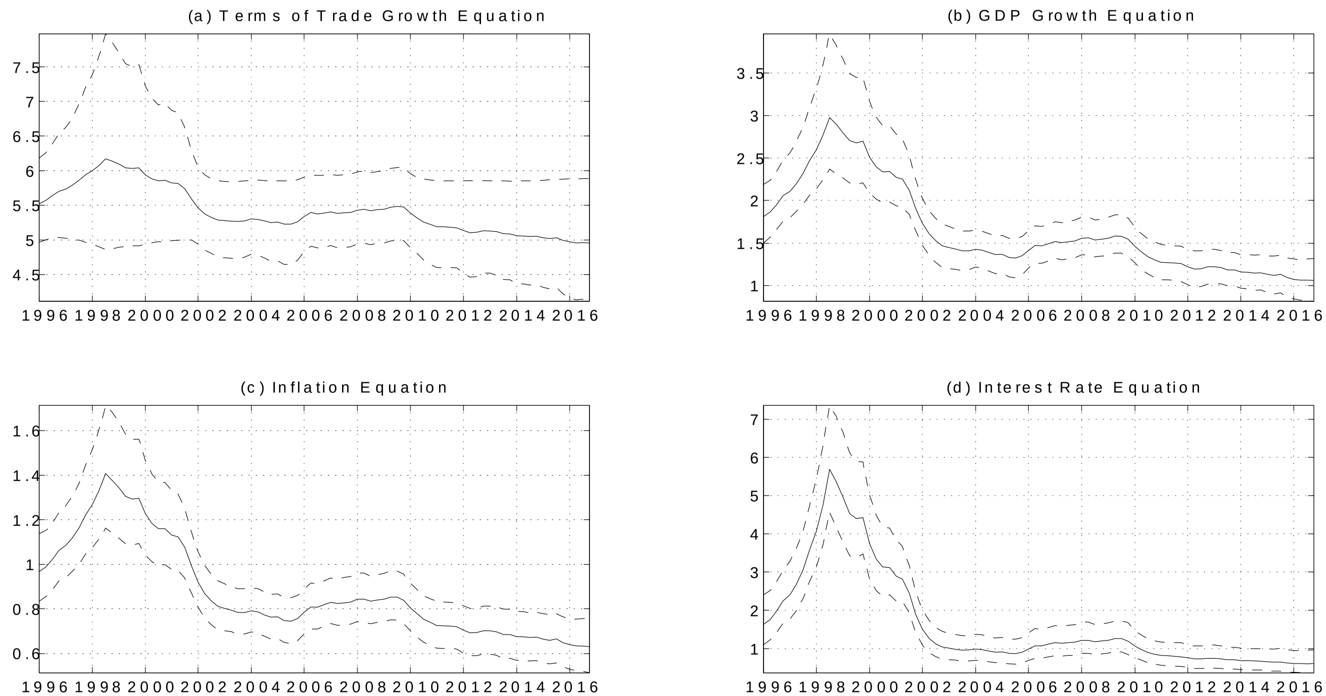

Figure 2. Posterior Mean, 16th and 84th Percentiles of the Stardand Deviation of Errors in the Four Equations for Benchmark Model (1996Q1-2016Q4)

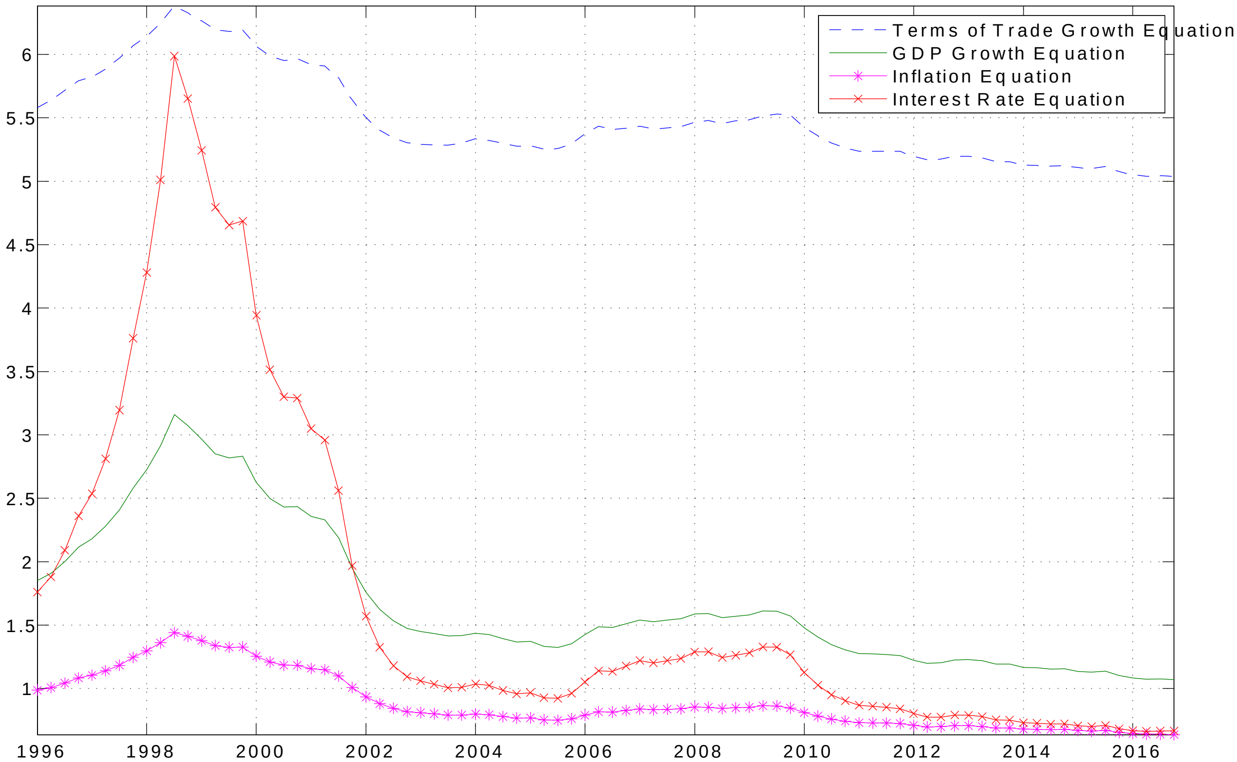

Figure 3. Posterior Mean of the Standard Deviations of Errors in the Four Equations for Benchmark Model (1996Q1-2016Q4)

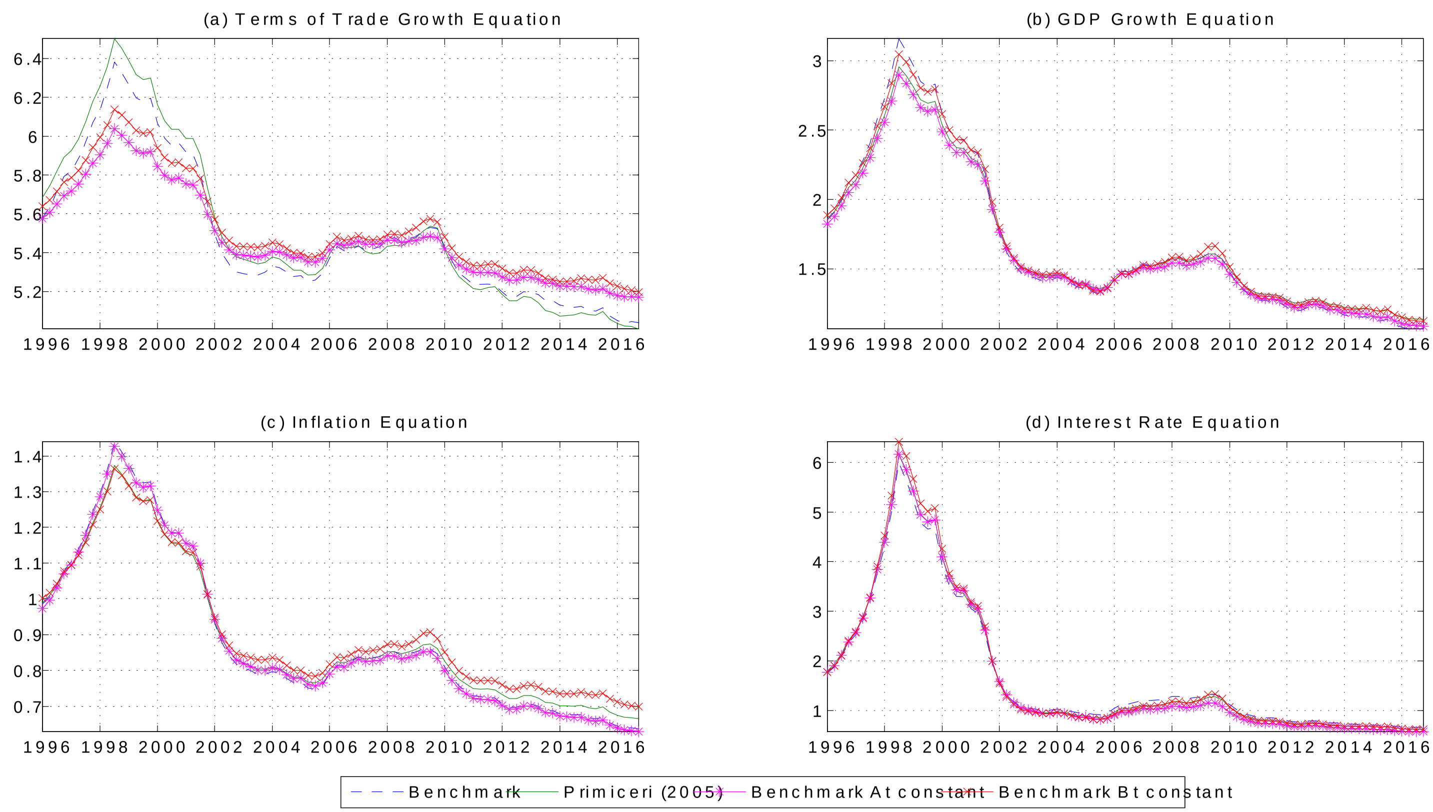

Figure 4. Posterior Mean of the Standard Deviations of Errors in the Four Equations for Various Models (1996Q1-2016Q4)

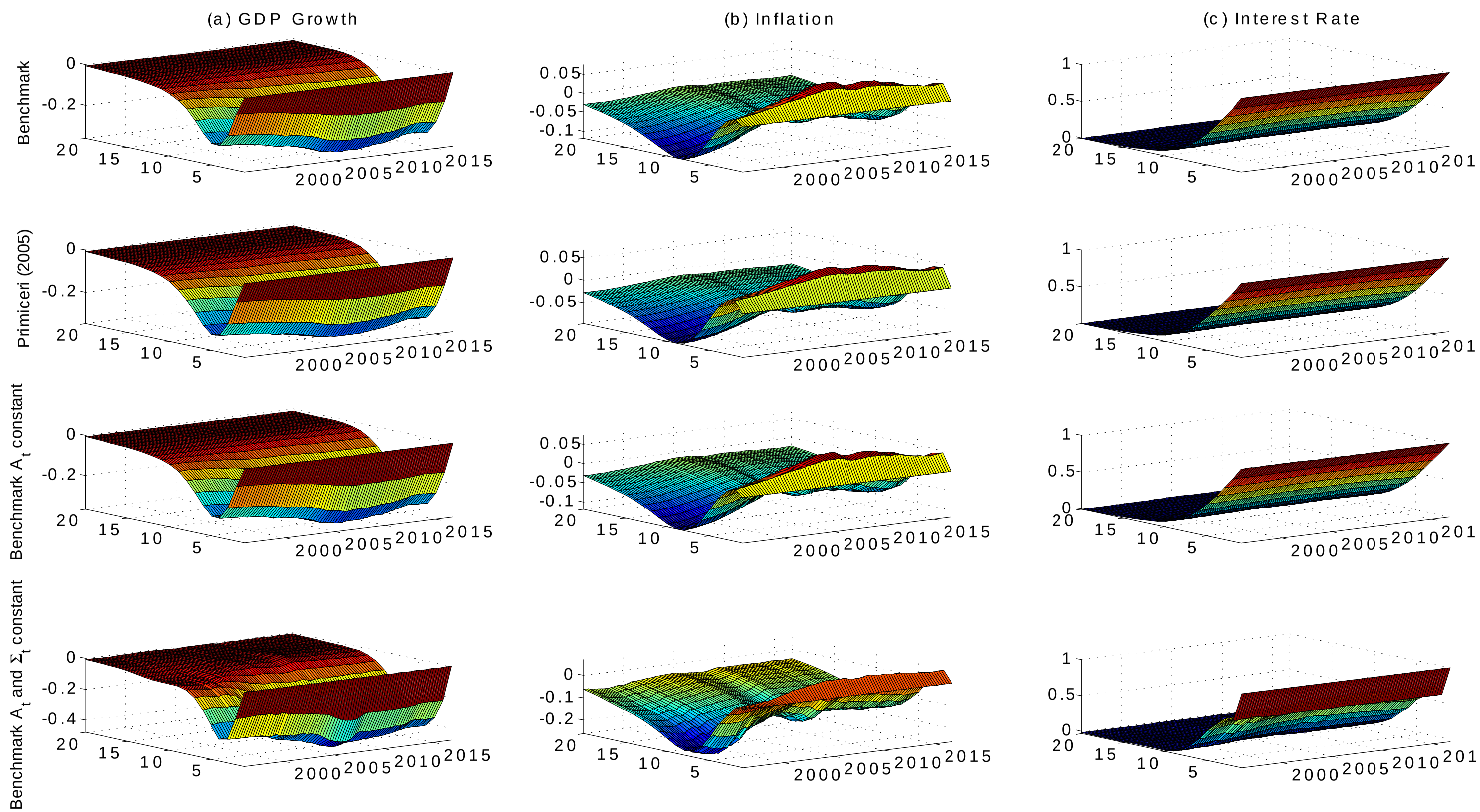

Figure 5. Median Time-Varying Impulse Response Functions to Monetary Policy Shock for Various Models

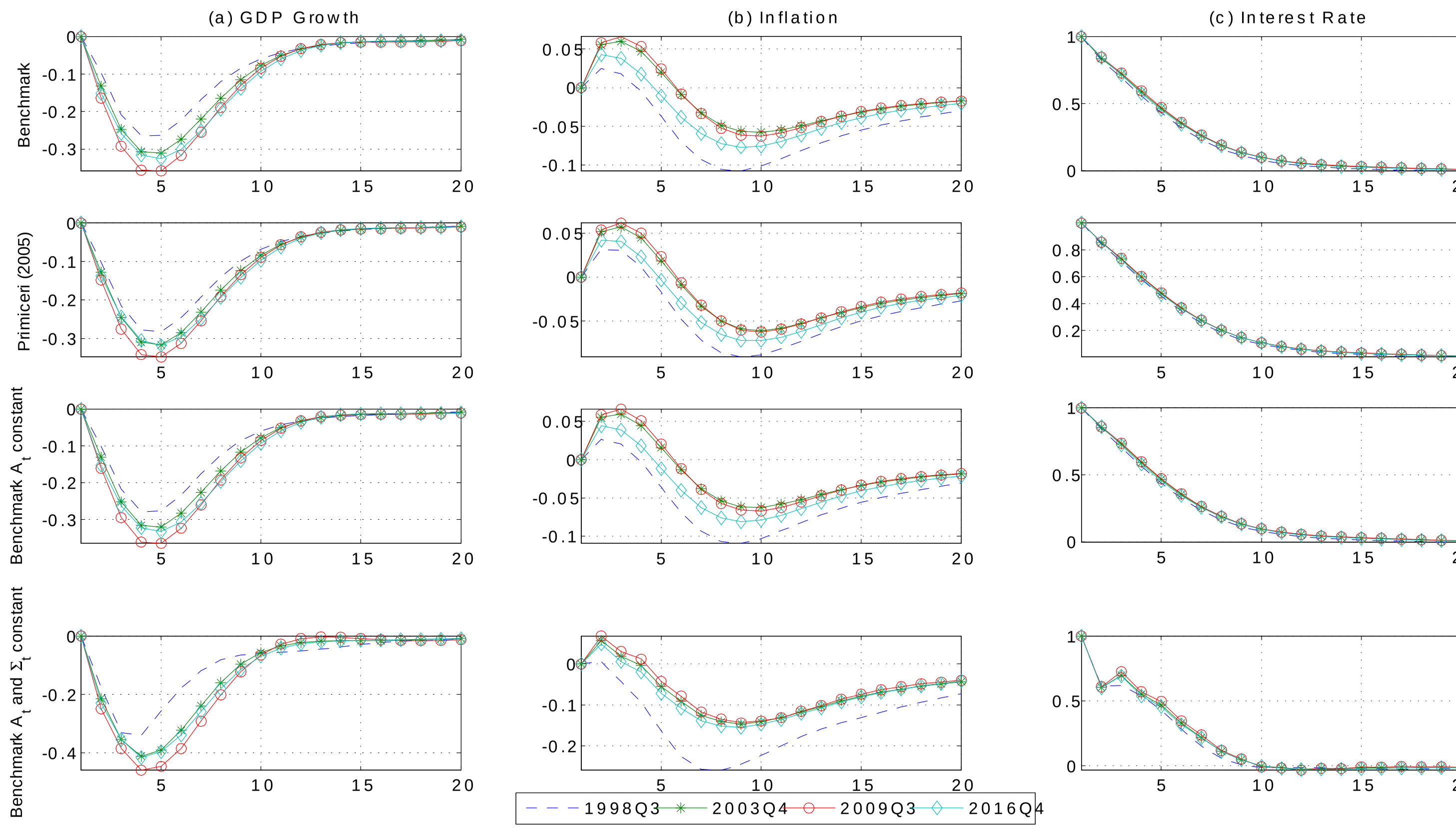

Figure 6. Impulse Reponse Functions to Monetary Policy Shock at Different Time Periods for Various Models

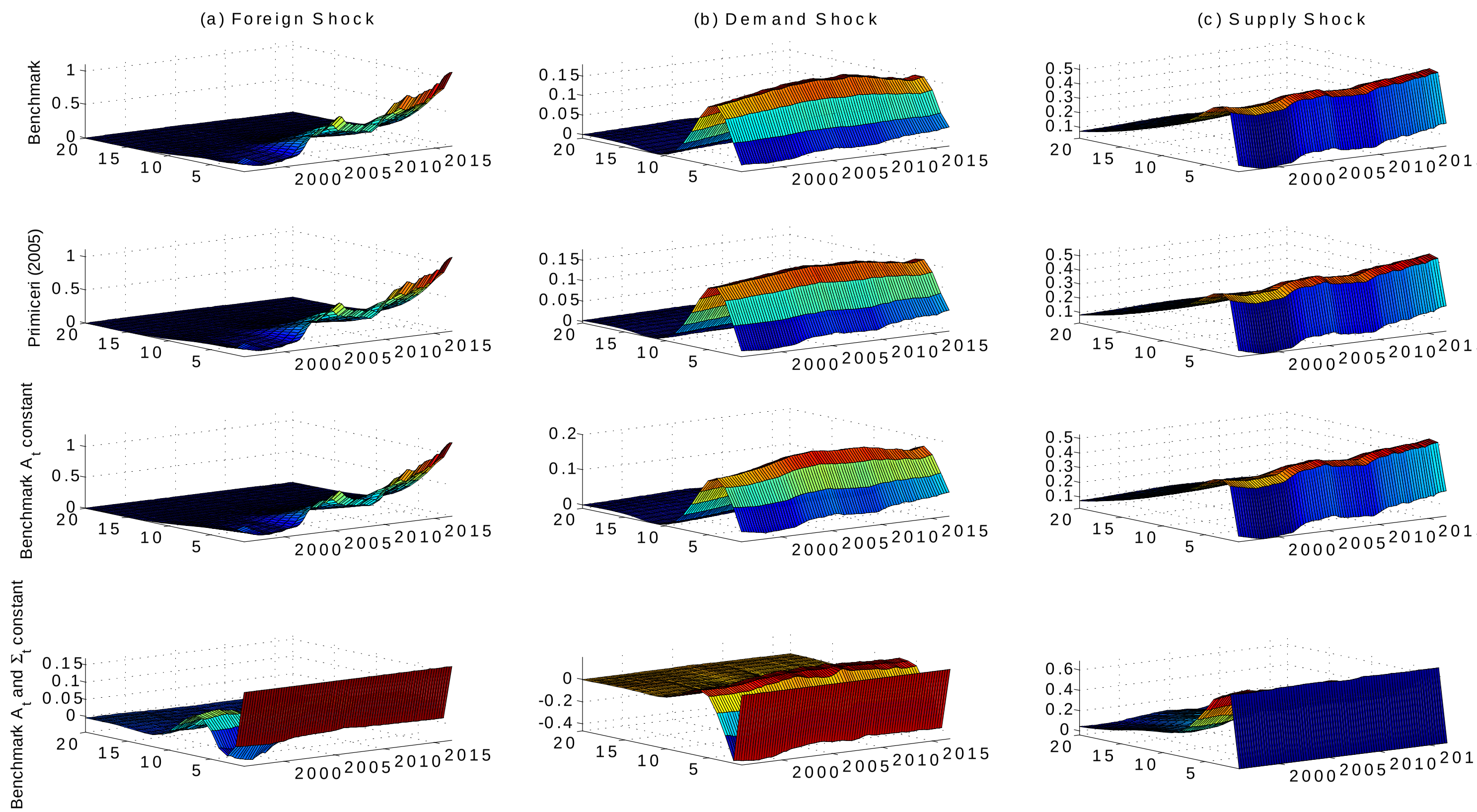

Figure 7. Median Time-Varying Impulse Response Functions of Interest Rate for Various Models

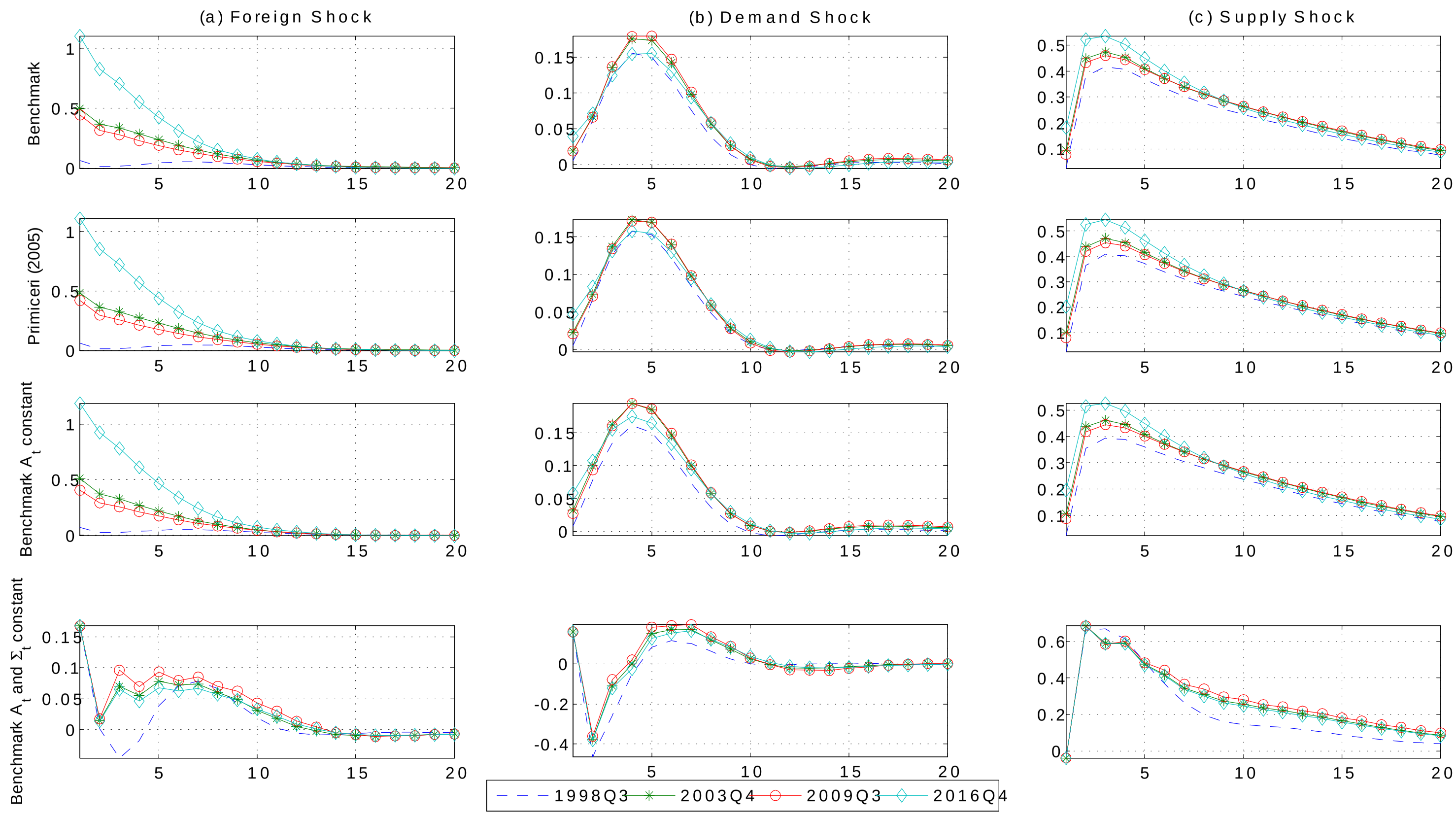

Figure 8. Impulse Reponse Functions of Interest Rate at Different Time Periods for Various Models

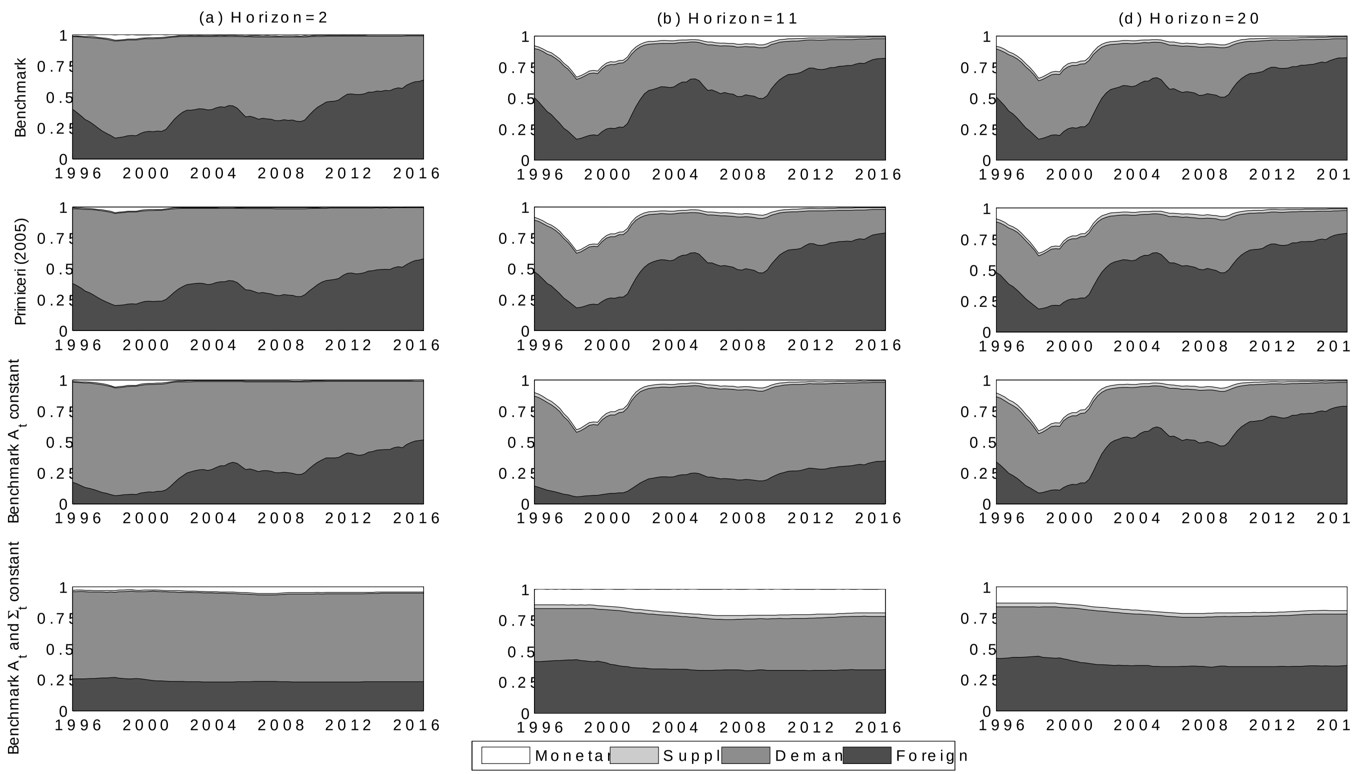

Figura 9. Time Evolution of the Forescating Error Variance Decomposition of GDP Growth for Various Models at Different Horizons

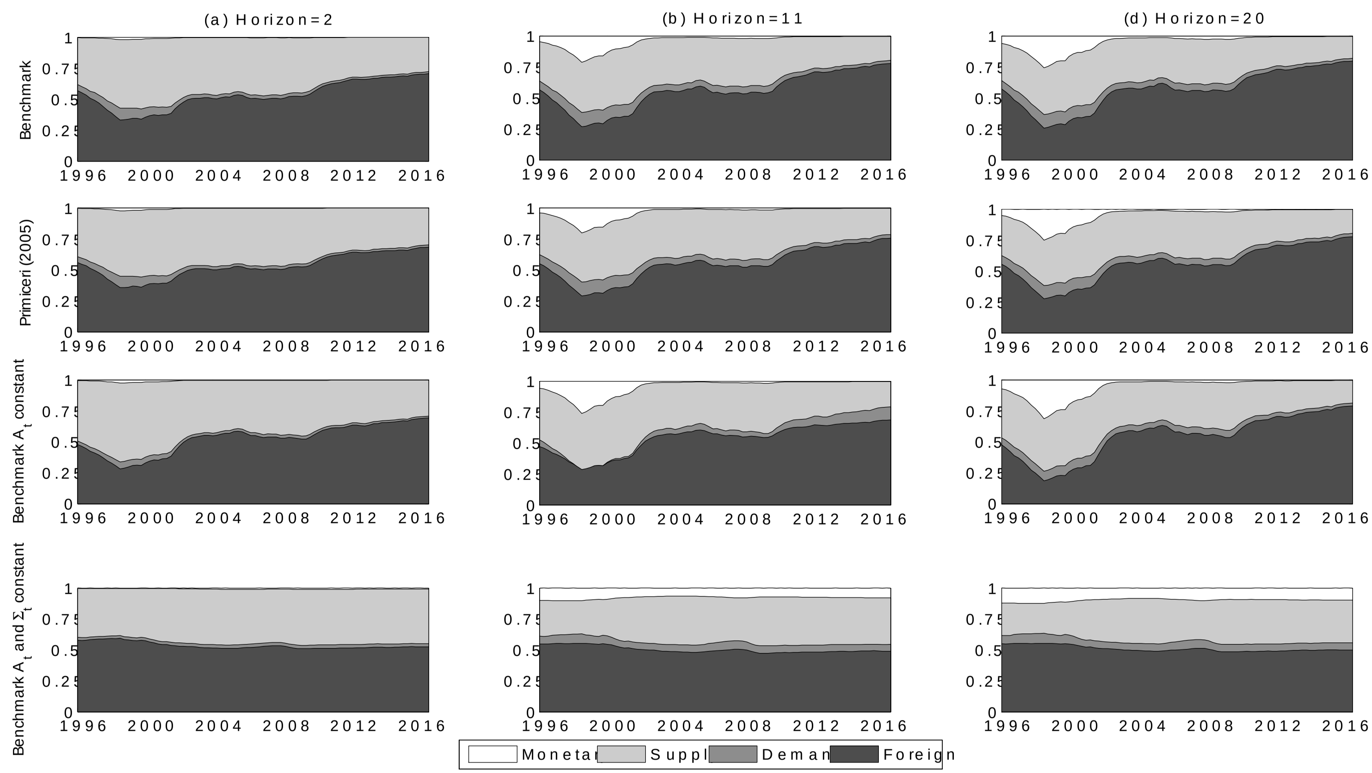

Figura 10. Time Evolution of the Forescating Error Variance Decomposition of Inflation for Various Models at Different Horizons

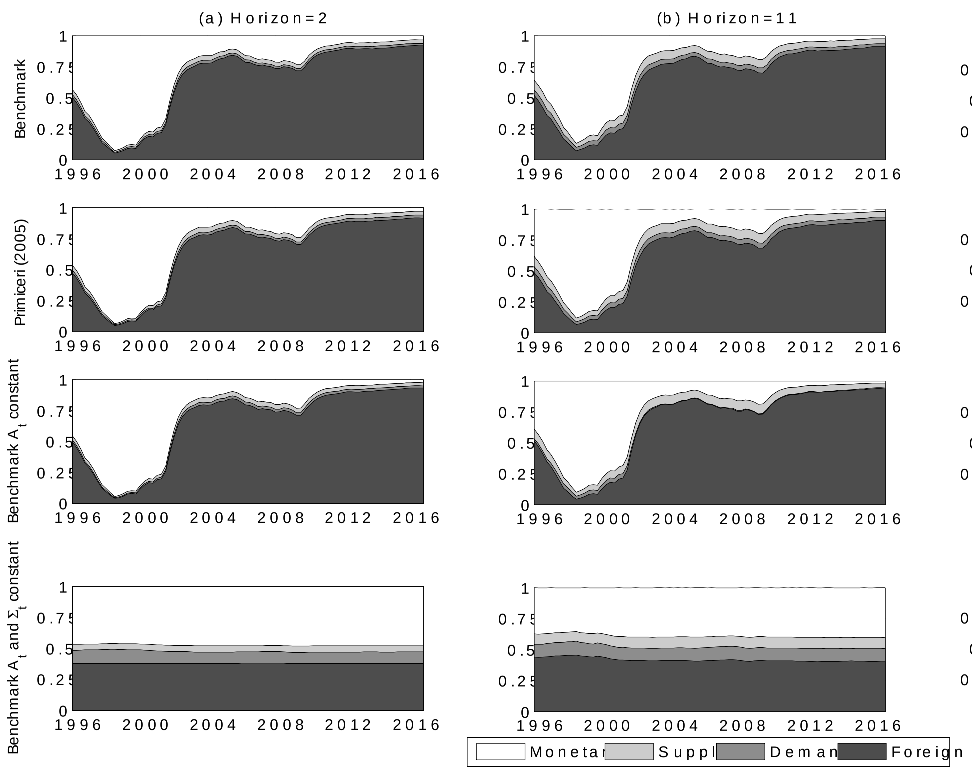

Figura 11. Time Evolution of the Forescating Error Variance Decomposition of Interest Rate for Various Models at Different Horizons

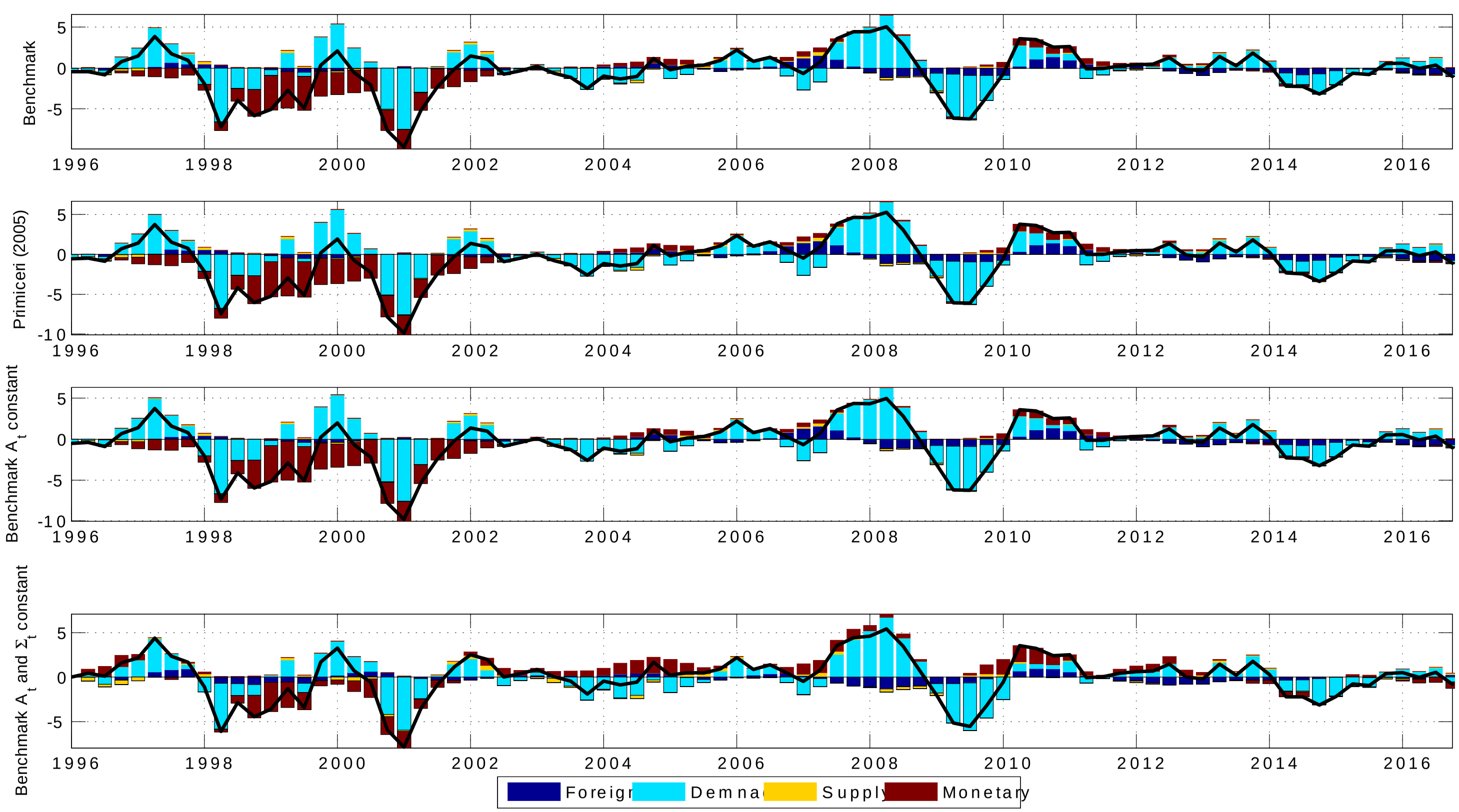

Figure 12. Historical Decomposition of GDP growth for Different Models

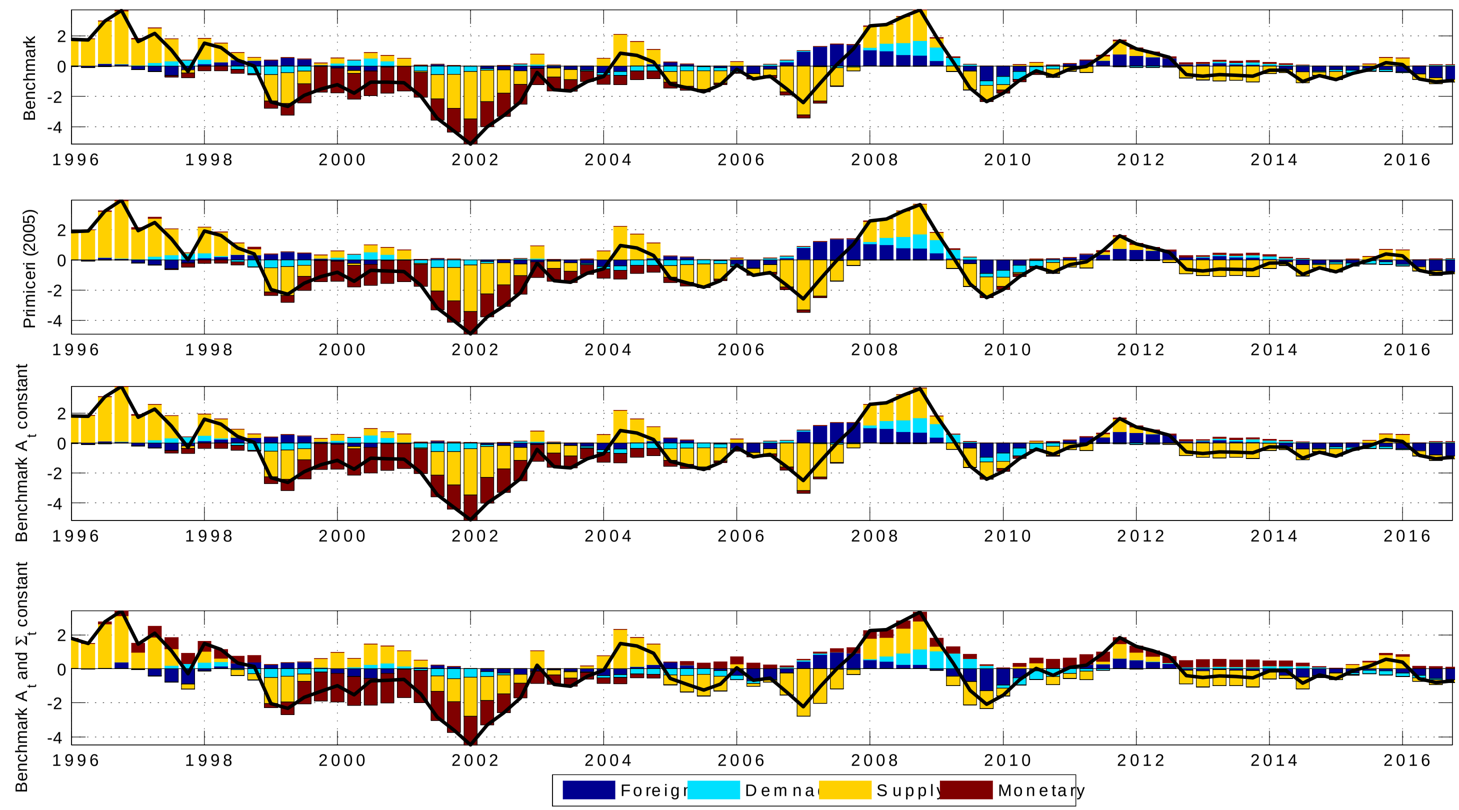

Figure 13. Historical Decomposition of Inflation for Different Models

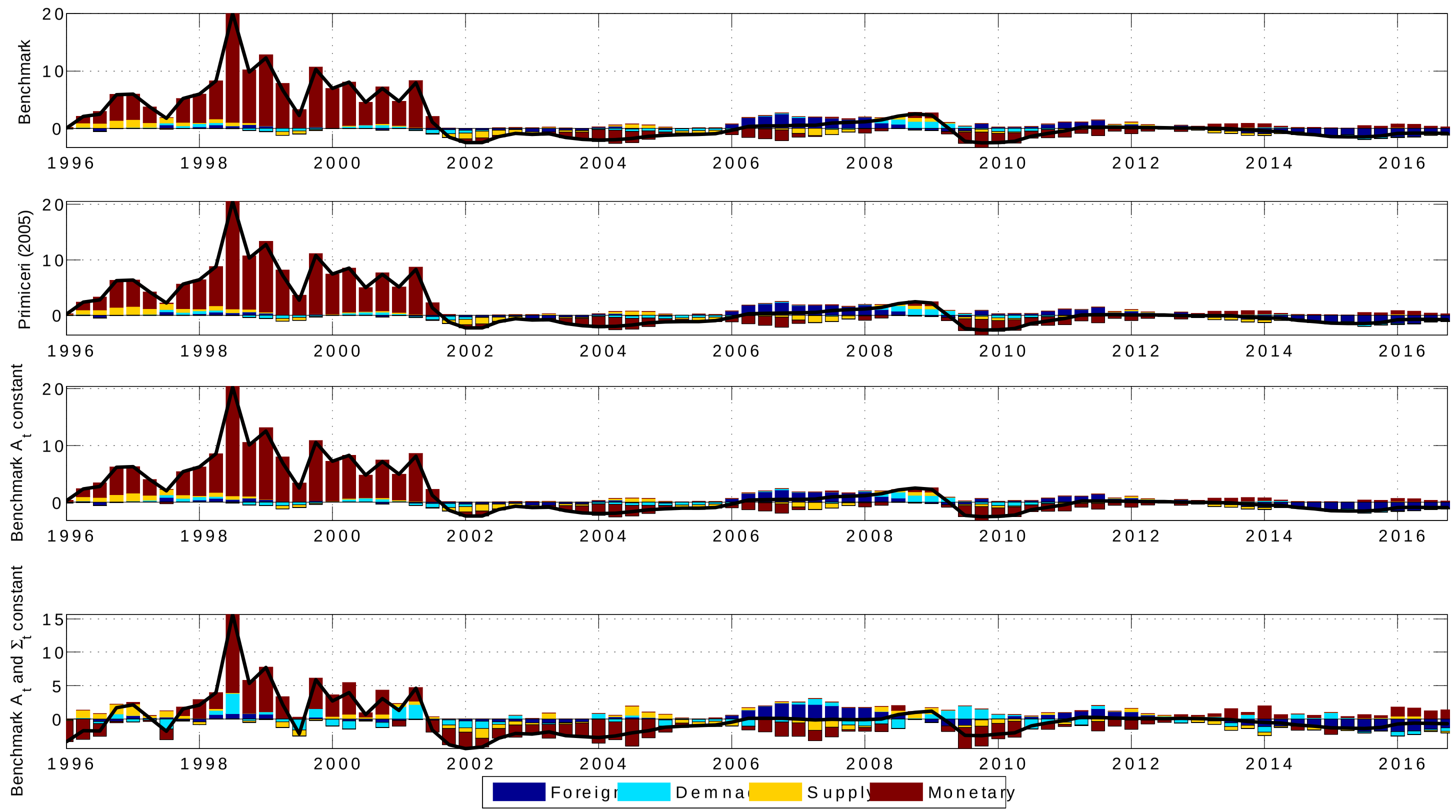

Figure 14. Historical Decomposition of Interest Rate for Different Models

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