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A Dynamic Econometric Model for Inflationary Inertia In Brazil

Márcio Poletti Laurini[1]

Abstract

In this article we model the inflationary inertia in Brazil, as measured by the monthly series of IPCA (Aggregate Consumer Prices Index), for the period of inflationary transition from August of 1994 until January of 2003. The concept of inflationary inertia is defined as the value of the first order autoregressive parameter for the IPCA, in a dynamic econometric model with time varying parameters and a GARCH component to control the presence of conditional heteroscedasticity. The model shows that the increasing periods of inflationary inertia are on the crisis moments, and we can identify two periods associated with this phenomenon, being the first moment after the exit of the target zone regime in 1999 and the second associated to the presidential election in 2002. The same analysis is realized with a decomposition of IPCA in free and monitored components showing that inflationary inertia can be identified with the free component of prices in Brazil.

Mathematics Subject Classification: 62, 91
Keywords: Inflationary Inertia, Time Varying Parameters, Conditional Heteroscedasticity

[1] Department of Economics, FEA-RP USP and associated researcher at CNPq.

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1 Introduction

The hypothesis of Inertial Inflation tried to explain the process of persistent high inflation in Brazil in years before 1994 as been the result of mechanisms of price and wage indexation mechanisms present in Brazilian economy. The most relevant academic works for the Inertial Inflation hypothesis are the articles of Modiano (1983 and 1985), Arida and Lara Resende (1985) and Lopes (1986). An econometric model for the inflation rate, according to Inflationary Inertia hypothesis, was formulated by Novaes (1993). Modifying the staggered contracts model of Taylor (1979), introducing a completely backward looking behavior to wage readjustments, he obtains as a result that the inflation index should have a unit root, that is, it should be a process of random walk with an autoregressive coefficient equals one. The unit root in the inflation rate causes shocks to be permanently incorporated in the inflation structure, preventing any tendency of mean reversion. Unit root tests for the inflation index can be found in Cardoso (1983) and Novaes (1993), and in this studies the null hypothesis of a unit root cannot be rejected, a evidence to validity of Inertial Inflation hypothesis.

The implementing of a economic stabilization plan called as Plano Real in 1994, through a sophisticated mechanism of currency substitution, eliminate hyperinflation in the Brazilian economy, taking from the inflation index the inflationary feedback component correspondent to an autoregressive coefficient equals one. Although the Real Plan has been successful in eliminating hyperinflation, a significant parcel of the economy still was based on indexed contracts based on past inflation, and thus still exists an inertial component in Brazilian economy, justifying an econometric analysis on the possible inertial component in the inflation.

In this article we attempted to show that the inflationary inertia component can be modeled with a dynamic process, in which we replace constant inflationary inertia with a varying inertia coefficient. When we allow inflationary inertia to be altered in time, we show that it tends to accelerate in two crisis moments in the Brazilian economy: the moment after the cambial crisis who forced the ends of the target zone regime in February 2002 and the months before the presidential elections in 2002; both periods marked by a strong uncertainty related to political and economic policies that would be adopted in the future.

To model inertia in the inflation rate measured by IPCA as a dynamic process, we used a state space model with time varying parameters with a GARCH component to control the existence of conditional heteroscedasticity. The necessity of a GARCH component is related to the fact that the existence of time varying parameters in econometric models can be caused by uncontrolled conditional heteroscedasticity, and to avoid this effect, we estimated a time varying parameters structure with conditional heteroscedasticity.

2 Regressions with Time Varying Parameters and GARCH (1,1)

The simplest formulation to allow the time variation of inertial inflation parameter would be to assume a linear regression model with time varying parameters, a model easily estimated by the Kalman Filter. However, there is a problem in the estimation of models with parameters that change in time: the existence of time variation in the parameters can be caused by problems of incorrect specification of the model, related to the presence of uncontrolled conditional heteroscedasticity in the model. The omission of this component would lead to the exacerbation of the possible time variation in the parameters, in which an extreme case would be the identification of a spurious model of regression with time varying parameters, in which the real data generating model would be the regression with constant parameters with heteroscedastic shocks.

The presence of conditional heteroscedasticity is directly related to the existence of parameter changes in the data generating process. That a model of regression with random coefficient and constant variance can be transformed into a heteroscedastic regression with fixed parameters (Bauwens, Lubrano and Richard (1999)) is a known result in Bayesian literature. The relation between conditional heteroscedasticity and parameter change is also explored in Tsay (1987) CHARMA (Conditional Heteroscedastic ARMA) model and in Nicholls (1987) and Quinn (1982) RCA (Random Coefficients Autoregressive) model, which use random coefficients to produce conditional heteroscedasticity.

The application of time varying parameters models to explain inflationary behavior can be found in Cogley and Sargent (2001), who model an inflationary process to the United States after World War II, with a system of equations with time varying parameters. The objective of this model is to examine the existence of changes in the conduction of economic policy in relation to the fight against inflation and the exploration of a possible trade-off between inflation and unemployment, occasioned by the existence of a Phillips curve for American data.

Sims (2001) and Stock (2001) criticize the result found by Cogley and Sargent (2001) about changes in the conduction of economic policy, correspondent to the existence of time varying parameters, affirming that the change of parameters examined by them was due to the hypothesis that the variance of each estimated equation in the model was constant to the whole sample. According to Sims (2001) and Stock (2001), if a conditional heteroscedasticity component were included in the model, the parameters variance found by Cogley and Sargent (2001) would not be significant. As a response to this analysis, Cogley and Sargent (2001) modify their time varying parameter model to include a stochastic volatility component, and in this model, Cogley and Sargent (2002) can find indication of time variance in economic policy parameters.

To avoid the problem of spurious time variance in the parameters, due to the lack of a conditional heteroscedasticity component, we estimated a time varying parameters (TVP) model with a component GARCH. The model used is a variant of the general state space model suggested by Harvey, Ruiz and Sentana (1992). This formulation of this model, as presented by Kim and Nelson (1999), is the following:

$$y_t = H\beta_t + Az_t + \epsilon_t + \Lambda\epsilon^* \tag{1}$$

$$\beta_t = \widetilde{\mu} + F\beta_{t-1} + \omega_t + \lambda\omega_t^* \tag{2}$$

$$\epsilon_t \sim N(0, R),\ \omega_t \sim N(0, Q) \tag{3}$$

In this representation, the equation 1 shows the observation equation (measure), being y_t, of dimension (n x K),a vector of K observed variables and size n; H is a matrix that relates the observable components to the ones that are unobservable, which are measured by β_t, and A is a matrix that relates a matrix of exogenous variables z_t to observed variables.

The equation 2 is the state equation that represents the behavior of unobservable components β_t and in this equation matrix F captures the evolution of parameter β between t-1 and t periods. The terms ϵ_t, ϵ^*, ω_t, ω_t^* are the shocks of equations of measure and observation. Matrices R and Q contains the distributions of the shocks, assumed as multivariate normal.

To avoid the problem of spurious time variance in the parameters, due to the lack of the heterokedastic component, we adopted the time varying parameters model by Harvey, Ruiz and Sentana (1992). This model is different from the classic model state space with time varying parameters, for the introduction of $\Lambda\epsilon^*$ and $\lambda\omega_t^*$, which allow the introduction of heteroscedasticity components when we define the following structure:

$$\begin{aligned} \epsilon_t^*|\psi_{t-1} &\sim N(0, h_{1t}) \\ \omega_t^*|\psi_{t-1} &\sim N(0, h_{2t}) \end{aligned} \tag{4}$$

This representation for the conditional variance uses the class of models known as GARCH (Generalized Autoregressive Conditional Heteroscedasticity), originally introduced by Engle (1982) and generalized by Bollerslev (1986)[2].

In model TVP-GARCH (1,1), the components of conditional volatility in the state and observation equations will be given by:

$$\begin{aligned} h_{1t} &= \alpha_0 + \alpha_1 \epsilon_{t-1}^{*\,2} + \alpha_2 h_{1t-1} \\ h_{2t} &= \gamma_0 + \gamma_1 \omega_{t-1}^{*\,2} + \gamma_2 h_{2t-1} \end{aligned} \tag{5}$$

The determination of which shocks in the system are liable to GARCH structures is determined by loading matrices Λ and λ. In our model only the first element of Λ different from zero, while all the elements of Λ are fixed in zero, which makes that GARCH heteroscedasticity be only present in the observation equation, avoiding the econometric identification problem that occurs when $\Lambda$and λ are simultaneously different from zero. When $\Lambda = 0$ and $\lambda = 0$, the model is reduced to a time invariant state space model.

Given the state space formulation of this model, the usual method of estimation would be the application of Kalman filter, which, in this case, would be given by the following equations:

$$\beta_{t|t-1} = \widetilde{\mu} + F\beta_{t-1|t-1} \tag{6}$$

[2]See Appendix on a more detailed discussion about GARCH models.

$$P_{t|t-1} = FP_{t-1|t-1}F' + Q + \lambda h_{2t}\lambda' \tag{7}$$

$$\eta_{t|t-1} = y_t - H\beta_{t|t-1} - Az_t \tag{8}$$

$$f_{t|t-1} = HP_{t|t-1}H' + R + \Lambda h_{1t}\Lambda' \tag{9}$$

$$\beta_{t|t} = \beta_{t|t-1} + P_{t|t-1}H' f_{t|t-1}^{-1}\eta_{t|t-1} \tag{10}$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1}H' f_{t|t-1}^{-1} HP_{t|t-1} \tag{11}$$

The equations 6, 7, 8 and 9 are known as prediction equations, and the equations 10 e 11 are known as updating equations of Kalman Filter. The terms in these equations are: P_t the covariance matrix of parameters β_t, η_t represents the forecast error and β_t, η_t is conditional covariance of prediction error. All these matrices are conditioned to a set of information ψ, which can be dated in t-1 or t.

However, Kalman filter represented by equations 6 to 11 is not directly useful, once terms h_{1t} and h_{2t} are functions of previous shocks, and this formulation is not allowed by the linear Kalman Filter. To overcome this problem, Harvey, Ruiz and Sentana (1992) replace the terms h_{1t} and h_{2t} with its conditional expectation given by:

$$\begin{aligned} h_{it} &= \alpha_0 + \alpha_1 E[\epsilon_{t-1}^* | \psi_{t-1}] + h_{1t-1} \\ h_{2t} &= \gamma_0 + \gamma_1 E[\omega_{t-1}^* | \psi_{t-1}] + h_{2t-1} \end{aligned} \tag{12}$$

To put these approximations in the model, Harvey, Ruiz and Sentana (1992) define the following matrices[3]:

$$\begin{bmatrix} \beta_t \\ \epsilon_t^* \\ \omega_t^* \end{bmatrix} = \begin{bmatrix} \widetilde{\mu} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} F & 0_k & 0_k \\ 0_k & 0 & 0 \\ 0_k & 0 & 0 \end{bmatrix} \begin{bmatrix} \beta_{t-1} \\ \epsilon_{t-1}^* \\ \omega_{t-1}^* \end{bmatrix} + \begin{bmatrix} I & 0_k & \lambda \\ 0_k' & 1 & 0 \\ 0_k' & 0 & 1 \end{bmatrix} \tag{13}$$

which is an increased representation of equation 6:

$$\beta_{t|t-1}^* = \widetilde{\mu}^* + F^* \beta_{t-1|t-1}^* + G^* \upsilon_t^* \tag{14}$$

and we defined Q_t^* as:

$$Q_t^* = E\left[\upsilon_t^* \upsilon_t^{*\prime} | \psi_{t-1}\right] = \begin{bmatrix} Q & 0_k & 0_k \\ 0_k & h_{1t} & 0 \\ 0_k & 0 & h_{2t} \end{bmatrix} \tag{15}$$

[3]Matrices 0_k and 0_n are vectors K to 1 and n to 1 of zeros.

The observation equation is now given by the expression:

$$y_t = \begin{bmatrix} H & \Lambda & 0_n \end{bmatrix} \begin{bmatrix} \beta_t \\ \epsilon_t^* \\ \omega_t^* \end{bmatrix} + Az_t + \epsilon_t \tag{16}$$

and $E\left[\epsilon_t \epsilon_t^{,}\right] = R$. Replacing 15 and 16 in Kalman Filter, the new prediction and updating equations are:

$$\beta^*_{t|t-1} = \widetilde{\mu}^* + F^* \beta^*_{t-1|t-1} \tag{17}$$

$$P^*_{t|t-1} = F^* P^*_{t-1|t-1} F^{*,} + G^* Q^*_t G^{*,} \tag{18}$$

$$\eta^*_{t|t-1} = y_t - H^* \beta^*_{t|t-1} - Az_t \tag{19}$$

$$f^*_{t|t-1} = H^* P^*_{t|t-1} H^{*,} + R \tag{20}$$

$$\beta^*_{t|t} = \beta^*_{t|t-1} + P^*_{t|t-1} H^{*,} f^{*-1}_{t|t-1} \eta^*_{t|t-1} \tag{21}$$

$$P^*_{t|t} = P^*_{t|t-1} - P^*_{t|t-1} H^{*,} f^{*-1}_{t|t-1} H^* P^*_{t|t-1} \tag{22}$$

The terms $E\left[\epsilon^{*2}_{t-1}|\psi_{t-1}\right]$ and $E\left[\omega^{*2}_{t-1}|\psi_{t-1}\right]$ necessary to the calculation of h_{1t} and h_{2t}, are given by:

$$\begin{aligned} E\left[\epsilon^{*2}_{t-1}|\psi_{t-1}\right] &= E\left[\epsilon^*_{t-1}|\psi_{t-1}\right]^2 + E\ \left[\epsilon^*_{t-1} - E\left[\epsilon^*_{t-1}|\psi_{t-1}\right]^2\right] \\ E\left[\omega^{*2}_{t-1}|\psi_{t-1}\right] &= E\left[\omega^*_{t-1}|\psi_{t-1}\right]^2 + E\ \left[\omega^*_{t-1} - E\left[\omega^*_{t-1}|\psi_{t-1}\right]^2\right] \end{aligned} \tag{23}$$

With these approximations, we can use Kalman filter to obtain the estimators of Maximum likelihood through the of the prediction error decomposition 24 for the unknown parameters of the model:

$$ln\, L = -\frac{1}{2}\sum_{t=1}^{T} ln((2\pi)^n |f^*_{t|t-1}|) - \frac{1}{2}\sum_{t=1}^{T} \eta^{*,}_{t|t-1} f^*_{t|t-1} \eta^*_{t|t-1} \tag{24}$$

The likelihood function defined in 24 can be maximized by numerical methods as usual.

Table 1: Unit Root Tests

Series	ADF Stat	Model	Integration Order
IPCA	-4.8199	intercept, 1 lag	I(0)
Unemployment	-2.8528	intercept ,12 lags	I(1)
SELIC	-2.6514	intercept, 1 lag	I(1)
Exchange Rate	-2.8943	intercept, trend	I(1)

3 Linear Model

To verify the need for a model with time varying parameters, we started from a linear model estimated by ordinary least squares and through specification tests and structural break tests, to check if a model that allowed a time dynamics to the parameters was necessary. To define the linear models, we selected the unemployment rate measured by IBGE, interest rate on federal bonds (SELIC) and BRL/US$ exchange rate as control variables[4]. These variables aim to control the effects that the level of economic activity, influence of prices of imported products and expectatives would have on current inflation rate, avoiding that the model estimation be inconsistent due to the absence of relevant explicative variables.

We tested the order of integration of the series through an ADF (Augmented Dickey-Fuller) test, set in Table 1. The tests shows that we can reject the presence of a unit root to the inflation rate measured by IPCA to the period in analysis, and that we can not reject the hypothesis of a unit root SELIC, unemployment and exchange rate series. The results of these tests show that we must set the inflation series of IPCA in level, and the other series in first differences in the equations to be estimated, so that all the series be in the same order of the integration in the model specification.

The linear model selected by the Bayes Information Criteria (BIC) corresponds to the model set in Table 2[5]. The linear estimation indicates that in

[4]The series of monthly unemployment rate and IPCA inflation are calculated by IBGE, Instituto Brasileiro de Geografia e Estatstica, the Brazilian Bureau of Statistics. The monthly data on SELIC and Exchange Rates are supplied by BACEN, Central Bank of Brazil. The sample utilized is from February of 1994 until January of 2003.

[5]Due to the evidence of heteroscedasticity indicated by the White test (Table3), the standard errors were calculated using Newey-West heteroscedasticity and autocorrelation

Table 2: Linear Model

	Parameter	Std. Error	t Stat	Pr(>|t|)
Intercept	0.6218	0.0610	10.19	0.0000
$IPCA_1$	0.1442	0.0120	11.97	0.0000
$dExchange_5$	1.5181	0.7107	2.14	0.0352
$dSELIC_3$	−0.0353	0.0132	−2.68	0.0087
$dSELIC_4$	−0.0265	0.0133	−1.99	0.0492
$dUnemployment_1$	−0.1886	0.1090	−1.73	0.0869
$dUnemployment_7$	−0.2651	0.1110	−2.39	0.0189

this period the inertial component is very low, corresponding to an autoregressive coefficient of 0.1442 for the first lag of IPCA. In this model, lags 3 and 4 of SELIC interest rate and lags 1 and 7 of unemployment, with expected negative signs, were included, showing negative relations between the inflation and rates of interest and unemployment. In this linear model, the inflation rate is reduced with the increasing of SELIC with a 3 and 4 month lag, and it also negatively responds to the increasing of unemployment rates.

To verify if the linear model was correctly specified, we used the White heteroscedasticity test, a RESET test and a test for ARCH conditional heteroscedasticity, set in Table 3. The White test rejects the null hypothesis that the linear model residuals are homoscedastic, indicating the need of a heteroscedasticity correction for the estimation of the correct covariance matrix and also showing that estimation is inefficient. The Reset general test specification rejects, in any level of significance, that the proposed linear model have a correct specification, which could happen due to the absence of relevant explicative variables, incorrect functional form or structural breaks in the model. The ARCH test, however, does not reject the null hypothesis that the linear model does not have an ARCH conditional variance structure.

Although this result is an initial evidence against the inclusion of a GARCH structure, it notices that as a model with a GARCH structure can be written as a model where the parameters of conditional mean are time varying and

consistent covariance matrix.

Table 3: Specification Tests - Linear Model

Test	White		
F Stat.	2.6412	Probability	0.0045
LM Stat.	26.7856	Probability	0.0082
Test	Reset		
F Stat.	7.4558	Probability	0.0000
LM Stat.	42.5462	Probability	0.0000
Test	ARCH		
F Stat.	0.1281	Probability	0.7211
LM Stat.	0.1305	Probability	0.7178

the variance is constant, this result can show the necessity of the control of the changes of parameter in conditional mean, what will be confirmed by the estimation of the model of time varying parameters presented in section 2, where the GARCH component will be relevant, as it will be seen in section 4.

To test the constancy of parameters in the estimate linear model, we used the tests proposed by Andrews (1993) and Andrews and Ploberger (1994) to test for structural breaks when the breakpoint is unknown. The Sup, AveF and ExpF tests used are defined as:

$$SupF = \sup_{\underline{i} \leq i \leq \overline{i}} F_i \tag{25}$$

$$AveF = \frac{1}{\overline{i} - \underline{i} + 1} \sum_{i=\underline{i}}^{\overline{i}} F_i \tag{26}$$

$$ExpF = \log\left(\frac{1}{\overline{i} - \underline{i} + 1} \sum_{i=\underline{i}}^{\overline{i}} \exp\left(0.5 \cdot F_i\right)\right) \tag{27}$$

These tests are calculated estimating a series of statistics F_i of structural break for a whole sequence of possible structural breakpoints for the samples defined in $k < \underline{i} \leq i \leq \overline{i} < n-k$, in the interval $\left[\underline{i}, \overline{i}\right]$,where k and n-k determine the beginning and the end of the tested sample. Thus, SupF, AveF and ExpF tests allow the test of structural break without determining the breakpoint to be tested.

Table 4: Parameter Constancy Tests

Test	F Stat.	Prob.
SupF	20.5366	0.07792
AveF	12.5633	0.03018
ExpF	8.1094	0.03782

Table 4 contains these tests results for the linear model. The three tests show that we can reject the null hypothesis for parameters constancy and must consider an alternative hypothesis that the parameters are not constant, showing that there is a structural break in one or more points in the estimated sample. This result shows that the linear model is not able of controlling all the dynamics in the inflation series measured by IPCA for the analyzed period, indicating the necessity of controlling the time variation in the parameters that cause the structural breaks captured by SupF, AveF and ExpF tests.

4 TVP-GARCH (1,1) Results

The results of specification tests for the linear model shows the possible presence of a time varying structure in parameters, it is justified the estimation of a more complex model for the data in analysis. To estimate time varying parameters model and GARCH (named TVP-GARCH (1,1)), we began with the choice of linear model variables as a general model. The final model chosen is presented in Table 5. The vector of estimated hyperparameters of exchange rate series was not statistically different from zero, and for this reason, it was removed from the estimated TVP-GARCH (1,1) model.

The final TVP-GARCH Model (1,1) corresponds to the results presented in Table5. In this model the hyperparameters of all included variables are significantly different from zero in any level of significance, which also happens to GARCH components. The fact that there is a significant GARCH structure shows that the result of time variation in the parameters is valid even controlling the conditional variance structure existing in the series.

The GARCH component show that shocks persistence in the conditional volatility is very low, once the persistence measured by the addition of α and

Table 5: Model TVP-GARCH(1,1)

Series	Hyperpar. sd	Std. Error	t Stat	Pr(> $\|t\|$)
Intercept	0.1204	0.0368	14.1243	0.0000
$IPCA_1$	0.0757	0.0171	30.2720	0.0000
$dSELIC_3$	0.0000	0.0015	334.5158	0.0000
$dSELIC_4$	0.0222	0.0163	31.7233	0.0000
$dUnemployment_1$	0.0000	0.0053	97.1896	0.0000
$dUnemployment_7$	0.01381	0.0139	39.5747	0.0000
GARCH ω	0.0682	0.0202	9.8990	0.0000
GARCH α	0.01001	0.0002	37.6362	0.0000
GARCH β	0.5063	0.1653	5.9861	0.0000
log-lik	-58.8566			

β parameters is bellow one, showing that shocks rapidly dissipates in the conditional variance of this series. The fact that theα coefficient value, which measures the effects of square shocks of the medium structure in the conditional variance a moment ahead, is very low shows that the shocks in the mean have very small immediate effects on the inflation rate variance, and that the permanent effect of these shocks is close to zero. The conditional variance structure is basically influenced by the variance in the previous moment measured by coefficient β.

Figures 1, 2, 3 and 4 show the hyperparameters vectors estimated by TVP-GARCH (1,1) model, showing the time evolution of these parameters. Given the non-linear formulation of the model and the reduced size of the sample, to construct the intervals of confidence for the parameters, we used the block bootstrap methodology[6].

The behavior of Inflationary Inertia can be seen in Figure 1, which shows the estimated values for the autoregressive parameter for the IPCA. Taking as analysis reference the value estimated by the linear model for the autoregressive parameter of IPCA, with value 0.14, we can observe that inflationary inertia tends to increase in the periods of uncertainty in the Brazilian economy. It can be seen that the inertia tends to increase abruptly after January 1999, which corresponds to the exchange crisis that indicated the end of target zone

[6] See Appendix for the description of the bootstrap methodology utilized.

regime, where there was a great expectation of inflationary acceleration, which turned not to be true, as the behavior of consecutive reductions of inflationary inertia in the months following February 1999 shows.

Another great increase in the Inflationary Inertia corresponds the months from June to December of 2002. The estimated values for the Inertia from June 2002 to January 2003 are respectively 0.072, 0.083, 0.95, 0.142, 0.748 and 0.584. We can associate this acceleration in the inertia and in the inflation rate with the presidential election in that year.

From June 2002 on, the election surveys indicated the victory of the opposition candidate and the current governments growing incapacity to react in the presidential running. This was considered by the economic agents as victory indicator of the opposition candidate, whose campaign mainly focused on the retaking of growth, through the reduction of interests rate and emphasis on social policies, which was associated by some economic agents as abandoning the fiscal policy adjustment and inflationary goals used by the present government.

The acceleration of inflation would be caused by an increase in the uncertainty of economic agents, which was reflected in expectations for higher inflation in the future, leading to a preventive behavior of agents with decision power on prices of increasing prices on that moment to avoid future losses with a realized higher inflation. This view, consistent with the theory of Inertial Inflation, and supported by TVP-GARCH (1,1) model, would ascribe all the responsibility of inflationary acceleration to the process of expectative formation, in opposition to the hypothesis that there is a connection between expectations and inflation increase in the exchange depreciation on this period, another explication to the inflation acceleration in this period.

The hyperparameter associated to the intercept (Figure 2) explain the behavior of the inflation in the analyzed period, when we analyze the values of the intercept with the values of the inflationary inertia. Maintaining the other variables constant, the effect of the intercept and the IPCA autoregressive parameter shows that the period of decrease of the inflationary inertia from the beginning of the sample to approximately August 1998 is marked by a tendency of inflation decrease. That happens due to fact that the intercept estimated by the model is also in reduction in this period. From this date, we can notice an increase tendency in the inflation index, which is captured by

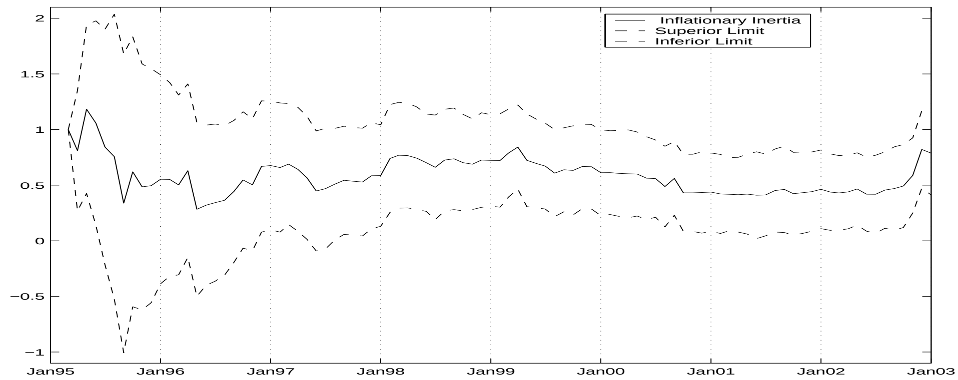


Figure 1: Inflationary Inertia - TVP- GARCH(1,1)

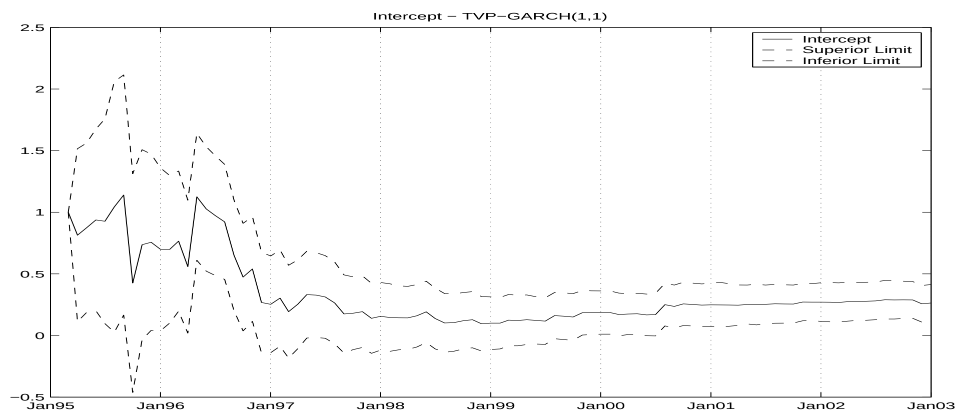
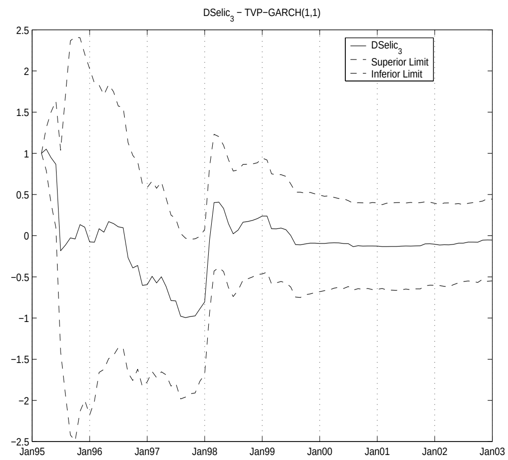


Figure 2: Intercept - TVP- GARCH(1,1)

a simultaneous elevation in the intercept and the autoregressive coefficient for IPCA.

The vectors of estimated parameters for the interest rate SELIC (Figure 3)) show more complex behavior. The estimated parameters for the third time lag, while the parameters become positive in the fourth lag, mainly starting from January 1999, being this sign the contrary of what we expected. As January 1999 marks the end of the period of the target zone, it would be possible to interpret this sign change as an alteration in the economic policy.

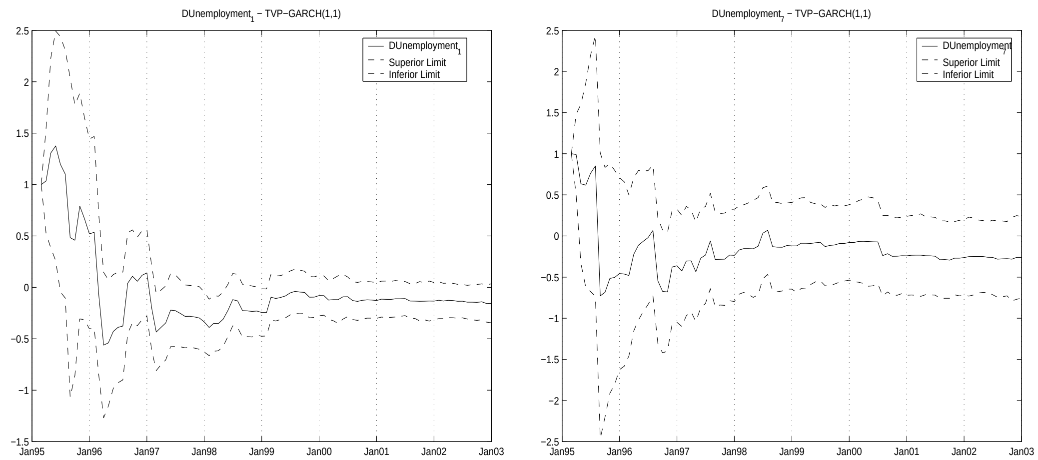
The estimated parameters for the first difference of the unemployment index (Figure 4) show that there is a reduction in the negative relationship between inflation and unemployment in that period, since the estimated values



(a) DSelic_3 (b) DSelic_4

Figure 3: SELIC - TVP- GARCH(1,1)

for the first lag of the difference of the unemployment have become negative lately. That can be interpreted as the fact that the unemployment index has increased in this period, but with an effect that is becoming smaller on the inflation index. The behavior of the parameters associated to the seventh lag of the unemployment index does not show a clear tendency, having a reduction in the values until January 1998 and from that some fluctuations without a clear tendency.



(a) DUnemployment_1 (b) DUnemployment_7

Figure 4: Unemployment - TVP- GARCH(1,1)

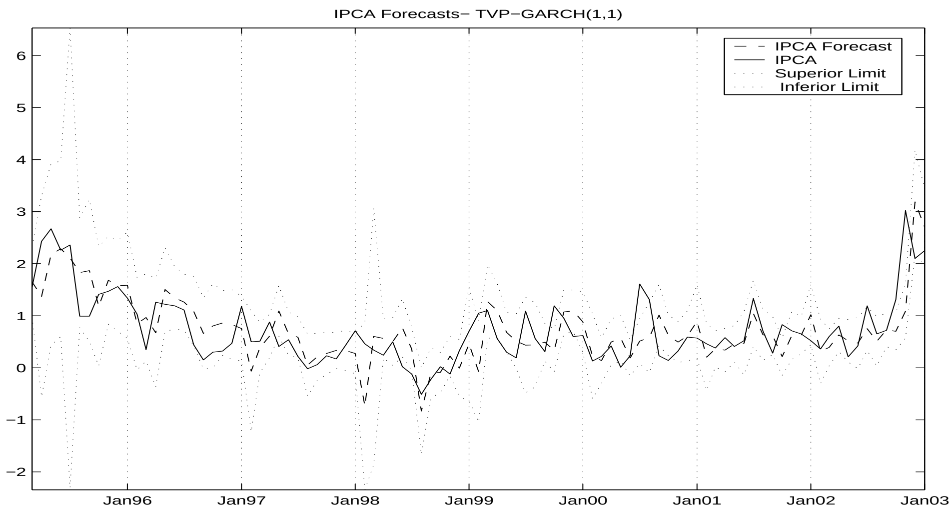


Figure 5: IPCA Forecasts- TVP-GARCH(1,1) Model

4.1 Specification Analysis

The analysis of serial correlation for the linear model and for the model TVP-GARCH(1,1) is in the Table 6. By the Q statistics, none of the two models presents any evidence of residual serial correlation. The model TVP-GARCH(1,1), besides avoiding the problem of serial auto-correlation, still controls the heteroscedasticity presence and it represents an efficiency gain in the econometric estimate for the behavior of IPCA, which will be reflected in the confidence interval of the forecasts of this model, as presented in section 5.

5 Forecast analysis

The one step-ahead forecasts of the model TVP-GARCH(1,1) in the Figure 5. The model TVP-GARCH(1,1) can follow in a very close way the behavior of IPCA, which we can notice when the forecasts of the model do not exhibit any tendency of being below or above the observed values, what effectively happens with the forecasts of the linear model, present in the Figure 6. The forecasts of the linear model had almost always been smaller than the values observed for IPCA until approximately January 1997, and from this date they have tended to be higher than the observed values.

Table 6: Residual Autocorrelation

	Linear Model				TVP Model			
	AC	ACP	Q-STAT	Prob	AC	ACP	Q-STAT	Prob
1	0.075	0.075	0.5498	0.458	0.096	0.096	0.9010	0.343
2	-0.106	-0.112	1.6623	0.436	-0.145	-0.155	2.9746	0.226
3	0.008	0.025	1.6682	0.644	-0.095	-0.066	3.8717	0.276
4	0.001	-0.014	1.6682	0.796	-0.074	-0.083	4.4271	0.351
5	-0.017	-0.012	1.6987	0.889	-0.127	-0.142	6.0845	0.298
6	0.014	0.015	1.7180	0.944	-0.054	-0.064	6.2856	0.381
7	0.042	0.037	1.9016	0.965	-0.066	-0.120	6.8423	0.445
8	0.037	0.034	2.0444	0.980	0.045	0.010	7.0580	0.530
9	0.129	0.134	3.8270	0.922	0.074	0.008	7.6416	0.571
10	-0.064	-0.082	4.2697	0.934	0.013	-0.031	7.6613	0.662
11	0.042	0.088	4.4633	0.954	0.081	0.078	8.3745	0.679
12	0.187	0.164	8.3351	0.758	0.300	0.297	18.394	0.104
13	0.022	0.010	8.3903	0.817	0.041	0.046	18.759	0.137
14	-0.121	-0.091	10.044	0.759	-0.122	0.003	20.263	0.122
15	-0.059	-0.053	10.451	0.790	-0.153	-0.058	22.958	0.085
16	0.029	0.010	10.550	0.836	-0.080	-0.014	23.705	0.096
17	-0.046	-0.061	10.779	0.867	-0.076	-0.045	24.380	0.109
18	-0.009	-0.027	10.810	0.902	0.011	0.007	24.395	0.142
19	-0.081	-0.105	11.603	0.902	-0.022	-0.059	24.453	0.179
20	0.034	0.019	11.748	0.924	0.091	0.026	25.469	0.184
21	0.077	0.029	12.495	0.925	0.053	-0.047	25.819	0.213
22	-0.048	-0.029	12.783	0.939	0.011	-0.021	25.853	0.259
23	0.046	0.081	13.053	0.951	0.015	-0.012	25.864	0.307
24	-0.002	-0.049	13.053	0.965	0.070	-0.009	26.491	0.329

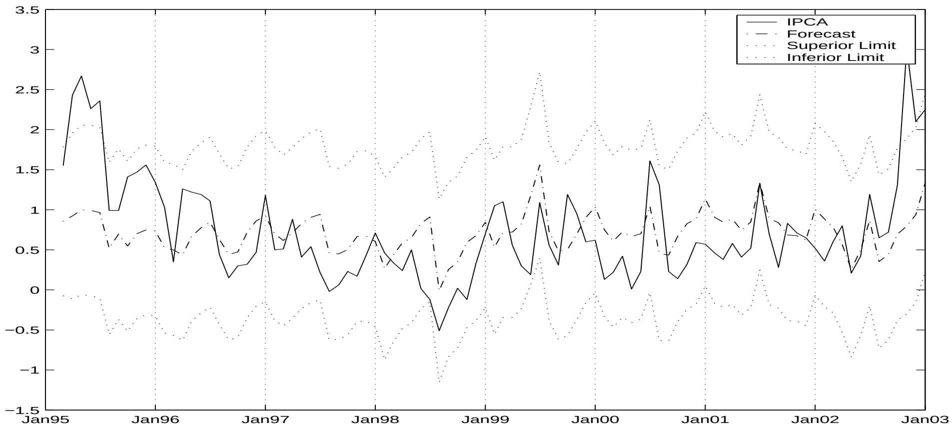


Figure 6: IPCA Forecasts - Linear Model

The property that the values foreseen by the model TVP-GARCH(1,1) are not biased, in contrast with the bias observed in the linear model, can be quantified by the measures of predictive performance in the Table 7. The bias proportion of the linear model is very superior compared to the model TVP-GARCH, as well as the variance proportion that measures how much the variance of the forecast is far from the variance of the observed values. The covariance proportion measures the non systematic part of the forecast errors is close to one for the model TVP-GARCH(1,1) and has value 0.5619 for the linear model, confirming that the linear model makes systematic forecast errors. A model with good predictive performance is the one that the values of the bias proportions and variance are very close to zero, concentrating all the values on the non systematic part of the forecast mistakes in the covariance proportion, what happens for the model TVP-GARCH(1,1).

The Table 7 also shows that the model TVP-GARCH(1,1) is superior in forecast terms for the three analyzed predictive criteria, that are the Root Mean Squared Error, the Mean Absolute Error and the Theil Inequality index. The Root Mean Squared Error and the Mean Absolute Error are comparative criteria, where the best model for these criteria is the one that has the smallest value. The Theil Inequality Index is always restricted among values 0 and 1, where 0 would be a perfect adjustment and 1 would be a totally imperfect adjustment.

The superior predictive performance of TVP-GARCH(1,1) model can be explained by the adaptative structure represented by the time varying param-

Table 7: One Step Ahead Forecast Analysis

Measure	Linear Model	TVP-GARCH(1,1)
Root Mean Squared Error	0.5977	0.4903
Mean Absolut Error	0.4845	0.3637
Theil Inequality	0.3338	0.2501
Bias Proportion	0.0026	0.0003
Variance Proportion	0.4353	0.0015
Covariance Proportion	0.5619	0.9981

eters. A large forecast error is a signal of a change in the parameters of model, what it can be captured by a model of time varying parameters but not for linear model, who assumes a fixed parameter. This is the most important evidence in favor of TVP-GARCH(1,1).

6 Uncertainty and Inflation

The conditional variance estimated by the model TVP-GARCH(1,1) is presented in the Figure 7. The graph confirms that the persistence of the average shocks in the structure of the variance is very low, since volatility groupings are not present, and the reversion to the unconditional variance is very fast, as expected because of the relatively low value of persistence.

An important subject is to verify if moments of uncertainty on the inflation index, measured by the conditional variance, influence the inflation index. This subject could be formulated as a hypothesis that the agents would react to a larger uncertainty on the inflation index, increasing its prices in a preventive way. One simple way to test this hypothesis is verify if exists a positive relationship between the present inflation and the volatility of the inflation in the past.

In order to verify the validity of this hypothesis, we formulated a simple test through a linear regression having the inflation as a dependent variable and the past values of the volatility of the inflation as explanatory variables. Estimating this relationship, the model selected by the criterion of information BIC has the conditional variance lagged just one period as explanatory

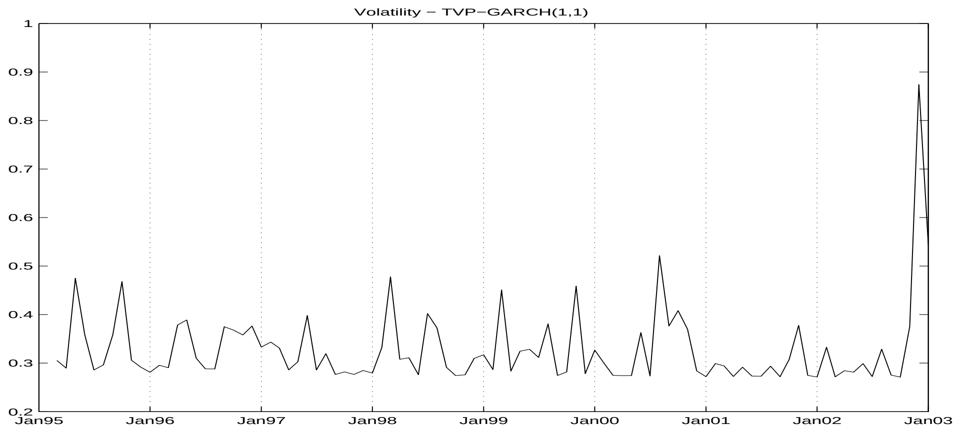


Figure 7: Conditional Volatility

Table 8: Regression - Inflation and Uncertainty

	Parameter	Std. Error	t Stat	Pr ($>\|t\|$)
Intercept	0.1850	0.0989	1.8700	0.0647
Variance_1	2.7111	0.4188	6.4730	0000
F Test	41.90	Prob. F	0.0000	

variable.

The Table 8 shows that the null hypothesis that there isn't a relationship between inflation and the past volatility of inflation is rejected at any significance level, being an indication in favor of the hypothesis that the agents react to the uncertainty about the inflation passed with preventive increases of prices[7].

[7]However, the results obtained by this regression should be carefully considered, since the efficient form of estimation would be to simultaneously estimate the parameter of the past variance as explanatory variable in the conditional mean and the component GARCH of conditional volatility, through a model of GARCH-in-mean model with time varying parameters. But the presence of a GARCH component in the equation of the conditional mean in the leads to a non-linear state space that cannot be estimated by the usual tool of the Kalman Filter. The accomplished estimate is inherently inefficient and in this way the power of the accomplished test is reduced.

Table 9: TVP-GARCH - Free and Monitored Prices

	Free	Prices	Monitored	Prices
	Hyperpar. sd	Pr(> $\|t\|$)	Hyperpar. sd	Pr(> $\|t\|$)
Intercept	0.000008	0.000000	0.124890	0.000000
IPCA_1	0.079091	0.000000	0.000010	0.000000
dSELIC_3	0.000000	0.000000	0.567193	0.196843
dSELIC_4	0.000080	0.000000	0.248861	0.024182
dUnemployment_1	0.036008	0.000000	0.058694	0.000002
dUnemployment_7	0.009781	0.000000	0.000030	0.000000
GARCH ω	0.000020	0.000000	0.341664	0.585119
GARCH α	0.098710	0.000000	0.276353	0.634358
GARCH β	0.000020	0.886143	0.490568	0.013933
log-lik	-68.7870		-174.8518	

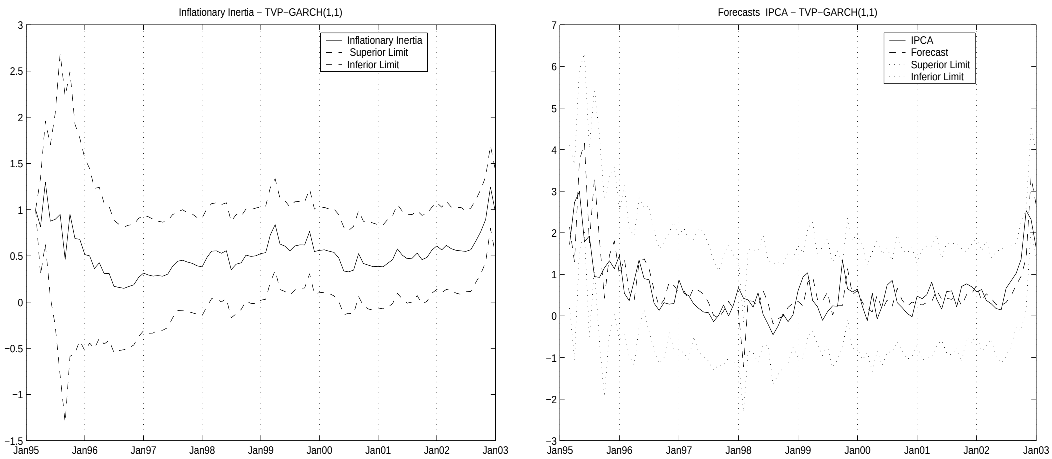
7 Free and Monitored prices

A subject involved in the discussion of the existence of the inflationary inertia is to verify if the inertia component is due to the components of free or monitored prices that compose the series of IPCA. IPCA is constituted by two groups of prices, the free prices, that constitutes about 72% of the index, and the prices monitored by the government, that constitutes the remaining 28% of IPCA. The application of the model of time variant parameters allows verifying if the origin of the inflationary inertia is due to the agents behavior in the formation of the free prices or if it is caused by the public policies of price control in controlled sectors of economy.

In order to verify this, we applied the same model TVP-GARCH for the of IPCA-Free prices and for the IPCA-Monitored prices, with the arranged results in the Figures 8 and 9 and in the Table 9. The Figures show the component of estimated inflationary inertia for each one of the series and the one step-ahead forecasts of the each model [8].

The estimated inflationary inertia component for the series of free prices has a similar behavior to the one of the series of full IPCA index, what suggests

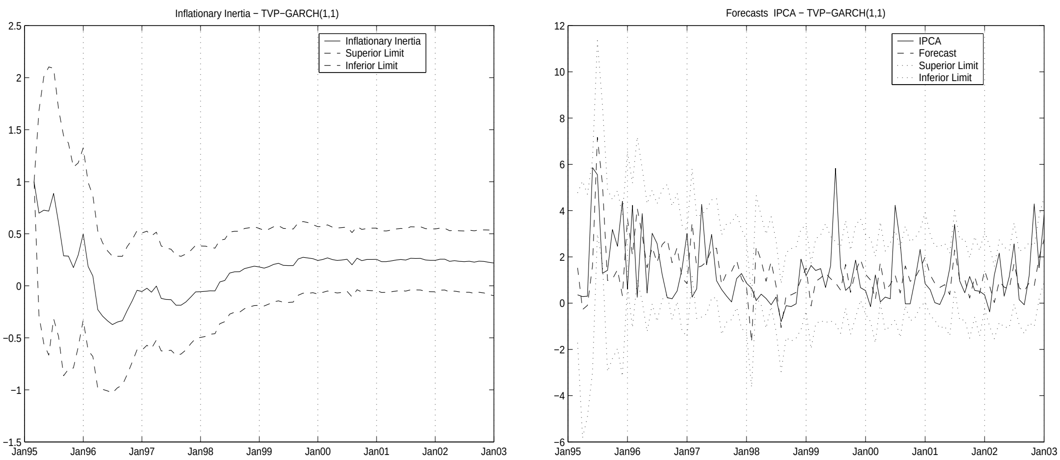
[8]The other figures and results are not shown due to space constraints, but they are available with the authors.



(a) Inertia (b) Forecasts

Figure 8: Free Prices - Inertia and Forecasts

that the component of varying inertia in the series of full IPCA index is caused mainly by the behavior of the free prices. This hypothesis is also supported when we look at the estimated inertia component for the series of monitored prices, in the beginning of the series the inertia is close to 1, but it tends to stabilize starting from January 1999 in values close to 0.23.



(a) Inertia (b) Forecasts

Figure 9: Monitored Prices - Inertia and Forecasts

The component GARCH shows that while the volatility of the free prices is owed to the past shocks (the coefficient β is not statistically significant), the

Table 10: Linear Model - Free Prices

	Parameter	Std. Error	t Stat	Pr(> $\|t\|$)
Intercept	0.12052	0.05593	2.155	0.0339
$IPCA_1$	0.80650	0.06526	12.359	¡2e-16
$DExchange_5$	0.09520	0.52647	0.181	0.8569
$DSELIC_3$	-0.21214	0.13161	-1.612	0.1106
$DSELIC_4$	0.12468	0.13901	0.897	0.3722
$dUnemployment_1$	-0.12908	0.07762	-1.663	0.0999
$dUnemployment_7$	-0.06252	0.80450	-0.777	0.4392
		SupF	28.2398	0.005184
		AveF	14.8828	0.007817
		ExpF	11.2641	0.002804

process of conditional volatility for the monitored prices is only formed by the own volatility in the past, since just the coefficient β is statistically significant.

We also verified that if it would be really necessary to estimate a model of time variant parameters for free and monitored prices. This verification is justified by the fact that the behavior of the inflationary inertia for the monitored prices tends to stabilize in time, what could indicate that a model of constant parameters can be more indicated for these series. The linear models estimated for the series of free and monitored prices are in the 10 and 11.

We compared the linear specification with constant parameters and the model TVP-GARCH through predictive criteria, disposed in the Table 12. Through the analysis of the forecast criteria, the model TVP-GARCH(1,1) is more adapted for the series of free prices, since this model overcomes the linear model in all the criteria. For the series of monitored prices, the result is inverted, since the linear model is superior to the model TVP for the criteria of the Root Mean Squared Error, Mean Absolute Error and for the Theil Inequality, but the forecast bias of the linear model is superior to the one from the model TVP-GARCH(1,1), since the bias and variance proportions of the linear model for these series are still larger than the ones calculated for the forecasts of the model TVP-GARCH. The need of a model with time variant parameters for the series of free prices and the evidence that a linear model with

Table 11: Linear Model - Monitored Prices

	Parameter	Std. Error	t stat	Pr(> $\|t\|$)
Intercept	0.92452	0.19097	4.841	5.47e-06
$IPCA_1$	0.27404	0.09815	2.792	0.00642
$DExchange_5$	3.21674	1.77949	1.808	0.07407
$DSELIC_3$	0.19138	0.45579	0.420	0.67559
$DSELIC_4$	0.43347	0.47336	0.915	0.36261
$dUnemployment_1$	-0.35325	0.26696	-1.323	0.18918
$dUnemployment_7$	-0.82048	0.27853	-2.946	0.00412
		SupF	29.0425	0.003809
		AveF	10.5700	0.08826
		ExpF	11.5765	0.002138

Table 12: Forecast Analysis - Free and Monitored Prices

	Free	Prices	Monitored	Prices
Measure	Linear.	TVP-GARCH(1,1)	Linear	TVP-GARCH(1,1)
Root Mean Squared Error	0.5759	0.5775	1.315	1.5783
Mean Absolut Error	0.4368	0.4013	1.0004	1.1947
Theil Inequality	0.2668	0.1781	0.3013	0.3634
Bias Proportion	0.0026	0.0134	2.78e-05	7.94e-05
Variance Proportion	0.5792	0.0928	0.4114	0.0359
Covariance Proportion	0.4183	0.8938	0.5856	0.9640

constant parameters is enough for the series of monitored prices corroborate the hypothesis that the inflationary inertia is caused by the agents's behavior with power of price formation in the markets.

8 Conclusions

The article shows that there are evidences that point for a dynamics of time variation in the parameters for the behavior of the Brazilian inflation in the analyzed period. A model formulated in space state with a component to control the existence of conditional heteroscedasticity was estimated for one time variant regression among the index of measured inflation for IPCA, last IPCA and a series of control variables, showing that the component of inflationary inertia, given by the vector of parameters for the first lag of IPCA, can explain the behavior of the inflation in moments of economic uncertainty in Brazil.

Predictive analyses show that the inflation forecasts given by the model TVP-GARCH(1,1) are non biased and superior to the forecasts of the linear model. That is consistent with the fact that the tests of constancy of parameters and structural breaks, with unknown breakpoints, showed that there is some structural break related to the time variation in the parameters of the model for IPCA, which makes the forecasts of the linear model, that maintain the parameters fixed, to be biased and with mean squared and absolute errors superior compared to the models TVP-GARCH(1,1), that allow the adaptation of the parameters.

The model shows that two moments of great increase of the inflationary inertia are related to the periods of crisis and uncertainty in Brazilian economy. The first moment is after the exchange rate crisis of 1999, and the second moment is related to the presidential election in 2002. The behavior of the inflationary inertia can explain the acceleration of the inflation in these periods, consistent with the interpretations related with Inertial Inflation hypothesis.

We tested the hypothesis that there is a positive relationship among the uncertainty in the inflation index and the volatility of past inflation. The test, accomplished through a simple regression between the present inflation and the past volatility of the inflation index, indicates that the hypothesis that the economic agents which formulate prices react to the uncertainty in the inflation index with positive readjustment of prices is justified by the data.

The decomposing of the component of inflationary inertia, through the separated estimate for the free and monitored prices, shows that we can identify the component of inflationary inertia as caused directly by the behavior of the free prices, that show an inertia component similar to the one shown by the series of total IPCA, while the inertia component in the series of monitored prices tends to stabilize in time and can be appropriately modeled as a time inavariant parameter.

Appendix

GARCH Models

Engle (1982) ARCH model applied to a time-fixed parameters process defines the conditional volatility behavior of a series as a linear function of square shocks which occurred in the past of the series. We can represent the behavior of the mean of the series as:

$$y_t = X\beta + \varepsilon_t \tag{28}$$

$$\varepsilon_t = z_t\sqrt{h_t} \tag{29}$$

where X is a matrix of explicative variables, which can include lags of y_t. The process is IID Normal (identically and independently distributed) with zero mean and unitary variance. A process ARCH (1) is represented as:

$$h_t = w + \alpha_1\varepsilon_{t-1}^2 \tag{30}$$

where h_t represents the conditional variance of the series in moment t. That all the realizations of h_t be not negative is a necessary condition, which requires that w be greater than 0 and that α_1 be ≥ 0. If α_1 is 0, the model is conditionally homoscedastic.

The representation 30 shows that the model ARCH captures volatility groupings, due to the fact that shock ε_t is increasing function of previous shock ε_{t-1}^2.

Model ARCH (1) can be generalized to a general form ARCH (q) represented as:

$$h_t = w + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + ... + \alpha_3\varepsilon_{t-q}^2 \tag{31}$$

where the unconditional variance σ^2 is defined by:

$$\sigma^2 = \frac{w}{1 - \alpha_1 - \alpha_2 - ... - \alpha_q}$$

The model will be stationary covariance if all the roots of polynomial 1-$\alpha_1 L - \alpha_2 L^2 - ... - \alpha_q L^q$ are out of the unit circle, which is equivalent to say that shocks do not have permanent effects, and there is a reversion to the mean in the volatility.

It is common the necessity of a representation with a high q value in model ARCH to properly represent the volatility existing in financial series. Bollerslev (1986) suggested a general formulation, known as GARCH (Generalized ARCH), which is a generalization of model ARCH, to include lags of h_t in 31. Model GARCH (1,1) is represented as:

$$h_t = w + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{32}$$

The positivity conditions are that w and α_1 ¿ 0 and $\beta_1 \geq 0$.This representation avoids the necessity of many lags of ε_t , which we can notice if 32 is written as:

$$h_t = w + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 (w + \alpha_1 \varepsilon_{t-2}^2 + \beta_1 h_{t-2}) \tag{33}$$

Continuing this recursion we reach:

$$h_t = \sum_{i=1}^{\infty} \beta^i w + \alpha_1 \sum_{i=1}^{\infty} \beta_i^{i-1} \varepsilon_{t-i}^2 \tag{34}$$

Representation 34 corresponds to a model $ARCH(\infty)$ for ε_t^2. Adding ε_t^2in both sides of 32 and moving the term h_t to the right side of the equation, model GARCH (1,1) can be written as a model ARMA (1,1) to ε_t^2:

$$\varepsilon_t^2 = w + (\alpha_1 + \beta_1) \varepsilon_{t-1}^2 + v_t - \beta_1 v_{t-1} \tag{35}$$

where $v_t = \varepsilon_t^2 - h_t$. The process defined in 35 to ε_t^2 be stationary covariance if $\alpha_1 + \beta_1 < 0$.

We defined the unconditional variance of ε_t as:

$$\sigma^2 = \frac{w}{1 - \alpha_1 - \beta_1} \tag{36}$$

An important characteristic derived by Bollerslev (1986) is that the autocorrelations of ε_t are given by:

$$\rho_\varepsilon = (\alpha_1 + \beta_1)^{k-1} \rho_1 \tag{37}$$

that is, the correlations exponentially decline, but in the factor of $\alpha_1 + \beta_1$. When $\alpha_1 + \beta_1$ is close to one, the decline is very slow, as it occurs in the autoregressive model with unit roots.

In the same way that the model ARCH (1) can be generalized to a process ARCH(q), we can generalize a process GARCH (1,1) to a process GARCH (p,q) given by:

$$h_t = w + \sum_{i=1}^{q} \varepsilon_{t-i}^2 + \sum_{i=1}^{p} h_{t-i} \tag{38}$$

Although the estimation of models GARCH of order greater than (1,1) is trivial, the most employed specification is the one of a GARCH (1,1); this seems to be the most adequate formula in practice, according to Bollerslev, Chou and Kroner (1992).

Block Bootstrap

To obtain the confidence interval for the hyperparameters estimated by the model TVP, we used the bootstrap methodology. The bootstrap method, introduced by Efron (1979) is a non-parametric method which consists of treating the available sample as the population, and from consecutive resampling of this sample, obtaining the distribution of the estimators or test statistics. Due to the need of very little restrictive regularity conditions, the bootstrap method allows accurate close estimate of the distributions in finite samples.

The bootstrap algorithm can be described in the following way. Having a sample χ_n with units $\{X_1, X_2, ...X_n\}$, we construct a new sample from this sample, with M-sized reposition, in which M is usually equal to the sample original size, which we denoted as χ_n^*=$\{X_1^*, X_2^*, ...X_n^*\}$. The units of χ_n^* conditioned to χ_n are IID random variables with probabilities given by:

$$P_*(X_1^* = X_i) = \frac{1}{n}$$

For each replication χ_n^* of the bootstrap, we calculate the value of the estimators of interest. Replicating this process many times we obtain empirical distribution of the estimators, which is easily visualized by a histogram. Two usual ways of obtaining confidence intervals from the estimators using this method are the percentile bootstrap, in which we fixed the confidence intervals such as percentiles ($\alpha/2$) e (1-$\alpha/2$) of the estimators empirical distribution, and the bootstrap-t method, in which the estimators confidence interval will be given by the estimator value around the percentiles ($\alpha/2$) e (1-$\alpha/2$) of the bootstrap estimators empirical distribution multiplied by the estimators standard deviation calculated using the original sample.

However the main condition for the validity of the ordinary method of bootstrap is that data of the original sample be from an independent process, since the resampling process for the construction of the bootstrap sample is independent too. In the case of data with some structure of dependence, the ordinary method of bootstrap is inadequate, since the bootstrap samples do not reproduce the structure of existent dependence in the original sample of the data. When the bootstrap is applied to a dependent process, the variance of the bootstrap estimator does not converge to the real variance of the estimator, causing it to be an inconsistent estimator, as shown initially by Singh (1981). In the case of time series, the bootstrap method is inadequate for the destruction of the whole structure of temporal dependence existing in data generating process.

To apply the bootstrap method to dependent processes, we should modify the procedure of resampling in order to reproduce the process of existent dependence in the data. Knsh (1989) and Liu and Singh (1992) independently proposed the procedure known as bootstrap in moving blocks, or block bootstrap. The idea of the block bootstrap is, instead of taking observations in an independent way, to remove consecutive blocks observations from the data original sample. Consequently, the bootstrap samples would reproduce the structure of dependence of the series, allowing the obtaining of correct distributions to the estimators in the presence of dependence. When the process is weakly dependent, the size of the blocks should increase with the size of the sample and the bootstrap should asymptotically reproduce the structure of original time dependence.

There are some distinctive ways of accomplishing the procedure of choice of the blocks. The simplest way is to choose size-fixed blocks and allow the overlay of the blocks. The bootstrap proposed by Carlstein (1986) is composed of blocks with no overlay. These two procedures are asymptotically equivalent. One problem of these methods is that they suffer from a border problem - the observations closest to the beginning or the end of the series have smaller probability of being included in the bootstrap samples. Politis and Romano (1992) proposed two ways of solving the problem - the circular block bootstrap method and the stationary bootstrap method. In the circular block bootstrap the data are placed in a circular way, allowing the end of the series to be connected to the beginning of the series, therefore attributing the same weight to the borders in the resampling process. The stationary bootstrap is equally formulated, but in that case the block size is a random variable[9].

An additional problem is how to choose the mean size of the blocks used in the stationary bootstrap method, once the bootstrap performance critically depends on the size of the used block. To select the optimum size, we used the methodology proposed by Politis and White (2004). According to this methodology, the mean size for the blocks used in the stationary bootstrap is of 5 observations.

[9] For further definitions and properties of the bootstrap methods for dependent processes, see Lahiri (2003), especially pgs. 34-36 for the properties of the stationary boostrap.

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