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From the "Great Inflation" to the "Great Moderation" in Peru: A Time Varying Structural Vector Autoregressions Analysis

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From the "Great Inflation" to the "Great Moderation" in Peru: A Time Varying Structural Vector Autoregressions analysis[*]

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Abstract

Over the last 30 years, the Peruvian economy has shown a dramatic decrease in the volatility of its macroeconomic aggregates. Following Primiceri (2005), Benati (2008) and Galí and Gambetti (2009), a Bayesian structural vector autoregression with time-varying parameters and variance covariance matrix of the innovations is used to analyse the underlying causes of Peruvian "Great Moderation". The peruvian economy is modelled using real GDP growth, inflation and the rate of growth of M1 (money base). Our main results show: (1) Monetary policy has contributed significantly to the "Great Moderation" by reducing the volatility of its non-systematic component and by changing its reaction function to demand and supply shocks; (2) Structural reforms also contributed to reduce the responsiveness of GDP and inflation to demand and supply shocks (3) During the period of high volatility, supply and policy shocks were the most important determinants of macroeconomic instability.

Keywords: time varying coefficients, multivariate stochastic volatility, Gibbs sampling, systematic monetary policy, monetary policy shocks, identification

JEL Classification: C15, C22, E23, E24, E31, E32, E47, E52, E58

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1 Introduction

What drives macroeconomic volatility? The literature is mainly divided into three possible explanations: changes in policy, changes in private sector behavior and changes in volatility of fundamental shocks. In this paper, we estimate the contribution of these three factors in explaining the significant decline in macroeconomic volatility observed in Peru since the early 1990s.

Peru went through periods of heightening volatility during the 1980s and moved to an environment of macroeconomic stability, particularly after 2000s. Also, it has experimented substantial changes in its macroeconomic policy framework, moving from a period of fiscal dominance that end up in a hiperinflation at the end of the 1980s to a period of price stability under an inflation targeting regime since 2002, after a succesful stabilization program based on money aggregate management during the 1990s[1]. Key in achieving price stability was the adoption of a flexible exchange rate regime in 1991 and the adoption of a new monetary policy framework that granted independece to the central bank and asigned a unique objetive for monetary policy, price stability [2] Peru has also experimented deep structural reforms particularly in early the 1990s, which increased the efficiency of the goods and labor market. All these elements can contribute to significant changes in macroeconomic volatility. On one hand, price stability, by reducing nominal uncertainty, can contribute to the development of long-term capital markets in domestic currency, which can reduce financial risks. Also, by focusing on price stability, monetary policy can avoid becoming a source of macroeconomic volatility. On the other hand, structural reforms can have significant impact on the way the economy responds to macroeconomic shocks. The liberalization of the current and capital account in Peru, jointly with the reforms in the financial system have contributed to a more efficiently functioning of the economy, which can also reduce its sensitivity to macroeconomic shocks.

To disentangle the importance of changes in policy from changes in the size of macroeconomic shocks in explaining macroeconomic volatility in Peru, we require an empirical framework that can handle both time varying dynamics and time varying volatility. To accomplish our objective we

[1] Inflation went down from 7481 percent in 1990s to 8.5 percent in 1997 and to 2.0 percent in 2000.

[2] A series of prohibitions were placed on the Central Bank to guarantee its independence. For instance, the Central Bank was prohibited from financing the public sector, financing any state development bank, granting guarantees, granting credit to any particular sector of the economy, and establishing multiple exchange rate regimes.

use bayesian structural vector autoregression model with time-varying parameters (TV-SVAR), as in Primiceri (2005), Benati (2008), Gambetti, Pappa and Canova (2008) and Galí and Gambetti (2009). The model is estimated using quarterly data of three fundamental macroeconomic variables: real GDP growth, the inflation rate and the growth rate of money for the period that spans from 1981:I-2014:III. Structural shocks are identified following Christiano, Eichenbaum and Evans (1996) and Primiceri (2005)

Our main results show that monetary policy has contributed significantly to the decline in macroeconomic volatility in Peru by reducing the size of the monetary policy shocks and by changing its reaction function in response to demand and supply shocks. In contrast with the high correlations observed between inflation volatility and money growth rate volatility during 1980s, in the 1990s these correlations weaken drastically and in the 2000s, with the adoption of the inflation-targeting regime, they become no significant. A key driver of the fall in the correlation between the volatility of these variables is the change in the response of monetary policy to supply shocks. During the 1980s, money supply increased in response to a supply shock, which implied that the central bank accommodated shifts in inflation expectations, whereas after 1993, money supply responded differently, falling in response to the same type of supply shock, which is consistent with a systematic component of monetary policy that intends to stabilize inflation expectations and not to validate them. According to our results, around 50 percent of the fall in GDP volatility can be explained by the fall in the volatility of policy and supply shocks since 1994.

This paper is related to a recent literature that has documented, for developed economies, evidence of a substantial decline in the volatility of the Gross Domestic Product (GDP) before the global financial crisis of the 2000s, a phenomenon known as the "Great Moderation"[3].

Clarida, Gali and Gertler (2000) attribute the reduction of GDP volatility to better monetary policy. They estimated a forward-looking monetary policy reaction function for the postwar United States economy, before and after Volcker's appointment as Fed Chairman in 1979, and find a substantial improvement in monetary policy in the USA. In contrast, Primiceri (2005), using a vector autorregresive model with time varying parameters, finds that the reduction of volatility was caused by the reduction in exogenous non-policy shocks rather than interest rate policy. Also, Cogley and Sargent (2005) infer that monetary policy rules have changed and that the persis-

[3] Blanchard and Simon (2000) for the United States economy, and Stock and Watson (2003) for a larger set of industrialized economies

tence of inflation itself has drifted over the post-World War II explaining the fall in GDP volatility in the USA.

Sims and Zha (2006) find that the differences in the behavior of the economy between periods is the reflection of the variation in the sources of economic disturbances and not in the dynamics of the effects of a given disturbance on the economy. Arias, Hansen and Ohanian (2007) suggest that the post-1983 decline in business cycle volatility requires a change in the volatility of the productivity shocks. Gambetti, Pappa and Canova (2008) attribute the phenomenon to changes in the behaviour of the private sector to supply and real demand shocks, together with changes in the variability of structural shocks. Gali and Gambetti (2009) argue that the Great Moderation period appears to be the result of a smaller contribution of non-technological shocks that generated a dramatic fall in the correlation between hours and labor productivity. Canova and Gambetti (2010) show that expectations explain the dynamics of inflation and interest rates but their importance is roughly unchanged over time.

For the Euro area, there has also been considerable research about the "Great Moderation" episode. Batini (2002) presents evidence of a drop in German inflation persistence and a sizeable shift in the mean of inflation in Italy and France. Gadzinski and Orlandi (2004) find a moderate inflation persistence in the euro area in line with the USA inflation persistence. O'Really and Whelan (2004) show that there has been little instability in the parameters of the Euro-area inflation process. Rubio Ramírez, Waggoner and Zha (2005), using vector autoregression models that allows for regime switching in coefficients and variances, show that regime changes in shock variances instead of changes in coefficients.

Canova, Gambetti and Pappa (2007) examine the dynamics of GDP growth and inflation in the USA, Euro area and UK, and conclude that it is impossible to explain the "Great Moderation" episode with one single explanation: (i) for USA, changes in the transmission and in the variability of demand shocks were important, (ii) for the Euro area, changes in the transmission and the volatility of monetary policy shocks and in the volatility of supply shocks mattered, and (iii) in the UK, changes in the transmission of demand shocks and in the volatility of supply and monetary policy shocks appeared to be the relevant ones. Benati (2008) find that, for the UK case, good luck was the real cause of the "Great Moderation".

For the Latin America, few papers have addresed changes in macroeconomic volatility. Caballero (2000) reviews the sources of volatility in Argentina, Chile and Mexico. Singh (2006) describes the long history of macroeconomic volatility in Latin America and concludes that it is linked to weaknesses in institutions and instability in policies. Goyal and Sahay (2006) examine the role of policy volatility in 17 Latin American countries and show that outcomes and policies are more volatile in low growth episodes. Larrain and Parro (2008) analyze the role played by the introduction of a floating exchange rate and the use of structural surplus fiscal rule in transforming Chile into a less volatile economy. For the Peruvian economy, Castillo, Humala and Tuesta (2012) find a substantial reduction on the volatility of transitory and permanent component of inflation shocks. They argue that the reduction in the size of permanent component shocks of inflation is linked to lower monetary policy uncertainty and therefore with a stronger central bank credibility.

The rest of the paper is organized as follows. Section II describes the decline in Peruvian GDP and inflation volatility. Section III lays out the general framework. Section IV details the estimation method. Section V describes the data. Section VI shows the results. Section VII concludes the paper.

2 The decline in GDP Volatility

As Figure 1 shows, since the end of the 1990s, Peru has experimented a significant decline in output volatility. Output volatility, measured by a 4-quarter rolling window standard deviation, has fallen from about 15 percent per quarter in the early 1990s to less than 3 percent in the late 2000s. This stylized fact is robust to alternative measures of GDP volatility. Figure 2 depicts a 20-quarter rolling window standard deviation(labelled as BS), which follows Blanchard and Simons (2001) and the implied volatility estimated using a Markov Switching model for GDP volatility(labelled as SS), following Smith and Summers (2001). Both measures of GDP volatility show a substantial reduction since the mids of the 90s. Consistent with this pattern, the Markov Switching model identifies a high volatility state from the period that spans the first quarter of 1983 to the second quarter of 1994, and a state of low GDP volatility from 1995 to 2014.

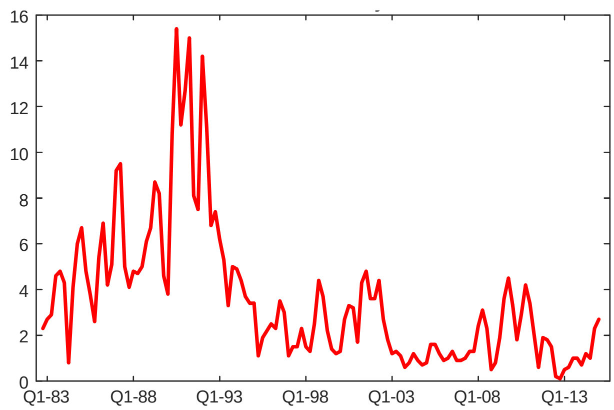

Figure 1: Peruvian GDP Volatility

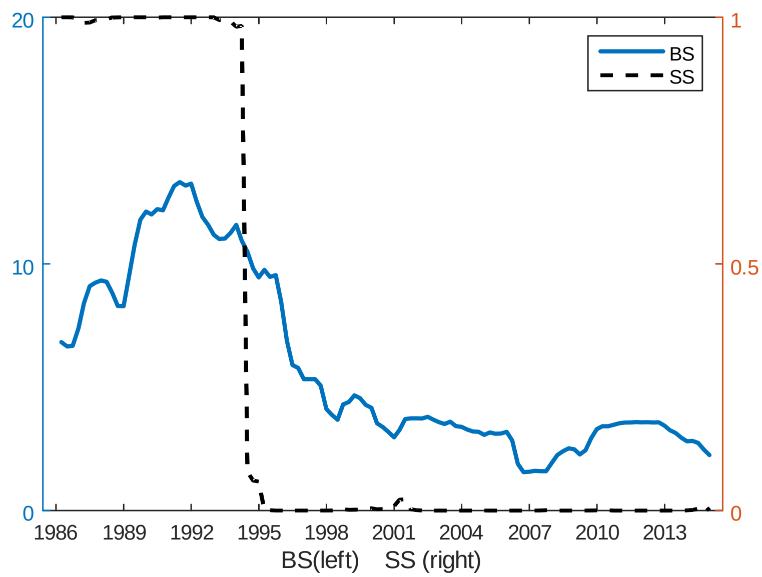

Figure 2: Peruvian GDP Volatility Regimes

This reduction in volatility can also be observed in all components of GDP, as Table 1 illustrates. During the period of high volatility (1983-1994), public investment was the most volatile component of aggregate expenditure, followed by private investment, whereas private consumption remained the most stable one. This pattern is consistent with the historical evidence that shows that, particularly during the 80s, fiscal policy was characterized by persistent primary deficits to finance very innefficient forms of public investment, crowding out private investment. After 1994, all these macroeconomic aggregates have shown a significant reduction in volatility, which is especially noticeable in the case of private consumption, whose volatility decreased 25 percent from the level observed in the period 1983-1994. Equally significant has been the reductions in the volatility of private investment and public investment, around 38 and 46 percent respectively from previous levels.

Table 1: Standar Deviations of Quarterly Growth rates

Macroeconomic Aggregates	1983-1994 (A)	1995-2014 (B)	(B/A*100)
GDP	7.13	2.36	33
Private Consumption	8.36	2.06	25
Private Investment	22.55	8.56	38
Government Consumption	16.92	4.34	26
Government Investment	29.76	13.70	46
Exports	10.18	6.10	60
Imports	17.70	8.62	49

What explains this fall in macroeconoimc volatility? For developed countries, the literature has considered three possible explanations: good policy, a change in the private sector behavior and good luck. According to the former view, monetary policy by achieving low and stable inflation may have contributed to reduce macroeconomic volatility. The second one suggests that information-technology-led improvements in inventory management, which in turn contributed to a more stable behaviour of investment and therefore of the GDP. The good luck view rests on the observation of relatively benign international economic conditions over the "Great Moderation" episode can explain the lower volatility observed during the 90s and half of the 2000s. These hypothesis can be also tested for the case of Peru. On one hand, the substantial improvement in macroeconomic managment in Peru since the 90s, not only through better monetary policy, which achieved price stability since 1996 onwards, but also through better fiscal policy can explain the significant reduction in output volatility. Moreover, the impact of structural reforms that were not only widespread across different sectors of the economy but also very deep in sectors such as the financial system, and the labor market, may also have led to significant changes in the way the economy responds to shocks, reducing macroeconomic volatility. Also the hipotheis of good luck can be consider as relevant for Peru, given the importance of commodity prices in the dynamics of exports and GDP in Peru, a factor that has been particular relevant for the 1990s and 2000, when Peru was more open to global financial conditions.

In order to evaluate these three alternative hypothesis for Peru, in the next section we estimate a time varying structural vector autorresive model, following Primaceri (2005) with quarterly data from 1980 to 2014. The model, by allowing time varying parameters and volatility is suitable to quantify the impact of both lower volatility in structural shocks, including policy shocks and changes in the response of the economy to these shocks.

2.1 Inflation and output volatility

During the 1980s, the Peruvian economy undergone a period of high and volatile inflation that ended up with an hiperinflation at the end of the 1980s. That inflation itself may have led to an increase in GDP volatility does not seem implausible for this particularly period of Peruvian economic history, given the drastic changes in both the average level and the volatility of inflation. Figures 3 and 4 illustrate GDP growth volatility against the four-quarter rolling mean of the inflation rate and against inflation volatility. As these figures illustrate, it can be seen that the temporary increase in GDP volatility in the late 1980s and early 1990s is clearly correlated with the temporary increase in the level of inflation. GDP volatility seems, however, more strongly related to the volatility than to the level of inflation. Although, the correlation between inflation and GDP volatility does not imply causality, this correlation suggests the potential role of monetary policy shocks in generating both inflation and GDP volatility during the period before 1994. This pattern is also consistent with the view that fiscal dominance was a key institutional feature that contributed to generate both output and inflation volatility during the 1980s and that the reforms that end up with fiscal dominance in the 1990s and the strength of the fiscal and monetary policy frameworks may explain the drastic fall in ouput and inflation after 1994.

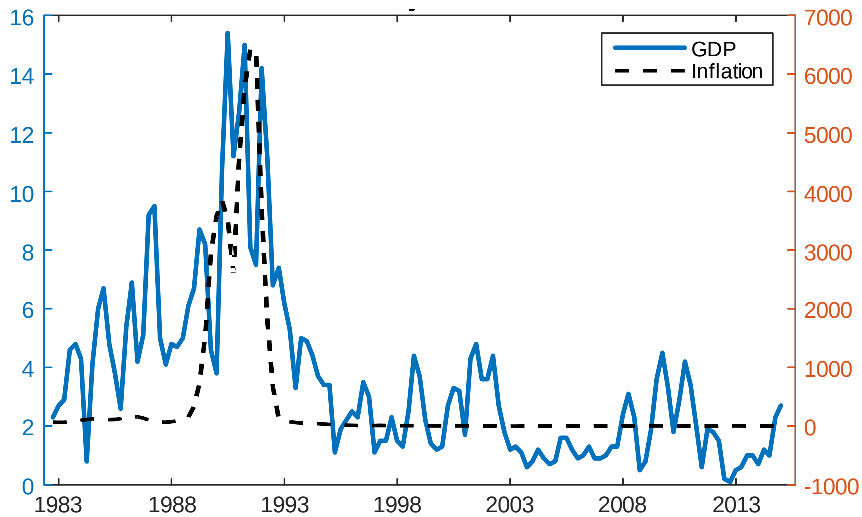

Figure 3: GDP volatility and Inflation

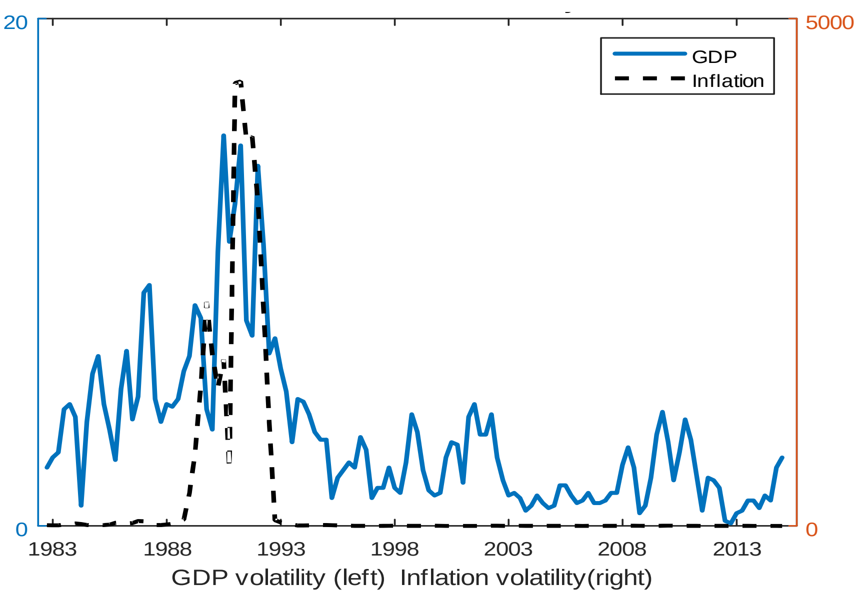

Figure 4: GDP volatility and Inflation volatility

2.2 Monetary Policy

Many papers have studied extensively whether improvements in monetary policymaking has been largely responsible for the drop in output volatility in advance economies. The idea has also considerable intuitive appeal for Peru. According to this view, lower output volatility is the result of central bankers' greater emphasis on, and success at, controlling inflation. The explanation rests on the argument that monetary policy is an important determinant of business cycle, both because it can be a primary source of macroeconomic volatility through its non-systemic component and also because it can contribute to smooth busincess cycle fluctuations by implementing effective counter-cyclical monetary policy.

By achieving low and stable inflation, monetary policy provides a favorable environment for economic activity. Such an environment could contribute to more stable output growth in several ways. Lower inflation reduces nominal distortions, and removes one source of uncertainty that might cloud firms' investment decisions. Finally, to the extent that low and stable actual inflation translates into low and stable expected inflation, policymakers might have more flexibility in responding to unforeseen events, such as financial or banking crises.

In Peru, the stabilization program put in place in the early 90s, the adoption of a flexible exchange rate and the structural reforms that accompanied this program, which granted independence to the central bank and a unique objective for monetary policy, price stability, were fundamental to achieve low and stable inflation rates since middle of the 1990s. In 2002, the central bank adopted an inflation target regime with the objective to secure the gains in price stability that the previous money target framework delivered. A simple inspection of the evolution of inflation and its volatility illustrates the dramatic change in the effectiveness of monetary policy to achive price stability. As we emphasized previously, the improvement in monetary policy and the consequent lower and stable inflation rates are highly correlated with the fall in GDP volatility.

In order to analyze the contribution of monetary policy to the volatility of GDP and inflation in Peru, we use M1 growth as a policy variable. As it is evident from Figure 5, there is a strong realtionship between the volatility of monetary policy, and GDP volatility.

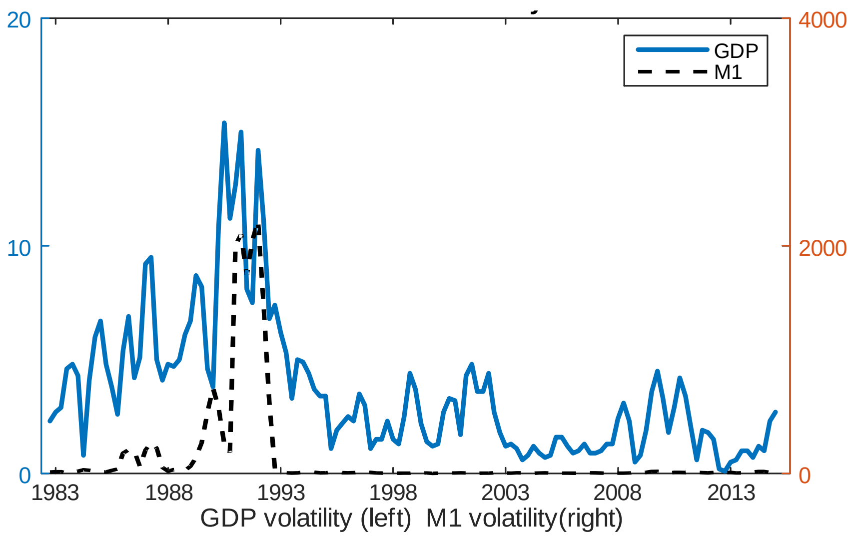

Figure 5: GDP volatility and M1 volatility

It order to assess the contribution of monetary policy shocks to the "Great Moderation", it is necessary to use a model that allows for both time varying shocks variances and structural parameters. To achieve this objective, next we use TV-SVAR approach .

3 The model: a TV-SVAR

Following Primiceri (2005), Benati (2007), Gambetti, Pappa and Canova (2008) and Galí and Gambetti (2009), a multivariate time series model with both time varying coefficients and time varying variance covariance matrix of the additive innovations is used to model the monetary policy, the GDP anf inflation behaviour of Peruvian economy. The main reason for choosing this model is that it allows to capture possible heteroscedasticity of the shocks and nonlinearities in the simultaneous relations among the variables of the model. Thererfore, the advantage of using this model is that it will help us to determine whether the time variation derives from changes in the size of the shocks or from changes in the propagation mechanism.

Let y_t be a 3×1 vector of time series including real GDP growth, the inflation rate and the growth rate of money with a reduced-form representation:

$$y_t = A_{0,t} + \sum_{j=1}^{p} A_{j,t} y_{t-j} + u_t \quad , \tag{1}$$

where $A_{0,t}$ is a 3×1 vector of time varying intercepts; $A_{j,t}$ are 3×3 matrices of time varying coefficients, for each j and u_t is a 3×1 vector of heteroscedastic unobservable shocks with variance covariance matrix Ω_t and and with all lags of y_t. For reasons of comparability with other papers in the literature we set the lag order to $p = 2$. In this reduced-form, $A_{0,t}$, $A_{j,t}$ and u_t involve the structural parameters and shocks, ε_t, across equations, making it impossible to distinguish regime shifts from one structural equation to another. Following Christiano, Eichenbaum and Evans (1996), Primiceri (2005) and Sims and Zha (2006), we use a triangular time varying coefficients system to identify the structural shocks as follows:

$$B_t = \begin{bmatrix} 1 & 0 & 0 \\ \beta_{21,t} & 1 & 0 \\ \beta_{31,t} & \beta_{32,t} & 1 \end{bmatrix} , \tag{2}$$

Since in this identification scheme the order of variables matters, we follow Christiano, Eichenbaum, and Evansand order the variables in the following way: P, M and Y. Hence, a structural shock to GDP will only affect GDP, a structural shock to the growth rate of money will affect GDP and M, and a structural shock to inflation will affect GDP, M and inflation. Each structural shock is identified as follows: for the GDP equation, demand shock; for the Inflation equation, supply shock; and for the monetary policy equation, policy shock.

Following Primiceri (2005) and Galí and Gambetti (2009) we consider the triangular reduction of Ω_t defined as $B_t \Omega_t B_t' = \Sigma_t \Sigma_t'$, where Σ_t is a diagonal matrix. Therefore, we assume $B_t u_t = \Sigma_t \varepsilon_t$.

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & 0 \\ 0 & \sigma_{2,t} & 0 \\ 0 & 0 & \sigma_{3,t} \end{bmatrix} , \tag{3}$$

Then, equation (1) can be rewritten as:

$$y_t = X_t' A_t + B_t^{-1} \Sigma_t \varepsilon_t \quad , \tag{4}$$

with

$$X_t = I_{\mathbf{3}} \otimes [1, y_{t-1}, ..., y_{t-p}] \quad , \tag{5}$$

The dynamics of the model's time varying parameters is specified as follows:

$$
\begin{aligned}
A_t &= A_{t-1} + v_t \quad , &(6)\\
\beta_t &= \beta_{t-1} + \zeta_t \quad , &(7)\\
\log \sigma_t &= \log \sigma_{t-1} + \eta_t \quad , &(8)
\end{aligned}
$$

Following Primiceri (2005), we assume $\varepsilon_t, v_t, \zeta_t$ and η_t to be distributed as:

$$
\begin{bmatrix} \varepsilon_t \\ v_t \\ \zeta_t \\ \eta_t \end{bmatrix} \sim N(0, V), \text{ with } V = \begin{bmatrix} I_3 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}, \tag{9}
$$

where I_3 is an 3-dimensional identity matrix, Q, S and W are positive definite matrices. As Primiceri (2005) pointed out, there are two justifications for assuming a block-diagonal structure for V. First, parsimony, as the model is already quite heavily parameterized. Second, "allowing for a completely generic correlation structure among different sources of uncertainty would preclude any structural interpretation of the innovations".

Finally, following, again, Primiceri (2005) we adopt the additional simplifying assumption of postulating a block-diagonal structure for S,with blocks corresponding to parameters belonging to separate equations. The coefficients of the contemporaneous relations among variables are assumed to evolve independently in each equation. As discussed in Primiceri (2005), this assumption simplifies the inference and increases the efficiency of the estimation algorithm.

4 Estimation method: A Bayesian framework

Our approach follows Primiceri (2005), we estimate the model via Bayesian methods for four reasons. First, we deal with unobservable components, where the distinction between parameters and shocks is less clear than in other situations. Second, if the variance of the time varying coefficients is small, the classical maximum likelihood estimator of this variance has a point mass at zero. Third, the high dimensionality and nonlinearity of the model will quite possibly have a likelihood with multiple peaks, some of which are in uninteresting or implausible regions of the parameter space. Finally, Bayesian methods deal efficiently with the high dimension of the parameter space and the nonlinearities of the model, splitting the original estimation problem in smaller and simpler ones. Gibbs sampling is used for the posterior numerical evaluation of the parameters of interest. Gibbs sampling is a particular variant of Markov chain Monte Carlo (MCMC) methods that consists of drawing from lower dimensional conditional posteriors as opposed to the high dimensional joint posterior of the whole parameter set.

The rest of the section contains the estimation method, a description of the priors and the details of the estimation strategy.

4.1 Priors

We assume that the initial states for the coefficients, for the covariances, for the log volatilities and the hyperparameters are independent of each other. Second, that Q, S and W are distributed as independent inverse-Wishart. Third, that the priors for the initial states of the time varying coefficients, simultaneous relations and log standard errors, $p(A_0)$, $p(\beta_0)$ and $p(\log \sigma_0)$, are normally distributed.

For calibrating the priors distributions we use 40 observations, from 2003:I to 2012:IV. The mean of A_0 is chosen to be the OLS point estimates ($\hat{A}_{OLS}$) and the variance of A_0 is four times the $\hat{A}_{OLS}$ variance. The mean and variance of β_0 are obtained in the same way. For $\log \sigma_0$, the mean of the distribution is chosen to be the logarithm of the OLS point estimates of the standard errors of the same time invariant VAR, while the variance covariance matrix is assumed to be the identity matrix.

Degrees of freedom and scale matrices are needed for the inverse-Wishart prior distributions of the hyperparameters. We set the degrees of freedom to 4 for W and 2 and 3 for the two blocks of S: S_1 and S_2. As Primiceri (2005) pointed out, the reason that the degrees of freedom are chosen differently is that for the inverse-Wishart distribution to be proper the degrees of freedom must exceed the dimension respectively to W and the blocks of S. For Q, we set the degrees of freedom to the size of the previous initial subsample.

Following Cogley and Sargent (2001, 2003), Cogley (2003) and Primiceri (2005), the matrices, Q, W, S_1 and S_2, are chosen to be constant fractions of the variances of the corresponding OLS estimates on the initial subsample multiplied by the degrees of freedom, because, in the inverse-Wishart distribution, the scale matrix has the interpretation of sum of squared residuals.

We can summarize the priors as follows:

$$
\begin{aligned}
A_0 &\sim N(\hat{A}_{OLS}, 4 \times V(\hat{A}_{OLS}), & (10)\\
\beta_0 &\sim N(\hat{\beta}_{OLS}, 4 \times V(\hat{\beta}_{OLS}) \ , & (11)\\
\log \sigma_0 &\sim N(\log \hat{\sigma}_{OLS}, I_3) \ , & (12)\\
Q &\sim IW(k_Q^2 \times 40 \times V(\hat{A}_{OLS}), 40), & (13)\\
W &\sim IW(k_W^2 \times 4 \times I_3, 4) \ , & (14)\\
S_1 &= IW(k_S^2 \times 2 \times V(\hat{\beta}_{1,OLS}), 2) \ , & (15)\\
S_2 &= IW(k_S^2 \times 3 \times V(\hat{\beta}_{2,OLS}), 3) \ , & (16)
\end{aligned}
$$

where S_1 and S_2 denote the two blocks of S, while $\hat{\beta}_{1,OLS}$ and $\hat{\beta}_{2,OLS}$ are the two corresponding blocks of $\hat{\beta}_{OLS}$. It is important noting that k_Q, k_s and k_w do not parameterize time variation, but just prior beliefs about the amount of time variation. As Primiceri (2005), the results presented in this paper are obtained using the values o f $k_Q = 0.01$ and $k_s = 0.1$.In the case of k_w, we have changed the original value proposed by Primiceri from $k_w = 0.01$ to $k_w = 1$. A discussion of the robustness of the period chosen to calibrate the prior distributions, the k_w selected and the variables ordering is shown in Section 7.

4.2 Simulating the posterior distribution

We simulate the posterior distribution of the hyperparameters and the states conditional on the data via the Markov Chain Monte Carlo (MCMC) algorithm. Gibbs sampling is carried out in four steps conditional on the observed data and the rest of the parameters. First we draw in turn time varying coefficients (A^T). Second, we draw in turn the simultaneous relations (B^T). Third, we draw in turn the volatilities (Σ^T). Finally we draw in turn hyperparameters (V).

The rest of the subsection contains the details of this estimation strategy. In what follows, T is the sample length, $p(.)$ is used to denote a generic density function and N denotes the Gaussian distribution.

4.2.1 Drawing coefficient states

Conditional on B^T , Σ^T and V, equation (x) is linear with Gaussian innovations and a known covariance matrix. Following Fruhwirth-Schnatter (1994) and Carter and Kohn (2004) the density $p(A^T \mid y^T, B^T, \Sigma^T, V)$ can be factored as:

$$p(A^T \mid y^T, B^T, \Sigma^T, V) = p(A_T \mid y^T, B^T, \Sigma^T, V) \prod_{t=1}^{T-1} p(A_t \mid A_{t+1}, y^t, B^T, \Sigma^T, V), \tag{17}$$

where

$$\begin{aligned} A_t &\mid A_{t+1}, y^t, B^T, \Sigma^T, V \sim N(A_{t|t+1}, P_{t|t+1}), & (18)\\ A_{t+1} &= E(A_t \mid A_{t+1}, y^t, B^T, \Sigma^T, V), & (19)\\ P_{t+1} &= Var(A_t \mid A_{t+1}, y^t, B^T, \Sigma^T, V), & (20) \end{aligned}$$

The vector of A's can be drawn because $A_{t|t+1}$ and $P_{t|t+1}$ can be computed using the Kalman filter and the backward recursions reported in Primiceri (2005, Appendix A.6) , applied to the state space form given by (4) and (5). The backward recursion starts with the last recursion of the filter which provides $A_{T|T}$ and $P_{T|T}$, i.e. the mean and variance of the posterior distribution of A_T . Drawing a value from this distribution, the draw is used in the backward recursion to obtain $A_{T-1|T}$ and $P_{T-1|T}$ and so on until $t = 1$.

4.2.2 Drawing covariance states

Equations (4) can be written as:

$$B_t(y_t - X_t' A_t) = B_t \hat{y}_t = \Sigma_t \varepsilon_t, \tag{21}$$

where taking A_t as given, $\hat{y}_t$ is observable. Since B_t is a lower triangular matrix with ones on the main diagonal, it can be rewritten as:

$$\hat{y}_t = Z_t \beta_t + \Sigma_t \varepsilon_t, \tag{22}$$

β_t is defined in (6) and Z_t is the following 3×3 matrix:

$$Z_t = \begin{bmatrix} 0 & 0 & 0 \\ -\hat{y}_{1,t} & 0 & 0 \\ 0 & -\hat{y}_{[1,2],t} & 0 \end{bmatrix}, \tag{23}$$

where, $\hat{y}_{1,t}$ is the first row vector of $\hat{y}_t$ and $\hat{y}_{[1,2],t}$ denotes the row vector $[\hat{y}_{1,t}, \hat{y}_{2,t}]$

The vector $[\hat{y}_t, \beta_t]$ is not jointly normal and, thus, the conditional distributions cannot be computed using the standard Kalman filter recursion.

However, under the additional assumption of S block diagonal, this problem can be solved by applying the Kalman filter and the backward recursion equation by equation.

4.2.3 Drawing volatility states

Equations (21) can be written as:

$$B_t(y_t - X_t' A_t) = y_t^* = \Sigma_t \varepsilon_t, \tag{24}$$

where taking A^T and B^T as given, y_t^* is observable. This is a system of nonlinear measurement equations, but can be expressed as a linear one:

$$\begin{aligned} y_t^{**} &= 2h_t + e_t, && (25) \\ h_t &= h_{t-1} + \eta_t, && (26) \end{aligned}$$

with

$$\begin{aligned} y_{i,t}^{**} &= \log\left[\left(y_{i,t}^*\right)^2 + 0.001\right], && (27) \\ e_{i,t} &= \log\left(\varepsilon_{i,t}^2\right) && (28) \\ h_{i,t} &= \log \sigma_{i,t} && (29) \end{aligned}$$

Observe that since ε's and η's are not correlated, then e's and η's are also independent. However, as Primiceri (2005) pointed out, the system has an approximate linear and Gaussian state space form conditional on A^T , B^T , V and s^T , with $s^T = [s1, ..., sT]'$ defined as the matrix of indicator variables selecting at every point in time which member of the mixture of the normal approximation has to be used for each element of e. Like in the previous steps of the sampler, this procedure allows one to recursively recover:

$$h_{t|t+1} = E(h_{t|t+1}, y^t, B^T, A^T, V, s^T), \tag{30}$$

$$H_{t|t+1} = Var(h_{t|t+1}, y^t, B^T, A^T, V, s^T), \tag{31}$$

and recursively draw every $h_t$from $p(h_{t|t+1}, y^t, B^T, A^T, V, s^T)$, which is $N(h_{t|t+1}, H_{t|t+1})$.

Conditional on y^{**T} and the new h^T, the new s^T matrix is sample to be used in the next iteration.

4.2.4 Drawing hyperparameters

Finally, conditional on A^T , Σ^T , B^T and y^T, the innovations are observable, which allows us to draw the hyperparameters- diagonal blocks of V -from their respective distributions.

5 Data

The method described above is applied for the estimation of a small quarterly model of the Peruvian Economy. Three variables are included in the model: real GDP growth, the inflation rate and the growth rate of money. Even though most of the literature has preferred larger sets of variables, the cost would be tighter priors, necessary to avoid ill behaviours. Each structural shock is identified as follows: for the GDP equation, demand shock; for the Inflation equation, supply shock; and for the monetary policy equation, policy shock.

Quarterly sample runs from 1981:I-2014:III .The data of the three variables are from the Central Bank of Peru database. For reasons of comparability with other papers in the literature, two lags are used for the estimation[4]. The choice is mostly due to the attempt to reduce the number of parameters of the model. Simulations are based on 50 000 iterations of the Gibbs sampler, discarding the first 20 000 for convergence. We also assess the convergence of the Markov chain by inspecting the autocorrelation properties of the ergodic distribution's draws.

6 Results

In this section, we present the main empirical results of the paper. Figure 6 depicts the estimated standard deviation of the three shocks of the model. The identification strategy used allows to identify the residual of inflation as an structural supply shock that generates an increase in inflation and a fall in output.This shock can be also interpreted as a shock in inflation expectations, since it shifts the phillips curve. The second shock is interpreted as a monetary policy shock and the third one, as a aggregate demand shock.

Interestingly, monetary policy shocks exhibits a spike in its standard deviation during the second half of the 1980s, which coincides with the rapid

[4]The same analysis that we present in this paper was done for one lag and the results were similar.

increase in inflation and GDP volatility, a result that highlights the importance of the non-systematic component of monetary policy as a source of macroeconomic volatility during this period. Large and unexpected changes in money supply, accelerated inflation and inflation expectations, and further fuelled macroeconomic volatility. The contribution of policy shocks to inflation and GDP growth rate volatility were particularly larger during 1985 and 1986, where hefty monetary stimulus contributed to accelerate inflation and GDP growth. The substantial decline in the volatility of monetary policy shocks since the early 1990s preceded the fall in volatility of both inflation and GDP, which also indicates how the change in the monetary policy framework, by granting independence to the central bank and assigning a unique objective to monetary policy, price stability, reduced a significant source of macroeconomic instability and through this channel contributed to lower macroeconomic volatility after 1993[5].

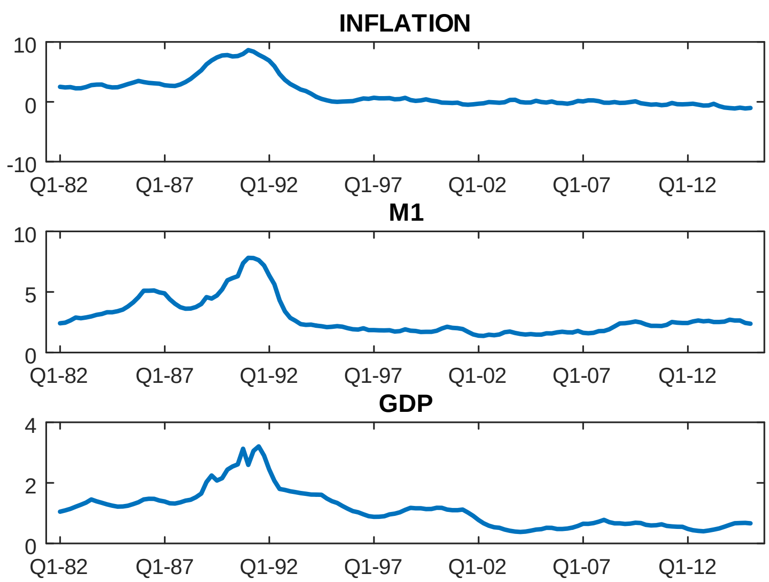

Figure 6: Posterior mean of the standard deviation of the residuals

[5]The average standard deviation of quarterly inflation fell ten times from 1981-1994 to 1994-2014, from 8.1 percent to 0.8 percent quarterly. For the same period, the estimated standard deviation of money growth rate fell by 65 percent from 6.7 percent to 3.7 percent.

6.1 Explaining the fall in GDP volatility

In order to identify which shocks contributed the most to generate high macroeconomic volatility during the 1980s, we simulate the values of output growth shutting down one structural shock at the time. The results of those simulations are depicted in the Figure 7 and in Table 2. In figure 7 the dotted black line represents the volatility of output attributed to monetary policy shocks and supply shocks. Overall the results shows that estimated model explains almost all the decline in GDP volatility. Demand shocks contributed the most to generate the higher GDP volatility during the 1980s, whereas monetary policy shocks, play an important role from 1986 to 1987. As table 2 illustrates, the combination of policy and supply shocks explains close to 50 percent of the decline in GDP volatility. Why these shocks were so important during the 1980s? One explanation is that they are capturing shifts in inflation expectations, triggered by the effects of fiscal dominance on the determination of inflation and by the widespread system of price controls that were in place in Peru during that period. Price controls artificially contained inflation for same time to fuel larger inflation expectations later as prices were gradually adjusted in response to past inflation. This result is also consistent with Sargent, Williams and Zha (2008) that find, using a non-linear markov switching model for Peru that, inflation dynamics from 1980s until 1993 can be explained by persistent jumps in inflationary expectations, triggered by continuous fiscal deficits financed with seignorage[6].

Table 2 : Contribution of structural shocks to GDP volatility

GDP average volatility	1983-1994	1994-2014	change
Observed	7.13	2.36	4.70
Estimated	6.68	1.98	4.77
Demand shocks	3.914	1.00	2.23
Policy and supply shocks	3.46	0.98	2.46

[6] Indeed Sargent, Williams and Zha (2008) report that both inflation and inflation expectatios fall dramatically in 1990 and 1991, even when fiscal reforms were not fully in place. Accoding their results, fiscal reforms had its full impact around 1994.

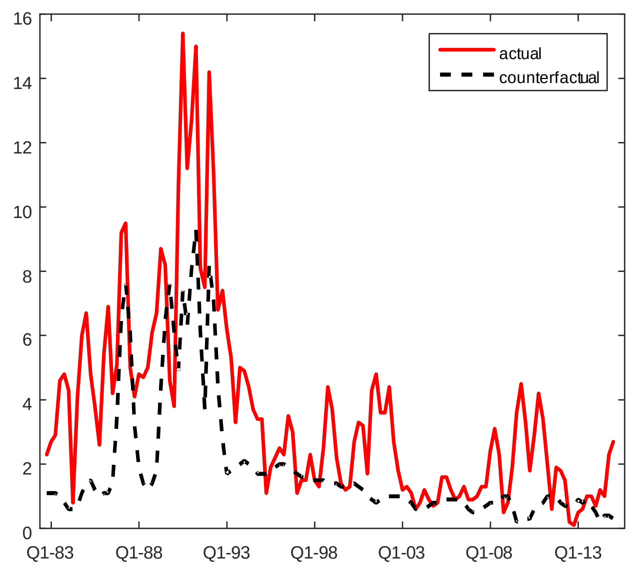

Figure 7: GDP volatility with non-demand shocks

6.2 The role of the systemic component of monetary policy in generating output volatility

Not only the non-systematic component of monetary policy contributed to macroeconomic volatility, but also its systemic component, which by accommodating demand and supply shocks became a source of amplification of macroeconomic volatilityAs Figure 8 shows, the volatility of M1 is highly correlated with the volatility of inflation and that of GDP for the period that preceded the adoption of the inflation-targeting regime. These correlations weaken drastically during the adoption of the inflation-targeting regime to the extent that they become negative for the case of inflation and M1 and close to cero for the case of GDP and M1.

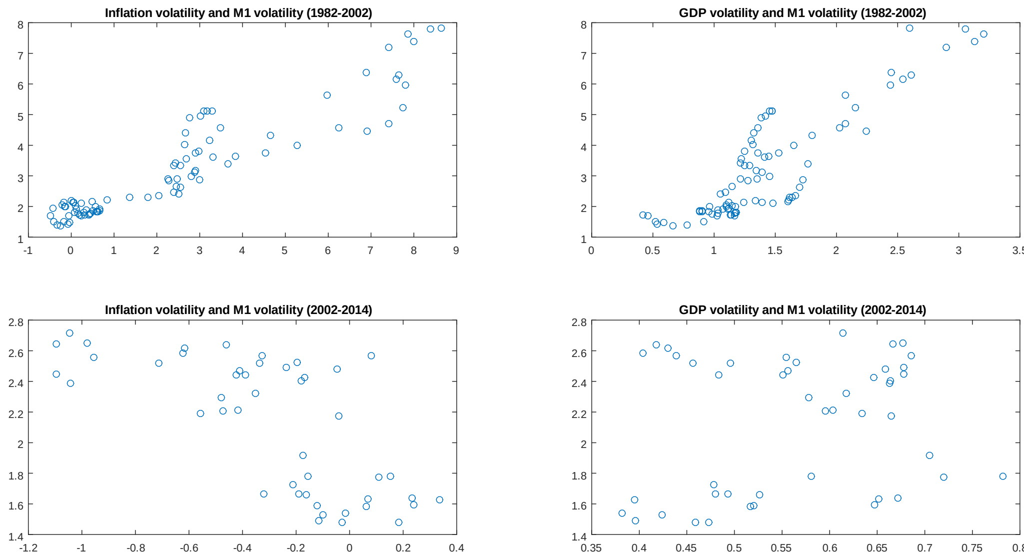

Figure 8: Correlations between volatilities

A key driver of the fall in the correlation between the volatility of these variables is the change in the response of monetary policy to supply shocks. During the 1980s, money supply increased in response to a supply shock, which implied that the central bank accommodated shift in inflation expectations, whereas after, 1993, money supply responded differently, falling in response to the same type of supply shock, which is consistent with a systematic component of monetary policy that intends to stabilize inflation expectations and not to validate them. Figure 9.a illustrates the time evolution of the parameter $\beta_{21,t}$ that captures the contemporaneous response of money to a supply shock. As this figure illustrate this parameter was positive and larger before 1993 and particularly larger in 1990 and 1991, which is consistent with the initial response of the central bank to the liberalization of regulated prices in August 1990s as part of the stabilization program. From 1994 onwards, this parameter becomes negative, which implies that the central bank contracts money supply in response to a supply shock, which is consistent with a monetary policy regime that is more successful in anchoring inflation expectations.

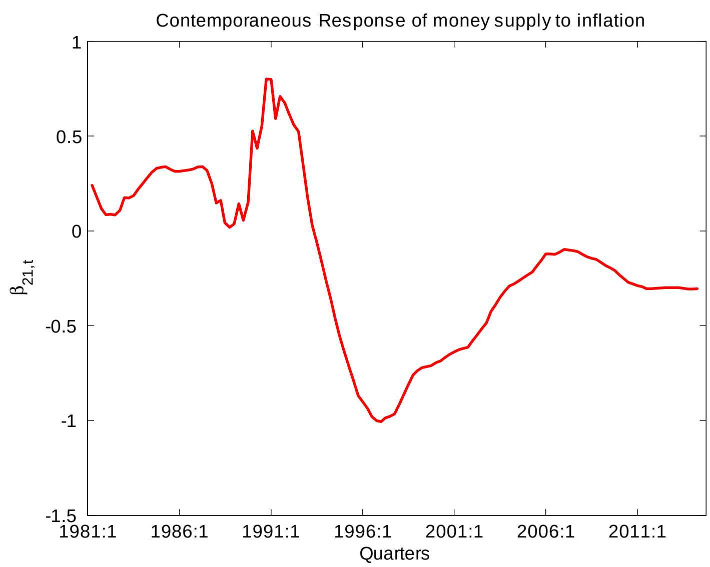

Figure 9.a Estimated response of money supply to inflation.

An alternative way to illustrate the previous result is to use the impulse response functions of M1, the variable that best captures monetary policy during the 1980s and 1990s, to supply and demand shocks.

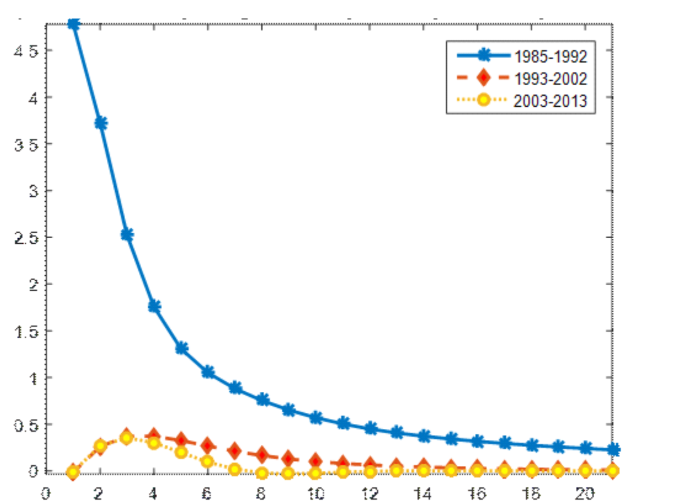

Figure 9b: M1 response to inflation (average of the impulse responses for selected periods)

As Figure 9b shows, there is a striking difference between the response of M1 to supply shocks in the late 1980s and mid-1990s. In the first period, an increase in inflation leads to a large and persistent jump in M1 growth rate, which is almost eleven times larger than the initial increase in inflation, consistent with an extremely accommodative monetary policy, under a regime of fiscal dominance. In contrast, during the 1990s, M1 increased less than inflation, which is consistent with a money aggregate target, the regime in place during that period. It is important to highlight that from 2002 onwards, M1 shocks cannot be directly interpret as monetary policy shocks, since during this period, monetary policy uses as policy instrument, the short-term interest rate. However, it is interesting to observe that the response of M1 to an inflationary shock is even more muted from 2002 onwards than during the period of money-targeting.

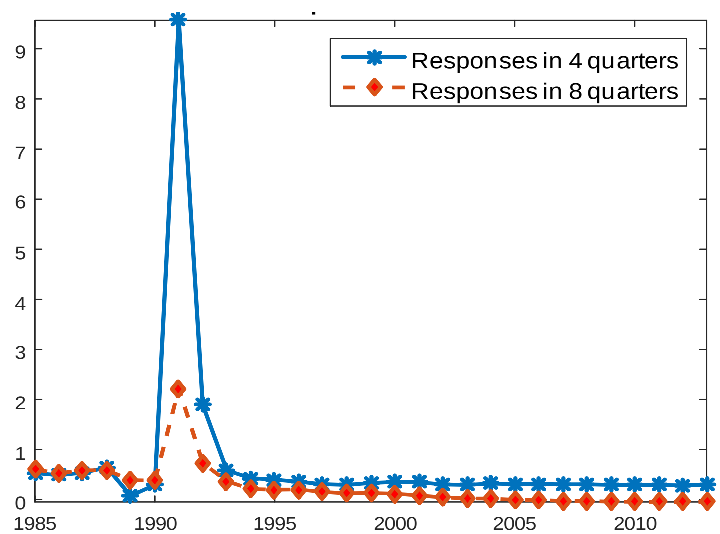

Figure 10: Time varying M1 response (monetary policy response) to supply shocks.

Figure 10 ilustrates the time varying estimation of the M1response to supply shocks. The dotted line corresponds to the response up to 4 quarters, whereas the solid line up to 8 quarters. The figure highights the differences of monetary policy during the sample period. The accomodation of supply shocks is much more intense during 1991, which is consistent with the response of central bank after the liberalization of controlled prices in August 1990, which sharply increased inflation. The larger response of M1 to supply shocks that we observe for the 1980s is particularly large during the 1990 and 1991, period where inflation rates in Peru reached three digit figures. Clearly, this response becomes much more muted during the 1990s and

2000s, which is consistent with a different policy regime, characterized by an independent central bank with the sole objective of achieve price stability. A lower impact of supply shocks on inflation is also consistent with a improve in the central bank credibility that contributes to anchor inflation expectation in a more efficiente way. Castillo, Humala and Tuesta (2012) find empirical evidence that shows that the fall in inflation volatility observed after 1994 is consistent with a improvement in the central bank credibility[7] .

The change in the policy reaction function of the central bank to supply and demand shocks, has also affected the way inflation responds to these shocks. As figure 11 illustrates demand shocks had a larger and more persistent impact on inflation during the 1980s, which reflects the accommodative monetary policy in place during that period and consistent with a monetary policy regime that better anchors inflation expectations and do not accomodate demand shocks, the response of inflation to demand shocks have significantly declined and become less persistent during the 1990s and 2000s.

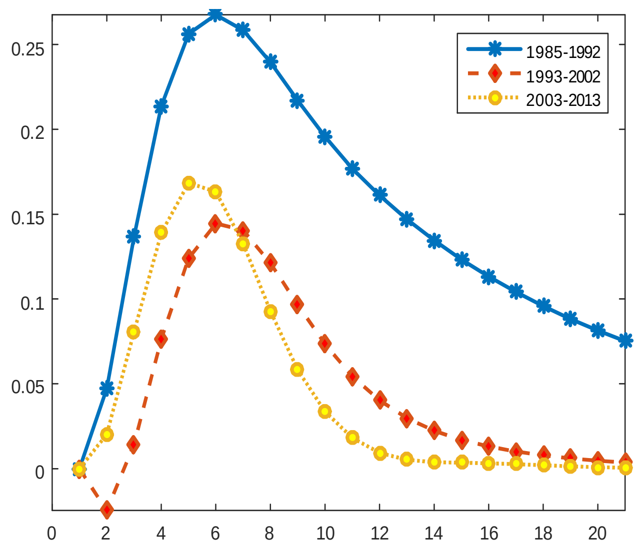

Figure 11: Inflation response to demand shocks (average of the impulse responses for selected periods)

The time varying estimation of the inflation response to demand shocks depicted in Figure 12 shocks shows that the largest impacts of demand

[7]Castillo, Humala and Tuesta (2012) find a substantial reduction on the volatility of transitory and permanent component of inflation shocks. They argue that the reduction in the size of permanent component shocks of inflation is linked to lower monetary policy uncertainty and therefore with a stronger central bank credibility.

shocks on inflation occurred in 1985 and the lowest impacts around 1994. Interestingly, the response after 4 quarters shows a persistent increase since 2000s, which becomes more significant from 2010 onwards as it can be seen on Figure 12.

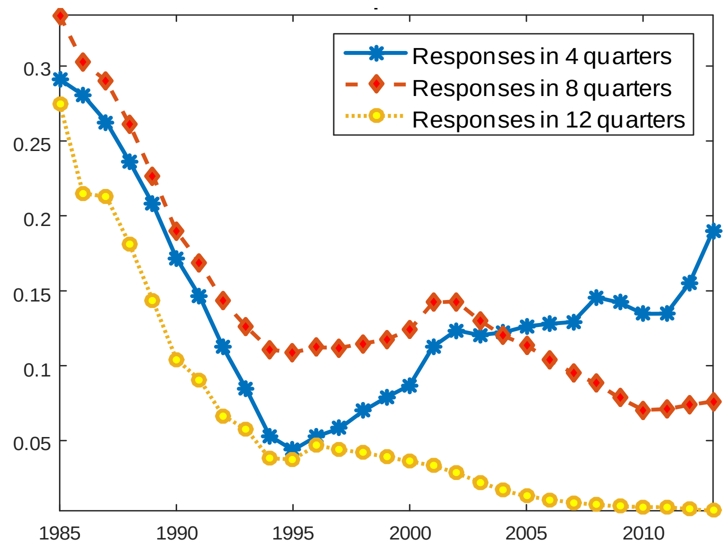

Figure 12: Time evolution of the inflation response to demand shocks.

Figure 13 illustrates that also the inflation response to supply shock has dramatically changed after 1994. As this figure depicts inflation was more responsive to supply shocks during the 1980s than during the 1990s and the 2000s. This response was also more long-lasting during the 1980s, as the impact on inflation did not died after 20 quarters during this period, instead for the 2000s, the same type of shock only affected inflation for 8 quarters.

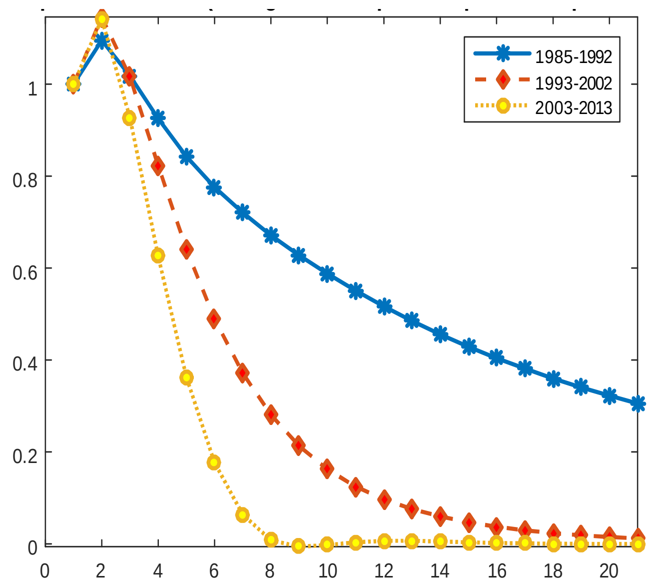

Figure 13: Inflation response to inflation (average of the impulse response for the selected periods)

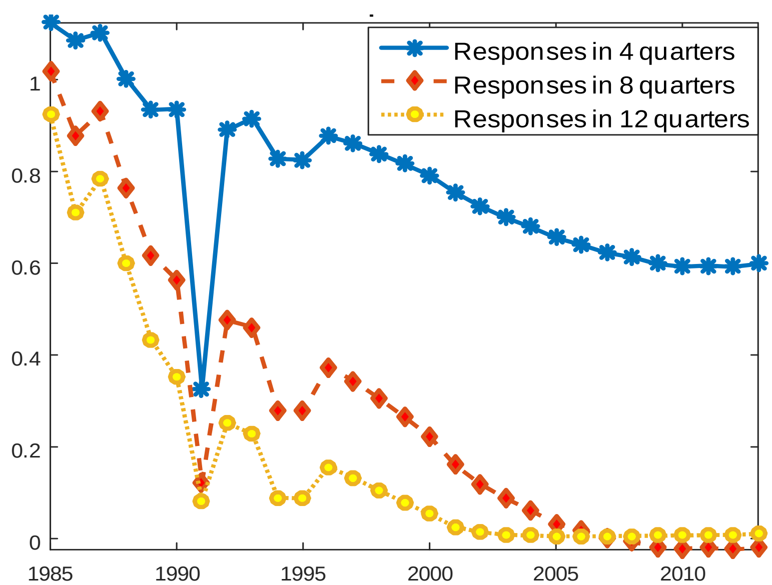

Figure 14: Time varying response of inflation to supply shocks.

Interestingly, the response of inflation to supply shocks falls considerable during 1990, the year that in Peru was put in place the stabilization program aiming at bringing inflation down.

The GDP response to a supply shock has also experimented significant changes in the last three decades. In the 1980s, a supply shock generated a drastic fall in GDP growth, whereas in the 2000s, the impact is very small. These changes in the response of GDP to supply shocks can also be linked to the deep structural reforms that the Peruvian economy experimented in the 1990s, which contributed to reduce the GDP sensitivity to this type of shock, a factor that has also helped to reduce the overall macroeconomic volatility observed in the last two decades.

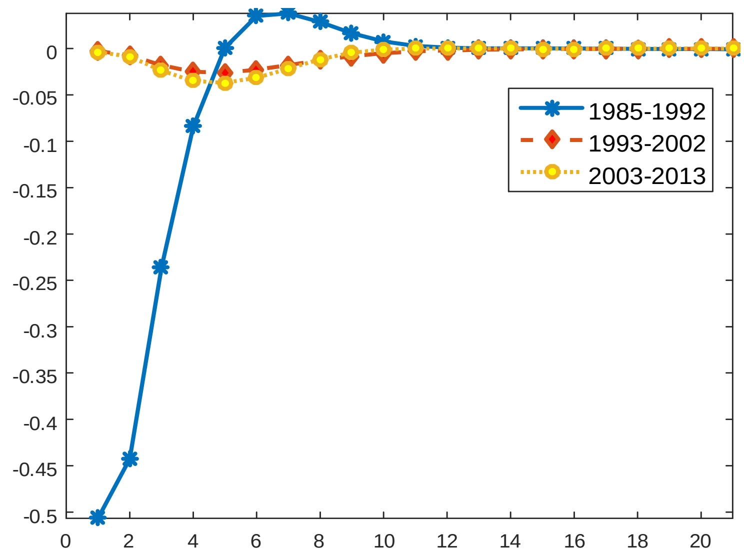

Figure 15: GDP response to inflation (average of the impulse response for the selected periods)

Overall, our findings reflect that the substantial reduction in the volatility of GDP and inflation observed since the early 1990s is the result of a combination of two trends. First, a substantial decline in the volatility of structural shocks, supply, demand and policy shocks have become more stable since the first half of the 1990s. Furthermore, GDP and inflation have become much less responsive to supply and demand shocks, reflecting structural changes and a different policy regime. An illustrative case of these two trends is the evolution of monetary policy, which in the 1980s represented an important source of volatility both by generating unexpected large changes in monetary conditions and by responding pro-cyclically to demand and supply shocks. In contrast, during the 1990s and 2000s, unexpected changes in monetary policy become less volatile, and the central bank has been able to respond counter-cyclically to mitigate the impact of large external shocks like the global financial crisis in 2008 and 2009 and the tapering tantrum in 2013.

7 Robustness to alternative specifications

7.1 Calibration of prior distributions

As we stated in Section 4, the prior distributions are calibrated using the observations from 2003:I to 2012:IV. This period is selected for two reasons: (i) we lose less observations of a stable period. If we choose an earlier period, we can potentially loose a significant fraction of the data for the more volatile period; (ii) the selected period in the base line model corresponds to relatively stable period, which is more representative of the whole sample used. However, our robustness exercises show that our results are not sensitive to the selection of alternative prior's calibration. As Figure 17 illustrates, the time path of the estimated standard deviations of the three shocks in the model are not significantly different if we use alternative prior training periods for the estimation. It is important to highlight that only when observations from 1991 to 1992 are included in the prior's selection sample, the results generated explosive results. This is consistent with the high volatility experimented by Peruvian inflation on those years.

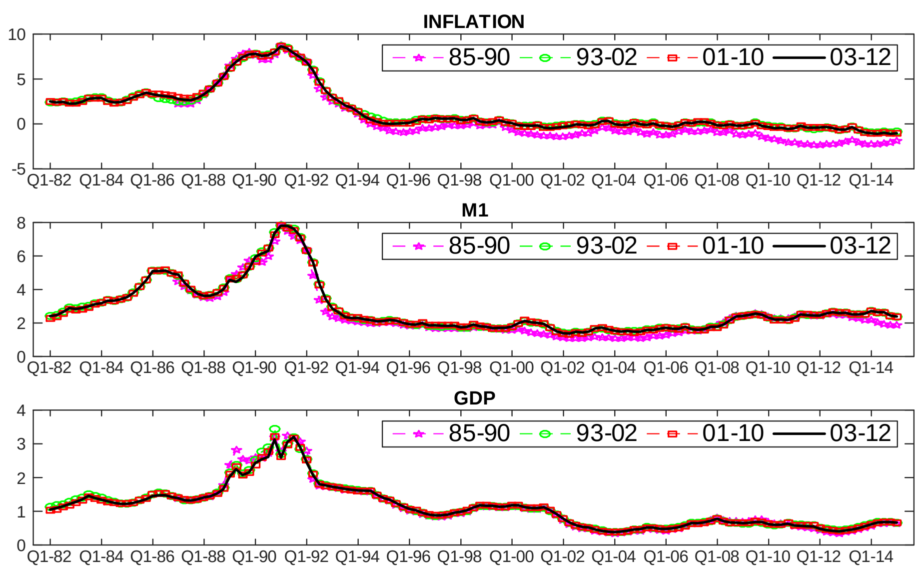

Figure 16: Posterior mean of the standard deviation of the residuals for different period sets in the calibration

7.2 Priors

Since there is a high number of free parameters, the specification of a sensible prior becomes essential, in order to prevent cases of ill-determination like the ones described in Primiceri (2005). It is relevant to notice that k_q, k_s and k_w do not parameterize time variation but just prior beliefs about the amount of time variation. First, we considered using the same set of values proposed by Primiceri (2005). Nevertheless, this was problematic due to the fact that Peruvian data presents really high volatility periods. Therefore, a small value of k_w does not allow the estimates to reproduce the original data and generates impulse response functions where the shocks effects are permanent, reflecting erroneously that our variables that are nonstationary. By setting $k_w = 1$, the model recognises that the variables are $I(0)$. It is relevant for the reader to know that just by selecting a value for k_w higher than 0.02, the model will generate well-behaved impulse response functions and the results will stay similar, as we can see in Figure 17.

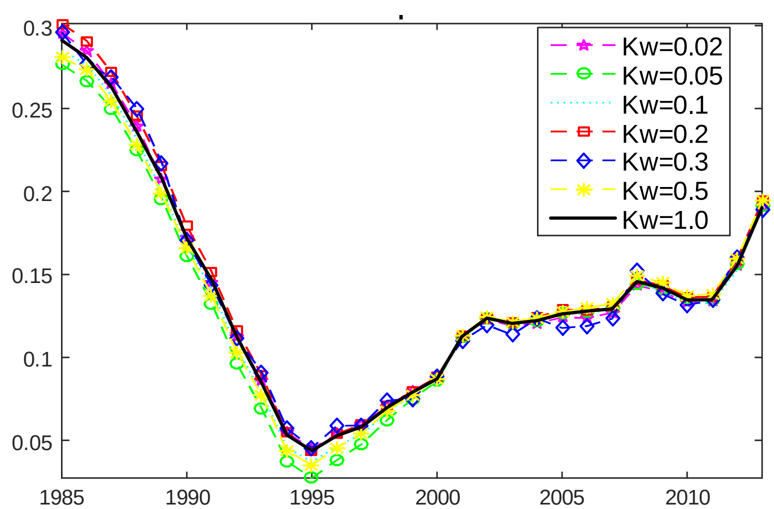

Figure 17: Inflation response to GDP for different values for k_w

7.3 Variables ordering

Our model assumes that monetary policy reacts contemporaneously to inflation. One of our most interesting findings is that the coefficient that captures this relationship shows a change in its sign which clearly marks the transition of the monetary policy behaviour to bringing stability to the

Peruvian economy. As other authors have already pointed out, results of a VAR estimation are almost probable to be different if the variables ordering changes. Despite this possibility, in order to test if this particular result will keep its robustness, we estimate the whole system for different orderings. Results show that, as long as other orderings maintain this relationship between $M1$ and inflation, the sign change in this coefficient still shows up and goes in the same direction, as we can see in Figure 18. Consequently, the results of our analysis are maintained.

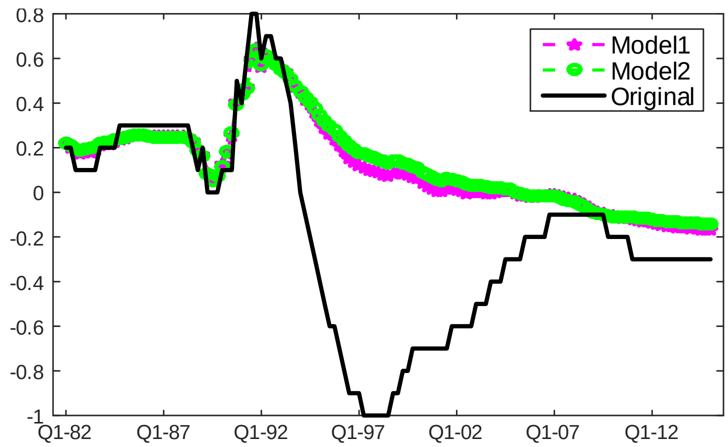

Figure 18: Contemporaneously reaction of monetary policy to inflation for different variables ordering. Model 1= GDP growth, inflation rate and growth rate of money; Model 2 = inflation rate, GDP growth and growth rate of money, Origina l= inflation rate, growth rate of money and GDP growth.

8 Conclusions

The time profile of the dynamics of the aggregate real GDP and inflation have been under intense analysis among many economists over the last decades. Recently, a large body of papers have documented evidence, for the period that preceded the global financial crisis, of a substantial decline in the volatility of the Gross Domestic Product (GDP) for a large set of advance economies, a phenomenon known as the "Great Moderation".

In this paper, we documented a significant decline in the volatility of Peruvian GDP over the last 30 years, particularly since 1995 and we use a Time Varying structural vector autoregressive model Primiceri (2005), Benati (2007), Gambetti, Pappa and Canova (2008) and Galí and Gambetti (2009), to study the determinants of this fall in GDP volatility for Peru.

Our main results show that monetary policy has contributed significantly to the decline in macroeconomic volatility in Peru by reducing the size of the monetary policy shocks and by changing its reaction function in response to demand and supply shocks. In contrast with the high correlations observed between inflation volatility and money growth rate volatility during 1980s, in the 1990s these correlations weaken drastically and in the 2000s, with the adoption of the inflation-targeting regime, they become no significant. A key driver of the fall in the correlation between the volatility of these variables is the change in the response of monetary policy to supply shocks. During the 1980s, money supply increased in response to a supply shock, which implied that the central bank accommodated shifts in inflation expectations, whereas after 1993, money supply responded differently, falling in response to the same type of supply shock, which is consistent with a systematic component of monetary policy that intends to stabilize inflation expectations and not to validate them. According to our results, around 50 percent of the fall in GDP volatility can be explained by the fall in the volatility of policy and supply shocks since 1994.

Overall, our results shows that the substantial reduction in the volatility of GDP and inflation observed since the early 90s is the result of the combination of two trends. First, a substantial decline in the volatility of structural shocks, supply, demand and policy shocks have become more stable since the first half of the 90s. Second, GDP and inflation have become much less responsive to supply and demand shocks, reflecting structural changes and a different policy regime.

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