Good Luck or Good Policy: A Time-Varying Parameters VAR Analysis in the BRICS

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Abstract

By analyzing the evolution of exchange rate pass-through we investigate the Great Moderation that has occurred since the beginning of the 1990s in the BRICS countries. We focus our study on the two main theories that explain the reduction of macroeconomic variables volatility: the ≪good policy≫theory with the adoption by central banks of an inflation targeting framework coupled with a flexible exchange rate regime and the ≪good luck≫theory with the reduction of external shocks persistence. The distinction between both theories is made by testing several Time-Varying Parameters Vector AutoRegressive models with different prior on VAR parameters for the structural changes, and on the variance-covariance matrix for the stochastic volatility. Even if the ≪good luck≫theory seems to be the dominant factor, the 2008 financial crisis shows that it is not enough to explain the Great Moderation that has occurred in emerging countries since the 1990s.

Keywords: great moderation; exchange rate pass-through; emerging economies;bayesian VAR
JEL classification: C11; C32; E31; E42; E58

≪*Given that the structure of an econometric model consists of optimal decision rules of economic agents, and that optimal decision rules vary systematically with changes in the structure of series relevant to the decision maker, it follows that any change in policy will systematically alter the structure of econometric models.*≫ Lucas (1976)

1 Introduction

Economic literature shows that the volatility of macroeconomic variables has decreased over time since the Second World War in developed countries. This phenomenon named the Great Moderation consists in explaining the reasons for which countries are more and more willing to be immunized against external shocks as oil prices for example.

Even if papers propose several explanations as the decrease of the oil share in the production process or a better financial system that permits to smooth both consumption and investment over time, economic literature generally agrees to say that the ≪good policy≫theory with the adoption by central banks of an inflation targeting (IT) framework coupled with a flexible exchange rate (NEER) regime and the ≪good luck≫theory with the reduction of external shocks persistence are the two main causes of the Great Moderation.

The aim of this article is to analyze the exchange rate pass-through (ERPT), or the impact of the NEER on domestic inflation (CPI) to know which of these two theories explains the reduction of macroeconomic variables volatility in BRICS countries. We decide to use this group of countries to study the Great Moderation because all of them have adopted either an IT framework or have changed their NEER regime. We compare the evolution of estimates before and after countries experience monetary changes. This is relevant because the stabilization of CPI dynamics with a better communication and an anchoring of the private agents′ expectations, and the flexibility of NEER are prerequisites to decrease the ERPT.

Since Sims (1980), Vector AutoRegressive (VAR) models have become very popular and useful to study the relationships between macroeconomic variables. However, this model is criticized because parameters are considered as being constant over time and this assumption has attained some limits. Estimates of both structural parameters and macroeconomic variables volatility can evolve over time. Even if VAR models permit to regress a high number of parameters on a short sample without having problems of tractability or over-parameterization, considering time variation in parameters or in the variance-covariance matrix increases significantly the number of estimates.

A solution is to consider Bayesian methods that impose prior on parameters. We decide to use a Time-Varying Parameters VAR model (TVP VAR) because it permits to solve over-parameterization problems as explained later. This condition is essential in the study of nonlinear relationships. A limit of this model is that breaks in data are gradual and constant over time. To solve it, we use a dynamic mixture model whose the algorithm was proposed by Gerlach, Carter and Kohn (2000) and already used in Koop et al. (2009). It permits to put different prior on probabilities of having changes in estimates and let the data speak and choose themselves the occurence of a break. Then, we compute the model with the probabilities of getting a break in estimates. Impulse Response Functions (IRFs) are used for interpretations.

We show that the best results are obtained with stochastic volatility of macroeconomic variables but without structural parameter changes. Inversely, models allowing structural changes get the worst results. These results seem to validate that the ≪good luck≫theory has played a dominant role in the reduction of macroeconomic variables and we cannot conclude that the implementation of an IT regime or NEER regime changes with more flexibility in the currency fluctuations have played any role. However, by analyzing results obtained during the 2008 financial crisis, the ≪good luck≫is not the only one factor that explains the ERPT evolution over time. Indeed, even if it has increased significantly for almost all the countries in 2008, the ERPT is of the same magnitude as during the 1998 Asian and 1999 Russian crises, previous currency crises as at the end of 2001 in South Africa or NEER regime changes as in China and India whereas the NEER volatility was greater in 2008. Other reasons as a greater interconnection among economies or stronger economic fundamentals in emerging countries can explain the disconnection between NEER and the CPI.

The article is organized as follows. Section 2 reviews the existing literature about the Great Moderation and TVP VAR models. The methodology and data are presented in the third section. Section 4 states the results and our interpretations. Section 5 provides the conclusion. Appendices A and B present respectively the data sources with size samples and stationary tests, and summarize the central bank's monetary objectives with a short recall of events that can affect the economic structure. Appendix C presents the bayesian methodology, tables of results and graphs representing the posterior mean of standard deviation of NEER. Appendices D and E contain graphs showing the convergence of the Markov Chain Monte Carlo (MCMC) algorithm and IRFs.

2 Review of literature

Economic literature agrees about the diminution in macroeconomic variables volatility in developed countries since the mid-1980s. Authors focused their attention on the evolution of business cycle or of its components. However, they disagree about the causes of this trend.

2.1 The ≪good policy≫theory

The first cause refers to the adoption of an IT regime coupled with a flexible NEER regime. This new framework allows central banks to get a lower and a more stable CPI environment thanks to a better knowledge of transmission mechanisms. In a monopolistic model in which there is a link between the persistence in the cost function and the firm′s pricing power, Taylor (2000) shows that firms have no incentive to update their prices because of the decrease in cost changes persistence since the CPI dynamics are fully managed by the central bank.

Another explanation consists in considering a country with a flexible NEER regime. International firms know that the currency value is fully determined by the demand and supply in the foreign NEER market. Any changes in the currency value that impact their cost functions by using foreign inputs will not be permanent. Thus, firms have no incentive to change their prices to get a given level of profit contrary to firms located in a country with a fixed NEER regime. In the later case, the currency value is directly set by the central bank and any decisions of this institution are likely to be persistent.

Clarida, Galí and Gertler (2000) show that the dynamics of both CPI and the production were more instable before the 1970s. The monetary policy proxied by a forward-looking Taylor type rule with these two components was not agressive enough vis-a-vis the CPI. The anchoring of private agents' expectations about the future CPI dynamics give more flexibility for the central bank to manage an unforeseen adverse shock – Summers (2005). Clarida, Galí and Gertler (2000) also show that countries having adopted an IT framework have got less unstable CPI dynamics before or during the Great Moderation.

Blanchard and Galí (2010) focus on the evolution of oil prices and its impact on US GDP. They find that, in the 1970s, oil shocks were associated with other large shocks as commodity prices for example. The evolution of oil prices cannot explain all the decrease of macroeconomic volatility. They conclude that monetary policy decisions in targeting CPI dynamics have played a dominant role in the reduction of macroeconomic volatility. Barsky and Kilian (2002) confirm this result by showing that the stagflation which occurs in the 1970s, i.e. a very low growth coupled with a very high level of CPI, is not only explained by oil prices shocks but also by monetary policy decisions.

By studying the relationships between CPI, unemployment and a proxy of interest rates on post World War II US data, Cogley and Sargent (2002) are the pioneers in the using of a TVP VAR model but without stochastic volatility. It means that the innovation covariance matrix is set to be constant over time. They forecast the core CPI and natural rate of unemployment by using both the long term forecast of CPI and unemployment with Clarida, Galí and Gertler (2000) structural identification. The persistence and variance in the CPI dynamics are also analyzed and they estimate a Taylor-type rule in order to highlight changes in the central bank′s monetary policy. Their goal is to confirm the Lucas's (1976) suggestion about the evolution of the systematic part of monetary policy rule[1]. They find that the adoption of an IT framework has allowed central banks to reduce both the CPI and its persistence because of their positive relationship. Other papers have shown structural changes by using a TVP VAR model.

Baumeister and Peersman (2012) study the evolution of the impact of an oil supply shock on the US economy. They prove that the reduction in the effects of oil prices is better explained by the demand side since unfavorable supply shock does not explain the high levels of CPI in the 1970s. Moreover, Clark and Terry (2009) show that energy prices have less impact on core CPI even if central banks take less commodity prices into account in their monetary strategies and in spite of recent increases in this component of CPI.

Muntaz and Sunder-Plassmann (2010) study the impact of demand, supply and nominal shocks on the evolution of real NEER, the output, and CPI by considering four major economies (the UK, Japan, Canada, and the Eurozone). They prove that the transmission mechanisms have evolved over time but that both the sign and timing of these changes vary according to the country. For example, there has been a greater impact of nominal shocks on the real NEER for all the countries since the mid-1980s except for Canada for which these changes have occurred since the 1990s. Moreover, a supply shock appreciates the real NEER for the UK and the Eurozone whereas this shock depreciates it for Japan.

Franta, Horváth and Rusnák (2011) study the evolution of monetary policy in the Czech Republic since 1996 and focus on the current financial crisis. They prove that the ERPT has been reduced over time because of a better central bank′s credibility in attaining the CPI targets. They also show that the deepening of financial sector explains the rise in the response of prices and output to a monetary shock.

2.2 The ≪good luck≫theory

Several papers assess the idea that the Great Moderation has taken place because shocks that have occurred since the mid-1980s as oil prices have become smaller than in previous periods. Even if Summers (2005) rejects the ≪good luck≫theory, others as Stock and Watson (2003, 2005) that work on heterokedasticity of error terms show that the occurrence of smaller shocks explains the reduction in the volatility

[1] The systematic part of monetary policy represents the interest changes involved by both unemployment and CPI. On the other side, non-systematic part of monetary policy consists of ≪policy mistakes≫and the interest rates changes explained by other factors than CPI and unemployment

of macroeconomic aggregates.

Cogley and Sargent (2005) complete Cogley and Sargent (2002) by adding stochastic volatilities in a TVP VAR model. They confirm both the positive relationship between the mean of CPI and its own persistence, and their diminutions in the 1980s and 1990s compared to the 1970s. However, they only confirm the ≪good luck≫theory since, by allowing stochastic volatility in the model, parameters of the monetary policy rule do not evolve over time.

Primiceri (2005) also uses a TVP VAR model in which simultaneous relations among variables evolve over time. To do it, a MCMC algorithm is used to compute both the likelihood and the posterior numerical evaluation. Primiceri (2005) estimates a multiple equations model and proves that, even if parameters of monetary policy rule have evolved over time, the ≪good luck≫theory plays a significant role in the reduction of volatility. Indeed, even if the US central bank has been more concerned about CPI and unemployment since the 1980s with changes in its reaction function, the high levels of these two last components during the 1970s are more explained by non-policy shocks than interest rate movements. Thus, the US interest rate changes cannot explain the periods with high levels of CPI and unemployment.

Sims and Zha (2006) confirm Primiceri′s (2005) results by using a Markov Switching model. They test several versions of the framework by allowing for example only stochastic volatility with no parameters changes (≪good luck≫theory) and inversely (≪good policy≫theory). Even if they show that the monetary policy in the 1980s is different from the one of the 1970s, regime changes are explained by the evolution of variance of monetary policy residuals and not by parameters changes in the equations. This result confirms the ≪good luck≫theory at the detrimental of the ≪good policy≫theory.

Other papers have used the model proposed by Primiceri (2005) as Benati and Muntaz (2007). They confirm that the ≪good luck≫theory has played a great role in the reduction of macroeconomic volatilities by proving that, even if the systematic part of the monetary policy has been improved, it has had no dominant effect in explaining the Great Moderation.

To finish, Canarella et al. (2008) find that, in the case of the UK and the USA, the Great Moderation terminates at the beginning of the current financial crisis. They conclude that the occurrence of great unforeseen adverse shocks since 2007 reinforces the ≪good luck≫theory.

2.3 Other causes of the Great Moderation

2.3.1 A well-developed financial system

To foresee a future loss of revenue, households and firms can smooth respectively their consumption and production in an economy with a well-developed financial system. It is reinforced for countries with financial innovations that permit to create more sophisticated credits. The financial openness also permits to get financing from the rest of the world and to reduce the dependence of investment project to the economic situation of only one country (Cecchetti, Flores-Lagunes, and Krause (2006), and Dynan, Elmendorf, and Sichel (2006)).

2.3.2 Inventory management

Another factor refers to the inventory management as explained by McConnell and Perez Quiros (2000), Kahn, McConnell, and Perez Quiros (2000), Kahn et al. (2002), and Ramey and Vine (2006). Summers (2005) explains that inventories ≪act as buffer between production and sales≫. Almost visible in the mid-1980s, the reduction in the production volatility associated to a constant volatility of sales explains the reduction in the volatility of GDP. Summers (2005) concludes that a better inventory management coupled with a better monetary policy can be considered as a cause of the Great Moderation. Herrera and Pesavento (2009) confirm this theory by explaining that a better inventory management does not need to be associated to a better monetary policy to highlight a reduction in macroeconomic aggregates volatility.

2.3.3 A decrease of the oil share in the economy

Blachard and Galí (2010) explain the decrease of the effect of an oil shock on both CPI and economic activity over time by the diminution of oil share in both consumption and production.

A common limit of papers using a TVP VAR model as Cogley and Sargent (2002 and 2005) and Primiceri (2005) is that coefficients of parameters and/or variance-covariance matrix vary at each period. Koop et al. (2009) use an algorithm of Gerlach et al. (2000) that permits to compute the probabilities of changes in the coefficients at each period of a sample. In their framework, data chooses if a change in estimates of parameters or variance-covariance matrix occurs. As TVP VAR models imply gradual but constant evolutions in the parameters, they test different prior to get models having few breaks with great changes, or multiple changes with small breaks for example. By using the same methodology as Primiceri (2005), they run a TVP-VAR model with dynamic mixtures on the federal funds rate, unemployment level, and CPI dynamics. They prove that a hierarchical prior with a Bernoulli distribution according to which the probability of estimates changes is equal to 0.5 is the best model compared to other prior including changes at each period as in Primiceri (2005), or changes in some estimates as in Cogley and Sargent (2002 and 2005), or a VAR model without time varying parameters.

3 The model and data

3.1 State space representation

To present the model, we adopt the notations of Primiceri (2005) and Koop et al. (2009).

Under a state space representation, the measurement equation is:

$$Y_t = Z_t \alpha_t + \epsilon_t \tag{1}$$

Where Y_t, Z_t, α_t, and ϵ_t are respectively a p-column vector of dependent variable, a p by m matrix of explanatory variables consisted of dependent variables, the intercepts, and exogenous terms, a m-column vector of VAR coefficients and a p-column vector of error terms such that $\epsilon_t \rightsquigarrow N(0, H_t)\ \forall t = 1, \ldots, t$.

Under a triangular reduction form, the error covariance matrix H_t of (1) is

$$A_t H_t A_t' = \Sigma_t \Sigma_t \tag{2}$$

A_t and Σ_t are respectively a lower triangular matrix

$$\begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{n1,t} & \cdots & a_{n(n-1),t} & 1 \end{pmatrix} \tag{3}$$

And a diagonal matrix

$$\begin{pmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{pmatrix} \tag{4}$$

Finally, the reduced form model is

$$y_t = Z_t \alpha_t + A_{t-1} \Sigma_t v_t \tag{5}$$

Such that v_t is identically and independently distributed and $var(v_t) = I_n$.

To get time-varying parameters, we need to specify three state equations.

- Homoskedastic case as in Cogley and Sargent (2002): estimates of VAR parameters change over time but the measurement error covariance matrix H_t is constant. It means that a shock at the i^{th} period has the same effect on the other variables for all the periods

$$\begin{aligned} \alpha_{t+1} &= \alpha_t + \epsilon_t \\ ln(h_{t+1}) &= h_t \\ a_t &= a_{t-1} \end{aligned} \tag{6}$$

  With $\eta_t \rightsquigarrow N(0, Q_t)$ which is independent of ϵ_t $\forall t$

- Heteroskedastic case as in Primiceri (2005): estimates change at each period with a random walk process for the free elements of A_t and a geometric random walk process for Σ_t to get a stochastic volatility framework

$$\begin{aligned} \alpha_{t+1} &= \alpha_t + \epsilon_t \\ ln(h_{t+1}) &= h_t + u_t \\ a_t &= a_{t-1} + \zeta_t \end{aligned} \tag{7}$$

  $u_t \rightsquigarrow N(0, W)$, and $\zeta_t \rightsquigarrow N(0, C)$ with C being a block diagonal matrix and parameters of each equation being independent among them. u_t, and ζ_t are independent of ϵ_t, η_t and among them $\forall t$. Notice that the matrices Q, S and C are positive definite. Moreover, the simultaneous relationships among variables vary independently of each other since the matrix S is block diagonal

- Dynamic mixture model: TVP VAR models are known to let the coefficients vary over time but these changes occur at each period and they are gradual and constant. The main advantage of the dynamic mixture model is that data chooses the periods at which a break occurs and its size. In our regressions we will consider several kinds of breaks. To assess them, we consider the following random walk processes

$$\begin{aligned} \alpha_{t+1} &= \alpha_t + K_{1,t}\epsilon_t \\ ln(h_{t+1}) &= h_t + K_{2t}u_t \\ a_t &= a_{t-1} + K_{2t}\zeta_t \end{aligned} \tag{8}$$

  With $K_{j,t} \in \{0, 1\}$ $\forall j = \{1, 2\}$. The prior and distribution of K are explained in the appendix C.

  Notice that we make the reasonable assumption that if there is stochastic volatility in the model then the simultaneous relations between the variables vary too. Thus, either all the elements of the measurement error covariance matrix evolve over time, or they are restricted to be constant during the regressions

The MCMC algorithms used to draw the different parameters are described in the appendix C. All these regressions will be compared with a VAR model without time varying parameters and we will retain the model that maximizes the information criteria.

3.2 Restrictions and structural representation

To get identification of the model, let us consider the following structural VAR

$$Y_t = Z_t A_t + \Gamma_t z_t \tag{9}$$

Where $z_t \rightsquigarrow N(0, I)$. We need to specify $\frac{n(n-1)}{2}$ restrictions in Γ_t to get a well identified model.

We decide to apply a Cholesky decomposition of innovations as in Ito and Sato (2007 and 2008) to get this identification. It means that a variable ordered earlier has an immediate effect on the following variables and a variable ordered later has a lagged effect on the previous variables. Consequently, Γ_t is a lower triangular matrix. Thus, the relationships between the reduced form model and the structural VAR become:

$$\Gamma_t = A_{t-1}\Sigma_t \tag{10}$$

A_t and Σ_t can be used to get the draws of Γ_t and allow us to compute directly the IRFs.

3.3 Data

We focus our study on BRICS countries (Brazil, China, India, Russia and South Africa). Data start in January 1994 and are seasonally adjusted on the frequence of monthly. Ends of samples vary according to data availability and are specified in the appendix A with data sources and their definitions, size samples, descriptive statistics (table 1) and ADF tests (table 2).

Data series are considered in their natural logarithm. We follow the methodology proposed by Ito and Sato (2007 and 2008) who study the evolution of the ERPT on a panel of Asian countries since the Asian crisis. Thus we use

- World oil prices representing the supply side of the economy
- Output gap computed with a Hodrick Prescott filter on the composite leading indicators. It represents the demand side of the economy
- Money supply by using M1 as proxy of the central bank′s monetary policy
- Bilateral NEER – national currency per US dollar
- CPI

ADF tests have confirmed that variables are not stationary in level, except for the output gap. We differentiate once the four other variables and we confirm their stationarity with another ADF test.

In our regressions, oil prices and output gap are listed first. It means that both the supply and demand shocks are predetermined and are not immediately influenced by other variables. Then, we rank the money supply, NEER, and CPI. The central bank′s decisions have immediate effects on both the NEER and CPI. It also means that the central bank′s reaction according to the NEER and CPI dynamics are taken with a lag. To finish, the NEER is placed before the CPI in order to analyze the ERPT evolution.

4 Results and interpretations

4.1 Econometric results

Tables 4 to 8 available in the appendix C present results for each country with the number of lag, information criteria and probability of changes in both parameters and volatility estimates. By regressing models with structural changes and stochastic volatilities and models without estimates changes, we have seen that better results are always obtained with one lag. Consequently, regressions with only structural changes or stochastic volatility are only tested with one lag.

We can establish a ranking of model performance. From the worst to the best model we get

- Models with no possibility of volatility changes and with Primiceri prior for parameters coefficients ($K_{1,t} = 1$ and $K_{2,t} = 0$)
- Models with no possibility of volatility changes and mixture innovation for parameters coefficients ($K_{1,t} \in [0, 1]$ and $K_{2,t} = 0$)
- Primiceri prior for both groups of coefficients ($K_{j,t} = 1 \; \forall j = \{1, 2\}$)
- Mixture innovation for both groups of coefficients ($K_{j,t} \in [0, 1] \; \forall j = \{1, 2\}$)
- Constant VAR ($K_{j,t} = 0 \; \forall j = \{1, 2\}$)
- Mixture innovation or Primiceri prior for stochastic volatility but no possibility of VAR parameters changes ($K_{1,t} = 0$ and $K_{2,t} \in [0, 1]$)

We notice that the less VAR parameters are allowed to vary over time, the better the model performance is. This result is confirmed by analyzing the probability changes since they are always very low for the VAR parameters – even when we use a prior with a high probability of breaks – whereas they are always high for the stochastic volatility. The analysis of ERPT confirms previous results. Figure E.1 shows the responses of CPI when a shock on NEER occurs in January of each year. We find that these responses have the same pattern and do not vary enough over time to conclude that structural changes occur in the samples compared to previous studies using the same methodology on other subjects as in Koop et al. (2009).

Notice that the information criteria results between regressions using the same time-varying parameters but with different prior are very close. We consider that it has no incidence in our interpretations because graphics of IRFs (not represented in the appendix to save space but available on request) are the same regardless the prior used. Moreover, information criteria results between models with different time-varying parameters are different enough to draw robust conclusions.

At the beginning of our work, we expected to find structural changes for the five countries because of both monetary policy and NEER regime changes that have occurred since the 1990s. However, even if these changes had consequences on transmission channels, the aims of monetary policy do not evolve significantly as recalled in the appendix B. In the Brazilian and South African cases, the implementation of an IT framework should conduct to have structural breaks in the regressions at least respectively in June 1999 and February 2000. However, they have already adopted a disinflationary process at the beginning of our sample. In the three other countries and without taking the different crisis into account, changes concern the NEER regime with stochastic volatility as shown by the figures B.2 to B.4 and not the primary goals of monetary policy. Consequently, relationships among the five equations of the model do not change a priori. Moreover, for the reasons explained in section C, we calibrate our prior by considering the full sample and not only a given period as in Primiceri (2005) for example. This last specification avoids to get breaks in structural coefficients only by considering a period under a given monetary regime. Thus, it is not surprising that the best models are those with stochastic volatilities and no structural break.

4.2 Evolution of stochastic volatility

Our regressions seem to confirm that the ≪good luck≫theory has played a dominant role in the Great Moderation. To confirm this result, we are going to compare the evolution of an NEER shock on CPI for a given time horizon with both the NEER in first differences and the posterior mean of NEER standard deviation to identify the different episodes of NEER volatility.

We share our analysis in three sections by considering first the Asian and Russian crisis that is common for the five countries, then specific currency crisis or NEER regime changes that have occurred in each country, and the 2008 financial crisis as a possible end of the Great Moderation.

4.2.1 Asian and Russian crises

We consider the Asian crisis in 1998 and the Russian crisis in 1999 that caused NEER depreciations (figures B.1 to B.5) with strong negative capital inflows for emerging countries. These two crises implied ERPT for four countries. It becomes significant for India, Russia, and South Africa but it remains not different from zero for Brazil (figures E.2 to E.6). As for China for which the ERPT decreases and attains a through at this period, the presence of a currency peg regime can explain the non-significant Brazilian ERPT (Appendix B and figures B.1 and B.2). At the inverse, India and South Africa had already introduced more flexibility in their currency fluctuations (figures B.3 and B.5).

4.2.2 Specific crisis

Then, to study the ERPT evolution, we need to consider each country independently

Brazil Figure E.2 shows that the Brazilian ERPT becomes significant with the contagion of the Tequila crisis from Argentina and attains a peak in mid-2003. After this crisis, it has decreased continuously to become non-significant in 2011

China Chinese ERPT evolution corresponds to the NEER regime changes with a strong currency peg regime from 1997 up to 2005 and from the end of 2007 up to 2010 – figure B.2. Then we identify three increases in ERPT that refer to the two currency appreciation phases and the 2008 financial crisis. We also notice that, even if it is significant for all the studied period, the lowest and more stable ERPT is obtained during the first currency peg period

India As NEER volatility could not be controlled during the Asian crisis, the Indian authorities decided to peg the domestic currency to the dollar with sterilized interventions from August 1998 up to March 2004 (figure B.3). This period corresponds to a very low NEER volatility with no significant ERPT (figure E.4). Then, there is a constant increase in the NEER volatility with a significant ERPT. It corresponds to the Indian decision of allowing a greater flexibility in their currency fluctuations. However, the central bank has remained evasive about its operations to contain liquidity and NEER volatility

Russia We observe a decreasing but significant Russian ERPT from the 1999 debt crisis up to the 2008 financial crisis (figure E.5). This period corresponds to the peg regime against a bundle of currency (55% of dollar and 45% of euro) followed in 2004 by a middle approach with gradual appreciation coupled with efforts to reduce the CPI dynamics and excess liquidity (figure B.5).

South Africa South Africa was involved in two currency crisis in 1996 and at the end of 2001 (figure B.5). ERPT did not react significantly for the first crisis whereas it has become more volatile during the second crisis (figure E.6). The introduction of more volatility with the implementation of an IT regime in February 2000 can explain the stronger ERPT reaction during the second currency crisis.

We conclude that increases in ERPT correspond to currency crisis as in South Africa, contagion crisis as in Brazil or NEER regime changes as in China and India. A priori, it seems that the lowest ERPT periods are obtained when countries are under a currency peg regime (most of the time, it is not different from zero) whereas a more flexible NEER regime leads to more fluctuations in the NEER dynamics. Thus, no shock on NEER because of either a currency peg regime or no foreign crisis permits to minimize the ERPT. We could conclude that the ≪good luck≫theory seems a priori to be the dominant factor that explains the Great Moderation. However, the Brazilian case clearly shows that the ERPT can diminish to become non-significant under a flexible NEER regime and in spite of the 2008 financial crisis. Thus, the Brazilian case contradicts our first conclusion. To confirm it, we study the 2008 financial crisis in the four other countries to know if it constitutes the end of the Great Moderation as evoked in the review of literature. If the answer is positive then we could conclude that the ≪good luck≫theory is the only one factor that explains the reduction of macroeconomic variables volatility since the 1990s in emerging countries.

4.2.3 End of the Great Moderation with the 2008 financial crisis?

Figures C.1 to C.6 show that the NEER volatility attains a peak for the 2008 financial crisis for all the countries, except for Russia with its 1999 debt crisis. However, the ERPT is of same magnitude as previous international crisis as the Asian crisis, or domestic crisis for South Africa, and NEER regime changes for India in March 2004 or China during the two phases of currency appreciation. Thus, even if the NEER volatility attains a peak with the 2008 financial crisis for these three countries, it is not the case for the ERPT. These countries seem to be more immunized against external shocks nowadays.

Russia has seen a significant higher ERPT in 2008 whereas this economic phenomenon was previously being reduced since the 1999 debt crisis. The implementation of a middle approach with too many opposite objectives as the control of NEER fluctuations, CPI dynamics, and excess liquidity could explain this high ERPT. However, the absence of high NEER volatility since the 1999 crisis does not allow us to compare the ERPT during the 2008 financial crisis to other ERPT fluctuations.

We conclude that the ≪good luck≫is not the only one factor that explains the Great Moderation. Regressions do not allow us to conclude what factors also explain the reduction of the volatility of macroeconomic variables but a greater interconnection among economies during the 2008 global recession with disinflationary dynamics and a higher NEER volatility could explain the disconnection between NEER and the CPI.

5 Conclusion

In this paper, we were interested in studying the Great moderation, that is the reduction of macroeconomic variables volatility. Even if this phenomenon appeared in emerging countries since the 1990s, few papers concern this group of countries. We use data of BRICS countries by applying a TVP VAR model because it permits to avoid over-parameterization problems and allows the distinction between structural changes

(VAR parameters) and stochastic volatility (estimates of the variance-covariance matrix). This distinction highlights the two causes that are used to explain the Great Moderation: the ≪good policy≫theory with the implementation of an IT framework and more flexibility in the NEER fluctuations, and the ≪good luck≫theory with the reduction of external shocks persistence.

Contrary to Primiceri (2005) prior with which a break occurs at each period, we use dynamic mixture innovations to let the data speak and choose themselves the occurrence of breaks. We have used the same framework as Koop et al. (2009) and the algorithm of Gerlach and al. (2000).

Then, we have tested VAR models without structural changes and models allowing VAR parameters changes without stochastic volatility and inversely. These regressions have been run with several prior for the dynamic mixture model and compared them to Primiceri prior and VAR model without time-varying parameters.

We have shown that the best results are obtained with stochastic volatility of macroeconomic variables but without structural parameter changes. Inversely, models allowing structural changes get the worst results. Our regressions confirm previous studies as Cogley and Sargent (2005), Primiceri (2005), and Sims and Zha (2006) among others.

Even if these results seem to confirm that the ≪good luck≫theory has played a dominant role in the reduction of macroeconomic variables, in regards to the 2008 financial crisis, we cannot conclude that it is the only factor that explains the great moderation. Results during this last crisis show that countries seem more immunized against external shocks than previously as we have seen it in the Brazilian case. Even if, ERPT has increased significantly for the four other countries, the ERPT is of the same magnitude as the 1998 Asian and 1999 Russian crises, previous currency crises as at the end of 2001 in South Africa or NEER regime changes as in China and India.

Several reasons can explain the disconnection between NEER and the CPI as a greater interconnection among economies during the 2008 financial crisis leading to dinsinflationary dynamics and a greater NEER volatility in emerging countries, or stronger economic fundamentals with the implementation of countercyclical policies. A more complex model taking into account this kind of specification could permit to continue these investigations. We leave them for further research.

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A Data Description

The following appendix presents data and stationarity tests. They are taken from EcoWin Pro and are seasonally adjusted (SA) on the frequence of monthly. If the series is not SA, we use the Census X-12 method.

For the commodity prices proxied by the world energy oil prices, we use the OPEC (Organization of the Petroleum Exporting Countries) Reference Basket Price (monthly average) in US dollar per barrel.

The output gap, or the difference between the actual production and the full-capacity production, is computed with a Hodrick-Prescott filter. This series is assessed by the Organization for Economic Co-operation and Development (OECD) and serves to identify the peaks and troughs of business cycle.

The consumer price index is a weighted average of prices on a bundle of consumer goods and services according to their importance. It refers to the living cost and takes into account price changes for each item in the predetermined basket of goods by averaging them. We use this series because the share of consumption spending is higher in the emerging economies than in the developed ones because the former are lower-income countries.

The central bank's monetary policy is represented by M1 that include money in current accounts and all banknotes and coins in the economy as well as the deposits in the central bank.

Sample sizes and data sources for respectively the output gap, money supply, NEER, and CPI are:

- Brazil

  From January 1994 to March 2012 (sample size: 219)

  Composite leading indicators, Amplitude adjusted, SA, OECD

  Money supply, M1, BRL, International Financial Statistics (IFS)

  NEER, Fund Position and International Liquidity, Principal rate National currency per US Dollar, Period Average, IFS

  Consumer prices, All items, Index, 2005=100, OECD

- China

  From January 1994 to March 2012 (sample size: 219)

  Composite leading indicators, Amplitude adjusted, SA, OECD

  Money supply, M1, CNY, Central Bank of China

  NEER, Fund Position and International Liquidity, Principal rate National currency per US Dollar, Period Average, IFS

  Consumer prices, All items, Index, 2005=100, OECD

- India

  From April 1994 to February 2012 (size sample: 215)

  Composite leading indicators, Amplitude adjusted, SA, OECD

  Money supply, M1, INR, IFS

  NEER, Fund Position and International Liquidity, Market rate National Currency per US dollar, Period Average, IFS

  Consumer prices, All items, Index, 2005=100, OECD

- Russia

  From July 1995 to November 2011 (size sample: 209)

  Composite leading indicators, Amplitude adjusted, SA, OECD

  Narrow Money and Components, M1 and Components, Monetary aggregate M1, RUB, OECD

  NEER, Average of Daily Rates, National currency per US dollar, OECD

  Consumer Prices, Total, Index, 2000=100, IFS

- South Africa

From January 1994 to March 2012 (sample size: 219)

Composite leading indicators, Amplitude adjusted, SA, OECD

Narrow Money and Components, M1 and Components, Monetary aggregate M1, SA, ZAR, OECD

NEER, Fund Position and International Liquidity, Principal rate, National currency per US Dollar, Period Average, IFS

Consumer prices, All items, Index, 2005=100, OECD

Table 1: Descriptive statistics (in annual percentage variation)

Country	*Variable*	*Outputgap*	*MoneySupply*	*NEER*	*CPI*
Brazil	*Mean*	0.46	0.67	3.87	1.68
	Standard deviation	0.26	0.44	19.64	1.15
	Median	0.45	0.62	5.78	1.34
	Minimum	-0.04	-0.16	-29.44	0.39
	Maximum	1.63	2.20	60.21	6.49
	Range	1.67	2.36	89.65	6.10
China	*Mean*	-0.05	15.94	1.67	2.53
	Standard deviation	2.99	4.87	2.56	3.31
	Median	0.09	15.63	0.17	1.70
	Minimum	-9.61	3.10	-0.26	-2.32
	Maximum	9.73	32.90	10.30	15.38
	Range	19.34	29.80	10.56	17.70
India	*Mean*	-0.17	13.20	-2.47	6.66
	Standard deviation	1.88	3.52	7.71	3.26
	Median	-0.30	12.73	-2.39	6.09
	Minimum	-3.84	1.21	-23.86	0
	Maximum	4.10	24.39	14.04	17.97
	Range	7.94	23.19	37.90	17.97
Russia	*Mean*	0.11	26.89	11.64	16.39
	Standard deviation	4.86	13.40	32.77	15.25
	Median	0.75	28.80	2.47	12.33
	Minimum	-15.36	-11.34	-16.93	5.34
	Maximum	9.27	52.31	139.63	81.71
	Range	24.63	63.66	156.56	76.37
South Africa	*Mean*	-0.02	13.61	-4.26	5.70
	Standard deviation	1.91	8.19	17.24	3.08
	Median	0.19	13.66	-4.67	5.96
	Minimum	-4.90	-6.28	-41.10	-2.04
	Maximum	3.58	39.26	39.57	13.16
	Range	8.47	45.55	80.68	15.20

Table 2: Stationarity tests

Country	*Variable*	*Lag*	*Value*	*Country*	*Lag*	*Value*
Brazil	*Output gap*	p=1	-2.985			
	Money supply	p=3	4.718	$\Delta(Money\ supply)$	p=2	-1.914
	NEER	p=3	-0.146	$\Delta(NEER)$	p=2	-3.225
	CPI	p=3	3.524	$\Delta(CPI)$	p=2	-2.552
China	*Output gap*	p=5	-7.313			
	Money supply	p=3	5.886	$\Delta(Money\ supply)$	p=2	-1.949
	NEER	p=5	1.711	$\Delta(NEER)$	p=4	-6.478
	CPI	p=5	2.806	$\Delta(CPI)$	p=4	-2.532
India	*Output gap*	p=3	-5.640			
	Money supply	p=2	5.078	$\Delta(Money\ supply)$	p=1	-1.964
	NEER	p=3	1.765	$\Delta(NEER)$	p=2	-3.002
	CPI	p=2	4.769	$\Delta(CPI)$	p=1	-2.337
Russia	*Output gap*	p=4	-3.966			
	Money supply	p=2	4.748	$\Delta(Money\ supply)$	p=1	-2.528
	NEER	p=4	0.363	$\Delta(NEER)$	p=3	-4.231
	CPI	p=4	3.171	$\Delta(CPI)$	p=3	-8.815
South Africa	*Output gap*	p=3	-4.159			
	Money supply	p=2	6.261	$\Delta(Money\ supply)$	p=1	-1.732
	NEER	p=2	2.067	$\Delta(NEER)$	p=1	-3.265
	CPI	p=3	4.197	$\Delta(CPI)$	p=2	-1.965

Critical values at 1%, 5% and 10% are respectively -2.652, -1.991 and -1.666

B Review of Monetary Policy Evolution

We state the *de jure* central bank's monetary objectives and we recall a short list of events that had an effect on their monetary policy

B.1 Brazil

- Objectives: the mission is ≪to ensure the currency's purchasing power and a solid and efficient financial system≫
- Important dates:

  Mid-1994: the stabilization program (pre-IT framework) is launched

  1997-1999: Asian and Russian crisis

  On January 15, 1999: the Brazilian currency is allowed to float

  June 1999: implementation of an IT framework

  Three periods of devaluation took place and were considered as a test for the IT framework: 48.9% in 1999, 18.5% in 2001 and 53.2% in 2002

  2002-2003: Tequila crisis in Argentina

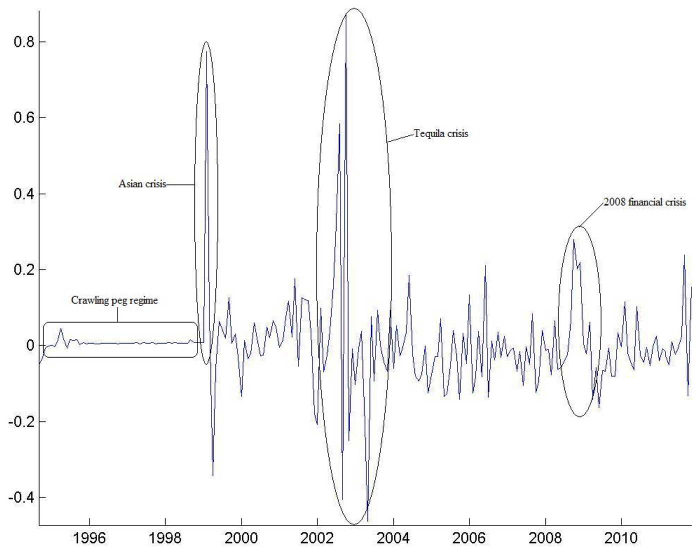

Figure B.1: Brazilian NEER in first difference

B.2 China

- ≪The objective of the monetary policy is to maintain the stability of the value of the currency and thereby promote economic growth≫
- Important dates:

  On January 1, 1994: adoption of a unified managed floating NEER regime based on market supply and demand. Up to 1997, the renminbi appreciated by 4.8%

  After the Asian crisis of 1997-1998, reduction of the NEER band in order to prevent huge currency depreciations

  2005: adoption of a managed floating NEER regime based on market supply and demand with reference to a basket of currencies. Up to the end of 2007, the NEER appreciated respectively by 11% and 26.6% compared to 2005 and 1994

End-2007-Mid-June 2010: currency peg regime

Mid-June 2010: China starts again to increase the flexibility of the renminbi

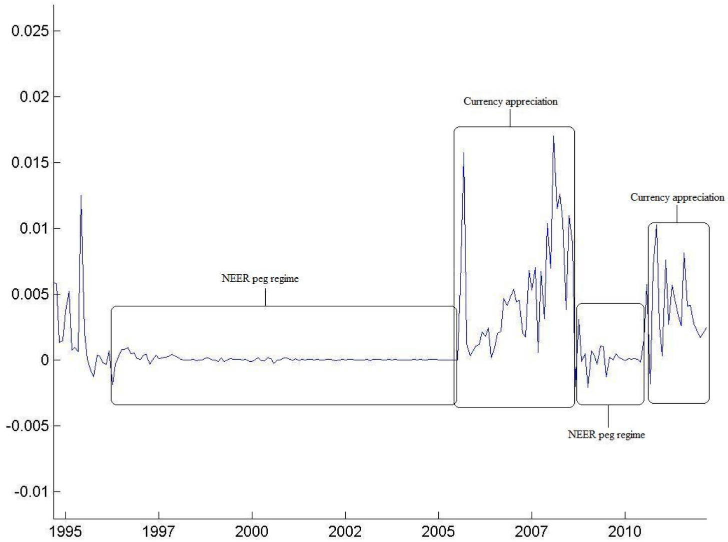

Figure B.2: Chinese NEER in first difference

B.3 India

- Objectives: ≪maintaining price stability, ensuring adequate flow of credit to the productive sectors of the economy to support economic growth and financial stability≫
- Objectives

  1985-1997: flexible monetary targeting (M3) to favor GDP and a tolerable level of CPI

  1991: balance of payments crisis because of a loss in the market confidence. It is partly explained by an over-valuation of the currency and a current account deficit

  1993: the NEER is determined by the market (managed float)

  August 1998 up to March 2004: after the Asian crisis, adoption of a currency peg regime with sterilized interventions

  1998-today: multiple indicator approach for the monetary policy as interest rates, CPI rate, money supply, credit, NEER, trade, capital flows, fiscal position and output according to the Indian central bank

  March 2004: The Indian monetary authorities decide to introduce a greater flexibility in the fluctuations of their currency. However, the central bank has remained evasive about its operations to contain liquidity and NEER volatility

B.4 Russia

- Objectives: ≪the purposes of the Bank of Russia are to protect the ruble and ensure its stability, promote the development and strengthen the Russian banking system and ensure the efficient and uninterrupted functioning of the payment system≫
- Important dates

  Before 1998: NEER peg regime

  On 17 August, 1998: financial crisis with depreciations of the currency and debt defaults

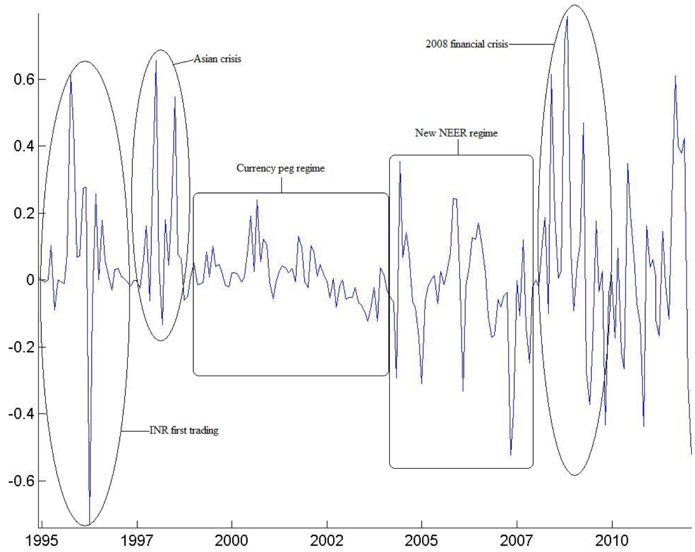

Figure B.3: Indian NEER in first difference

2000-2004: currency board regime vis-a-vis a bundle of two currencies: 55% of dollar and 45% of euro

2004-2007: middle approach to get gradual appreciation of NEER with acceptable levels of CPI and liquidity

Since the last crisis, the central bank of Russia has moved towards the adoption of an IT regime with more flexibility in the NEER regime

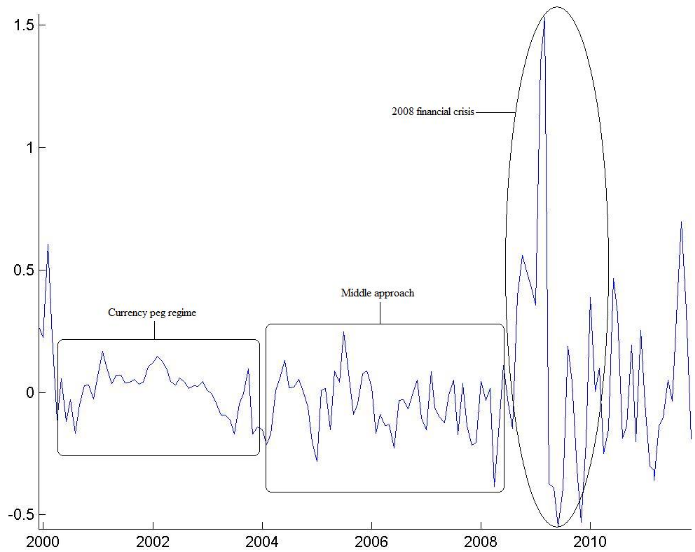

Figure B.4: Russian NEER in first difference

B.5 South Africa

- Objectives: ≪the primary purpose of the Bank is to achieve and maintain price stability in the interest of balanced and sustainable economic growth in South Africa. Together with other institutions, it also plays a pivotal role in ensuring financial stability≫

- Important dates

  1990-1999: eclectic approach with M3 as principal intermediate target among others as asset prices, yield curve or NEER... to reduce CPI dynamics

  February 1996: currency crisis

  October 1996, November 1997 and April 1998: NEER volatility (contagion from the Asian crisis)

  February 2000: adoption of an IT framework

  1^{st}-September-31^{st}, 2001: the currency devalues by 42% against the US dollar

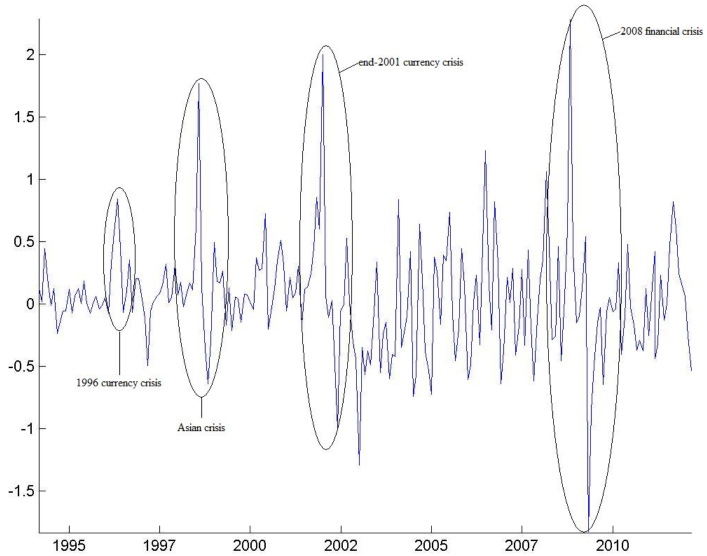

Figure B.5: South African NEER in first difference

C Bayesian Methodology

In this appendix, we explain briefly the framework of the MCMC algorithm that is used in this paper. We refer the reader to Carter and Kohn (1994), Primiceri (2005), and Koop and Korobilis (2009) to get more details about the algorithms, their properties and a presentation of the state space models. We prefer highlighting the main differences between our paper and Primiceri (2005) as the introduction of a dynamic mixture framework that allows the data to choose when a break occurs. Tables of results and posterior mean of NEER standard deviation are available at the end of this appendix.

Before starting, let us precise that Koop and Korobilis (2009) show that Bayesian methodology can be used in the state space models when algorithms as Carter and Kohn (1994) are added to MCMC algorithm.

C.1 Coefficients states

The first step of the MCMC algorithm is to draw the coefficient states. This is done by using the generic density function $p(\alpha^T|Data, A^T, \Sigma^T, Q, W, C)$ and backward recursions. Thus we have

$$p(\alpha^T|y^T, A^T, \Sigma^T, Q, W, C) = p(\alpha_T|y^T, A^T, \Sigma^T, Q, W, C) \prod_{t=1}^{T-1} p(\alpha_t|y^t, A^T, \Sigma^T, Q, W, C) \tag{C.1}$$

With

$$\begin{array}{c} \alpha_t|\alpha_{t+1}, y^t, A^T, \Sigma^T, Q, W, C \rightsquigarrow N(B_{t|t+1}, P_{t|t+1}) \\ \alpha_{t|t+1} = E(\alpha_t|\alpha_{t+1}, y^t, A^T, \Sigma^T, Q, W, C) \\ P_{t|t+1} = Var(\alpha_t|\alpha_{t+1}, y^t, A^T, \Sigma^T, Q, W, C) \end{array} \tag{C.2}$$

Algorithms as Carter and Kohn (1994) assume that prior and initial states of parameters do not have a specific distribution. This is not the case in this framework and we use Inverse-Wishart distribution as done in the literature – Primiceri (2005) and Koop et al. (2009).

The prior distribution of H_t and of the hyperparameter Q_t are

$$\begin{array}{c} H^{-1} \rightsquigarrow W(\underline{v}_H, \underline{H}^{-1}) \\ Q^{-1} \rightsquigarrow W(\underline{v}_Q, \underline{Q}^{-1}) \end{array} \tag{C.3}$$

This implies that, conditional on the states, the posteriors of H_t and Q_t have the same distribution

$$H^{-1}|Data \rightsquigarrow W(\overline{v}_H, \overline{H}^{-1}) \tag{C.4}$$

With

$$\begin{array}{c} \overline{v_H} = T + \underline{v}_H \\ \overline{H}^{-1} = [H + \sum_{t=1}^{T}(y_t - Z_t\alpha_t)(y_t - Z_t\alpha_t)']^{-1} \end{array} \tag{C.5}$$

And,

$$Q_{-1}|Data \rightsquigarrow W(\underline{v}_Q, \overline{Q}^{-1}) \tag{C.6}$$

With

$$\begin{array}{c} \overline{v_Q} = T + \underline{v}_Q \\ \overline{Q}^{-1} = [Q + \sum_{t=1}^{T}(\alpha_{t+1} - \alpha_t)(\alpha_{t+1} - \alpha_t)']^{-1} \end{array} \tag{C.7}$$

C.2 Stochastic volatility framework

In the benchmark model, we have time varying parameters for both the variances contained in the matrix Σ_t and the simultaneous relations between variables that are represented by the free elements of A_t. We need to have a normal linear state space representation to apply the algorithm of Carter and Kohn (1994). We start by the variance matrix Σ_t.

C.2.1 Stochastic volatility

Let us consider that α_t and A_t are given, and y_t is observable, the two equations

$$y_t = Z_t \alpha_t + \epsilon_t \tag{C.8}$$

And,

$$H_t = A_t^{-1} \Sigma_t \Sigma_t' (A_t^{-1})' \tag{C.9}$$

Become:

$$y_t^* = A_t(y_t - Z_t \alpha_t) = \Sigma_t \epsilon_t \tag{C.10}$$

Where $var(y_t^*)$ is a diagonal matrix such that $var(y_t^*) = \Sigma_t \Sigma_t'$.

To get a normal linear state space representation we derive the previous system of equations by squaring each element and considering their logarithm. We have a linear state space representation such that:

$$\begin{aligned} y_t^{**} &= 2h_t + e_t \\ h_t &= h_{t-1} + \eta_t \end{aligned} \tag{C.11}$$

With $y_{i,t}^{**} = log[(y_{i,t}^*)^2 + c]$, $h_{i,t} = log(\sigma_{i,t})$ and $e_{i,t} = log(\epsilon_{i,t}^2)$. Notice that c is an offset constant without any consequences on the last derivation in order to get a more robust estimation via the Quasi-Maximum Likelihood estimator. This specification was introduced into the stochastic volatility model literature by Fuller (1995). This setting is justified by the very small values that can take the elements of $y_{i,t}$. We set $c = 0.001$ as in previous literature using this algorithm. Moreover, the residuals of the two previous equations, e_t and η_t, are independent.

Even if the previous system is linear, it is not Gaussian yet since $e_t \rightsquigarrow \chi(1)$. As the equations composing y_t^* are independent among them, it means that their residuals are also independent. Kim and al. (1998) propose to use a mixture of seven Normals as an approximation of the distribution of e_{jt} available in the table 3.

Table 3: Mixture of Normal distributions

ω	$q_j = Pr(\omega = j)$	m_j	v_j^2
1	0.00730	-10.12999	5.79596
2	0.10556	-3.97281	2.61369
3	0.00002	-8.56686	5.17950
4	0.04395	2.77786	0.16735
5	0.34001	0.61942	0.64009
6	0.24566	1.79518	0.34023
7	0.25750	-1.08819	1.26261

With q_j, m_j, and v_j^2 being respectively the probabilities, means and variances of components of variable mixture $\forall j \in [1; 7]$.

Notice that the vector $S = (S_1', \dots, S_T')$ such that $S_{jt} = (S_{j1}, \dots, S_{jT})'$ is used to match at each element of e_t its corresponding normal approximation.

With this last approximation, the system of equations (C.11) is a normal linear state space representation of the model. Thus we can draw h_t with the algorithm of Carter and Kohn (1994).

As previously, h_t is drawn recursively from the density with:

$$\begin{aligned} p(h_t | h_{t+1}, y^t, A^T, B^T, Q, W, C) &\rightsquigarrow N(h_{t|t+1}, H_{t|t+1}) \\ h_{t|t+1} &= E(h_t | h_{t+1}, y_t, A_t, \alpha_t, V, s_T) \\ H_{t|t+1} &= V(h_t | h_{t+1}, y_t, A_t, \alpha_t, V, s_T) \end{aligned} \tag{C.12}$$

Where $h_t \rightsquigarrow N(h_{t|t+1}, H_{t|t+1})$ is drawn recursively from $p(h_t | h_{t+1}, y_t, A_t, \alpha_t, V, s_T)$.

Then, we draw s_T conditionally on y^{**T} and h^t that we have just determined. We use the discrete density defined by Kim et al. (1998) for each $s_{i,t}$, $\forall j = 1, \dots, 7$ and $\forall i = 1, \dots, n$

$$Pr(s_{i,t} = j|y^{**}_{i,t}, h_{i,t})\alpha q_j f_N(y^{**}_{i,t}|2h_{i,t} + m_j 1.2704, v_j^2) \tag{C.13}$$

Remembering that the prior of the hyperparameter W has an Inverse-Wishart distribution

$$W^{-1} \rightsquigarrow W(\underline{v}_W, \underline{W}^{-1}) \tag{C.14}$$

This implies that, conditional on the states, posteriors of W have the same distribution

$$W^{-1}|Data \rightsquigarrow W(\overline{v}_W, \overline{W}^{-1}) \tag{C.15}$$

With

$$\begin{aligned} \overline{v}_W &= T + \underline{v}_W \\ \overline{W}^{-1} &= [\underline{W} + \textstyle\sum_{t=1}^{T}(h_{t+1} - h_t)(h_{t+1} - h_t)]^{-1} \end{aligned} \tag{C.16}$$

C.2.2 The covariance states

We stack the free elements of A_t in a vector with $\frac{p(p-1)}{2}$ rows such that $a_t = (a_{21,t}, a_{31,t}, a_{32,t}, \ldots, a_{p(p-1),t})'$.

Let us consider that α is given and $\hat{y}_t$ is observable. As previously, we write the equation (C.10) as

$$A_t(y_t - Z_t\alpha_t) = A_t\hat{y}_t = \gamma_t \tag{C.17}$$

Notice that $\gamma_t \rightsquigarrow N(0, \Sigma_t\Sigma_t)$ and is independent of ζ_t.

Since A_t is a lower triangular matrix consisted of one on its diagonal, we can modify the previous equation and write

$$\hat{y}_t = C_t a_t + \gamma_t \tag{C.18}$$

Where C_t is such that:

$$\begin{pmatrix} 0 & \cdots & \cdots & 0 \\ -\hat{y}_{1,t} & 0 & \cdots & 0 \\ 0 & -\hat{y}_{[1,2],t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & -\hat{y}_{[1,\cdots,(n-1)],t} \end{pmatrix} \tag{C.19}$$

As $\zeta \rightsquigarrow N(0, C)$ and as C is a block diagonal matrix, we draw the covariance states by using the Kalman filter and the backward recursions equation by equation $\forall t$. With this method, we can determine $p(a_{i,t}|a_{i,t+1}, y^t, \alpha^T, \Sigma^T, Q, W, C) \rightsquigarrow N(a_{i,t|t+1}, \Gamma_{i,t|t+1})$ where the two elements of the Gaussian distribution are previously computed recursively such that

$$\begin{aligned} a_t^j|a_{t+1}^j, y^t, \alpha^T, \Sigma^T, Q, W, C &\rightsquigarrow N(a^j_{t|t+1}, \Gamma^j_{t|t+1}) \\ a^j_{t|t+1} &= E(a_t^j|a_{t+1}^j, y^t, \alpha^T, \Sigma^T, Q, W, C) \\ \Gamma^j_{t|t+1} &= Var(a_t^j|a_{t+1}^j, y^t, \alpha^T, \Sigma^T, Q, W, C) \end{aligned} \tag{C.20}$$

With a_t^j representing the elements of a_t associated to C_j

As previously, let us remember that the prior distribution of C is an Inverse-Wishart distribution such that

$$C_j^{-1} \rightsquigarrow W(\underline{v}_{cj}, \underline{C}_j^{-1}) \tag{C.21}$$

This implies that, conditional on the states, posteriors of C have the same distribution

$$C_j^{-1}|Data \rightsquigarrow W(\overline{v}_{cj}, \overline{C_j}^{-1}) \tag{C.22}$$

With

$$\begin{array}{c} \overline{v}_{cj} = T + \underline{v}_{cj} \\ \overline{C_j}^{-1} = [\underline{C}_j + \sum_{t=1}^{T}(a_{t+1}^j - a_t^j)(a_{t+1}^j - a_t^j)']^{-1} \end{array} \tag{C.23}$$

C.3 Determination of the prior of parameters and hyperparameters

As in Primiceri (2005), we decide to run a time-invariant VAR model to determine the prior of the initial state of the VAR coefficients α_0, of the error covariance matrix of the measurement equation a_0, and of the variances of the state equations h_0.

We use the entire sample to calibrate the prior because it permits to take into account the changing regimes in monetary policy that took place in the different countries. Calibrating the prior on only the first forty data as suggested by Primiceri (2005) would restrict us to consider only a period during which the central bank had the objective to reduce the fluctuations of the value of currency at a given level without considering the CPI dynamics.

Thus the prior for the initial conditions are

$$\begin{array}{c} \alpha_0 \rightsquigarrow N(\hat{\alpha}_{OLS}, 4V(\hat{\alpha}_{OLS})) \\ a_0 \rightsquigarrow N(\hat{a}_{OLS}, 4V(\hat{a}_{OLS})) \\ log(h_0) \rightsquigarrow N(log(\hat{h}_{OLS}), I_5) \end{array} \tag{C.24}$$

As previous literature, we assume that prior for matrices containing the error terms of measurement and the three state equations have an inverse-Wishart distribution. Notice that the small degrees of freedom with regard to the sample size translate that, relative to data, little information is contained in the prior.

$$\begin{array}{c} \underline{Q}^{-1} \rightsquigarrow W(40, 0.0001\hat{V}_{aj})\forall j = 1, 2 \\ \underline{W}^{-1} \rightsquigarrow W(4, 0.0001I_5) \\ \underline{C}_1^{-1} \rightsquigarrow W(2, 0.01\hat{V}_{a1}) \\ \underline{C}_2^{-1} \rightsquigarrow W(3, 0.01\hat{V}_{a2}) \end{array} \tag{C.25}$$

$\underline{C}_1$ and $\underline{C}_2$ respectively $\hat{V}_{a1}$, and $\hat{V}_{a2}$ correspond to the blocks of C – respectively $4V(\hat{a}_{OLS})$

The degrees of freedom are the same as Primiceri (2005). We refer the reader to this paper for more details about the justification of these prior.

C.4 Dynamic mixture model

To finish, we need to precise the hierarchical prior for K_t – meaning that K depends on its own prior. As Koop Leon-Gonzales and Strachan (2009), we make the assumption that it follows a Bernoulli distribution such that $p(K_{jt}) = p_j$ for $j = 1, 2$.

As already noticed, we want to test several kinds of time varying parameters as a model with many small breaks or a model with large few breaks for instance. This choice is made by using a Beta distribution for p_j. It permits to get the conditional posterior of a break probability in the algorithm.

$$B(\beta_{1j}, \beta_{2j}) \tag{C.26}$$

With

$$\begin{array}{c} \beta_{1j} = \beta_{1j} + \sum_{t=1}^{T} K_{jt} \\ \beta_{2j} = \beta_{2j} + T - \sum_{t=1}^{T} K_{jt} \end{array} \tag{C.27}$$

Thus, the probability that a break occurs is:

$$E(p_j) = \frac{\beta_{1j}}{\beta_{1j} + \beta_{2j}} \tag{C.28}$$

We test three different values for β_{1j} and β_{2j} for $j = 1, 2$

- Benchmark case: probability of 50 % that a break occurs at each period: $\beta_{1j} = \beta_{2j} = 1$
- Few breaks case: $\beta_{1j} = 0.1$ and $\beta_{2j} = 10$
- Least informative prior: $\beta_{1j} = \beta_{2j} = 0.5^{\frac{1}{2}}$

Notice that if we set $E(p_j) = 1$ then we obtain the heteroskedastic case of Primiceri (2005).

C.5 Procedure in the case of a dynamic mixture model

1. Initialization of all the parameters of the model: α^T, Σ^T, A^T, K, Q, W, C and s^T
2. We draw α_t from the generic density function $p(\alpha^T|y^T, A^T, \Sigma^T, Q, W, C, K)$ after having drawn K_1 and the related probabilities
3. We draw the covariance states A^T from the generic density function $p(A^T|y^T, \alpha^T, \Sigma^T, Q, W, C, K)$
4. We draw the diagonal elements of the variance-covariance matrix H_t from the generic density function $p(\Sigma^T|y^T, A^T\alpha^T, Q, W, C, K)$ after having drawn $K_{2,t}$ and the related probabilities
5. We draw s^T from the generic density function $p(s^T|y^T, A^T, \Sigma^T, Q, W, C, K)$
6. We draw Q, W and C from the generic density function $p(Q, W, C|y^T, \alpha^T, \Sigma^T, A^T, K)$ computed as

   $$\begin{aligned} p(Q, W, C|y^T, \alpha^T, \Sigma^T, A^T, K) = p(Q|y^T, \alpha^T, \Sigma^T, A^T, K) \cdot p(W|y^T, \alpha^T, \Sigma^T, A^T, K) \cdot \\ \cdot p(C_1|y^T, \alpha^T, \Sigma^T, A^T, K) \cdot \ldots \cdot p(C_4|y^T, \alpha^T, \Sigma^T, A^T, K) \end{aligned}$$

   since we have 5 dependent variables in the model
7. Go to the second step

Table 4: Brazil Results

Model	*Lags*	*AIC*	*BIC*	*HQIC*	*E(p1|y)*	*E(p2|y)*
Benchmark Prior	1	11.929	11.942	11.961	0.15	0.96
Benchmark Prior	2	11.703	11.716	11.735	0.16	0.98
Few Breaks Prior	1	11.944	11.957	11.976	0.07	0.77
Few Breaks Prior	2	10.361	10.374	10.393	0.09	0.74
Least Info Prior	1	11.893	11.906	11.925	0.32	0.85
Least Info Prior	2	11.748	11.761	11.780	0.53	0.92
Constant VAR	1	11.975	11.988	12.008	0	0
Constant VAR	2	11.748	11.758	11.777	0	0
Primiceri Prior	1	11.861	11.874	11.893	1	1
Primiceri Prior	2	11.660	11.673	11.693	1	1
Benchmark Prior $k1 = 0$	1	11.979	11.992	12.011	0	0.96
Benchmark Prior $k2 = 0$	1	11.860	11.873	11.893	0.50	0
Few Breaks Prior $k1 = 0$	1	11.974	11.987	12.006	0	0.78
Few Breaks Prior $k2 = 0$	1	11.906	11.919	11.938	0.23	0
Least Info Prior $k1 = 0$	1	11.977	11.990	12.010	0	0.92
Least Info Prior $k2 = 0$	1	11.859	11.872	11.891	0.49	0
Primiceri Prior $k1 = 0$	1	11.985	11.998	12.017	0	1
Primiceri Prior $k2 = 0$	1	11.786	11.799	11.818	1	0

Table 5: China Results

Model	*Lags*	*AIC*	*BIC*	*HQIC*	*E(p1|y)*	*E(p2|y)*
Benchmark Prior	1	8.761	8.774	8.793	0.68	1
Benchmark Prior	2	8.653	8.666	8.685	0.02	1
Few Breaks Prior	1	8.763	8.776	8.795	0.10	0.88
Few Breaks Prior	2	8.666	8.679	8.698	0.09	0.84
Least Info Prior	1	8.763	8.776	8.795	0.53	0.97
Least Info Prior	2	8.668	8.681	8.700	0.53	0.97
Constant VAR	1	8.763	8.776	8.795	0	0
Constant VAR	2	8.662	8.675	8.694	0	0
Primiceri Prior	1	8.658	8.671	8.690	1	1
Primiceri Prior	2	8.493	8.506	8.525	1	1
Benchmark Prior $k1 = 0$	1	8.761	8.774	8.793	0	1
Benchmark Prior $k2 = 0$	1	8.756	8.769	8.788	0.02	0
Few Breaks Prior $k1 = 0$	1	8.762	8.775	8.794	0	0.82
Few Breaks Prior $k2 = 0$	1	8.756	8.769	8.788	0.01	0
Least Info Prior $k1 = 0$	1	8.764	8.777	8.796	0	0.97
Least Info Prior $k2 = 0$	1	8.746	8.759	8.778	0.07	0
Primiceri Prior $k1 = 0$	1	8.766	8.779	8.798	0	1
Primiceri Prior $k2 = 0$	1	8.656	8.668	8.687	1	0

Table 6: India Results

Model	*Lags*	*AIC*	*BIC*	*HQIC*	*E(p1|y)*	*E(p2|y)*
Benchmark Prior	1	9.027	9.040	9.059	0.68	1
Benchmark Prior	2	8.976	8.989	9.009	0.05	0.99
Few Breaks Prior	1	9.029	9.042	9.061	0.10	0.85
Few Breaks Prior	2	8.983	8.996	9.015	0.53	0.97
Least Info Prior	1	9.028	9.041	9.060	0.54	0.97
Least Info Prior	2	8.984	8.997	9.016	0.10	0.85
Constant VAR	1	9.026	9.039	9.058	0	0
Constant VAR	2	8.980	8.994	9.013	0	0
Primiceri Prior	1	8.926	8.939	8.958	1	1
Primiceri Prior	2	8.849	8.862	8.881	1	1
Benchmark Prior $k1 = 0$	1	9.029	9.042	9.061	0	0.99
Benchmark Prior $k2 = 0$	1	9.021	9.035	9.054	0.02	0
Few Breaks Prior $k1 = 0$	1	9.029	9.042	9.061	0	0.89
Few Breaks Prior $k2 = 0$	1	9.023	9.036	9.055	0.01	0
Least Info Prior $k1 = 0$	1	9.028	9.041	9.061	0	0.97
Least Info Prior $k2 = 0$	1	9.009	9.022	9.041	0.08	0
Primiceri Prior $k1 = 0$	1	9.028	9.041	9.060	0	1
Primiceri Prior $k2 = 0$	1	8.919	8.931	8.950	1	0

Table 7: Russia Results

Model	*Lags*	*AIC*	*BIC*	*HQIC*	*E(p1|y)*	*E(p2|y)*
Benchmark Prior	1	16.305	16.319	16.339	0.63	0.96
Benchmark Prior	2	16.278	16.292	16.312	0.99	0.99
Few Breaks Prior	1	16.222	16.236	16.256	0.09	0.82
Few Breaks Prior	2	16.205	16.219	16.240	0.10	0.78
Least Info Prior	1	16.314	16.328	16.349	0.54	0.86
Least Info Prior	2	16.222	16.236	16.257	0.53	0.93
Constant VAR	1	16.337	16.351	16.371	0	0
Constant VAR	2	16.325	16.339	16.359	0	0
Primiceri Prior	1	16.243	16.257	16.278	1	1
Primiceri Prior	2	16.246	16.260	16.280	1	1
Benchmark Prior $k1 = 0$	1	16.328	16.342	16.362	0	0.97
Benchmark Prior $k2 = 0$	1	16.188	16.202	16.222	0.90	0
Few Breaks Prior $k1 = 0$	1	16.333	16.347	16.368	0	0.75
Few Breaks Prior $k2 = 0$	1	16.281	16.295	16.316	0.22	0
Least Info Prior $k1 = 0$	1	16.337	16.351	16.372	0	0.91
Least Info Prior $k2 = 0$	1	16.192	16.206	16.226	0.73	0
Primiceri Prior $k1 = 0$	1	16.331	16.345	16.365	0	1
Primiceri Prior $k2 = 0$	1	16.178	16.192	16.212	1	0

Table 8: South Africa Results

Model	*Lags*	*AIC*	*BIC*	*HQIC*	*E(p1|y)*	*E(p2|y)*
Benchmark Prior	1	12.743	12.756	12.774	0.05	0.99
Benchmark Prior	2	12.691	12.703	12.722	0.05	0.99
Few Breaks Prior	1	12.745	12.757	12.776	0.03	0.81
Few Breaks Prior	2	7.754	7.766	7.785	0.53	0.97
Least Info Prior	1	12.708	12.721	12.739	0.17	0.92
Least Info Prior	2	7.751	7.764	7.783	0.10	0.85
Constant VAR	1	12.757	12.770	12.789	0	0
Constant VAR	2	12.704	12.717	12.736	0	0
Primiceri Prior	1	12.639	12.651	12.670	1	1
Primiceri Prior	2	12.576	12.589	12.608	1	1
Benchmark Prior $k1 = 0$	1	12.761	12.773	12.792	0	0.98
Benchmark Prior $k2 = 0$	1	12.720	12.732	12.751	0.10	0
Few Breaks Prior $k1 = 0$	1	12.761	12.774	12.793	0	0.82
Few Breaks Prior $k2 = 0$	1	12.702	12.714	12.733	0.10	0
Least Info Prior $k1 = 0$	1	12.760	12.773	12.791	0	0.96
Least Info Prior $k2 = 0$	1	12.684	12.697	12.715	0.24	0
Primiceri Prior $k1 = 0$	1	12.761	12.774	12.793	0	1
Primiceri Prior $k2 = 0$	1	12.570	12.583	12.601	1	0

These tables contain regression results for the five countries
≪*Benchmark Prior*≫, ≪*Few Breaks Prior*≫, and ≪*Least Info Prior*≫refer to the dynamic mixture model according to a given prior
≪*Primiceri Prior*≫refers to the Primiceri (2005) model in which a break occurs at each period. Inversely, ≪*Constant VAR*≫refers to a VAR model without break
$k1 = 0$ refers to models with no changes in estimates of VAR parameters but the measurement error covariance matrix can evolve over time according to a given prior
$k2 = 0$ refers to models with a constant measurement error covariance matrix and time-varying VAR parameters according to a given prior

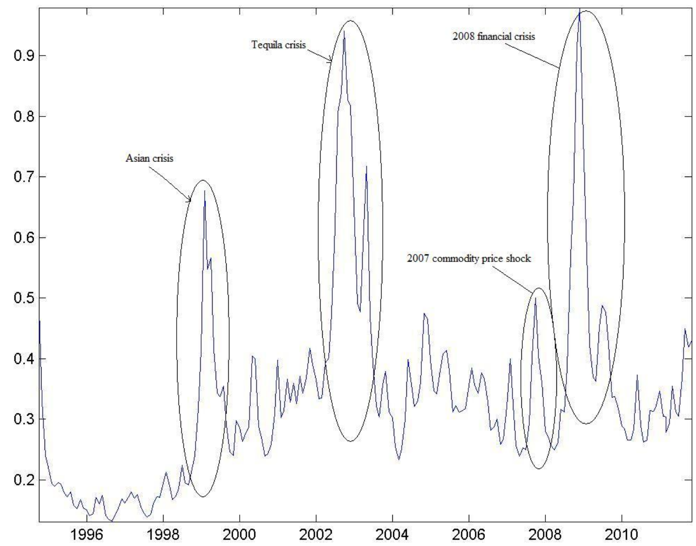

Figure C.1: Posterior mean of standard deviation of Brazilian NEER

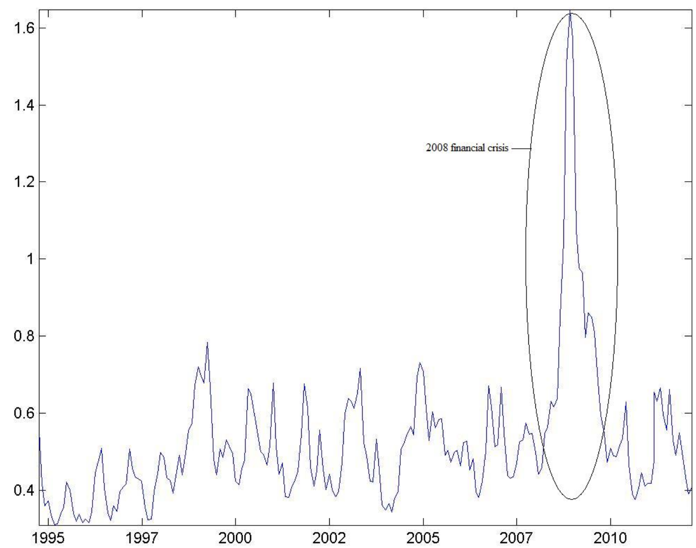

Figure C.2: Posterior mean of standard deviation of Chinese NEER

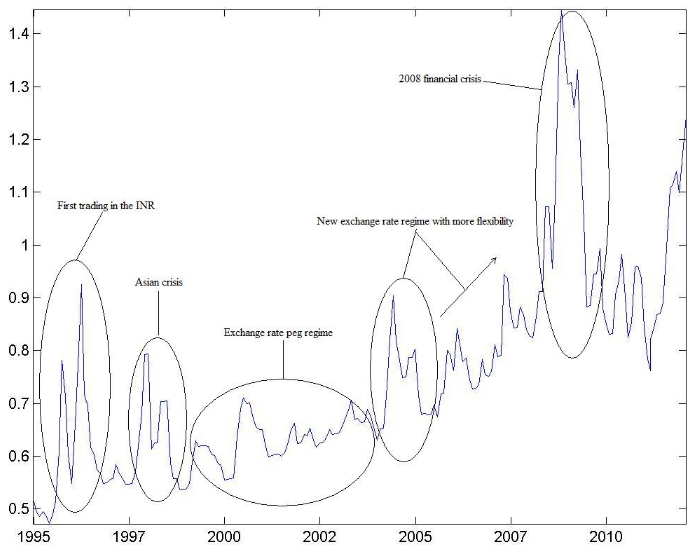

Figure C.3: Posterior mean of standard deviation of Indian NEER

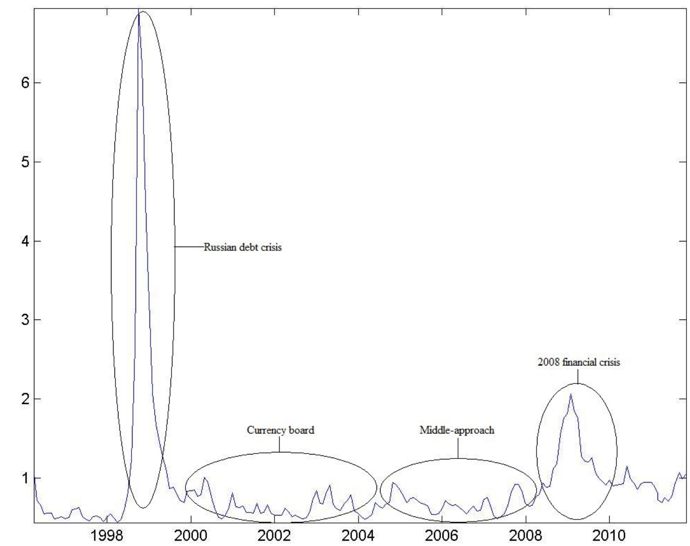

Figure C.4: Posterior mean of standard deviation of Russian NEER

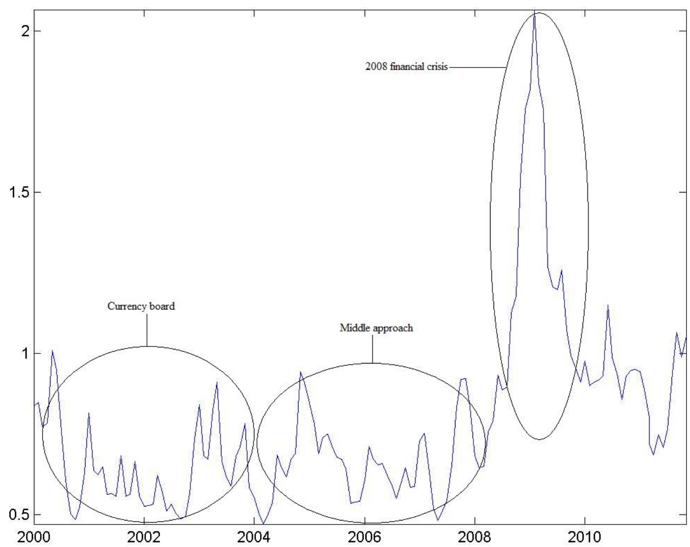

Figure C.5: Posterior mean of standard deviation of Russian NEER

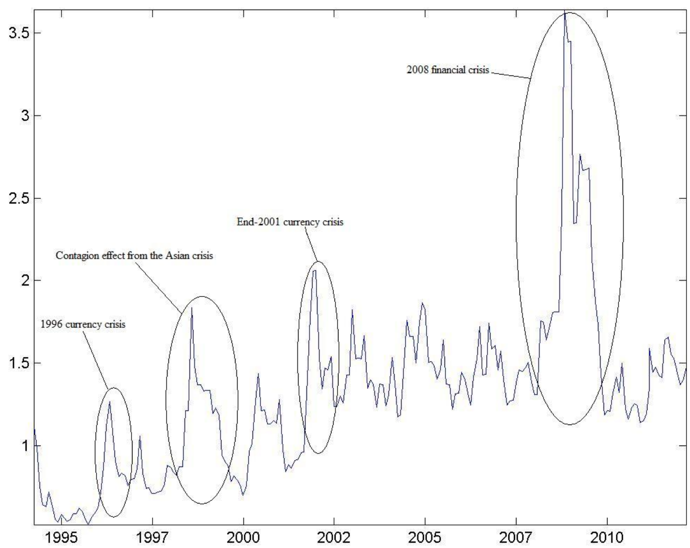

Figure C.6: Posterior mean of standard deviation of South African NEER

D Convergence of the MCMC algorithm

As explained in the core of this paper, Markov Chain does not produce independent draws. To leave this problem, there are two strategies: either by discarding a given number of the firsts iterations or by only retaining every fifth, tenth and so on iterations. The disadvantage of the first strategy is that it takes more time to do whereas the second strategy increases the variance of all the estimated parameters as explained in Cogley and Sargent (2005). We choose the first strategy and we determine the minimum number of iterations by using the method introduced by Raftery and Lewis (1992).

In our regressions, we run 40000 iterations by discarding the first 10000 iterations. Table 9 presents the number of parameters and hyperparameters. Figures D.1 and D.2 present respectively the 10^{th} order sample autocorrelation of the draws and the minimum number of iteration to obtain convergence for parameters and hyperparameters classified in the same order as in the table 9. The last graph shows that we have always chosen a number of iterations higher than requested to get convergence of the algorithm whereas figure D.1 shows a very low autocorrelation for the time-varying parameters and the stochastic volatility.

Notice also that we only present convergence diagnostics for regressions that we use for interpretations. Thus, there is neither autocorrelation nor a minimum number of iterations to get convergence for the hyperpaparmeter Q since our best models are those for which there is no structural parameter changes.

Table 9: Number of parameters

Parameter	*Brazil*	*China*	*India*	*Russia*	*South Africa*
B	6210	6300	6210	56701	6480
Σ	1035	1050	1035	945	1080
Q	900	900	900	900	900
W	25	25	25	25	25
S	30	30	30	30	30

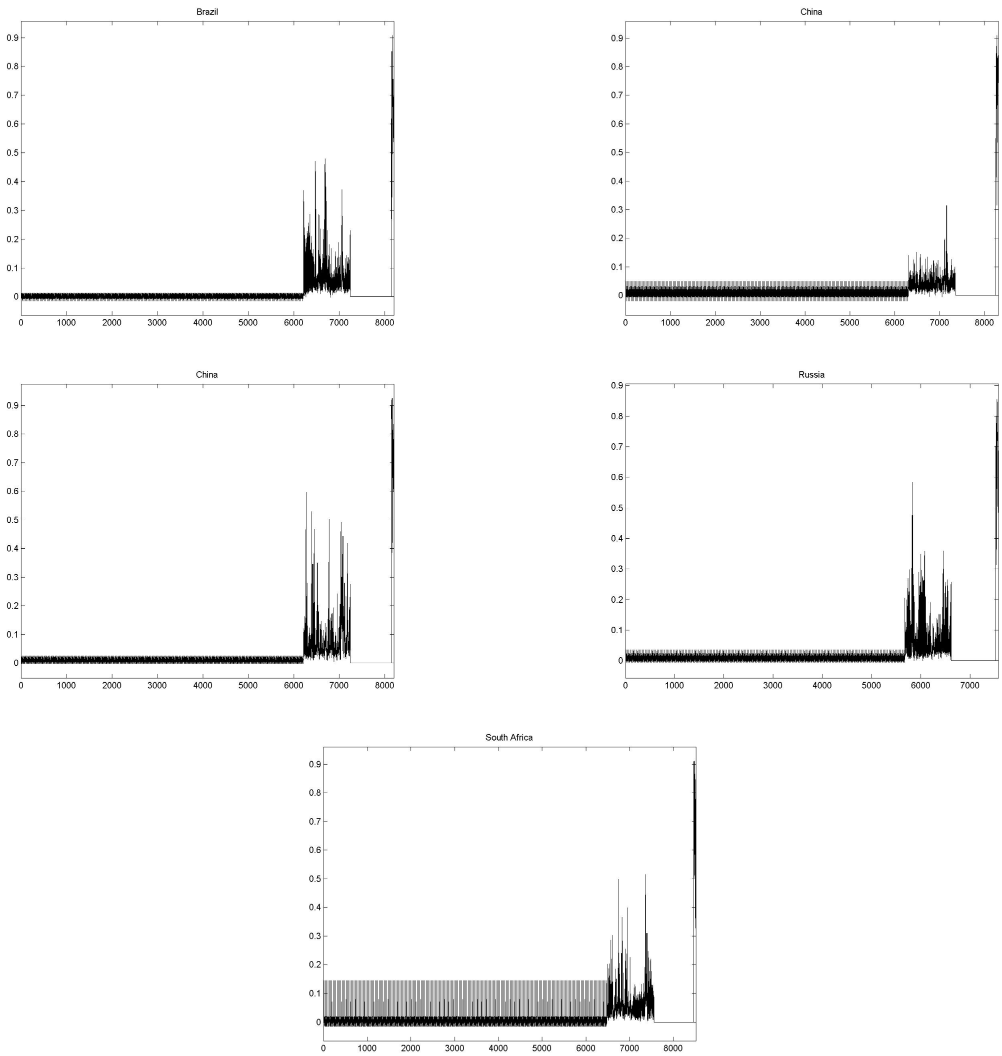

Figure D.1: 10^{th} order sample autocorrelation of the draws

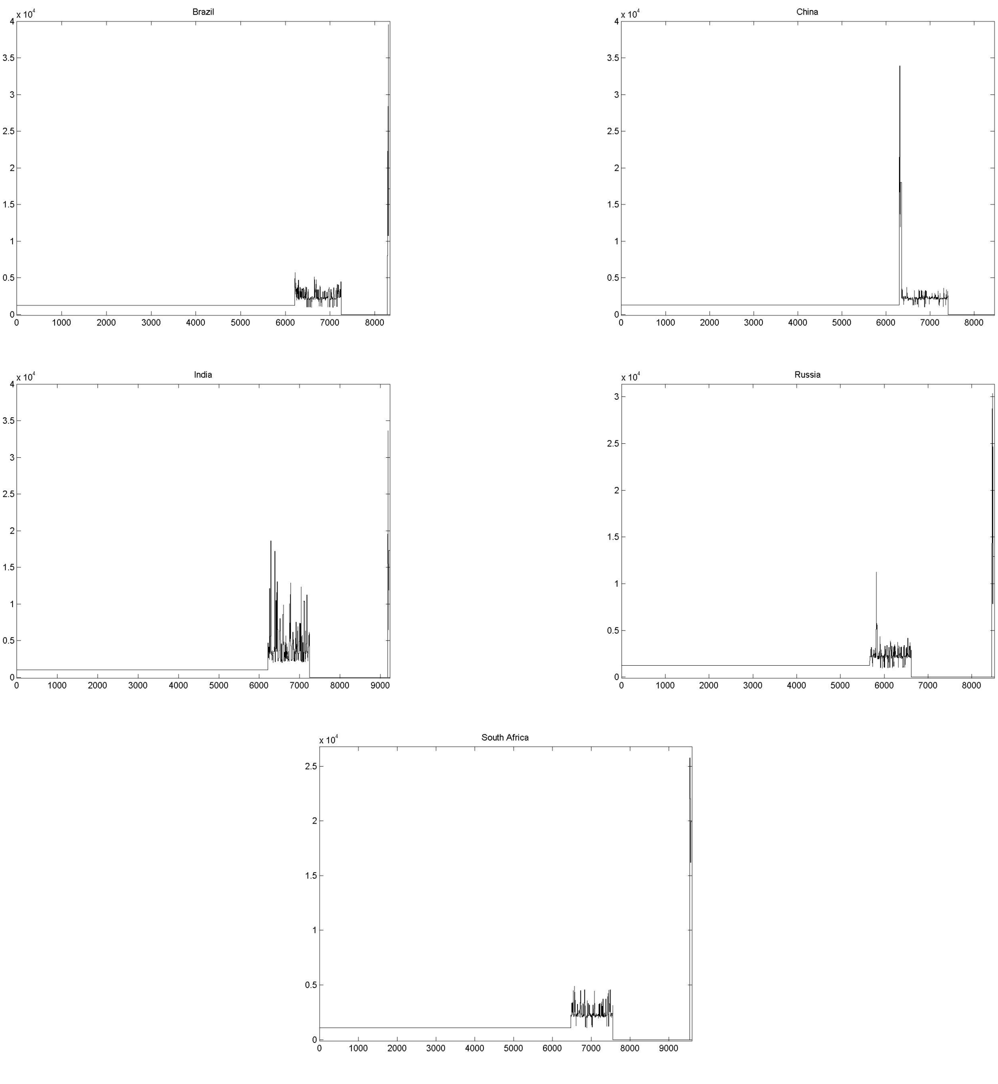

Figure D.2: Minimum number of iterations to obtain convergence

E Impulse Response Functions

In the case of a time-invariant VAR model, impulse responses are written as

$$y_t = \Psi(\alpha)v_t y_t = \sum_{i=0}^{\infty} \psi_i v_{t-i} \tag{E.29}$$

Where ψ_i measures the impulse responses and corresponds to the moving average coefficients. With a time-varying parameters model, the formula of the impulse responses becomes:

$$y_t = \sum_{i=0}^{\infty} \psi_{t-i,i} v_{t-i} \tag{E.30}$$

The aim of the study of the impulse responses is to know whether the good luck theory can explain the Great Moderation. To do it, we plot both the impulse responses of different dates of the sample and the evolution over time of the impulse responses for a given time horizon.

The difficulty with the impulse responses of a TVP VAR model is that values of parameters have changed between the period at which the shock occurs and the impulse response horizon. For simplicity, we suppose that the expected values of all shocks between these two periods are equal to zero. It means that if a shock is simulated at the period t then the impulse responses from t and the time horizon are calculated with the parameters of period t.

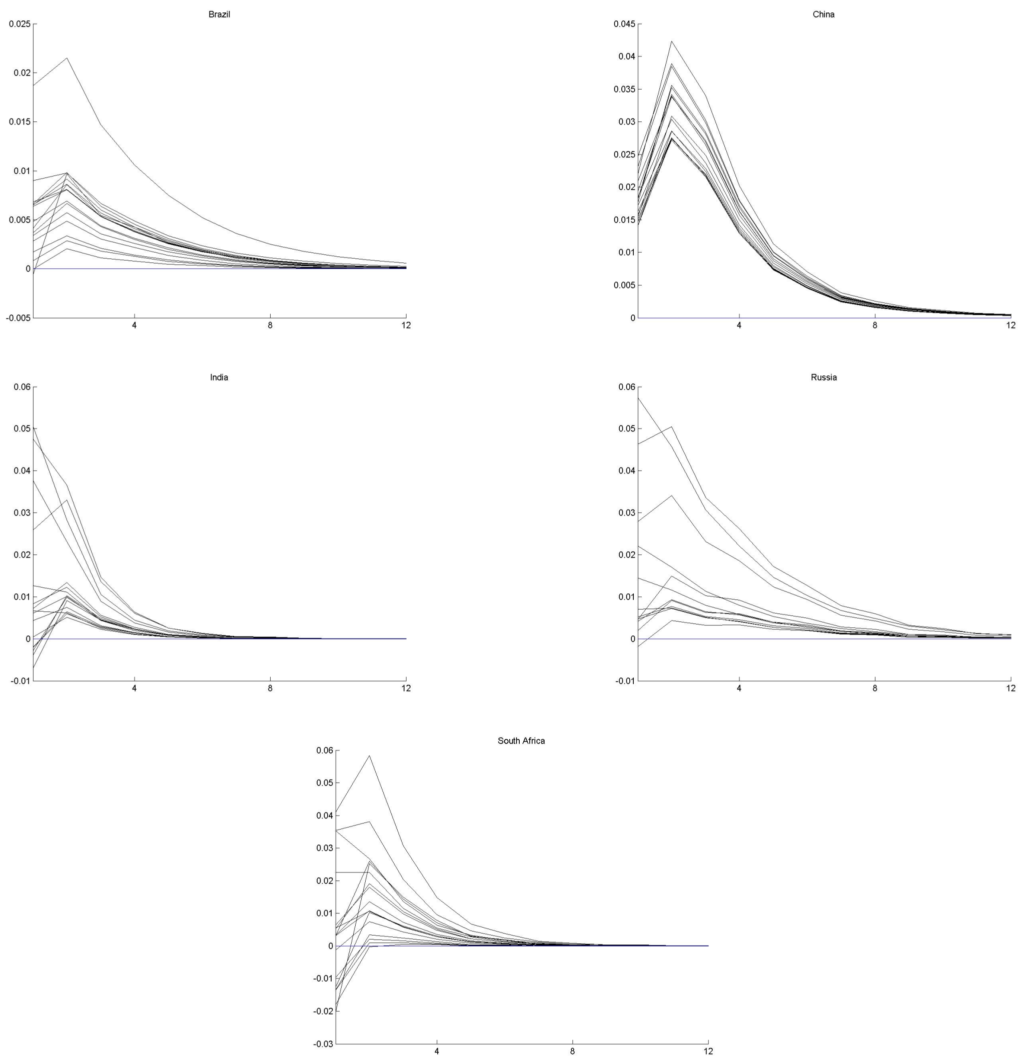

Figure E.1: Response of CPI, shock to NEER in January

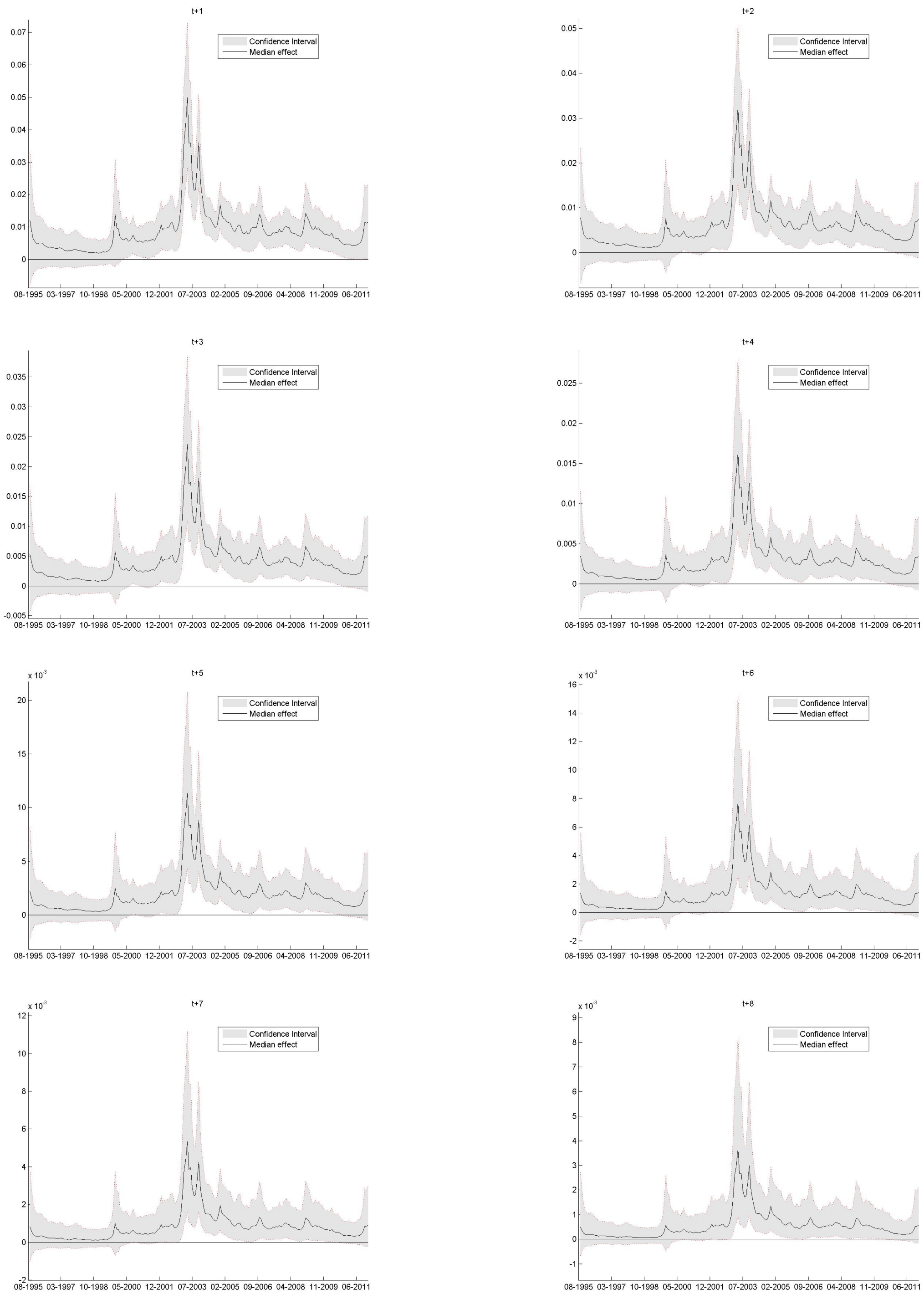

Figure E.2: Response of CPI, shock to NEER (Brazil)

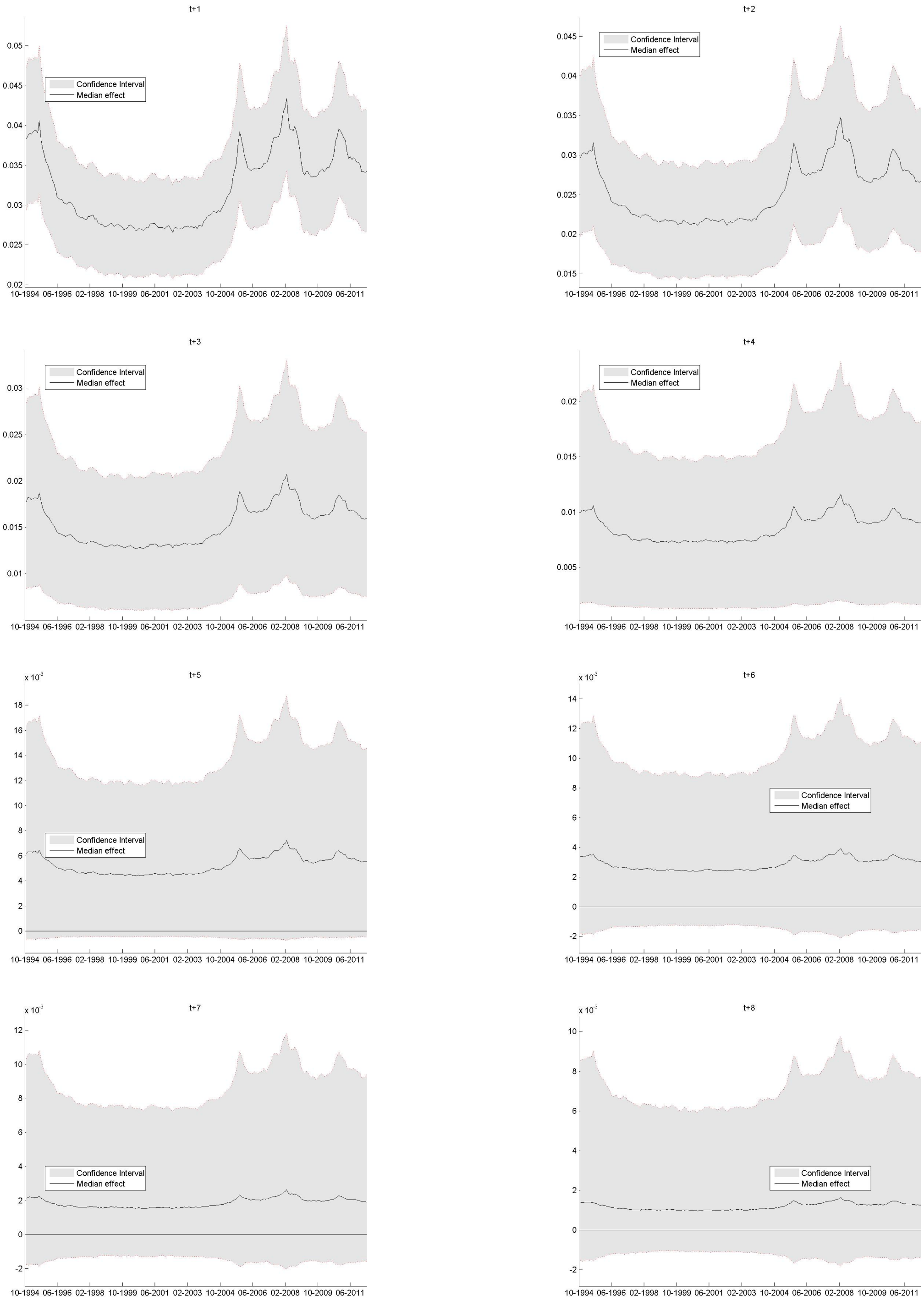

Figure E.3: Response of CPI, shock to NEER (China)

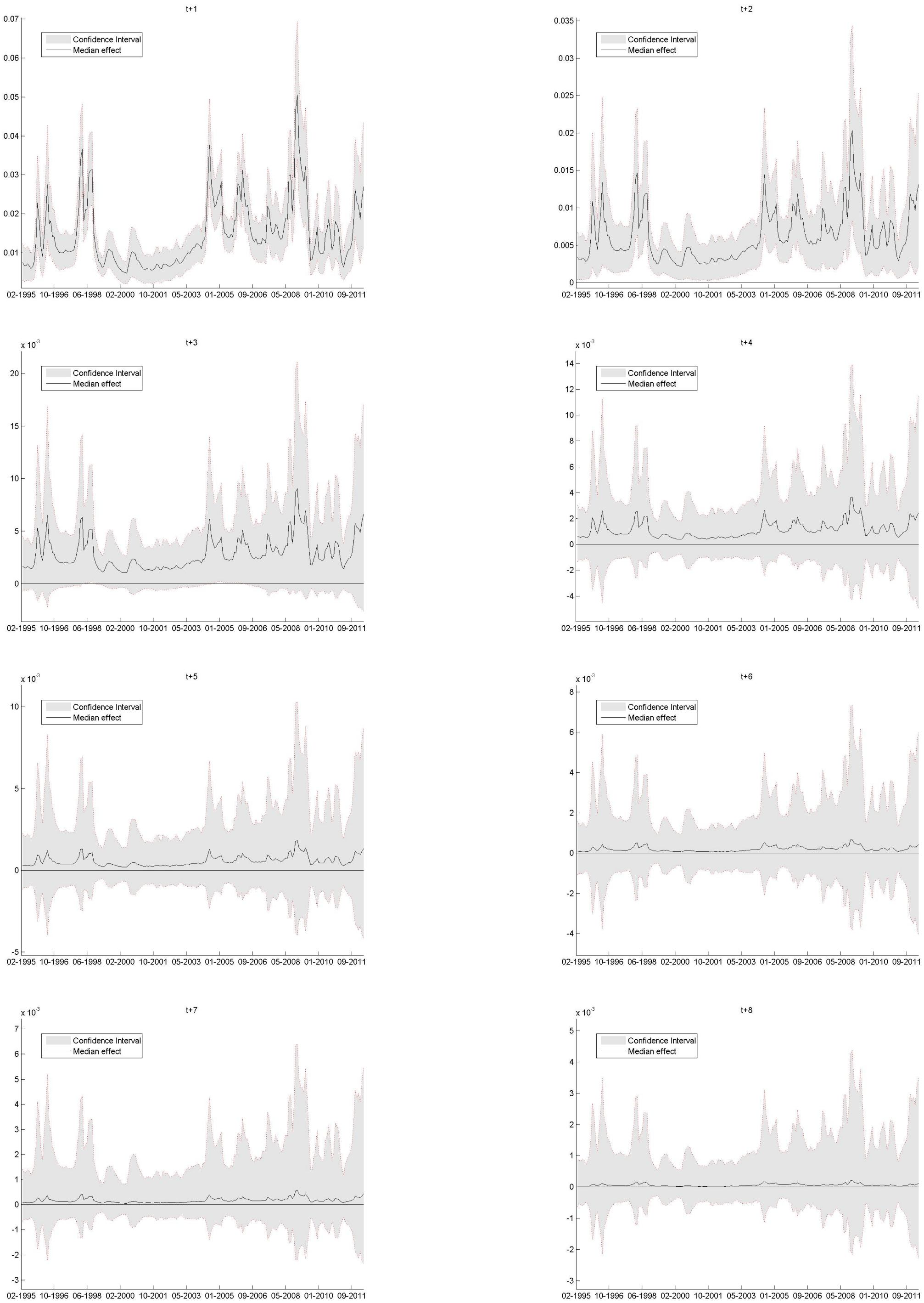

Figure E.4: Response of CPI, shock to NEER (India)

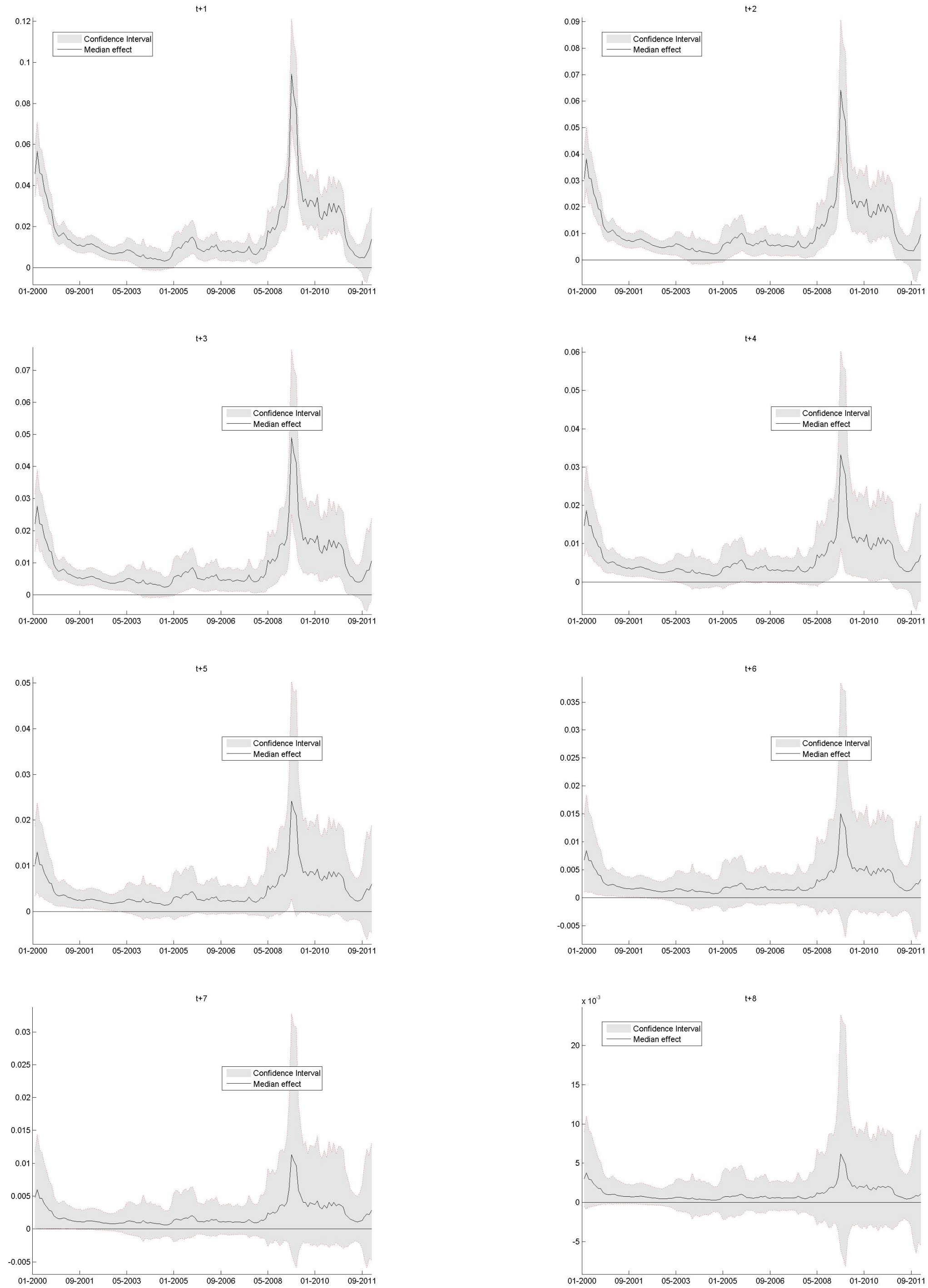

Figure E.5: Response of CPI, shock to NEER (Russia)

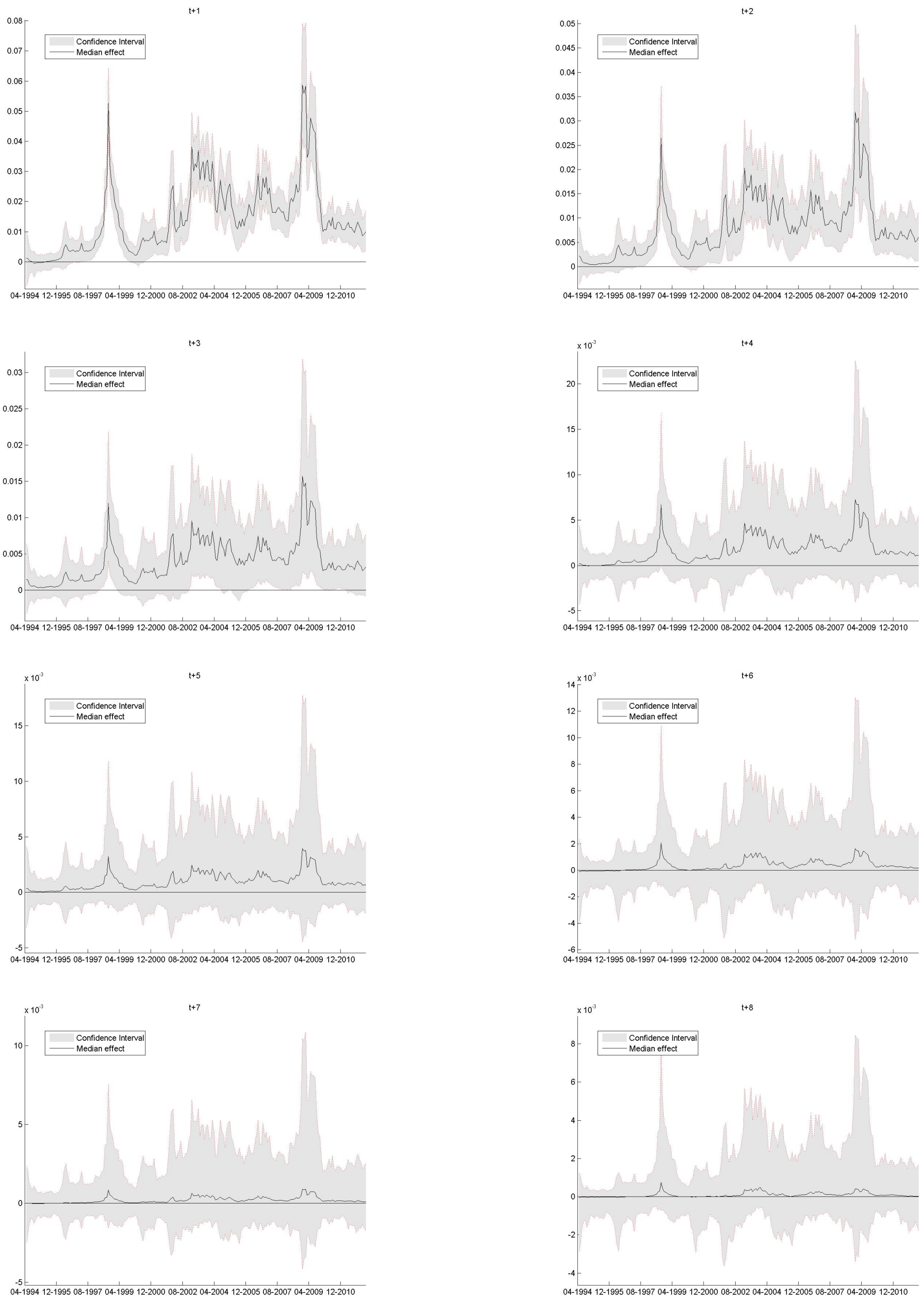

Figure E.6: Response of CPI, shock to NEER (South Africa)