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**Evolution of the Monetary Policy in Peru: An Empirical Application Using
a Mixture Innovation TVP-VAR-SV Model**

TESIS PARA OPTAR EL TÍTULO DE LICENCIADO EN ECONOMÍA

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Abstract

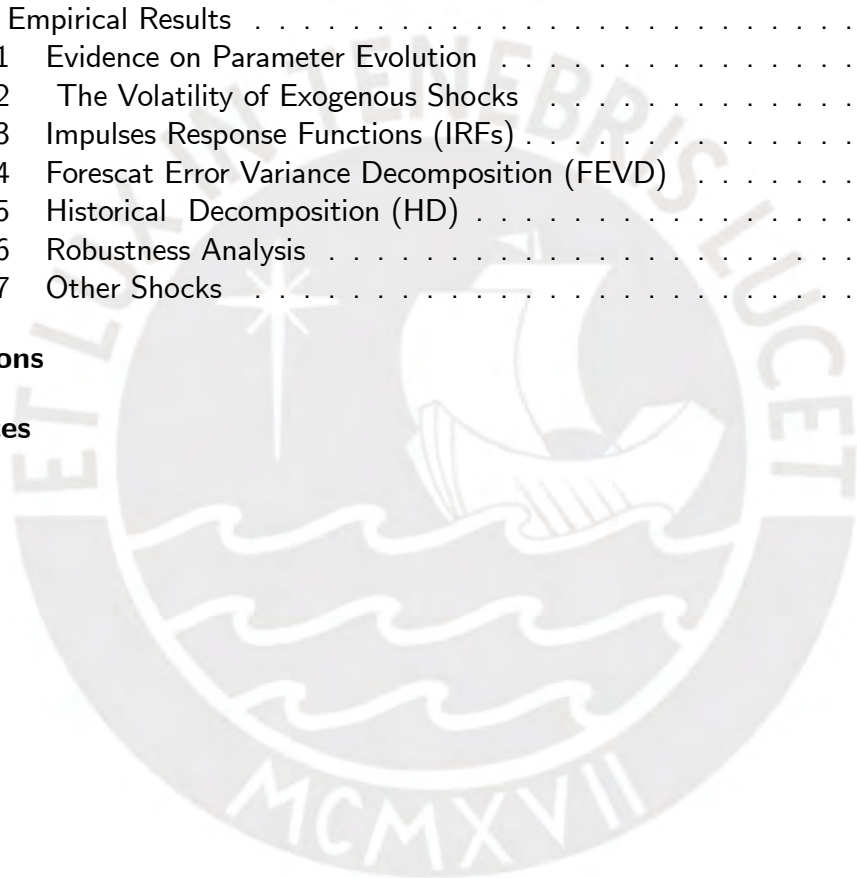
This paper investigates the evolution of the monetary policy in Peru between 1996Q1 and 2016Q4 using a mixture innovation time-varying parameter vector autoregressive model with stochastic volatility (TVP-VAR-SV) model proposed by Koop et al. (2009). The main empirical results are: (i) VAR coefficients and volatilities change more gradually than covariance errors over time; (ii) the volatility of monetary policy shocks is higher during 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 against aggregate supply shocks than aggregate demand shocks; (v) monetary policy shocks explain a high percentage of domestic variables during pre-IT regime and then, their contribution decrease during IT-regime.

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



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1 Introduction

Deep structural reforms in the economy have a major impact on how the economy responds to macroeconomic shocks and the volatility of exogenous shocks. It is highly possible that these changes in the structure of the economy will alter the effects of monetary policy on the aggregate economy, that is, the existence of changes in the transmission mechanisms of monetary policy over the years. These changes may be due to exogenous issues to monetary policy, such as the transition to a free market economy, or endogenous issues like as changes in monetary policy regime. All this suffered the Peruvian economy since the decade of the 90s.

The decade of the 90s has been characterized as a period of deep economic reforms in different areas that allowed a transition to a free market economy. For example, the elimination of price controls, capital controls and quantitative trade restrictions, unifying and allowing the floating of the exchange rate and liberalizing the financial market. The government allowed the participation of the private sector in different areas of the economy that were previously only reserved for the public sector. The strengthening of the institutional framework and autonomy of the Central Reserve Bank of Peru, henceforth BCRP, and the Superintendency of Banking, Insurance. Finally, from 2000 until now, the Peruvian economy enjoys a long macroeconomic stability and a sustainable economic growth; see Rossini and Santos (2015).

About the monetary policy regimes, after the episode of hyperinflation in the 1980s, monetary policy was re-structured to achieve low inflation in the 1990s, with the BCRP being the main actor. In the transition towards a single-digit inflation, the scheme implemented was the control of aggregates, taking as nominal anchor the monetary base (1995-2001). Subsequently, since 2002, the Inflation Targeting (IT) regime was adopted, setting an inflation target ranging from 1.5% to 3.5%. In addition, the current account of banks in the BCRP was used as an operating target until September 2003, where the interbank interest rate was adopted as the operational target. Subsequently, in 2007, the target inflation was lowered, now goes from 1% to 3%. On the other hand, due to the Peruvian context of financial dollarization, the BCRP also uses alternative instruments simultaneously such as the reserve ratio or interventions in the foreign exchange market, which allow it to fulfill its final objective while maintaining the interbank market in balance; see Castillo et al. (2011). All of the above have an impact on the transmission mechanisms of monetary policy and the volatility of monetary policy shocks. Hence, the transmission mechanism or the volatility could be different over time due to structural reforms of the Peruvian economy or changes in monetary policy regime.

This paper analyzes the evolution of the monetary policy in Peru between 1996Q1 and 2016Q4. We evaluate whether the response of GDP growth and inflation to monetary shocks have changed over time, if it has changed, when and how it has changed. In addition, we analyze the evolution of the monetary policy shocks. Also, we evaluate the responses of interest rate to foreign, demand and supply shocks over time. The importance of this research is due to the fact that the transmission mechanism and the volatility of monetary policy are related to the how monetary policy affects the real sector of the economy. This is an important issue because its study depends on the establishment of monetary policy objectives and the predictable effect of these objectives on the real sector of the economy. Hence, this paper provides a better understanding of Peruvian monetary policy that it is essential for its design and implementation. Moreover, it provides evidence on the possibility that monetary policy could play an important role in the good performance of the Peruvian economy since 1996. Finally, it contributes to the extant literature on the changes in the monetary transmission mechanism and the volatility of exogenous shocks by providing new stylised facts .

It is common to use VAR models to analyze the monetary policy, but it is better to use a flexible framework that it allows us to take into account both variation of the transmission mechanism and the variances of the exogenous shocks. Consequently, we need that the coefficients of the VAR and the error variance-covariance matrix can change over time. Thus, we use a mixture

innovation time-varying parameter with stochastic volatility (TVP-VAR-SV) model proposed by Koop et al. (2009). The advantage of the model is that it allows estimating whether, where, when and how parameters change is occurring.

We apply this approach to Peruvian data for the period 1996Q1-2016Q4. The variables used are terms of trade growth, real GDP growth, inflation and interest rate. About the parameter evolution, our results suggest that the three blocks of parameter (VAR coefficients, the volatilities and error covariances) change over period. About the volatility of exogenous shocks, we find two volatility peaks: 1998Q3 and 2009Q3 where the first peak is higher than the second one. These peaks of volatility are related to two international economic crises: the Asian-Russian crisis and the "Great Recession" in the world, respectively. These results suggest a great influence of the international economic context on the Peruvian economy. In addition, the volatility of monetary policy shocks is higher in the pre-IT regime than in IT regime.

Regarding impulse response functions (IRFs) to monetary policy shock, a surprise increase in the interest rate, the GDP growth tends to fall, having the greatest impact after one year on average. Moreover, a contractionary monetary policy reduces inflation in the long run, having the desired effect after two and a half years on average. Our results suggest that IRFs to monetary policy shocks do not vary much over time. About the IRFs of interest rate, foreign shocks (FSs) have a positive effect on interest rate with a higher reaction after the adoption of IT regime. On the other hand, the IRFs of interest rate to aggregate demand (AD) shocks have a positive hump-shaped response with the highest peak between fourth and fifth quarters. Finally, the IRFs of interest rate to aggregate supply (AS) shocks have a positive hump-shaped response with the highest peak in third quarter. We do not find any remarkable difference on IRFs to AD and AS shocks over time. In addition, our results suggest the interest rate reacts more quickly against AS shocks than AD shocks. This is consistent with the principal purpose of the BCRP which is preserving monetary stability.

Moreover, we find evidence that monetary policy shocks explain great percentage of the forecast error variance decomposition (FEVD) of the domestic variables (GDP growth, inflation and interest rate), especially interest rate, during pre-IT regime. However, during IT regime, the contribution of monetary shocks to domestic variables decreases over time. In the same line, the historical decomposition (HD) of domestic variables show that monetary policy shocks have a major contribution during pre-IT-regime than IT regime. Concerning methodological implications of our results, we find that a TVP-VAR with constant error variance-covariance matrix have a poor performance to capture the dynamic between variables in comparison to others models where variance errors can change. This result suggests that the volatility of errors should change over time.

The paper is organized as follow: Section 2 presents the literature review. Section 3 presents the mixture innovation TVP-VAR-SV model of Koop et al. (2009). Section 4 discusses the empirical results including robustness analysis. Finally, Section 5 concludes.

2 Literature Review

Understanding how the transmission mechanisms of macroeconomic variables behave is a one of the keys objectives for researchers. Sims (1980) introduces the VAR model as a tool for investigating the inter-relationships between several macroeconomic variables. Since this seminal contribution, VAR frameworks has become an important tool for investigating monetary policy transmission mechanism.

Sims (1992) estimates several VAR models for France, Germany, Japan, the U.K., and the U.S. and shows that the positive response of prices to monetary shocks tends to become smaller when commodity prices and exchange rates are included. Others VAR studies are Bernanke and Blinder (1992), Gordon and Leeper (1994) Christiano et al. (1996), Bernanke and Mihov

(1998), among others. Leeper et al. (1996) and Christiano et al. (1999) have reviewed what one has learned from this extensive literature regarding the monetary transmission mechanism in the U.S. Basically, these papers show that following a contractionary monetary policy shock, economic activity declines quickly in a hump-shaped manner; by contrast, the negative reaction with respect to price level is more delayed and persistent. Mojon and Peersman (2001) investigate the effects of monetary policy shocks in the individual countries of the Euro area 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 a gradual decrease in prices for all countries. On the other hand, Peersman and Smets (2001) study the monetary policy transmission mechanism for the Euro area as a whole and find that a temporary rise in the short-term interest rate leads a real appreciation of the exchange rate, a temporary fall in output and prices start to fall significantly several quarters after output decreases.

All the above models are based on the assumption of constant VAR coefficients and constant error variance-covariance matrix. However, it is better to use multivariate models where the transmission mechanism and the variance of the exogenous shocks can both change over time because the inter-relationships between the variables may change over time; see Koop et al. (2009). Taking into account the latest considerations, the time-varying components have been incorporated into the VAR analysis. Cogley and Sargent (2001) analyze inflation-unemployment dynamics in the U.S. from 1948Q1 to 2000Q4 using a Bayesian VAR with TVP, but with the assumption of the constant variance matrix and find that the mean and persistence of inflation are strongly positively correlated and the degree of persistence in inflation has been drifting downward as inflation has come under control. However, the assumption of the constant variances denies that the volatility of shocks hitting the economy evolves 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 persistence of inflation increases during the 1970s, then it falls in the next decades; and the innovation variances are larger in the late 1970s than during other times.

However, in the previous models, the simultaneous relation among variables are time-invariant. This is a disadvantage because can not distinguish between changes in the typical size of exogenous innovations and changes in the transmission mechanism. Therefore, Primiceri (2005) develops a TVP-VAR-SV model where the coefficients and the entire variance covariance-matrix of the shocks are allowed to vary over time¹. Primiceri (2005) uses this flexible framework to investigate the potential causes of the poor economic U.S. performance of the 1970's and early 1980's 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 the predictability of U.S inflation has fallen sharply over the post-1984 period which are due to the more aggressive behavior of the Fed against inflation. The authors document a strong negative correlation between the evolution of the long-run coefficient on inflation in the monetary rule and the evolution of the persistence and predictability of inflation relative to a trend component. Based on an estimated DSGE model, they find that a more aggressive policy stance towards 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 they allow

¹See also Del Negro and Primiceri (2015).

for more flexibility using a mixture innovation model which extends the class of TVP-VAR-SV models. The advantage of this extension is that it allows estimating whether, where, when and how parameters change is occurring. The model is used for investigating whether the monetary transmission mechanism of U.S. has changed or whether apparent changes are due to changes in the volatility of exogenous shocks. Moreover, the question of whether any changes have been gradual or abrupt is also considered. The authors find that the transmission mechanism, the volatility of exogenous shocks and the correlations between exogenous shocks are all changing gradually.

About evidence of other countries, Nakajima (2011) explores monetary policy transmission of Japan under zero interest rates by explicitly incorporating the zero lower bound (ZLB) of 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. Furthermore, the explicit consideration of the ZLB does not otherwise affect macroeconomic dynamics. Franta et al. (2013) use a TVP-VAR-SV model to investigate the evolution of the monetary policy transmission mechanism in the Czech Republic. The results suggest that prices have become increasingly responsive to monetary policy 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 the monetary transmission has changed over time since Malawi adopted financial reforms in the 1980's. The authors find that inflation and real output responses to monetary policy shocks changed over the period under study. Importantly, beginning mid-2000, the monetary transmission performed consistently with predictions of economic theory partly due to stable macroeconomic conditions and positive structural changes in the economy.

About literature of monetary policy for Peru, most of the papers estimate a standard VAR model and its extensions with recursive or non-recursive identifying assumptions. Quispe (2000) analyzes the monetary policy of Peru between 1980 and 1998 using three VAR models where the main conclusion is that shocks to the money base explain most of the variance in inflation. Furthermore, since 1994, the money-base control has been successful in keeping the inflation around its target range. Quispe (2001) investigates different topics of the monetary policy for Peru. First, the author documents that the inflation process in Peru is mostly driven by AD shocks, with monetary shocks accounting for 30-40% of inflation rate variance. Second, tries to identify the best indicator of the monetary policy and finds that different studies for Peru on this topic have shown that money aggregates are the best indicators of the monetary policy. Third, the author designs a model to describe the operating procedures of the BCRP, principally its interactions 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 monetary policy shock on inflation rate is between eight and sixteen months. Finally, he 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 between 1995M1 and 2009M12. The authors find that in the face of a contractionary monetary policy shock, interest rate rise, monetary aggregates contract, local currency appreciates, aggregate demand slows and inflation finally falls. Also, the exchange rate shocks turn out to be an important determinant of the money market and their results show that the BCRP responds more strongly to demand shocks for money than to exchange rate shocks during the period following the adoption of IT regimen.

Other studies related to Peruvian monetary policy are Winkelreid (2004), Bigio and Salas (2006), Rossini and Vega (2007), Lahura (2010) and Pérez (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 policy position and the real exchange rate generate nonlinear effects on output and inflation and find evidence of nonlinearities in the face of monetary policy shocks, which would 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 Quarterly Projection Model of the BCRP and document that the direct channel of the interest rate and the channel of expectations have become more important in recent years, especially since the adoption of the IT regime. Lahura (2010) uses a Factor-Augmented VAR benchmark to analyze the effects of monetary policy shocks. Pérez (2015) estimates a Hierarchical Panel VAR to assess and compare the effects of monetary policy shocks across Latin American countries that put in practice the IT regime (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 (2015) finds some degree of heterogeneity on the impact and propagation of monetary shocks across countries.

Finally, Castillo et al. (2016) estimate a TVP-VAR-SV model to analyze the underlying causes of Peruvian “Great Moderation”. In other words, the authors analyze the determinants of the reduction in the volatility of GDP growth and inflation over the sample 1981Q1 to 2014Q3. They find that the monetary policy has contributed significantly to the “Great Moderation” of Peru by reducing the volatility of its non-systematic component and changing its reaction function to aggregate demand and aggregate supply shocks. Moreover, the aggregate supply and monetary policy shocks have been the most important determinants of macroeconomic instability during the period of high volatility.

From the perspective of the empirical application, our paper contributes to the extant literature on the changes in the monetary policy transmission mechanism and the volatility of exogenous shocks by providing new stylized facts. Moreover, a new methodological framework, a TVP-VAR-SV model proposed by Koop et al. (2009), is used to understand the evolution of Peruvian monetary policy transmission mechanism.

3 Methodology

The econometric model is a mixture innovation TVP-VAR-SV model 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 which relates to the error variances and another relating to error covariances) can evolve in completely different ways.

Literature has two extreme forms of modeling the change of parameters: models with very few (but usually large) breaks or those with many (usually small) breaks. For the estimation of the number of breaks, Koop et al. (2009) nest the two extreme cases and can estimate if there are few (or no) changes in the parameters or whether the change is constant and gradual. The authors draw on the mixture innovation approach of Gerlach et al. (2000) and Giordani and Kohn (2008) as a way of keeping the model more tightly parameterized in key dimensions. The advantage of the model is that we can estimate if, where, when and how the parameter change is occurring, as opposed to assuming a particular model of a parameter change like as Primiceri (2005). In the following, we briefly describe the methodology of mixture innovation TVP-VAR-SV model proposed by Koop et al. (2009).

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

$$y_t = X_t B_t + u_t, \quad t = 1, 2, \dots, T \quad (1)$$

$$B_{t+1} = B_t + v_t, \quad t = 1, 2, \dots, T \quad (2)$$

where y_t is a $n \times 1$ vector of observations on the dependent variables, B_t is a $m \times 1$ vector of states (the VAR coefficients), X_t is a $n \times m$ matrix of data on explanatory variables (each row

of X_t contains lags of all dependent variables, an intercept and other deterministic variables), u_t are independent $N(0, H_t)$ random vectors and, finally, 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) varies over time because many important aspects of the transmission mechanism are related to 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:

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

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

About the mixture innovation, the model allows some or all of the states and parameters to be determined by a sequence of Markov random vectors $K = (K_1, \dots, K_T)'$ which control the structural breaks in the model. The model allows for breaks in the VAR coefficients (B_t) and the error variance-covariance matrix H_t (Σ_t and A_t) and these breaks may occur at different times, that is, $K_t = (K_{1t}, K_{2t}, K_{3t})'$ 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:

$$B_{t+1} = B_t + K_{1t} v_t, \quad (3)$$

$$h_{t+1} = h_t + K_{2t} \eta_t, \quad (4)$$

$$\alpha_{t+1} = \alpha_t + K_{3t} \zeta_t, \quad (5)$$

where a Bernoulli distribution is used for 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 .

3.1 Posterior Computation

All posteriors described below are the full conditionals required to set up a valid 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: $Q^{-1}|Data \sim W(\bar{v}_Q, \bar{Q}^{-1})$ where $\bar{v}_Q = \sum_{t=1}^T K_{1t} + \underline{v}_Q$ and $\bar{Q}^{-1} = (\underline{Q} + \sum_{t=1}^T (B_{t+1} - B_t)(B_{t+1} - B_t)')^{-1}$.

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:

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

where ϵ_t are independent $N(0, I_t)$. This is a system of nonlinear measurement equations but can be converted in a linear one by squaring and taking logarithms of every element of (6) $y_{i,t}^{**} = \log [(y_{i,t}^*)^2 + \bar{c}]$ where \bar{c} is an offset constant 0.001 that is used to ensure non zero values. This leads to the following approximating state space form:

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

where $e_t = \ln(\epsilon_t^2)$. Note that the e_t and the η_t are not correlated and e_t is not Normally distributed. Moreover, $e_t = (e_{1t}, \dots, e_{nt})'$ are independent because $y_{i,t}^*$ and $y_{j,t}^*$ are independent for $i \neq j$. Despite it, Kim et al. (1998) show how its distribution can be approximated to an extremely high degree of accuracy by a mixture of seven Normals. If $C_{jt} \in \{1, 2, 3, \dots, 7\}$ denotes which of the seven Normals e_{jt} is drawn from, we can construct $C_j = (C_{j1}, \dots, C_{jT})'$ and $C = (C_1, \dots, C_p)'$ as component indicators for all elements of e_t . With the approach of Kim et al. (1998), we have a Normal linear state space model (conditioned on C and other parameters) and the algorithm of Carter and Kohn (1994) 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 $i = 1, \dots, 7$ 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 $j = 1, \dots, 7$, $i = 1, \dots, p$, and $t = 1, \dots, T$. Finally, a Wishart prior is used for W^{-1} to complete the description of the MCMC algorithm relating to 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: $W^{-1}|Data \sim W(\bar{v}_w, \bar{W}^{-1})$ where $\bar{v}_w = \sum_{t=1}^T K_{2t} + \underline{v}_w$ and $\bar{W}^{-1} = (\underline{W} + \sum_{t=1}^T (h_{t+1} - h_t)(h_{t+1} - h_t)')^{-1}$.

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

$$\hat{y}_t = Z_t a_t + \xi_t, \quad (8)$$

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

Finally, regarding hierarchical prior of K_{jt} which depends on the parameters p_j , 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:

$$p_j \sim B(\bar{\beta}_{1j}, \bar{\beta}_{2j}) \text{ where } \bar{\beta}_{1j} = \underline{\beta}_{1j} + \sum_{t=1}^T K_{jt} \text{ and } \bar{\beta}_{2j} = \underline{\beta}_{2j} + T - \sum_{t=1}^T K_{jt}.$$

About drawing K_t , Gerlach et al. (2000) develop an algorithm which integrates out 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 $Data$. For 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 set out 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, 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, they 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 model parameters including K_{2t} and $K_{3,t}$).

3.2 Values for the Priors

We use a training sample of the first 15 quarters of data (from 1992Q2-1995Q4) to choose the priors hyperparameters. With our training sample, we estimate a standard (time-invariant) VAR to obtain the coefficients VAR, \hat{B}_{OLS} , and the error variance covariance matrix can be decomposed to produce \hat{A}_{OLS} and $\hat{\sigma}_0$. We also obtain the variance-covariance matrices of \hat{B}_{OLS} and \hat{A}_{OLS} which are labeled $V(\hat{B}_{OLS})$ and $V(\hat{A}_{OLS})$, respectively. Using these above values, we set the following priors for the initial conditions in each of state equation: $B_0 \sim N(\hat{B}_{OLS}, 4V(\hat{B}_{OLS}))$, $A_0 \sim N(\hat{A}_{OLS}, 4V(\hat{A}_{OLS}))$ and $\log(\hat{\sigma}_0) \sim N(\log(\hat{\sigma}_0), 4I_n)$. Next, we set the priors for the error variances in the state equation, allowing these priors depend on the prior about the number of breaks which occur. It is important to remember that the Beta prior that we use 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, we set these following prior for the error variances in the state equation: $\underline{v}_Q = 37, \underline{Q} = (k_Q)^2 V(\hat{B}_{OLS})(1/E(p_1)), \underline{v}_w = 5, \underline{W} = 4(k_W)^2 (I_3)(1/E(p_2)), \underline{v}_{S_j} = j + 1$ and $\underline{S}_j = (j + 1)(k_s)^2 V(\hat{A}_{m,OLS})(1/E(p_3))$ for $j = 1, 2, 3$. Notice that k_Q, k_W and k_s are prior values about the amount of time variation and we set $k_Q = 0.01, k_W = 0.01$ and $k_s = 0.1$ as in Primiceri (2005).

3.3 Evaluating the Performance of the Models

Following Carlin and Louis (2000), we use the expected value of the log-likelihood function like as a conventional information criteria (eg. Schwarz criteria). The advantage of this approach is that the expected value of the log-likelihood function will be less sensitive to 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 calculate $p(\mathbf{Y}|K_t, \boldsymbol{\lambda})$. Therefore, we 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.

4 Empirical Evidence

In this section, we present the data used in the estimation. Then, we discuss our empirical results that 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.

4.1 The Data

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

4.2 The Empirical Results

The simulations are based on 70000 iterations of the Gibbs Sampler, discarding the first 20000 for convergence. We employ the following order of the variables in the vector y_t : terms of trade growth, real GDP growth, inflation and interest rate. Furthermore, we use two lags for the estimation. About identifying assumption, we can rewrite equation (1) as $y_t = X_t B_t + \Upsilon_t \epsilon_t$, where $\Upsilon_t = A_t^{-1} \sum_t$ and 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. It implies that the monetary shock has no immediate effect on the other variables. This standard assumption is used by many researchers like as Primiceri (2005), Koop et al. (2009) among others. Each structural shock is identified as follows: for Terms of Trade equation, foreign shock (FS); for GDP growth equation, aggregate demand (AD) shock; for inflation equation, aggregate supply (AS) shock; and for interest rate equation, MP shock.

4.2.1 Evidence on Parameter Evolution

We present some evidence on whether breaks have occurred in our three blocks of parameters: VAR coefficients (B_t), the volatilities (Σ_t) and the error covariances (A_t); and, if so, of what sort. It is necessary to analyze the variables which 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 of Koop et al. (2009) is that it allows obtaining different models of interest from imposing values to K_1 , K_2 and K_3 . We consider different restricted versions of the Benchmark (mixture innovation TVP-VAR-SV) that have been employed in the literature to answer the question of which type of model receives support from the data. The models that we consider are listed in Table 1. We consider the model of Primiceri (2005) which can be obtained assuming $K_{1t} = K_{2t} = K_{3t} = 1$ (in other words, this model assumes that the three blocks of parameters always change). We also consider a model which restricts error covariances to be constant over time (Benchmark A_t constant), assuming $K_{3t} = 0$, similar to Cogley and Sargent (2005). Then we consider a model which restricts the volatilities and error covariances to be constant over time (Benchmark A_t and Σ_t constant), assuming $K_{2t} = K_{3t} = 0$, similar to Cogley and Sargent (2001). We also consider a model which restricts to be VAR coefficients constant over time (Benchmark B_t constant), assuming $K_{1t} = 0$, motivated by Sims and Zha (2006) who have found 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 $K_{1t} = K_{2t} = K_{3t} = 0$.

For the Benchmark, we use Beta priors for p_j , therefore, $B(\beta_{1j} = 1, \beta_{2j} = 1)$ for $j = 1, 2, 3$. Based on the properties of Beta distribution, we have $E(p_j) = 0.5$ with 0.29 of standard deviation. This Benchmark prior means that, a priori, there is a 50% probability that a break occurs in any period for the three blocks of parameters. Moreover, the standard deviation is very large indicating a relatively noninformative prior. This Benchmark prior is used for the others restrictive models depending on which parameter block changes.

The empirical results about the evidence of breaks in our three blocks of parameters and which type of model receives support from the data are summarized in Table 2. We present the expected value of the log-likelihood function, $E(\log L)$, to evaluate the performance of the models listed in Table 1. In the Benchmark, 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 there is a high probability that VAR coefficients and the volatilities change in any time period and this change is gradual. On the other hand, the expected transition probability $E(p_3|Data)$ related to A_t is 50%. This result indicates we would expect a break to occur about twice per year. These results are evidence against the abrupt breaks of conventional structural break models (eg, Pesaran et al., 2007). In conclusion, we obtain a more parsimonious model with the Benchmark model, compared with its restricted versions. The same results are maintained for the restricted models depending on which parameter block changes.

About the performance of the models, the Benchmark model does the best performance because has a higher expected log-likelihood than its restricted versions. Among the restricted versions, Primiceri (2005)'s model and the Benchmark A_t constant model do the best. The Benchmark A_t and Σ_t constant model and the Benchmark B_t constant model receive little support. Finally, the constant and invariant VAR model does the worst performance. Therefore, as a first conclusion, we find evidence that parameter evolution is an important issue to be considered.

We conclude that all three blocks of parameters change over time. These changes are more gradual for B_t and Σ_t than for A_t . We also find strong evidence in favor of the Benchmark model. Nevertheless, these arguments are purely statistical. In the following sections, we analyze what kind of implications the parameter evolution has in the monetary policy.

4.2.2 The Volatility of Exogenous Shocks

The non-systematic monetary policy capture both “policy mistakes” and interest rate movements that are responses other than inflation and GDP 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 from 1996 to 2001, the exogenous shock of interest rate equation cannot be directly interpret as monetary policy shock because, during this period, the policy instrument was monetary base growth. Nevertheless, interest rate can be used as proxy of policy instrument². On the other hand, from 2002 to 2016, the interest rate is the policy instrument since the adoption of IT regime.

Figure 2 presents the posterior mean, 16th and 84th percentiles of the time-varying standard deviation in the four different shocks for the Benchmark model. This Figure present different interesting features. First, there is a huge peak of volatility in 1998Q3 related to the Asian-Russian crisis in the four exogenous shocks. In addition, there is also a little peak, compared to the first peak mentioned, in 2009Q3 related to the “Great Recession” in the four exogenous

²Winkelried (2004), Bigio and Salas (2006) and Castillo et al. (2011) also use the interest rate as proxy of policy instrument although their samples covers pre-IT regime.

shocks. These two international economic crises mentioned are associated with a strong global contraction of the metals prices that the Peruvian economy exports and a strong fall in the credit provided by the local Peruvian banking system in foreign currency to companies and families. This adversely affects aggregate demand and price stability; see Dancourt (2015). These results suggest a great influence of the international economic context on the Peruvian economy. About the difference between both peaks mentioned above could be explained by the preventive policy measures taken before and policy actions during each crisis; see Dancourt (2015), Velarde (2015) and Rossini (2016). On the other hand, since 1998Q3, the volatilities of the four exogenous shocks have a downward trend, indicating a period of low volatility in Peruvian economy, due to a good decisions taken by policy-makers after the Asian-Russian crisis, such as the adoption of IT regime in the case of monetary policy; see Velarde (2015) and Rossini (2016).

Regarding monetary policy, we can observe in Figure 2(d) that the volatility of MP shocks are on average higher in the pre-IT regime (1996Q1-2001Q4) than in the IT regime (2002Q1-2016Q4)³. Therefore, the adoption of the IT regime could have played a key role in the reduction of the MP shocks volatility. In addition, 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 variation of the interest rate during Asian-Russian crisis is due to monetary policy of BCRP. Likewise, Castillo et al. (2009) document that the volatilities of inflation, GDP and interest rate are higher during 1994-2001 period than 2002-2005 period. The authors also conclude that use of interest rate as policy instrument induces a reduction on the macroeconomic risk. Finally, Castillo et al. (2016) document a significant decline in the volatility of AS, AD and MP shocks since the early 1990s. However, their results are not totally comparable with our results because their monetary policy variable is monetary base growth and their sample is different (1981Q1-2014Q3).

About the comparison between volatility magnitudes of the exogenous shocks, Figure 3 presents the posterior mean of the time-varying standard deviation of the four exogenous shocks for the Benchmark model. The volatility of FS is the largest during the entire sample because the Peruvian economy is small, open and mining export economy and the terms of trade are influenced by the prices of mining commodities. About the other exogenous shocks, the volatility of the MP shocks is greater than the volatility of AD shocks until 2002. Since 2002Q1, the volatility of the MP shocks ceases to be an important source of macroeconomic volatility for the Peruvian economy, compared with volatility of AD shock. Another interesting feature is that the volatility of AS shock is the lowest shock over the entire sample.

Furthermore, we present the volatility of exogenous shocks for the models where the volatility (Σ_t) changes: Benchmark, Primiceri (2005), Benchmark A_t constant, and Benchmark B_t constant. Figure 4 presents the posterior mean of the time-varying standard deviation in the four exogenous shocks for the four different models mentioned above. All these models capture the same broad patterns of volatility for all exogenous shocks. In Figure 4(a), the Benchmark with A_t constant and Benchmark with B_t constant models present a much smoother pattern of volatility for the terms of trade growth equation. For the other three equations (see Figures 4(b), 4(c) and 4(d)), there are not noticeable differences between models.

In conclusion, our results suggest that volatility of MP shocks is on average higher in the pre-IT regime than in the IT regime. We also find the MP shocks are not longer an important source of macroeconomic volatility in the Peruvian economy since the adoption of IT regime. Finally, the Benchmark model and its restricted versions capture the same broad patterns of volatility for all exogenous shocks.

³The AD and AS shocks present the same feature; see Figure 2(b) and Figure 2(c).

4.2.3 Impulses Response Functions (IRFs)

Given our interest in the monetary policy, we analyze the IRFs to MP shocks and the IRFs of interest rate. The IRFs are normalized to unity at all t because we want to describe the changes in the propagation of the shocks. Furthermore, we present the results for four models that are listed in Table 1: Benchmark, Primiceri (2005), Benchmark A_t constant, and Benchmark A_t and Σ_t constant⁴.

Figure 5 presents the posterior medians of the IRFs of GDP growth, inflation and interest rate to a MP shock for models mentioned above. In theory, a surprise increase in the interest rate should make output growth and inflation fall. This pattern is present over all sample for each model. Therefore, we conclude that the effect of MP shock is robust to the model specification.

Then, we analyze the IRFs of GDP growth, inflation and interest rate to MP shock for each model at four representative time periods: 1998Q3, 2003Q4, 2009Q3 and 2016Q4. We select 1998Q3 and 2009Q3 because they are the time periods of the peaks of volatility in the sample. We also select 2003Q3 because it is a time period after the adoption the IT regime and before the "Great Recession". Finally, we select 2016Q4 because it is a time period after the "Great Recession". Figure 6 presents the posterior medians of the IRFs of GDP growth, inflation and interest rate to a MP shock of each model at different time periods mentioned above.

Concerning the effect of MP shock on GDP growth, our results suggest that the MP shock have the major effect on GDP growth between fourth and fifth quarter. In addition, all models have 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 MP shock in all selected periods, indicating a bad performance. Regarding the effect of MP shock on inflation, our results indicate that the MP shock affects inflation in long term, with a strong effect between eighth and tenth quarter. In addition, the IRFs of inflation also exhibit a small price puzzle which is more noticeable in periods of IT regime. About the differences between models, again the Benchmark A_t and Σ_t constant model overestimates the effect of MP shock, indicating again bad performance while the remain models have almost the same pattern in each period. Finally, concerning the effect of MP shock on interest rate, only the Benchmark A_t and Σ_t constant model presents a quite different pattern compared to the others models.

Furthermore, we analyze the responses of the interest rate to FS, AD and AS shocks. Figure 7 presents the posterior medians of the IRFs of interest rate to a FS, AD and AS shocks for models mentioned above. Our results suggests a bad performance of the Benchmark A_t and Σ_t constant model because this model does not present the same pattern of the other models' IRFs. Therefore, it is very important that the volatility of errors should change over time in order to estimate the IRFs.

About the IRFs to a FS shock, our results suggest that the interest rate increases after it and its effect had increased over time. Regarding the IRFs to AD shock, we find that the IRFs have a positive hump-shaped response and the interest rate reacts gradually to AD shock with the higher effect after one year. Finally, the IRFs to AS shock present a quickly positive response of interest rate with a higher effect after 2 quarters. Therefore, the responses to AS shock are more immediate and stronger than the responses to AD shock. This conclusion is consistent with the principal purpose of the BCRP which is preserving monetary stability and inflation within its range.

Figure 8 presents the posterior medians of the IRFs of interest rate to FS, AD and AS shock

⁴We only consider these models because the IRFs to MP shocks change over time. Concerning the other models, in the case of Benchmark B_t constant model, the IRFs to MP do not change because VAR coefficients are constant, a recursive identification is employed and interest rate is treated as the most endogenous variable. Therefore, the IRFs to MP shocks of the Benchmark B_t constant model are the same over period. Likewise, the case of the constant VAR model is obvious.

of each model at selected periods. The IRFs of interest rate to FS present more interesting features. The response of interest rate at 2016Q4 is stronger than the other time periods. We confirm that the response of interest rate is growing over time and the BCRP reacts more aggressively to FSs over time. Regarding the IRFs of interest rate to AD shock, the IRFs of the different time periods do not vary much. Finally, about the IRFs of interest rate to AS shock, there are any remarkable differences. Therefore, we conclude that the responses of BCRP to AD and AS shocks are consistent over time.

Summarizing, the responses to MP shocks have not considerably changed over time due to we do not find any remarkable difference between selected periods. In addition, these responses are robust to model specification. Moreover, the patterns of the responses to MP shocks are consistent with Winkelried (2004), Bigio and Salas (2006), Lahura (2010), Castillo et al. (2011) and Perez (2015). On the other hand, the response of the interest rate to FS increased over time and the responses to AD and AS shocks do not change significantly over time. In addition, the responses of the interest rate to AS shock are more immediate and stronger than the responses to AD shock.

4.2.4 Forecast Error Variance Decomposition (FEVD)

Other important issue of monetary policy is the forecast error variance decomposition (FEVD) of variables due to MP. We present the FEVD of domestic variables in the short term (second horizon), medium term (eleventh horizon) and long term (twentieth horizon)⁵. Figure 9 presents the time evolution of the FEVD of GDP growth for various model at different horizons. For the Benchmark model, MP shocks explain less than 4.5% in the short term over time. On the other hand, in the medium and long terms, MP shocks present a greater contribution and variation. During the pre-IT regime, in the long term, MP shocks' contribution is 8.1% in 1996Q1, then, their contribution increases to their highest value of 33.8% in 1998Q3, then the trend changes and their contribution decreases to 12.3% in 2001Q4. Finally, during IT regime, MP shocks' contribution continues to decrease to 0.7% until the end of the sample. Therefore, monetary policy shocks are more important to explain the FEVD of GDP growth during pre-IT regime than IT-regime.

Figure 10 presents the time evolution of the FEVD of inflation for various models at different horizons. For the Benchmark model, MP shocks explain less than 2.04% in the short run. However, in the long term, the FEVD of inflation due to MP shocks is 5.8% in 1996Q1, then increases to its highest value of 25.5% in 1998Q3 and finally decrease to 6.3% in 2001Q4 during pre-IT regime. On the other hand, during the IT-regime, the MP shocks explain 4.3% in 2002Q1 and their contribution decreases to 0.3% in 2016Q4. Therefore, MP shocks become less important in IT-regime to explain the FEVD of inflation.

Finally, Figure 11 presents the time evolution of the FEVD of interest rate for various models at different horizons. For the Benchmark model, in the short run, the FEVD of interest rate due to MP shocks is 43.2% in 1996Q1, then increases to 92.7% in 1998Q3 and finally decrease to 52.2% in 2001Q4 during pre-IT regime. However, during IT-regime, MP shocks' contribution 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 above decrease to a maximum of 11% in the medium and long terms. Thus, MP shocks explain a higher percentage of FEVD of pre-IT regime compared to IT regime. Another result is MP shocks are more important than FS shocks to explain the FEVD of interest rate during pre-IT regime, while, FS shocks have the major contribution to the FEVD of interest rate during IT-regime.

⁵The medium term's values of FEVD are quite similar to the long term's values of FEVD. Therefore, we only describe the last ones.

The above results are in line Castillo et al. (2009) who argue the adoption of IT regime reduced the volatilities of domestic variables. Moreover, Armas y Grippa (2008) conclude that inflation's fluctuations are explained by AS shocks and international prices of our imports since IT regime. In addition, Mendoza (2013) document a greater trade openness since 2003 that can explain the higher contribution of FS to FEVD of domestic variables during IT regime.

Regarding the results of 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 of shock's participation over time.

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

4.2.5 Historical Decomposition (HD)

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

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

Finally, Figure 14 present the HD of interest rate for different models. For the Benchmark model, MP shocks are bigger than the others shocks during pre-IT regime. On the other hand, during IT regime, their contribution to interest rate decreases and FS shocks become relevant to explain the interest rate.

Summarizing, MP shocks play a relevant role to explain the domestic variables during pre-IT regime, while their contribution decreases after the adoption of IT regime. Regarding the other models, the model of Primiceri (2005) and the Benchmark A_t constant model have quite similar results. In the case of the Benchmark A_t and Σ_t constant model, this model overestimates or subestimates the contribution of the shocks.

4.2.6 Robustness Analysis

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

For informative prior, the posterior means for transition probabilities are above 90% in VAR coefficients (B_t) and the volatilities (Σ_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 transition probabilities is almost 50%. This result indicates we would expect a

break to occur about twice a year. On the other hand, using few breaks prior, the posteriors means for transition probabilities are $E(p_1|Data) = 0.73$, $E(p_2|Data) = 0.72$ and $E(p_3|Data) = 0.01$. We still notice that even with the prior information of transition probabilities are near zero, we would expect a break to occur about three times per year in VAR coefficients (B_t) and the volatilities (Σ_t). However, we would expect very few changes in the error covariances (A_t) over period. In conclusion, we still find evidence of gradual change of parameters (at least in VAR coefficients and the volatilities) in both alternative priors.

On other hand, we use uninformative values for 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 transition probabilities of error covariances (A_t) changes ($E(p_3|Data) = 0.03$). However, the pattern of IRFs to different shocks do not change. Moreover, if we use much flatter specifications of these priors, with variances ten or twenty times bigger, the results do not change⁶.

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 presents the posteriors of transition probabilities that a break occurs 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 time variation, but just prior beliefs about the amount of time variation. 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, we set $k_W = 1$ and maintain the other values. The posterior means for transition probabilities are the same results of the Benchmark model. In the third row, we set $k_S = 1$ and maintain the other values. Only the posterior mean for transition probabilities of error covariances (A_t) changes ($E(p_3|Data) = 0.03$). Finally, in the fourth row, we set $k_Q = 1$ and maintain the other values. The posterior mean for transition probabilities in the volatilities (Σ_t) is the same as Benchmark's 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 transition probabilities.

About IRFs, only when we set $k_Q = 1$, we have IRFs without a good behavior. According to Primiceri (2005), $k_Q = 0.01$ is a value that does not particularly penalize 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, for example $k_Q = 1$, the coefficients change very little and can not explain the outliers of our sample. For these reasons, the results of transition probabilities related to VAR coefficients and IRFs are not the best. In conclusion, the value of $k_Q = 0.01$ is 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, we estimate with a different variable ordering in order to test the robustness of our results⁷. We employ the new following ordering: terms of trade growth, inflation, GDP growth and interest rate. The posterior means for transition probabilities do not change. Concerning the volatility of exogenous shocks, there is a high peak of volatility at 1998Q3 in the four shocks as the baseline model. However, the peak at 2009Q3 is not clear as the baseline model, but there is a period of an increase of volatility between 2006Q1 and 2010Q1. About the comparison of volatility magnitudes of the exogenous shocks, the volatilities of FS shock and AS shock are the largest and lowest over period, respectively; as well as the Benchmark model. However, the robustness results present that MP shock is always bigger than AD shock that it is different from our baseline results. About IRFs of robustness analysis, the patterns of responses of variables to MP shock are very similar in both estimations, the responses' pattern of interest rate to FS and AS shock are similar in both models. However, the responses of interest rate to AD shocks are negative in the first quarters, but is positive in the rest of quarters as well as the Benchmark

⁶All results are available upon to request.

⁷All results are available upon to request.

model.

4.2.7 Other Shocks

We present the results associated to FS, AD and AS shocks, considering the same models employed before⁸. Concerning the effect of the FS shocks, the response of GDP growth changes over time; for Benchmark model, the response of GDP growth is positive for most of the pre-IT regime, while the response of GDP growth is negative during IT regime. These results are similar for the others models, except for the Benchmark A_t and \sum_t constant model. On the other hand, the response of inflation is always negative over time and across the models. Regarding their contribution to FEVD of domestic variables in the long term, FS explains at least 17%, 25% and 7% of FEVD of GDP growth, inflation and interest rate, respectively, during pre-IT regime. Nonetheless, these results change during IT-regime where FS have a contribution of at least 40% of FEVD of each domestic variable. Finally, about FSs' contribution to HD of domestic variables, their contribution to HD of GDP growth does not change over the sample, while their contribution to HDs of inflation and interest rate becomes more important since IT regime.

About the effect of domestic variables to AD shocks, the response of inflation is positive over time with a strong effect in fourth quarter and the results are similar across the models. Regarding their contribution to FEVD of domestic variables in the long term, AD shocks get to 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 FEVD of inflation and interest rate, respectively. Finally, concerning AD shocks' contribution to HDs domestic variables, AD shocks present a high contribution to HD of GDP growth, while their contributions to HDs of inflation and interest rate are lower compared to other shocks.

Finally, the effect of domestic variables to AS shocks, the response of GDP growth is negative over time with a strong effect in second quarter and the results are similar across the models. Concerning their contribution to FEVD of domestic variables in the long term, AS shocks have a higher contribution of FEVD of inflation during pre-IT regime (between 30% and 44%) in comparison during IT regime (40% in 2002Q1 to 17% in 2016Q4). In addition, AS shocks explain less than 3% and 9% of FEVD of GDP growth and interest rate, respectively. Concerning HDs of domestic variables, AS shocks have an important contribution to HD of inflation. On the other hand, their contributions to 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 between 1996Q1 and 2016Q4. This model allows estimating whether, where, when and how parameter change is occurring. 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.

We find evidence that the three blocks of parameters (VAR coefficients, the volatilities and error covariances) change gradually. In addition, the transition probabilities of VAR coefficients (B_t) and the 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% that means that we would expect a break to occur about twice per year. We also evaluate the performance of the Benchmark model and its the restricted versions, finding the Benchmark model has a better performance.

⁸All Figures are available upon to request.

About the volatility of exogenous shocks, our results suggest two peaks of high volatility in 1998Q3 and 2009Q3 which are related to international economic events: Asian-Russian crisis and the “Great Recession” in the world. Moreover, the volatility of MP shock is on average higher in the pre-IT regime compared to the IT regime. In addition, since 2002Q1, we find that the MP shock volatility has ceased to be an important source of macroeconomic volatility in the Peruvian economy.

Regarding the contribution of MP shocks to FEVD of domestic variables, we find evidence that they explain great percentage in pre-IT regime, especially FEVD of interest rate. However, this scenario changes in IT-regime where MP shocks become less important and FSs explain at least 40% of FEVD of domestic variables. In the same line, the HD of domestic variables show monetary policy shocks decrease their participation in IT-regime compared to pre-IT regime.

Since the adoption of IT regime, the BCRP performance is good due to MP shocks are not longer an important source of macroeconomic volatility. Therefore, policy-makers should focus to mitigate the influence of the others shocks on the Peruvian economy, especially FSs. Likewise, monetary policy is an important tool to reduce the negative effects of these shocks to Peruvian economy. However, the biggest challenge is to identify what kind of shock is facing and design a monetary policy to deal with this shock. An adequate monetary policy will allow maintain a macroeconomic stability.

Finally, a future agenda includes a non-recursive identification or adding other variables to the model. Moreover, it is important to investigate other aspects of monetary policy such as lending or expectation channel of monetary policy transmission with the TVP-VAR-SV framework. Thus, we can better understand the Peruvian monetary policy.



6 References

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7 Tables

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.



8 Figures

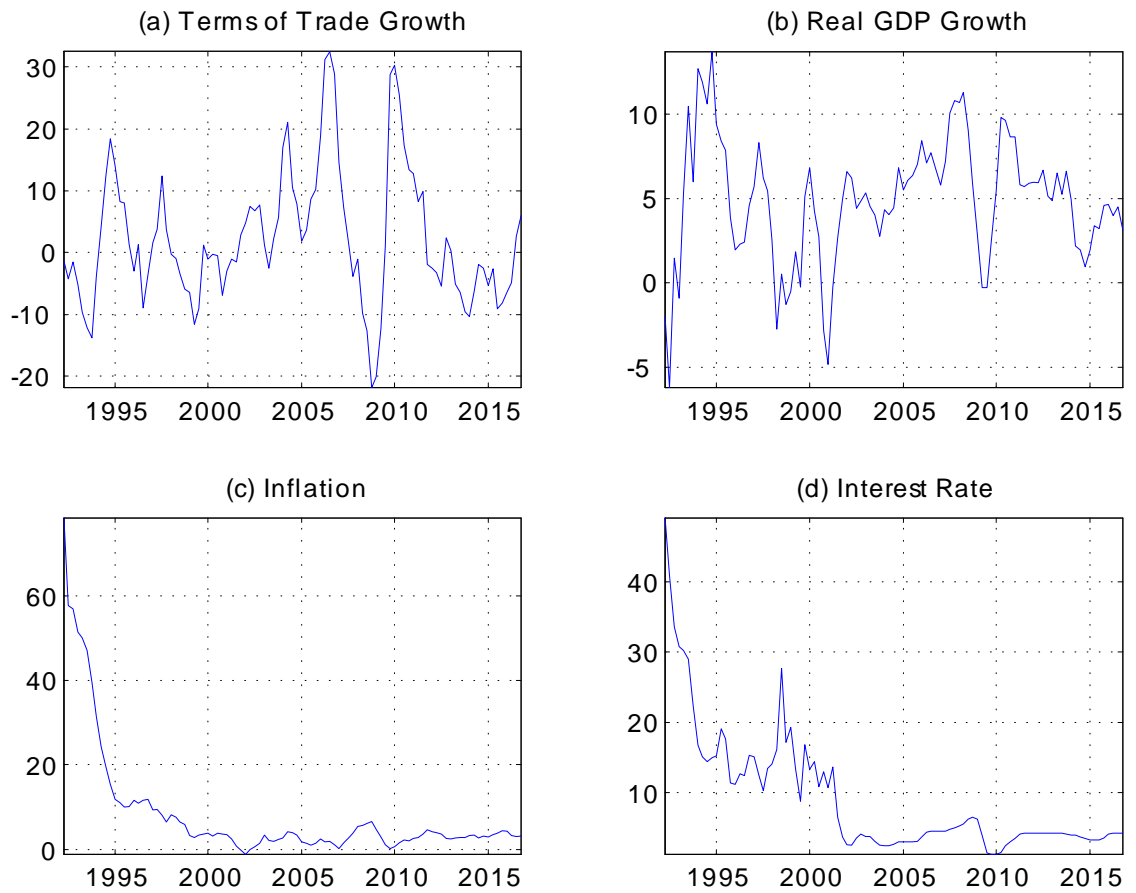
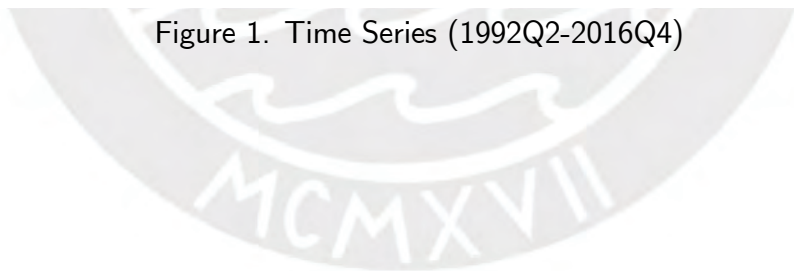


Figure 1. Time Series (1992Q2-2016Q4)



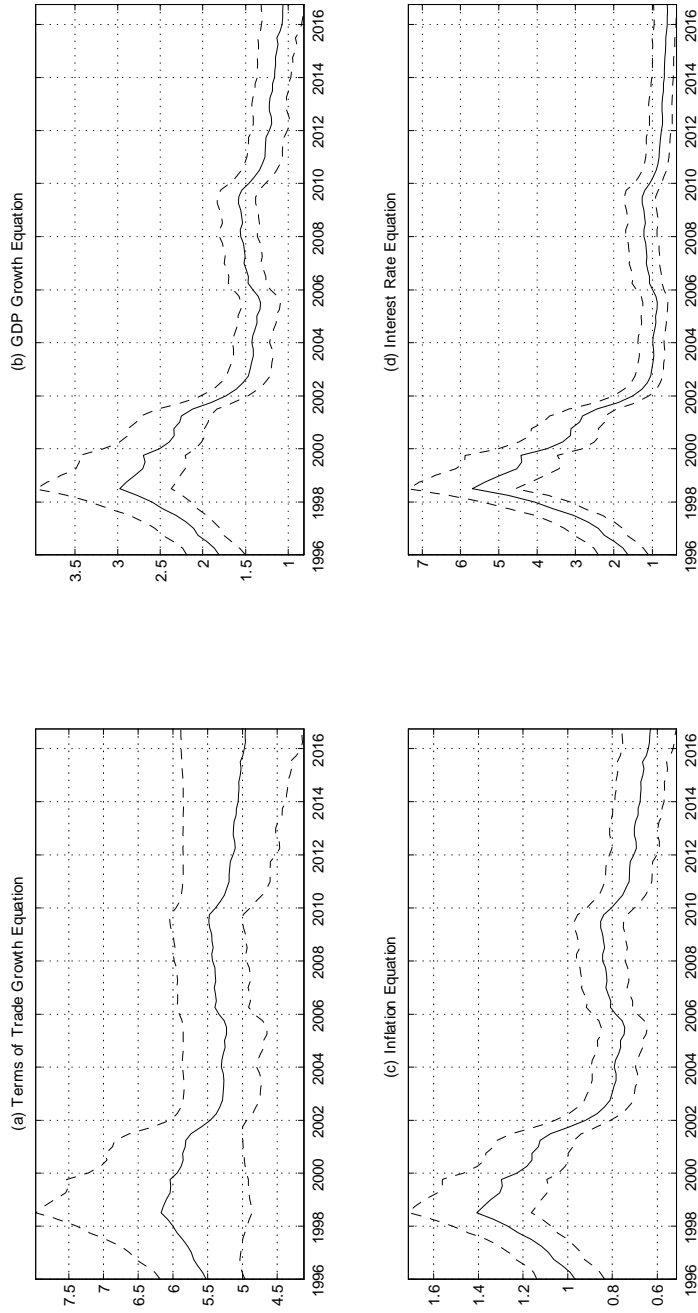


Figure 2. Posterior Mean, 16th and 84th Percentiles of the Standard Deviation of Errors in the Four Equations for Benchmark Model (1996Q1-2016Q4)



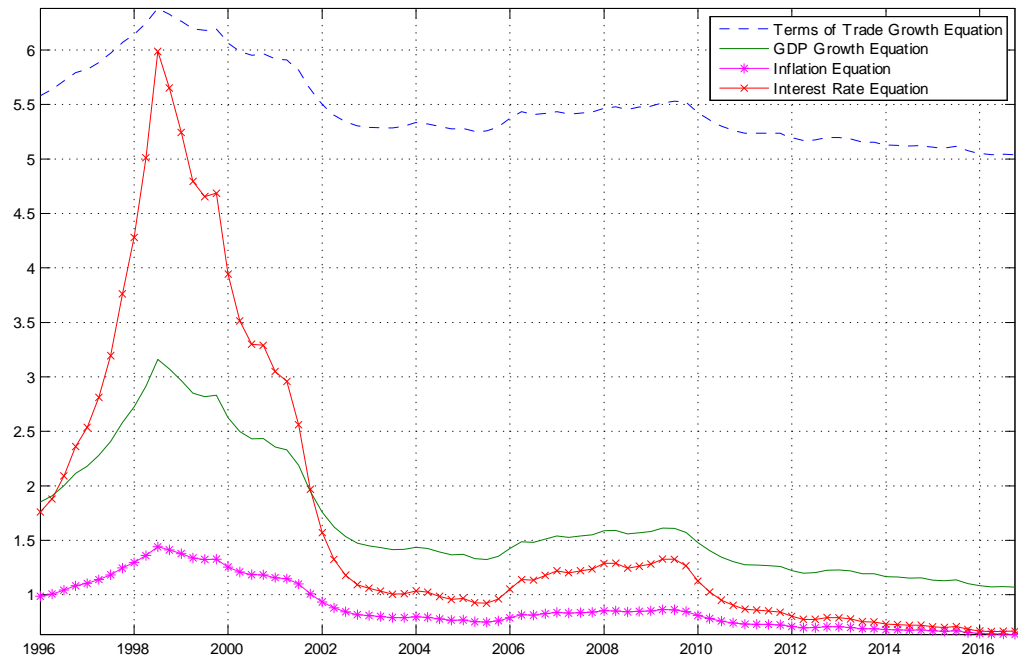


Figure 3. Posterior Mean of the Standard Deviations of Errors in the Four Equations for Benchmark Model (1996Q1-2016Q4)

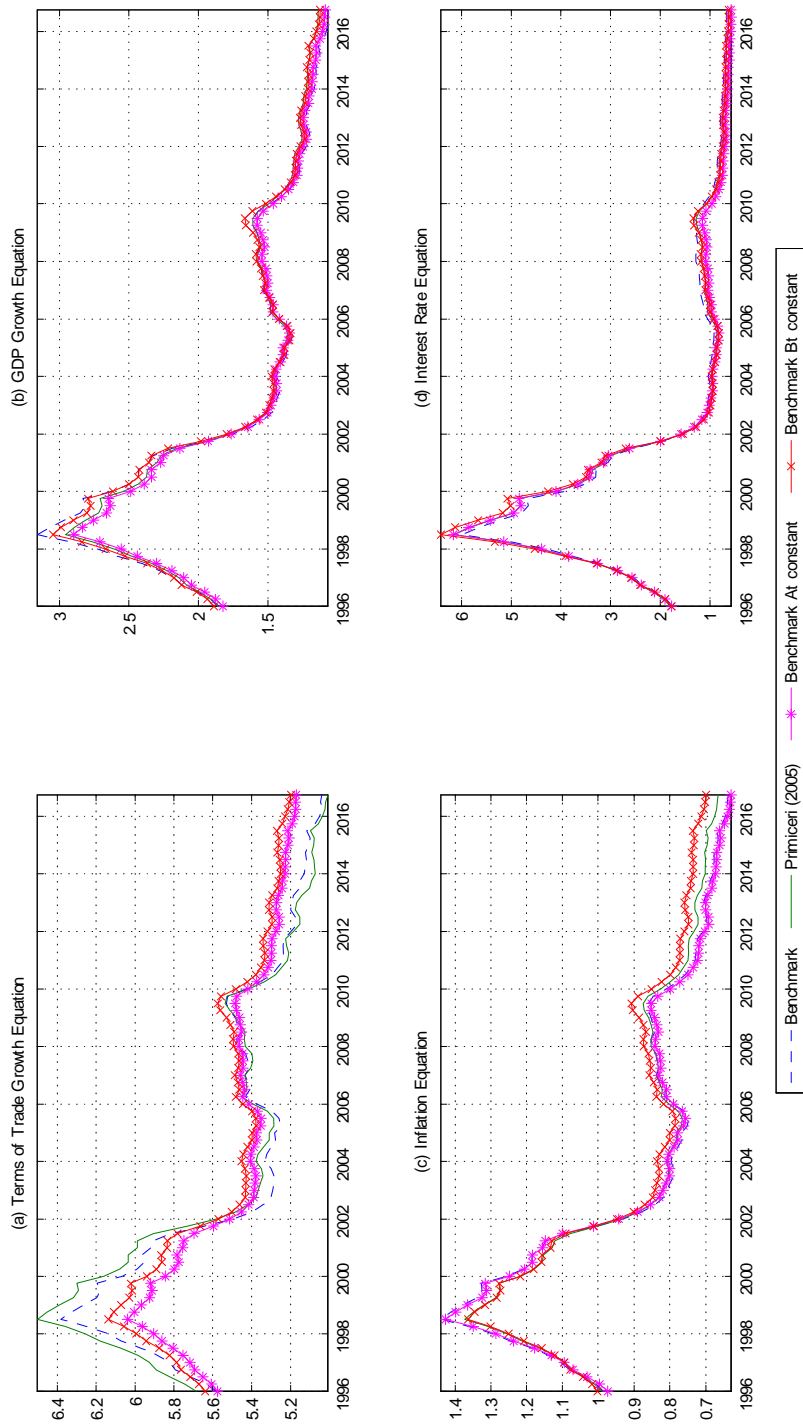


Figure 4. Posterior Mean of the Standard Deviations of Errors in the Four Equations for Various Models (1996Q1-2016Q4)

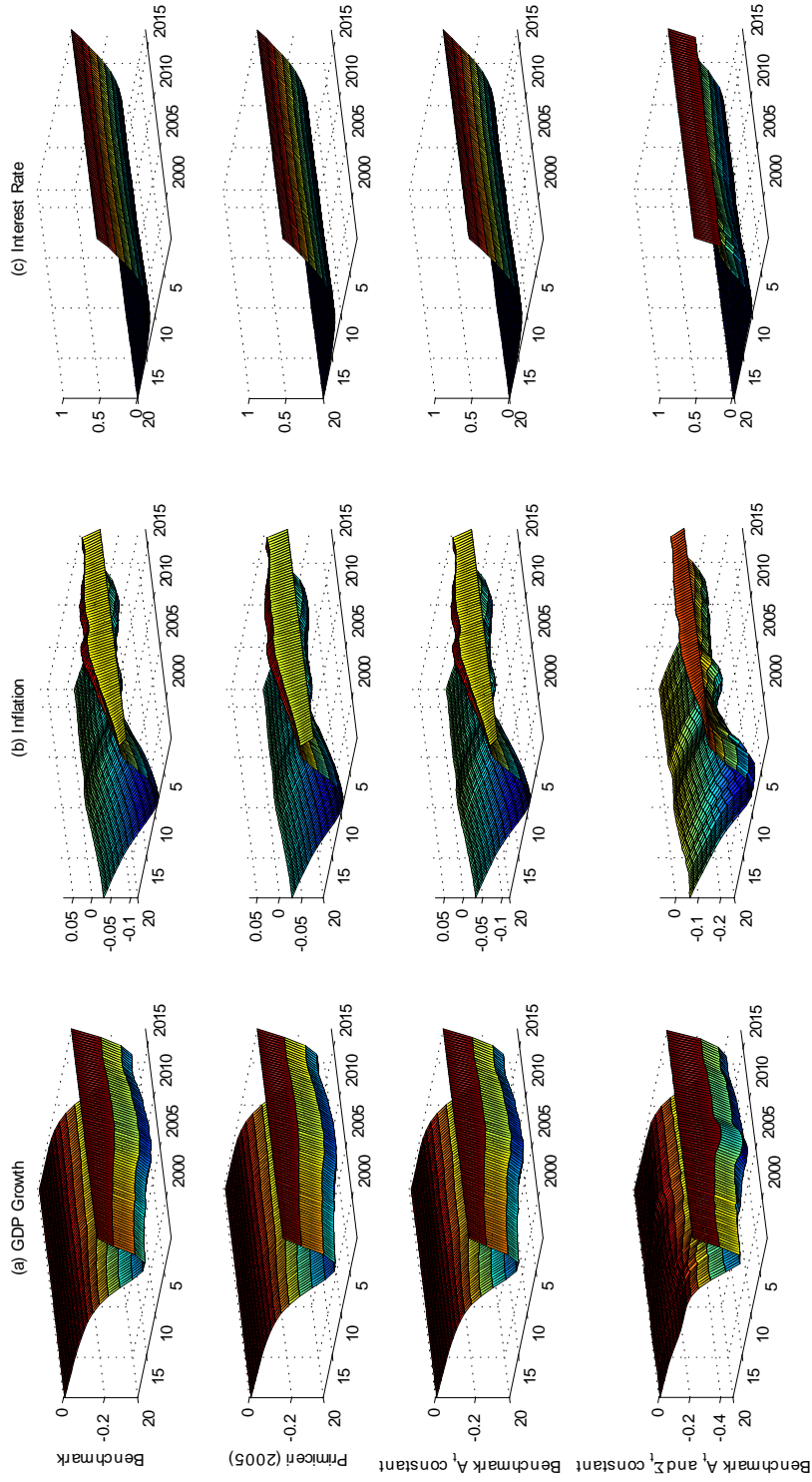


Figure 5. Median Time-Varying Impulse Response Functions to Monetary Policy Shock for Various Models



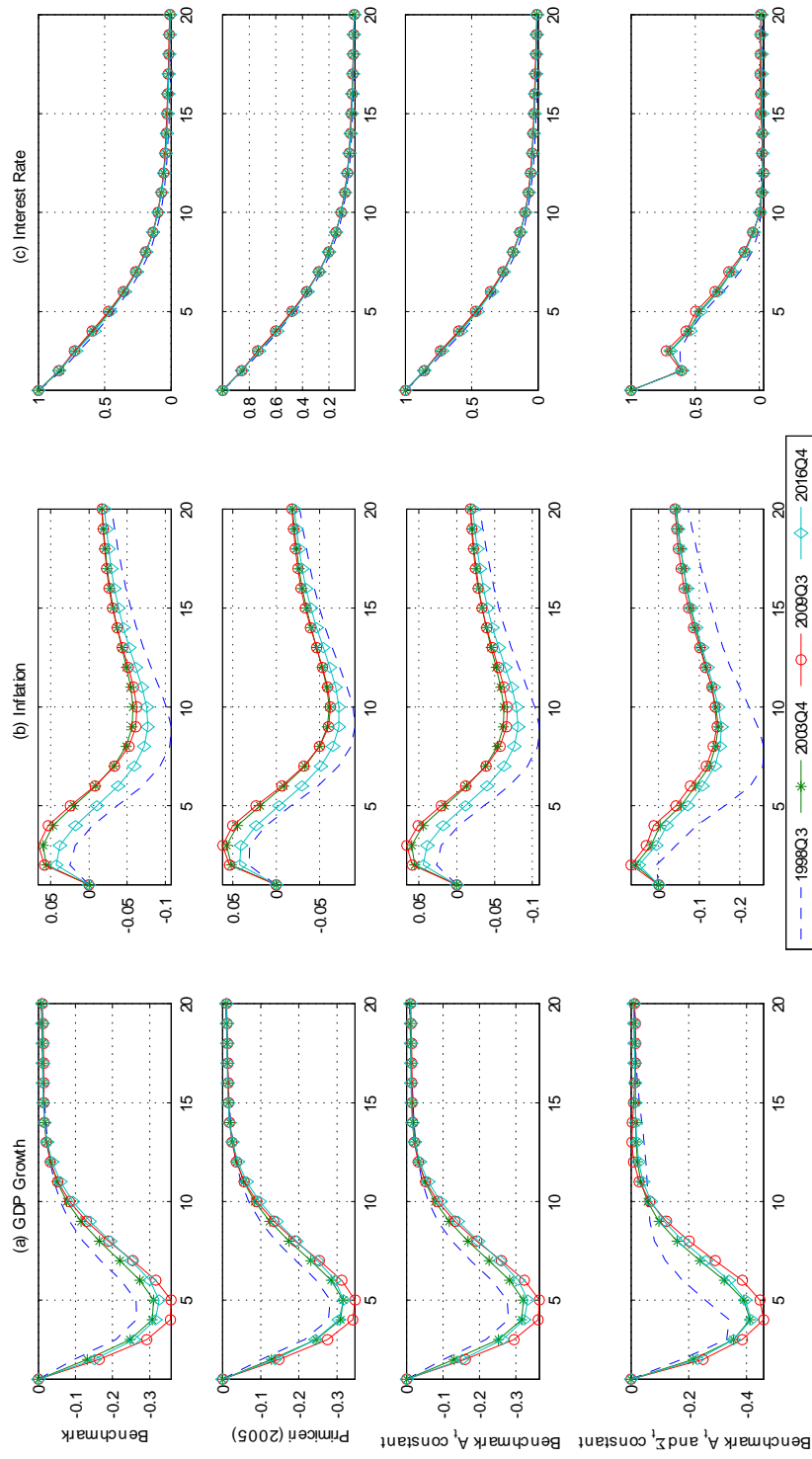


Figure 6. Impulse Response Functions to Monetary Policy Shock at Different Time Periods for Various Models

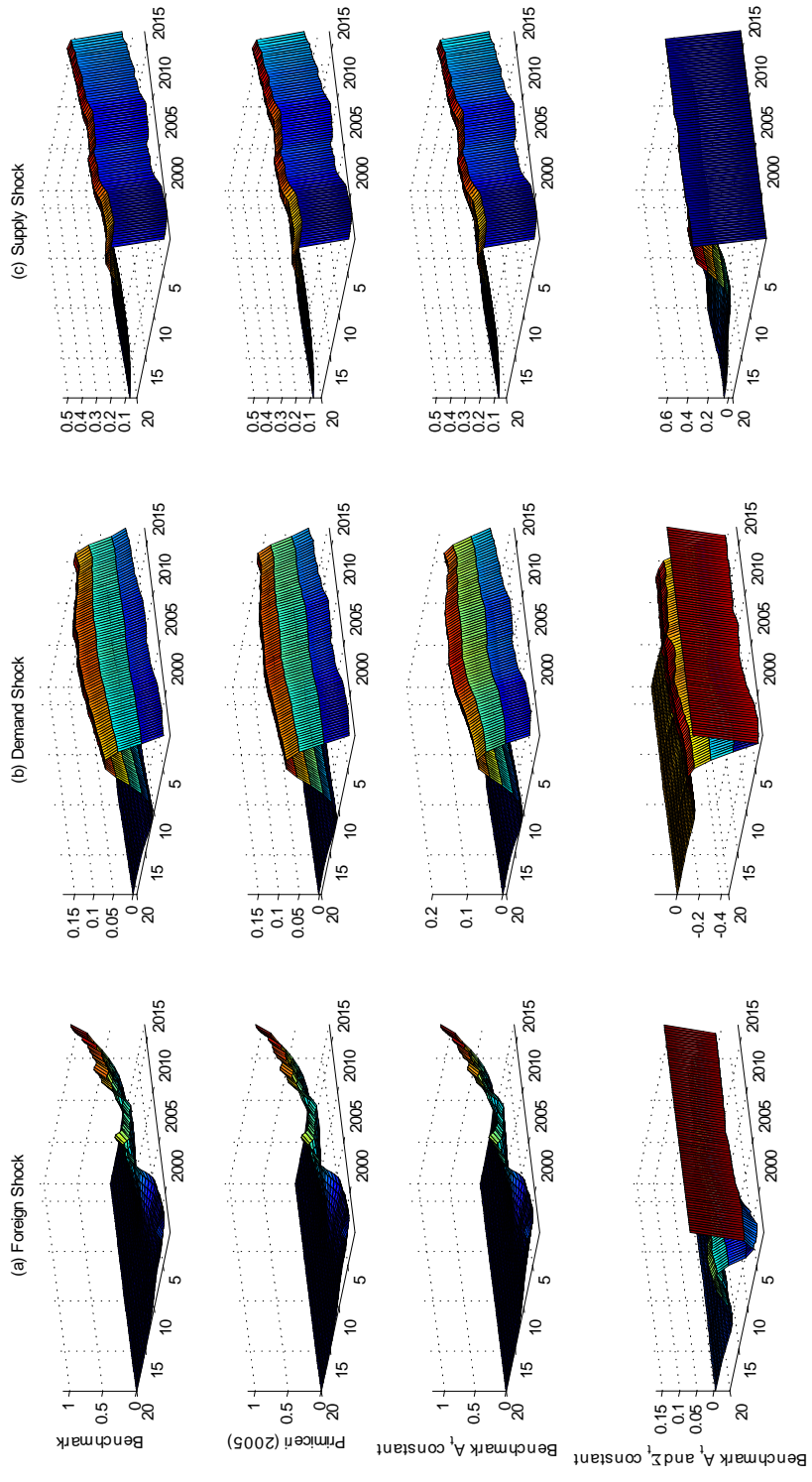


Figure 7. Median Time-Varying Impulse Response Functions of Interest Rate for Various Models



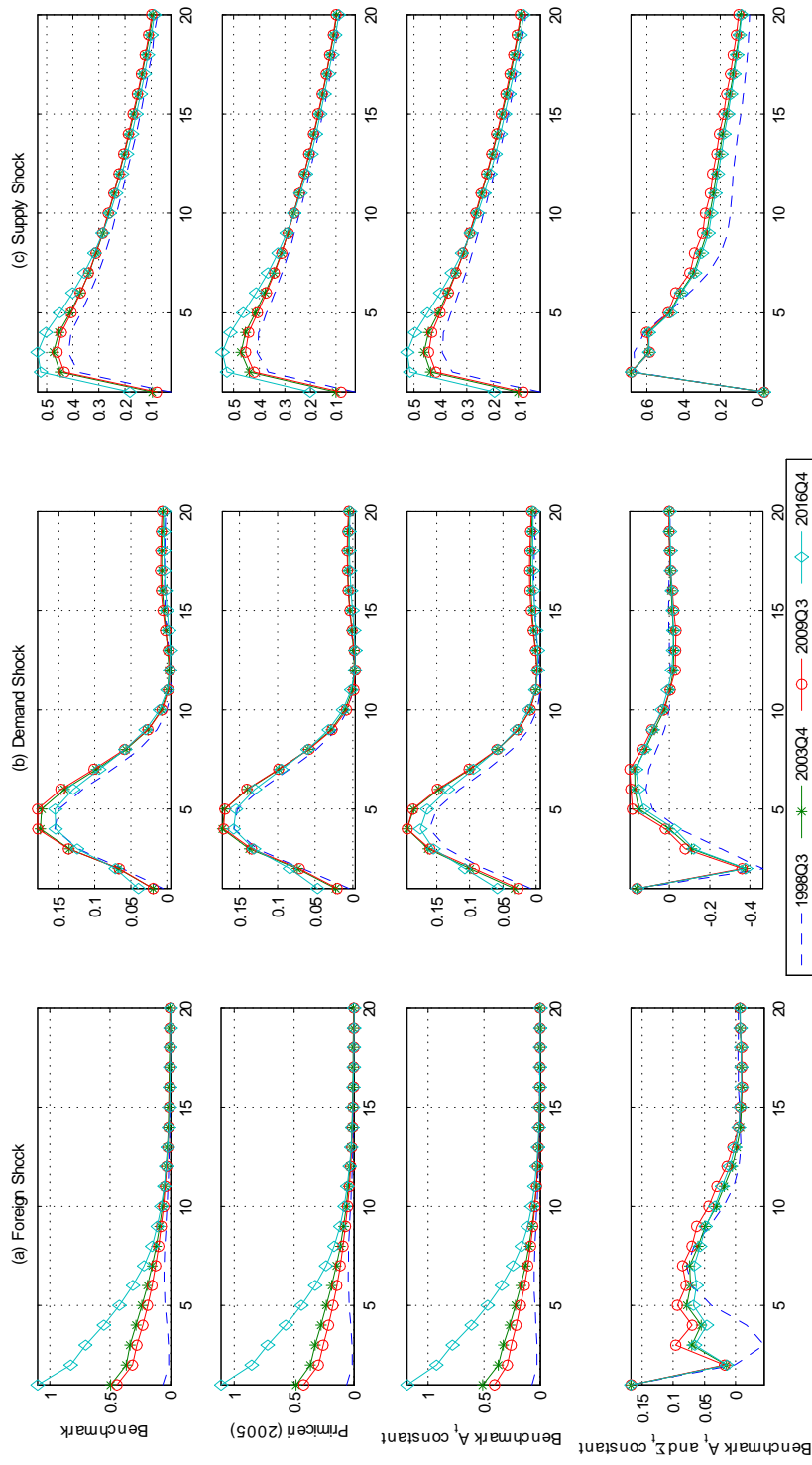


Figure 8. Impulse Response Functions of Interest Rate at Different Time Periods for Various Models

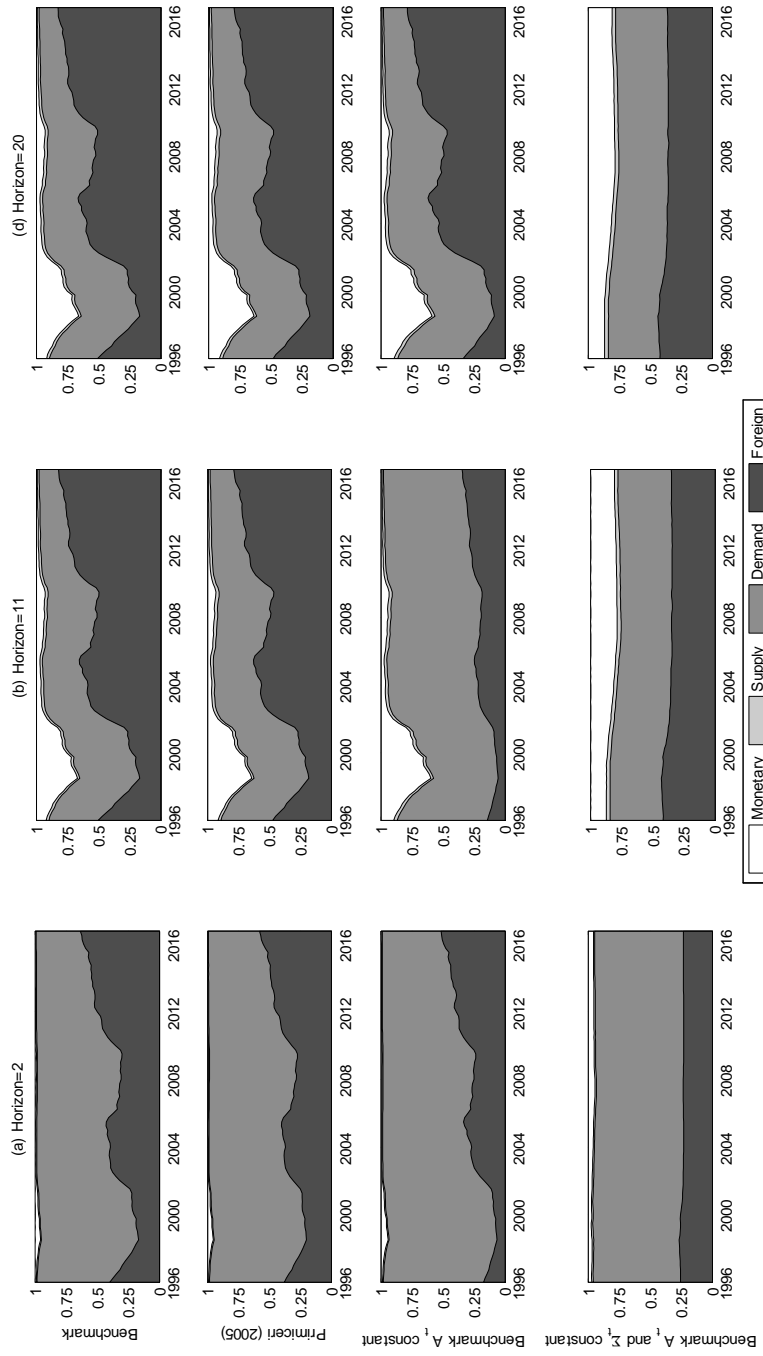
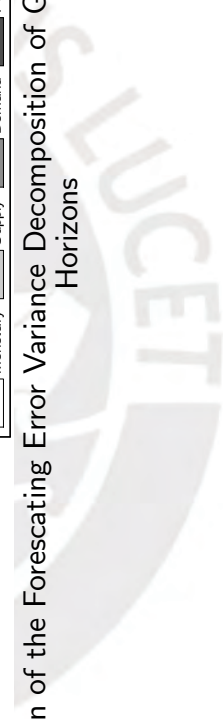


Figure 9. Time Evolution of the Forecasting Error Variance Decomposition of GDP Growth for Various Models at Different Horizons



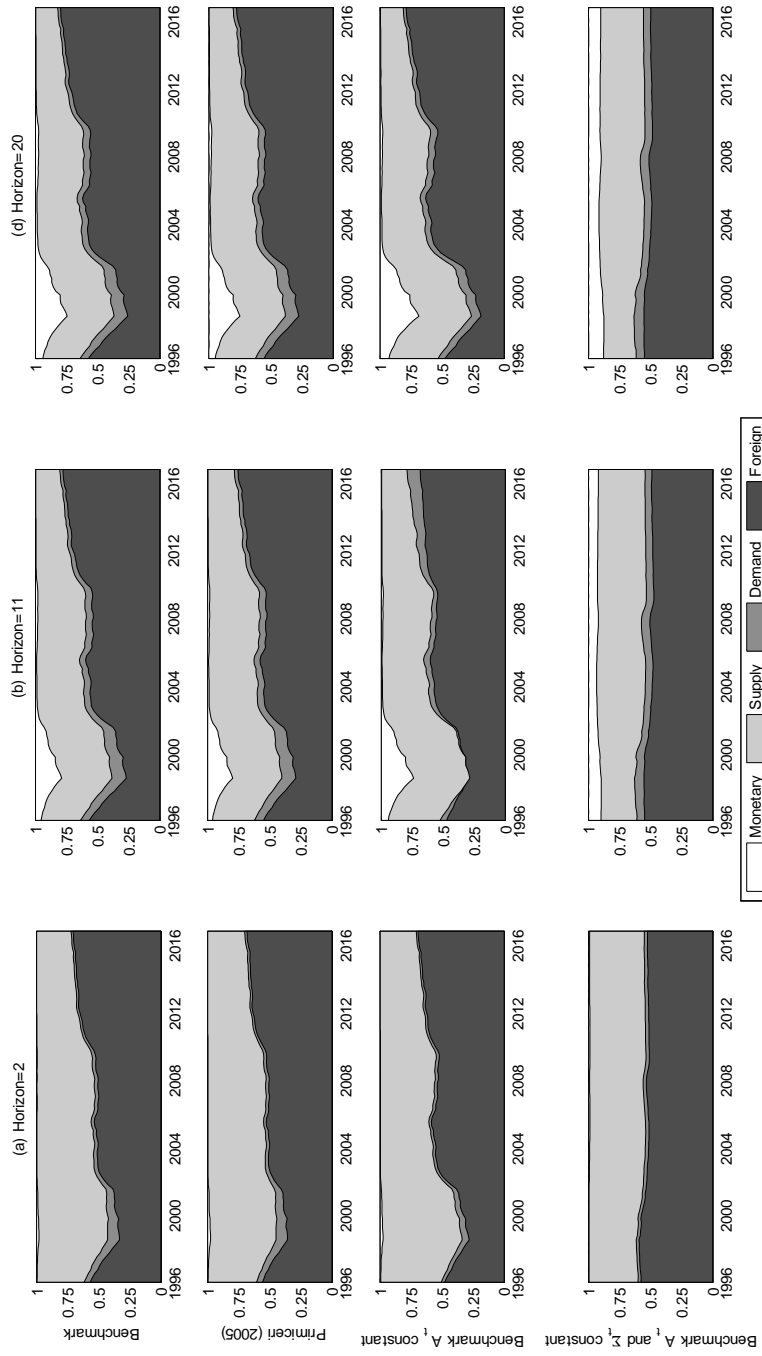


Figure 10. Time Evolution of the Forecasting Error Variance Decomposition of Inflation for Various Models at Different Horizons

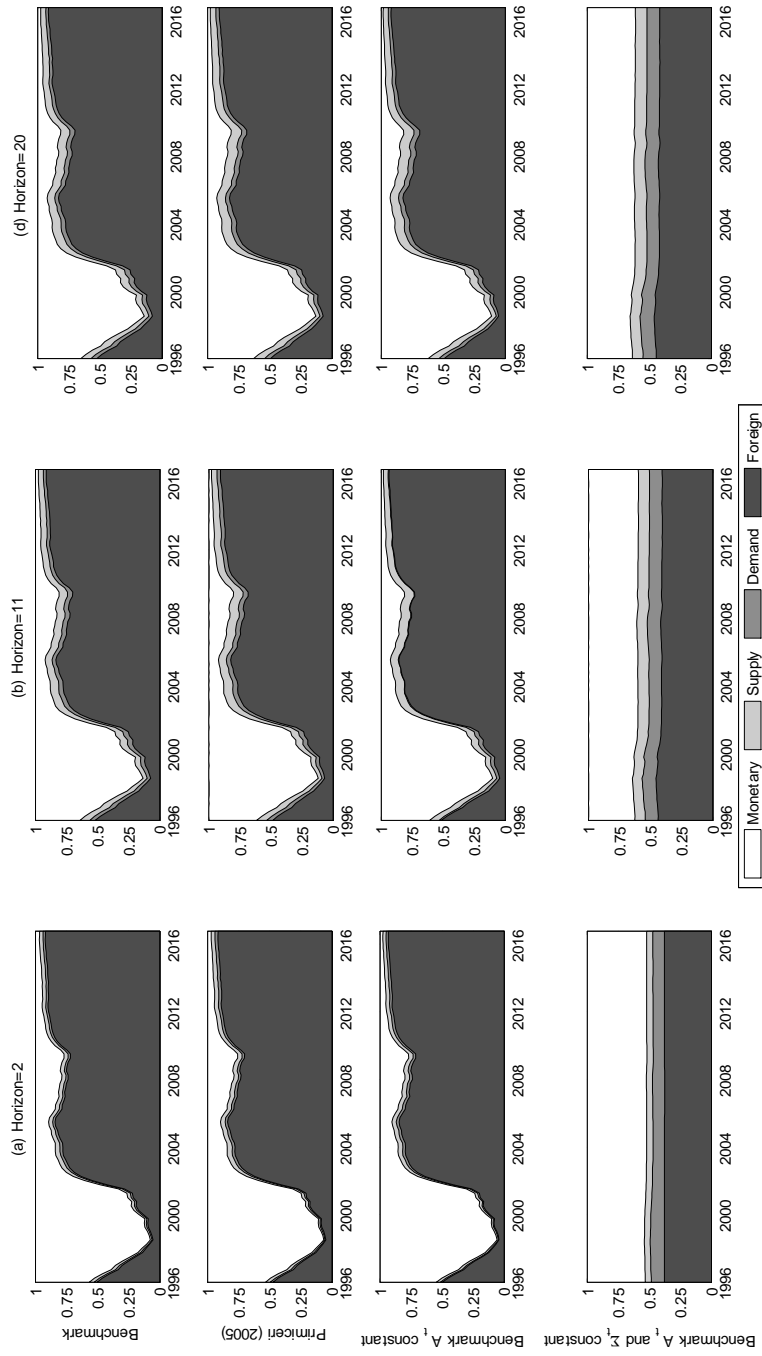
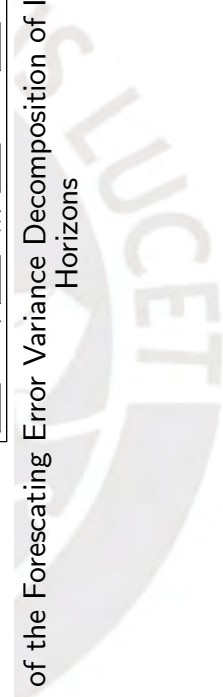


Figure 11. Time Evolution of the Forecasting Error Variance Decomposition of Interest Rate for Various Models at Different Horizons



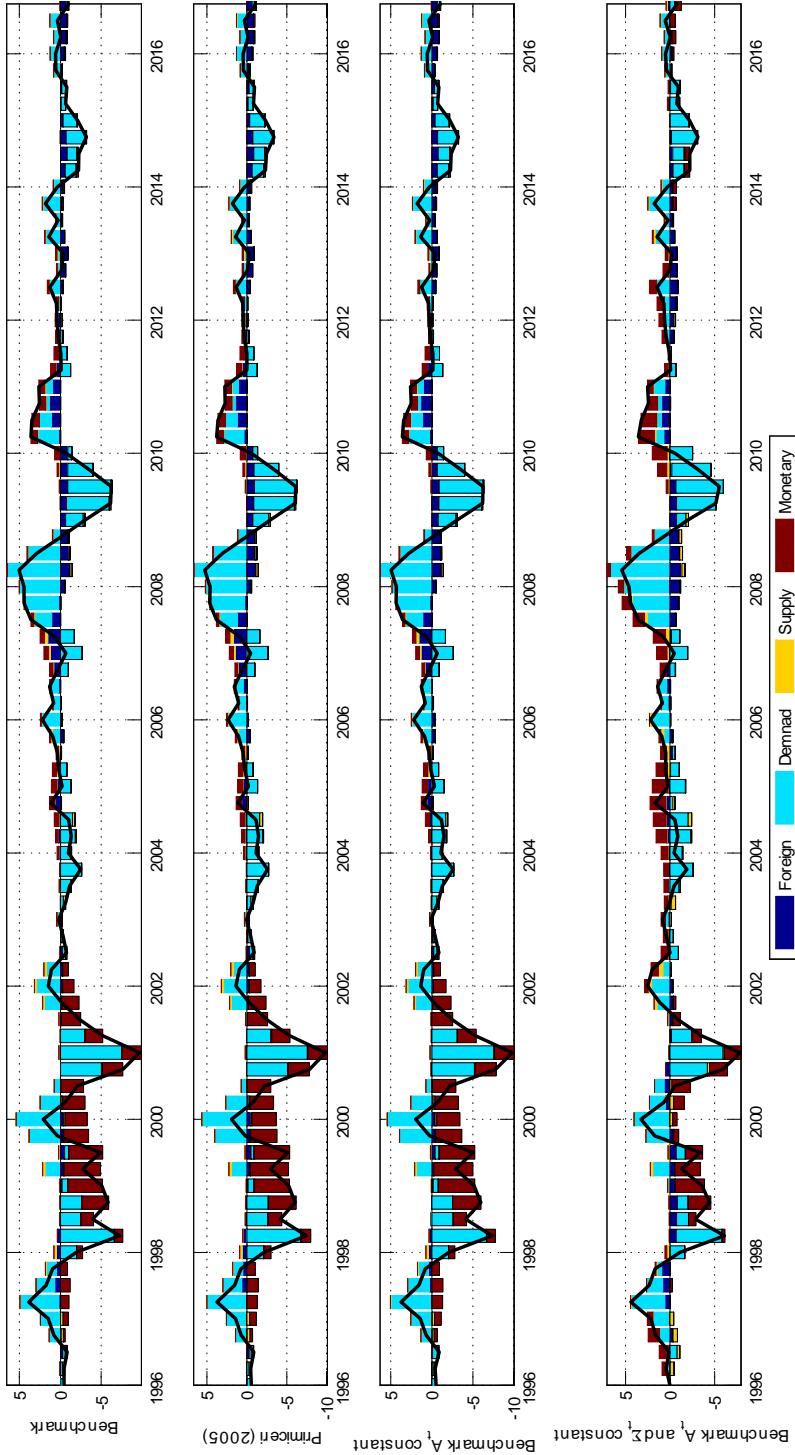


Figure 12. Historical Decomposition of GDP growth for Different Models



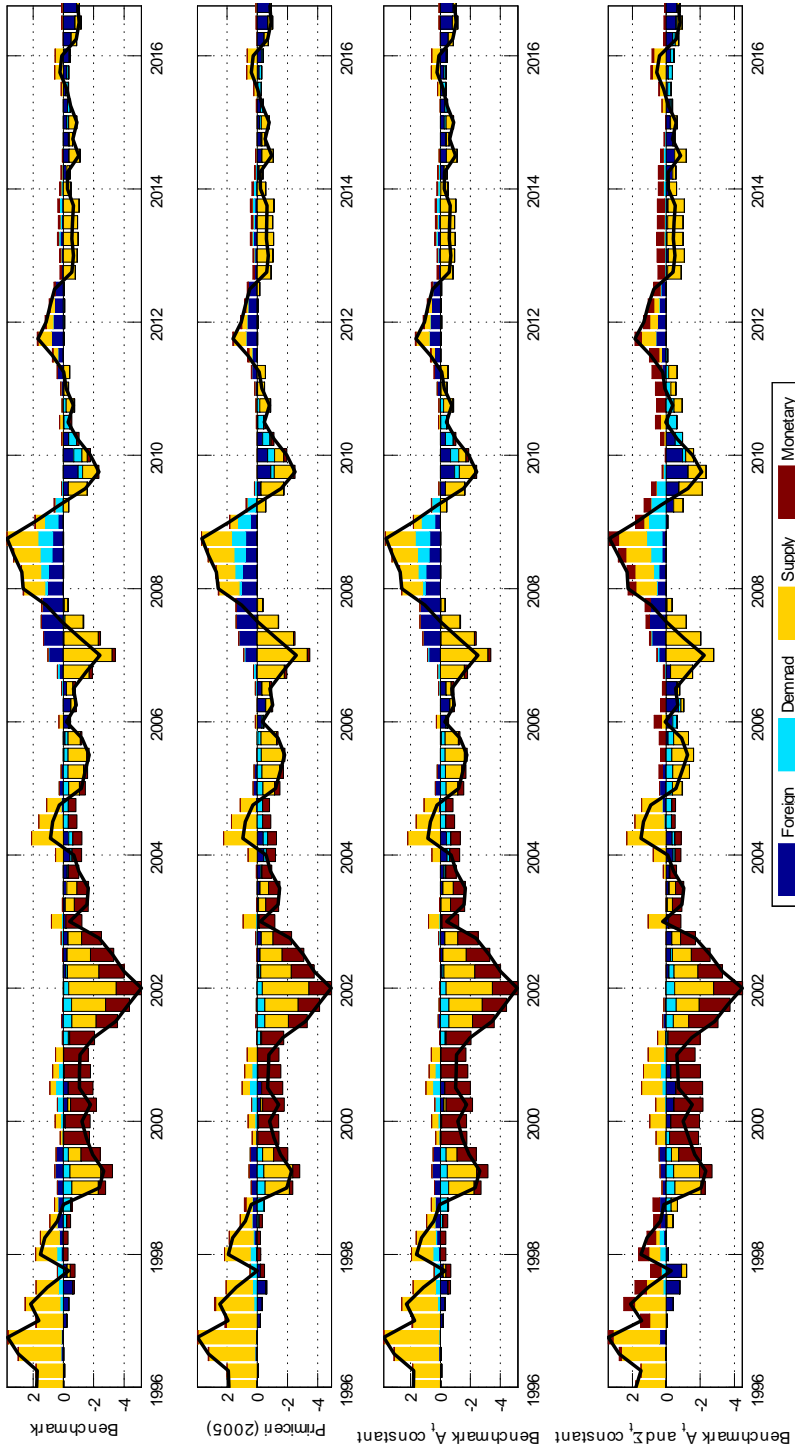


Figure 13. Historical Decomposition of Inflation for Different Models



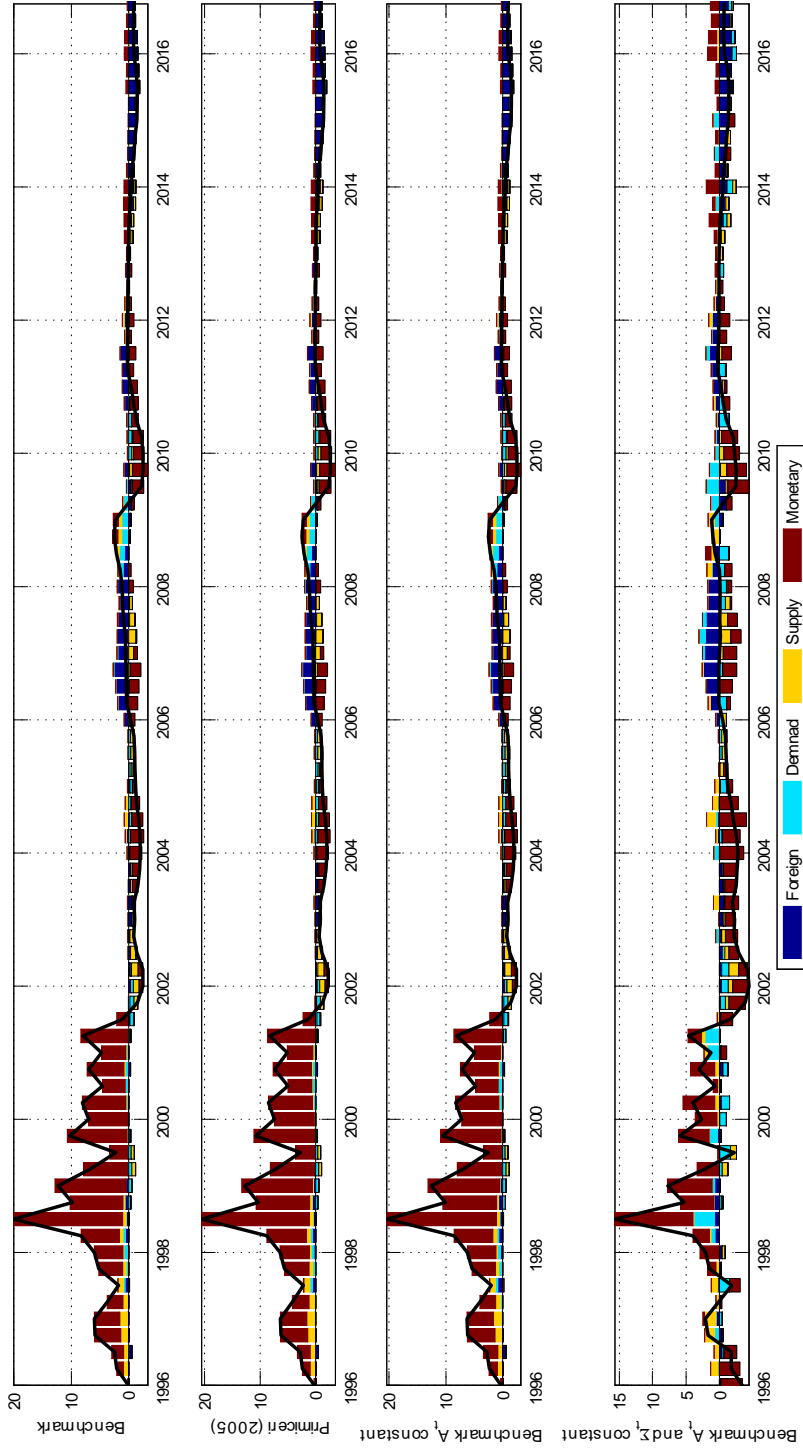


Figure 14. Historical Decomposition of Interest Rate for Different Models