UNIVERSIDADE FEDERAL DO PARANÁ

Diego Ferreira

Essays in Nonlinear Macroeconometrics: Fiscal Policy and Phillips Curve

Curitiba
2014

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Master's dissertation presented as a partial fulfillment of the requirement for the Master's degree in Development Economics, Graduate Program in Development Economics, Applied Social Science Sector, Federal University of Paraná.

Advisor: Fernando Motta Correia, Ph.D.
Co-Advisor: Andreza Aparecida Palma, Ph.D.

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We must trust to nothing but facts: These are presented to us by Nature, and cannot deceive. We ought, in every instance, to submit our reasoning to the test of experiment, and never to search for truth but by the natural road of experiment and observation.

- Antoine Lavoisier

Do nothing, say nothing, and be nothing, and you'll never be criticized.

- Elbert Hubbard

Abstract

This dissertation consists of two chapters about nonlinear macroeconometrics applied to Brazil. The first chapter analyzes the relationship between government spending and private consumption in Brazil through an application of a VAR with time-varying parameters and stochastic volatility, estimated with Bayesian simulation over the 1995:Q1–2013:Q1 period. Our findings reveal that fiscal policy is indeed effective in stimulating GDP and private consumption, which characterizes the presence of positive Keynesian multipliers. However, these positive effects are only sustained on the short-run. Also, stochastic volatility decreased from 2000 onwards, suggesting that Brazil has steadily improved its macroeconomic stability by adopting an inflation-targeting framework. Regarding the fiscal policy cyclicality, we further document that Brazil has maintained a stable procyclical activism in the recent years. The second chapter proposes a generalized Phillips curve in order to forecast Brazilian inflation over the 2003:M1–2013:M10 period. To this end, we employ the Dynamic Model Averaging (DMA) method, which allows for both model evolution and time-varying parameters. The procedure mainly consists in state-space representation and by Kalman filter estimation. Overall, the dynamic specifications deliver good inflation predictions for all the forecast horizons considered, underscoring the importance of time-varying features for forecasting exercises. As to the usefulness of the predictors on explaining the Brazilian inflation, there are evidences that the short- and long-term Phillips curve relationship may be rejected for Brazil while short- and medium-term exchange rate pass-through apparently has been decreasing in the last years.

Keywords: Fiscal Policy. Private Consumption. Phillips Curve. Forecast. Time-Varying Parameters.

Resumo

A presente dissertação trata da aplicação de métodos econométricos não-lineares a questões macroeconômicas brasileiras. O primeiro capítulo analisa a relação entre gasto público e consumo privado no Brasil através da aplicação de um modelo VAR com parâmetros variantes no tempo e volatilidade estocástica, estimado via simulação Bayesiana para o período 1995:T1–2013:T1. Os resultados revelam que a política fiscal é de fato capaz de efetivamente estimular PIB e consumo privado, caracterizando a presença de multiplicadores keynesianos positivos. Entretanto, tais efeitos positivos apenas se sustentam no curto-prazo. Além disso, a volatilidade estocástica reduziu a partir dos anos 2000, sugerindo que o Brasil melhorou sua estabilidade macroeconômica ao adotar o regime de metas para a inflação. Em relação a ciclicidade da política fiscal, há evidências de que o Brasil manteve um ativismo procíclico estável nos últimos anos. Já o segundo capítulo propõe uma curva de Phillips generalizada para prever a inflação brasileira no período 2003:M1–2013:M10. Neste sentido, emprega-se o método *Dynamic Model Averaging*, que permite tanto a evolução do modelo quanto parâmetros variando no tempo. O procedimento consiste basicamente em representação de estado-espaço e estimação via filtro de Kalman. De modo geral, as especificações dinâmicas proveram boas predições para todos os horizontes considerados, dando enfoque à importância de elementos variantes no tempo ao realizar previsões. Com relação a utilidade do conjunto de preditores para explicar a dinâmica da inflação brasileira, existem evidências de que a curva de Phillips pode não se adequar a economia nacional no curto e longo prazo, enquanto o repasse cambial de curto e médio-prazo aparenta ter se reduzido nos últimos anos.

Palavras-Chave: Política Fiscal. Consumo Privado. Curva de Phillips. Previsão. Parâmetros Variantes no Tempo.

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Chapter 1

The Time-(In)Variant Interplay of Government Spending and Private Consumption in Brazil*

1.1 Introduction

The depth of the recent global recession has rekindled the debate on the role of discretionary fiscal policy. In order to mitigate the potential economic downturn and ensure the resilience of the financial system, governments around the world have designed unprecedented fiscal stimulus packages. However, due to controversial predictions of neoclassical and Keynesian oriented models, there remains no macroeconomic consensus on the interplay of government spending shocks and private consumption.

Since the seminal paper by Barro (1974), which introduced the concept of *Ricardian Equivalence*, there has been a resurgence in the debate on the possible non-Keynesian effects of fiscal policies. By embodying this feature, the future tax burden of present fiscal stimulus restrains the Keynesian effects on private consumption (Mankiw and Summers, 1984; Blanchard, 1985). Moreover, models of Neoclassical tradition argues that the intertemporal substitution effects on labor supply are not strong enough to offset the negative wealth effects driven by an increase on government spending (see e.g. Barro and King (1984) and Baxter and King (1993)).

By amending the Real Business Cycles (RBC) framework to allow for monopolistic competition and nominal rigidities, macroeconomic modeling departed from price flexibility in order to achieve short-run non-neutrality of money. Regarding the effectiveness

*We do thank Jouchi Nakajima for his helpful comments. The usual disclaimer applies.

of fiscal policy to stimulate private consumption, these so called New Keynesian models formerly presented unexpected non-Keynesian responses. Smets and Wouters (2003) underscored the fact that price stickiness by itself could not overturn the crowding-out effects of public spending on private consumption, therefore endorsing the previous Neoclassical predictions.

However, empirical evidences - mainly based on vector autoregressions (VAR) - depicted another conclusion. For instance, by a structural VAR approach, Blanchard and Perotti (2002) obtained positive public spending multipliers for output and private consumption with US postwar data. Using the same estimation technique as the latter, Perotti (2002) verified positive multipliers for United Kingdom, Germany, Canada and Australia, despite their downward trend over time. Furthermore, many other papers have used similar approaches[1], including Fatás and Mihov (2001), Mountford and Uhlig (2002), Ramey (2008), Fisher and Peters (2009) and Ilzetzki et al. (2013).

Following Mankiw (2000)[2], Galí et al. (2004) proposed a new feature to the New Keynesian framework as an attempt to counter these theoretical and empirical divergences. By introducing the coexistence of non-Ricardian (*rule-of-thumb*) and intertemporal optimizing households, the authors generated standard Keynesian effects of government spending expansions for the US economy, arguing that the usual negative wealth effect was damped. The studies by Linnemann (2006), Ravn et al. (2006) and Forni et al. (2009) supported the latter results. On the other hand, one should not generalize these findings. Coenen and Straub (2005) showed that the presence of positive public spending multipliers for private consumption is directly related to the share of non-Ricardian households in the population. Moreover, Ratto et al. (2009) and Furceri and Mourougane (2010) highlighted labor market adjustment costs and financial market stress as restrictions to the expected Keynesian effects of fiscal policies, respectively.

Regarding the Brazilian economy, empirical evidences are ambiguous as well as scarce. From a VAR viewpoint, Silva and Cândido Júnior (2009) concluded that positive government spending shocks initially increases private consumption, although its overall reaction is non-Keynesian. On the contrary, Mendonça et al. (2009) and Peres (2012) identified standard Keynesian responses. With respect to New Keynesian mod-

[1]Despite the choice of a structural VAR framework, the identification restrictions imposed differ. For instance, Fatás and Mihov (2001) applied the standard recursive approach (Choleski decomposition) introduced by Sims (1980), while Mountford and Uhlig (2002) used the sign-restrictions scheme. Besides, Blanchard and Perotti (2002) and Perotti (2002) assigned structural restrictions based on fiscal institutional information.

[2]Mankiw (2000) pointed out that non-Ricardian households were a crucial element in order to explain heterogeneity in consumer behavior and, therefore, enhance the transmission channels of fiscal policies in Neoclassical and overlapping generation models.

els, results differ as well (see e.g. Silva and Portugal (2010), Carvalho and Valli (2010) and Mussolini and Kanczuk (2011)).

Although time-invariant analysis has been useful in order to evaluate the effects of discretionary fiscal policies, recent empirical studies have also accounted for potential time heterogeneity patterns. In general, fiscal policy has lost its effectiveness to stimulate output and consumption in the US and some European economies after 1980. For instance, based on a recursive structural VAR with time-varying parameters (TVP-VAR), Kirchner et al. (2010) discussed whether the effects of government spending shocks have changed in the Euro area, for the 1980-2008 period. Their results shows an initial increase in the short-run spending multipliers (early 1980s until late 1980s), but a decreasing trend thereafter. As to the US economy, Pereira and Lopes (2010) argues that fiscal policy has lost its capacity to stimulate output from 1965 to 2009, despite positive multipliers. Moreover, there are evidences of non-Keynesian effects of public spending shocks on private consumption.

In light of the facts mentioned above and given the lack of consensus towards the effects of government spending shocks on private consumption in Brazil, our study aims to estimate a TVP-VAR to gain a better understanding of this relationship and address its potential time-variation. To the best of our knowledge, this is the first study that investigates whether this relationship changed over time in Brazil. In addition, the present study represents the first application of TVP-VAR techniques using Brazilian quarterly fiscal data. In our empirical analysis, a four-variable system is estimated, following closely Kirchner et al. (2010). The model includes government spending, GDP, short-term interest rate and private consumption for the 1995:Q1–2013:Q1 period.

The remainder of the chapter is organized as follows. Section (1.2) introduces the vector autoregression (VAR) models and how *time-varying* features were implemented on these models, in order to capture potential changes on macroeconomic behavior over-time. Furthermore, it describes the data set and the Bayesian estimation procedure. Section (1.3) presents our empirical results, highlighting the effectiveness of government spending shocks and its cyclicality. We also perform a time-invariant comparison through an application of a Bayesian VAR as well as a prior sensitivity analysis. Finally, section (1.4) concludes.

1.2 Specification and Estimation Methodology

1.2.1 Data Description

In order to evaluate the time-variation and the potential effects of Brazilian fiscal policy, we use quarterly data from 1995:Q1 until 2013:Q1. The specification includes government spending (measured as government final consumption expenditure)[3], private consumption (measured as private final consumption expenditure), GDP (measured at factor prices) and short-term interest rate (measured as Brazilian Central Bank's overnight call rate). The time series were downloaded from the Brazilian Institute of Geography and Statistics (IBGE) and the Brazilian Central Bank (BCB).

Government spending, private consumption and GDP were first realized by the General Price Index - Internal Availability (IGP-DI), whose base is 1995:Q1, and then seasonally adjusted, applying the X-12-ARIMA method. Moreover, the latter data series enter the analysis in the form of their respective real *per capita*[4] values. The short-term interest rate is seasonally adjusted by the the X-12-ARIMA method as well and expressed in nominal, annual terms.

Figure 1.1 describes the data series movements over time. In general, the time series present contrasting patterns, which can be seen as a first indication that a time-varying parameter model might be the optimal choice. For instance, one can identify two sub-sample periods: from 1995 to the end of 2002, and from 2003 onwards.

Regarding the first phase (1995-2003), the evident downward trend in the macroeconomic performance as well as its volatile behavior are intrinsically attached to the economic and political reforms implemented by the Real Plan in 1994, considered a response to the inertial inflation phenomenon and the Debt Crisis episode in the early 1980's. For instance, tax revenues increased from 22% of GDP in 1994 to 34% of GDP in 2002 (Loureiro and Abrucio, 2004). As a result, real *per capita* government spending decreased by 2.5% per year in the period, while real *per capita* private consumption and GDP decreased by 1.8% per year and 2% per year, respectively.

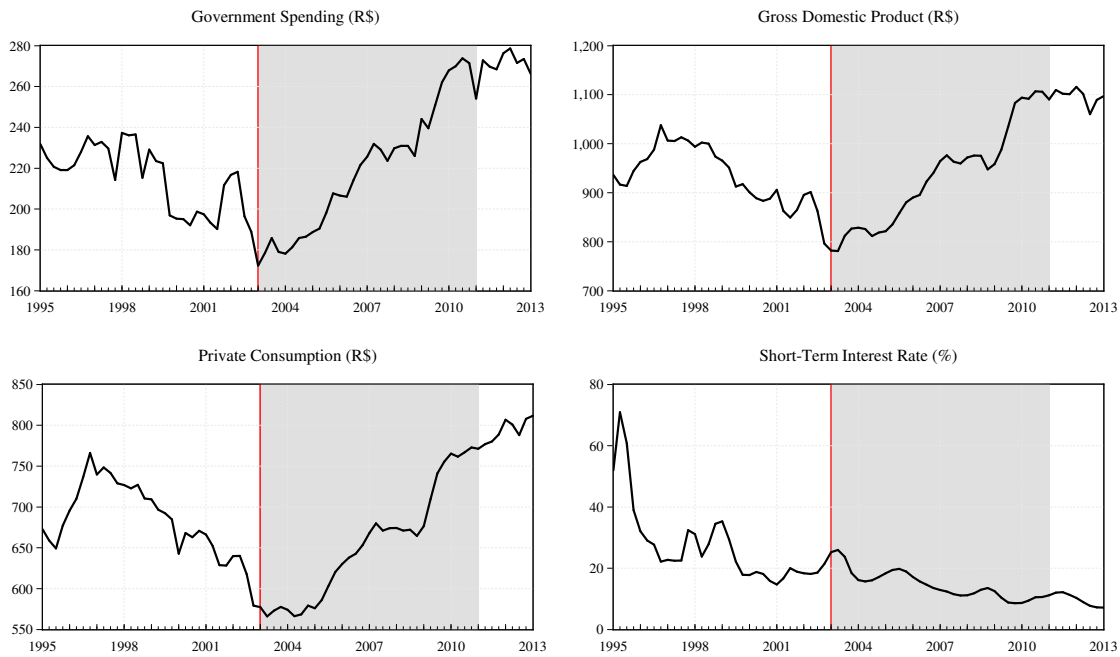
From the early 2003 onwards, Brazilian macroeconomic activity experienced a growing and less volatile path. The increase of international trade and voluntary capital flows to emerging countries are the main driven forces of the auspicious Brazilian growth, with

[3]The government final consumption expenditure time series sums up expenditures from central administration agencies and decentralized entities (independent agencies, foundations and funds) at federal, state and municipal spheres. It also considers parastatals entities, such as the S System and Federal Councils.

[4]In order to achieve quarterly data for population, it was applied a cubic spline interpolation to the annual data available (source: IBGE).

real *per capita* GDP increasing an average of 3.4% per year. The recovery of the global economy since 2001, due to Chinese and American economic growth, resulted in the increase of both external demand and commodities' prices (Teixeira and Pinto, 2012). In other words, one could argue that the Brazilian economic boom is strongly correlated to international conditions, therefore exposing the country's potential fragility.

Figure 1.1: Brazilian Data (1995:Q1–2013:Q1)



Notes. Shaded area corresponds to Luiz Inácio "Lula" da Silva 1st and 2nd terms as president; government spending, private consumption and GDP are all expressed in real *per capita* terms; short-term interest rate is measured in nominal, annual terms; all time series are seasonally adjusted; *Sources:* Brazilian Institute of Geography and Statistics (IBGE) and Brazilian Central Bank (BCB).

Although the main goal of fiscal policy in the period between 2003–2006 was the maintenance of public debt solvency, real *per capita* government spending increased by 4.4% per year until early 2013. One possible explanation is the creation and reinforcement of direct transfer programs as well as anti-cyclical fiscal stimulus packages enacted since 2009 to prevent the economic downturn from the recent global financial crisis.

Real *per capita* private consumption followed the same upper trend as the latter variables, with an increase by 3.4% per year. According to Teixeira and Pinto (2012), minimal wage increased by 5.9% per year since 2003 as well as expansion of personal loans went from 26.1% of GDP in 2003 to 45.2% of GDP in 2010, resulting in positive

effects on aggregate demand and income distribution. Therefore, one could point out these phenomena as the main causes of the private consumption growing.

Finally, throughout the whole period, there is clear downward trend regarding the short-term interest rate despite the Brazilian Central Bank efforts to control inflation. Between 1995 and 2003, the interest rate presented a rather volatile behavior, decreasing 3.8 percentage points per year. Moreover, from 2003 onwards, it decreased by 1.8 percentage points per year in average, reaching the lowest value at the first quarter of 2013: 7.1% per year.

Based on standard unit root tests, namely, the Augmented Dickey-Fuller (ADF) (1981) test, the Phillips-Perron (PP) (1985) test, the Dickey-Fuller test with generalized least squares detrending (DF-GLS) and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) (1992) test, the data series were found to be non-stationary in general, hence converted to their corresponding growth rate[5]. The test statistics and the specification for the deterministic terms are presented in Table (1.1).

Table 1.1: Unit Root Tests

Data	Deterministic Terms	ADF	PP	DF-GLS	KPSS
GS	Intercept	-0.9100	-0.8389	-0.9999	0.5026**
GS	Intercept, Trend	-1.7257	-1.6342	-1.3778	0.2672*
GDP	Intercept	-0.9039	-0.5843	-0.9271	0.4145***
GDP	Intercept, Trend	-1.2893	-1.1055	-1.3050	0.2545*
STIR	Intercept	-2.4878	-2.9633**	1.8368***	0.9544*
STIR	Intercept, Trend	-3.3638***	-3.0231	-0.6122	0.1387***
PC	Intercept	-0.4244	-0.3927	-0.4888	0.3208
PC	Intercept, Trend	-0.3668	-0.6691	-0.8693	0.2556*
GS Growth	Intercept	-9.2591*	-9.2824*	-7.5559*	0.2800
GDP Growth	Intercept	-6.1323*	-6.0787*	-0.5746*	0.2642
ΔSTIR	Intercept	-4.9671*	-7.9031*	-1.2472	0.1787
PC Growth	Intercept	-6.5123*	-6.5823*	5.2354*	0.3329

Notes. *, ** and *** indicate that the null hypothesis is rejected at the 1%, 5% and 10% significance level. For the ADF and ADF-GLS tests, the lag length selection was based on the Schwarz info criterion. The Bartlett kernel and the Newey-West Bandwidth were applied to the spectral estimation of PP and KPSS tests. The terms "GS", "STIR" and "PC" refer to government spending, short-term interest rate and private consumption, respectively.

[5]Regards the short-term interest rate, solely the usual difference operator was applied to the series. One should note that the results for the short-term interest rate are divergent among themselves. However, the tests depicted stationarity for its first difference (except the DF-GLS test), which was therefore used in the estimation process.

1.2.2 Time-Varying Parameter (TVP) Bayesian Vector Autoregression Model with Stochastic Volatility (SV)

Since Sims (1980), the *vector autoregression* (VAR) *model* has played a prominent role on macroeconometric analysis. Considered a flexible and easy tool for dealing with multivariate time series, it generally consists in a multi-equation system describing the economic dynamics. A basic structural VAR model can be defined as:

$$Ay_t = F_1 y_{t-1} + \cdots + F_s y_{t-s} + u_t, \quad t = s+1, \ldots, n, \tag{1.1}$$

where y_t is a $k \times 1$ vector of observed variables; A is a $k \times k$ matrix of contemporaneous relationships; $F_1, \ldots, F_n$ is a $k \times k$ matrix of coefficients; and $u_t \sim N(0, \Sigma\Sigma)$ is a $k \times 1$ structural shock vector, with:

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix}$$

However, one cannot directly estimate Equation (1.1) since its structure allows A and F to show an infinite set of different values with exactly the same probability distribution, hence data alone cannot provide the true values of A and F. Therefore, by assuming that the simultaneous relations of the structural shock are identified by a recursive approach, which imposes A to be a lower-triangular matrix with the diagonal elements equal to one, the Equation (1.1) can be re-specified as a reduced form VAR model:

$$y_t = B_1 y_{t-1} + \cdots + B_s y_{t-s} + A^{-1}\Sigma\varepsilon_t, \quad \varepsilon_t \sim N(0, I_k), \tag{1.2}$$

where $B_i \equiv A^{-1}F_i$, for $i = 1, \ldots, s$ and:

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{pmatrix}$$

Defining B as a stacked row of $B_1, \ldots, B_s$ and $X_t \equiv I_k \otimes (y'_{t-1}, \ldots, y'_{t-s})$, whose $\otimes$ represents the Kronecker product, the reduced form of Equation (1.2) can be rewritten as:

$$y_t = X_t\beta + A^{-1}\Sigma\varepsilon_t, \tag{1.3}$$

Although the parameters β, A and Σ in Equation (1.3) are time-invariant, these can re-specified to account for time-varying analysis as well. Following Primiceri (2005) and Nakajima (2011), one can rewrite Equation (1.3) as:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t, \quad t = s+1, \ldots, n, \tag{1.4}$$

whose parameters are all time-varying[6]. Let $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, \ldots, a_{k,k-1})'$ be a stacked vector of the lower-triangular elements in A_t and $h_t = (h_{1t}, \ldots, h_{kt})'$ with $h_{jt} = \log\sigma^2_{jt}$, for $j = 1, \ldots, k$ and $t = s+1, \ldots, n$, the parameters in Equation (1.4) are assumed to follow driftless random walk processes[7], given by:

$$\beta_{t+1} = \beta_t + u_{\beta t}, \quad a_{t+1} = a_t + u_{at}, \quad h_{t+1} = h_t + u_{ht},$$

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right),$$

for $t = s+1, \ldots, n$, where I is the identity matrix of k dimensions, while Σ_β, Σ_a and Σ_h are positive definite matrices, whose elements are usually called the hyperparameters. As in Nakajima (2011), shocks are assumed uncorrelated among the time-varying parameters and the covariance matrices Σ_β, Σ_a and Σ_h are assumed to be diagonal[8]. Moreover, $\beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0})$, $a_{s+1} \sim N(\mu_{a_0}, \Sigma_{a_0})$ and $h_{s+1} \sim N(\mu_{h_0}, \Sigma_{h_0})$, which are

[6] As discussed in Nakajima (2011), time-varying intercepts can also be incorporated in TVP-VAR models by defining $X_t \equiv I_k \otimes (1, y'_{t-1}, \ldots, y'_{t-s})$.

[7] One should note that the volatility states (h_t) evolve as geometric random walks, hence depicting a TVP-VAR model with stochastic volatility (SV) as in Primiceri (2005). By including the time-varying stochastic volatility to the VAR estimation, one can prevent potential biases in the covariance matrix for the disturbances and in the autoregressive coefficients because of the misspecification of the dynamics of the parameters (Nakajima et al., 2009).

[8] Nakajima (2011) argues that the diagonal assumption for Σ_β, Σ_a and Σ_h does not affect sensitively the results when compared to the non-diagonal assumption.

the initial states of the time-varying parameters.

Since TVP-VAR models with stochastic volatility are non-linear non-Gaussian state-space representations, the Maximum Likelihood (ML) approach cannot provide reliable estimates for the parameters. Also, allowing for time-variation in the parameters of a VAR framework as well as in the error covariance matrix causes serious concerns about over-parametrization (Koop and Korobilis, 2010). Therefore, the Bayesian approach using the Markov chain Monte Carlo (MCMC) method is by now fairly standard in dealing with this class of models (e.g. Primiceri (2005) and Nakajima (2011)).

By splitting up the original problem into a number of smaller steps, the Bayesian inference is able to deal with high-dimensional parameter space and potential non-linearities in the likelihood function. Under the assumption of a certain prior probability density, the MCMC algorithm is able to generate the joint posterior distribution of the parameters, given as:

$$p(\theta|y) = \frac{p(\theta)L(y|\theta)}{\int_\theta p(\theta)L(y|\theta)d\theta} \propto p(\theta)L(y|\theta) \tag{1.5}$$

where $y = \{y_t\}_{t=1}^n$; $\theta = \{\beta, a, h, \Sigma_\beta, \Sigma_a, \Sigma_h\}$; $p(\theta)$ is the prior density distribution; $p(\theta|y)$ is the posterior density distribution; and $L(y|\theta)$ is the likelihood function. In other words, given y, the MCMC simulation draws samples from $p(\theta|y)$ in order to achieve the values of θ. This drawing process can be described by the following MCMC algorithm[9]:

1. Initialize θ;
2. Sample $\beta \mid a, h, \Sigma_\beta$ and y;
3. Sample $\Sigma_\beta \mid \beta$;
4. Sample $a \mid \beta, h, \Sigma_a$ and y;
5. Sample $\Sigma_a \mid a$;
6. Sample $h \mid \beta, a, \Sigma_h$ and y;
7. Sample $\Sigma_h \mid h$;
8. Return to 2.

Regarding the choice of priors, this paper sets rather diffuse and uninformative priors in order to mitigate any identification issues. The main reason for these assumptions relies on the fact that, to the best of our knowledge, TVP-VAR applications to fiscal policy are inexistent for Brazilian data. Therefore, the priors follow closely the ones in Nakajima (2011):

[9]For technical details, see Nakajima et al. (2009).

$$(\Sigma_\beta)_i^{-2} \sim G(25, 0.01I), \quad (\Sigma_a)_i^{-2} \sim G(4, 0.01), \quad (\Sigma_h)_i^{-2} \sim G(4, 0.01)$$

where $(\Sigma_\beta)_i^{-2}$, $(\Sigma_a)_i^{-2}$ and $(\Sigma_h)_i^{-2}$ represents the i-th diagonal element of the matrices and G is the Gamma distribution. In addition, flat priors were set to the initial states of the time-varying parameters, such that $\mu_{\beta_0} = \mu_{a_0} = \mu_{h_0} = 0$ and $\Sigma_{\beta_0} = \Sigma_{a_0} = \Sigma_{h_0} = 10 \times I$. Also, following the Akaike information criterion (AIC) and the Schwarz information criterion (SBC), applied to a time-invariant VAR, the TVP-VAR is estimated based on two lags[10].

1.3 Estimation Results

In order to compute the posterior estimates, we draw $M = 50,000$ samples after the initial 5,000 samples were discarded in the burn-in period. Figure (1.2) presents the sample autocorrelation function, the sample paths and the posterior densities for selected parameters. In general, the sampling method efficiently produces uncorrelated samples, since the sample paths look stable and the sample autocorrelations drop stably.

Table (1.2) provides the estimates for posterior means, standard deviations, the 95% credible intervals, the convergence diagnostics (CD)[11] and the inefficiency factors[12] of Geweke (1992). According to the CD statistics obtained, one should observe that the null hypothesis of the convergence to the posterior distribution is not rejected for the parameters at the 10% significance level. Moreover, the sampling for the parameters and state variables is efficient since the inefficiency factors are rather low.

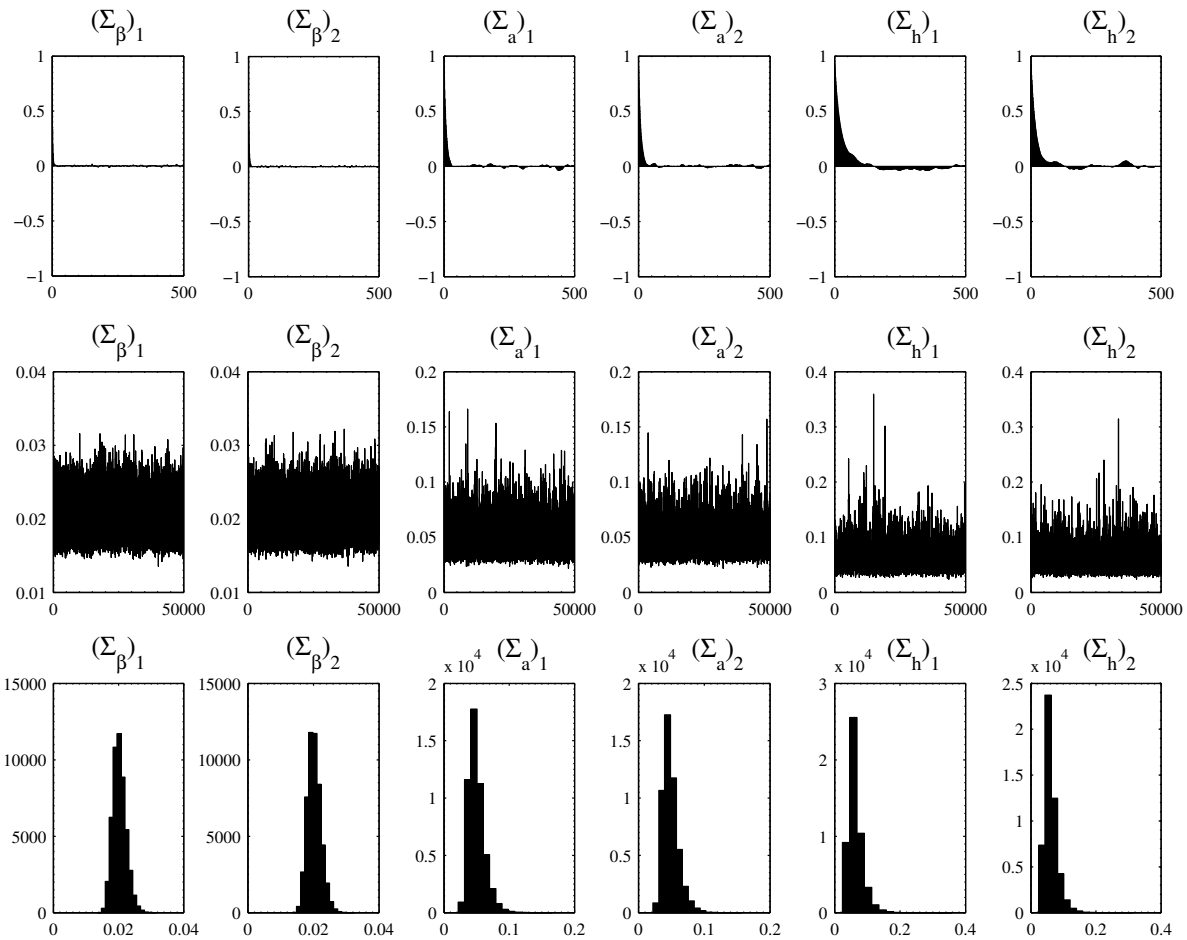
Figure (1.3) plots the posterior estimates of stochastic volatility of the structural shock, $\sigma_t^2 = \exp(h_{it})$, on four variables, based on the posterior mean, and the one-standard-deviation intervals. Regards the time-varying volatility of the government

[10] These results are available upon request from the author.

[11] Following Geweke (1992), the CD statistics can be obtained by $\text{CD} = (\bar{x}_0 - \bar{x}_1)/\sqrt{\hat{\sigma}_0^2/n_0 + \hat{\sigma}_1^2/n_1}$, where n_0 and n_1 are respectively the first and the last n draws, $\bar{x}_j = (1/n_j)\sum_{i=m_j}^{m_j+n_j-1} x^{(i)}$, $x^{(i)}$ is the i-th draw, and $\sqrt{\hat{\sigma}_j^2/n_j}$ is the standard error of $\bar{x}_j$, for $j = 0, 1$. If the sequence of the MCMC sampling is stationary, then it converges in distribution to a standard normal. Based on Nakajima et al. (2009), we set $m_0 = 1$, $n_0 = 5,000$, $m_1 = 25,001$ and $n_1 = 25,000$, while the $\hat{\sigma}_j^2$ is obtained using a Parzen window with bandwidth $B_m = 500$.

[12] The inefficiency factor is defined as $1 + 2\sum_{s=1}^{B_m} \rho_s$, with ρ_s being the sample autocorrelation at lag s. This factor measures how well the MCMC chain mixes. Besides, when the inefficiency factor is equal to k, we need to draw k times as many MCMC samples as uncorrelated samples. For instance, the inefficiency factor for $(\Sigma_\beta)_1$ is 4.18, which implies that we obtain about $50,000/4.18 = 11,961$ uncorrelated samples.

Figure 1.2: Estimation Results of Selected Parameters in the TVP-VAR model



Notes. Sample autocorrelations (top), sample paths (middle) and posterior densities (bottom).

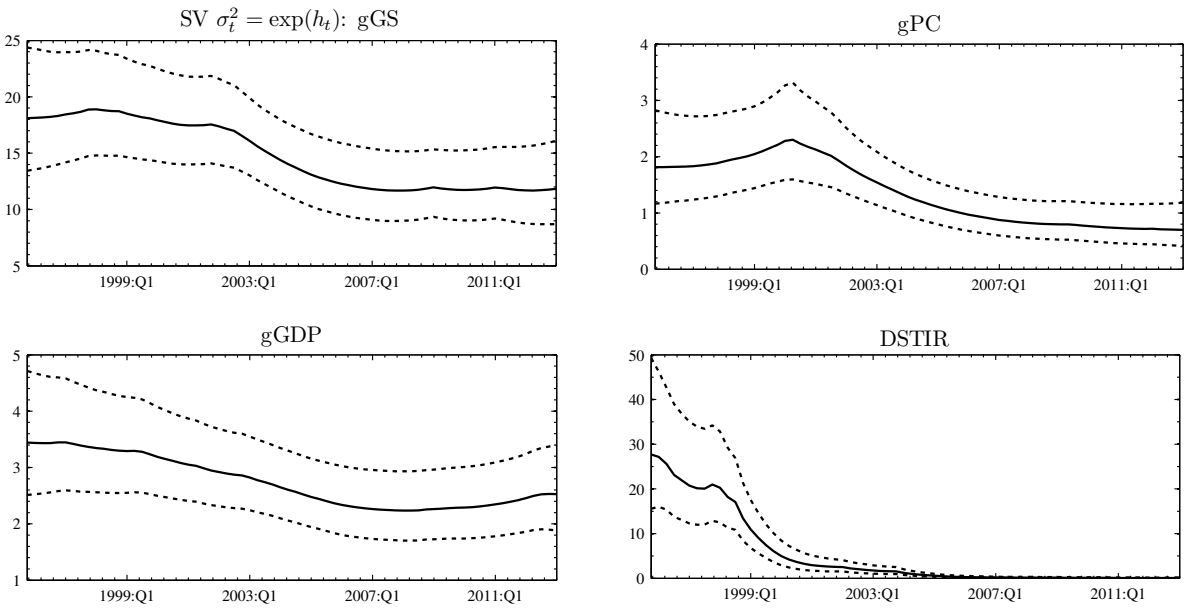
Table 1.2: Estimation Results of Selected Parameters in the TVP-VAR model

Parameter	Mean	Std. Dev.	95% Interval	CD	Inefficiency
$(\Sigma_\beta)_1$	0.0203	0.0021	[0.0167;0.0249]	0.752	4.18
$(\Sigma_\beta)_2$	0.0203	0.0021	[0.0167;0.0247]	0.444	3.96
$(\Sigma_a)_1$	0.0498	0.0124	[0.0322;0.0799]	0.347	16.48
$(\Sigma_a)_2$	0.0489	0.0120	[0.0317;0.0788]	0.254	17.88
$(\Sigma_h)_1$	0.0636	0.0216	[0.0363;0.1185]	0.853	45.79
$(\Sigma_h)_2$	0.0614	0.0201	[0.0359;0.1116]	0.978	35.85

Notes. The term "Std. Dev." refers to the standard deviation.

spending growth rate, the period 1995–2003 displays a high volatility level as compared to the period from 2003 onwards. The dampening behavior, and later stability, is in agreement with the establishment of the Brazilian Fiscal Responsibility Law (FRL) in 2000, which imposed limits to government budget in order to achieve the solvency of the public debt.

Figure 1.3: Posterior Estimates for Stochastic Volatility



Notes. The terms gGS, gPC and gGDP refer to government spending, private consumption and GDP growth rates, respectively. DSTIR is the short-term interest rate in its first difference. Only median responses are reported. Posterior mean (solid line) and 95% credible intervals (dotted line).

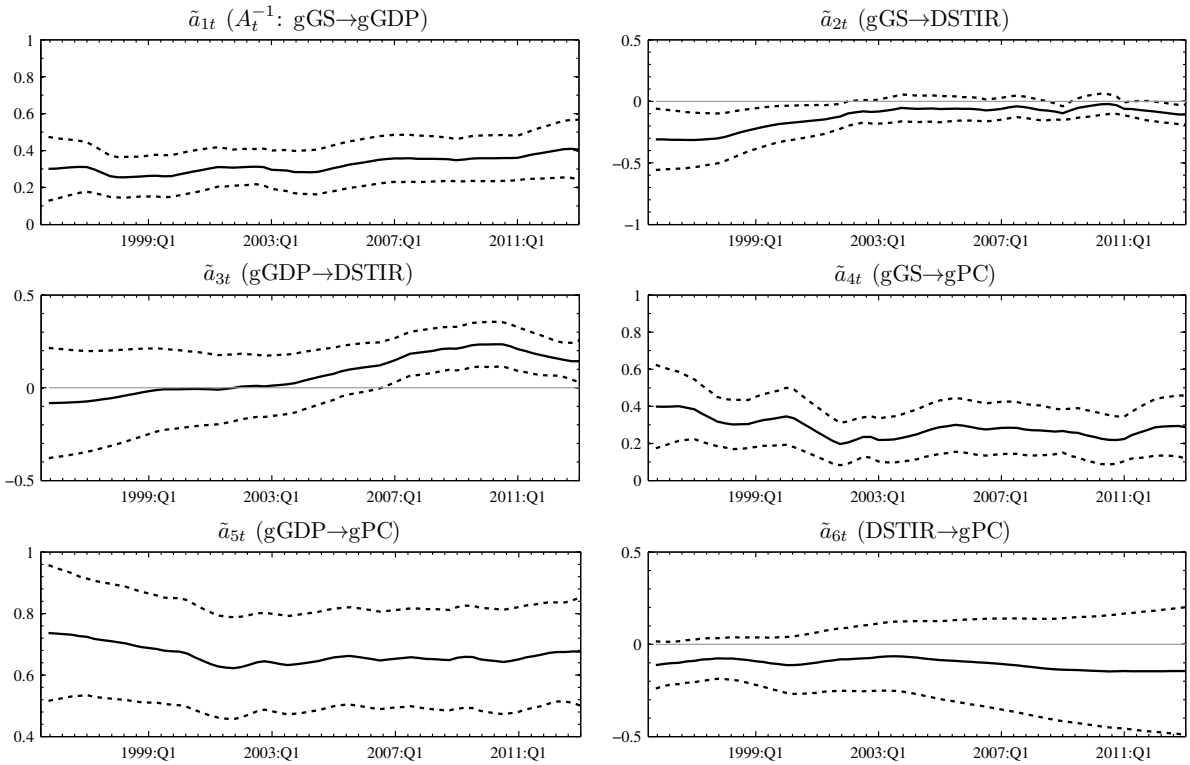
The time-varying volatility of the GDP growth rate shows a similar pattern, although smoother and on a lower level. It should be noted that the downward path until 2008 reflects the absence of external restrictions to growth as well as the solid conduct of macroeconomic policies. From 2008 onwards, the time-varying volatility slight increases, being consistent with the effects of the recent global economic crisis. On the other hand, the stochastic volatility of the private consumption growth rate spikes at the last quarter of 1999, then decreasing from 2000 onwards. The fluctuation until 2000 can be explained by the tight fiscal policy stance of the Brazilian government after the Real Plan and the FRL, mainly through tax rates expansion.

In mid-1999, less than six months after moving to a floating exchange rate system, Brazil adopted an inflation-targeting framework for monetary policy. The short-term interest rate thus became the Brazilian Central Bank's main instrument to manage infla-

tion. Moreover, since the Brazilian government established a sustained fiscal austerity, the Monetary Policy Committee (Copom) decided in favor of a downward bias, as the public debit is indexed to the short-term interest rate. Therefore, the estimated time-varying volatility for its first difference drops sharply until 2000, reaching values close to zero towards the rest of the sample. This result further suggests a rather steady stance on the control of the monetary policy by the Brazilian Central Bank.

But how the simultaneous relations among the variables have changed over time? Based on the recursive identification from the lower triangular matrix A_t, one can obtain the posterior estimates of the free elements in A_t^{-1}, denoted $\tilde{a}_{it}$. In other words, these free elements depict the size of the simultaneous effect of other variables to one unit of the structural shock[13], presented on Figure (1.4).

Figure 1.4: Posterior Estimates for Simultaneous Relations



Notes. The terms gGS, gPC and gGDP refer to government spending, private consumption and GDP growth rates, respectively. DSTIR is the short-term interest rate in its first difference. Only median responses are reported. Posterior mean (solid line) and 95% credible intervals (dotted line).

[13]With exception of the short-term interest rate in its first difference, the variables presented positive time-varying intercepts, though almost constant throughout the whole sample. These results are available upon request from the author.

The simultaneous relations of the short-term interest rate in its first differences to the government spending growth rate shock ($\tilde{a}_{2t}$: $g_{GS} \rightarrow$ DSTIR) are negative and vary over time, going from near -0.3 in 1995 to almost zero in 2012. Similarly, the simultaneous relations of the private consumption growth rate to the short-term interest rate in its first differences ($\tilde{a}_{6t}$: DSTIR $\rightarrow g_{PC}$) are negative throughout the sample, but more constant than the latter. Furthermore, the estimated results suggest that these relationships are insignificantly different from zero since the probability bands include the zero line.

Both simultaneous relations of the GDP growth rates to the government spending growth rate shock ($\tilde{a}_{1t}$: $g_{GS} \rightarrow g_{GDP}$) and the private consumption growth rates to the GDP growth rate shock ($\tilde{a}_{5t}$: $g_{GDP} \rightarrow g_{PC}$) stay positive and rather constant over the sample period. Also, with respect to the simultaneous relations of the private consumption growth rates to the government spending growth rate shock ($\tilde{a}_{4t}$: $g_{GS} \rightarrow g_{PC}$), these are positive and rather volatile between 1995 and 2003, following a downward trend. From Lula's election onwards, the relations remains almost constant.

From the idea of a Taylor Rule for monetary policy (Taylor, 1993), the short-term interest rate usually responds positively to the GDP growth rate. Therefore, the inflation-targeting adoption in mid-1999 reversed the simultaneous relations of the short-term interest rate in its first differences to the GDP growth rate shock ($\tilde{a}_{3t}$: $g_{GDP} \rightarrow$ DSTIR) from negative to positive. One should note that the positive relation spikes in mid-2010, which suggests that the Brazilian Central Bank gave a more prominent role to GDP growth when determining the short-term interest rate after the recent global financial crisis.

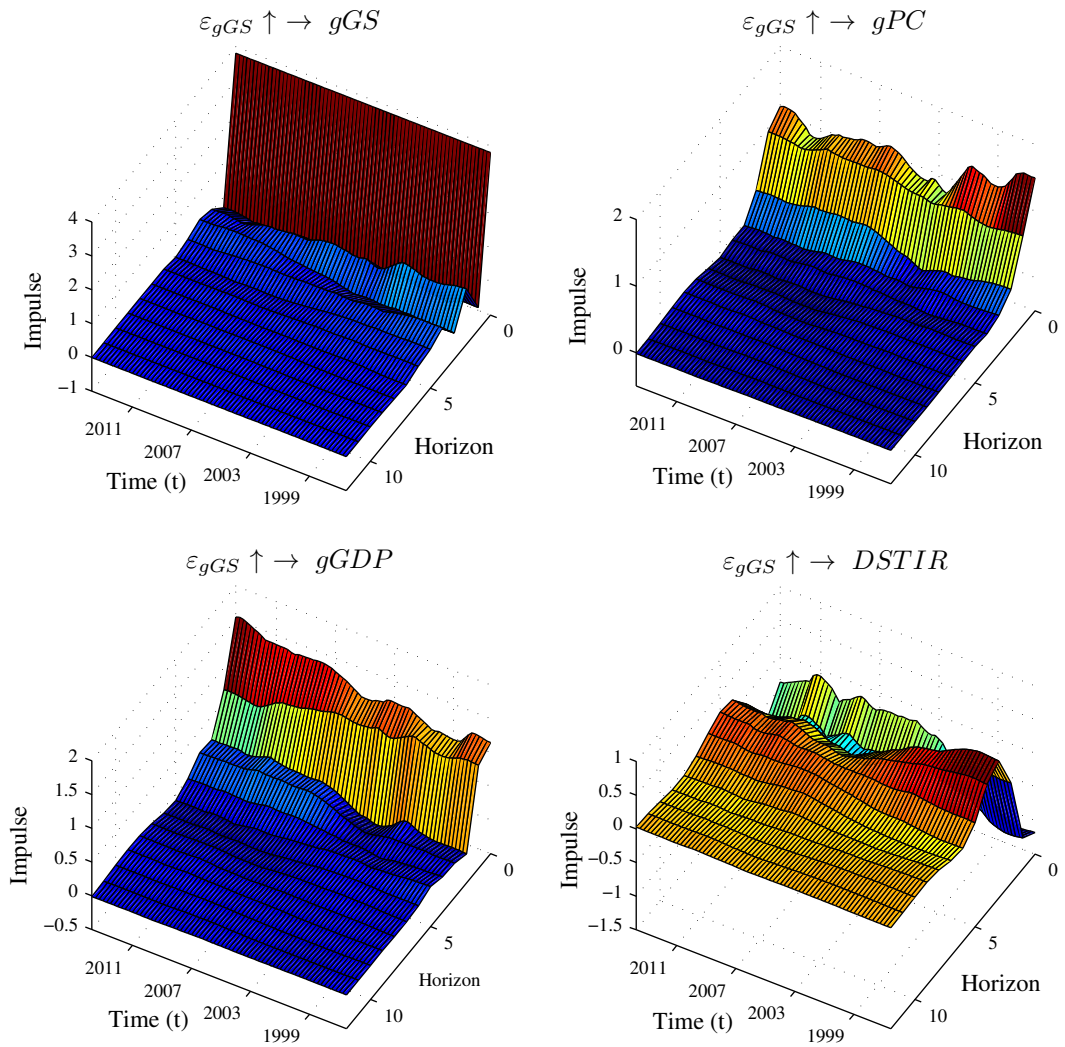
1.3.1 (In)Effectiveness of Government Spending Shocks

Since the time-varying VAR framework is able to compute state-dependent impulse responses at each individual quarter, potential changes on the macroeconomic dynamics can be evaluated over the sample period. As proposed by Nakajima (2011), these impulse responses are calculated after fixing an initial shock size equal to the time-series average of stochastic volatility over the sample period, and using the simultaneous relations at each point in time, in order to achieve comparability over time.

Figure (1.5) reports the estimated time-varying impulse responses for the variables to a positive government spending growth rate shock. The results show that the recovery of the government spending growth rate to its initial level was more volatile at the beginning of the sample, even though the overall response is rather similar throughout the whole period.

Regarding the short-term interest rate, the effects of spending shocks are negative at first, turning positive after the second quarter until reaching the initial level on the fifth quarter onwards. Kirchner et al. (2010), addressing the effects of fiscal stimulus with an estimated TVP-VAR for the Euro Area, found similar results. One possible explanation for this behavior is the Brazilian government commitment to the fiscal debt solvency, mainly since the FRL in 2000. Furthermore, the effects of spending shocks on the interest rate have lost persistence over time.

Figure 1.5: Time-Varying Impulse Responses of Government Spending Shocks



Notes. The terms gGS, gPC and gGDP refer to government spending, private consumption and GDP growth rates, respectively. DSTIR is the short-term interest rate in its first difference. Only median responses are reported.

But how effective is discretionary fiscal policy in stimulating economic activity? We

can immediately observe that the spending shocks increase the private consumption and the GDP growth rates, which is in line with other Brazilian studies (e.g. Mendonça et al. (2009), Carvalho and Valli (2010) and Peres (2012)). As discussed in Reis et al. (1998), and later corroborated in Gomes (2004), nearly 80% of Brazilian households are non-Ricardian and thus consume their income period by period. Consequently, the positive estimated effects of Brazil's fiscal stimulus arises from the fact that the *rule-of-thumb* consumption, to an extent sufficient, compensates the potential negative effects from Ricardian agents. Also, the initial impulse responses are larger at the beginning of the sample, whereas the shock persistence seems to have slightly increased after Lula's election at the end of 2002. However, one should mention that the estimated effects of government spending growth rate shocks on the private consumption growth rate seem rather time-invariant in the period.

As for the GDP growth rate results, the effectiveness of the fiscal stimulus increased since 2007, reaching the higher level at the end of 2012. The results further suggest that the effects on GDP have gained persistence from mid-2004 onwards. The positive impulse of a spending shock is visible for 6 months in mid-1995, whereas it starts persisting for nearly 12 months since 2004.

In general, even though the time-varying responses maintained a similar pattern from mid-1995 until late-2012, the results suggest that the government spending shocks could be indeed considered effective in promoting economic activity, but are only sustained on the short-run since positive effects are in average visible just until the horizon of four quarters. Silva and Cândido Júnior (2009) argue that this limited efficacy in stimulating macroeconomic aggregates through fiscal policy is a common feature among Latin America countries. Still, the time-varying techniques indicate some increasingly persistence of the latter shocks effectiveness.

1.3.2 Addressing the Cyclicality of Government Spending

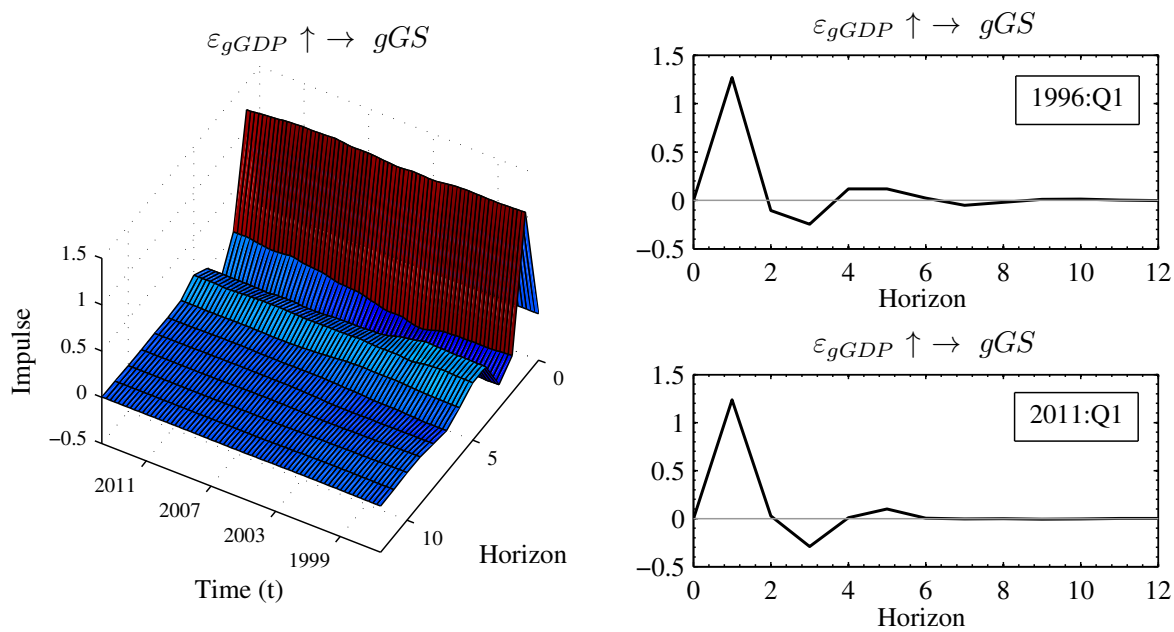
The cyclicality of fiscal policy has been a recurrent issue in macroeconomic research. The empirical findings for developing economies suggest that fiscal policy is procyclical, while counter-cyclical for developed ones (see e.g. Talvi and Végh (2005)). The literature usually assumes that the cyclicality of fiscal policies can be observed from the causality of the business cycle on government spending. But why emerging countries face the procyclical profile? There are two main arguments: (i) international liquidity restraints prevents these countries from borrowing in bad times (Gavin and Perotti, 1997; Catão and Sutton, 2002); and (ii) economic prosperity often abets fiscal profligacy and/or

rent-seeking behavior, leading to expansion of government spending (Tornell and Lane, 1999; Alesina et al., 2008).

Regarding the Brazilian economy, the literature generally presents results in line with the procyclical profile (Ellery Jr. and Gomes, 2005; Mendonça et al., 2009). Yet, has Brazil maintained this behavior in the recent? In order to address this question, we hence analyze the time-varying impulse responses of GDP growth rate shocks on government spending (Figure 1.6). Essentially, Brazil sustained a stable procyclical posture throughout the sample period. After the GDP shock, public spending rises and persists positive until the second quarter, becoming negative until the fourth quarter. These impulse responses tend to be near zero after about seven quarters.

Overall, the differences across time periods do not seem to be significant. Instead, the results suggest that Brazilian fiscal policy remained procyclical since 1995, though persistence slightly decreased.

Figure 1.6: Time-Varying Impulse Responses of GDP Shocks on Government Spending



Notes. The terms gGS and gGDP refer to government spending and GDP growth rates, respectively. Only median responses are reported.

1.3.3 Time-Invariant Comparison: A BVAR Approach

Modeling the relationship among macroeconomic variables has been a recurring challenge for economists. From the Lucas (1976) critique, empirical research has relied

upon time-varying models as an attempt to overcome parameter uncertainty over time (Hamilton, 1989; Canova, 1993; Cogley and Sargent, 2005; Primiceri, 2005; Koop et al., 2009).

While the previous empirical approach highlighted that the time-varying interplay of government spending and private consumption can be considered relevant for Brazilian data, our sample spams for a relatively short period (1995:Q1–2013:Q1). Given that the Brazilian economy has undergone few structural changes throughout these years, such as the abandonment of the crawling peg exchange rate regime on January 15, 1999 and the IT framework implementation on June of the same year, we now turn our attention to the impulse responses of a time-invariant Bayesian VAR (BVAR) for government spending and GDP shocks as a comparison to the TVP-VAR model.

Define a reduced-form VAR model as:

$$Y_t = X_t A + \varepsilon_t \qquad \varepsilon_t \sim N(0, \Sigma) \tag{1.6}$$

where $A = (a_0, A_1, \ldots, A_p)'$ and $X_t = (X_1, \ldots, X_T)'$. Through some matrix algebra, Equation (1.6) can be rewritten in the form of:

$$y_t = Z_t \alpha + \varepsilon_t \tag{1.7}$$

with $Z_t = (I_M \otimes X_t)$ and $\alpha = vec(A)$.

The likelihood function can be obtained by the sampling density, $p(y|\alpha, \Sigma)$. We impose a diffuse (or Jeffreys') prior for α and Σ, so that:

$$p(\alpha, \Sigma) \propto |\Sigma|^{-(M+1)/2}$$

Viewed as a function of the parameters, this problem can be split into two parts: (i) a normal distribution for α given Σ; and (ii) an inverse-Wishart distribution for Σ. That is:

$$\alpha|\Sigma, y \sim N(\hat{\alpha}, \Sigma) \tag{1.8}$$

and

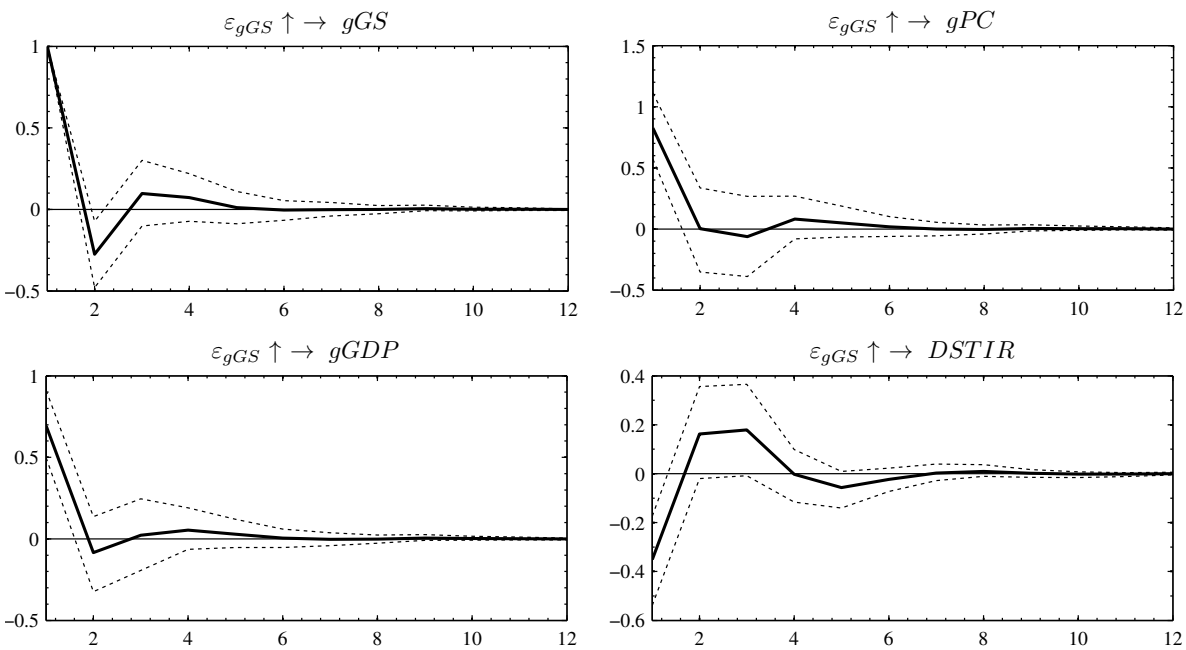
$$\Sigma|y \sim IW(\widehat{S}, T - K) \tag{1.9}$$

where $\widehat{A} = (X'X)^{-1}(X'Y)$ is the OLS estimate of A, $\hat{\alpha} = vec(\widehat{A})$ is a vector which stacks all the VAR coefficients (and the intercepts), $\widehat{S} = (Y - X\widehat{A})'(Y - X\widehat{A})$ is the sum of squared errors of the VAR, and $\widehat{\Sigma} = \widehat{S}/(T - K)$ is the OLS estimate of Σ.

According to the results in Figure (1.7), the recovery of the government spending to its initial level requires around five quarters. Despite some volatile behavior between 1994–2005 on Figure (1.5), the time-invariant dynamics is rather similar. To a lesser extent, the effects of spending shocks on private consumption also resembles the time-varying ones.

As to the effectiveness of discretionary fiscal policy on stimulating GDP growth, we observe positive response of output to an increase in the government spending. Even though corroborating the results previously obtained, the time-varying impulse responses revealed a growing shock persistence from the end of 2002 onwards. Hence, by applying a time-invariant BVAR model, one would underestimate the government capability to promote economic activity in the recent years.

Figure 1.7: Time-Invariant Impulse Responses of Government Spending Shocks



Notes. The terms gGS, gPC and gGDP refer to government spending, private consumption and GDP growth rates, respectively. DSTIR is the short-term interest rate in its first difference. Posterior mean (solid line) and 95% credible intervals (dotted line).

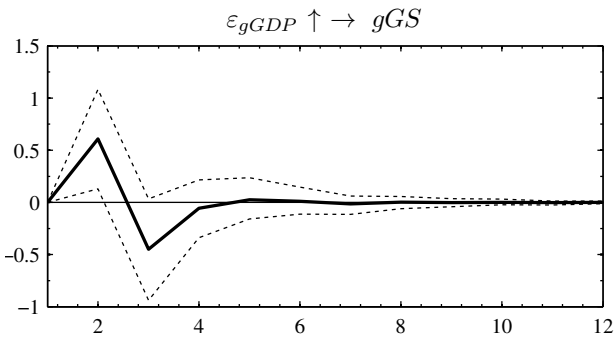
In terms of monetary policy, positive government spending shocks leads to a contemporaneous decrease of the short-term interest rate, increasing from thereafter until

reaching its initial level after 18 months. However, according to Figure (1.5), the intensity with which the STIR decreases is not constant over time neither is the shock persistence. The shortcomings of the time-invariant analysis are threefold: (i) it underestimates the positive response after the second quarter in the first half of the sample period; (ii) it does not capture the gradual decrease of STIR response after 2000s, and (iii) it displays a smaller shock persistence for the recent years.

Although Figure (1.8) reports a negative government spending response to a GDP shock after the second quarter, the evidences still corroborates the previous findings of a procyclical fiscal policy in Brazil given that the responses are statistically insignificant at 95% confidence interval after six months. Furthermore, there is evidence that the initial positive response might have been underestimated by the BVAR model.

Overall, despite the time-invariant impulse responses following closely the pattern of their time-varying counterparts, the BVAR usually underestimates the magnitude of these responses as well as the shock persistence, especially in the last years. That is, the TVP-VAR should thus be considered an appropriate method to overcome the issues concerning parameter uncertainty. Still, regardless of time features, the estimated impulse responses seem to be only sustained on the short-run.

Figure 1.8: Time-Invariant Impulse Response of a GDP Shock on Government Spending



Notes. The terms gGS and gGDP refer to government spending and GDP growth rates, respectively. Posterior mean (solid line) and 95% credible intervals (dotted line).

1.3.4 Prior Sensitivity Analysis: Model Robustness

In order to address any potential divergence on the results due to prior specification, we specify alternative priors for the TVP-VAR model. Therefore, we re-estimate it based on two different sets of diffuse and uninformative priors. The first prior set has an alternative value for the mean of the parameters $(\Sigma_\beta)_i^{-2}$, $(\Sigma_a)_i^{-2}$ and $(\Sigma_h)_i^{-2}$, while the

second set of priors focuses on the variance of these terms[14]:

$$\text{(I)} \quad (\Sigma_\beta)_i^{-2} \sim G(40, 0.01I), \quad (\Sigma_a)_i^{-2} \sim G(10, 0.01), \quad (\Sigma_h)_i^{-2} \sim G(10, 0.01)$$

$$\text{(II)} \quad (\Sigma_\beta)_i^{-2} \sim G(25, 0.02I), \quad (\Sigma_a)_i^{-2} \sim G(4, 0.01), \quad (\Sigma_h)_i^{-2} \sim G(4, 0.02)$$

The posterior estimates were obtained by drawing $M = 50,000$ samples after the initial 5,000 samples were discarded in the burn-in period. The complete results can be found in Appendix A. In general, both alternative specifications led to similar results in comparison to the chosen priors in Section 1.2.2. As Figure A.1 and Figure A.2 show that the sample paths look stable and the sample autocorrelations drop stably, the sampling method efficiently generates uncorrelated samples. These results are corroborated by Table A.1 and Table A.2 since the CD statistics imply that the null hypothesis of convergence to the posterior distribution is not rejected at the 10% significance level for both alternative prior sets. Moreover, the Inefficiency factors are rather low on both specifications.

The obtained results robustly confirm the downward trend of the stochastic volatility in the sample period, thus reaffirming the stable macroeconomic profile in the recent years. Posterior estimates for simultaneous relations also displayed a robust behavior in comparison to the baseline TVP-VAR model. Ergo, the robustness tests evolve consistently with the previous results.

1.4 Conclusions

In this chapter we presented empirical evidences about the relationship between government spending and private consumption in Brazil. We estimated a vector autoregression model with drifting coefficients and stochastic volatility for Brazil over the period 1995:Q1–2013:Q1.

Our findings suggest that the effectiveness of spending shocks in stimulating economic activity has increased since 2007, depicting positive Keynesian multipliers. The estimated time-varying impulse responses of GDP growth rate also shows higher persistence in the recent years. However, these positive effects are only sustained on the short-run. Regarding private consumption, the results further suggest a *crowding-in*

[14]One should notice that by imposing a more flexible prior for the covariance matrix of A, the Bayesian estimation process was not able to achieve the inverse matrix of A due to singularity. Therefore, in order to avoid implausible behaviors of the time-varying contemporaneous relationships parameters, $(\Sigma_a)_i^{-2}$ is specified as in Section 1.2.2. See Koop and Korobilis (2010) for a discussion on the methodology for the TVP-VAR model, including the issues about the prior specifications.

effect, despite the decrease of the initial positive response. Moreover, we document that the estimated effects of government spending growth rate shocks on private consumption growth rate seem rather time-invariant in the period.

As to the cyclicality of Brazilian fiscal policy, our results highlighted that government stimuli have remained procyclical throughout the sample period, even though differences across time do not seem to be significant.

By comparing time-invariant impulse responses of a Bayesian VAR (BVAR) with their time-varying counterpart, we were further able to provide empirical evidences that parameter uncertainty might be overcome with a TVP-VAR specification. Additionally, robustness analysis confirmed the downward trend of the stochastic volatility in the period, thus reaffirming that Brazil has steadily improved its macroeconomic stability in the recent years.

Appendix A

Prior Sensitivity Analysis: Supplementary Figures

Table A.1: Estimation Results of Selected Parameters in the TVP-VAR model – First Prior Set – Robustness Check

Parameter	Mean	Std. Dev.	95% Interval	CD	Inefficiency
$(\Sigma_\beta)_1$	0.0159	0.0013	[0.0137;0.0187]	0.407	2.78
$(\Sigma_\beta)_2$	0.0159	0.0013	[0.0137;0.0187]	0.422	2.78
$(\Sigma_a)_1$	0.0319	0.0051	[0.0238;0.0436]	0.829	9.24
$(\Sigma_a)_2$	0.0319	0.0051	[0.0238;0.0435]	0.496	7.38
$(\Sigma_h)_1$	0.0345	0.0063	[0.0249;0.0488]	0.675	14.74
$(\Sigma_h)_2$	0.0339	0.0060	[0.0247;0.0479]	0.932	12.89

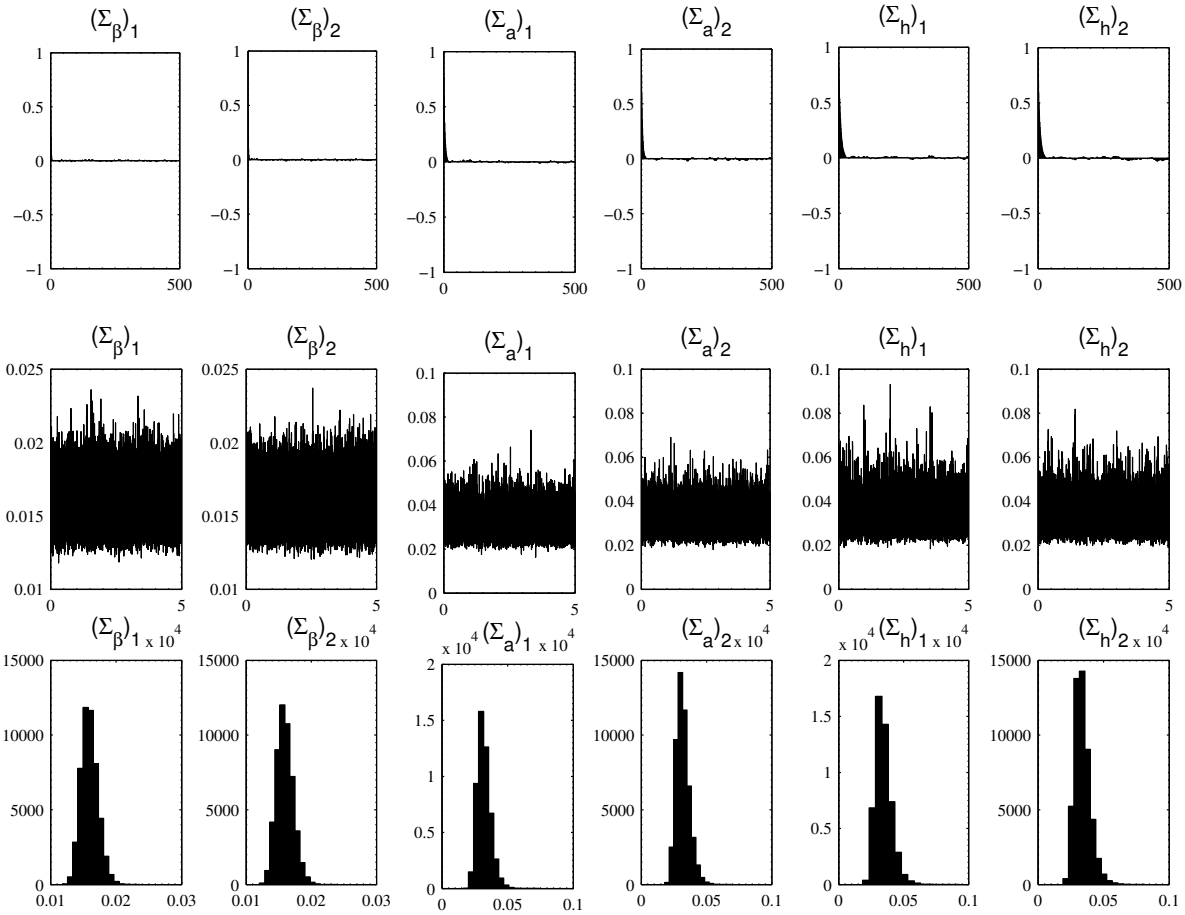
Notes. The term "Std. Dev." refers to the standard deviation.

Table A.2: Estimation Results of Selected Parameters in the TVP-VAR model – Second Prior Set – Robustness Check

Parameter	Mean	Std. Dev.	95% Interval	CD	Inefficiency
$(\Sigma_\beta)_1$	0.0287	0.0029	[0.0237;0.0349]	0.459	3.45
$(\Sigma_\beta)_2$	0.0287	0.0030	[0.0236;0.0352]	0.106	4.60
$(\Sigma_a)_1$	0.0498	0.0124	[0.0322;0.0800]	0.716	17.38
$(\Sigma_a)_2$	0.0494	0.0121	[0.0321;0.0791]	0.581	14.57
$(\Sigma_h)_1$	0.0895	0.0297	[0.0516;0.1627]	0.603	36.33
$(\Sigma_h)_2$	0.0832	0.0243	[0.0497;0.1428]	0.114	33.30

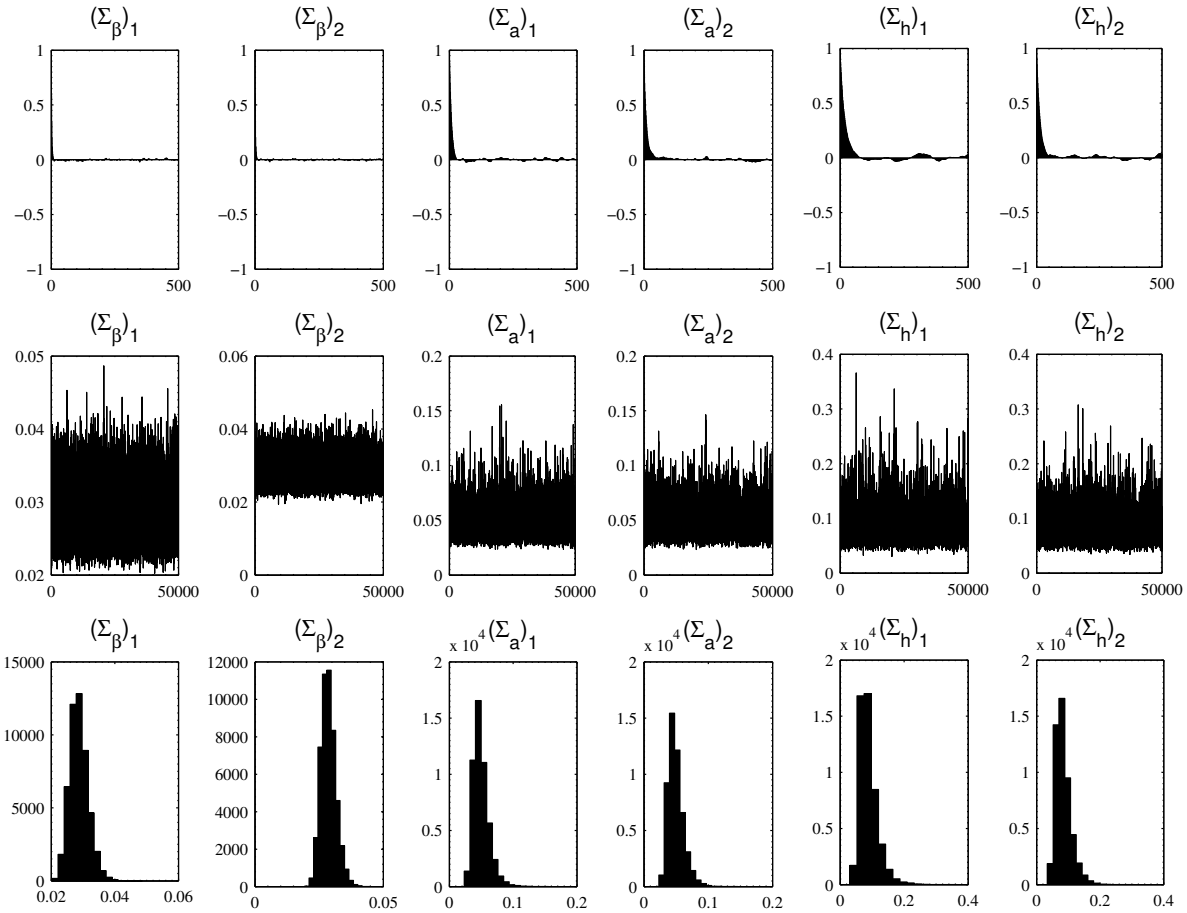
Notes. The term "Std. Dev." refers to the standard deviation.

Figure A.1: Estimation Results of Selected Parameters in the TVP-VAR model – First Prior Set – Robustness Check



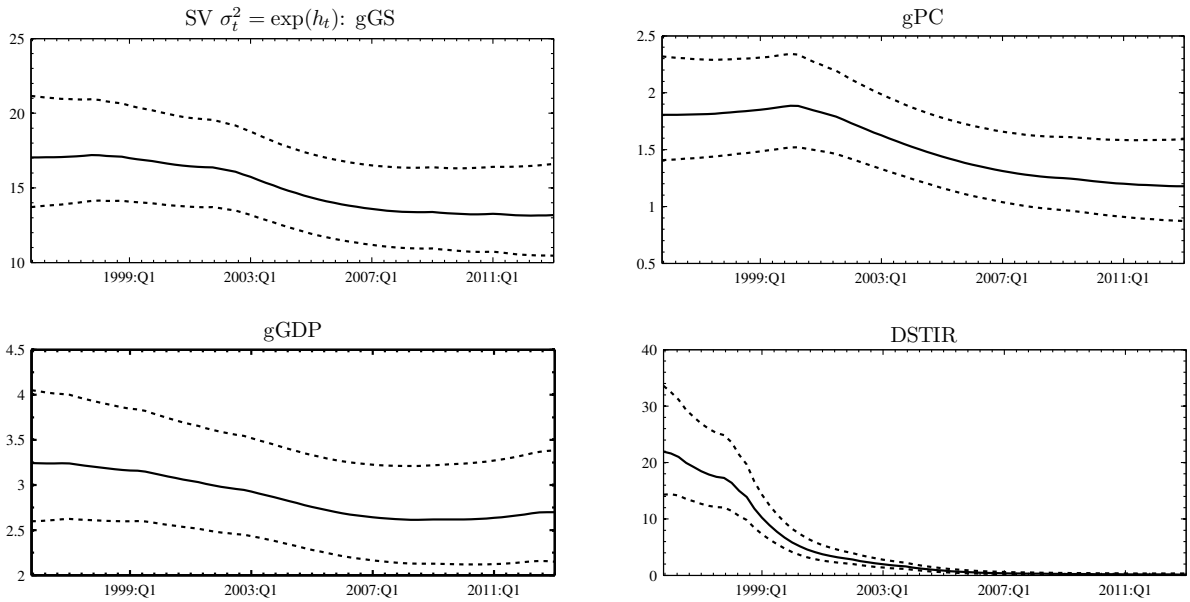
Notes. Sample autocorrelations (top), sample paths (middle) and posterior densities (bottom).

Figure A.2: Estimation Results of Selected Parameters in the TVP-VAR model – Second Prior Set – Robustness Check



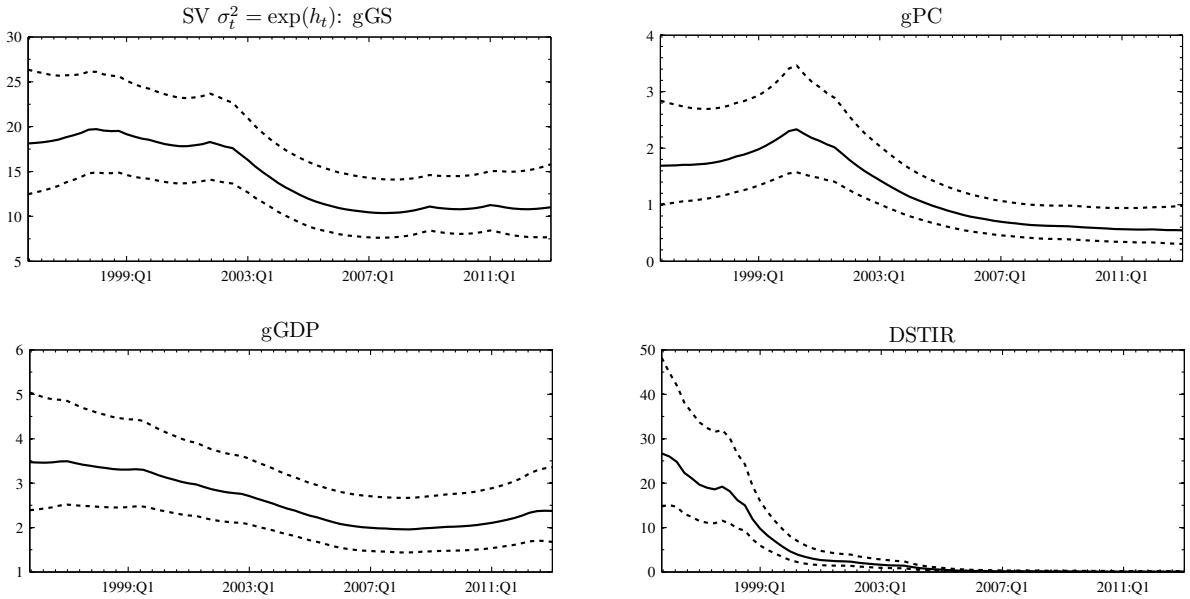
Notes. Sample autocorrelations (top), sample paths (middle) and posterior densities (bottom).

Figure A.3: Posterior Estimates for Stochastic Volatility – First Prior Set – Robustness Check



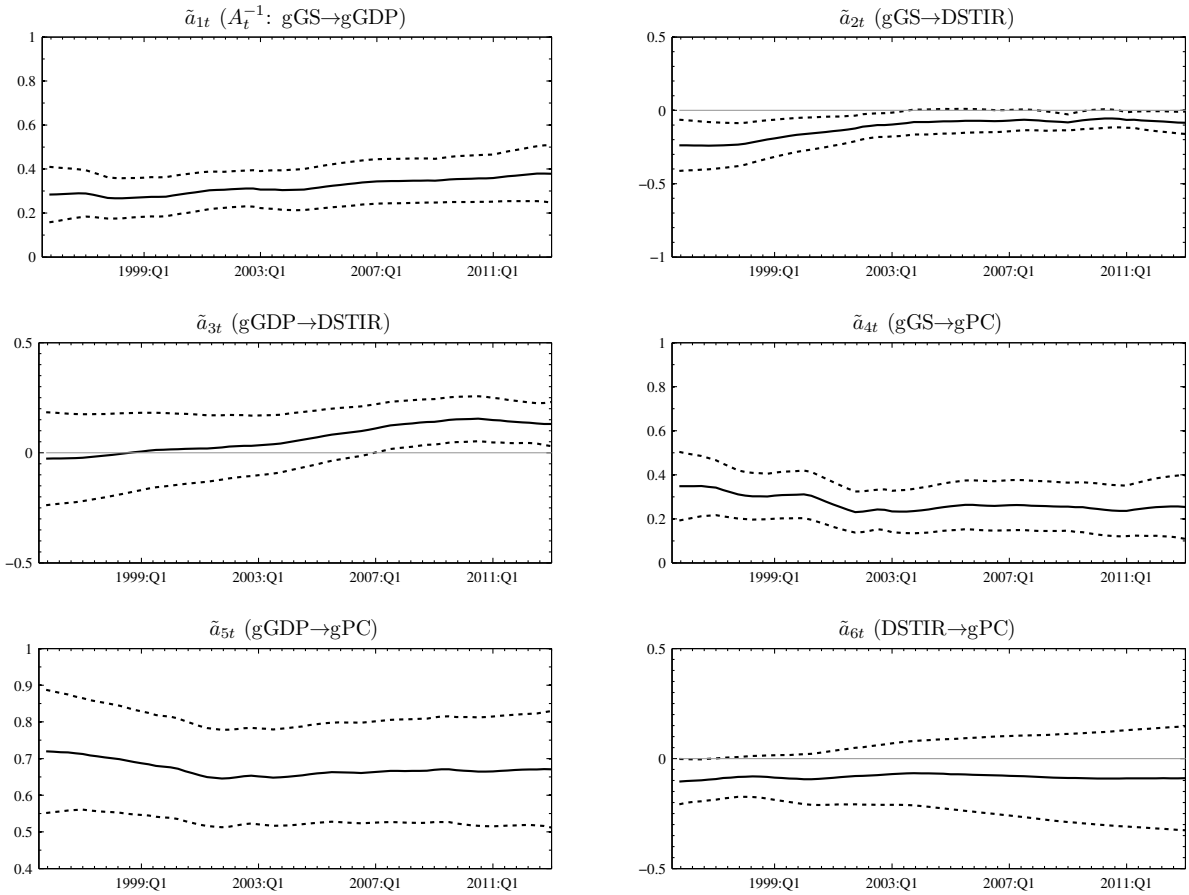
Notes. The terms gGS, gPC and gGDP refer to government spending, private consumption and GDP growth rates, respectively. DSTIR is the short-term interest rate in its first difference. Only median responses are reported. Posterior mean (solid line) and 95% credible intervals (dotted line).

Figure A.4: Posterior Estimates for Stochastic Volatility – Second Prior Set – Robustness Check



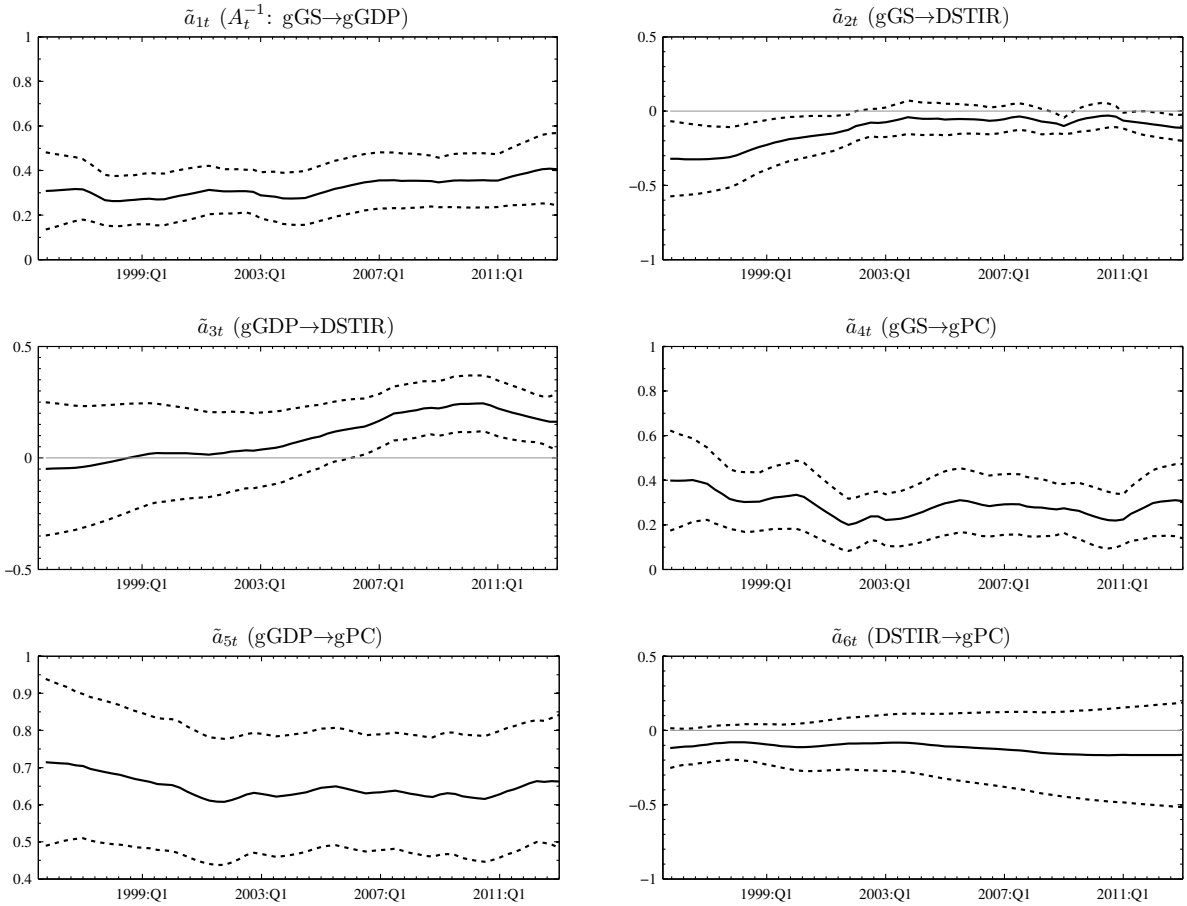
Notes. The terms gGS, gPC and gGDP refer to government spending, private consumption and GDP growth rates, respectively. DSTIR is the short-term interest rate in its first difference. Only median responses are reported. Posterior mean (solid line) and 95% credible intervals (dotted line).

Figure A.5: Posterior Estimates for Simultaneous Relations – First Prior Set – Robustness Check



Notes. The terms gGS, gPC and gGDP refer to government spending, private consumption and GDP growth rates, respectively. DSTIR is the short-term interest rate in its first difference. Only median responses are reported. Posterior mean (solid line) and 95% credible intervals (dotted line).

Figure A.6: Posterior Estimates for Simultaneous Relations – Second Prior Set – Robustness Check



Notes. The terms gGS, gPC and gGDP refer to government spending, private consumption and GDP growth rates, respectively. DSTIR is the short-term interest rate in its first difference. Only median responses are reported. Posterior mean (solid line) and 95% credible intervals (dotted line).

Chapter 2

Forecasting Inflation with the Phillips Curve: A Dynamic Model Averaging Approach for Brazil

2.1 Introduction

Forecasting the behavior of inflation has been a common procedure for economies under the inflation-targeting regime. Given the lags with which monetary policy ultimately affects the macroeconomic environment, Central Banks must take a forward-looking stance in order to maintain the stability of prices. Moreover, since long-term nominal commitments (e.g. labor contracts and mortgages) and price stickiness are usual features of modern economies, forecasting inflation is also crucial for private sector decision-making. Although many different approaches have been suggested by macroeconomic research, the Phillips curve remains the conventional framework for inflation forecasts.

Ever since the paper of Phillips (1958), which provided the first[1] formal statistical evidence of the relationship between wages and unemployment in the United Kingdom, the trade-off between inflation and real economic activity has been intensely discussed by theoretical and empirical research. Samuelson and Solow (1960) hypothesized the same trade-off for the US economy, arguing that it provided a menu of policy choices since governments could always reduce unemployment by bearing some inflation. Hence,

[1] Although the work of Fisher (1926) had previously established a correlation between unemployment rates and inflation for the US economy, the author interprets the transmission process with the reverse direction of causation. From a theoretical viewpoint, Humphrey (1985) argues that early writings on the inflation-unemployment correlation can be found on the works of David Hume and Henry Thornton in the 18th century.

these findings favored the Keynesian counter-cyclical policy prescriptions (quantitative easing), whose effectiveness was intrinsically related to the assumption of non-neutral impact of monetary policy in the short-run.

By amending the Phillips curve to allow for agents' expectations, Phelps (1967) established the so-called *expectations-augmented Phillips curve* (EAPC) through explicitly modeling firms' wage and price-setting behavior. From an intertemporal perspective, the author argued that inflation expectations would induce future changes on the trade-off between inflation and unemployment since the adjustments of wages and prices are infrequently and based on inflation forecasts. On the other hand, in the presence of *rational agents*, Lucas (1976) asserted that inflation expectations could not systematically differ from actual inflation, establishing what was later called the *new Classical Phillips curve* (NCPC).

In the recent economic modeling, theoretical microfoundations based on staggering prices and monopolistic competitive firms have taken a prominent role. The standard *new Keynesian Phillips curve* (NKPC) therefore specifies that current inflation is a function of forward-looking inflation expectations and of real marginal costs. By reassuring the short-run non-neutrality of money due to nominal and real rigidities (Christiano et al., 2005), this approach has validated the idea that increasing inflation might reduce unemployment, even though not permanently (Roberts, 1995; Fuhrer and Moore, 1995; Galí and Gertler, 1999; Blanchard and Galí, 2007).

However, from an empirical perspective, the literature presents a wide range of issues; see Gordon (2011) for an in-depth survey. In general, there is disbelief on whether the Phillips curve baseline is appropriate in tracking inflation dynamics. Despite the evidences of Stock and Watson (1999), Galí and Gertler (1999) and Galí et al. (2001) in favor of the inflation-unemployment correlation, the studies of Atkeson and Ohanian (2001), Lindé (2005) and Rudd and Whelan (2005) revealed that those results essentially relied on the sample period and the forecast horizon.

Furthermore, conventional regression-based methods usually deal with time inconsistency. According to Lucas (1976), the structure of an econometric model is built on optimal decision rules of economic agents, hence policy regime shifts might influence the coefficients of the estimated behavioral equations. Macroeconomic research has often attempted to overcome such restraint.

Two main outcomes arise from time heterogeneity: (i) uncertainty with respect to the relevant set of predictors at each period (Gordon, 1982, 1990; Stock and Watson, 1999, 2008); and (ii) potential parameter instability (Canova, 2007; Musso et al., 2009). Such time-varying behavior may emerge from e.g. structural breaks and business cy-

cle dynamics, thus damping the effectiveness of traditional Phillips curve estimations. In order to address the latter issues, sophisticated methods of forecast combination have been employed. As to the US economy, Wright (2009) showed that the Bayesian Model Averaging (BMA) has provided a good performance on forecasting inflation while Kapetanios et al. (2008) found similar results for UK with the method of Information-Theoretic Model Averaging (ITMA).

Regarding the Brazilian literature, Sachsida (2014) provides a recent comprehensive survey. Similarly to the international experience, Brazilian research has yet to achieve a consensus on the implications of the Phillips curve for monetary policy and business cycle fluctuations. While some studies advocate against the inflation-unemployment correlation depicted by the Phillips curve (Cysne, 1985; Sachsida et al., 2009; Maka and Barbosa, 2013), evidences of its existence for Brazilian data can also be found (Portugal and Madalozzo, 2000; Correa and Minella, 2005; Areosa and Medeiros, 2007; Mazali and Divino, 2010). However, little attention has been given to forecasting inflation with potential time-varying features for Brazil (see e.g. Arruda et al. (2011) and Carlos and Marçal (2013)). To the best of our knowledge, there is no analysis on forecasting Brazilian inflation taking into account both model and parameter uncertainty.

It is the purpose of this chapter to provide some insights on the latter matters. We underscore the importance of a time-varying method to forecast Brazilian inflation given the potential sub-sample instability from some economic changes experienced in the recent years. For instance, one could mention the burdensome macroeconomic effects in the aftermath of a confidence crisis triggered in financial markets by the anticipation of Lula's victory in late-2002, the monetary tightening engendered by Afonso Bevilaqua in 2005 and the 2007 US subprime mortgage crisis. Therefore, the empirical strategy adopted follows closely Koop and Korobilis (2012). Based on the previous work of Raftery et al. (2010), the authors recently proposed a Dynamic Model Averaging (DMA) approach to forecast US inflation, which allows for the forecasting model to change over time as well as its parameters. The exercise mainly consists on state-space representation and Kalman filter estimation. We also account for a variety of alternative forecasting procedures in order to compare predictive performance. The models include Brazilian monthly data for the period 2003:M1–2013:M10[2]. The Broad National Consumer Price Index (IPCA) is used as the measure of inflation along with eight potential predictors.

The results have shown that DMA and DMS are able to deliver good inflation predictions for all forecast horizons considered, highlighting the importance of time-varying

[2]As will be discussed in Subsection (2.3.1), the sample period was established in order to cope with a major methodological break within the Monthly Unemployment Survey (PME) in 2002.

features. Also, evidences suggest that the short- and long-term Phillips curve relationship may be rejected for Brazil while short- and medium-term exchange rate pass-through has been recently decreasing. From a monetary policy viewpoint, the short-term interest rate and the inflation expectations seem to have remained useful inflation predictors throughout the sample period.

The outline of the chapter is as follows. Besides this introduction and the conclusion, this chapter is divided into two parts. The first addresses the Dynamic Model Averaging approach, underscoring its differences to the Bayesian Model Averaging and discussing how both model and parameter uncertainty are taken into account. The second initially proposes a reduced form generalized Phillips Curve model as our theoretical framework, centering our attention in the set of predictors as well as the data transformations. Later, we present our empirical results, exploiting the usefulness of the chosen predictors and comparing models' forecasting performance.

2.2 Forecasting with Dynamic Model Averaging

Since the seminal forecasting paper by Bates and Granger (1969)[3], model averaging has become a recurrent empirical tool to deal with model uncertainty. Even though many different approaches have been suggested, the Bayesian Model Averaging (BMA) is considered a well-established methodology for linear regression models when there is uncertainty about which variables to include.

Given that a single linear model which includes all variables may be inefficient or even infeasible due to limited data, uncertainty arises from the existence of $N = 2^m$ different set of models denoted as $\mathcal{M} = \{M_i\}_{i=1}^N$, where m is the number of potential regressors and M_i is the i-th of the N models considered. From the posterior model probabilities, BMA explicitly incorporates this uncertainty into statistical inference. Briefly, the output of a Bayesian analysis is the probability distribution for some quantity of interest (e.g. a forecast), Ω, given $\mathcal{M}$ and the observed data at time t, D_t. Therefore, the probability distribution is given by:

$$p(\Omega|D_t, \mathcal{M}) = \sum_{i=1}^{N} p(\Omega|M_i, D_t)p(M_i|D_t) \tag{2.1}$$

where $p(\Omega|M_i, D_t)$ is the conditional probability distribution of Ω given a model M_i and

[3]Despite the seminal contributions of Bates and Granger (1969) on model averaging and forecast, the first mention of model combination in statistical literature dates back to Barnard (1963).

the data D_t, and $p(M_i|D_t)$ is the conditional probability of the model M_i being the true model given the data. In other words, equation (2.1) is an average of the posterior distributions under each of the models considered, weighted by their posterior model probability. The posterior probability for model M_i is defined as:

$$p(M_i|D_t) = \frac{p(D_t|M_i, D_{t-1})p(M_i|D_{t-1})}{\sum_{i=1}^{N} p(D_t|M_i, D_{t-1})p(M_i|D_{t-1})} \tag{2.2}$$

where

$$p(D_t|M_i, D_{t-1}) = \int p(D_t|\theta_i, M_i, D_{t-1})p(\theta_i|M_i, D_{t-1})d\theta_i \tag{2.3}$$

is the *integrated* likelihood of model M_i, θ_i is the vector of parameters of model M_i, $p(\theta_i|M_i, D_{t-1})$ is the prior density of θ_i under model M_i and the previous period's data, and $p(D_t|\theta_i, M_i, D_{t-1})$ is the likelihood. Equation (2.2) therefore provides a coherent way of summarizing model uncertainty after observing the data. Moreover, one should notice that the weights are formed as part of a stochastic process since $p(M_i|D_t)$ is obtained from $p(M_i|D_{t-1})$ *via* intermediate steps (Kapetanios et al., 2008) and that all probabilities are implicitly conditional on $\mathcal{M}$.

Given the latter procedures, the estimated posterior mean and variance of Ω are then constructed as:

$$E\left[\Omega|D_t\right] = \sum_{i=1}^{N} \hat{\Omega}_i p(M_i|D_t) \tag{2.4}$$

$$Var\left[\Omega|D_t\right] = \sum_{i=1}^{N} (Var\left[\Omega|D_t, M_i\right] + \hat{\Omega}_i^2)p(M_i|D_t) \tag{2.5}$$

where $\hat{\Omega}_i = E\left[\Omega|D_t, M_i\right]$ (Raftery, 1993; Draper, 1995).

Despite the improvement in dealing with model uncertainty, the BMA is restricted to static linear models. Allowing for the set of regressors as well as their marginal effects to vary over time may provide in-depth information on how a process is likely to evolve. For instance, Koop and Korobilis (2012) argued that time-varying features are of great interest in empirical macroeconomics due to the potential occurrence of structural breaks and to business cycle dynamics. Hence, Raftery et al. (2010) developed the Dynamic Model Averaging (DMA) methodology, encompassing the BMA as well as hidden Markov models, forgetting in state-space modeling and Kalman filter estimation.

Consider a linear time-varying model structure, with y_t being the dependent variable, $z_t = [1, x_{t-h}]$ a $1 \times m$ vector of regressors, θ_t an $m \times 1$ vector of coefficients (states), $\varepsilon_t \overset{ind}{\sim} N(0, H_t)$, and $u_t \overset{ind}{\sim} N(0, Q_t)$:

$$y_t = z_t \theta_t + \varepsilon_t \tag{2.6a}$$

$$\theta_{t+1} = \theta_t + u_t \tag{2.6b}$$

for $t = 1, \ldots, T$. Furthermore, the errors, ε_t and u_t, are assumed to be mutually independent at all leads and lags. Despite allowing for the parameters to evolve over time following a driftless random walk process, equations (2.6a) and (2.6b) still incur model uncertainty since it is assumed that z_t is the relevant set of regressors at all points in time. Thus, given the existence of $N = 2^m$ set of models with different subsets of z_t as regressors, Koop and Korobilis (2012) rewrite the latter equations as:

$$y_t = z_t^{(k)} \theta_t^{(k)} + \varepsilon_t^{(k)} \tag{2.7a}$$

$$\theta_{t+1}^{(k)} = \theta_t^{(k)} + u_t^{(k)} \tag{2.7b}$$

where $\varepsilon_t^{(k)}$ is $N(0, H_t^{(k)})$, $u_t^{(k)}$ is $N(0, Q_t^{(k)})$ and $z_t^{(k)}$ is a subset of z_t, for $k = 1, \ldots, N$. Moreover, let $M_t \in \{1, 2, \ldots, N\}$ denote one of the models in the population at time, $\Theta_t = (\theta_t^{(1)\prime}, \ldots, \theta_t^{(k)\prime})'$ the state vector and $y^t = (y_1, \ldots, y_t)'$ the information available at each point of time, DMA involves obtaining $p(M_t = k | y^{t-1})$, which is the probability of model k holding at time t given data up to time $t-1$, and averaging some quantity of interest (e.g. a forecast) across models using these probabilities.

Since the model depicted by equations (2.7a) and (2.7b) is a switching linear Gaussian state-space representation, Koop and Korobilis (2012) asserted that the time-varying features could be addressed with a transition matrix P in the sense of Hamilton (1989), with elements $p_{ij} = p(M_t = i | M_{t-1} = j)$, for $i, j = 1, \ldots, N$. However, given that $N = 2^m$ and m may be large, P is often high-dimensional, derailing the results of standard recursive algorithms such as the Kalman filter.

In order to deal with these restraints, Raftery et al. (2010) developed an approximation which operates without explicitly specifying a transition matrix such as P, reducing therefore the computational burden of the latter recursive approaches. This procedure embodies two parameters, λ and α, referred as the *forgetting factors*. Following the state-state model in equations (2.6a) and (2.6b), for given values of H_t and Q_t, Kalman filtering begins with the result that:

$$\theta_{t-1}|y^{t-1} \sim N(\hat{\theta}_{t-1}, \Sigma_{t-1|t-1}) \tag{2.8}$$

where formulae for $\hat{\theta}_{t-1}$ and $\Sigma_{t-1|t-1}$ are standard, depending on H_t and Q_t. Subsequently, Kalman filtering continues, with:

$$\theta_t|y^{t-1} \sim N(\hat{\theta}_{t-1}, \Sigma_{t|t-1}) \tag{2.9}$$

where

$$\Sigma_{t|t-1} = \Sigma_{t-1|t-1} + Q_t \tag{2.10}$$

Since specifying Q_t is demanding and often little information is available, Raftery et al. (2010) imposed an exponential decay and replaced equation (2.10) by:

$$\Sigma_{t|t-1} = \lambda^{-1}\Sigma_{t-1|t-1} \tag{2.11}$$

or, equivalently, $Q_t = (1-\lambda^{-1})\Sigma_{t-1|t-1}$. Hence, there is no need to estimate or simulate Q_t, but only H_t. Also, the forgetting factor λ implies that observations j periods in the past have weight λ^j. Given that $0 < \lambda \leq 1$, setting $\lambda = 0.99$ indicates that observations five months ago receive approximately 80% as much weight as last period's observation (for monthly data). Following the related literature, we consider $\lambda \in (0.95, 0.99)$.

According to Koop and Korobilis (2012), inference in the one-model case is then completed by the *updating equation*:

$$\theta_t|y^t \sim N(\hat{\theta}_t, \Sigma_{t|t}) \tag{2.12}$$

where

$$\hat{\theta}_{t|t} = \hat{\theta}_{t|t-1} + \Sigma_{t|t-1}z_t^{'}(H_t + z_t\Sigma_{t|t-1}z_t^{'})^{-1}(y_t - z_t\hat{\theta}_{t-1}) \tag{2.13}$$

and

$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1}z_t^{'}(H_t + z_t\Sigma_{t|t-1}z_t^{'})^{-1}z_t\Sigma_{t|t-1} \tag{2.14}$$

As new data become available, this process is recursively repeated. Thus, recursive forecasting is done by using the one-step-ahead predictive distribution of y_t:

$$y_t|y^{t-1} \sim N(z_t\hat{\theta}_{t-1}, H_t + z_t\Sigma_{t|t-1}z_t^{'}) \tag{2.15}$$

Since the results in equation (2.15) are all analytical, conditional on H_t, Koop and Korobilis (2012) highlighted that no Markov chain Monte Carlo (MCMC) algorithm is required, reducing computational costs.

In order to consider multiple models and uncertainty about which one is the best, Raftery et al. (2010) proposed a multi-model case based on the state-space representation depicted by equations (2.7a) and (2.7b). In this sense, estimation is analogous to the one-model case. Conditional distribution of the state at time $(t-1)$ given the data up to that time is:

$$p(\theta_{t-1}, M_{t-1}|y^{t-1}) = \sum_{k=1}^{N} p(\theta_{t-1}^{(k)}|M_{t-1} = k, y^{t-1})p(M_{t-1} = k|y^{t-1}) \tag{2.16}$$

whose conditional distribution of $\theta_{t-1}^{(k)}$ could be approximated by a normal distribution, denoted by:

$$\theta_{t-1}^{(k)}|M_{t-1} = k, y^{t-1} \sim N(\hat{\theta}_{t-1}^{(k)}, \Sigma_{t-1|t-1}^{(k)}) \tag{2.17}$$

Then, one must proceed to the prediction step. Raftery et al. (2010) argued that this procedure is twofold: (i) prediction of the model indicator, M_t, *via* the model prediction equation; and (ii) conditional prediction of the parameter, $\theta_t^{(k)}$, given that $M_t = k$, *via* the parameter prediction equation.

Let $\pi_{t-1|t-1,l} = p[M_{t-1} = l|y^{t-1}]$. With the use of an unrestricted matrix of transition probabilities in P with elements p_{kl}, the *model prediction equation* is then specified as:

$$\pi_{t|t-1,k} \equiv p[M_t = k|y^{t-1}] = \sum_{l=1}^{N} \pi_{t-1|t-1,l}p_{kl} \tag{2.18}$$

However, as discussed before, P is often high-dimensional. Therefore, Raftery et al. (2010) proposed an approximation for equation (2.18), such as:

$$\pi_{t|t-1,k} = \frac{\pi^{\alpha}_{t-1|t-1,k}}{\sum\limits_{l=1}^{N} \pi^{\alpha}_{t-1|t-1,l}} \tag{2.19}$$

where $0 < \alpha \leq 1$ is a forgetting factor in the sense of λ. Even though comparable, α refers to the weight applied to model performance. For instance, if $\alpha = 0.99$, forecast performance five months ago receives 80% as much weight as forecast performance last period (for monthly data). Following the literature, we consider $\alpha \in (0.95, 0.99)$. By applying the forgetting factor in the model prediction equation, Koop and Korobilis (2012) asserted that there is no need of an MCMC algorithm to draw transitions between models.

With exponential decay, the *parameter prediction equation* in a multi-model setup is similar to the one in equation (2.9), with the superscript (k) added to all quantities:

$$\theta_t^{(k)} | M_t = k, y^{t-1} \sim N(\hat{\theta}_{t-1}^{(k)}, \Sigma_{t|t-1}^{(k)}) \tag{2.20}$$

where $\Sigma_{t|t-1}^{(k)} = \lambda^{-1} \Sigma_{t-1|t-1}^{(k)}$.

Furthermore, Koop and Korobilis (2012) argued that the *model updating equation* is also analogous to the updating equation of the one-model setup, then being written as:

$$\pi_{t|t,k} = \frac{\pi_{t|t-1,k} p_k(y_t|y^{t-1})}{\sum\limits_{l=1}^{N} \pi_{t|t-1,l} p_l(y_t|y^{t-1})} \tag{2.21}$$

whose $p_l(y_t|y^{t-1})$ is the predictive density for model l evaluated at y_t.

In general, the multi-model predictions of y_t are a weighted average of the predictions for every model $\hat{y}_t^{(k)}$, whose weights are the *posterior predictive model probabilities*, $\pi_{t|t,k}$. Thus, the recursive forecasting performed by DMA is given by:

$$\hat{y}_t^{DMA} \equiv E(y_t|y^{t-1}) = \sum_{k=1}^{N} \pi_{t|t-1,k} z_t^{(k)} \hat{\theta}_{t-1}^{(k)} \tag{2.22}$$

Additionally to the DMA approach, Koop and Korobilis (2012) argued that one could instead choose to select the single model with the highest value for $\pi_{t|t,k}$ at each point in time and then perform forecasts. This exercise consists in the Dynamic Model Selection (DMS). Also, all the recursions for estimation and forecasting presented in this chapter are based on choosing a prior for $\pi_{0|0,k}$ and $\theta_0^{(k)}$, for $k = 1, \ldots, N$.

Due to potential changes in the error variance over time, we set a rolling version of the recursive method of Raftery et al. (2010) as a consistent estimator of $H_t^{(k)}$, so that:

$$\widetilde{H}_t^{(k)} = \frac{1}{t^*} \sum_{j=t-t^*+1}^{t} \left[(y_t - z_t^{(k)} \hat{\theta}_{t-1}^{(k)})^2 - z_t^{(k)} \Sigma_{t|t-1}^{(k)} z_t^{(k)\prime} \right] \tag{2.23}$$

To allow for substantial change in the error variances, we set $t^* = 24$ and, thus, use a rolling estimator based on two years of data. Moreover, to avoid the rare possibility that $\widetilde{H}_t^{(k)} < 0$, Raftery et al. (2010) suggested replacing $H_t^{(k)}$ by $\widehat{H}_t^{(k)}$, where:

$$\widehat{H}_t^{(k)} = \begin{cases} \widetilde{H}_t^{(k)} & \text{if } \widetilde{H}_t^{(k)} > 0 \\ \widehat{H}_{t-1}^{(k)} & \text{otherwise.} \end{cases}$$

2.3 Forecasting Inflation

Inflation is an intriguing phenomenon, driving both monetary and fiscal policy (Sargent and Wallace, 1975; Leeper, 1991; Taylor, 1993). Accordingly, under the inflation-targeting regime, achieving and maintaining price stability are the primary objectives of Central Banks around the world. Thus, given the forward-looking nature of monetary policy, forecasting inflation has portrayed an prominent role on designing optimal policy decision-making.

In order to provide some insights on the Brazilian inflation dynamics, this chapter aims to evaluate the predictive performance of time-varying forecasting models, namely the Dynamic Model Averaging (DMA) method discussed previously. We also propose a generalized Phillips curve specification as the theoretical background since macroeconomic research has yet to achieve a consensus on the implications of different Phillips curve specifications. Overall, this procedure follows closely Koop and Korobilis (2012).

2.3.1 A Reduced Form Generalized Phillips Curve Model

Despite the Phillips curve ubiquity in macroeconomic literature, there remains no consensus on its specification and thus its implication for inflation dynamics. Given the existence of rigidities in the structure of the economy (e.g. sticky wages and prices, information asymmetry and menu costs), recent empirical research has extended the standard Phillips curve by including additional measures of real activity as potential predictors for future inflation (Stock and Watson, 1999; Galí and Gertler, 1999; Atkeson

and Ohanian, 2001; Sbordone, 2002; Christiano et al., 2005).

While most works focused at uncovering structural parameters, this chapter proposes a reduced form Phillips curve representation for the purpose of inflation forecasting. Therefore, based on Koop and Korobilis (2012), we apply the following generalized Phillips curve specification as our predictive regression:

$$y_t = \mu + x_{t-1}^{'}\beta + \sum_{j=1}^{p} \varphi_j y_{t-j} + \varepsilon_t \tag{2.24}$$

where y_t is the inflation measure, defined as $y_t = \Delta ln(P_t) = ln(P_t) - ln(P_{t-1})$ with P_t being the free IPCA inflation (headline inflation measured by the Broad National Consumer Price Index, excluding administered prices), and x_t is the set of predictors. The specification thus includes unemployment rate, real GDP growth (measured at factor prices, realized by the IPCA), industrial capacity utilization, commodities price index, nominal exchange rate (units of home currency per unit of foreign currency, $R\$/US\$$), import price index, inflation expectations[4] (measured as the averaged expectation at time t for inflation at time $t+1$) and short-term interest rate (measured as Brazilian Central Bank's overnight call rate). This set of variables is in line with empirical works regarding the generalized Phillips curve (Stock and Watson, 1999; Tombini and Alves, 2006; Fonseca Neto, 2010; Koop and Korobilis, 2012). The time series were downloaded from the Brazilian Institute of Geography and Statistics (IBGE), the Institute of Applied Economic Research (IPEA) and the Brazilian Central Bank (BCB).

Sample period spams from 2003:M1 to 2013:M10. Despite the recurrent lack of long period data for Brazil, the sample period is also restricted due to a methodological break in 2002 within the Monthly Unemployment Survey (PME). In general, PME started considering working-age population those aged ten or older (instead of fifteen or older, as before) as well as broadened the geographic area covered, including several municipalities to the six metropolitan regions surveyed before. As a result, unemployment rates increased more than 50% when compared to the old series.

All series were seasonally adjusted by the X-12-ARIMA method. All variables are transformed to be approximately stationary. The commodities price index and the import price index were transformed to their respective growth rates, thus reflecting measures of inflation. The nominal exchange rate enters the analysis in its first differ-

[4]The present chapter uses inflation expectations from the Focus-Market Readout, published by the Brazilian Central Bank's Investor Relations Group (Gerin). This report consists on a daily survey of forecasts of roughly 100 banks, asset managers and other institutions (real sector companies, brokers, consultancies and others) for a vast set of Brazilian economic indicators.

ence in order to evaluate its pass-through degree on inflation; a positive variation means depreciation. Finally, unemployment rate, industrial capacity utilization, inflation expectations and short-term interest rate underwent no further transformations.

2.3.2 Forecast Performance

Before evaluating the DMA performance on forecasting Brazilian inflation, some remarks must be made. First, as discussed previously, the benchmark values of the forgetting factors were set to $\alpha = 0.99$ and $\lambda = 0.99$. Second, according to Koop and Korobilis (2012), we impose a uninformative prior over the models ($\pi_{0|0,k} = \frac{1}{N}$ for $k = 1, \ldots, N$, i.e. initially all models are equally likely) and a diffuse prior on the initial states, such that $\theta_0^{(k)} \sim N(0, 100I_{n_k})$, with n_k being the number of variable in model k, for $k = 1, \ldots, N$.

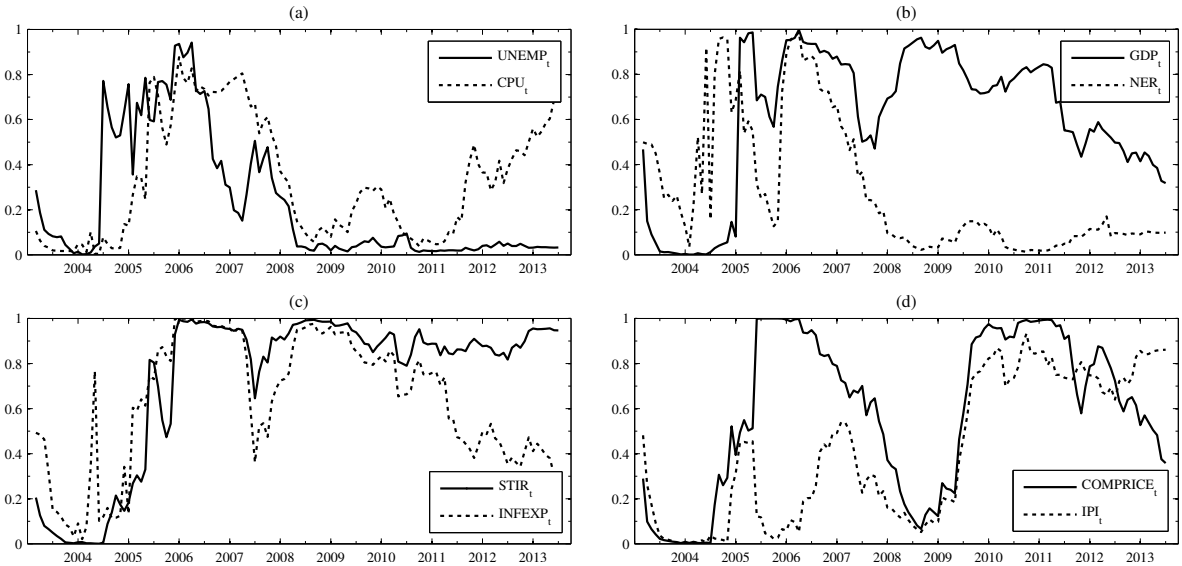
Following the recent Brazilian literature on inflation dynamics, whose overall results favor a short-term autoregressive process (Figueiredo and Marques, 2009; Arruda et al., 2011; Santos and Holland, 2011), all models are set to include an intercept and two lags of the dependent variable. Furthermore, the latter lag length depicts a more parsimonious specification since the estimation procedure involves a wide range of parameters.

Figures (2.1) to (2.3) provide the posterior inclusion probability of predictor. In other words, they present the probability of a predictor being useful for forecasting inflation at time t, that is, they are equivalent to the weight used by DMA attached to models with at least one predictor. We then consider three forecast horizons: short-term ($h = 1$), medium-term ($h = 6$) and long-term ($h = 12$). Overall, there are evidences that the set of predictors is changing over time, taking into account model uncertainty. Therefore, our empirical strategy seems to be suitable for dealing with potential time inconsistency while forecasting Brazilian inflation over the sample period.

As stated in Koop and Korobilis (2012), even though the posterior inclusion probability of predictor provides in-depth insights on whether a given variable bears information to explain the nature of inflation dynamics, providing economic reasoning from such reduced-form forecasting exercise might not be reasonable. Also, the aim of this chapter is not to examine the macroeconomic implications of the following results, but rather evaluate forecasting performance. Yet, we still attempt to discuss some of them in light of macroeconomic theory.

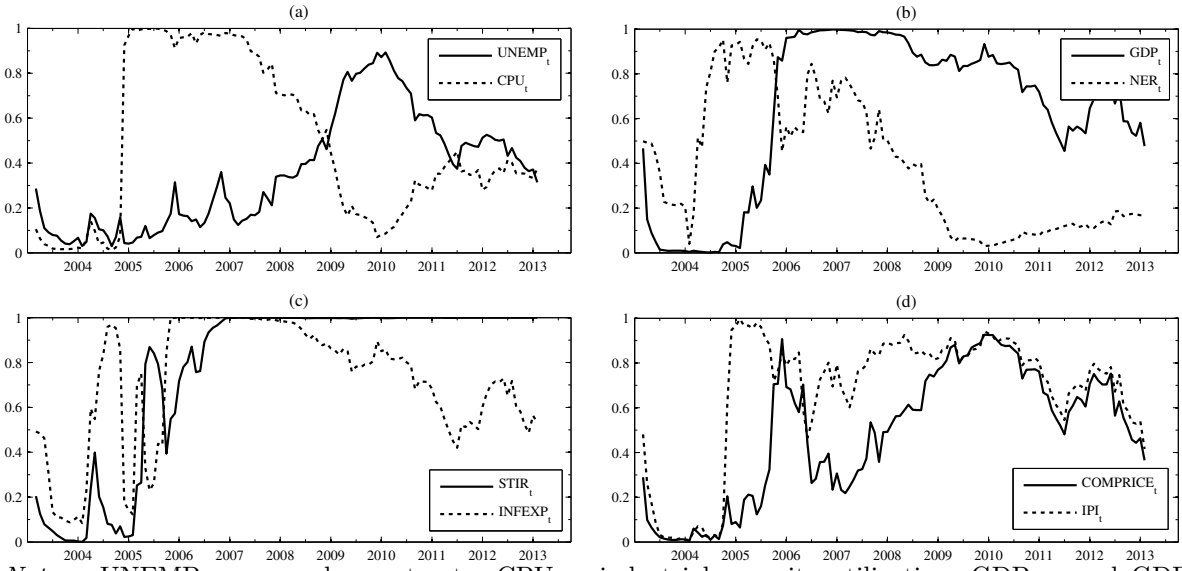
With exception of the medium-term, there is evidence that the unemployment rate is a useful inflation predictor in the beginning of the sample period. However, after mid-2008, the variable practically lost its capability to forecast $t+1$ and $t+12$ inflation. Regarding the medium-term, unemployment regained its predictive power from 2009

Figure 2.1: Posterior Inclusion Probability of Predictors ($h = 1$)



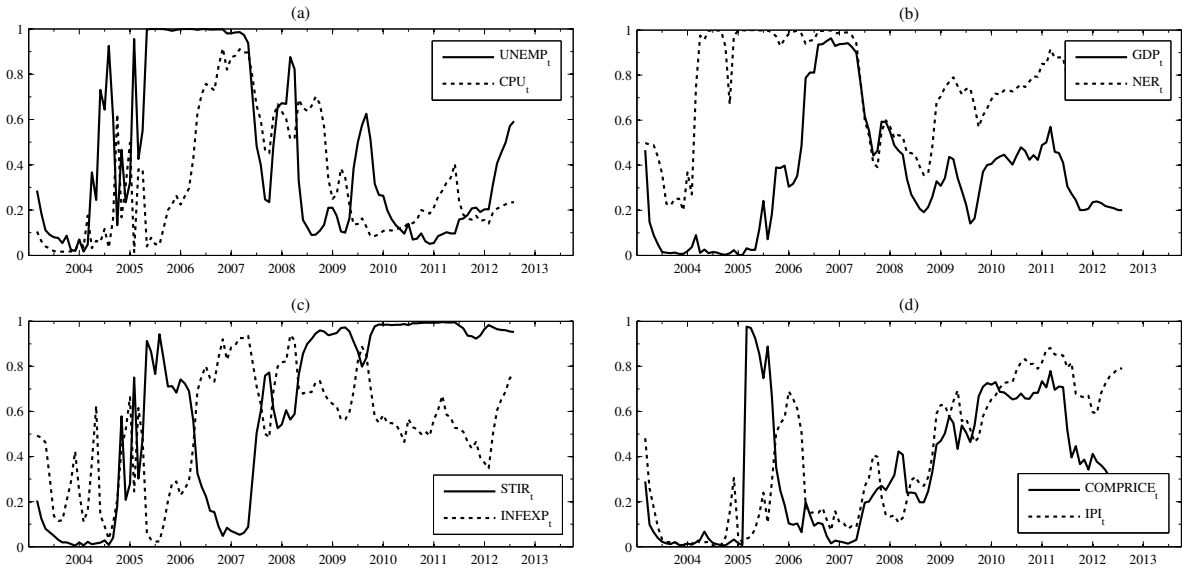
Notes. UNEMP = unemployment rate; CPU = industrial capacity utilization; GDP = real GDP growth; NER = nominal exchange rate; INFEXP = inflation expectations ($t + 1$); STIR = short-term interest rate; COMPRICE = commodities price index; IPI = import price index.

Figure 2.2: Posterior Inclusion Probability of Predictors ($h = 6$)



Notes. UNEMP = unemployment rate; CPU = industrial capacity utilization; GDP = real GDP growth; NER = nominal exchange rate; INFEXP = inflation expectations ($t + 1$); STIR = short-term interest rate; COMPRICE = commodities price index; IPI = import price index.

Figure 2.3: Posterior Inclusion Probability of Predictors ($h = 12$)



Notes. UNEMP = unemployment rate; CPU = industrial capacity utilization; GDP = real GDP growth; NER = nominal exchange rate; INFEXP = inflation expectations ($t + 1$); STIR = short-term interest rate; COMPRICE = commodities price index; IPI = import price index.

until mid-2011. In general, this result provides empirical evidence that the short- and long-term Phillips curve relationship, in the recent years, may be rejected for Brazil; see e.g. Minella et al. (2003) and Mendonça et al. (2012) for similar results.

Regarding the industrial capacity utilization, its usefulness as an inflation predictor is more prominent in the first half of the sample period, especially for short- and medium-term forecasts. However, despite the downward trend since mid-2007, it has regained its short-term predictive power for changes in consumer price inflation after 2011. Moreover, except for $h = 12$, real GDP growth remained a useful predictor from 2005 to 2011.

As to the nominal exchange rate, we found evidences that its capability to predict inflation has substantially weakened since 2007, for $h = 1$ and $h = 6$. One could thus argue these evidences favor the idea that the short- and medium-term degree of the Brazilian exchange rate pass-through (ERPT) have been recently decreasing; see e.g. Minella et al. (2003), Muinhos (2004) and Nogueira Junior (2007) for similar results. One intuition behind this result is that the adoption of the IT regime led to credibility gains of monetary policy, therefore keeping low inflation expectations even after depreciation (Nogueira Junior, 2007). Yet, since the nominal exchange rate generally prevails as a useful inflation predictor throughout the sample period for long-term forecasts, there is also empirical evidence for the presence of long-term ERPT in Brazil.

In mid-1999, the Brazilian Central Bank adopted an inflation-targeting (IT) frame-

work for monetary policy with the short-term interest rate (STIR) as the main instrument. Hence, the STIR has been a consistent inflation predictor from mid-2005 onwards. This result further strengthens the idea of a steady stance on the control of inflation by the Central Bank.

Besides providing a nominal anchor for monetary policy, the IT regime was also designed to anchor inflation expectations. For short-term forecasts, inflation expectations followed a similar pattern to the STIR from 2005 until late-2010, though with a downward trend thereafter. As to medium-term, the posterior inclusion probability reached its maximum value in 2006, remaining as a useful predictor throughout the rest of the sample. Regarding long-term forecasts, the posterior inclusion probability presents a rather volatile behavior. Consequently, we find that inflation contains an important forward-looking component despite inflation expectations losing predictive power in the recent years.

Regardless the forecast horizon, we observe a bimodal posterior inclusion probability for the commodities price index (COMPRICE) and the import price index (IPI). On the other hand, as the forecast horizon increases, their predictive power seems to decrease, with the partial exception of IPI, for $h = 6$. Ergo, there are empirical evidences that foreign prices movements are indeed transmitted to Brazilian consumer prices, especially in the last years. However, these results do not provide information to whether the transmission mechanism is direct, for instance when consumers buy imported goods, or indirect, when prices of domestically produced goods and services are affected by changes in the cost of imported inputs.

In order to evaluate the forecasting performance of DMA models, we employ the Mean Squared Forecast Error (MSFE) and the Mean Absolute Forecast Error (MAFE) as comparison metrics[5], which are calculated beginning in 2003:M5 $+ h + 1$. We thus present results for 8 different models, namely:

- DMA with $\alpha = \lambda = 0.99$;
- DMS with $\alpha = \lambda = 0.99$;
- DMA with $\alpha = \lambda = 0.95$;
- DMS with $\alpha = \lambda = 0.95$;
- DMA with time-invariant coefficients, i.e. with $\alpha = 0.99$ and $\lambda = 1$;
- BMA as a special case of DMA, i.e. with $\alpha = \lambda = 1$;
- Time-Varying Parameter (TVP) AR(2), with $\lambda = 0.99$;

[5]The MSFE can be obtained by $MSFE = \frac{1}{T-t_1+1}\sum_{t=t_1-1}^{T-1}(y_{t+1} - \hat{y}_{t+1|t})^2$, while the MAFE is given by $MAFE = \frac{1}{T-t_1+1}\sum_{t=t_1-1}^{T-1}|(y_{t+1} - \hat{y}_{t+1|t})|$, for $t = t_1, \ldots, T$.

- Recursive OLS using all of the predictors.

Table (2.1) reports the MSFE and the MAFE for the latter models. In general, DMA and DMS specifications deliver good inflation predictions for all three forecast horizons, with DMS ($\alpha = \lambda = 0.95$) being the best model.

For instance, the TVP-AR(2) specification provides predictions as accurate as the ones from DMS ($\alpha = \lambda = 0.95$) for short-term forecasts. This implies that inflation bears sufficient information to explain its own $t + 1$ behavior. This perhaps is not surprising given that the Brazilian macroeconomic literature has already pointed out the short-term nature of inflation persistence in the recent years (Figueiredo and Marques, 2009; Arruda et al., 2011; Santos and Holland, 2011). However, Table (2.1) also provides evidences that the TVP-AR(2) predictive power falls as the forecast horizon increases.

Table 2.1: Predictive Performance Comparison

	$h = 1$		$h = 6$		$h = 12$	
	MSFE	MAFE	MSFE	MAFE	MSFE	MAFE
DMA ($\alpha = \lambda = 0.99$)	0.0446	0.1645	0.0525	0.1850	0.0566	0.1854
DMS ($\alpha = \lambda = 0.99$)	0.0414	0.1594	0.0490	0.1785	0.0476	0.1679
DMA ($\alpha = \lambda = 0.95$)	0.0446	0.1657	0.0489	0.1819	0.0487	0.1708
DMS ($\alpha = \lambda = 0.95$)	0.0362	0.1474	0.0400	0.1665	0.0405	0.1531
DMA ($\alpha = 0.99$, $\lambda = 1$)	0.0456	0.1679	0.0549	0.1885	0.0580	0.1896
BMA (DMA with $\alpha = \lambda = 1$)	0.0480	0.1732	0.0581	0.1927	0.0626	0.1972
TVP-AR(2) ($\lambda = 0.99$)	0.0392	0.1519	0.0606	0.1949	0.0563	0.1827
Recursive OLS	0.0496	0.1769	0.0571	0.1850	0.0516	0.1746

Notes. The forecast evaluation period is 2003:M5 + h + 1–2013:M10.

Since both DMA ($\alpha = 0.99$, $\lambda = 1$) and BMA exhibited two of the worst forecasting performances, our results further suggest that allowing for model and parameter to change over time increase predictive power.

Despite Recursive OLS and TVP-AR(2) performing relatively better than some DMA and DMS specifications, overall both dynamic specifications still provide more accurate forecasts, with results rather favoring DMS models. As discussed in Koop and Korobilis (2012), by imposing zero weight on all models other than the best one, DMS "shrinks" the contribution of all models except a single one towards zero. Ergo, this shrinkage might have granted additional forecast benefits over DMA. On the other hand, given the constantly model switching nature of the DMS approach, the authors

also argued that policymakers may disapprove it as a forecasting procedure, finding the gradual reweighting of DMA more appealing.

2.3.3 Sensitivity Analysis

Even though Raftery et al. (2010) argued that $\alpha = \lambda = 0.99$ would lead to robust results, we carry out a sensitivity analysis in order to address any potential divergence on the forecasting performance due to the specification of the forgetting factors. Following Koop and Korobilis (2012), we specify four alternative models using different factor combinations within the range $\alpha, \lambda \in (0.95, 0.99)$.

From the results in Table (2.2), one should note that the alternative specifications led to similar results in comparison to the ones reported in previous section, i.e., this robustness analysis evolve consistently with the previous results. However, despite DMS with $\alpha = 0.95$ and $\lambda = 0.99$ forecasting a bit better than some specifications of Table (2.1), DMS with $\alpha = \lambda = 0.95$ still provided the best forecasts overall. Hence, based on these evidences, our data set seems to favor model evolution over time-varying parameters.

Table 2.2: Predictive Performance Comparison – Sensitivity Analysis

	$h = 1$		$h = 6$		$h = 12$	
	MSFE	MAFE	MSFE	MAFE	MSFE	MAFE
DMA ($\alpha = 0.99, \lambda = 0.95$)	0.0460	0.1684	0.0527	0.1883	0.0519	0.1725
DMS ($\alpha = 0.99, \lambda = 0.95$)	0.0444	0.1637	0.0495	0.1854	0.0459	0.1616
DMA ($\alpha = 0.95, \lambda = 0.99$)	0.0418	0.1574	0.0487	0.1777	0.0510	0.1777
DMS ($\alpha = 0.95, \lambda = 0.99$)	0.0331	0.1405	0.0404	0.1597	0.0422	0.1587

Notes. The forecast evaluation period is 2003:M5 + h + 1–2013:M10.

2.4 Conclusions

In this chapter, we have proposed a generalized Phillips curve in order to forecast Brazilian inflation over the 2003:M1–2013:M10 period. Through an application of the Dynamic Model Averaging (DMA) approach, our specification has allowed for both model evolution and time-varying parameters, thus being less susceptible to the Lucas (1976) critique.

Our results indicate that DMA and DMS deliver good inflation predictions for all the forecast horizons considered, with DMS ($\alpha = \lambda = 0.95$) being the best model. However, some dynamic specifications have showed difficulty in beating naïve models (i.e. TVP-AR and recursive OLS) for short-term forecasts. Overall, the inclusion of time-varying

features is found to increase predictive power, with data especially favoring changes on the set of predictors. Ergo, we underscore the usefulness of considering both model and parameter uncertainty rather than relying on traditional linear static forecasting devices.

Furthermore, the posterior inclusion probability of predictors enables explicitly evaluation of the probability of a predictor being useful for forecasting inflation. Therefore, our findings suggests that the short- and long-term Phillips curve relationship may be rejected for Brazil while short- and medium-term exchange rate pass-through has been recently decreasing. From a monetary policy viewpoint, the results indicate that price stability has remained one of the primary goals of the Brazilian Central Bank. Moreover, despite inflation expectations losing predictive power in the recent years, we have shown that the dynamics of inflation still contain an important forward-looking component.

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